Household Activity-Travel Behavior

TOWARD AN OPERATIONAL MODEL OF DAILY HOUSEHOLD ACTIVITY-TRAVEL BEHAVIOR

By

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Abstract

Since the late 1970s, the rapidly expanding literature subsumed under the activity-based paradigm has increased significantly our understanding of urban travel behavior and provided insights into new approaches to replace current models of urban travel demand—namely, the Urban Transportation Modeling System. A basic tenet of this paradigm is that decision-making occurs in a household context, taking into account interactions among household members. This differs, however, from the reality of activity-based research to date. With few exceptions, the decision-making unit in both empirical studies and modeling efforts is the individual, not the household.

In this dissertation, it is argued that there is a need to develop activity-based travel demand forecasting models at the household level. To this end, a conceptual framework is proposed for modeling daily household activity-travel behavior. This framework is developed for the heads of five common household types and consists of two modules: *Activity-Episode Generation* and *Activity-Episode Scheduling*. The statistical models underlying the former module are discussed and estimated using data from a trip diary survey conducted in the Greater Toronto Area in 1987. The Activity-Episode Generation module is then implemented as an object-oriented simulation model. This model is used to evaluate the effects of a large-scale adoption of the compressed workweek on the daily number of out-of-home activity episodes for the heads of households in the Greater Toronto Area in 1986.

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Preface

The four substantive chapters of this dissertation (i.e. Chapters 2 to 5) are papers that have been prepared with the intention of submitting them to journals for publication. For this reason, there is some degree of repetition among the chapters, particularly in their introductions. Furthermore, all four papers are co-authored by Dr. Pavlos Kanaroglou and myself with Dr. Kanaroglou assuming an editorial role in their preparation. In other words, the content of this dissertation is my own. The destinations for the papers are as follows:

Chapter 2: Activity-Based Travel Analysis: A Review
Prepared for submission to *Journal of Transport Geography*

Chapter 3: Modeling Daily Household Activity-Travel Behavior: A Conceptual Framework
Prepared for submission to *Transportation*

Chapter 4: Household Activity-Episode Generation: Empirical Analysis
Submitted to *Transportation Research B*

Chapter 5: Household Activity-Episode Generation: An Object-Oriented Simulation Model
Prepared for submission to *Computers, Environment and Urban Systems*

1 Introduction

1.1 Justification of Research Topic

Since the late 1970s, the rapidly expanding literature subsumed under the activity-based paradigm has increased significantly our understanding of urban travel behavior and provided insights into new approaches to replace current models of urban travel demand—namely, the Urban Transportation Modeling System (UTMS). Unlike trip-based approaches, the activity-based paradigm, more commonly known as *activity analysis*, recognizes explicitly that travel is a demand derived from the need to participate in out-of-home activities. In other words, discrete activities or patterns of activities are investigated, not trips. Jones *et al.* (1990) identify several features of the paradigm including recognition that decision-making occurs in a household context, taking into account interactions among household members. This differs, however, from the reality of activity-based research to date.

With few exceptions, the decision-making unit in both empirical studies and modeling efforts is the individual, not the household. This does not mean that the household is excluded from such research. In fact, most empirical investigations recognize the importance of household attributes in defining an individual's activity-travel behavior. For example, the presence of children in the household has long been identified as an important constraint on such behavior and is, therefore, included as an explanatory variable in many studies (e.g. Bhat 1997, 1998a; Damm and Lerman 1981; Kitamura and Kermanshah 1983; Niemeier and Morita 1996). In the very few instances where the decision-making unit is the household, the sum of household activities is typically investigated, ignoring interactions among household members. Strathman *et al.* (1994), for example, examine how household structure and other factors affect a household's allocation of non-work activities to alternative types of trip chains. In terms of operational activity-based forecasting models, only Wen and Koppelman's (1998, 1999) model is developed at the household level, accounting explicitly for interactions among household members. Models that require an activity agenda, such as STARCHILD (Recker *et al.* 1986a, 1986b), SMASH (Ettema *et al.* 1993, 1996) and SCHEDULER (Gärling *et al.* 1989, 1998; Golledge *et al.* 1994), can, however, account implicitly for household interactions by altering agenda attributes.

The conscious disregard for household decision-making in activity-based research to date is largely a pragmatic artifact of the past. Heggie and Jones (1978) identify four domains applicable to the classification of most activity-based studies based on assumptions concerning the decision-making process underlying travel—namely, (1) independence, (2) spatio-temporal linkages, (3) inter-personal linkages and (4) full interdependence. As noted by the authors, incorporating household interactions explicitly into research (Domains 3 and 4) is not only more realistic than assuming an individual makes activity-travel decisions independently (Domains 1 and 2), but is exceedingly difficult to do. This problem does not appear to be conceptual given the inclusion of the household in the frameworks underlying several operational and proposed activity-based forecasting models (Gärling *et al.* 1989; Recker *et al.* 1986a; Stopher *et al.* 1996; Wen and Koppelman 1998). It does, however, appear to be methodological because the statistical tools available for such a complex treatment of activity-travel behavior are virtually nonexistent[1]. The lack of such tools is related directly to available computer technology. In other words, computer technology largely defines the boundaries of activity-based research, not to mention that of other fields. This is why such research to date has been mostly confined to Domains 1 and 2 in Heggie and Jones' (1978) classification. It has only been in very recent years that computer technology has improved to the point where researchers can develop and apply advanced statistical tools in activity-based studies (e.g. Bhat 1997, 1998a). Since such technology is no longer the impediment that it once was to research, the onus is now on researchers to develop statistical tools capable of analyzing the activity-travel behavior of households while accounting for interactions among household members. This comes at a time when the need to explicitly recognize the household as the primary decision-making unit in activity-based research has never been greater.

In the industrialized world, transport is responsible for a large share of harmful environmental emissions of which the vast majority is from motor vehicles[2], particularly the automobile (OECD 1997a). In terms of amount, however, three trends are evident. First, transport emissions of several air pollutants have been decreasing in some

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[1] Notable exceptions include structural equations models (Golob and McNally 1997) and nested logit models (Wen and Koppelman 1999).
[2] Major air pollutants emitted by motor vehicles include carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxides (NO_x), particulate matter (PM) and volatile organic compounds (VOC) (OECD 1997b).

industrialized countries since the late 1970s and early 1980s. In the United States, for example, carbon monoxide (CO), particulate matter (PM) and volatile organic compounds (VOC) have all declined despite an increase in vehicle-miles traveled (VMT)[3]. Second, transport emissions of carbon dioxide (CO_2), the primary greenhouse gas emitted by human activities, continue to increase in all industrialized nations as transport maintains its reliance on fossil fuels. Finally, in recent years, nitrogen oxides (NO_x) appear to have leveled off in some countries.

To date, the approach taken in most industrialized countries to reduce air pollution from transport has been to incite improvements in vehicle technologies by introducing or tightening vehicle emissions standards (OECD 1997b). These technologies either control emissions directly, such as catalytic converters[4], or improve vehicle fuel efficiency[5]. There is, however, growing concern that any gains made in reducing transport emissions of air pollutants will be reversed in the future for the following reasons (OECD 1997b; USDOT BTS 1998). First, vehicle fuel efficiency has remained virtually unchanged since the mid-1980s (OECD 1997b; USEPA OP 1999; USDOT BTS 1998). This means that future reductions in transport emissions from vehicle stock turnover will be almost nonexistent as the average fuel efficiency of the on-road fleet approaches that of new

[3] Between 1980 and 1996, VMT grew from 1.53 to 2.48 trillion in the United States for an increase of 63 percent (USDOT BTS 1998).
[4] The use of catalytic converters, which is now mandatory in North America and much of Europe, actually increases CO_2 emissions.
[5] Vehicle technologies that improve fuel efficiency, such as reduced vehicle weight, fuel injection and improved aerodynamics, generally reduce air pollutant emissions. However, there are some exceptions to this. For example, the use of higher air-fuel ratios and combustion temperatures actually increase NO_x emissions.

vehicles[6]. Second, the increasing popularity of less fuel-efficient light-duty trucks and sport utility vehicles, especially in North America, suggests the possibility that the average fuel efficiency of the on-road fleet may decline, thereby increasing emissions. In the United States, for example, such vehicles accounted for 40 percent of the light-duty vehicle market in 1997, up from 10 percent in 1979 (USDOT BTS 1998). Moreover, their average fuel efficiency was 20.4 miles per gallon (mpg) as opposed to 28.5 mpg for automobiles (USDOT BTS 1998). Third, vehicular traffic continues to grow in all industrialized nations without any sign of leveling off (OECD 1997b). Eventually, this alone will offset any improvements in air quality from transport. More importantly, however, such growth will lead to more congestion in the absence of increased network capacity. In turn, emissions of several air pollutants will rise[7].

The realization that technology alone will be unable to maintain, let alone further reduce transport emissions in the future has prompted many industrialized nations to consider using travel demand management (TDM), which consists of strategies that influence the demand for vehicular travel. Such measures are increasingly necessary if these countries are to meet reductions in air pollutants set out in international agreements such as the 1997 Kyoto Protocol to the United Nations Framework Convention on

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[6] In the United States, the average fuel efficiency of on-road automobiles increased from 13.8 miles per gallon (mpg) in 1976 to 21.2 mpg in 1991, for an average annual improvement rate of 3.6 percent per year. In contrast, from 1991 to 1996, this rate decreased to 0.1 percent per year as mpg increased to only 21.3 (USDOT FHWA 1997).

[7] Driving characteristics play an important role in emissions of air pollutants. Specifically, CO, CO_2, PM and VOC emissions are highest when a vehicle is accelerating, decelerating or idling. Such conditions are synonymous with congestion. In contrast, NO_x emissions increase with speed.

Climate Change[8]. In the United States, the 1990 Clean Air Act Amendments (CAAA) set the stage for achieving such goals by emphasizing the role of TDM strategies in meeting mandated reductions in transport emissions. In turn, these amendments were the major motivation behind the Travel Model Improvement Program (TMIP), which is the most ambitious undertaking to date to replace current models of urban travel demand with those that are policy sensitive, and therefore, capable of evaluating such strategies.

Under this program, activity-based replacements are favored (Barrett *et al.* 1995; Spear 1996). Moreover, to meet expectations concerning the accuracy and reliability of forecasts, it is imperative that such models be developed at the household level, taking into account interactions among household members. Two reasons are suggested for this. First, individual-level models are incapable of handling complex responses to TDM strategies. For example, a person who performs an activity during the evening commute may forgo the activity when working a compressed workweek. This response obviously favors the alternative work-schedule strategy. However, the individual-level model does not consider that this activity may be reassigned to another household member who also undertakes it after work. In this case, the TDM strategy would prove ineffective in reducing travel demand. Second, such models do not account for joint out-of-home activities—namely, activities in which more than one household member participates. This means that predictions of activity-travel behavior are likely to be inaccurate. For

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[8] In this agreement, industrialized nations consented to reduce greenhouse gas emissions, notably CO_2, to five percent less than 1990 levels by 2008 to 2012.

example, multiple out-of-home activities may be predicted for household members when, in fact, only one exists.

1.2 Scope of Research Topic

The need to explicitly recognize the household as the primary decision-making unit in activity-based research is the fundamental motivation for this dissertation. Specifically, the research topic investigated concerns the development of a daily model of household activity-travel behavior that captures explicitly interactions among household members. Obviously, such a task is an enormous undertaking. For this reason, the scope of the research is narrowly defined, consisting of four objectives. First, activity-based research is reviewed. This includes both empirical findings and modeling efforts. Second, a conceptual framework for modeling daily household activity-travel behavior is developed for five common household types: single, non-worker; single-worker; couple, non-worker; couple, one-worker; and couple, two-worker households. Third, the statistical models underlying the *Activity-Episode Generation* module of the conceptual framework are estimated. Finally, this module is implemented as an object-oriented simulation model and is used to evaluate the impacts of a specific TDM strategy (i.e. large-scale adoption of a compressed workweek). Details concerning each of these objectives are found in the following section.

1.3 Contents of Dissertation

Chapter 2 reviews the progress of activity-based research to date. It differs from previous reviews in terms of its emphasis on activity-based models that have been developed to predict activity-travel behavior for a one-day period. These models are classified as utility-maximization models, computational process models and microsimulation models. In recent years, the number of activity-based models have increased given the fact that under TMIP such models are favored as replacements for UTMS (Barrett *et al.* 1995; Spear 1996). For the sake of completeness, however, this chapter also summarizes empirical findings from activity-based research. These findings are classified according to the unit or process investigated: activity-travel patterns, activity-time allocation, activity episodes and activity scheduling.

In Chapter 3, it is argued that activity-based travel demand forecasting models be developed that are capable of generating and scheduling activities—a sentiment that is shared by others (e.g. Bhat and Koppleman 1999). Moreover, these models must be developed at the household level, taking into account interactions among household members. To this end, a comprehensive conceptual framework for modeling daily household activity-travel behavior is proposed. Besides being developed at the household level, this framework is distinguished from those underlying the activity-based models reviewed in Chapter 2 by three features. First, it is developed for the heads of five common household types. Second, interactions between household heads are captured explicitly in the modeling framework for three of the household types. Finally, two activity settings are recognized: independent and joint activities. Such activities are generated by the *Activity-Episode Generation* module and scheduled by *the Activity-Episode Scheduling* module.

Chapter 4 presents the empirical findings for the models underlying the Activity-Episode Generation module of the conceptual framework. Specifically, the daily number of out-of-home activity episodes[9] for non-work purposes is modeled for the heads of the five household types. To capture interactions between such household members, a joint model is developed, which accounts for both independent and joint activity episodes. This model is applied to three of the five household types. A comparison of the results with those obtained from models that ignore household interactions suggests that daily activity episodes are determined jointly by household members.

The Activity-Episode Generation module is implemented, using C++, as an object-oriented simulation model. This is the topic of Chapter 5. Specifically, this chapter has two objectives. First, an overview of object-oriented modeling (OOM) is provided, including reasons for its use in computer simulation modeling besides its role as a common modeling language for researchers. Moreover, the Activity-Episode Generation model is used to demonstrate the concepts discussed. Second, this model is employed to evaluate the impact of a TDM strategy on the daily number of out-of-home activity episodes estimated for household heads in the Greater Toronto Area (GTA) in 1986. Specifically, the effects of a compressed workweek are evaluated for two scenarios. The first scenario assumes that all full-time workers adopting the strategy work a 10-hour day,

[9] An activity episode is a period of time characterized by a uniform purpose and spatial setting.

whereas the second scenario applies to their day off. The simulation results demonstrate that the impact of the latter scenario is much greater than the former.

Finally, Chapter 6 discusses the major findings of this body of work and suggests directions for future research.

2 Activity-Based Travel Analysis: A Review

2.1 Introduction

In the late 1970s, travel behavior research entered a new paradigm. Activity-based travel analysis, more commonly known as *activity analysis,* seeks an understanding of travel behavior by recognizing explicitly that travel is a demand derived from the need to participate in out-of-home activities. In other words, discrete activities or patterns of activities are investigated, not trips. Since that time, the rapidly expanding literature subsumed under the paradigm has increased significantly our understanding of travel behavior and provided insights into new approaches to replace current models of urban travel demand—namely, the Urban Transportation Modeling System (UTMS). Several reviews of activity-based travel analysis have been written at various times in the past 20 years, summarizing the state-of-the-art in such research (Bhat and Koppelman 1999; Damm 1983; Ettema and Timmermans 1997a; Fox 1995; Jones *et al.* 1990; Kitamura 1988). Furthermore, the proliferation of activity-based research in recent years has led to the publication of several books on the subject (Ettema and Timmermans 1997b; Gärling *et al.* 1998; Jones 1990; Stopher and Lee-Gosselin 1996).

This chapter reviews the progress of activity-based research to date. It differs from previous reviews in terms of its emphasis on activity-based models that have been developed to predict activity-travel behavior for a one-day period. These models are classified as utility-maximization models, computational process models or empirical microsimulation models. In recent years, the number of activity-based models have increased given the fact that under the Travel Model Improvement Program (TMIP) such models are favored as replacements for UTMS (Barrett *et al.* 1995; Spear 1996). For the sake of completeness, however, this chapter also summarizes empirical findings from activity-based research. These findings are classified according to the unit or process investigated: activity-travel patterns, activity-time allocation, activity episodes and activity scheduling.

The remainder of this chapter is organized as follows. The next section reviews briefly empirical findings from activity-based research. Activity-based models are discussed thoroughly in the third section. Finally, the contributions of this chapter to activity-based research are summarized in the final section.

2.2 Empirical Findings

2.2.1.1 Activity-Travel Patterns

Much activity-based research has focused on *activity-travel patterns*. Although the conceptualization of an activity-travel pattern is consistent among studies, researchers have used a variety of methods, which vary in complexity, to classify such patterns. In this chapter, an activity-travel pattern is defined as a sequence of out-of-home activities undertaken over a period of time, such as a period of the day or the day itself. Two themes have emerged from this line of research: classification of activity-travel patterns and their association with explanatory factors, and variability in activity-travel patterns over time.

Household lifecycle has played an important role in activity-based research because of the complex constraints that children impose on the activity-travel patterns of adults. Kostyniuk and Kitamura (1982) examined the impact of this factor, along with household work-trip status and household role, on the evening activity-travel patterns of adult household members. Such patterns were classified according to whether they were made independently or jointly by household adults. The findings suggest that household lifecycle stage is related to several aspects of the evening activity-travel patterns of adults, particularly their type—that is, whether or not adults participate in out-of-home activities in the evening, and if so, whether such activities are undertaken alone or together. Pas (1984) reports similar findings regarding the role of lifecycle on the daily activity-travel patterns of individuals.

Several researchers have investigated variability in activity-travel patterns over time. Hanson and Huff (1982, 1988) and Huff and Hanson (1986) used the Uppsala, Sweden Household Travel Survey to investigate the activity-travel behavior of a sample of individuals over a 35-day period. Their findings suggest that both repetition and variability characterize the activity-travel patterns of individuals. However, the most important finding is that individuals exhibit more than one characteristic daily pattern. In related research, Pas and Koppelman (1986) investigated the determinants of day-to-day variability in the activity-travel behavior of individuals. Their findings indicate that individuals who have fewer household and employment-related constraints exhibit more day-to-day variability in their activity-travel patterns. The work of Pas and Sundar (1995) support these earlier findings.

2.2.1.2 Activity-Time Allocation

Activity analysis adds a temporal dimension to travel behavior research. Two areas have been investigated in this regard: the amount of time spent pursuing particular activity types over a period of time such as a day, and the duration of a particular activity episode. The former area of research concerns *activity-time allocation*, whereas the latter concerns activity episodes.

Many researchers have attempted to explain individuals' daily allocation of time to different activities (e.g. Becker 1965; Kitamura 1984a; Levinson and Kumar 1995). Others have investigated individuals' time allocation over longer periods (Golob and McNally 1997; Kumar and Levinson 1995). In these investigations, the activities are first classified. A common classification scheme is between mandatory and discretionary activities, which is most often a difference between work and non-work activities. For example, Kitamura (1984a) examined workers' out-of-home activity time allocation for non-work activities. The results indicate that auto-oriented individuals with a driver's license, more autos per driver and auto as the work-trip mode, tend to allocate more time to non-work activities. In contrast, work duration decreases the amount of time allocated to non-work activities.

Another classification scheme employed by Golob and McNally (1997) consisted of three activity types: work, maintenance and discretionary activities. This study is particularly insightful because it considers interactions between husbands and wives. The findings indicate that the amount of time allocated to out-of-home activities exhibits a hierarchy for both men and women—that is, work negatively affects the amount of time allocated to the other activity types and maintenance activity negatively affects the amount of time allocated to discretionary activity.

2.2.1.3 Activity Episodes

An *activity episode* is defined as a period of time characterized by a uniform purpose and spatial setting. Over the course of a day, an individual participates in many activity episodes both in-home and out-of-home. For the most part, researchers have focused on out-of-home activity episodes because they are the ones that generate travel. Moreover, researchers have investigated many attributes of activity episodes including activity choice (e.g. Kitamura and Kermanshah 1983), duration (e.g. Bhat 1996a, 1996b; Ettema *et al.* 1995; Niemeier and Morita 1996), destination choice (e.g. Kitamura 1984b; Miller and O'Kelly 1983) and sequencing (e.g. Kitamura 1983; Kostyniuk and Kitamura 1984; O'Kelly and Miller 1984; Strathman *et al.* 1994). As well, some researchers have investigated several attributes jointly such as activity choice and duration (e.g. Bhat 1998a; Damm 1980, 1982; Damm and Lerman 1981), activity choice and destination (e.g. Kitamura and Kermanshah 1984), activity choice and home-stay duration (e.g. Mannering *et al.* 1994) and mode choice and number of episodes (e.g. Bhat 1997). Finally, some researchers have reported results for several attributes that are investigated sequentially (e.g. Hamed and Mannering 1993; Kitamura *et al.* 1997).

Kitamura and Kermanshah (1983) identified time-of-day and history dependencies of activity choice. For both home-based and non-home-based choice, time-of-day has a significant influence on activity engagement. History dependence has a more complex representation. Whether an individual has pursued an activity in the past influences his or her present activity choice in the home-based case. However, in the non-home-based case, only activities pursued during the current trip chain (i.e. a sequence of out-of-home activity episodes that begin and end at home) influence activity choice. These findings are supported by later work (Kitamura *et al.* 1997).

Hazard modeling is the main analytical tool used by researchers to investigate the duration of activity episodes. With the exception of work by Ettema *et al.* (1995), the factors investigated are those that can be obtained from either trip or activity diaries. Ettema *et al.* (1995) investigated factors that describe the process of activity scheduling, which is the subject of the next section. Their findings indicate that the time of day when an activity episode begins influences its duration. As well, factors such as the opening and closing times of activity sites and the priority that individuals assign to activity types influence activity episode duration. Similar to the findings for activity choice, the time spent in the same activity in the past influences its current duration.

A considerable body of literature has developed concerning trip chaining (see Thill and Thomas [1987] for a review). This literature is related to activity analysis in that it concerns sequencing tendencies for out-of-home activity episodes. Kitamura (1983) found that there exists a consistent hierarchical order in activity sequencing in that activities, which are less flexible, tend to be pursued first. Strathman *et al.* (1994) show that the likelihood of forming complex commuting chains is higher for women, people who drive alone to work and workers from high-income households. Furthermore, commuting during peak periods (i.e. morning and evening rush hours) shifts non-work activities away from the work commute. Household type is also shown to influence the propensity to form complex commuting chains with single working adults with preschool children having the highest propensity.

2.2.1.4 Activity Scheduling

Activity scheduling describes the process concerned with the explicit timing, sequencing, activity choice, duration, location and mode associated with all activity episodes engaged in over a particular period of time such as a day or a week. This process has received increasing attention in recent years as researchers attempt to develop models of all-day activity-travel behavior. Some researchers have investigated activity scheduling as a planning process, whereby individuals plan activities that they will undertake over the course of a day or a week (e.g. Doherty and Miller 1997; Ettema *et al.* 1994; Hayes-Roth and Hayes-Roth 1979). The primary reason for such research is to identify heuristics that individuals use when scheduling their daily or weekly activities. For example, Ettema *et al.* (1994) show that individuals plan activities in the order in which they are to be executed. Moreover, the choice of activities, their location and sequence are found to be affected by the priorities that individuals assign them, as well as their duration, possible start and end times and travel times between locations.

2.3 Activity-Based Models

2.3.1 Utility-Maximization Models

2.3.1.1 Definition

As mentioned at the outset of this chapter, activity-based models of all-day travel behavior can be classified as utility-maximization models, computational process models or empirical microsimulation models. Utility-maximization models are based on the specification of a utility function for the postulated choice process underlying daily activity-travel behavior. In all cases, such models are operationalized as nested logit models. Given the complexity of daily activity-travel behavior, the choice process is simplified to obtain models that can be readily estimated. Furthermore, use of the nested logit model assumes that the choice process is hierarchical.

2.3.1.2 Kawakami and Isobe's Model

Kawakami and Isobe (1990) developed the first utility-maximization model of daily activity-travel behavior. Recognizing that the decision-making process underlying such behavior is exceedingly complex, they made two simplifying assumptions to obtain an operational model. First, they assume that the decision-making process underlying daily activity-travel behavior can be converted to one involving a choice between activity-travel patterns. Second, they limit their model to workers because the existence of work activity means that an individual's daily schedule can be divided into two branches: one before work and the other after work.

Given these assumptions, a worker's daily activity-travel behavior is conceptualized as resulting from a hierarchical choice process for each branch. At the first level, the worker decides whether to participate in discretionary activities (i.e. non-work activities). At the second level, an activity-travel pattern is chosen. Finally, at the third level, a destination is selected for the first activity in the pattern only despite the fact that some patterns contain two destinations. This implies that such activities must occur within the same zone.

By analyzing the behavior of a sample of workers from Nagoya, Japan, Kawakami and Isobe identify four activity-travel patterns for the morning branch and seven for the evening branch. The patterns for each branch are distinguished from one another by the number of discretionary activities they contain (i.e. one or two) and by the frequency of temporarily returning home. By combining both sets of patterns, workers can choose between 28 alternatives.

The primary problem with Kawakami and Isobe's model is that the two branches exist independently of one another. In reality, however, such behavior is interdependent (Kitamura and Kermanshah 1983). Furthermore, the model is of limited use in predicting the explicit timing of activities throughout the day given its crude conceptualization of time.

2.3.1.3 Ben-Akiva and Bowman's Model

Unlike Kawakami and Isobe (1990), Ben-Akiva and Bowman (1995; Ben-Akiva *et al.* 1996) assume that an individual's daily activity-travel behavior can be decomposed into a set of home-based tours that are tied together by the choice of a daily activity pattern.

Specifically, their model is based on a series of hierarchical decisions, which are: choice of a daily activity pattern, choice of the primary tour time of day, choice of the primary tour destination and mode, choice of the time of day for secondary tours and choice of the destination and mode for secondary tours.

The first decision in their model system is decomposed into three choices. The first choice is for the primary activity of the day. The alternatives for this decision are: home, work, school and other. The second choice involves the type of tour for the day's primary activity, which is defined by the number, purpose and sequence of activity stops. For example, Ben-Akiva and Bowman identify five such tours for work, including Home-Work-Home (HWH) and Home-Work-Other-Work-Home (HWOWH). Finally, the third choice is for the number and purpose of secondary tours, which are defined as additional home-based tours made for the purpose of lower priority activities. Two purposes (i.e. time constrained and not time constrained) and three frequencies (i.e. 0, 1 and 2+) are identified, yielding a total of six alternatives for this decision. As a result of the decomposition, the daily activity pattern choice set for workers consists of 55 alternatives, including the choice to remain home all day. Only 25 alternatives are identified for non-workers.

For the time-of-day choices, Ben-Akiva and Bowman first divide the day into four periods: AM peak, PM peak, afternoon and evening. These periods are then used to define 16 alternatives, each of which consist of one period for leaving home and one period for returning home. In the model, these alternatives define the timing of out-of-home activities. Furthermore, for the destination and mode choices, six alternatives are defined for mode choice: drive alone, shared ride, combined transit and auto, combined transit and walking, walking and bicycling.

Ben-Akiva and Bowman use a nested logit model to estimate the above decision structure using a sample of individuals obtained from a 1991 travel survey conducted in Boston. Furthermore, models are estimated separately for workers and non-workers. The model structure is attractive in that it recognizes explicitly interdependencies in activity-travel behavior throughout the day. In practice, however, the complexity of the model system limited the extent to which these interdependencies could be incorporated in the estimated model. Other shortcomings of the model include the fact that secondary destinations are excluded from tours and that only one model is estimated for secondary tour choices. Also, Ettema and Timmermans (1997a) note that the conceptualization of timing in the model is weak.

2.3.1.4 Wen and Koppelman's Model

Wen and Koppelman (1998, 1999) recognize explicitly that decisions underlying daily activity-travel behavior are made within a household context. Specifically, two sets of hierarchical decisions comprise their model, which is developed for married couples without other adults or older children (i.e. 13 years and older) present in the household. The first set of decisions is formulated at the household level. First, household members generate collectively the number of maintenance stops to be undertaken on a given day. Second, these stops are then assigned to husbands and wives. For example, if the household generates two stops, either the husband or wife can undertake both stops, or one stop can be undertaken by each. Finally, household vehicles are allocated to these members. This is defined in terms of the number of maintenance stops for which a vehicle is available. For example, if a wife is assigned two such stops, a vehicle may be available for one stop or two stops, or it may be entirely unavailable. Moreover, vehicle allocation is important only if the household has one vehicle.

The second set of decisions is formulated at the individual level and is conditional on the first set of decisions. For husband and wife, these choices include determining the number of home-based tours to be undertaken and assigning maintenance stops to these tours. In practice, however, husband and wife each choose an activity-travel pattern from one of two choice sets defined for workers and non-workers. The alternatives comprising each set emphasize the location of maintenance stops, if any, in the daily activity-travel pattern. Furthermore, leisure stops may be included in these patterns. The model is estimated using a nested logit model.

Wen and Koppelman's model is noteworthy in that it considers explicitly interactions between household members in terms of their daily activity-travel behavior. Moreover, the model represents an important first step in the development of future activity-based models at the household level. However, despite its unique features, the model has several shortcomings. First, it is limited to couples that do not engage in maintenance stops together, thereby ignoring joint activities. Second, although the nested logit model allows household decisions to be estimated simultaneously, it does not account for the ordinal nature of the first decision—that is, the number of out-of-home maintenance stops. Finally, the conceptualization of timing is very weak in the model.

2.3.2 Computational Process Models

2.3.2.1 Definition

A common feature of the preceding utility-maximization models is that they specify factors that influence daily activity-travel behavior. For this reason, they can be easily estimated using data from traditional trip and activity diaries. However, as noted by others (Gärling *et al.* 1994; Kwan and Golledge 1997), if the objective is to replicate the process that gives rise to observed behavior—namely, the *activity-scheduling* process—then an alternative modeling approach must be used. Specifically, computational process models are used for this task.

Computational process models are defined as production system models implemented as computer programs (Gärling *et al.* 1994). Newell and Simon (1972) developed production systems as models of human problem solving. In essence, a production system model is a set of rules in the form of condition-action pairs that specify how a problem is solved. For example, if a task requires an individual to choose an alternative from a choice set, the rules may specify what information is searched under different conditions. Production system models usually distinguish between a long-term memory (LTM) and a short-term memory (STM). The former contains information about the solution space, whereas the latter contains information about the solution path. Furthermore, a control mechanism is often specified to determine which rule is implemented if multiple conditions are met.

2.3.2.2 STARCHILD

STARCHILD (Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions) is generally acknowledged as the first operational model of daily activity-travel behavior (Kitamura 1988; McNally 1997). It is based on the theoretical framework discussed in Recker *et al.* (1986a), the highlights of which are as follows. To begin, the day is divided into two periods: a planning period and an action period. During the planning period, activities are generated by the household and allocated to members for completion during a specified time interval. These activities, along with their salient attributes, form an individual's daily activity program. Such programs are synonymous with the activity agendas of more recent modeling efforts. Specifically, each activity comprising the activity program has an expected duration and desired location. Furthermore, the activity program also contains potential unplanned activities. Through a set of activity scheduling rules, the activity program is transformed into a set of feasible activity-travel patterns. Recker *et al.* recognize that this set of patterns will undoubtedly be quite large. Moreover, an individual may not be able to discriminate between the patterns. To overcome this problem, the authors postulate that a classification reduction process operates on the opportunity set to produce distinct alternatives. It is from these alternatives that an individual selects an activity-travel pattern, which is a manifestation of activity-travel behavior during the action period.

STARCHILD is implemented as a series of five modules (Recker *et al.* 1986b). The first module is supposed to simulate interactive household forces that give rise to the activity programs of household members. In practice, however, the module is simply a data preparation routine that generates all required files for use by subsequent modules. For example, one such file, the Activity Program Data Array, contains an individual's activity program. In this file, each activity is described by its type, desired duration, preferred location and its spatial, temporal and transportation constraints.

The second module uses a constrained, combinatorial algorithm to generate a set of feasible activity-travel patterns for the activity program provided. Furthermore, the module assigns a mode to each home-based tour. This implies that each tour is completed using a single mode, and therefore, a change in mode can occur only at home. The set of feasible patterns is then reduced to a set of representative activity-travel patterns (RAPs) by the third module. The procedure underlying this module is based on earlier work (Recker *et al.* 1985; Pas 1982). From this set, the fourth module identifies a set of non-inferior RAPs. The reason for this is that the set generated by the third module is unlikely to be small enough for an individual to compare alternatives and choose the one that maximizes utility. Finally, the fifth module employs a multinomial logit model to choose an activity-travel pattern from the choice set of non-inferior RAPs.

Despite its comprehensiveness, STARCHILD has been criticized on many occasions. For example, Recker (1995) identifies four shortcomings of the model system. First, it provides no mechanism to accommodate household interactions. Instead, it models the activity-travel patterns of household members separately. Second, it relies on a heuristic solution procedure based on exhaustive enumeration and evaluation of all feasible solutions. Third, it treats time discretely and relies on pattern recognition algorithms to distinguish between simple temporal displacements of vastly similar solutions. Finally, STARCHILD has no provision for addressing either activity or vehicle allocation decisions in a household context or for considering complex mode choice decisions, such as ridesharing. Kwan and Golledge (1997) suggest that the weakest features of the model are its acceptance of utility-maximizing assumptions and its use of a combinatorial algorithm to evaluate all feasible activity-travel patterns. A further criticism is that STARCHILD does not model explicitly the duration and location of activities. In many respects, this shortcoming limits the model's usefulness in forecasting urban travel and predicting impacts from transportation-related policies.

2.3.2.3 SCHEDULER and GISICAS

SCHEDULER is based on the theory of activity scheduling proposed by Gärling *et al.* (1989). Furthermore, it is interfaced with a geographical information system (GIS) for reasons that are self-evident in the following discussion (Golledge *et al.* 1994). In essence, the model schedules a set of activities that are retrieved from an individual's long-term calendar (LTC). The LTC serves SCHEDULER in the same manner as an activity program serves STARCHILD—that is, it stores a list of activities, along with their salient attributes. However, in the case of the LTC, the attributes for each activity include its duration and priority. The set of activities selected for scheduling is based on these attributes.

Information concerning spatio-temporal constraints (i.e. feasible locations to perform activities and their opening hours) are obtained from a memory representation of the environment, which is known as the cognitive map (CMAP). The GIS provides factual information about the environment through buffering, overlaying and path selection operations. After such information is retrieved, SCHEDULER sequences the activities based on temporal constraints. Next, the location for each activity is selected, taking into account the temporal sequencing of activities. If there are no temporal constraints, the location choices are based on a nearest-neighbor heuristic. A detailed schedule in finally formed using all the information in the CMAP and in the LTC. At this point, conflicts may be noted. These are resolved by changing the original sequence of the activities that are in conflict. The final schedule is stored in the short-term calendar (STC), which guides the execution of activities.

Golledge *et al.* (1994) identify several shortcomings of the theoretical framework on which SCHEDULER is based. First, there are no guidelines on how priorities should be assigned to activities. Second, the opportunity sets for activity locations are defined arbitrarily. For example, in the case study discussed in Golledge *et al.* (1994), a 10-mile buffer zone was used to delineate locations. Finally, the nearest-neighbor heuristics is too simplistic. Given the arbitrary nature of its assumptions, the usefulness of SCHEDULER as a predictive model is questionable. Moreover, a predictive model should account endogenously for activity duration. SCHEDULER does not.

GISICAS (GIS-Interfaced Computational process model for Activity Scheduling) extends the SCHEDULER model in two ways (Kwan 1997; Kwan and Golledge 1997). First, an individual's home and work locations, as well as preferred and fixed destinations for non-work activities are included in the CMAP. Second, several new spatial search heuristics are incorporated in GISICAS to overcome the simplicity of the nearest-neighbor heuristic used in SCHEDULER. GISICAS is designed as a decision-support system for Advanced Travel Information Systems (ATIS), and is therefore, an interactive activity-scheduling model. For this reason, it is of limited use in predicting the daily activity-travel behavior of individuals.

2.3.2.4 SMASH

Ettema *et al.* (1993, 1996) developed SMASH (Simulation Model of Activity Scheduling Heuristics) to simulate the daily activity-scheduling process. Conceptually, the model is based on the theories of Root and Recker (1983) and Gärling *et al.* (1989). Furthermore, the latest version of SMASH integrates the attractive features of discrete-choice modeling and computational process modeling (Ettema *et al.* 1996). The following discussion is based on the latest version.

Like STARCHILD, SCHEDULER and GISICAS, SMASH requires an agenda as input. Specifically, the agenda contains 31 activities and the following information for each activity: its possible locations, the number of times per day it can be performed, the available time slots within which it can be performed at each location, how often it is performed, its duration, its priority and the last time it was performed. Furthermore, it is assumed that the travel times between each activity site are known.

The daily schedule is conceptualized as a sequence of activities performed at specific locations. The activity-scheduling process is depicted as the stepwise adaptation of the schedule by adding activities from the agenda. This differs from the previous version of SMASH, which incorporated two additional actions—namely, deleting an activity from the schedule and substituting an activity from the schedule with one from the agenda.

At each step of the activity-scheduling process, an individual must decide whether to stop the process or continue adding activities to the schedule. A two-tier nested logit model is used to represent this choice process. At the first level, the decision is whether to stop the scheduling process and accept the current state of the schedule as satisfactory or add another activity to the schedule. If the latter alternative is selected, a specific ADD operation must be chosen—that is, what activity is added, where does it take place and when does it take place.

Like STARCHILD, SCHEDULER and GISICAS, SMASH has limited potential in predicting urban travel demand and responses to transportation-related policies because of its reliance on an agenda. The model does, however, appear to replicate the activity-scheduling process in considerable detail.

2.3.2.5 AMOS

AMOS (Activity MObility Simulator) is unique in that it predicts changes in daily travel behavior that result from changes in the travel environment. A prototype of AMOS has been implemented for the Washington, D.C. metropolitan area to predict traveler responses to select travel demand management (TDM) strategies. Discussions of AMOS can be found in Kitamura *et al.* (1996), Kitamura and Fujii (1998) and RDC (1995).

Conceptually, AMOS works as follows. Given an initial activity-travel pattern, the model simulates an individual's adaptation process and finally determines how he/she will adapt to a new travel environment. However, before a behavioral change can occur, the individual must first recognize a change in the travel environment and perceive a need to modify his/her behavior. Given this, the search for a suitable modification begins with the identification of possible response options. Once the individual identifies a response, or a preferred set of responses, the options are executed until a suitable activity-travel pattern is established.

In practice, AMOS consists of four modules. The first module, the Baseline Activity-Travel Pattern Analyzer, generates a baseline activity-travel pattern for an individual from an observed pattern contained in trip records found in a travel diary. Following logical consistency checks, the analyzer then identifies the types and durations of out-of-home activities and determines, based on a set of rules, the types of constraints associated with any trips made.

The second module, the Response Option Generator, generates and prioritizes a series of options that an individual is likely to consider when faced with changes in his/her travel environment. These options include trip chaining, changing mode, changing trip frequency and changing departure time. In addition, options can be defined using any combination of these options. A final option is to do nothing—that is, maintain the same activity-travel pattern. A neural network is used to determine which response options an individual will consider in the event of a change in the travel environment.

The third module, the Activity-Travel Pattern Modifier, simulates the daily activity-travel pattern for each option identified in the second module. A screening procedure, based on a set of rules, is used to eliminate any infeasible patterns. Finally, the fourth module, the Evaluation Routine, develops measures that determine how good a particular adjusted activity-travel pattern is.

2.3.2.6 PCATS

PCATS (Prism-Constrained Activity-Travel Simulator) (Kitamura *et al.* 1996; Kitamura and Fujii 1998) simulates the daily activity-travel behavior of individuals within time-space prisms (Hägerstrand 1970). In defining these prisms, it is assumed that the day can be divided into two periods: open periods and blocked periods. Within open periods, an individual has the option of participating in out-of-home activities. In contrast, blocked periods define coupling constraints—that is, activities in which the individual must participate. An example of a blocked period is the period of time an individual spends at work. Furthermore, a distinction is made between activities undertaken during an open period and those pursued during a blocked period. The former activities are referred to as flexible activities while the latter ones are known as fixed activities. Time-space prisms are established in PCATS between blocked periods. It is assumed that an individual makes decisions regarding activity-travel behavior at the beginning of each open period. Moreover, these decisions are made sequentially based on past decisions. In other words, history dependencies are incorporated in the model (Kitamura and Kermanshah 1983).

The decision structure within an open period is as follows. First, an individual must choose an activity in which to participate. In practice, this decision is implemented as a two-tier nested logit model. On the first tier, a decision is made between three broad categories of activities: in-home activity, activity at or near the location of the next fixed activity and general out-of-home activity. The second tier under in-home activity includes two choices: engage in out-of-home activity subsequently and do not engage in out-of-home activity within the current open period. Six activity types comprise the second tier under general out-of-home activity. Once an activity is chosen, a destination and mode is selected for it. These decisions are modeled using a nested logit model. Finally, the duration of the activity is ascertained. This process is repeated until no time remains in the open period.

Unlike STARCHILD, SCHEDULER, GISICAS and SMASH, PCATS does not require an activity agenda. For this reason, its potential for predicting urban travel demand and impacts from transportation-related policies is considerable. In fact, PCATS has already been used to evaluate the impacts of three TDM measures in Kyoto, Japan (Kitamura *et al.* 1997).

2.3.3 Microsimulation Models

Bhat (1998b) has developed a comprehensive microsimulation model of daily activity-travel behavior for workers using home-based tours. Conceptually, the structure of CATGW (Comprehensive Activity Travel Generation for Workers) is based on the spatial and temporal fixity of work. Given this, a worker's daily activity-travel pattern consists of four sub-patterns: before morning commute pattern, work commute pattern, midday pattern and post-home arrival pattern. With the exception of the work commute pattern, the daily patterns may contain one or more tours. Furthermore, each tour may consist of one or more activity stops. Similarly, the morning and evening components of the work commute pattern may contain one or more stops.

Bhat identifies three types of attributes for use in characterizing the daily activity-travel patterns of workers. Pattern level attributes include the number of tours in each pattern that can contain tours and the home-stay duration before the morning commute. Tour level attributes include travel mode, number of stops, home-stay duration before each tour in the before work and post-home arrival patterns, work-stay duration before each tour in the midday pattern and sequence of tour in the pattern. Stop level attributes include activity type, travel time to stop from previous stop, location of stop, activity duration and sequence of stop in the tour.

The operational framework of CATGW is based on empirical analyses of activity diary data collected in Boston and Washington, D.C. From these analyses, Bhat concludes that work mode choice, the number of evening commute stops and the number of post-home arrival stops must be modeled jointly. Furthermore, this model begins the simulation of daily activity-travel behavior. Following this, for each of the non-work patterns, a joint model is used to model tour level attributes—namely, the presence or absence of a tour, mode used and number of stops. This is followed by the home/work-stay duration for the tour. Conditional on the presence of a first tour, a second tour is modeled for each of these patterns. Next, stop level attributes are modeled for each tour. For each stop, activity type, activity duration and travel time to the stop are modeled jointly. This is followed by the location of the stop.

Bhat identifies two important features of CATGW. First, its structure emphasizes spatial and temporal detail, while allowing for interactions across different times of the day. Second, CATGW models activity duration and travel time jointly to accommodate the joint nature of these choices.

2.3.4 Model Comparison

Table 2.1 summarizes salient features of the daily activity-based models discussed in the preceding sections. Moreover, these features can be used to compare the usefulness of these models in terms of predicting urban travel demand, as well as the impacts from transportation-related policies, such as various TDM strategies. These features include the behavior unit for which the model is designed, a summary of activity attributes and two types of interrelationships. Furthermore, for those models that employ an activity agenda, agenda attributes are defined. These attributes, which are the same as those defined for activities, include timing, sequencing, activity type, duration, location and mode.

In Table 2.1, inclusion of these attributes for activities is based on a very stringent criterion. Simply, the model must determine explicitly each attribute in such a way that the resulting activity-travel pattern represents both an accurate and precise account of daily activity-travel behavior. For example, the timing of activities is not included for Kawakami and Isobe's model nor Ben-Akiva and Bowman's model simply because its conceptualization is very crude in both models. In the former model, it is only known whether activities take place before or after work. In other words, the model does not specify their exact timing, which is a necessary prerequisite for activity-based models capable of predicting urban travel over a continuous time domain. In the latter model, the timing of activities is specified by 16 alternatives, each of which consists of one of four periods (i.e. AM peak, PM peak, afternoon and evening) for when the activity commences and one of four periods for when the activity ends.

Table 2.1
Characteristics of daily activity-based models

Model	Behavioral Unit	Agenda Attributes[a]	Activity Attributes	Interrelationships	
				Activities	Household Members
Utility-Maximization Models					
Kawakami and Isobe	Workers		S	No	No
Ben-Akiva and Bowman	Workers/Non-workers		S, A, M	Yes	No
Wen and Koppleman	Household Members		A	No	Yes
Computational Process Models					
STARCHILD	Workers/Non-workers	A, D, L	T, S, A, M	Yes	No
SCHEDULER	Workers/Non-workers	A, D	T, S, A, L	Yes	No
GISICAS	Workers/Non-workers	A, D, L	T, S, A, L	Yes	No
SMASH	Workers/Non-workers	A, D, L	T, S, A, L	Yes	No
AMOS	Workers/Non-workers		T, S, M	Yes	No
PCATS	Workers/Non-workers		T, S, A, D, L, M	Yes	No
Microsimulation Models					
CATGW	Workers		T, S, A, D, L, M	Yes	No

[a] T = timing, S = sequencing, A = activity type, D = duration, L = location, M = mode.

As shown in Table 2.1, only Wen and Koppelman's model predicts daily activity-travel behavior for household members. All other models are designed to predict such behavior for individuals. Wen and Koppelman's model is noteworthy in that it is the only model to incorporate explicitly interactions among household members. However, it is one of two models in which interrelationships among activities over the course of a day are not modeled explicitly.

In terms of activity attributes, computational process models appear to do a much better job in modeling them than utility-maximization models. However, the degree of separation is less than it seems because preferred locations are often specified for each activity comprising an agenda. Furthermore, computational process models that require agendas would be difficult to operationalize on a large scale because agendas would also have to be modeled for each individual. In addition, the greatest disadvantage of such models is that they do not model activity duration.

Ideally, the most useful activity-based model for predicting urban travel demand, as well as impacts from TDM strategies, would be developed at the household level to capture interactions among household members in terms of their daily activity-travel behavior. Furthermore, this model would explicitly model all of the activity attributes shown in Table 2.1 while capturing interrelationships among activities over the course of the day. To date, no such model exists. While all of the models shown in Table 2.1 contain elements of this ideal model, PCATS and CATGW come closest to it. The development of such a model is an important area for future research, particularly since activity-based models are envisioned as replacements for UTMS.

2.4 Conclusions

This chapter has discussed the progress in activity-based research to date. Specifically, empirical findings pertaining to activity-travel patterns, activity-time allocation, activity episodes and activity scheduling are reviewed. In recent years, the latter two categories have witnessed the most activity. A possible reason for this is the need to develop activity-based models of urban travel, which are favored as replacements for UTMS. To date, several such models exist. In this chapter, they are classified as utility-maximization models, computational process models and microsimulation models. This classification scheme represents the different approaches that have been used to obtain operational models. Furthermore, the models differ in terms of their complexity, the nature of their inputs (i.e. some models require an activity agenda) and the precision of their outputs. The models are compared according to a set of salient features that are defined to assess their usefulness in predicting urban travel demand, as well as impacts from various TDM strategies. To date, no model has been developed that contains all of the features defined. Of those that exist, PCATS and CATGW come closest to the ideal model. From this comparison, it can be concluded that a promising area for future research is the development of an ideal activity-based model—that is, a household-level model that captures explicitly interactions among household members and models all activity attributes (i.e. timing, sequencing, activity type, duration, location and mode) while capturing interactions among activities over the course of a day.

3 Modeling Daily Household Activity-Travel Behavior: A Conceptual Framework

3.1 Introduction

Jones *et al.* (1990) identify several features of the activity-based paradigm including recognition that decision-making occurs in a household context, taking into account interactions among household members. This differs, however, from the reality of most activity-based research to date. With few exceptions, the decision-making unit in both empirical studies and modeling efforts is the individual, not the household. Moreover, in the few empirical studies where the decision-making unit is the household, the sum of household activities is typically investigated, ignoring interactions among household members (e.g. Ma and Goulias 1997; Strathman *et al.* 1994; Vadarevu and Stopher 1996). In terms of operational activity-based models of urban travel demand, only Wen and Koppleman's (1998, 1999) model is developed at the household level, accounting explicitly for interactions among household members. However, as noted by Bhat and Koppleman (1999), models that employ an activity agenda can implicitly account for household interactions by altering agenda attributes. Examples of such models include STARCHILD (Recker *et al.* 1986a, 1986b), SMASH (Ettema *et al.* 1993, 1996) and SCHEDULER (Gärling *et al.* 1989, 1998; Golledge *et al.* 1994). A common feature of these models is that they do not generate activities, but instead, they simply schedule those that are provided in an agenda. From a pragmatic point of view, this feature limits their ability to forecast travel and evaluate travel demand management (TDM) strategies for an urban area.

In this chapter, it is argued that activity-based travel demand forecasting models be developed that are capable of generating and scheduling activities—a sentiment that is shared by others (e.g. Bhat and Koppleman 1999). Moreover, these models must be developed at the household level, taking into account interactions among household members. Two reasons are suggested for this. First, individual-level models are incapable of handling complex responses to TDM strategies. For example, a person who performs an activity during the evening commute may forgo the activity when working a compressed workweek. This response obviously favors the alternative work-schedule strategy. However, the individual-level model does not consider that this activity may be reassigned to another household member who also undertakes it after work. In this case, the TDM strategy would prove ineffective in reducing travel demand. Second, such models do not account for joint out-of-home activities—namely, activities in which more than one household member participates. This means that predictions of activity-travel behavior are likely to be inaccurate. For example, multiple out-of-home activities may be predicted for household members when, in fact, only one exists.

This chapter proposes a conceptual framework for modeling daily household activity-travel behavior. Besides being developed at the household level, the framework is distinguished from those underlying other activity-based forecasting models by three characteristics. First, it is developed for the heads of five common household types for reasons that will be discussed. Second, interactions between household heads are incorporated explicitly into the framework for three of the household types. Finally, two activity settings are recognized: independent and joint activities. Such activities are generated by the *Activity-Episode Generation* module and scheduled by the *Activity-Episode Scheduling* module.

The remainder of this chapter is organized as follows. The next section presents an empirical example of household activity-travel behavior taken from an activity-travel survey conducted in Portland, Oregon in 1994. This example demonstrates some of the underlying assumptions of the conceptual framework, which is described in-depth in section three. The contributions of this chapter to activity-based research are summarized in the final section.

3.2 Empirical Example

Figure 3.1 illustrates graphically an example of daily household activity-travel behavior constructed from data contained in the 1994 Portland Activity-Travel Survey. The household consists of four members: a working husband, a non-working wife and two school-age children. Furthermore, the household has one automobile and resides in a house in the suburbs.

On the survey day, all members participate in out-of-home activities. The husband takes public transit to work, which means that the automobile is left at home for use by the wife. In fact, the wife participates in six out-of-home *activity episodes* while the husband is at work. Furthermore, these episodes form one home-based *tour*. Specifically, the wife undertakes two shopping episodes—one in the morning and the other in the

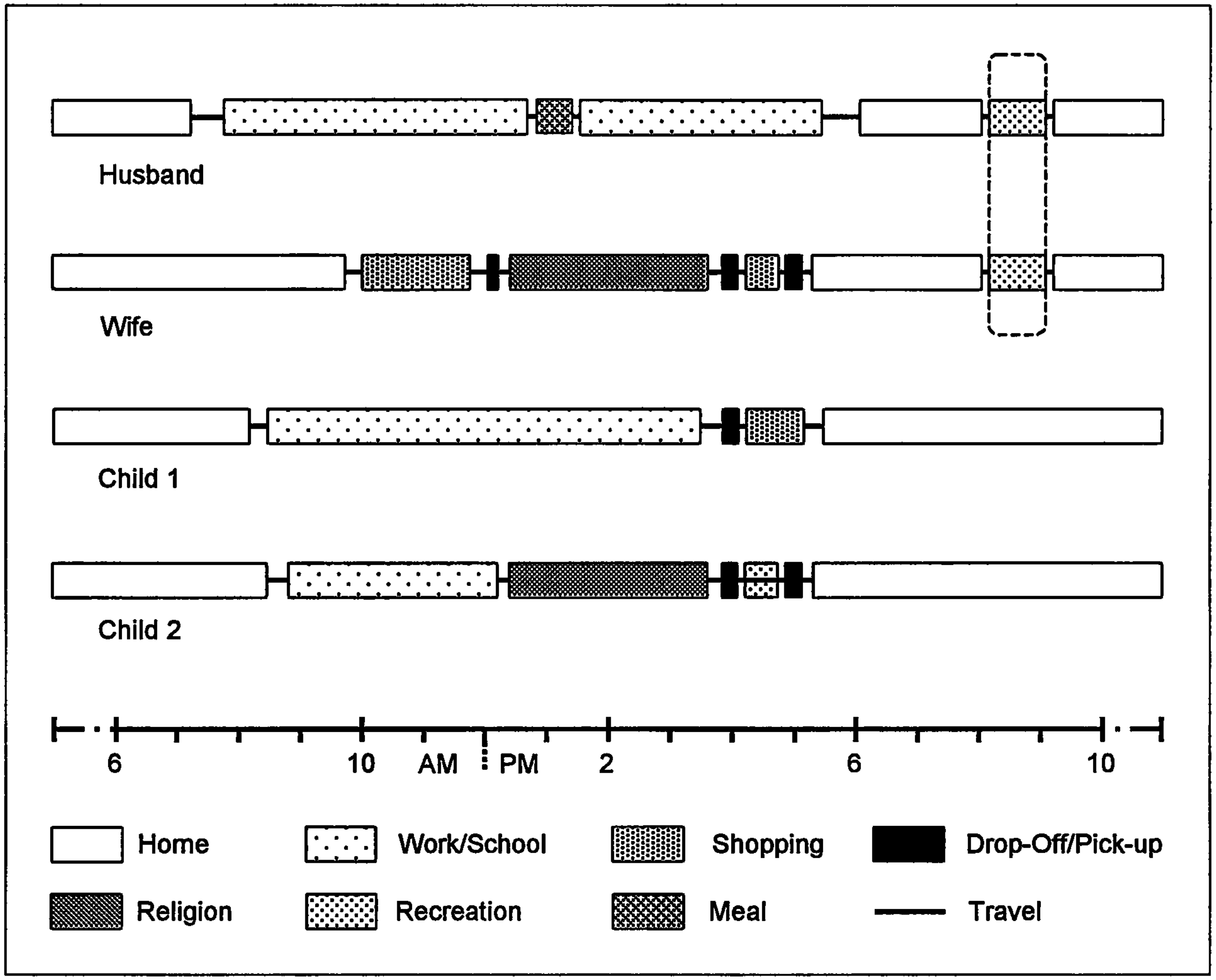

Figure 3.1
An example of household activity-travel behavior for a one-day period.

afternoon. After the morning episode, she picks up one of her sons (i.e. Child 2) and takes him to a religious activity. Once this activity is over, the wife returns briefly home to pick up her other son (i.e. Child 1). The wife then drops off both sons on her way to go shopping. Child 1 walks home after finishing shopping, whereas the wife picks up Child 2 on her way home from shopping. In the evening, husband and wife participate in a *joint* out-of-home recreational activity.

This empirical example demonstrates several aspects of daily household activity-travel behavior that are incorporated in the conceptual framework discussed in the next section. First, only the activity-travel behavior of household heads needs to be considered for practical travel demand forecasting purposes. The reason for this is that the activity-travel behavior of children manifests itself in that of their parents. As shown in Figure 3.1, four of the six out-of-home activities undertaken by the wife were for her children. Second, complex interactions between household heads underlie their activity-travel behavior. For instance, in the above example, the wife may have required the automobile on the survey day to take Child 2 to a regularly scheduled religious activity. Third, household heads often participate in the same type of activity on more than one occasion over the course of a day. Each occurrence of an activity is known as an activity episode, which is defined as a period of time characterized by a uniform purpose and spatial setting. Finally, engagement in joint activity episodes, particularly in the evening, is an important aspect of the activity-travel behavior of household heads (see also Kostyniuk and Kitamura [1982]).

3.3 Conceptual Framework

3.3.1 Assumptions

The conceptual framework for modeling daily household activity-travel behavior is based on several assumptions. First, household members interact on a daily basis to generate and schedule collectively out-of-home activity episodes, which they undertake to fulfill household needs and individual desires. Second, this complex decision-making process is limited to non-work activities because work is assumed to be fixed in the short term. Furthermore, activity-based research has shown that work governs the activity-travel behavior of household members (e.g. Golob and McNally 1997). Third, only the activity-travel behavior of household heads is considered for the reason given in the preceding section—that is, the activity-travel behavior of children manifests itself in that of their parents. As well, household heads undertake the vast majority of trips in urban areas. Fourth, daily household activity-travel behavior varies according to household type, which, for this framework, is defined by the number of household heads and their work status. The types are:

1. *single, non-worker households*: one-person and single-parent households in which the person or parent does not work,
2. *single-worker households*: one-person and single-parent households in which the person or parent works,
3. *couple, non-worker households*: married or unmarried, male-female couples with or without children in which neither household head works,

4. *couple, one-worker households*: married or unmarried, male-female couples with or without children in which only one household head works, and
5. *couple, two-worker households*: married or unmarried, male-female couples with or without children in which both household heads work.

Interactions between household heads occur only in the latter three household types. The activity episodes generated in these households fall into one of two settings based solely upon the number of household heads participating in them. In other words, the presence of other household members, such as children, is not used to define these settings. Activities undertaken by one household head are independent activities, whereas those undertaken by both household heads together are joint activities. The decision-making process underlying household activity-travel behavior in single, non-worker and single-worker households is much simpler, resulting in independent activity episodes only.

3.3.2 Overview

Figure 3.2 presents the general structure of the conceptual framework. As can be seen, it consists of two modules: *Activity-Episode Generation* and *Activity-Episode Scheduling*. The first module generates the daily number of out-of-home activity episodes undertaken by household heads in each of the five household types, whereas the second module is concerned with the explicit timing, sequencing, activity type, duration, location and mode for each episode. This module, in turn, consists of two submodules: *Period Assignment* and *Tour Generation*.

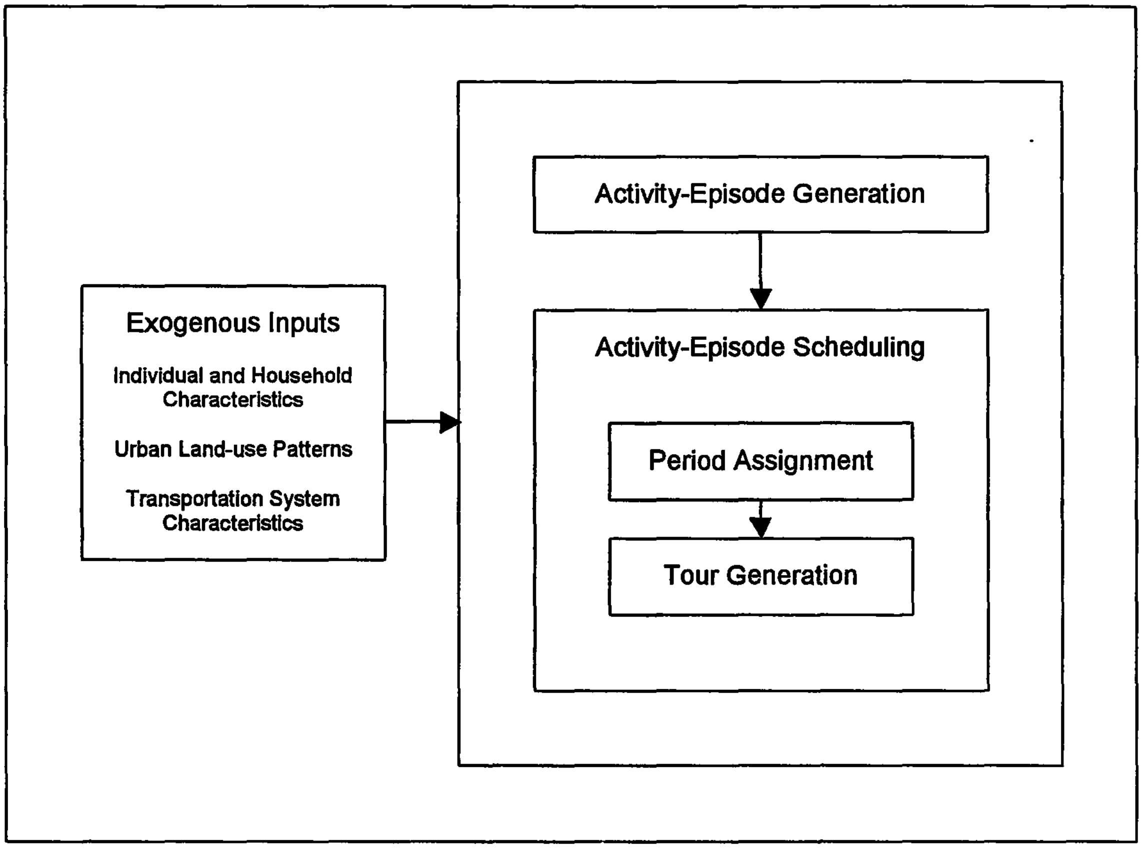

Figure 3.2
General structure of the conceptual framework.

Both modules are influenced by a number of exogenous factors, which are classified as individual and household characteristics, urban land-use patterns, and transportation system characteristics. The first set of factors includes socio-demographic characteristics (e.g. household income, presence of children and age), work characteristics (e.g. work duration and work mode) and residential location. Empirical studies have shown that these factors influence activity-travel behavior. For example, the presence of children in the household has long been recognized as an important constraint on such behavior and is, therefore, included as an explanatory variable in many studies (e.g. Bhat 1997, 1998a; Damm and Lerman 1981; Kitamura and Kermanshah 1983; Kostyniuk and Kitamura 1982; Niemeier and Morita 1996). Urban land-use patterns concern spatial distributions of activity sites in an urban area. Moreover, these patterns, along with transportation system characteristics, determine a household's accessibility to various types of out-of-home activities. Transportation system characteristics include the structure of the road network, congestion and the availability of public transportation.

3.3.3 Activity-Episode Generation Module

Figure 3.3 shows the general structure of the Activity-Episode Generation module. Chapter 4 confirms the importance of mode choice for work on the daily number of out-of-home activity episodes undertaken by household heads that work. Generally, commuting to work by public transit reduces the number of independent episodes, whereas driving to work alone increases their number. Furthermore, for couple, two-worker households, commuting to work together is shown to increase the number of joint

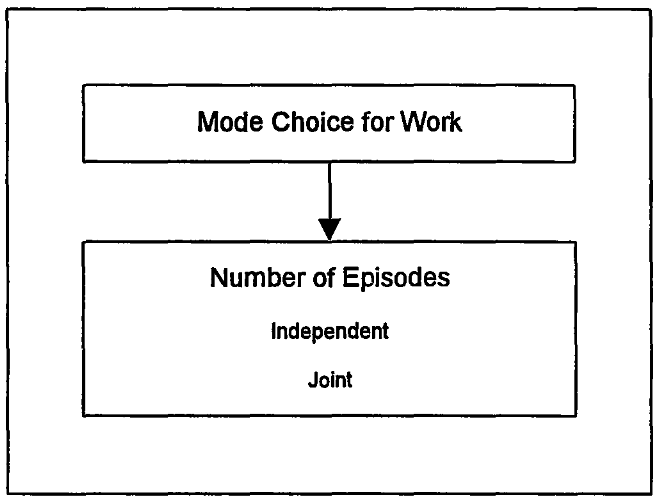

Figure 3.3
Activity-Episode Generation module.

episodes. The study also identifies other variables that influence household activity-episode generation. These variables include household income, presence of children, age and work duration, to name a few.

The module structure shown in Figure 3.3 varies according to household type. Mode choice for work is included for only three types: single-worker; couple, one-worker; and couple, two-worker households. Furthermore, for the heads of single, non-worker and single-worker households, the module generates independent episodes only. Joint out-of-home activity episodes are generated, along with independent episodes, for the heads of couple, non-worker, one-worker and two-worker households. Moreover, for these household types, the module captures interactions between household heads. The models underlying the Activity-Episode Generation module are discussed thoroughly in the following chapter.

3.3.4 Activity-Episode Scheduling Module

3.3.4.1 Period Assignment Submodule

The fact that activity-travel behavior generally occurs within distinct periods of the day has long been recognized by researchers (e.g. Bhat 1998b; Damm 1980, 1982; Damm and Lerman 1981; Kostyniuk and Kitamura 1982; Landau *et al.* 1981). For this reason, the Activity-Episode Scheduling module divides the day into several distinct periods that vary according to household type. For the heads of single, non-worker and couple, non-worker households, these periods correspond simply to morning, afternoon and evening. However, for the remaining household types, division of the day is based on the temporal fixity of work. Figure 3.4 illustrates how the day is divided into periods for the heads of couple, one-worker and couple, two-worker households. Furthermore, the periods shown for the working heads of these household types are the same as those identified for the heads of single-worker households.

For couple, two-worker households, each head's day is divided into five periods: before home to work commute, home to work commute, during work, work to home commute and after work to home commute. In most instances, there will be a considerable amount of overlap between the respective periods for each household head. In fact, the modeling results discussed in Chapter 4 show that synchronization of the work schedules of household heads has a negative impact on the number of independent out-of-home activity episodes undertaken by male heads. As explained, one possible reason for this is that both working heads want to spend time together at home or participating in joint out-of-home activities. This finding implies that the amount of overlap between the respective periods for each household head influences both the generation of out-of-home activity episodes and the assignment of joint episodes to periods of the day.

For couple, one-worker households, the worker's work activity is used to divide the non-worker's day into three periods: before worker's home to work commute, while worker is at work and after worker's work to home commute. As shown in Figure 3.4b, periods 1 and 3 for the non-worker are synchronous with periods 1 and 5, respectively, for the worker.

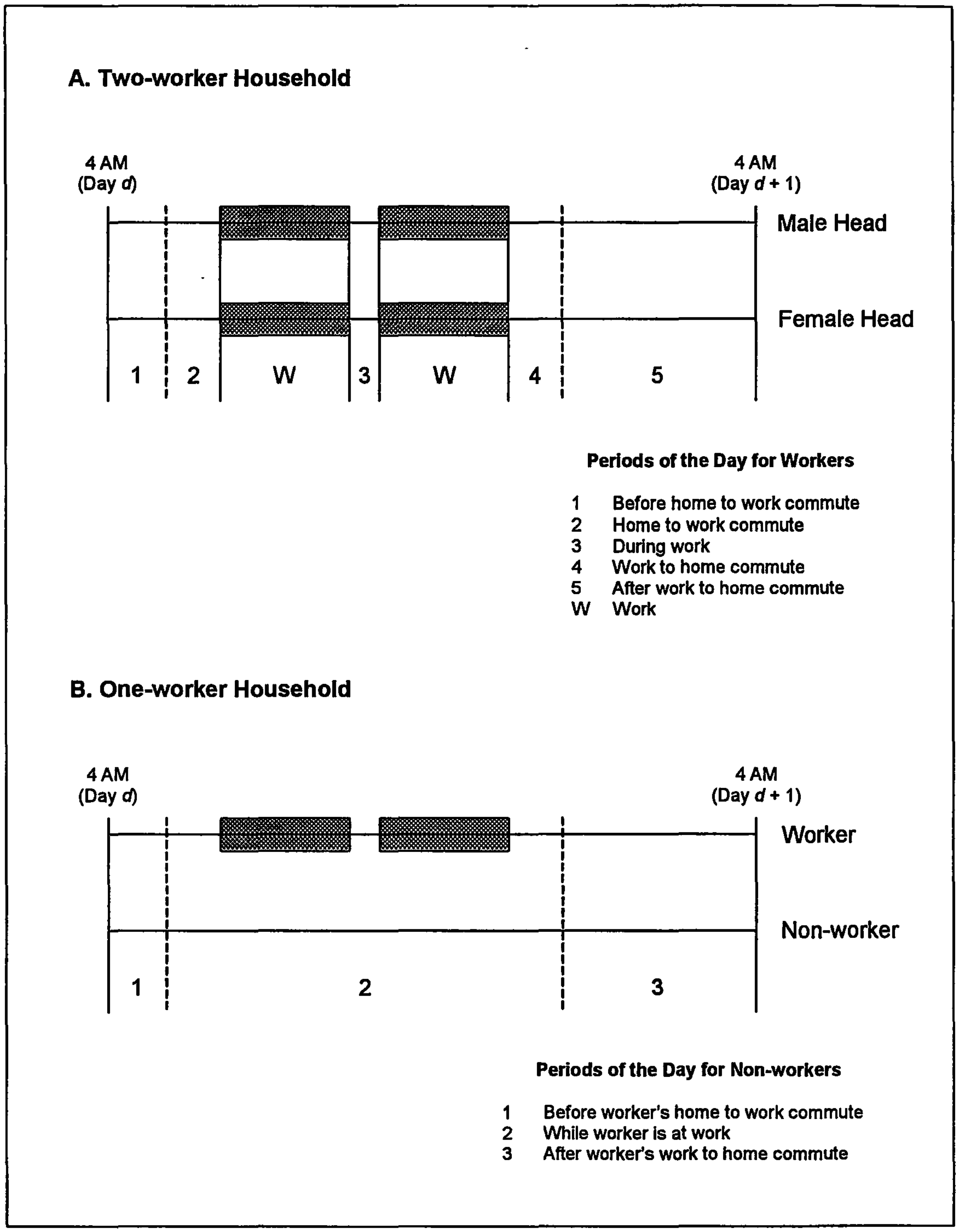

Figure 3.4
Periods of the day for the heads of (a) couple, two-worker households and (b) couple, one-worker households.

The general structure of the Period Assignment submodule is shown in Figure 3.5. For couple, non-worker, one-worker and two-worker households, joint activity episodes are assigned to periods of the day before independent activity episodes. The reason for this is that joint episodes impose greater constraints on household heads than independent activity episodes because of the need to coordinate schedules. Furthermore, for the latter household types, such episodes are likely to occur after work (Kostyniuk and Kitamura 1982). Once all joint episodes are assigned to periods of the day, independent activity episodes are assigned for each household head. This process is conditional based on the presence of one or more joint episodes in a period. For single, non-worker and single-worker households, only independent episodes are assigned to periods of the day.

3.3.4.2 Tour Generation Submodule

After all out-of-home activity episodes are assigned to periods of the day for household heads, the explicit timing, sequencing, activity type, duration, location and mode for each episode must be determined. Moreover, the conceptual framework recognizes that two or more episodes assigned to a particular period may be undertaken successively. This is known as *trip chaining* (see Thill and Thomas [1987] for a review). Specifically, for each period, out-of-home activity episodes are organized into *tours*. A tour is defined as a circuit of activity episodes that begins and ends at home. Furthermore, each episode takes place at a location that differs from that which precedes it. For working heads, a tour may also contain a *subtour*, which is defined as a tour that begins and ends at work. For example, a worker may decide to eat lunch in a nearby restaurant at midday.

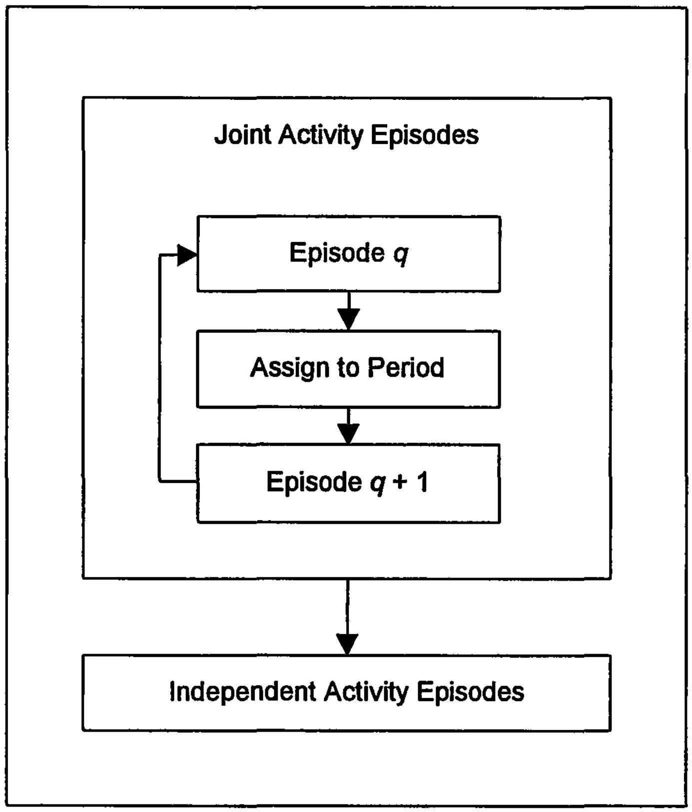

Figure 3.5
Period Assignment submodule.

The general structure of the Tour Generation submodule is shown in Figure 3.6. As shown in the figure, for each tour, a mode is first chosen. Second, conditional on this choice, home/work-stay duration is determined. Third, beginning with the first activity episode, its type and duration are determined. Fourth, conditional on this, a location for the episode is chosen. Fifth, the travel time to the location is provided exogenously from a travel time matrix. Finally, if two or more activity episodes have been assigned to a period, they may be undertaken in the same tour. This is determined by returning to the third step. However, in this instance, the activity choice is two-tiered. On the first level, the choices are to pursue another out-of-home activity episode or return home (or to work). On the second level, activity types are defined for the first alternative. If any episodes remain after the first tour, additional tours are undertaken until all episodes for the period have been assigned to tours.

The general structure of the Tour Generation submodule is modified in two situations. First, activities assigned to periods 2 and 4 for working heads are part of a home-based work tour. For this reason, such activities are pursued successively. In other words, the Tour Generation submodule is reduced to one of home/work-stay duration and the determination of successive episode attributes. The Activity-Episode Generation module determines the mode choice for work. Second, the Tour Generation submodule applies to both independent and joint out-of-home activity episodes. If, however, both types of episodes are assigned to a particular period, the submodule is modified to first determine the type of tour pursued.

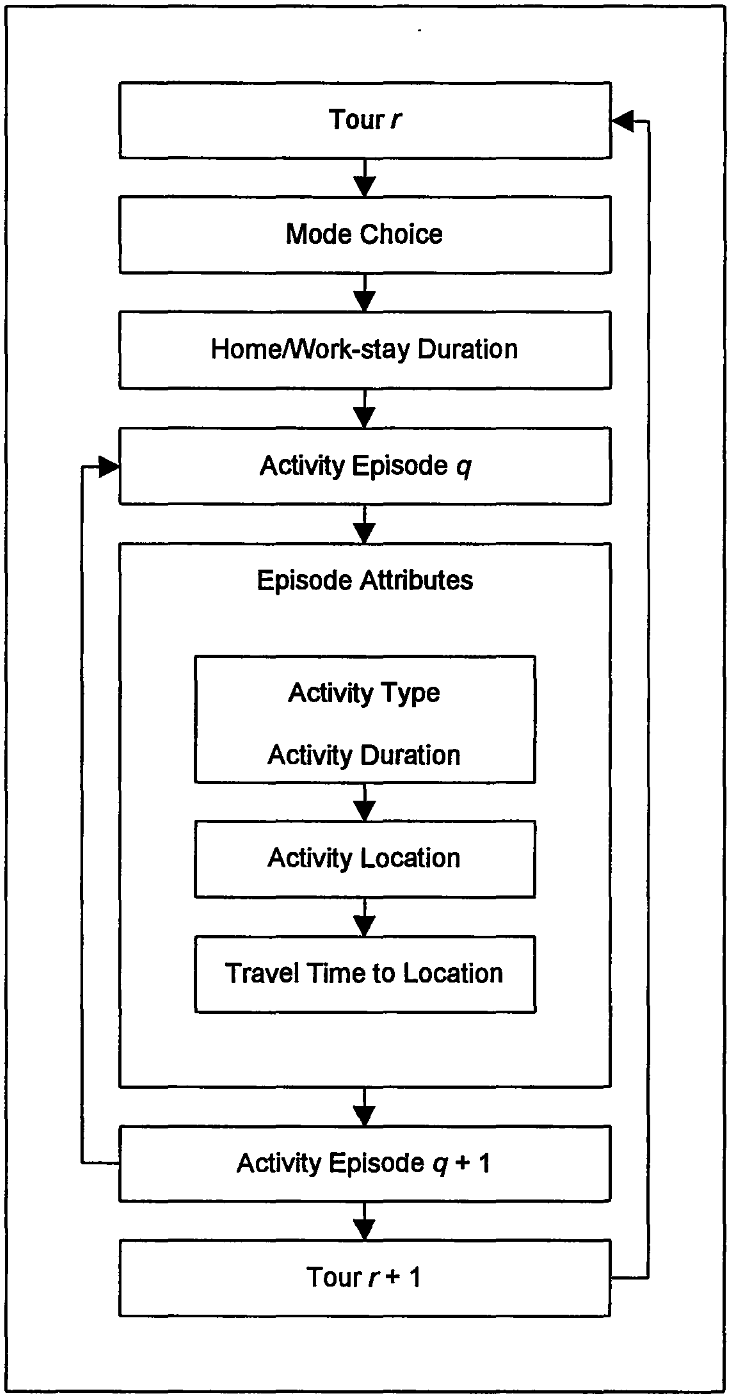

Figure 3.6
Tour Generation submodule.

3.4 Conclusions

This chapter has discussed a comprehensive conceptual framework for modeling daily household activity-travel behavior. Besides being developed at the household level, the framework is distinguished from those underlying other activity-based forecasting models by three characteristics. First, it is developed for the heads of five common household types: single, non-worker; single-worker; couple, non-worker; couple, one-worker; and couple, two-worker households. Second, interactions between household heads are incorporated explicitly into the framework for the latter three household types. Finally, two activity settings are recognized: independent and joint activities.

The conceptual framework consists of two modules. The Activity-Episode Generation module generates the daily number of out-of-home activity episodes undertaken by household heads in each of the five household types. The models underlying this module are discussed thoroughly in Chapter 4. In contrast, the Activity-Episode Scheduling module is concerned with the explicit timing, sequencing, activity type, duration, location, and mode for each episode. In turn, two submodules comprise this module: Period Assignment and Tour Generation.

The conceptual framework proposed in this chapter addresses the need to develop activity-based travel demand forecasting models that are capable of generating and scheduling activities at the household level, taking into account interactions among household members. Furthermore, the framework can be implemented using data that are readily available to most metropolitan planning organizations. For these reasons, the conceptual framework is an attractive alternative to existing activity-based models.

4 Household Activity-Episode Generation: Empirical Analysis

4.1 Introduction

Since the late 1970s, the rapidly expanding literature subsumed under the activity-based paradigm has increased significantly our understanding of urban travel behavior and provided insights into new approaches to replace current models of urban travel demand—namely, the Urban Transportation Modeling System (UTMS). Unlike trip-based approaches, the activity-based paradigm, more commonly known as *activity analysis*, recognizes explicitly that travel is a demand derived from the need to participate in out-of-home activities. In other words, discrete activities or patterns of activities are investigated, not trips. Jones *et al.* (1990) identify several features of the paradigm including recognition that decision-making occurs in a household context, taking into account interactions among household members. This differs, however, from the reality of activity-based research to date.

With few exceptions, the decision-making unit in both empirical studies and modeling efforts is the individual, not the household. This does not mean that the household is excluded from such research. In fact, most empirical investigations recognize the importance of household attributes in defining an individual's activity-travel behavior. For example, the presence of children in the household has long been identified as an important constraint on such behavior and is, therefore, included as an explanatory variable in many studies (e.g. Bhat 1997, 1998a; Damm and Lerman 1981; Kitamura and Kermanshah 1983; Niemeier and Morita 1996). In the very few instances where the decision-making unit is the household, the sum of household activities is typically investigated, ignoring interactions among household members. Strathman *et al.* (1994), for example, examine how household structure and other factors affect a household's allocation of non-work activities to alternative types of trip chains. In terms of operational activity-based forecasting models, only Wen and Koppelman's (1998, 1999) model is developed at the household level, accounting explicitly for interactions among household members. Models that require an activity agenda, such as STARCHILD (Recker *et al.* 1986a, 1986b), SMASH (Ettema *et al.* 1993, 1996) and SCHEDULER (Gärling *et al.* 1989, 1998; Golledge *et al.* 1994), can, however, account implicitly for household interactions by altering agenda attributes.

The conscious disregard for household decision-making in activity-based research to date is largely a pragmatic artifact of the past. Heggie and Jones (1978) identify four domains applicable to the classification of most activity-based studies based on assumptions concerning the decision-making process underlying travel—namely, (1) independence, (2) spatio-temporal linkages, (3) inter-personal linkages and (4) full interdependence. As noted by the authors, incorporating household interactions explicitly into research (Domains 3 and 4) is not only more realistic than assuming an individual makes activity-travel decisions independently (Domains 1 and 2), but is exceedingly difficult to do. This problem does not appear to be conceptual given the inclusion of the household in the frameworks underlying several operational and proposed activity-based

Table 4.1
Transport emission trends of air pollutants[a] in the United States, 1988 to 1997

Year	CO		CO_2[b]		NO_x		VOC		PM	
	Amount[c]	Share[d]	Amount	Share	Amount	Share	Amount	Share	Amount	Share
1988	77,819	73.9	-	-	10,577	49.2	9,601	44.0	773	24.2
1989	73,365	78.2	-	-	10,642	50.1	8,624	42.7	770	24.2
1990	66,429	76.4	405	30.5	10,231	48.1	7,952	41.9	754	24.9
1991	70,256	79.2	397	30.2	10,559	49.5	8,133	42.6	763	25.9
1992	68,504	80.0	402	30.2	10,660	49.4	7,774	41.5	758	25.4
1993	68,974	80.4	407	29.9	10,749	49.3	7,819	41.4	731	25.4
1994	70,655	78.8	422	30.5	10,949	49.6	8,110	41.6	728	25.6
1995	63,846	78.9	431	30.8	10,732	49.8	7,354	39.4	681	23.8
1996	62,917	76.5	445	30.8	10,569	49.8	7,166	40.9	665	23.2
1997	60,795	76.6	447	30.5	10,519	49.2	6,949	39.9	666	23.6

[a] Carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxides (NO_x), volatile organic compounds (VOC) and particulate matter between 2.5 and 10 microns in diameter (PM).
[b] Emissions from fossil fuel combustion.
[c] All emissions are measured in thousands of metric tons except for CO_2, which is measured in millions of metric tons of carbon equivalents.
[d] Contribution of transport to total emissions, measured in percent.

Source: USEPA OAQPS (1998); USEPA OP (1999).

forecasting models (Gärling *et al.* 1989; Recker *et al.* 1986a; Stopher *et al.* 1996; Wen and Koppelman 1998). It does, however, appear to be methodological because the statistical tools available for such a complex treatment of activity-travel behavior are virtually nonexistent[10]. The lack of such tools is related directly to available computer technology. In other words, computer technology largely defines the boundaries of activity-based research, not to mention that of other fields. This is why such research to date has been mostly confined to Domains 1 and 2 in Heggie and Jones' (1978) classification. It has only been in very recent years that computer technology has improved to the point where researchers can develop and apply advanced statistical tools in activity-based studies (e.g. Bhat 1997, 1998a). Since such technology is no longer the impediment that it once was to research, the onus is now on researchers to develop statistical tools capable of analyzing the activity-travel behavior of households while accounting for interactions among household members. This comes at a time when the need to explicitly recognize the household as the primary decision-making unit in activity-based research has never been greater.

In the industrialized world, transport is responsible for a large share of harmful environmental emissions of which the vast majority is from motor vehicles[11], particularly the automobile (OECD 1997a). In terms of amount, however, three trends are evident, as illustrated in Table 4.1. First, transport emissions of several air pollutants have been

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[10] Notable exceptions include structural equations models (Golob and McNally 1997) and nested logit models (Wen and Koppelman 1999).

[11] Major air pollutants emitted by motor vehicles include carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxides (NO_x), particulate matter (PM) and volatile organic compounds (VOC) (OECD 1997b).

decreasing in some industrialized countries since the late 1970s and early 1980s. In the United States, for example, carbon monoxide (CO), particulate matter (PM) and volatile organic compounds (VOC) have all declined despite an increase in vehicle-miles traveled (VMT)[12]. Second, transport emissions of carbon dioxide (CO_2), the primary greenhouse gas emitted by human activities, continue to increase in all industrialized nations as transport maintains its reliance on fossil fuels. Finally, in recent years, nitrogen oxides (NO_x) appear to have leveled off in some countries.

To date, the approach taken in most industrialized countries to reduce air pollution from transport has been to incite improvements in vehicle technologies by introducing or tightening vehicle emissions standards (OECD 1997b). These technologies either control emissions directly, such as catalytic converters[13], or improve vehicle fuel efficiency[14]. There is, however, growing concern that any gains made in reducing transport emissions of air pollutants will be reversed in the future for the following reasons (OECD 1997b; USDOT BTS 1998). First, vehicle fuel efficiency has remained virtually unchanged since the mid-1980s (OECD 1997b; USEPA OP 1999; USDOT BTS 1998). This means that future reductions in transport emissions from vehicle stock turnover will be almost nonexistent as the average fuel efficiency of the on-road fleet approaches that of new

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[12] Between 1980 and 1996, VMT grew from 1.53 to 2.48 trillion in the United States for an increase of 63 percent (USDOT BTS 1998).

[13] The use of catalytic converters, which is now mandatory in North America and much of Europe, actually increases CO_2 emissions.

[14] Vehicle technologies that improve fuel efficiency, such as reduced vehicle weight, fuel injection and improved aerodynamics, generally reduce air pollutant emissions. However, there are some exceptions to this. For example, the use of higher air-fuel ratios and combustion temperatures actually increase NO_x emissions.

vehicles[15]. Second, the increasing popularity of less fuel-efficient light-duty trucks and sport utility vehicles, especially in North America, suggests the possibility that the average fuel efficiency of the on-road fleet may decline, thereby increasing emissions. In the United States, for example, such vehicles accounted for 40 percent of the light-duty vehicle market in 1997, up from 10 percent in 1979 (USDOT BTS 1998). Moreover, their average fuel efficiency was 20.4 miles per gallon (mpg) as opposed to 28.5 mpg for automobiles (USDOT BTS 1998). Third, vehicular traffic continues to grow in all industrialized nations without any sign of leveling off (OECD 1997b). Eventually, this alone will offset any improvements in air quality from transport. More importantly, however, such growth will lead to more congestion in the absence of increased network capacity. In turn, emissions of several air pollutants will rise[16].

The realization that technology alone will be unable to maintain, let alone further reduce transport emissions in the future has prompted many industrialized nations to consider using travel demand management (TDM), which consists of strategies that influence the demand for vehicular travel. Such measures are increasingly necessary if these countries are to meet reductions in air pollutants set out in international agreements such as the 1997 Kyoto Protocol to the United Nations Framework Convention on

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[15] In the United States, the average fuel efficiency of on-road automobiles increased from 13.8 miles per gallon (mpg) in 1976 to 21.2 mpg in 1991, for an average annual improvement rate of 3.6 percent per year. In contrast, from 1991 to 1996, this rate decreased to 0.1 percent per year as mpg increased to only 21.3 (USDOT FHWA 1997).

[16] Driving characteristics play an important role in emissions of air pollutants. Specifically, CO, CO_2, PM and VOC emissions are highest when a vehicle is accelerating, decelerating or idling. Such conditions are synonymous with congestion. In contrast, NO_x emissions increase with speed.

Climate Change[17]. In the United States, the 1990 Clean Air Act Amendments (CAAA) set the stage for achieving such goals by emphasizing the role of TDM strategies in meeting mandated reductions in transport emissions. In turn, these amendments were the major motivation behind the Travel Model Improvement Program (TMIP), which is the most ambitious undertaking to date to replace current models of urban travel demand with those that are policy sensitive, and therefore, capable of evaluating such strategies.

Under this program, activity-based replacements are favored (Barrett *et al.* 1995; Spear 1996). Moreover, to meet expectations concerning the accuracy and reliability of forecasts, it is imperative that such models be developed at the household level, taking into account interactions among household members. Two reasons are suggested for this. First, individual-level models are incapable of handling complex responses to TDM strategies. For example, a person who performs an activity during the evening commute may forgo the activity when working a compressed workweek. This response obviously favors the alternative work-schedule strategy. However, the individual-level model does not consider that this activity may be reassigned to another household member who also undertakes it after work. In this case, the TDM strategy would prove ineffective in reducing travel demand. Second, such models do not account for joint out-of-home activities—namely, activities in which more than one household member participates. This means that predictions of activity-travel behavior are likely to be inaccurate. For

[17] In this agreement, industrialized nations consented to reduce greenhouse gas emissions, notably CO_2, to five percent less than 1990 levels by 2008 to 2012.

example, multiple out-of-home activities may be predicted for household members when, in fact, only one exists.

The need to explicitly recognize the household as the primary decision-making unit in activity-based research is the fundamental motivation for this chapter. Specifically, the daily number of out-of-home activity episodes[18] other than work is modeled for the heads of five common household types. To capture interactions between such household members, a joint model is developed, which accounts for both independent and joint activity episodes. This model is applied to three of the five household types. A comparison of the results with those obtained from models that ignore household interactions suggests that daily activity episodes are determined jointly by household members. Consequently, predictive accuracy is improved by using household-level models. Furthermore, the models developed herein form the *Activity-Episode Generation* module in the household-level, activity-based travel demand forecasting system discussed in Chapter 3.

The remainder of this chapter is organized as follows. The next section reviews briefly activity-based studies that have investigated interactions among household members. The statistical models and data used in the analysis of household activity-episode generation are detailed in the third section. Moreover, development of the joint model is discussed in depth. Section four presents the empirical findings. The contributions of this study to activity-based research are summarized in the final section.

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[18] An activity episode is a period of time characterized by a uniform purpose and spatial setting.

4.2 Prior Research

Very few studies have investigated interactions among household members in terms of their activity-travel behavior. Of those that have, the effects of one member's behavior on that of another are captured explicitly by joint modeling frameworks or implicitly through the use of variables in simpler models. In some instances, exogenous factors are shown to influence these interactions.

Landau *et al.* (1981) postulate that the daily activity-travel behavior of household members arises from a sequential decision-making process whereby out-of-home activities are generated collectively by the household and then assigned to specific members for execution. For modeling purposes, they limit their study to households in which only the husband works and divide the day into four periods based on the husband's work activity. For the first stage of the sequential process, linear probability models are estimated for maintenance and leisure activities ignoring interactions between the two, which Golob and McNally (1997) have since shown to be important. For the second stage, conditional probability models are estimated separately for husband and wife by activity type and time period. A fundamental shortcoming of this model system is that it does not consider the number of out-of-home activity episodes undertaken by these household members, but instead, only whether such activities occur. Interactions between husband and wife are incorporated in the second-stage models by dummy variables that measure characteristics of the spouse's daily activity-travel behavior and by variables that measure the husband's temporal constraints—namely, the amount of free time before and after work. The research findings clearly demonstrate the importance of interactions between household members in shaping their daily activity-travel behavior, suggesting that activity generation and allocation is a simultaneous process rather than a sequential one. Furthermore, there is evidence that leisure activities are executed jointly in the evening.

Kostyniuk and Kitamura (1982) address this phenomenon in their study of the evening time-space paths of household members. In fact, they select this period for investigation because it is a time when household members can participate together in out-of-home activities. They do, however, confine their empirical analysis to husbands and wives in households with at least one automobile. When these members pursue out-of-home activities, their time-space paths are classified as to whether such activities are undertaken independently or jointly with a spouse. A path is considered joint if all or part of it is common for both husband and wife. Furthermore, such paths are classified according to the location where they become joint—specifically, at home or away from home (i.e. workplace or activity site). The findings indicate that interactions between husbands and wives in terms of their activity-travel behavior are influenced by several exogenous factors, notably household life-cycle stage, work-trip status and household role. For example, young couples without children are oriented toward joint activities with many paths involving contact points away from home. In contrast, the paths of husbands and wives in households with preschool and/or school age children consist of independent activities. With respect to work-trip status, households in which both the husband and wife work on a given day are characterized by joint activity engagement at contact points other than home. Finally, wives are more likely to pursue joint activities than are husbands.

Golob and McNally (1997) use a structural equations model to capture explicitly interactions between male and female household heads in terms of their participation in work, maintenance and discretionary out-of-home activities. The endogenous variables included in their model consist of total duration and total travel time for each activity type aggregated over a two-day period for each member. In terms of endogenous effects, the results indicate that male participation in work activity governs interactions between household heads. Specifically, it is shown that an increase in such activity leads to an increase in female maintenance activity and travel and to a decrease in female discretionary activity and travel. In terms of exogenous effects, the number of young children in the household is related to the substitution of work and maintenance activities between male and female household heads. Overall, the research findings suggest that gender roles play an important part in interactions between these household members in terms of their participation in specific out-of-home activities.

Like Landau *et al.* (1981), Wen and Koppelman (1998, 1999) postulate a decision-making process whereby households first generate out-of-home maintenance activities and then assign them to specific members for execution. However, unlike the previous work, Wen and Koppelman incorporate the number of such activity episodes in their modeling framework, which is a necessary prerequisite for operational activity-based forecasting models. Furthermore, they extend the household decision-making process to include the allocation of automobiles to household members, which is defined in terms of the number of activity episodes for which an automobile is available. A three-tier nested logit model is used to implement the modeling framework, which, despite its advances over prior research, still has several shortcomings. First, it is limited to couples that do not engage in out-of-home maintenance activities together, thereby ignoring joint activity episodes. Second, although the nested logit model allows the household decisions to be estimated simultaneously, it does not account for the ordinal nature of the first decision—that is, the number of out-of-home maintenance activity episodes. Finally, the model cannot be used for forecasting purposes because several of the independent variables are endogenous.

From the research discussed in this section, several observations can be made regarding interactions among household members in terms of their activity-travel behavior. First, although such interactions exist among all household members, only those between household heads (i.e. both married and unmarried couples) need to be considered for practical travel demand forecasting purposes. The reason for this is that the activity-travel behavior of children manifests itself in that of their parents. For example, parents are largely responsible for taking their children to various activity sites, such as school. Second, the generation of out-of-home activity episodes other than work and their allocation to household heads for execution is a simultaneous process that is influenced by many exogenous factors including the presence of children in the household, work activity and household gender roles. This process, by its very nature, is based entirely upon interactions between these members. Third, engagement in joint activity episodes, particularly in the evening, is an important aspect of the activity-travel behavior of household heads. These observations are incorporated in the modeling framework presented in the next section.

4.3 Models and Data

4.3.1 Modeling Framework

For the research discussed herein, a number of assumptions are made. First, household members interact on a daily basis to generate collectively out-of-home activity episodes, which they undertake to fulfill household needs and individual desires. Second, this complex decision-making process is limited to non-work activities because work is assumed to be fixed in the short term. Furthermore, activity-based research has shown that work governs the activity-travel behavior of household members (e.g. Golob and McNally 1997). Third, only interactions between household heads are considered for the reason given in the preceding section—that is, the activity-travel behavior of children manifests itself in that of their parents. As well, household heads undertake the vast majority of trips in urban areas. Fourth, household activity-episode generation varies according to household type, which, for this study, is defined by the number of household heads and their work status. The types are:

1. *single, non-worker households*: one-person and single-parent households in which the person or parent does not work,
2. *single-worker households*: one-person and single-parent households in which the person or parent works,

3. *couple, non-worker households*: married or unmarried, male-female couples with or without children in which neither household head works,
4. *couple, one-worker households*: married or unmarried, male-female couples with or without children in which only one household head works, and
5. *couple, two-worker households*: married or unmarried, male-female couples with or without children in which both household heads work.

Interactions between household heads occur only in the latter three household types. The activity episodes generated in these households fall into one of two settings based solely upon the number of household heads participating in them. In other words, the presence of other household members, such as children, is not used to define these settings. Activities undertaken by one household head are independent activities, whereas those undertaken by both household heads together are joint activities. The decision-making process underlying household activity-episode generation in single, non-worker and single-worker households is much simpler, resulting in independent activity episodes only.

As mentioned, the objective of this research is to model the daily number of out-of-home activity episodes for household heads in each of the five household types. For this task, two types of models are used both of which recognize the ordinal and discrete nature of the household decision-making process. These models are discussed thoroughly in the next two sections.

4.3.1.1 Univariate Ordered Probit Model

The univariate ordered probit model, developed by McKelvey and Zavoina (1975), is used to model household activity-episode generation for the heads of single, non-worker and single-worker households. This model is based upon a latent regression, which is defined in this research as:

$$y_h^* = \beta x_h + \varepsilon_h \tag{4.1}$$

where y_h^* is the propensity for the head of household h to undertake out-of-home activity episodes for a one-day period, x_h is a vector of exogenous variables, β is a corresponding vector of parameters and ε_h is a random error term.

The dependent variable y_h^* is unobserved. Instead, what is observed is the actual number of out-of-home activity episodes that the household head participates in, denoted by y_h. The relationship between the two is defined as:

$$y_h = j \text{ if } \mu_j < y_h^* \le \mu_{j+1}, \text{ for } j = 0, 1, \ldots, J, \tag{4.2}$$

where J is the maximum number of episodes that the household head can undertake. For J, there are $J + 1$ ordered responses corresponding to 0, 1, …, J out-of-home activity episodes. These ordered responses are separated by threshold parameters defined by the μs. Furthermore, there are $J + 2$ parameters of which only $J - 1$ are estimated along with β because $\mu_0 = -\infty$, $\mu_1 = 0$ and $\mu_{J+1} = +\infty$. Additionally, $\mu_0 < \mu_1 < \ldots < \mu_{J+1}$.

The random error term ε_h is assumed to be normally distributed across household heads with a mean of zero and a variance of one. Given this assumption, it is possible to express (4.2) in probabilistic terms, thereby obtaining the univariate ordered probit model:

$$P_{hj} = \Phi(\mu_{j+1} - \beta x_h) - \Phi(\mu_j - \beta x_h) \tag{4.3}$$

where P_{hj} is the probability that the head of household h will participate in j out-of-home activity episodes and $\Phi(.)$ is the cumulative standard normal density function. Estimates of β and μ_2, …, μ_J are found for the heads of single, non-worker and single-worker households using a program written in GAUSS that employs the maximum likelihood method.

4.3.1.2 Trivariate Ordered Probit Model

A joint model is developed to model household activity-episode generation for the heads of couple, non-worker, one-worker and two-worker households. In the following presentation of the model's structure, for each household h, let j represent the number of out-of-home activity episodes that the male head undertakes independently during the day (j = 0, 1, …, J), let k represent the number of such episodes that the female head participates in (k = 0, 1, …, K) and let l represent the number of out-of-home activity episodes that both heads undertake together (l = 0, 1, …, L). It should be noted, however, that in the case of one-worker households, j and k refer to working and non-working heads, respectively. The equation system can now be written as:

$$
\begin{aligned}
y_{1h}^{*} &= \beta_1 x_{1h} + \varepsilon_{1h},\ y_{1h} = j \text{ if } \mu_{1,j} < y_{1h}^{*} \le \mu_{1,j+1} \\
y_{2h}^{*} &= \beta_2 x_{2h} + \varepsilon_{2h},\ y_{2h} = k \text{ if } \mu_{2,k} < y_{2h}^{*} \le \mu_{2,k+1} \\
y_{3h}^{*} &= \beta_3 x_{3h} + \varepsilon_{3h},\ y_{3h} = l \text{ if } \mu_{3,l} < y_{3h}^{*} \le \mu_{3,l+1}
\end{aligned}
\tag{4.4}
$$

where y_{1h}^{*}, y_{2h}^{*} and y_{3h}^{*} are respectively the propensity for the male head of household h to engage in out-of-home activity episodes independently for a one-day period, the propensity for the female head to engage in such activity episodes and the propensity for both heads to undertake joint activity episodes. The observed number of independent out-of-home activity episodes for the male head is represented by y_{1h} and for the female head, y_{2h}. y_{3h} represents the observed number of joint episodes. The xs are vectors of exogenous variables. The βs are corresponding vectors of parameters that are estimated along with the μs for each equation. The random error terms ε_{1h}, ε_{2h} and ε_{3h} are assumed to be distributed identically and independently across households in accordance with the standard normal distribution.

Male and female household heads interact to collectively make decisions regarding the choices in (4.4). From the analyst's point of view, these interactions are both observed and unobserved. For example, the heads of a couple, one-worker household may decide that the working head must leave the only household vehicle at home for use during the day by the non-working head. Such an arrangement would likely reduce the propensity for the working head to participate in independent out-of-home activity episodes, while increasing that of the non-working head. In other words, a negative association exists between the two choices. The analyst can easily capture such an interaction using dummy variables. In reality, however, interactions between household heads will be mostly unobserved. For example, one household head may be actively involved with community organizations in the evening. If the other household head is to participate in out-of-home activity episodes during this period, he or she must do so independently. This arrangement precludes any joint out-of-home activity episodes. The key to capturing such unobserved interactions between household heads is to correlate the random error terms ε_{1h}, ε_{2h} and ε_{3h}. For this, a standard normal trivariate distribution function is specified such that:

$$\phi_3(.) = \phi_3(\varepsilon_{1h}, \varepsilon_{2h}, \varepsilon_{3h}, \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}). \tag{4.5}$$

Likewise, the corresponding cumulative density function is given as:

$$\Phi_3(.) = \Phi_3(\varepsilon_{1h}, \varepsilon_{2h}, \varepsilon_{3h}, \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}). \tag{4.6}$$

The ρs represent the correlations between the random error terms.

From (4.4) and (4.6), the joint probability that the male and female heads of household h will participate respectively in j and k independent out-of-home activity episodes, as well as l joint episodes is:

$$
\begin{aligned}
P_{hjkl} = {} & \Phi_3\left[(\mu_{1,j+1} - \beta_1 x_{1h}), (\mu_{2,k+1} - \beta_2 x_{2h}), (\mu_{3,l+1} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] - \\
& \Phi_3\left[(\mu_{1,j} - \beta_1 x_{1h}), (\mu_{2,k+1} - \beta_2 x_{2h}), (\mu_{3,l+1} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] - \\
& \Phi_3\left[(\mu_{1,j+1} - \beta_1 x_{1h}), (\mu_{2,k} - \beta_2 x_{2h}), (\mu_{3,l+1} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] - \\
& \Phi_3\left[(\mu_{1,j+1} - \beta_1 x_{1h}), (\mu_{2,k+1} - \beta_2 x_{2h}), (\mu_{3,l} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] - \\
& \Phi_3\left[(\mu_{1,j} - \beta_1 x_{1h}), (\mu_{2,k} - \beta_2 x_{2h}), (\mu_{3,l} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] + \\
& \Phi_3\left[(\mu_{1,j} - \beta_1 x_{1h}), (\mu_{2,k} - \beta_2 x_{2h}), (\mu_{3,l+1} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] + \\
& \Phi_3\left[(\mu_{1,j} - \beta_1 x_{1h}), (\mu_{2,k+1} - \beta_2 x_{2h}), (\mu_{3,l} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right] + \\
& \Phi_3\left[(\mu_{1,j+1} - \beta_1 x_{1h}), (\mu_{2,k} - \beta_2 x_{2h}), (\mu_{3,l} - \beta_3 x_{3h}), \rho_{\varepsilon_1\varepsilon_2}, \rho_{\varepsilon_1\varepsilon_3}, \rho_{\varepsilon_2\varepsilon_3}\right].
\end{aligned}
\tag{4.7}
$$

This model is hereby known as the *trivariate ordered probit model.* The assumptions regarding the μs for the univariate ordered probit model also apply here. This means that there are $J + K + L - 3$ threshold parameters to be estimated along with the βs and ρs. The parameters for the model are obtained by maximizing the log-likelihood function:

$$
L^* = \sum_{h=1}^{H}\sum_{j=0}^{J}\sum_{k=0}^{K}\sum_{l=0}^{L} Z_{hjkl} \log P_{hjkl} \tag{4.8}
$$

where

$$
Z_{hjkl} = \begin{cases} 1 & \text{if the heads of household } h \text{ participate in } j, k \text{ and } l \text{ activity episodes,} \\ 0 & \text{otherwise.} \end{cases}
$$

A program is written in GAUSS for this task.

4.3.2 Data and Sample

The data for this research are derived from a trip diary survey that was conducted for the Ontario Ministry of Transportation during February and March 1987. The sample of households for this survey was selected from households that responded to a much larger survey conducted in the Greater Toronto Area in 1986—that is, the 1986 Transportation Tomorrow Survey. The trip diary survey used a mail questionnaire to obtain socio-demographic information on each household surveyed, including all members over the age of five. It also collected detailed information concerning the daily travel behavior of such members for a pre-selected weekday. Complete questionnaires were obtained for 1,948 households.

Of this total, only 1,298 households were used in the present study because of a rigorous screening procedure. The original sample was first classified by household type. Any household that did not fit into one of the five types identified for analysis was removed from the sample. Next, for household heads, the number of out-of-home activity episodes was recorded for each activity setting (i.e. independent and joint activities) by purpose. The trip diary identified six activity types besides work and home: shopping, entertainment/socializing/recreation, drop off/pick up passenger, personal business, school and other. Households were eliminated from the sample if a head went to school on the survey day. The reason for this is that school, like work, is a mandatory activity that imposes constraints on discretionary activities. The number of out-of-home activity episodes was then totaled for the heads of each household type by activity setting. Once again, households were removed from the sample if the number of episodes undertaken independently or jointly by a head was considered an outlier. This decision ensured an adequate number of observations for each ordered response of the dependent variable. Finally, the sample was checked for missing data. Upon completion of the screening procedure, the sample consisted of 210 single, non-worker households; 350 single-worker households; 120 couple, non-worker households; 249 couple, one-worker households; and 369 couple, two-worker households.

Observed distributions of the daily number of out-of-home activity episodes for the heads of these households are found in Table 4.2. Inspection of this table reveals some interesting findings. First, the non-working heads of couple, one-worker households are the most active, pursuing up to four independent episodes daily. Second, the male and female heads of couple, two-worker households appear to engage in a similar number of independent out-of-home activity episodes. Third, the heads of single, non-worker and single-worker households are more likely to engage in such episodes than the heads of the other household types. Finally, the heads of couple, non-worker, one-worker and two-worker households are more likely to pursue out-of-home activities independently than together.

4.4 Empirical Findings

4.4.1 Variables and Model Specification

The choice of independent variables for potential inclusion in the household activity-episode generation models was guided by the findings from previous activity-based research and intuitive arguments regarding the effects of variables designed to capture interactions between household heads. The variables included in the final model specifications are found in Table 4.3, along with their definitions. The first group of variables measures socio-demographic characteristics of households and their heads, whereas the second group is defined only for those heads that work. A more detailed

Table 4.2
Observed distributions of the daily number of out-of-home activity episodes by type

Number of Activity Episodes	Household Type				
	Single, Non-worker	Single-worker	Couple, Non-worker	Couple, One-worker	Couple, Two-worker
Male/Worker					
0		0.5057	0.5500	0.6707	0.5908
1		0.2800	0.2917	0.2329	0.2737
2		0.1429	0.1583	0.0964	0.0921
3		0.0714			0.0434
Female/Non-worker					
0	0.4619		0.7250	0.3976	0.5610
1	0.2810		0.2000	0.2851	0.2547
2	0.1714		0.0750	0.1687	0.1328
3	0.0857			0.0723	0.0515
4				0.0763	
Joint					
0			0.7917	0.8996	0.8862
1			0.1333	0.0843	0.0921
2			0.0750	0.0161	0.0217

Table 4.3
Independent variables used in the household activity-episode generation models

Variable	Definition
Socio-demographic Characteristics	
Age	Age of household head in years × 10^{-1}
Children ≤ 5 years present	1 if household contains children ≤ 5 years old; 0 otherwise
Children ≥ 6 years, ≤ 10 years present	1 if household contains children ≥ 6 years old and ≤ 10 years old; 0 otherwise
Children ≥ 6 years, ≤ 15 years present	1 if household contains children ≥ 6 years old and ≤ 15 years old; 0 otherwise
Female and children ≤ 5 years present	1 if head of single-worker household is female and household contains children ≤ 5 years old; 0 otherwise
Female and children ≥ 6 years, ≤ 10 years present	1 if head of single-worker household is female and household contains children ≥ 6 years old and ≤ 10 years old; 0 otherwise
Household income	Annual household income in dollars × 10^{-4}
Licensed and vehicle present	1 if female head of couple, non-worker household is licensed and the household has a vehicle; 0 otherwise
Licensed female and vehicle present	1 if head of single, non-worker or single-worker household is a licensed female and the household has a vehicle; 0 otherwise
Licensed, one-vehicle household and vehicle unavailable while worker is at work	1 if non-working head of couple, one-worker household is licensed and the only household vehicle is unavailable for use while the working head is at work; 0 otherwise
Licensed, one-vehicle household and vehicle available while worker is at work	1 if non-working head of couple, one-worker household is licensed and the only household vehicle is available for use while the working head is at work; 0 otherwise
Licensed and multiple-vehicle household	1 if non-working head of couple, one-worker household is licensed and the household has more than one vehicle; 0 otherwise
Male licensed, female licensed and vehicle present	1 if both heads of couple, non-worker household are licensed and the household has a vehicle; 0 otherwise
Only male licensed and vehicle present	1 if only male head of couple, non-worker household is licensed and the household has a vehicle; 0 otherwise
Only worker licensed and vehicle present	1 if only working head of couple, one-worker household is licensed and the household has a vehicle; 0 otherwise
Reside in Metropolitan Toronto	1 if household lives in Metropolitan Toronto; 0 otherwise
Work Characteristics	
Female and transit to work	1 if head of single-worker household is female and takes public transit to work; 0 otherwise
Part-time employment	1 if household head is employed part-time; 0 otherwise

Work duration	Work duration of household head in minutes × 10^{-2}
Same work schedule as female	1 if male head of couple, two-worker household has same work schedule as female head; 0 otherwise
Household heads commute together	1 if heads of couple, two-worker household commute to work together in a household vehicle; 0 otherwise
Transit to work	1 if household head takes public transit to work; 0 otherwise
Multiple-vehicle household and drive alone to work	1 if household has more than one vehicle and household head drives alone to work; 0 otherwise
One-vehicle household and drive alone to work	1 if household has only one vehicle and household head drives alone to work; 0 otherwise

account of these variables is given in the following section in reference to the models in which they are included.

To ascertain whether or not daily out-of-home activity episodes are determined jointly by the heads of couple, non-worker, one-worker and two-worker households, two models were specified for each household type. The first specification, which is denoted in this chapter as a joint model, captured any unobserved interactions between household heads by correlating the error terms in (4.4). For the second specification, these error terms were left uncorrelated by setting the ρs in (4.7) to zero, which implies that the number of daily out-of-home activity episodes for each equation in (4.4) is determined independently. This specification is appropriately denoted as an independent model. For each household type, the two models were compared using the following likelihood ratio test statistic:

$$-2[L_I^*(\beta) - L_J^*(\beta)] \tag{4.9}$$

which is χ^2 distributed with three degrees of freedom. $L_J^*(\beta)$ and $L_I^*(\beta)$ are respectively the log-likelihood values from the joint and independent model specifications.

4.4.2 Model Results

4.4.2.1 Single, Non-worker Households

Table 4.4 presents the model results for the heads of single, non-worker households. As can be seen, only three independent variables are found to influence significantly the propensity for household heads to engage in out-of-home activity episodes. This fact is

Table 4.4
Model results for single, non-worker households

Variable	Coefficient	*t*-statistic
Independent Activity Episodes for Non-worker		
Constant Term	1.3867	2.804
Socio-demographic Characteristics		
Age	-0.2295	-3.360
Household income	0.1516	2.373
Licensed female and vehicle present	0.3041	1.776
Threshold Values		
One and two activity episodes	0.8009	8.692
Two and three activity episodes	1.5522	11.417
SUMMARY STATISTICS		
n	210	
$L^*(0)$	-291.1	
$L^*(c)$	-257.5	
$L^*(\beta)$	-247.2	
$-2[L^*(c)-L^*(\beta)]$	20.6	
ρ^2	0.0400	
Percent right	47.1429	
Expected percent right	35.6341	

reflected in the low value of ρ^2, which is computed as follows for this model and those to be discussed:

$$\rho^2 = 1 - \frac{L^*(\beta)}{L^*(c)} \tag{4.10}$$

where $L^*(\beta)$ is the value of the log-likelihood function at its maximum—that is, when it includes independent variables—and $L^*(c)$ is the value of the log-likelihood function when it includes only constant terms and threshold values (i.e. the μs).

The effects of the socio-demographic characteristics are as anticipated. Age has a negative impact on the propensity for household heads to engage in out-of-home activity episodes. This is possibly due to the lower activity levels of older people, as suggested by Bhat (1997). The positive effect of household income on activity-episode generation is well documented in the activity-based literature (e.g. Bhat 1997; Strathman *et al.* 1994). With increasing income, there is likely more money available for participation in out-of-home discretionary activities, particularly those involving entertainment and socializing. Female household heads with a driver's license and access to a vehicle are likely to engage in more out-of-home activity episodes than other household heads. Two factors account for this finding. First, vehicle ownership is much lower for single, non-worker households than for other household types. Second, the vast majority of household heads is female. The legal ability to drive coupled with vehicle ownership greatly enhances personal mobility, thereby reducing constraints associated with participation in out-of-home activities.

Despite the low value of ρ^2, the model performs reasonably well in terms of its predictive ability. Two measures are used for this assessment: percent right and expected percent right. The former statistic is defined as:

$$\text{Percent right} = \frac{100}{H}\left(\sum_{h=1}^{H} y_h\right) \tag{4.11}$$

where y_h is one if the highest predicted probability corresponds to the observed number of out-of-home activity episodes for the head of household h and zero otherwise. The latter statistic is measured as:

$$\text{Expected percent right} = \frac{100}{H}\left(\sum_{h=1}^{H}\sum_{j=0}^{J} P_{hj} y_{hj}\right) \tag{4.12}$$

where P_{hj} is the predicted probability that the head of household h will participate in j out-of-home activity episodes, and y_{hj} is one if the head is observed to select j episodes and zero otherwise. The percent right and expected percent right for the model are respectively 47 and 36 percent.

4.4.2.2 Single-worker Households

The model results for the heads of single-worker households are found in Table 4.5. A total of eight explanatory variables are found to influence significantly the propensity for household heads to participate in out-of-home activity episodes. The overall goodness-of-fit of the model, as indicated by a ρ^2 value of approximately 0.116, is considerably higher than that for the heads of single, non-worker households. Furthermore, the model's

Table 4.5
Model results for single-worker households

Variable	Coefficient	*t*-statistic
Independent Activity Episodes for Worker		
Constant Term	1.8597	4.597
Socio-demographic Characteristics		
Age	-0.1193	-2.062
Household income	0.1622	2.907
Licensed female and vehicle present	0.2664	1.980
Female and children ≤ 5 years present	1.2402	2.524
Female and children ≥ 6 years, ≤ 10 years present	0.7377	2.108
Work Characteristics		
Work duration	-0.3641	-6.544
Part-time employment	-0.5982	-2.027
Female and transit to work	-0.4678	-2.791
Threshold Values		
One and two activity episodes	0.9390	11.216
Two and three activity episodes	1.7670	13.992
SUMMARY STATISTICS		
n	350	
$L^*(0)$	-485.2	
$L^*(c)$	-408.6	
$L^*(\beta)$	-361.4	
$-2[L^*(c)-L^*(\beta)]$	94.4	
ρ^2	0.1156	
Percent right	52.5714	
Expected percent right	42.6454	

predictive ability is greater—that is, the percent right is 53 percent and the expected percent right is 43 percent.

The effects of the first three socio-demographic characteristics in Table 4.5 on the propensity for household heads to engage in out-of-home activity episodes are the same as those for the heads of single, non-worker households. In addition, the presence of children in the household has a positive influence on the number of episodes undertaken by female heads. However, the magnitude of this effect depends on the age of children. Specifically, the presence of young children in the household (i.e. children less than six years old) has a greater impact on activity-episode generation than the presence of older children (i.e. children between six and ten years old). Moreover, children 11 years and older have no impact on this process. Two factors are responsible for this finding. First, children are more likely to reside with female heads than male heads. Second, the daily number of episodes for dropping off or picking up children decreases with their age. For example, in single-worker households, it is highly likely that young children are dropped off and picked up at daycare on a regular basis. This activity ceases when the children attend school, thereby reducing the propensity for female heads to participate in out-of-home activity episodes.

Several work characteristics are found to have negative impacts on activity-episode generation. Work is perhaps the single most important constraint on this process because it determines the amount of time available for participation in discretionary activities both at home and abroad. As shown in Table 4.5, as work duration increases, the propensity to engage in out-of-home activity episodes decreases. Furthermore, there is a distinction between full-time and part-time work. Specifically, the daily number of episodes is likely to be less for part-time workers than for full-time workers. This finding indicates that part-time workers are more likely to engage in out-of-home activities on non-working days than on working days—an option that is not available to full-time workers. As well, part-time workers are more likely to have less money to participate in discretionary activities. Finally, commuting to work by public transit reduces the number of episodes for female heads who are more likely than male heads to use this mode for their work commutes. This finding demonstrates the importance of chaining activities to the work commute, particularly that in the evening. Public transit reduces this possibility because it imposes greater constraints on female heads than would be realized if they drove to work alone.

4.4.2.3 Couple, Non-worker Households

Table 4.6 presents the model results for the heads of couple, non-worker households. For the joint model, three variables are found to influence significantly the propensities for male and female heads to participate in independent out-of-home activity episodes. For male heads, age has a negative impact on the number of such episodes, as does the presence of children between the ages of six and 15. The latter finding suggests that male heads spend more time at home nurturing young school-age children than older ones who are more independent. However, when only children less than six years old are present in the household, male heads undertake more episodes independently possibly because female heads are the primary caregivers for very young children. For female heads, those with a driver's license and access to a vehicle are likely to engage in more independent

Table 4.6
Model results for couple, non-worker households

Variable	Joint Model		Independent Model	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Independent Activity Episodes for Male				
Constant Term	2.9620	6.785	3.3673	4.309
Socio-demographic Characteristics				
Age	-0.4458	-7.356	-0.5019	-4.463
Children $\geq$ 6 years, $\leq$ 15 years present	-1.9097	-2.657	-2.3232	-2.854
Threshold Values				
One and two activity episodes	0.9663	6.785	0.9764	6.738
Independent Activity Episodes for Female				
Constant Term	-0.7535	-4.774	-0.7948	-4.034
Socio-demographic Characteristics				
Licensed and vehicle present	0.3849	1.698	0.4583	1.760
Threshold Values				
One and two activity episodes	0.8807	5.355	0.8702	5.326
Joint Activity Episodes				
Constant Term	-1.3408	-4.474	-1.4037	-4.607
Socio-demographic Characteristics				
Male licensed, female licensed and vehicle present	0.6052	1.675	0.6967	1.914
Only male licensed and vehicle present	0.7584	2.113	0.8311	2.277
Threshold Values				
One and two activity episodes	0.6615	4.316	0.6615	4.314
Correlation Coefficients				
Male and female	0.4356	3.657		
Female and joint	-0.3208	-2.023		
Male and joint	-0.0504	-0.333		
SUMMARY STATISTICS				
n	120		120	
$L^*(0)$	-395.5		-395.5	
$L^*(c)$	-285.2		-285.2	
$L^*(\beta)$	-264.5		-271.8	
$-2[L^*(c)-L^*(\beta)]$	41.4		26.8	
ρ^2	0.0726		0.0470	

out-of-home activity episodes than other female heads for reasons that have already been discussed.

For joint episodes, two variables are defined to capture interactions between male and female heads in terms of their mobility constraints. As shown in Table 4.6, both of these variables have significant positive effects on the propensity for household heads to participate in such out-of-home activity episodes. Moreover, their coefficient values are as anticipated. Specifically, male and female heads who are both licensed and have access to a vehicle are likely to engage in more joint episodes than household heads who do not have access to a vehicle. Furthermore, households in which only the male head is licensed and has access to a vehicle realize the greatest number of such episodes. The reason for this is that female heads depend on male heads for mobility.

The joint model is compared to the independent model in Table 4.6. A likelihood ratio test statistic of 14.6 with three degrees of freedom rejects the null hypothesis that all the correlation coefficients are zero. In other words, the number of daily out-of-home activity episodes is determined jointly by the heads of couple, non-worker households. However, as shown in the table, only two of the three correlation coefficients are significant. The error terms for the number of independent episodes undertaken by male and female heads are positively correlated. This indicates a positive unobserved interaction between household heads. In contrast, the error terms for the number of joint episodes and the number of independent episodes undertaken by female heads are negatively correlated. This suggests a substitution effect between the two activity settings—that is, unobserved interactions that increase the propensity for female heads to participate in independent activity episodes decrease the propensity for household heads to undertake joint episodes. Incorporating unobserved interactions between male and female heads in the modeling framework improves considerably the overall goodness-of-fit of the model. The value of ρ^2 is 0.073 for the joint model, which is considerably higher than a value of 0.047 for the independent model.

4.4.2.4 Couple, One-worker Households

The model results for the heads of couple, one-worker households are presented in Table 4.7. Five explanatory variables are found to influence significantly the daily number of out-of-home activity episodes undertaken independently by working heads. Age has a negative impact on such episodes, as does work duration. In contrast, household income increases the propensity for working heads to participate in independent episodes. The effects of the two work mode variables are as expected. Commuting to work by public transit reduces the number of independent activity episodes, whereas driving to work alone increases them. The magnitude of the latter effect depends on household vehicle ownership. Specifically, working heads who are members of multiple-vehicle households are likely to participate in more independent episodes than are those who are members of one-vehicle households. The reason for this is that vehicle constraints are much greater in one-vehicle households than in multiple-vehicle households.

Five socio-demographic characteristics are found to have significant positive effects on the propensity for non-working heads to participate in independent out-of-home activity episodes. As indicated in Table 4.7, such heads are responsible for dropping off and picking up young children (i.e. six to 10 years old) at school. Those who reside in

Table 4.7
Model results for couple, one-worker households

Variable	Joint Model		Independent Model	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Independent Activity Episodes for Worker				
Constant Term	0.9676	1.864	0.9569	1.760
Socio-demographic Characteristics				
Age	-0.2349	-3.553	-0.2378	-3.1515
Household income	0.1167	2.347	0.1187	2.348
Work Characteristics				
Work duration	-0.1895	-3.011	-0.1848	-2.825
Transit to work	-0.6227	-1.785	-0.6031	-1.699
Multiple-vehicle household and drive alone to work	0.3231	1.884	0.2914	1.675
Threshold Values				
One and two activity episodes	0.9749	8.481	0.9679	8.465
Independent Activity Episodes for Non-worker				
Constant Term	-0.6431	-3.782	-0.6563	-3.846
Socio-demographic Characteristics				
Children ≥ 6 years, ≤ 10 years present	0.4229	2.297	0.4271	2.309
Reside in Metropolitan Toronto	0.4635	2.868	0.4694	2.902
Licensed, one-vehicle household and vehicle unavailable while worker is at work	0.7866	3.462	0.8049	3.538
Licensed, one-vehicle household and vehicle available while worker is at work	1.4691	5.179	1.4906	5.260
Licensed and multiple-vehicle household	1.0268	5.606	1.0356	5.637
Threshold Values				
One and two activity episodes	0.8247	9.561	0.8237	9.562
Two and three activity episodes	1.4799	12.659	1.4779	12.655
Three and four activity episodes	1.9157	13.571	1.9134	13.559
Joint Activity Episodes				
Constant Term	-1.5534	-9.808	-1.5542	-9.841
Socio-demographic Characteristics				
Children ≤ 5 years present	0.4777	2.063	0.5042	2.150
Only worker licensed and vehicle present	0.4662	1.974	0.4614	1.923
Threshold Values				
One and two activity episodes	0.8942	4.663	0.9054	4.639
Correlation Coefficients				
Worker and non-worker	0.1242	1.396		
Non-worker and joint	-0.0132	-0.245		
Worker and joint	-0.4417	-3.477		

SUMMARY STATISTICS

n	249	249
$L^*(0)$	-947.8	-947.8
$L^*(c)$	-650.8	-650.8
$L^*(\beta)$	-599.9	-605.8
$-2[L^*(c)-L^*(\beta)]$	101.7	90.0
ρ^2	0.0781	0.0691

Metropolitan Toronto are likely to undertake more independent episodes than are those who do not live there. Two factors account for this. First, commercial and retail densities are much higher in Metropolitan Toronto than elsewhere in the Greater Toronto Area (GTA). Second, personal mobility is much greater in Metropolitan Toronto than in the remainder of the GTA because of convenient public transit, which includes a subway system. The remaining three variables are defined to capture constraints relating to the availability of household vehicles while the worker is at work. The reference category consists of unlicensed non-working heads and households without a vehicle, as well as a combination of the two. The values of the coefficients are as expected. Specifically, the availability of a vehicle in a one-vehicle household greatly enhances the propensity for the licensed non-working head to undertake independent out-of-home activity episodes. This indicates that the vehicle has most likely been left at home exclusively for this purpose. Further evidence to support this finding is suggested by the coefficient for non-working heads who reside in multiple-vehicle households—that is, such heads participate in fewer activity episodes despite the fact that they always have access to a vehicle. Finally, a non-working head in a one-vehicle household without access to a vehicle while the working head is at work can use the vehicle to participate in independent out-of-home activity episodes only when the working head is at home. This constraint is reflected in the value of the coefficient for this variable—that is, it is the smallest of the three coefficients.

Two variables are found to influence significantly the propensity for household heads to participate in joint out-of-home activity episodes. The presence of young children (i.e.

less than six years old) in the household has a positive effect on the number of such episodes. One possible reason for this is that the non-working head may require relief from the responsibilities of childcare. Thus, both household heads undertake out-of-home activities together. Alternatively, both heads may need to be present at some activity involving young children, such as a doctor's appointment. As shown in Table 4.7, the second variable also has a positive influence on joint episodes. Specifically, households in which only the working head is licensed and has access to a vehicle realize the greatest number of episodes for reasons that have already been given.

The joint model is compared to the independent model in Table 4.7. A likelihood test statistic of 11.8 with three degrees of freedom rejects the null hypothesis that all the correlation coefficients are zero. In other words, the number of daily out-of-home activity episodes is determined jointly by the heads of couple, one-worker households. However, as shown in the table, only one of the correlation coefficients is significant. The error terms for the number of joint episodes and the number of independent activity episodes undertaken by working heads are negatively correlated. This suggests a substitution effect between the two activity settings—that is, unobserved interactions that increase the propensity for working heads to undertake independent episodes decrease the propensity for household heads to engage in out-of-home activity episodes together. The overall goodness-of-fit of the joint model as measured by ρ^2 is 0.078, which is higher than that for the independent model.

4.4.2.5 Couple, Two-worker Households

Table 4.8 presents the results for the heads of couple, two-worker households. Five independent variables are found to influence the number of independent out-of-home activity episodes undertaken by male household heads. The effects of age, household income, work duration and commuting to work by public transit are the same as discussed for the working heads of other household types. Moreover, the same variables are found to influence the propensity for female heads to participate in independent episodes. Synchronization of the work schedules of male and female heads has a negative impact on the number of out-of-home activity episodes undertaken independently by male heads. A possible reason for this is that both working heads want to spend time together at home or participating in joint out-of-home activities. If their work schedules are not the same, male heads have more freedom to engage in independent episodes.

Besides the explanatory variables already mentioned, driving to work alone is found to have a positive influence on the number of episodes undertaken independently by female heads. However, the magnitude of this effect depends on household vehicle ownership. Specifically, female heads who reside in one-vehicle households are likely to undertake more independent episodes than are those who live in multiple-vehicle households. One possible explanation for this is that female heads who reside in the former household type are responsible for the majority of household maintenance activities, such as grocery shopping, which are chained to the work commute. For the latter household type, such activities can be shared more equitably because constraints involving vehicle allocation are virtually nonexistent. Alternatively, vehicles may be

Table 4.8
Model results for couple, two-worker households

Variable	Joint Model		Independent Model	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Independent Activity Episodes for Male				
Constant Term	1.6750	4.108	1.5989	3.786
Socio-demographic Characteristics				
Age	-0.2288	-3.690	-0.2070	-3.293
Household income	0.0688	1.977	0.0662	1.908
Work Characteristics				
Work duration	-0.2330	-4.595	-0.2329	-4.371
Transit to work	-0.5709	-2.484	-0.5649	-2.348
Same work schedule as female	-0.2401	-1.939	-0.2430	-1.853
Threshold Values				
One and two activity episodes	0.9457	11.421	0.9413	11.396
Two and three activity episodes	1.5693	12.958	1.5744	12.862
Independent Activity Episodes for Female				
Constant Term	0.9586	2.299	1.0129	2.410
Socio-demographic Characteristics				
Age	-0.1612	-2.363	-0.1442	-2.182
Household income	0.1019	2.962	0.1012	2.956
Children ≤ 5 years present	0.4944	2.783	0.5161	2.747
Work Characteristics				
Work duration	-0.2551	-5.091	-0.2797	-5.394
Transit to work	-0.6468	-3.053	-0.6045	-2.757
One-vehicle household and drive alone to work	0.4780	2.085	0.4291	1.780
Multiple-vehicle household and drive alone to work	0.2887	2.002	0.3025	2.015
Threshold Values				
One and two activity episodes	0.8651	10.978	0.8627	10.926
Two and three activity episodes	1.7003	13.356	1.7323	13.327
Joint Activity Episodes				
Constant Term	-1.2155	-12.543	-1.2152	-12.555
Socio-demographic Characteristics				
Children ≤ 5 years present	-0.8153	-1.901	-0.8141	-1.901
Work Characteristics				
Household heads commute together	0.5206	2.146	0.5138	2.129
Threshold Values				
One and two activity episodes	0.8380	6.041	0.8383	6.049
Correlation Coefficients				
Male and female	0.3909	6.060		
Female and joint	0.0331	0.542		
Male and joint	0.0103	0.198		

SUMMARY STATISTICS		
n	369	369
$L^{*}(0)$	-1428.4	-1428.4
$L^{*}(c)$	-931.6	-931.6
$L^{*}(\beta)$	-850.8	-866.0
$-2[L^{*}(c)-L^{*}(\beta)]$	161.6	131.1
ρ^{2}	0.0867	0.0703

allocated to the female heads of one-vehicle households for the explicit purpose of undertaking particular activities on a specific day. For example, the female head may have a doctor's appointment after work.

Two variables are found to influence the propensity for household heads to engage in joint out-of-home activity episodes. The presence of young children (i.e. less than six years old) in the household has a negative effect on the number of such episodes. The reason for this is that working parents want to spend time at home with young children after work. In contrast, commuting to work together in a vehicle has a positive impact on the number of joint episodes for obvious reasons.

The joint model is compared to the independent model in Table 4.8. A likelihood test statistic of 30.4 with three degrees of freedom rejects the null hypothesis that all the correlation coefficients are zero. In other words, the number of daily out-of-home activity episodes is determined jointly by the heads of couple, two-worker households. However, as shown in the table, only one correlation coefficient is significant. The error terms for the number of independent episodes undertaken by male and female heads are positively correlated, indicating a positive unobserved interaction between household heads. The overall goodness-of-fit of the joint model as measured by ρ^2 is 0.087, which is much higher than that for the independent model.

4.4.3 Model Comparison

The joint and independent models estimated for the heads of couple, non-worker, one-worker and two-worker households are also compared based on predictive ability. Three measures are used for this task: percent right, expected percent right and aggregate probability. The first two statistics are computed in a manner similar to those defined in (4.11) and (4.12), respectively. In comparison, the latter measure is obtained from predicted probabilities as follows:

$$P_{jkl}^{A} = \frac{1}{H}\sum_{h=1}^{H} P_{hjkl} \tag{4.13}$$

where P_{jkl}^{A} is the aggregate probability that male/working and female/non-working heads undertake respectively j and k independent out-of-home activity episodes, as well as l joint episodes. For each household type, the aggregate and observed probabilities are compared using a correlation coefficient. The results of the model comparison are found in Table 4.9. For each household type, all three measures confirm that the joint model predicts more accurately than the independent model.

4.5 Conclusions

This chapter demonstrates the importance of recognizing the household as the primary decision-making unit in activity-based research. Specifically, the number of daily out-of-home activity episodes for non-work purposes is modeled for the heads of five common household types. The models used for this purpose recognize the ordinal and discrete nature of the household decision-making process. For the heads of single, non-worker and single-worker households, the univariate ordered probit model developed by McKelvey and Zavoina (1975) is used. However, to account for interactions between

Table 4.9
Model comparison based on predictive ability

Number of Activity Episodes			Observed and Predicted Probability								
			Couple, Non-worker Households			Couple, One-worker Households			Couple, Two-worker Households		
M/W[a]	F/N[b]	Joint	Obs.	Joint	Ind.	Obs.	Joint	Ind.	Obs.	Joint	Ind.
0	0	0	0.3750	0.3441	0.3153	0.2610	0.2455	0.2432	0.3659	0.3521	0.3046
0	0	1	0.0667	0.0693	0.0530	0.0281	0.0329	0.0251	0.0379	0.0372	0.0335
0	0	2	0.0417	0.0404	0.0294	0.0040	0.0071	0.0050	0.0081	0.0088	0.0081
0	1	0	0.0417	0.0708	0.0860	0.1647	0.1642	0.1704	0.0949	0.1156	0.1303
0	1	1	0.0083	0.0063	0.0148	0.0281	0.0198	0.0152	0.0081	0.0119	0.0133
0	1	2	0.0000	0.0022	0.0082	0.0040	0.0040	0.0028	0.0000	0.0029	0.0032
0	2	0	0.0167	0.0164	0.0314	0.0964	0.0954	0.1032	0.0461	0.0458	0.0671
0	2	1	0.0000	0.0008	0.0055	0.0120	0.0111	0.0087	0.0108	0.0044	0.0063
0	2	2	0.0000	0.0002	0.0030	0.0000	0.0022	0.0015	0.0000	0.0011	0.0015
0	3	0				0.0281	0.0377	0.0424	0.0190	0.0129	0.0247
0	3	1				0.0040	0.0043	0.0035	0.0000	0.0011	0.0021
0	3	2				0.0000	0.0008	0.0006	0.0000	0.0003	0.0005
0	4	0				0.0321	0.0364	0.0432			
0	4	1				0.0040	0.0042	0.0035			
0	4	2				0.0040	0.0008	0.0006			
1	0	0	0.1000	0.1436	0.1670	0.0602	0.0774	0.0779	0.0976	0.1099	0.1283
1	0	1	0.0250	0.0304	0.0289	0.0040	0.0034	0.0084	0.0081	0.0115	0.0139
1	0	2	0.0167	0.0177	0.0161	0.0040	0.0004	0.0017	0.0054	0.0027	0.0033
1	1	0	0.1167	0.0661	0.0472	0.0562	0.0663	0.0612	0.0894	0.0730	0.0635
1	1	1	0.0083	0.0071	0.0083	0.0040	0.0028	0.0057	0.0081	0.0076	0.0064
1	1	2	0.0083	0.0027	0.0046	0.0000	0.0003	0.0011	0.0054	0.0018	0.0015
1	2	0	0.0167	0.0251	0.0176	0.0482	0.0439	0.0389	0.0298	0.0413	0.0350
1	2	1	0.0000	0.0015	0.0032	0.0000	0.0018	0.0035	0.0027	0.0041	0.0032
1	2	2	0.0000	0.0004	0.0017	0.0000	0.0002	0.0006	0.0027	0.0010	0.0007
1	3	0				0.0321	0.0189	0.0163	0.0217	0.0166	0.0138
1	3	1				0.0000	0.0008	0.0014	0.0027	0.0015	0.0011
1	3	2				0.0000	0.0001	0.0003	0.0000	0.0004	0.0002
1	4	0				0.0241	0.0200	0.0167			

1	4	1				0.0000	0.0008	0.0014			
1	4	2				0.0000	0.0001	0.0003			
2	0	0	0.0667	0.0564	0.0902	0.0361	0.0272	0.0301	0.0217	0.0264	0.0403
2	0	1	0.0250	0.0120	0.0152	0.0000	0.0005	0.0032	0.0000	0.0027	0.0043
2	0	2	0.0083	0.0071	0.0084	0.0000	0.0000	0.0006	0.0000	0.0006	0.0010
2	1	0	0.0167	0.0428	0.0258	0.0281	0.0276	0.0253	0.0298	0.0247	0.0213
2	1	1	0.0000	0.0053	0.0045	0.0000	0.0005	0.0024	0.0054	0.0026	0.0021
2	1	2	0.0000	0.0022	0.0025	0.0000	0.0000	0.0004	0.0000	0.0006	0.0005
2	2	0	0.0417	0.0264	0.0097	0.0120	0.0202	0.0165	0.0271	0.0176	0.0122
2	2	1	0.0000	0.0019	0.0017	0.0000	0.0003	0.0015	0.0000	0.0018	0.0011
2	2	2	0.0000	0.0006	0.0010	0.0000	0.0000	0.0003	0.0000	0.0004	0.0003
2	3	0				0.0080	0.0093	0.0070	0.0081	0.0091	0.0049
2	3	1				0.0000	0.0002	0.0006	0.0000	0.0008	0.0004
2	3	2				0.0000	0.0000	0.0001	0.0000	0.0002	0.0001
2	4	0				0.0120	0.0106	0.0072			
2	4	1				0.0000	0.0002	0.0006			
2	4	2				0.0000	0.0000	0.0001			
3	0	0							0.0136	0.0100	0.0201
3	0	1							0.0027	0.0010	0.0021
3	0	2							0.0000	0.0002	0.0005
3	1	0							0.0108	0.0126	0.0113
3	1	1							0.0027	0.0013	0.0011
3	1	2							0.0000	0.0003	0.0002
3	2	0							0.0108	0.0113	0.0066
3	2	1							0.0027	0.0011	0.0006
3	2	2							0.0000	0.0003	0.0001
3	3	0							0.0000	0.0077	0.0027
3	3	1							0.0000	0.0007	0.0002
3	3	2							0.0000	0.0002	0.0000
SUMMARY STATISTICS											
Percent right				38.3333	37.5000		24.8996	24.0964		36.3144	35.5014
Expected percent right				19.2359	18.4311		14.4885	14.4745		19.9763	18.6084
r^c				0.9738	0.9386		0.9939	0.9909		0.9947	0.9749

[a] Independent activity episodes for male or worker.
[b] Independent activity episodes for female or non-worker.
[c] Correlation between observed and predicted probability.

household heads, as well as independent and joint out-of-home activity episodes, a joint model is developed for couple, non-worker, one-worker and two-worker households. This model, known as the trivariate ordered probit model, is an important contribution to the discrete choice literature.

The models are estimated using data from a trip diary survey conducted in the Greater Toronto Area in 1987. As expected, the composition of significant explanatory variables differs for each of the household types, reflecting their inherent differences. Furthermore, the model results for couple, non-worker, one-worker and two-worker households suggest that household heads determine jointly the number of daily out-of-home activity episodes. Additional analysis reveals that the joint models predict more accurately than the independent ones.

5 Household Activity-Episode Generation: An Object-Oriented Simulation Model

5.1 Introduction

In the future, the models for predicting travel demand in urban areas will be radically different from those today. Most importantly, they will be activity-based (Barrett *et al.* 1995; Miller 1996; Spear 1996). In other words, patterns of activities will be modeled, not discrete trips. Furthermore, the complex interactions between travel demand and land-use patterns will be treated endogenously within the modeling frameworks (Kitamura *et al.* 1996; Miller and Salvini 1998; Stopher *et al.* 1996). Today, only state-of-the-art integrated urban land-use and transportation models incorporate such interactions. Finally, such models will be implemented as microsimulations, whereby travel demand is simulated over time as an aggregate outcome from the actions of decision-making units (Goulias 1997; Kitamura *et al.* 1996; Miller 1996; Miller and Salvini 1997, 1998; Stopher *et al.* 1996). These decision-making units include households and their members.

Presently, work is underway on several activity-based microsimulation models of urban travel demand. They include: ILUTE (Integrated Land-Use, Transportation and Environment modeling system) (Miller and Salvini 1997, 1998), SMART (Simulation Model for Activities, Resources and Travel) (Stopher *et al.* 1996) and SAMS (Sequenced Activity Mobility Simulator) (Kitamura *et al.* 1996). Models such as these are inherently complex and their development in an acceptable timeframe requires the cooperative and cumulative efforts of many researchers who may be from various disciplines. Effective communication among these researchers is possible only through a common modeling language.

As noted by Jackson (1994), the field of computer and information science has made considerable progress in formalizing a method for tackling complex problems for which solutions require the participation of many individuals. This method is known as object-oriented modeling (OOM). It is based on objects, not algorithms. The key to OOM is identifying objects from the vocabulary of a problem. Although this task can be quite complicated, for activity-based microsimulation models there is a one-to-one mapping of objects in the simulated world to objects in the real world. It is argued in this chapter that OOM provides a common modeling language for researchers who are developing future travel demand models. Furthermore, OOM is especially useful in computer simulation modeling because its constructs are readily implemented using an object-oriented programming (OOP) language such as C++ or Java. In other words, the direct linkage between OOM and OOP facilitates software development.

The objectives of this chapter are twofold. First, an overview of OOM is provided, including reasons for its use in computer simulation modeling besides its role as a common modeling language for researchers. An actual object-oriented simulation model is used to demonstrate the concepts discussed. This model generates the daily number of out-of-home activity episodes undertaken by the heads of five common household types. Moreover, it is the *Activity-Episode Generation* module of a household-level, activity-based travel demand forecasting system discussed in Chapter 3. This model alone demonstrates two important advantages of OOM—modularity and incremental development. Second, the household activity-episode generation model is used to evaluate the impact of a travel demand management (TDM) strategy on the daily number of out-of-home activity episodes estimated for household heads in the Greater Toronto Area (GTA) in 1986. Specifically, the effects of a compressed workweek are evaluated for two scenarios. The first scenario assumes that all full-time workers adopting the strategy work four 10-hour days, whereas the second scenario applies to their day off. The results demonstrate that the impact of the latter scenario is much greater than the former.

The remainder of this chapter is organized as follows. The next section provides an overview of object-oriented modeling. The household activity-episode generation model is described in the third section. Moreover, the Universal Modeling Language (UML) is used to document the structural and behavioral characteristics of the model. Section four presents the scenarios and simulation results. The contributions of this study to activity-based research are summarized in the final section.

5.2 Overview of Object-Oriented Modeling

5.2.1 History

Over time, software engineers have had to model increasingly complex systems. To deal with this complexity, the traditional algorithmic approach to software design has been replaced by an object-oriented one whose roots can be traced to the development of the

SIMULA programming language in the 1960s (Dahl and Nygaard 1966). Object-oriented modeling gained momentum in the 1970s with the development of the Smalltalk language whose concepts have influenced the design of almost every subsequent object-oriented programming language (Booch 1994). Today, OOM is the accepted standard in the design of increasingly complex software applications.

Over the years, numerous texts have been written on the subject (Booch [1994] contains a classified bibliography of such texts). Moreover, many of these texts describe different approaches to OOM. For example, between 1989 and 1994, the number of such approaches increased from fewer than 10 to more than 50 (Booch *et al.* 1999). These approaches fueled the so-called *method wars* throughout most of the 1990s. The dominant approaches that emerged included Booch (Booch 1994), OOSE (Object-Oriented Software Engineering) (Jacobson *et al.* 1992) and OMT (Object Modeling Technique) (Rumbaugh *et al.* 1991). Furthermore, many of these approaches included graphical languages for visualizing their constructs. Fortunately, the confusion caused by these alternative approaches ended in 1997 when the Object Modeling Group adopted the Universal Modeling Language as the standard approach to OOM (Booch *et al.* 1999). Given this development, the remainder of this section draws upon three texts that describe the UML approach (Booch *et al.* 1999; Quatrani 1998; Rumbaugh *et al.* 1999). The following discussion is not meant to offer a definitive account of this rich approach to OOM. Instead, it covers basic concepts of object-oriented modeling and the UML.

5.2.2 Structural Modeling

Object-oriented modeling consists of both structural modeling and behavioral modeling. The former is concerned with the organization of a system. Specifically, structural modeling identifies classes and their relationships to one another from the vocabulary of a problem.

5.2.2.1 Classes and Objects

Classes are the basic building blocks of an object-oriented model. A class is a description of a set of objects that share the same attributes, operations and relationships to other objects. In other words, a class is not an individual object, but instead it represents a set of objects. Classes are associated with the nouns of a problem. For example, in the household activity-episode generation model to be discussed in section 5.3, there is a *household* class. This class has several attributes, which are its quantifiable properties. These include *income* and *number of vehicles*. The operations of a class define what it can do—that is, they capture behaviors. For example, the household class can *generate activities*. Combining attributes and operations within a class is known as encapsulation.

Encapsulation is an important property of OOM because it promotes information hiding, whereby the internal details of a class are hidden from view. These details include both attributes and the implementation of operations. Information hiding is achieved by specifying a class interface, which is simply a collection of its operations. Furthermore, the interface must include operations to set and retrieve data values for attributes of the class. In this manner, the integrity of a class is preserved because its attributes are directly accessible only to it. In other words, other classes cannot inadvertently alter its attributes. Furthermore, encapsulation allows new attributes and operations to be added to a class without affecting those that already exist. Through encapsulation, classes are virtually self-contained entities.

Objects are individual instances of the classes to which they belong—that is, they are tangible entities, whereas classes are not. Furthermore, objects possess three properties: identity, state and behavior. Identity distinguishes an object from all other objects. When an object is created, its identity is established and maintained until it is destroyed. The state of an object is defined by the current values of its attributes. As these values change, so does the object's state. In other words, an object's state is dynamic because of its behavior. Behavior is how an object interacts with other objects.

5.2.2.2 Relationships

Classes do not stand alone in an object-oriented model. Instead, they collaborate with other classes in many ways. Three types of relationships define how classes stand in relation to one another: generalization, association and dependency.

Generalization defines a hierarchical relationship between a more general superclass and a more specialized subclass. For this reason, it is often referred to as an *is-a-kind-of* relationship. From section 5.3, for example, the class *single-worker household* is a kind of household. Through generalization, a subclass or child inherits all of the attributes and operations of its superclass or parent. Furthermore, a subclass is distinguished from its superclass by its own distinctive attributes and operations. This property of OOM is known as inheritance. It not only reduces complexity and repetition, but it promotes polymorphism, which is another important property of OOM. Polymorphism means that operations of the same name can be implemented differently for various classes and that attributes of the same name can have different data structures. Through polymorphism, operations and attributes of a superclass can be overridden by a subclass.

Association defines a relationship between two classes that are connected in some meaningful way. When a class participates in an association, it performs a specific role in that relationship. For example, two classes, *worker* and *firm*, define a relationship whereby a worker playing the role employee is associated with a firm playing the role of employer. Such a plain association between two classes represents a relationship between peers—that is, both classes are conceptually at the same level and no one is more important than the other (Booch *et al.* 1999). Sometimes, however, it is necessary to model a *whole/part* relationship in which one class (i.e. the whole) contains other classes (i.e. the parts). This type of association is called aggregation. It represents a *has-a* relationship. From section 5.3, for example, the class *single-worker household* contains class *worker*.

The final type of structural relationship is dependency. It defines a *using* relationship, which means that one class uses another class in one of its operations. For example, in an activity-based microsimulation model, a *household* class would likely contain both an *automobile* class and a *person* class. In turn, the person class would use the automobile class. In other words, a household may have an automobile, which is used by its members to undertake out-of-home activities.

5.2.3 Behavioral Modeling

Behavioral modeling is concerned with the dynamic aspects of a system—that is, its functionality. Specifically, behavioral modeling focuses on interactions among objects. Booch *et al.* (1999) define an interaction as a behavior that consists of a set of messages exchanged sequentially among a set of objects to accomplish a specific purpose. Whereas classes are the nouns of a problem, interactions are the verbs.

Objects that participate in an interaction must be connected by links. In general, a link is an instance of an association. In other words, a link can exist between two objects only if their classes are connected by an association relationship. Links define the paths over which messages can be sent between objects. Booch *et al.* (1999) define a message as the specification of a communication between objects that conveys information with the expectation that activity will ensue. For the most part, messages consist of calls in which one object (i.e. the sender) invokes an operation of another (i.e. the receiver). This action may return information to the sender.

5.2.4 Universal Modeling Language

As mentioned, the Universal Modeling Language is now the standard approach to object-oriented modeling in the software industry. The main reason for this is that it unifies the strengths of the three dominant approaches that emerged during the method wars—namely, Booch, OMT and OOSE. Readers interested in the UML should consult Booch *et al.* (1999) and Rumbaugh *et al.* (1999) for a discussion of its vocabulary and rules.

The UML is a graphical modeling language with rich semantics. Figure 5.1 illustrates some of its basic notation. Furthermore, diagrams play an important role in the UML. Those that are most important to the discussion of OOM in this chapter are class diagrams and interaction diagrams. The former are used for structural modeling and the latter, behavioral modeling. A class diagram shows a set of classes and their relationships. In contrast, an interaction diagram shows an interaction, consisting of a set of objects and their links, including messages sent between them. Moreover, there are two types of interaction diagrams: sequence diagrams and collaboration diagrams. A sequence diagram emphasizes the time ordering of messages, whereas a collaboration diagram is concerned with the structural organization of objects that send and receive messages. These diagrams are isomorphic, meaning that one can be transformed into the other. Examples of class diagrams and interaction diagrams are found in section 5.3.

5.2.5 Advantages

Object-oriented modeling using the UML offers many advantages over the traditional algorithmic approach to computer simulation modeling. First, OOM provides a common modeling language for researchers. As mentioned, the UML is a standard modeling language with rich semantics. In addition, *Rational Rose 98*, a computer aided software engineering (CASE) tool, supports the UML and can, therefore, be used to facilitate model development.

Second, it is much clearer conceptually to think of objects than algorithms. This is particularly true for activity-based microsimulation models. In such models, there is a

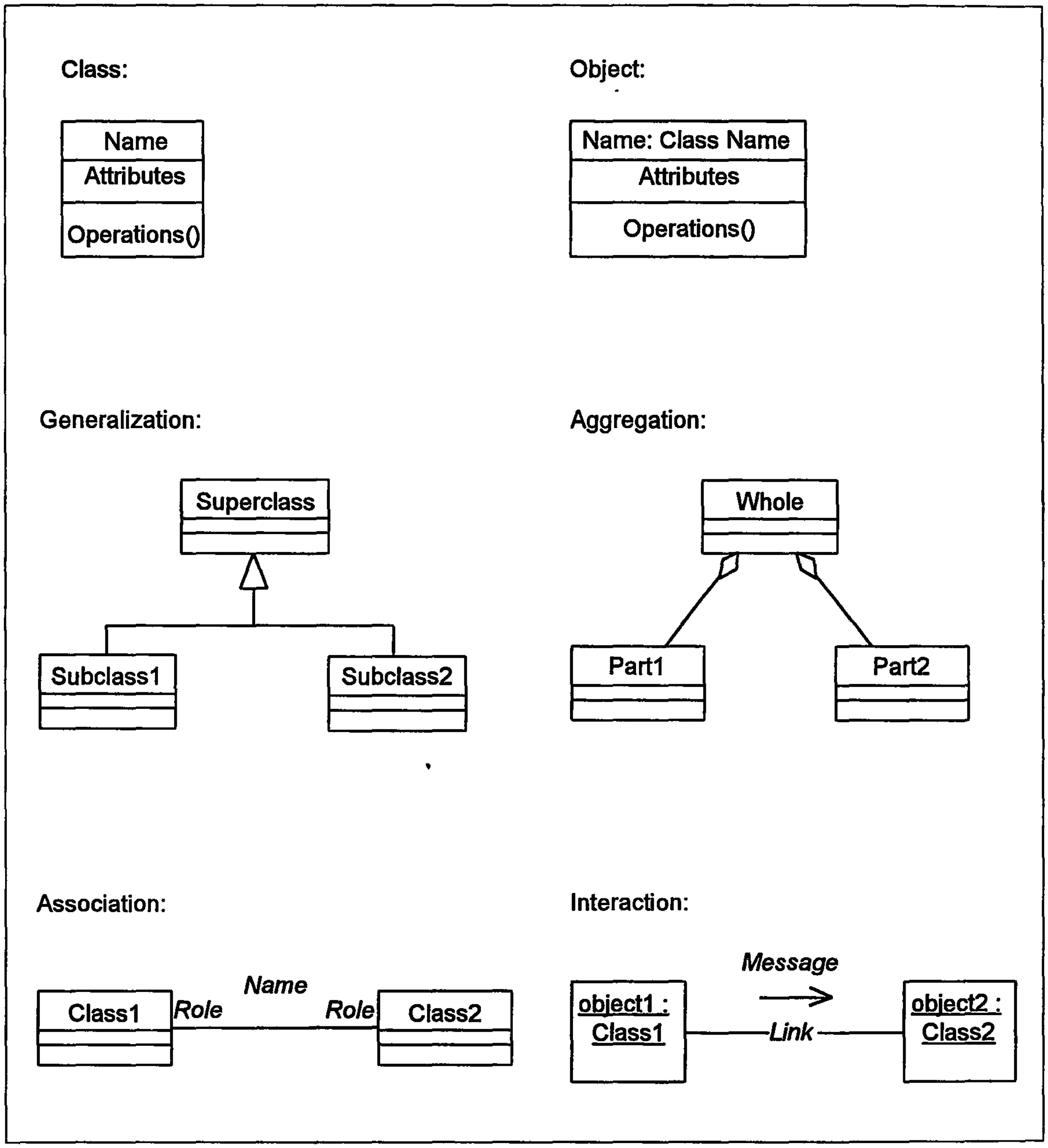

Figure 5.1
Basic UML notation.

one-to-one mapping of objects in the simulated world to objects in the real world. This alone reduces the inherent complexity of the problem. Furthermore, there is explicit recognition of object identity. For example, workers who undertake activities during the evening commute are the same workers who move and age.

A third advantage of object-oriented modeling is modularity. Given their complexity, activity-based microsimulation models are likely to be developed by a team of researchers. To facilitate development in a reasonable timeframe, several modules may be developed simultaneously—for example, residential mobility and activity-travel behavior. In this example, many classes are likely to be the same for both modules. However, each one can be developed independently. Any new attributes and operations specified for one module can be added to the classes without affecting the other module. This is due to encapsulation.

Incremental development is a fourth advantage of OOM. This implies that all modules need not be specified for the simulation model to be used effectively. For example, an activity-based microsimulation model may be developed initially without operations for updating attributes of people over time, such as age. However, such operations can be added easily at a later date.

Finally, OOM allows different modules or models to be substituted for one another and their results compared without compromising the integrity of the simulation model. For example, the results from two model specifications for generating the daily number of out-of-home activity episodes are compared using the household activity-episode generation model described in the next section.

5.3 Household Activity-Episode Generation

5.3.1 Assumptions

Several assumptions underlie the household activity-episode generation model discussed in this section. First, household members interact on a daily basis to generate collectively out-of-home activity episodes, which they undertake to fulfill household needs and individual desires. Second, this complex decision-making process is limited to non-work activities because work is assumed to be fixed in the short term. Furthermore, activity-based research has shown that work governs the activity-travel behavior of household members (e.g. Golob and McNally 1997). Third, only interactions between household heads are considered because the activity-travel behavior of children manifests itself in that of their parents. As well, household heads undertake the vast majority of trips in urban areas. Fourth, household activity-episode generation varies according to household type, which is defined by the number of household heads and their work status. The types are:

1. *single, non-worker households*: one-person and single-parent households in which the person or parent does not work,
2. *single-worker households*: one-person and single-parent households in which the person or parent works,
3. *couple, non-worker households*: married or unmarried, male-female couples with or without children in which neither household head works,

4. *couple, one-worker households*: married or unmarried, male-female couples with or without children in which only one household head works, and
5. *couple, two-worker households*: married or unmarried, male-female couples with or without children in which both household heads work.

Interactions between household heads occur only in the latter three household types. The activity episodes generated in these households fall into one of two settings based solely upon the number of household heads participating in them. In other words, the presence of other household members, such as children, is not used to define these settings. Activities undertaken by one household head are independent activities, whereas those undertaken by both household heads together are joint activities. The decision-making process underlying household activity-episode generation in single, non-worker and single-worker households is much simpler, resulting in independent activity episodes only.

5.3.2 Model Structure and Behavior

Several classes comprise the household activity-episode generation model. These classes fall into two hierarchies—one for households and the other for persons. Figure 5.2 shows the household class hierarchy. The *household* class is the superclass for this hierarchy. Furthermore, it is both a base class and an abstract class. A base class is the most generalized class in a class hierarchy. In other words, it has no superclass. In comparison, an abstract class is one that has no instances—that is, objects are not created for the class. Such classes are used to promote inheritance, which means that they will be followed by

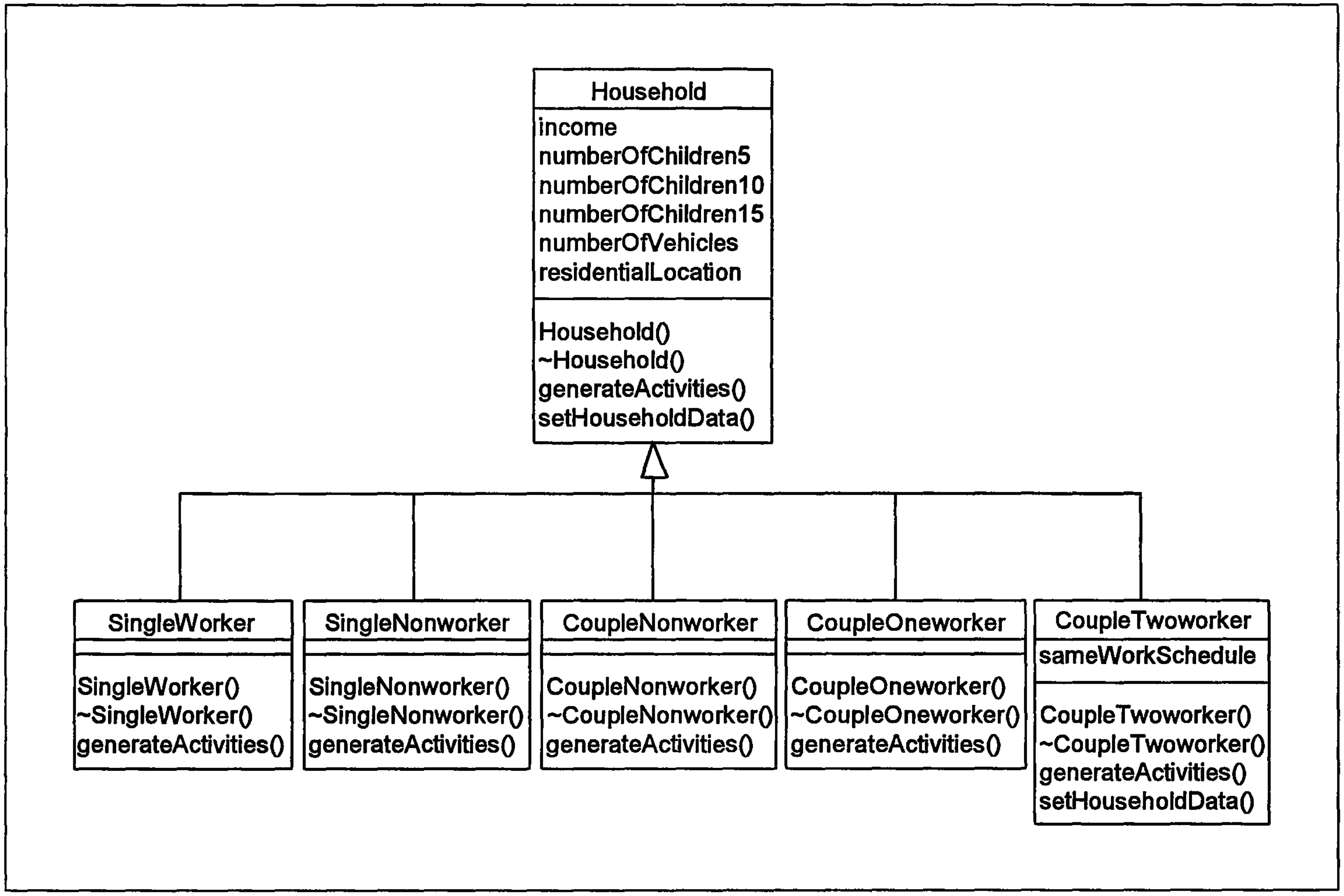

Figure 5.2
Household class diagram.

subclasses. In other words, abstract classes reduce repetition in OOM by containing attributes and operations that are common for its subclasses. In the simulation model, only objects of the household subclasses are instantiated.

The household class has several attributes and operations, which are inherited by each of its subclasses. The attributes include household income, the number of children in the household less than six years old, the number of children between the ages of six and 10, the number of children between the ages of 11 and 15, the number of household vehicles and residential location. Chapter 4 shows that these attributes, along with those defined for other classes in the simulation model, influence household activity-episode generation. The operations defined for the household class comprise its interface. They include a constructor, a destructor, the ability to set attribute data and the ability to generate the daily number of out-of-home activity episodes for household heads. The first two operations are defined for all classes. A constructor creates an object and a destructor destroys it. The third operation is necessary because of information hiding. From Figure 5.2, it can be seen that the final operation, *generateActivities*, is implemented differently for each household subclass. The details concerning these implementations are documented thoroughly in Chapter 4.

Figure 5.3 shows the person class hierarchy. The *person* class, like the household class, is both a base class and an abstract class. Its attributes and operations are inherited by its subclasses—namely, the *worker* class and the *nonworker* class. The attributes include age, possession of a driver's license, employment status and sex. The interface of the person class includes operations to set and retrieve data values for these attributes.

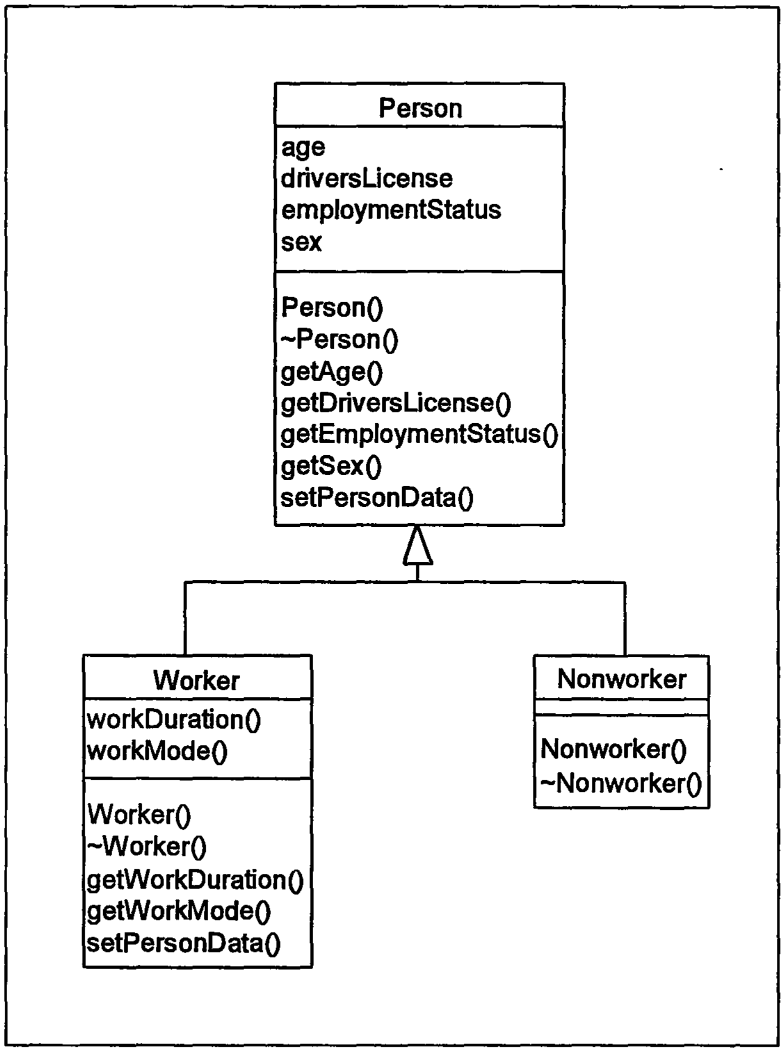

Figure 5.3
Person class diagram.

The worker class is distinguished from the nonworker class in that it has two additional attributes: work duration and work mode. Because of this, the operation *setPersonData* is implemented differently than that which is inherited. Furthermore, additional operations are specified to retrieve data values for these attributes.

The household subclasses are distinguished from one another in terms of their members, as is shown in Figure 5.4. For example, the *singleNonworker* class contains one non-worker from class *nonworker*, whereas the *coupleTwoworker* class contains two workers from class *worker*. More importantly, these relationships are aggregations, in which household subclasses represent wholes and person subclasses, parts. Figure 5.4 documents all structural aspects of the household activity-episode generation model including multiplicity, which is the number of objects connected across an instance of an association.

The behavioral aspects of the simulation model are illustrated by means of the example shown in Figure 5.5. Specifically, this figure documents the interaction among one instance of class *coupleTwoworker* and two instances of class worker for the *generateActivities* operation. The interaction is illustrated by means of a sequence diagram, as well as a collaboration diagram. In both diagrams, object *h*, which is an instance of class *coupleTwoworker*, passes sequentially three messages to object *m*, which is an instance of class worker. These messages invoke, respectively, the operations *getAge*, *getWorkDuration* and *getWorkMode* of object *m*. Each operation returns a data value to object *h*. This process is then repeated for object *f*, which is another instance of class worker. The data values returned to object *h* are then used, along with data values

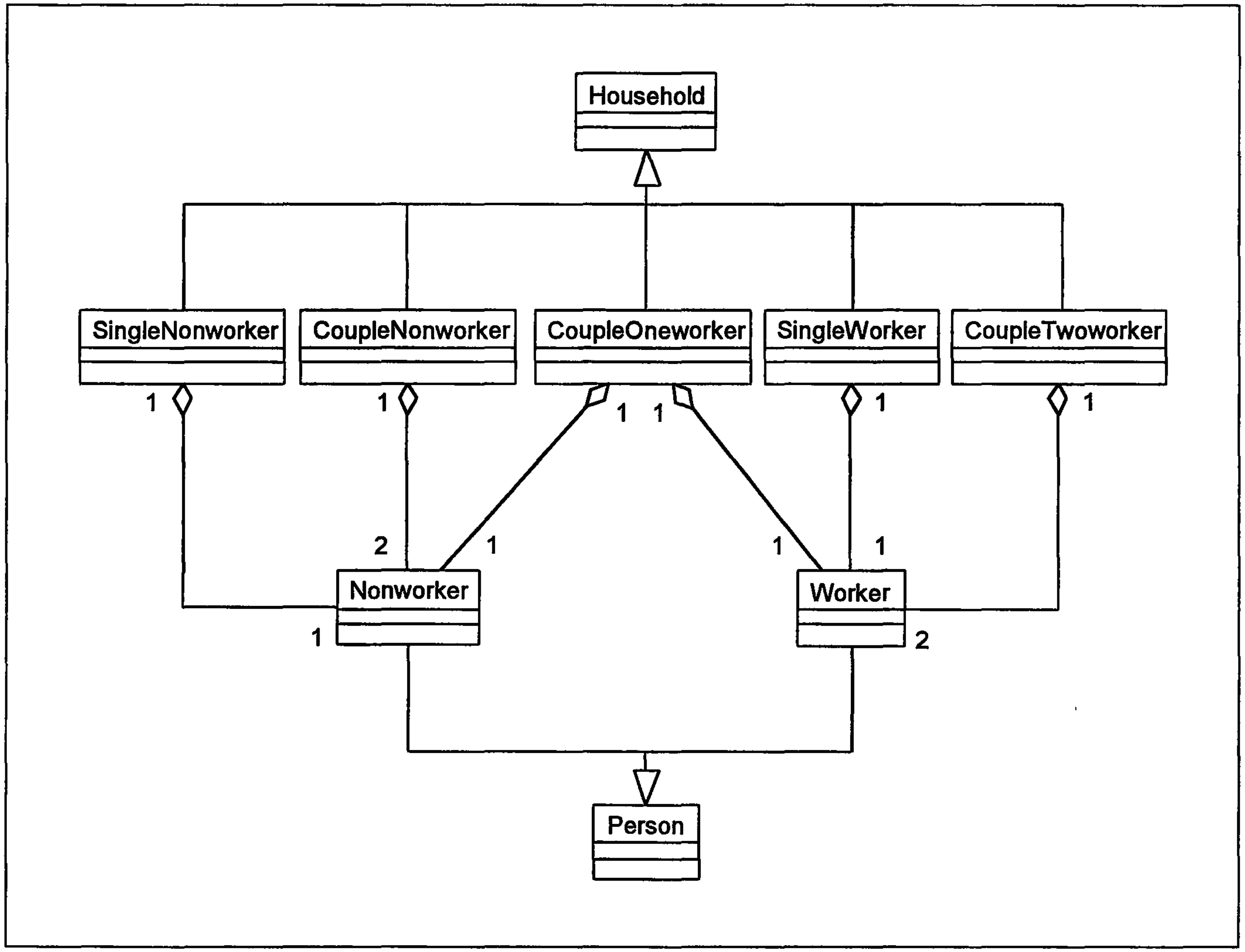

Figure 5.4
Household activity-episode model structure.

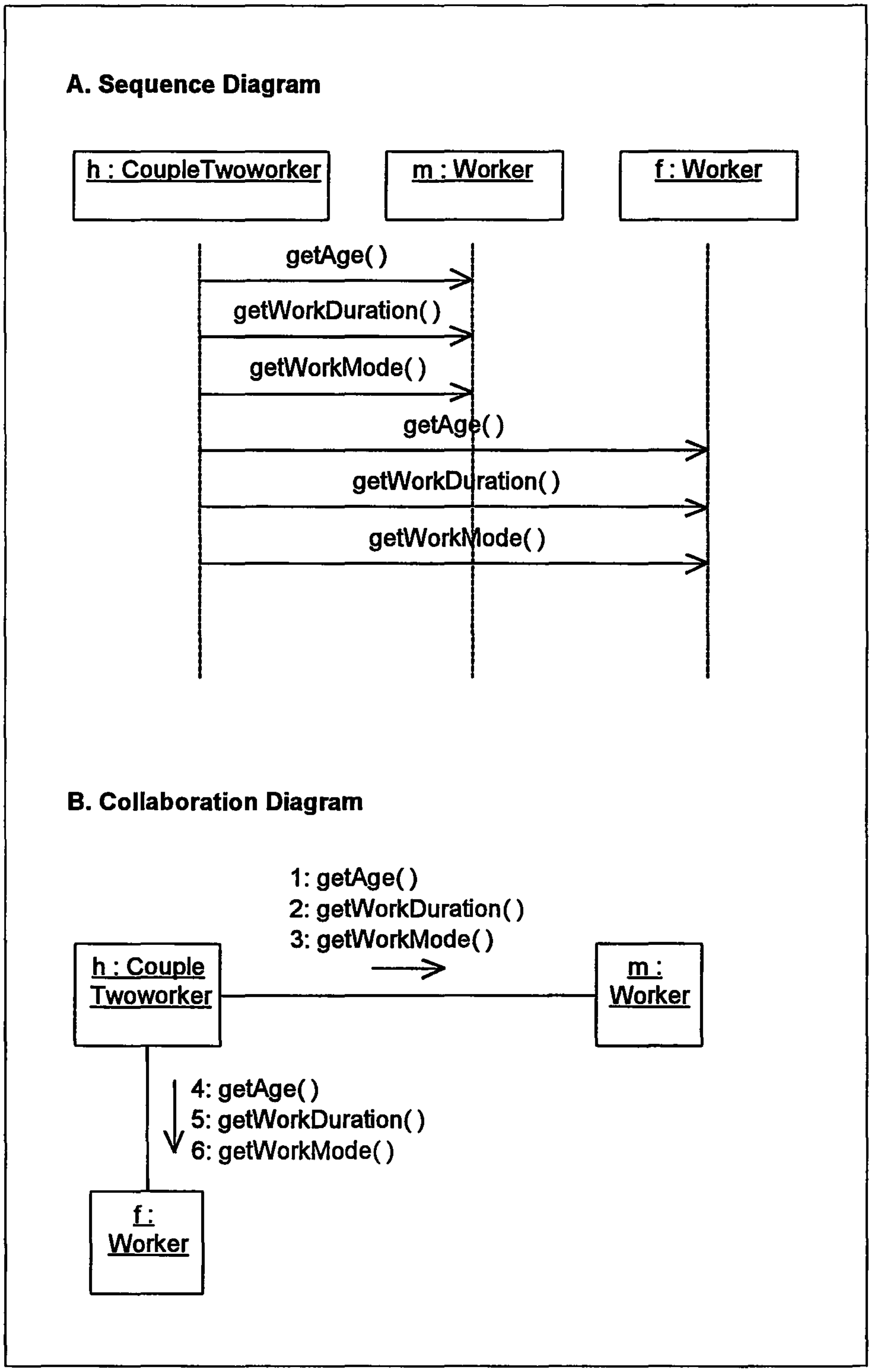

Figure 5.5
Interaction diagrams for couple, two worker households.

for household attributes, to compute the daily number of out-of-home activity episodes undertaken by the heads of household *h*. Similar interactions are observed for the *generateActivities* operations of the remaining household subclasses.

5.4 Simulations

5.4.1 Data and Sample

The household activity-episode generation model discussed in the previous section is operationalized for households in the Greater Toronto Area. Three sources of data were used for this: a trip diary survey that was conducted in 1987 for the Ontario Ministry of Transportation, the 1986 Census of Canada for Ontario and a 1986 survey of the Canadian labor force (Statistics Canada Household Surveys Division 1989).

The sample of households for the trip diary survey was selected from households that responded to a much larger survey that was conducted in the GTA in 1986—that is, the 1986 Transportation Tomorrow Survey. The trip diary survey used a mail questionnaire to obtain socio-demographic information on each household surveyed, including all members over the age of five. It also collected detailed information concerning the daily travel behavior of these members. Completed questionnaires were obtained for 1,948 households.

Of this total, only 1,298 households were used to calibrate econometric models for predicting the daily number of out-of-home activity episodes for household heads. These episodes correspond to non-work activities only. Details concerning the household screening procedure, econometric models and empirical results are documented in the preceding chapter. The calibrated econometric models are used to implement the *generateActivities* operation of each household subclass. The sample of households that form the objects in the simulation model consists of 210 *singleNonworker* households, 350 *singleWorker* households, 120 *coupleNonworker* households, 249 *coupleOneworker* households and 369 *coupleTwoworker* households.

In order to predict the total number of daily episodes undertaken by household heads in the Greater Toronto Area, each household subclass was given a weight. These weights were computed from all three data sources. The total number of households in the GTA was given by the 1986 Census of Canada for Ontario. Moreover, this total was subdivided into three types: one-person households, husband-wife households and lone-parent households. The first and third types were aggregated to form single-head households, whereas the second type corresponded to couple-head households. The 1986 survey of the Canadian labor force was used to subdivide these household types into the subclasses found in the simulation model. This was possible given detailed labor force information based on household composition. Finally, the total number of households in the GTA for each household subclass was divided by the corresponding number of observations to obtain the weights used in the simulation model.

5.4.2 Scenarios

The primary reason for developing activity-based microsimulation models is to increase the policy sensitivity of urban travel demand modeling. Specifically, such models will be capable of evaluating various travel demand management strategies, which are designed to manipulate the demand for travel. Among these strategies are those corresponding to alternative work schedules. Many studies have documented the importance of work to daily activity-travel behavior (e.g. Golob and McNally 1997). Plane (1995) identifies four types of alternative work schedules. The first corresponds to flexible work hours in which employees choose their own schedules in the context of constraints established by employers. For example, workers may begin work any time between 6:30 and 9:30 AM. Second, employees work a five-day week, but daily starting and ending times are spread over a wider time period than usual. This is known as staggered work hours. The third alternative is a four-day or compressed workweek in which employees work the same number of hours as usual, but report to work only four times per week. The final work schedule corresponds to part-time work.

Given the importance of alternative work schedules to travel demand management, the object-oriented simulation model discussed in this chapter is used to evaluate the effects of a large-scale adoption of the compressed workweek on the daily number of out-of-home activity episodes for the heads of households in the Greater Toronto Area in 1986. Specifically, two scenarios are investigated by making three assumptions. First, only full-time workers can adopt a compressed workweek. Second, for those who do, they must work four 10-hour days. Finally, all such workers work on the same days and have the same day off. Scenario 1 corresponds to a workday for full-time workers adopting the strategy, whereas Scenario 2 corresponds to the day off. In reality, it is highly unlikely that all such workers will work on the same days and have the same day off. However, the scenarios are very useful in that they define the limits for observed behavior. Furthermore, for each scenario, the proportion of full-time workers adopting a compressed workweek is varied. Specifically, results are obtained assuming that five, 10, 15 and 20 percent of all full-time workers in the GTA adopt the strategy. These workers are selected randomly. Moreover, each successive proportion builds upon that which precedes it.

As mentioned, the *generateActivities* operation for each household subclass is implemented using an econometric model. More importantly, two model specifications are provided for three subclasses—namely, *coupleNonworker*, *coupleOneworker* and *coupleTwoworker* households. The first specification considers explicitly interactions between household heads when estimating the daily number of out-of-home activity episodes for the household. For comparative purposes, the second specification ignores these interactions. Scenario results are obtained for both specifications. Furthermore, the first specification gives rise to a *joint* model of household activity-episode generation, whereas the second gives rise to an *independent* one.

5.4.3 Results

Table 5.1 documents the daily number of out-of-home activity episodes predicted for each scenario. Furthermore, the total number of episodes is given for a base run of each model. These runs serve as points of departure for evaluating each scenario. As can be seen from the table, the total number of episodes predicted for the base run of the joint model is less than that predicted for the independent model. The same is true for the results obtained for each scenario. This finding suggests that the independent model

Table 5.1
Daily number of out-of-home activity episodes estimated for the heads of five common household types in the Greater Toronto Area, 1986

Percentage of Full-time Workers	Base		Scenario 1		Scenario 2	
	Joint[a]	Independent[b]	Joint	Independent	Joint	Independent
0	1,788,714	1,791,110				
5			1,780,865	1,782,834	1,861,674	1,866,589
10			1,768,086	1,769,790	1,922,807	1,929,187
15			1,757,845	1,759,157	1,993,012	2,001,255
20			1,744,414	1,745,472	2,057,319	2,067,377

[a] Joint model.
[b] Independent model.

overpredicts the daily number of out-of-home activity episodes. As expected, the number of such episodes decreases for Scenario 1 and increases for Scenario 2.

Detailed results for Scenario 1 are summarized in Table 5.2. As can be seen for both models, the number of episodes undertaken by household heads decreases steadily as the proportion of full-time workers adopting a compressed workweek increases. However, these decreases are less than expected. For example, even with 20 percent of full-time workers working a compressed workweek, the reduction in episodes is only about 2.5 percent. Decreases are observed for all applicable activity-episode categories—namely, one, two and three episodes. Moreover, these reductions increase with the number of episodes undertaken. Returning to the previous example, occurrences of one episode are reduced by approximately one percent, two episodes, three percent; and three episodes, six percent. A comparison of the results for the independent model to those obtained for the joint model yields an interesting finding. Not only does the independent model overpredict the total number of episodes; it also overpredicts the impact of Scenario 1. In other words, the impact of the compressed workweek is greater for the independent model than the joint model. This has the potential to misinform the decisions of planners.

Results for the second scenario are found in Table 5.3. As can be seen for both the joint and independent models, the number of episodes undertaken by household heads increases with the proportion of full-time workers adopting a compressed workweek. More importantly, these increases are several times greater than the reductions observed for Scenario 1. For example, a 20 percent adoption rate increases the daily number of episodes by approximately 15 percent, which is six times greater than the corresponding

Table 5.2
Impact of Scenario 1 on the daily number of out-of-home activity episodes estimated for the heads of five common household types in the Greater Toronto Area, 1986

Percentage of Full-time Workers	Percentage Change from Base					
	0 Episodes	1 Episode	2 Episodes	3 Episodes	4 Episodes	All Episodes
Joint Model						
5	0.198	-0.198	-0.531	-0.956	0.020	-0.439
10	0.490	-0.468	-1.235	-2.966	0.008	-1.153
15	0.736	-0.709	-1.921	-4.263	0.020	-1.726
20	1.060	-1.054	-2.760	-6.029	0.032	-2.477
Independent Model						
5	0.203	-0.212	-0.564	-0.987	0.008	-0.462
10	0.502	-0.488	-1.294	-3.019	0.000	-1.190
15	0.756	-0.742	-2.014	-4.341	0.012	-1.784
20	1.089	-1.091	-2.877	-6.122	0.008	-2.548

Table 5.3
Impact of Scenario 2 on the daily number of out-of-home activity episodes estimated for the heads of five common household types in the Greater Toronto Area, 1986

Percentage of Full-time Workers	Percentage Change from Base					
	0 Episodes	1 Episode	2 Episodes	3 Episodes	4 Episodes	All Episodes
Joint Model						
5	-1.290	0.025	3.455	16.257	0.008	4.079
10	-2.413	0.182	6.435	29.379	0.008	7.497
15	-3.687	0.288	9.888	44.556	0.008	11.422
20	-4.870	0.491	12.896	58.541	0.008	15.017
Independent Model						
5	-1.322	-0.034	3.499	17.204	0.012	4.214
10	-2.456	0.094	6.468	30.951	0.024	7.709
15	-3.750	0.156	9.966	46.809	0.044	11.733
20	-4.951	0.319	13.033	61.422	0.044	15.424

reduction for the first scenario. Furthermore, occurrences of one, two and three episodes are observed to increase at an increasing rate. Once again, the results for the independent model are compared to those obtained for the joint model. As expected, the independent model overpredicts the impact of Scenario 2.

5.5 Conclusions

The development of activity-based microsimulation models of urban travel demand is undoubtedly a complex task. To facilitate such development in a reasonable timeframe, researchers require a powerful tool that not only simplifies complexity, but also increases communication among them. This chapter has argued that object-oriented modeling is one such tool. In fact, it is used everyday by software engineers in the design of complex computer applications. OOM is based on objects, not algorithms, and is thus consistent with how humans understand the world around them. In other words, OOM enhances the conceptual clarity of research problems. For example, in an object-oriented, activity-based microsimulation model there is a one-to-one mapping of objects in the simulated world to objects in the real world. In both worlds, these objects possess identities, states and behaviors. In OOM, the coupling of state and behavior within an object is known as encapsulation. This property, along with inheritance and polymorphism, makes OOM a very powerful modeling tool. Furthermore, the constructs of OOM are easily visualized by means of an object-oriented modeling language, such as the UML. Moreover, this language is now the standard approach to OOM in the software industry.

Basic concepts of OOM are discussed in this chapter. Furthermore, an actual simulation model is used to demonstrate them. This model is the *Activity-Episode Generation* module of a household-level, activity-based travel demand forecasting system discussed in Chapter 3. Specifically, it generates the daily number of out-of-home activity episodes for the heads of five common household types. The model is used to evaluate the effects of a large-scale adoption of the compressed workweek on the daily number of episodes undertaken by the heads of households in the Greater Toronto Area in 1986. The findings suggest that the TDM strategy may not achieve the results desired by planners. In fact, it is highly likely that a large-scale adoption of the compressed workweek will maintain the status quo or even increase travel within an urban area. The reason for this is that workers have more time on their day off to pursue out-of-home activities. Furthermore, the results also demonstrate the importance of incorporating explicitly household interactions in model specifications. Specifically, models that do not are likely to overpredict the impact of TDM measures, thereby misinforming planners.

6 Conclusions

Activity analysis is now the dominant force in travel behavior research. The reason for this is that it recognizes explicitly that travel is a demand derived from the need to undertake out-of-home activities. As discussed in Chapter 2, two streams of research characterize the activity-based paradigm. The first seeks to further our understanding of travel behavior by investigating the activities people participate in. The intent of such research is to develop a comprehensive theoretical understanding of travel behavior, which can inform the development of future travel demand forecasting models. On the other hand, the second stream seeks to develop such models today based on existing theory. In recent years, activity in this stream has grown for a number of reasons—the most important of which is the Travel Model Improvement Program (TMIP). Under this program, activity-based models are favored as replacements for existing travel demand forecasting models, such as the Urban Transportation Modeling System (UTMS) (Barrett *et al.* 1995; Spear 1996).

This dissertation contributes significantly to both streams of research. Specifically, it represents a pioneering effort to emphasize household decision-making in daily activity-travel behavior—an area that has been largely neglected by researchers in favor of individuals as decision-making units. Chapter 1 presents both theoretical and practical arguments in favor of household decision-making. Moreover, the findings discussed in Chapters 4 and 5 confirm that the household is the appropriate decision-making unit for understanding and modeling travel behavior. The contributions of this research to travel-behavior theory and travel-behavior modeling are discussed in the following section.

6.1 Findings

6.1.1 Contributions to Travel-Behavior Theory

The most important contribution of the research discussed in this dissertation to travel-behavior theory is that decisions concerning the daily activity-travel behavior of household heads occur within a household context. Furthermore, the nature of this decision-making process varies according to household type.

Single, non-worker and single-worker households contain only one household head. Obviously, this implies a relatively simple decision-making process in the sense that another household head is not considered regarding out-of-home activities. In other words, a single individual makes all decisions. Furthermore, the household head participates in independent activities only—as defined in the context of this research.

By comparison, the decision-making process for couple, non-worker, one-worker and two-worker households is far more complex. Two reasons account for this complexity. First, such households by their very nature have two heads. Second, these heads can participate in out-of-home activities together (i.e. joint activities) or by themselves (i.e. independent activities). As documented in Chapter 4, the decision-making process for such households is characterized by complex interactions between household heads. In couple, non-worker households, there is a positive interaction between male and female heads for independent activities. For females, there is also a substitution effect between such activities and joint activities. By comparison, there is a substitution effect between independent and joint activities for workers in couple, one-worker households and a positive interaction between male and female heads for independent activities in couple, two-worker households.

A second important contribution of this research to travel-behavior theory concerns the impact of Travel Demand Management (TDM) strategies on daily travel behavior. Theoretically, such strategies are designed to reduce traffic during peak periods. The results obtained from an experiment designed to simulate the effects of a large-scale adoption of the compressed workweek on the daily number of out-of-home activities undertaken by household heads suggests that such strategies may produce undesired results. In fact, the results discussed in Chapter 5 for the compressed workweek imply that this strategy is likely to increase daily traffic.

6.1.2 Contributions to Travel-Behavior Modeling

The research discussed in this dissertation makes two important contributions to travel-behavior modeling. First, the trivariate ordered probit model was developed to model daily household activity-episode generation for the heads of couple, non-worker, one-worker and two-worker households. Second, the merits of using object-oriented modeling (OOM) to develop activity-based forecasting models were discussed and demonstrated. Both contributions are reviewed in turn.

The trivariate ordered probit model is based on the univariate ordered probit model developed by McKelvey and Zavoina (1975). The model was employed in the research discussed herein to capture interactions between household heads in terms of the daily number of out-of-home activity episodes (i.e. both independent and joint) each head participates in. The results obtained from the trivariate ordered probit models estimated for each of the household types above confirm that household decision-making underlies the daily activity-travel behavior of household heads. Furthermore, the results discussed in Chapters 4 and 5 demonstrate that the model performs better than an independent one in terms of predictive ability. The primary shortcoming of the model is that it takes a considerable time to converge using the estimation software found in Appendix 1.

Activity-based models are inherently superior to aggregate travel demand models, such as UTMS, because they are developed for decision-making units such as households and their members. Obviously, this implies that such models will be implemented as microsimulations. It is argued in Chapter 5 that the timely development of activity-based microsimulation models is possible only through a common modeling language such as OOM. Furthermore, OOM is especially useful in computer simulation modeling because its constructs are readily implemented using an object-oriented programming (OOP) language such as C++ or Java. The direct linkage between OOM and OOP promotes software development.

Implementation of the *Activity-Episode Generation* module, discussed in Chapter 2, as an object-oriented simulation model did, however, reveal an important shortcoming of OOM. Specifically, multivariate probability distributions, such as the trivariate normal, are virtually impossible to implement using existing OOP languages. Furthermore, such distributions are presently unavailable from commercial software vendors. GAUSS, a matrix programming language, offers a solution to this problem. Moreover, a commercial interface is now available for GAUSS and C++ (i.e. Mercury GE). This interface allows the user to combine the merits of OOM with the number-crunching ability of GAUSS.

6.2 Directions for Future Research

The research discussed in this dissertation represents an initial step towards developing an activity-based forecasting model. The conceptual framework described in Chapter 2 underlies this model. Obviously, an immediate point of departure for future research is development of the *Activity-Episode Scheduling* module. This module is concerned with the explicit timing, sequencing, activity type, duration, location and mode for each activity episode generated by the *Activity-Episode Generation* module. It is anticipated that each of these episode attributes will generate a number of research questions.

Another avenue that requires further investigation is joint activities. In the context of activity scheduling, a question that needs to be addressed is how do independent and joint activity episodes interact if they are assigned to the same period of the day? The answer to this question is important because predictive accuracy depends on it. In other words, incorrect sequencing of such episodes will lead to overpredictions and underpredictions of urban travel during specific periods of the day.

Finally, it is important that the trivariate ordered probit model be estimated for other data sets—especially, those containing larger samples. Such an endeavor would further travel-behavior theory by determining whether the results reported in this research hold for different spatial and temporal contexts. If they do not, then an additional set of research questions are generated. For example, in terms of activity-episode generation, why have interactions between household heads changed over time?

Appendix 1

Statistical Estimation Programs

```
/* *****************************************************************
ORD.PRG
This program estimates an ordered probit model. Input to the model consists of two
matrices: an Nx1 matrix of values for the dependent variable and an NxK matrix of
values for the independent variables.
***************************************************************** */

new;
format /rdn 1,0;
library maxlik;
#include maxlik.ext;
maxset;
_title = "Ordered Probit Model";

/* Generation of dummy variable matrix for the dependent variable */

print;
print "Would you like to generate a dummy variable matrix for the dependent variable?";
print "Enter 1 for YES or 0 for NO:";
z = con(1,1);
print;

if z .eq 1;
    print "How many observations does your sample contain?";
    s = con(1,1);
    print;
    load dep[s,1] = c:\gauss\ord\data\dep.csv;
    dim = maxc(dep)+1;
    zmat = zeros(s,dim);
    ct = 1;
    do while ct .le s;
        col = dep[ct,1]+1;
        zmat[ct,col] = 1;
        ct = ct+1;
    endo;
    save path = c:\gauss\ord\data;
    save zmat;
else;
    loadm zmat = c:\gauss\ord\data\zmat;
    s = rows(zmat);
endif;

/* Generation of GAUSS data set for the independent variables */
```

```
print "Would you like to generate a GAUSS data set for your independent variables?";
print "Enter 1 for YES or 0 for NO:";
i = con(1,1);
print;

if i .eq 1;
    print "How many independent variables does your data set contain?";
    v = con(1,1);
    print;
    load ind[s,v] = c:\gauss\ord\data\ind.csv;
    create xmat1 = c:\gauss\ord\data\indvar with var, v, 8;
    writer(xmat1,ind);
    closeall xmat1;
    print;
endif;

/* Selection of independent variables */

open xmat1 = c:\gauss\ord\data\indvar;
r = rowsf(xmat1);
c = colsf(xmat1);
xmat2 = readr(xmat1,r);
print "Your data set contains " ;; c ;; " independent variables.";
print;
xv = ones(r,1);
print "How many independent variables would you like analyzed?";
ivar1 = con(1,1);
print;
print "Enter the numbers corresponding to these variables:";
ct = 1;
do while ct .le ivar1;
    ivar2 = con(1,1);
    ivar3 = xmat2[.,ivar2];
    xv = xv~ivar3;
    ct = ct+1;
endo;
print;

/* Starting values for the parameter vector */

load dep[r,1] = c:\gauss\ord\data\dep.csv;
dim = maxc(dep)-1;
mu = ones(dim,1);
bt = zeros(cols(xv),1);
```

```
if dim .ge 2;
    ct = 2;
    do while ct .le dim;
        mu1 = mu[ct,1]+0.5;
        mu = mu|mu1;
        ct = ct+1;
    endo;
    mu = mu[(rows(mu)-dim+1):rows(mu),.];
endif;

print "Would you like to alter the initial values of the mu parameters?";
print "Enter 1 for YES or 0 for NO:";
m = con(1,1);
print;

if m .eq 1;
    ct = 1;
    print "Enter the values:";
    do while ct .le dim[1,1];
        mu1 = con(1,1);
        mu = mu|mu1;
        ct = ct+1;
    endo;
    mu = mu[(dim+1):rows(mu),.];
    print;
endif;

x0 = bt|mu;

/* Generation of GAUSS data set for input to PROC LPR */

dset1 = zmat~xv;

r = cols(dset1);
create dset2 = c:\gauss\dset with var, r, 8;
writer(dset2,dset1);
closeall dset2;

output file = c:\gauss\ord\output\results.out reset;
call maxprt(maxlik("dset",0,&lpr,x0));
format /rdn 9,3;
load nllike = c:\gauss\ord\output\nllike;
load cllike = c:\gauss\ord\output\cllike;
print;
```

```
print "The naive log-likelihood is " ;; nllike ;; ".";
print;
print "The log-likelihood at convergence is " ;; cllike ;; ".";
output off;
closeall;

/* *********************************************************************
PROC LPR
This procedure computes the current value of the log-likelihood function.
********************************************************************* */

proc lpr(p,dset);
    local cl1, cl2, dep, x1, r1, b1, m1, prob, cllike, nllike;
    cl1 = cols(zmat);
    cl2 = cols(xv);
    dep = dset[.,1:cl1];
    x1 = dset[.,(cl1+1):cols(dset)];
    r1 = rows(bt);
    b1 = p[1:r1,1];
    m1 = p[(r1+1):rows(p),1];
    m1 = 0|m1|1000;
    prob = probm(x1,b1,m1);
    cllike = sumc(sumc(dep.*ln(prob)));
    nllike = rows(dep).*ln(1./cols(dep));
    save path = c:\gauss\ord\output;
    save prob, cllike, nllike;
    retp(cllike);
endp;

/* *********************************************************************
PROC PROBM
This procedure computes the probability matrix.
********************************************************************* */

proc(1) = probm(x1,b1,m1);
    local d1, di1, p1, p2;
    di1 = dim+1;
    p2 = zeros(rows(x1),1);
    d1 = 0;
    do while d1 .le di1;

        if d1 .gt 0;
            p1 = cdfn(m1[d1+1]-x1*b1)-cdfn(m1[d1]-x1*b1);
        else;
```

```
        p1 = cdfn(m1[d1+1]-x1*b1);
    endif;

    p2 = p2~p1;
    d1 = d1+1;
  endo;
  p2 = p2[.,2:cols(p2)];
  retp(p2);
endp;
```

```
/* ************************************************************************
TRIORD.PRG
This program estimates a trivariate ordered probit model. Input to the model consists of
two matrices: an Nx3 matrix of values for the three dimensions and an NxK matrix of
values for the independent variables.
************************************************************************ */

new;
format /rdn 1,0;
library maxlik;
#include maxlik.ext;
maxset;
_title = "Trivariate Ordered Probit Model";

/* Generation of dummy variable matrix for the dependent variable */

print;
print "Would you like to generate a dummy variable matrix for the dependent variable?";
print "Enter 1 for YES or 0 for NO:";
z = con(1,1);
print;

if z .eq 1;
    print "How many observations does your sample contain?";
    s = con(1,1);
    print;
    load dep[s,3] = c:\gauss\triord\data\dep.csv;
    dim = maxc(dep);
    dim1 = dim[1,1]+1;
    dim2 = dim[2,1]+1;
    dim3 = dim[3,1]+1;
    zmat = zeros(s,dim1*dim2*dim3);
    ct = 1;
    do while ct .le s;
        col1 = (dep[ct,2].*dim3) + (dep[ct,3]+1);
        col2 = dep[ct,1].*dim2.*dim3;
        colfin = col1+col2;
        zmat[ct,colfin] = 1;
        ct = ct+1;
    endo;
    save path = c:\gauss\triord\data;
    save zmat;
else;
    loadm zmat = c:\gauss\triord\data\zmat;
```

```
    s = rows(zmat);
endif;

/* Generation of GAUSS data set for the independent variables */

print "Would you like to generate a GAUSS data set for your independent variables?";
print "Enter 1 for YES or 0 for NO:";
i = con(1,1);
print;

if i .eq 1;
    print "How many independent variables does your data set contain?";
    v = con(1,1);
    print;
    load ind[s,v] = c:\gauss\triord\data\ind.csv;
    create xmat1 = c:\gauss\triord\data\indvar with var, v, 8;
    writer(xmat1,ind);
    closeall xmat1;
    print;
endif;

/* Selection of independent variables for each dimension */

open xmat1 = c:\gauss\triord\data\indvar;
r = rowsf(xmat1);
c = colsf(xmat1);
xmat2 = readr(xmat1,r);
print "Your data set contains " ;; c ;; " independent variables.";
print;
ct1 = 1;
xv1 = ones(r,1);
xv2 = ones(r,1);
xv3 = ones(r,1);
do while ct1 .le 3;
    ct2 = 1;
    print "How many independent variables would you like analyzed for the";

    if ct1 .eq 1;
        print ct1 ;; "st dimension of your model?";
    elseif ct1 .eq 2;
        print ct1 ;; "nd dimension of your model?";
    else;
        print ct1 ;; "rd dimension of your model?";
    endif;
```

```
    ivar1 = con(1,1);
    print;
    print "Enter the numbers corresponding to these variables:";
    do while ct2 .le ivar1;
        ivar2 = con(1,1);
        ivar3 = xmat2[.,ivar2];

        if ct1 .eq 1;
            xv1 = xv1~ivar3;
        elseif ct1 .eq 2;
            xv2 = xv2~ivar3;
        else;
            xv3 = xv3~ivar3;
        endif;

        ct2 = ct2+1;
    endo;
    print;
    ct1 = ct1+1;
endo;

/* Starting values for the parameter vector */

load dep[r,3] = c:\gauss\triord\data\dep.csv;
dim = maxc(dep);
dim1 = dim[1,1]-1;
dim2 = dim[2,1]-1;
dim3 = dim[3,1]-1;
mu1 = ones(dim1,1);
mu2 = ones(dim2,1);
mu3 = ones(dim3,1);
bt1 = zeros(cols(xv1),1);
bt2 = zeros(cols(xv2),1);
bt3 = zeros(cols(xv3),1);
cr1 = 0;
cr2 = 0;
cr3 = 0;
ct1 = 1;
do while ct1 .le 3;

    if (ct1 .eq 1) .and (dim1 .ge 2);
        ct2 = 2;
        do while ct2 .le dim1;
            mu11 = mu1[ct2,1]+0.5;
```

```
            mu1 = mu1|mu11;
            ct2 = ct2+1;
        endo;
        mu1 = mu1[(rows(mu1)-dim1+1):rows(mu1),.];
    endif;

    if (ct1 .eq 2) .and (dim2 .ge 2);
        ct2 = 2;
        do while ct2 .le dim2;
            mu22 = mu2[ct2,1]+0.5;
            mu2 = mu2|mu22;
            ct2 = ct2+1;
        endo;
        mu2 = mu2[(rows(mu2)-dim2+1):rows(mu2),.];
    endif;

    if (ct1 .eq 3) .and (dim3 .ge 2);
        ct2 = 2;
        do while ct2 .le dim3;
            mu33 = mu3[ct2,1]+0.5;
            mu3 = mu3|mu33;
            ct2 = ct2+1;
        endo;
        mu3 = mu3[(rows(mu3)-dim3+1):rows(mu3),.];
    endif;

    ct1 = ct1+1;
endo;
print "Would you like to alter the initial values of the mu parameters?";
print "Enter 1 for YES or 0 for NO:";
m = con(1,1);
print;

if m .eq 1;
    ct1 = 1;
    do while ct1 .le 3;
        ct2 = 1;
        print "Enter the values for dimension ";; ct1 ;; ":";
        do while ct2 .le (dim[ct1,1]-1);
            mu = con(1,1);

            if ct1 .eq 1;
                mu1 = mu1|mu;
            elseif ct1 .eq 2;
```

```
            mu2 = mu2|mu;
        else;
            mu3 = mu3|mu;
        endif;

        ct2 = ct2+1;
    endo;
    print;

    if ct1 .eq 1;
        mu1 = mu1[(dim1+1):rows(mu1),1];
    elseif ct1 .eq 2;
        mu2 = mu2[(dim2+1):rows(mu2),1];
    else;
        mu3 = mu3[(dim3+1):rows(mu3),1];
    endif;

    ct1 = ct1+1;
  endo;
endif;

print "Would you like to alter the initial values of the correlation parameters?";
print "Enter 1 for YES or 0 for NO:";
c = con(1,1);
print;

if c .eq 1;
  ct = 1;
  do while ct .le 3;

    if ct .eq 1;
        print "Enter the value for the correlation between "\
        print "dimensions 1 and 2:";
        cr1 = con(1,1);
    elseif ct .eq 2;
        print "Enter the value for the correlation between "\
        print "dimensions 2 and 3:";
        cr2 = con(1,1);
    else;
        print "Enter the value for the correlation between "\
        print "dimensions 3 and 1:";
        cr3 = con(1,1);
    endif;
```

```
        print;
        ct = ct+1;
    endo;
else;
endif;

x0 = bt1|mu1|bt2|mu2|bt3|mu3|cr1|cr2|cr3;

/* Generation of GAUSS data set for input to PROC LPR */

dset1 = zmat~xv1~xv2~xv3;
r = cols(dset1);
create dset2 = c:\gauss\dset with var, r, 8;
writer(dset2,dset1);
closeall dset2;

output file = c:\gauss\triord\output\results.out reset;
call maxprt(maxlik("dset",0,&lpr,x0));
format /rdn 9,3;
load nllike = c:\gauss\triord\output\nllike;
load cllike = c:\gauss\triord\output\cllike;
print;
print "The naive log-likelihood is " ;; nllike ;; ".";
print;
print "The log-likelihood at convergence is " ;; cllike ;; ".";
output off;
closeall;

/* *******************************************************************
PROC LPR
This procedure computes the current value of the log-likelihood function.
******************************************************************* */

proc lpr(p,dset);
    local cl1, cl2, cl3, cl4, dep, x1, x2, x3, r1, r2, r3, r4, r5, r6, b1, m1, b2, m2;
    local b3, m3, c1, c2, c3, prob, cllike, nllike;
    cl1 = cols(zmat);
    cl2 = cols(xv1);
    cl3 = cols(xv2);
    cl4 = cols(xv3);
    dep = dset[.,1:cl1];
    x1 = dset[.,(cl1+1):(cl1+cl2)];
    x2 = dset[.,(cl1+cl2+1):(cl1+cl2+cl3)];
    x3 = dset[.,(cl1+cl2+cl3+1):cols(dset)];
```

```
    r1 = rows(bt1);
    r2 = rows(mu1);
    r3 = rows(bt2);
    r4 = rows(mu2);
    r5 = rows(bt3);
    r6 = rows(mu3);
    b1 = p[1:r1,1];
    m1 = p[(r1+1):(r1+r2),1];
    m1 = 0|m1|1000;
    b2 = p[(r1+r2+1):(r1+r2+r3),1];
    m2 = p[(r1+r2+r3+1):(r1+r2+r3+r4),1];
    m2 = 0|m2|1000;
    b3 = p[(r1+r2+r3+r4+1):(r1+r2+r3+r4+r5),1];
    m3 = p[(r1+r2+r3+r4+r5+1):(r1+r2+r3+r4+r5+r6),1];
    m3 = 0|m3|1000;
    c1 = p[(rows(p)-2),1];
    c2 = p[(rows(p)-1),1];
    c3 = p[rows(p),1];
    prob = probm(x1,x2,x3,b1,b2,b3,m1,m2,m3,c1,c2,c3);
    cllike = sumc(sumc(dep.*ln(prob)));
    nllike = rows(dep).*ln(1./cols(dep));
    save path = c:\gauss\triord\output;
    save prob, cllike, nllike;
    retp(cllike);
endp;

/* *******************************************************************
PROC PROBM
This procedure computes the probability matrix.
******************************************************************* */

proc(1) = probm(x1,x2,x3,b1,b2,b3,m1,m2,m3,c1,c2,c3);
    local d1, d2, d3, di1, di2, di3, p1, p2, z1, z2, z3, z4, z5, z6;
    di1 = dim1+1;
    di2 = dim2+1;
    di3 = dim3+1;
    p2 = zeros(rows(x1),1);
    d1 = 0;
    do while d1 .le di1;
        d2 = 0;
        do while d2 .le di2;
            d3 = 0;
            do while d3 .le di3;
                z1 = m1[d1+1]-x1*b1;
```

```
            z3 = m2[d2+1]-x2*b2;
            z5 = m3[d3+1]-x3*b3;
            p1 = cdftvn(z1,z3,z5,c1,c2,c3);

            if d1 .gt 0;
                z2 = m1[d1]-x1*b1;
                p1 = p1-cdftvn(z2,z3,z5,c1,c2,c3);
            endif;

            if d2 .gt 0;
                z4 = m2[d2]-x2*b2;
                p1 = p1-cdftvn(z1,z4,z5,c1,c2,c3);
            endif;

            if d3 .gt 0;
                z6 = m3[d3]-x3*b3;
                p1 = p1-cdftvn(z1,z3,z6,c1,c2,c3);
            endif;

            if (d1 .gt 0) .and (d2 .gt 0) .and (d3 .gt 0);
                p1 = p1-cdftvn(z2,z4,z6,c1,c2,c3);
            endif;

            if (d1 .gt 0) .and (d2 .gt 0);
                p1 = p1+cdftvn(z2,z4,z5,c1,c2,c3);
            endif;

            if (d1 .gt 0) .and (d3 .gt 0);
                p1 = p1+cdftvn(z2,z3,z6,c1,c2,c3);
            endif;

            if (d2 .gt 0) .and (d3 .gt 0);
                p1 = p1+cdftvn(z1,z4,z6,c1,c2,c3);
            endif;

            p2 = p2~p1;
            d3 = d3+1;
        endo;
        d2 = d2+1;
    endo;
    d1 = d1+1;
endo;
p2 = p2[.,2:cols(p2)];
retp(p2); endp;
```

```
/* ********************************************************************
PRED.PRG
This program computes the following predictive diagnostics for use with joint and
independent trivariate ordered probit models: percent right (raw classification), expected
percent right and observed and predicted probabilities for the choice set. The input to the
program consists of three matrices: an NxK matrix of observed choices, and NxK matrix
of probabilities estimated with the joint model and an NxK matrix of probabilities of
estimated with the independent model. The output consists of one file, "pred.out."
******************************************************************** */

new;
loadm z = c:\gauss\triord\data\zmat.fmt;
loadm ip = c:\gauss\triord\data\pind.fmt;
loadm jp = c:\gauss\triord\data\pjoint.fmt;
r = rows(z);

/* Calculation of percent right */

prj1 = maxc(jp');
prj2 = z.*jp;
prj3 = sumc(prj2');
pri1 = maxc(ip');
pri2 = z.*ip;
pri3 = sumc(pri2');
ctj = 1;
incj1 = 0;
do while ctj .le r;

    if prj1[ctj,1] .eq prj3[ctj,1];
        incj1 = incj1+1;
    endif;

    ctj = ctj+1;
endo;
incj2 = incj1/r*100;
cti = 1;
inci1 = 0;
do while cti .le r;

    if pri1[cti,1] .eq pri3[cti,1];
        inci1 = inci1+1;
    endif;

    cti = cti+1;
```

```
endo;
inci2 = inci1/r*100;

/* Calculation of expected percent right */

eprj = sumc(sumc(prj2))*100/r;
epri = sumc(sumc(pri2))*100/r;

/* Calculation of observed probabilities */

op = sumc(z)./r;

/* Calculation of estimated probabilities */

epj = sumc(jp)./r;
epi = sumc(ip)./r;

/* Generation of "pred.out" */

output file = c:\gauss\triord\output\pred.out reset;
format /rdn 7,4;
print "PRED.OUT";
print;
print "Percent right for the joint model is " ;; incj2 ;; ".";
print "Percent right for the independent model is " ;; inci2 ;; ".";
print "Expected percent right for the joint model is " ;; eprj ;; ".";
print "Expected percent right for the independent model is " ;; epri ;; ".";
print;
print;
print "The observed probabilities are:";
print;
print op;
print;
print;
print "The estimated probabilities for the joint model are:";
print;
print epj;
print;
print;
print "The estimated probabilities for the independent model are:";
print;
print epi;
output off;
closeall;
```

Appendix 2

Object-Oriented Simulation Model

HOUSEHOLD.H

```
#ifndef HOUSEHOLD_H
#define HOUSEHOLD_H
#include <iostream.h>
#include <fstream.h>
#include <iomanip.h>

class Household
{
public:
    Household();
    ~Household();
    void setHouseholdData(int v,float i,int c5,int c10,int c15,int r);
    void generateActivities();
protected:
    int numberOfVehicles;
    float income;
    int numberOfChildren5;
    int numberOfChildren10;
    int numberOfChildren15;
    int residentialLocation;
};

#endif
```

HOUSEHOLD.CPP

```
#include "Household.h"

Household::Household()
{
}

Household::~Household()
{
}

void Household::setHouseholdData(int v,float i,int c5,int c10,int c15,int r)
{
    numberOfVehicles = v;
    income = i;
    numberOfChildren5 = c5;
    numberOfChildren10 = c10;
    numberOfChildren15 = c15;
    residentialLocation = r;
}

void Household::generateActivities()
{
    return;
}
```

SINGLENONWORKER.H

```
#ifndef SINGLENONWORKER_H
#define SINGLENONWORKER_H
#include "Household.h"
#include "Nonworker.h"

class SingleNonworker:public Household
{
public:
    SingleNonworker(Nonworker *n);
    ~SingleNonworker();
    void generateActivities();
private:
    Nonworker *nw;
};

#endif
```

SINGLENONWORKER.CPP

```
#include "SingleNonworker.h"

SingleNonworker::SingleNonworker(Nonworker *n)
{
    nw = n;
}

SingleNonworker::~SingleNonworker()
{
}

void SingleNonworker::generateActivities()
{
    float a = nw->getAge();
    float x1 = a/10;

    float x2 = income/10000;

    int x3;
    int g = nw->getGender();
    int l = nw->getDriversLicence();
    if ((g == 1) && (l == 1) && (numberOfVehicles > 0))
    {
        x3 = 1;
    }
    else
    {
        x3 = 0;
    }

    double betaX = 1.3867 + (-0.2295 * x1) + (0.1516 * x2) + (0.3041 * x3);

    ofstream outSNWACT("c:\\gauss\\actgen\\data\\SNWACT.TXT",ios::app);
    outSNWACT << setw(15) << betaX << endl;
    outSNWACT.close();

    return;
}
```

SINGLEWORKER.H

```
#ifndef SINGLEWORKER_H
#define SINGLEWORKER_H
#include "Household.h"
#include "Worker.h"

class SingleWorker:public Household
{
public:
    SingleWorker(Worker *w);
    ~SingleWorker();
    void generateActivities();
private:
    Worker *wkr;
};

#endif
```

SINGLEWORKER.CPP

```
#include "SingleWorker.h"

SingleWorker::SingleWorker(Worker *w)
{
    wkr = w;
}

SingleWorker::~SingleWorker()
{
}

void SingleWorker::generateActivities()
{
    float a = wkr->getAge();
    float x1 = a/10;

    float x2 = income/10000;

    int x3;
    int g = wkr->getGender();
    int l = wkr->getDriversLicence();
    if ((g == 1) && (l == 1) && (numberOfVehicles > 0))
    {
        x3 = 1;
    }
    else
    {
        x3 = 0;
    }

    int x4;
    if ((g == 1) && (numberOfChildren5 > 0))
    {
        x4 = 1;
    }
    else
    {
        x4 = 0;
    }

    int x5;
    if ((g == 1) && (numberOfChildren10 > 0))
```

```
    {
        x5 = 1;
    }
    else
    {
        x5 = 0;
    }

    float wd = wkr->getWorkDuration();
    float x6 = wd/100;

    int x7;
    int e = wkr->getEmploymentStatus();
    if (e == 1)
    {
        x7 = 1;
    }
    else
    {
        x7 = 0;
    }

    int x8;
    int wm = wkr->getWorkMode();
    if ((g == 1) && (wm == 1))
    {
        x8 = 1;
    }
    else
    {
        x8 = 0;
    }

    double betaX = 1.8597 + (-0.1193 * x1) + (0.1622 * x2) + (0.2664 * x3) + (1.2402 *
    x4) + (0.7377 * x5)+ (-0.3641 * x6) + (-0.5982 * x7) + (-0.4678 * x8);

    ofstream outSWACT("c:\\gauss\\actgen\\data\\SWACT.TXT",ios::app);
    outSWACT << setw(15) << betaX << endl;
    outSWACT.close();

    return;
}
```

COUPLENONWORKER.H

```
#ifndef COUPLENONWORKER_H
#define COUPLENONWORKER_H
#include "Household.h"
#include "Nonworker.h"

class CoupleNonworker:public Household
{
public:
    CoupleNonworker(Nonworker *m, Nonworker *f);
    ~CoupleNonworker();
    void generateActivities();
private:
    Nonworker *nm;
    Nonworker *nf;
};

#endif
```

COUPLENONWORKER.CPP

```
#include "CoupleNonworker.h"

CoupleNonworker::CoupleNonworker(Nonworker *m, Nonworker *f)
{
    nm = m;
    nf = f;
}

CoupleNonworker::~CoupleNonworker()
{
}

void CoupleNonworker::generateActivities()
{
    float am = nm->getAge();
    float x1 = am/10;

    int x2;
    if ((numberOfChildren10 > 0) || (numberOfChildren15 > 0))
    {
        x2 = 1;
    }
    else
    {
        x2 = 0;
    }

    int x3;
    int lf = nf->getDriversLicence();
    if ((lf == 1) && (numberOfVehicles > 0))
    {
        x3 = 1;
    }
    else
    {
        x3 = 0;
    }

    int x4;
    int lm = nm->getDriversLicence();
    if ((lm == 1) && (lf == 1) && (numberOfVehicles > 0))
    {
```

```
        x4 = 1;
    }
    else
    {
        x4 = 0;
    }

    int x5;
    if ((lm == 1) && (lf == 0) && (numberOfVehicles > 0))
    {
        x5 = 1;
    }
    else
    {
        x5 = 0;
    }

    double jBetaXm = 2.9620 + (-0.4458 * x1) + (-1.9097 * x2);
    double jBetaXf = -0.7535 + (0.3849 * x3);
    double jBetaXj = -1.3408 + (0.6052 * x4) + (0.7584 * x5);

    ofstream outCNWACTJ("c:\\gauss\\actgen\\data\\CNWACTJ.TXT",ios::app);
    outCNWACTJ << setw(15) << jBetaXm << setw(15) << jBetaXf << setw(15) <<
    jBetaXj << endl;
    outCNWACTJ.close();

    double iBetaXm = 3.3673 + (-0.5019 * x1) + (-2.3232 * x2);
    double iBetaXf = -0.7948 + (0.4583 * x3);
    double iBetaXj = -1.4037 + (0.6967 * x4) + (0.8311 * x5);

    ofstream outCNWACTI("c:\\gauss\\actgen\\data\\CNWACTI.TXT",ios::app);
    outCNWACTI << setw(15) << iBetaXm << setw(15) << iBetaXf << setw(15) <<
    iBetaXj << endl;
    outCNWACTI.close();

    return;
}
```

COUPLEONEWORKER.H

```
#ifndef COUPLEONEWORKER_H
#define COUPLEONEWORKER_H
#include "Household.h"
#include "Worker.h"
#include "Nonworker.h"

class CoupleOneworker:public Household
{
public:
    CoupleOneworker(Worker *w, Nonworker *n);
    ~CoupleOneworker();
    void generateActivities();
private:
    Worker *wkr;
    Nonworker *nw;
};

#endif
```

COUPLEONEWORKER.CPP

```
#include "CoupleOneworker.h"

CoupleOneworker::CoupleOneworker(Worker *w, Nonworker *n)
{
    wkr = w;
    nw = n;
}

CoupleOneworker::~CoupleOneworker()
{
}

void CoupleOneworker::generateActivities()
{
    float awkr = wkr->getAge();
    float x1 = awkr/10;

    float x2 = income/10000;

    float wd = wkr->getWorkDuration();
    float x3 = wd/100;

    int x4;
    int wm = wkr->getWorkMode();
    if (wm == 1)
    {
        x4 = 1;
    }
    else
    {
        x4 = 0;
    }

    int x5;
    if ((numberOfVehicles > 1) && (wm == 0))
    {
        x5 = 1;
    }
    else
    {
        x5 = 0;
    }
```

```
int x6;
if (numberOfChildren10 > 0)
{
    x6 = 1;
}
else
{
    x6 = 0;
}

int x7 = residentialLocation;

int x8;
int ln = nw->getDriversLicence();
if ((ln == 1) && (numberOfVehicles == 1) && (wm == 0))
{
    x8 = 1;
}
else
{
    x8 = 0;
}

int x9;
if ((ln == 1) && (numberOfVehicles == 1) && (wm != 0))
{
    x9 = 1;
}
else
{
    x9 = 0;
}

int x10;
if ((ln == 1) && (numberOfVehicles > 1))
{
    x10 = 1;
}
else
{
    x10 = 0;
}
int x11;
if (numberOfChildren5 > 0)
```

```
    {
        x11 = 1;
    }
    else
    {
        x11 = 0;
    }

    int x12;
    int lw = wkr->getDriversLicence();
    if ((lw == 1) && (ln == 0) && (numberOfVehicles > 0))
    {
        x12 = 1;
    }
    else
    {
        x12 = 0;
    }

    double jBetaXw = 0.9676 + (-0.2349 * x1) + (0.1167 * x2) + (-0.1895 * x3) + (-
    0.6227 * x4) + (0.3231 * x5);
    double jBetaXn = -0.6431 + (0.4229 * x6) + (0.4635 * x7) + (0.7866 * x8) + (1.4691
    * x9) + (1.0268 * x10);
    double jBetaXj = -1.5534 + (0.4777 * x11) + (0.4662 * x12);

    ofstream outCOWACTJ("c:\\gauss\\actgen\\data\\COWACTJ.TXT",ios::app);
    outCOWACTJ << setw(15) << jBetaXw << setw(15) << jBetaXn << setw(15) <<
    jBetaXj << endl;
    outCOWACTJ.close();

    double iBetaXw = 0.9569 + (-0.2378 * x1) + (0.1187 * x2) + (-0.1848 * x3) + (-
    0.6031 * x4) + (0.2914 * x5);
    double iBetaXn = -0.6563 + (0.4271 * x6) + (0.4694 * x7) + (0.8049 * x8) + (1.4906
    * x9) + (1.0356 * x10);
    double iBetaXj = -1.5542 + (0.5042 * x11) + (0.4614 * x12);

    ofstream outCOWACTI("c:\\gauss\\actgen\\data\\COWACTI.TXT",ios::app);
    outCOWACTI << setw(15) << iBetaXw << setw(15) << iBetaXn << setw(15) <<
    iBetaXj << endl;
    outCOWACTI.close();

    return;
}
```

COUPLETWOWORKER.H

```
#ifndef COUPLETWOWORKER_H
#define COUPLETWOWORKER_H
#include "Household.h"
#include "Worker.h"

class CoupleTwoworker:public Household
{
public:
    CoupleTwoworker(Worker *m, Worker *f);
    ~CoupleTwoworker();
    void setHouseholdData(int v,float i,int c5,int c10,int c15,int r, int s);
    void generateActivities();
private:
    Worker *wkrm;
    Worker *wkrf;
    int sameWorkSchedule;
};

#endif
```

COUPLETWOWORKER.CPP

```
#include "CoupleTwoworker.h"

CoupleTwoworker::CoupleTwoworker(Worker *m, Worker *f)
{
    wkrm = m;
    wkrf = f;
}

CoupleTwoworker::~CoupleTwoworker()
{
}

void CoupleTwoworker::setHouseholdData(int v,float i,int c5,int c10,int c15,int r, int s)
{
    numberOfVehicles = v;
    income = i;
    numberOfChildren5 = c5;
    numberOfChildren10 = c10;
    numberOfChildren15 = c15;
    residentialLocation = r;
    sameWorkSchedule = s;
}

void CoupleTwoworker::generateActivities()
{
    float am = wkrm->getAge();
    float x1 = am/10;

    float x2 = income/10000;

    float wdm = wkrm->getWorkDuration();
    float x3 = wdm/100;

    int x4;
    int wmm = wkrm->getWorkMode();
    if (wmm == 1)
    {
        x4 = 1;
    }
    else
    {
        x4 = 0;
```

```
}

int x5 = sameWorkSchedule;

float af = wkrf->getAge();
float x6 = af/10;

int x7;
if (numberOfChildren5 > 0)
{
    x7 = 1;
}
else
{
    x7 = 0;
}

float wdf = wkrf->getWorkDuration();
float x8 = wdf/100;

int x9;
int wmf = wkrf->getWorkMode();
if (wmf == 1)
{
    x9 = 1;
}
else
{
    x9 = 0;
}

int x10;
if ((numberOfVehicles == 1) && (wmf == 0))
{
    x10 = 1;
}
else
{
    x10 = 0;
}

int x11;
if ((numberOfVehicles > 1) && (wmf == 0))
{
```

```
        x11 = 1;
    }
    else
    {
        x11 = 0;
    }

    int x12;
    if (wmm == 2)
    {
        x12 = 1;
    }
    else
    {
        x12 = 0;
    }

    double jBetaXm = 1.6750 + (-0.2288 * x1) + (0.0688 * x2) + (-0.2330 * x3) + (-
    0.5709 * x4) + (-0.2401 * x5);
    double jBetaXf = 0.9586 + (-0.1612 * x6) + (0.1019 * x2) + (0.4944 * x7) + (-0.2551
    * x8) + (-0.6468 * x9) + (0.4780 * x10) + (0.2887 * x11);
    double jBetaXj = -1.2155 + (-0.8153 * x7) + (0.5206 * x12);

    ofstream outCTWACTJ("c:\\gauss\\actgen\\data\\CTWACTJ.TXT",ios::app);
    outCTWACTJ << setw(15) << jBetaXm << setw(15) << jBetaXf << setw(15) <<
    jBetaXj << endl;
    outCTWACTJ.close();

    double iBetaXm = 1.5989 + (-0.2070 * x1) + (0.0662 * x2) + (-0.2329 * x3) + (-
    0.5649 * x4) + (-0.2430 * x5);
    double iBetaXf = 1.0129 + (-0.1442 * x6) + (0.1012 * x2) + (0.5161 * x7) + (-0.2797
    * x8) + (-0.6045 * x9) + (0.4291 * x10) + (0.3025 * x11);
    double iBetaXj = -1.2152 + (-0.8141 * x7) + (0.5138 * x12);

    ofstream outCTWACTI("c:\\gauss\\actgen\\data\\CTWACTI.TXT",ios::app);
    outCTWACTI << setw(15) << iBetaXm << setw(15) << iBetaXf << setw(15) <<
    iBetaXj << endl;
    outCTWACTI.close();

    return;
}
```

PERSON.H

```
#ifndef PERSON_H
#define PERSON_H

class Person
{
public:
    Person();
    ~Person();
    void setPersonData(int g,float a,int l,int e);
    int getGender();
    float getAge();
    int getDriversLicence();
    int getEmploymentStatus();
protected:
    int gender;
    float age;
    int driversLicence;
    int employmentStatus;
};

#endif
```

PERSON.CPP

```
#include "Person.h"

Person::Person()
{
}

Person::~Person()
{
}

void Person::setPersonData(int g,float a,int l,int e)
{
    gender = g;
    age = a;
    driversLicence = l;
    employmentStatus = e;
}

int Person::getGender()
{
    int g;
    g = gender;
    return g;
}

float Person::getAge()
{
    float a;
    a = age;
    return a;
}

int Person::getDriversLicence()
{
    int l;
    l = driversLicence;
    return l;
}

int Person::getEmploymentStatus()
{
    int e;
```

```
    e = employmentStatus;
    return e;
}
```

NONWORKER.H

```
#ifndef NONWORKER_H
#define NONWORKER_H
#include "Person.h"

class Nonworker:public Person
{
public:
    Nonworker();
    ~Nonworker();
private:
};

#endif
```

NONWORKER.CPP

```
#include "Nonworker.h"

Nonworker::Nonworker()
{
}

Nonworker::~Nonworker()
{
}
```

WORKER.H

```
#ifndef WORKER_H
#define WORKER_H
#include "Person.h"

class Worker:public Person
{
public:
    Worker();
    ~Worker();
    void setPersonData(int g,float a,int l,int e,float wd,int wm);
    float getWorkDuration();
    int getWorkMode();
private:
    float workDuration;
    int workMode;
};

#endif
```

WORKER.CPP

```
#include "Worker.h"

Worker::Worker()
{
}

Worker::~Worker()
{
}

void Worker::setPersonData(int g,float a,int l,int e,float wd,int wm)
{
    gender = g;
    age = a;
    driversLicence = l;
    employmentStatus = e;
    workDuration = wd;
    workMode = wm;
}

float Worker::getWorkDuration()
{
    float wd;
    wd = workDuration;
    return wd;
}

int Worker::getWorkMode()
{
    int wm;
    wm = workMode;
    return wm;
}
```

MAIN.CPP

```
#include <iostream.h>
#include <fstream.h>
#include "Household.h"
#include "SingleNonworker.h"
#include "SingleWorker.h"
#include "CoupleNonworker.h"
#include "CoupleOneworker.h"
#include "CoupleTwoworker.h"
#include "Person.h"
#include "Nonworker.h"
#include "Worker.h"

void main()
{
    ifstream inSNW("SNW.TXT");
    int v;
    float i;
    int c5;
    int c10;
    int c15;
    int r;
    int g;
    float a;
    int l;
    int e;

    while (!inSNW.eof())
    {
        inSNW >> v >> i >> c5 >> c10 >> c15 >> r >> g >> a >> l >> e;
        inSNW.eatwhite();
        Nonworker n;
        n.setPersonData(g,a,l,e);
        SingleNonworker hhld(&n);
        hhld.setHouseholdData(v,i,c5,c10,c15,r);
        hhld.generateActivities();
    }

    inSNW.close();

    ifstream inSW("SW.TXT");
    float wd;
    int wm;
```

```
while (!inSW.eof())
{
    inSW >> v >> i >> c5 >> c10 >> c15 >> r >> g >> a >> l >> e >> wd >> wm;
    inSW.eatwhite();
    Worker w;
    w.setPersonData(g,a,l,e,wd,wm);
    SingleWorker hhld(&w);
    hhld.setHouseholdData(v,i,c5,c10,c15,r);
    hhld.generateActivities();
}

inSW.close();

ifstream inCNW("CNW.TXT");
int gmw;
float amw;
int lmw;
int emw;
int gfn;
float afn;
int lfn;
int efn;

while (!inCNW.eof())
{
    inCNW >> v >> i >> c5 >> c10 >> c15 >> r >> gmw >> amw >> lmw >> emw
    >> gfn >> afn >> lfn >> efn;
    inCNW.eatwhite();
    Nonworker m, f;
    m.setPersonData(gmw,amw,lmw,emw);
    f.setPersonData(gfn,afn,lfn,efn);
    CoupleNonworker hhld(&m,&f);
    hhld.setHouseholdData(v,i,c5,c10,c15,r);
    hhld.generateActivities();
}

inCNW.close();

ifstream inCOW("COW.TXT");

while (!inCOW.eof())
{
    inCOW >> v >> i >> c5 >> c10 >> c15 >> r >> gmw >> amw >> lmw >> emw
    >> wd >> wm >> gfn >> afn
```

```
            >> lfn >> efn;
        inCOW.eatwhite();
        Worker w;
        Nonworker n;
        w.setPersonData(gmw,amw,lmw,emw,wd,wm);
        n.setPersonData(gfn,afn,lfn,efn);
        CoupleOneworker hhld(&w,&n);
        hhld.setHouseholdData(v,i,c5,c10,c15,r);
        hhld.generateActivities();
    }

    inCOW.close();

    ifstream inCTW("CTW.TXT");
    int s;
    float wdm;
    int wmm;
    float wdf;
    int wmf;

    while (!inCTW.eof())
    {
        inCTW >> v >> i >> c5 >> c10 >> c15 >> r >> s >> gmw >> amw >> lmw >>
        emw >> wdm >> wmm >> gfn
            >> afn >> lfn >> efn >> wdf >> wmf;
        inCTW.eatwhite();
        Worker m;
        Worker f;
        m.setPersonData(gmw,amw,lmw,emw,wdm,wmm);
        f.setPersonData(gfn,afn,lfn,efn,wdf,wmf);
        CoupleTwoworker hhld(&m,&f);
        hhld.setHouseholdData(v,i,c5,c10,c15,r,s);
        hhld.generateActivities();
    }

    inCTW.close();
}
```

```
/* *******************************************************************
ACTGEN.PRG
This program estimates the number of daily out-of-home activity episodes for the heads
of five common household types in an urban area. Input to the program consists of eight
files: SNWACT.TXT, SWACT.TXT, CNWACTJ.TXT, CNWACTI.TXT,
COWACTJ.TXT, COWACTI.TXT, CTWACTJ.TXT and CTWACTI.TXT.
******************************************************************* */

new;
{snw} = snwhhld();
{sw} = swhhld();
{cnwj,cnwi} = cnwhhld();
{cowj,cowi} = cowhhld();
{ctwj,ctwi} = ctwhhld();
format /rd 10,0;
outwidth 256;
output file = c:\gauss\actgen\output\resultsh.txt reset;
screen off;

/* Hardcopy output */

print "The results for single, non-worker households are:";
print;
print snw;
print;
print;
print "The results for single-worker households are:";
print;
print sw;
print;
print;
print "The results for couple, non-worker households are:";
print;
print cnwj;
print;
print cnwi;
print;
print;
print "The results for couple, one-worker households are:";
print;
print cowj;
print;
print cowi;
print;
```

```
print;
print "The results for couple, two-worker households are:";
print;
print ctwj;
print;
print ctwi;
print;
print;
output off;
screen on;

/* File output */

col1 = cols(snw);
col2 = cols(sw);
col3 = cols(cnwj);
col4 = cols(cowj);
col5 = cols(ctwj);
colv = col1|col2|col3|col4|col5;
maxcol = maxc(colv);

if col1 .lt maxcol;
    diff = maxcol-col1;
    diffm = zeros(1,diff);
    snw = snw~diffm;
endif;

if col2 .lt maxcol;
    diff = maxcol-col2;
    diffm = zeros(1,diff);
    sw = sw~diffm;
endif;

if col3 .lt maxcol;
    diff = maxcol-col3;
    diffm = zeros(3,diff);
    cnwj = cnwj~diffm;
    cnwi = cnwi~diffm;
endif;

if col4 .lt maxcol;
    diff = maxcol-col4;
    diffm = zeros(3,diff);
    cowj = cowj~diffm;
```

```
    cowi = cowi~diffm;
endif;

if col5 .lt maxcol;
    diff = maxcol-col5;
    diffm = zeros(3,diff);
    ctwj = ctwj~diffm;
    ctwi = ctwi~diffm;
endif;

output file = c:\gauss\actgen\output\resultsf.txt reset;
screen off;
print snw;
print sw;
print cnwj;
print cnwi;
print cowj;
print cowi;
print ctwj;
print ctwi;
output off;
screen on;

cls;
end;


/* ***********************************************************************
PROC SNWHHLD
This procedure estimates the daily number of out-of-home activity episodes for the heads
of single, non-worker households.
*********************************************************************** */

proc(1) = snwhhld();
    local bx, w, m, prob, hhld, nhhld, result;
    load bx[] = c:\gauss\actgen\data\snwact.txt;
    w = 1036;
    m = {0,0.8009,1.5522,1000};
    {prob} = uprob(bx,m);
    hhld = w*prob;
    nhhld = round(hhld);
    format /rd 10,0;
    outwidth 256;
    output file = c:\gauss\actgen\output\snwhhld.txt reset;
```

```
    screen off;
    print nhhld;
    output off;
    screen on;
    {result} = ustats(nhhld);
    retp(result);
endp;


/* *******************************************************************
PROC SWHHLD
This procedure estimates the daily number of out-of-home activity episodes for the heads
of single-worker households.
******************************************************************* */

proc(1) = swhhld();
    local bx, w, m, prob, hhld, nhhld, result;
    load bx[] = c:\gauss\actgen\data\swact.txt;
    w = 660;
    m = {0,0.9390,1.7670,1000};
    {prob} = uprob(bx,m);
    hhld = w*prob;
    nhhld = round(hhld);
    format /rd 10,0;
    outwidth 256;
    output file = c:\gauss\actgen\output\swhhld.txt reset;
    screen off;
    print nhhld;
    output off;
    screen on;
    {result} = ustats(nhhld);
    retp(result);
endp;


/* *******************************************************************
PROC CNWHHLD
This procedure estimates the daily number of out-of-home activity episodes for the heads
of couple, non-worker households.
******************************************************************* */

proc(2) = cnwhhld();
    local bxsj, bxsi, w, m1j, m2j, m3j, m1i, m2i, m3i, c1j, c2j, c3j, c1i, c2i, c3i;
    local prob, hhld, nhhldj, nhhldi, resultj, resulti;
```

```
    load bxsj[] = c:\gauss\actgen\data\cnwactj.txt;
    load bxsi[] = c:\gauss\actgen\data\cnwacti.txt;
    bxsj = reshape(bxsj,rows(bxsj)/3,3);
    bxsi = reshape(bxsi,rows(bxsi)/3,3);
    w = 1522;
    m1j = {0,0.9663,1000};
    m2j = {0,0.8807,1000};
    m3j = {0,0.6615,1000};
    m1i = {0,0.9764,1000};
    m2i = {0,0.8702,1000};
    m3i = {0,0.6615,1000};
    c1j = 0.4356;
    c2j = -0.3208;
    c3j = -0.0504;
    c1i = 0;
    c2i = 0;
    c3i = 0;
    {prob} = tprob(bxsj,m1j,m2j,m3j,c1j,c2j,c3j);
    hhld = w*prob;
    nhhldj = round(hhld);
    format /rd 10,0;
    outwidth 256;
    output file = c:\gauss\actgen\output\cnwhhldj.txt reset;
    screen off;
    print nhhldj;
    output off;
    screen on;
    {resultj} = tstats(nhhldj,m1j,m2j,m3j);
    {prob} = tprob(bxsi,m1i,m2i,m3i,c1i,c2i,c3i);
    hhld = w*prob;
    nhhldi = round(hhld);
    output file = c:\gauss\actgen\output\cnwhhldi.txt reset;
    screen off;
    print nhhldi;
    output off;
    screen on;
    {resulti} = tstats(nhhldi,m1i,m2i,m3i);
    retp(resultj,resulti);
endp;
```

```
/* ********************************************************************
PROC COWHHLD
This procedure estimates the daily number of out-of-home activity episodes for the heads
of couple, one-worker households.
******************************************************************** */

proc(2) = cowhhld();
    local bxsj, bxsi, w, m1j, m2j, m3j, m1i, m2i, m3i, c1j, c2j, c3j, c1i, c2i, c3i;
    local prob, hhld, nhhldj, nhhldi, resultj, resulti;
    load bxsj[] = c:\gauss\actgen\data\cowactj.txt;
    load bxsi[] = c:\gauss\actgen\data\cowacti.txt;
    bxsj = reshape(bxsj,rows(bxsj)/3,3);
    bxsi = reshape(bxsi,rows(bxsi)/3,3);
    w = 1367;
    m1j = {0,0.9749,1000};
    m2j = {0,0.8247,1.4799,1.9157,1000};
    m3j = {0,0.8942,1000};
    m1i = {0,0.9679,1000};
    m2i = {0,0.8237,1.4779,1.9134,1000};
    m3i = {0,0.9054,1000};
    c1j = 0.1242;
    c2j = -0.0132;
    c3j = -0.4417;
    c1i = 0;
    c2i = 0;
    c3i = 0;
    {prob} = tprob(bxsj,m1j,m2j,m3j,c1j,c2j,c3j);
    hhld = w*prob;
    nhhldj = round(hhld);
    format /rd 10,0;
    outwidth 256;
    output file = c:\gauss\actgen\output\cowhhldj.txt reset;
    screen off;
    print nhhldj;
    output off;
    screen on;
    {resultj} = tstats(nhhldj,m1j,m2j,m3j);
    {prob} = tprob(bxsi,m1i,m2i,m3i,c1i,c2i,c3i);
    hhld = w*prob;
    nhhldi = round(hhld);
    output file = c:\gauss\actgen\output\cowhhldi.txt reset;
    screen off;
    print nhhldi;
    output off;
```

```
    screen on;
    {resulti} = tstats(nhhldi,m1i,m2i,m3i);
    retp(resultj,resulti);
endp;


/* ********************************************************************
PROC CTWHHLD
This procedure estimates the daily number of out-of-home activity episodes for the heads
of couple, two-worker households.
******************************************************************** */

proc(2) = ctwhhld();
    local bxsj, bxsi, w, m1j, m2j, m3j, m1i, m2i, m3i, c1j, c2j, c3j, c1i, c2i, c3i;
    local prob, hhld, nhhldj, nhhldi, resultj, resulti;
    load bxsj[] = c:\gauss\actgen\data\ctwactj.txt;
    load bxsi[] = c:\gauss\actgen\data\ctwacti.txt;
    bxsj = reshape(bxsj,rows(bxsj)/3,3);
    bxsi = reshape(bxsi,rows(bxsi)/3,3);
    w = 1207;
    m1j = {0,0.9457,1.5693,1000};
    m2j = {0,0.8651,1.7003,1000};
    m3j = {0,0.8380,1000};
    m1i = {0,0.9413,1.5744,1000};
    m2i = {0,0.8627,1.7323,1000};
    m3i = {0,0.8383,1000};
    c1j = 0.3909;
    c2j = 0.0331;
    c3j = 0.0103;
    c1i = 0;
    c2i = 0;
    c3i = 0;
    {prob} = tprob(bxsj,m1j,m2j,m3j,c1j,c2j,c3j);
    hhld = w*prob;
    nhhldj = round(hhld);
    format /rd 10,0;
    outwidth 256;
    output file = c:\gauss\actgen\output\ctwhhldj.txt reset;
    screen off;
    print nhhldj;
    output off;
    screen on;
    {resultj} = tstats(nhhldj,m1j,m2j,m3j);
    {prob} = tprob(bxsi,m1i,m2i,m3i,c1i,c2i,c3i);
```

```
    hhld = w*prob;
    nhhldi = round(hhld);
    output file = c:\gauss\actgen\output\ctwhhldi.txt reset;
    screen off;
    print nhhldi;
    output off;
    screen on;
    {resulti} = tstats(nhhldi,m1i,m2i,m3i);
    retp(resultj,resulti);
endp;


/* *******************************************************************
PROC UPROB
This procedure computes probabilities for the univariate ordered probit model.
******************************************************************* */

proc(1) = uprob(bx,m);
    local d1, di1, p1, p2;
    di1 = rows(m)-1;
    p2 = zeros(rows(bx),1);
    d1 = 0;
    do while d1 .le di1;

        if d1 .gt 0;
            p1 = cdfn(m[d1+1]-bx)-cdfn(m[d1]-bx);
        else;
            p1 = cdfn(m[d1+1]-bx);
        endif;

        p2 = p2~p1;
        d1 = d1+1;
    endo;
    p2 = p2[.,2:cols(p2)];
    retp(p2);
endp;


/* *******************************************************************
PROC TPROB
This procedure computes probabilities for the trivariate ordered probit model.
******************************************************************* */

proc(1) = tprob(bxs,m1,m2,m3,c1,c2,c3);
```

```
local bx1, bx2, bx3, d1, d2, d3, di1, di2, di3, p1, p2, z1, z2, z3, z4, z5, z6;
bx1 = bxs[.,1];
bx2 = bxs[.,2];
bx3 = bxs[.,3];
di1 = rows(m1)-1;
di2 = rows(m2)-1;
di3 = rows(m3)-1;
p2 = zeros(rows(bx1),1);
d1 = 0;
do while d1 .le di1;
    d2 = 0;
    do while d2 .le di2;
        d3 = 0;
        do while d3 .le di3;
            z1 = m1[d1+1]-bx1;
            z3 = m2[d2+1]-bx2;
            z5 = m3[d3+1]-bx3;
            p1 = cdftvn(z1,z3,z5,c1,c2,c3);

            if d1 .gt 0;
                z2 = m1[d1]-bx1;
                p1 = p1-cdftvn(z2,z3,z5,c1,c2,c3);
            endif;

            if d2 .gt 0;
                z4 = m2[d2]-bx2;
                p1 = p1-cdftvn(z1,z4,z5,c1,c2,c3);
            endif;

            if d3 .gt 0;
                z6 = m3[d3]-bx3;
                p1 = p1-cdftvn(z1,z3,z6,c1,c2,c3);
            endif;

            if (d1 .gt 0) .and (d2 .gt 0) .and (d3 .gt 0);
                p1 = p1-cdftvn(z2,z4,z6,c1,c2,c3);
            endif;

            if (d1 .gt 0) .and (d2 .gt 0);
                p1 = p1+cdftvn(z2,z4,z5,c1,c2,c3);
            endif;

            if (d1 .gt 0) .and (d3 .gt 0);
                p1 = p1+cdftvn(z2,z3,z6,c1,c2,c3);
```

```
            endif;

            if (d2 .gt 0) .and (d3 .gt 0);
                p1 = p1+cdftvn(z1,z4,z6,c1,c2,c3);
            endif;

            p2 = p2~p1;
            d3 = d3+1;
        endo;
        d2 = d2+1;
    endo;
    d1 = d1+1;
endo;
p2 = p2[.,2:cols(p2)];
retp(p2);
endp;


/* ****************************************************************
PROC USTATS
This procedure computes totals for the univariate ordered probit model.
**************************************************************** */

proc(1) = ustats(nhhld);
    local total;
    total = sumc(nhhld);
    total = reshape(total,1,rows(total));
    retp(total);
endp;


/* ****************************************************************
PROC TSTATS
This procedure computes totals for the trivariate ordered probit model.
**************************************************************** */

proc(1) = tstats(nhhld,m1,m2,m3);
    local d1, d2, d3, total, ct1, ct2, ct3, n1, n2, dim1, dim2, dim3, joint, v, mv;
    local diff, diffm;
    d1 = rows(m1);
    d2 = rows(m2);
    d3 = rows(m3);
    total = sumc(nhhld);
```

```
/* Computation of totals for dimension one */

n2 = 0;
ct1 = 1;
ct2 = d2*d3;
do while ct1 .le d1*d2*d3;
    n1 = total[ct1:ct2,1];
    n1 = sumc(n1);
    n2 =n2~n1;
    ct1 = ct2+1;
    ct2 = ct2+(d2*d3);
endo;
dim1 = n2[1,2:cols(n2)];

/* Computation of totals for dimension two */

dim2 = 0;
ct1 = 1;
do while ct1 .le d2*d3;
    n2 = 0;
    ct2 = ct1;
    ct3 = ct2+d3-1;
    do while ct2 .le d1*d2*d3;
        n1 = total[ct2:ct3,1];
        n1 = sumc(n1);
        n2 =n2+n1;
        ct2 = ct2+(d2*d3);
        ct3 = ct3+(d2*d3);
    endo;
    dim2 = dim2~n2;
    ct1 = ct1+d3;
endo;
dim2 = dim2[1,2:cols(dim2)];

/* Computation of totals for dimension three */

dim3 = 0;
ct1 = 1;
do while ct1 .le d3;
    n2 = 0;
    ct2 = ct1;
    do while ct2 .le d1*d2*d3;
        n1 = total[ct2,1];
        n2 =n2+n1;
```

```
            ct2 = ct2+d3;
        endo;
        dim3 = dim3~n2;
        ct1 = ct1+1;
    endo;
    dim3 = dim3[1,2:cols(dim3)];

    /* Results matrix */

    v = d1|d2|d3;
    mv = maxc(v);

    if d1 .lt mv;
        diff = mv-d1;
        diffm = zeros(1,diff);
        dim1 = dim1~diffm;
    endif;

    if d2 .lt mv;
        diff = mv-d2;
        diffm = zeros(1,diff);
        dim2 = dim2~diffm;
    endif;

    if d3 .lt mv;
        diff = mv-d3;
        diffm = zeros(1,diff);
        dim3 = dim3~diffm;
    endif;

    total = dim1|dim2|dim3;
    retp(total);
endp;
```

Appendix 3

Glossary

activity episode
A period of time characterized by a uniform purpose and spatial setting.

activity-episode generation
The process whereby household heads decide collectively how many out-of-home activity episodes each head will participate in over a given period of time.

activity-episode scheduling
The process whereby household heads make decisions concerning the explicit timing, sequencing, activity type, duration, location and mode for each out-of-home activity episode to be undertaken over a given period of time.

couple, non-worker household
Married or unmarried, male-female couples with or without children in which neither household head works.

couple, one-worker household
Married or unmarried, male-female couples with or without children in which only one household head works.

couple, two-worker household
Married or unmarried, male-female couples with or without children in which both household heads work.

household head
An adult member of a household who is responsible for its maintenance.

independent activity
An activity undertaken by one household head.

joint activity
An activity undertaken by two household heads together.

single, non-worker household
A one-person or single-parent household in which the person or parent does not work.

single-worker household
A one-person or single-parent household in which the person or parent works.

subtour
A tour that begins and ends at work.

tour
A circuit of out-of-home activity episodes that begins and ends at home.

Appendix 4

List of Acronyms

AMOS	Activity MObility Simulator
ATIS	Advanced Traveler Information System
CAAA	Clean Air Act Amendments
CASE	Computer Aided Software Engineering
CATGW	Comprehensive Activity Travel Generation for Workers
CMAP	Cognitive MAP
GIS	Geographical Information System
GISICAS	GIS-Interfaced Computational process model for Activity Scheduling
GTA	Greater Toronto Area
ILUTE	Integrated Land-Use, Transportation and Environment modeling system
LTC	Long-Term Calendar
LTM	Long-Term Memory
OMT	Object Modeling Technique
OOM	Object-Oriented Modeling
OOP	Object-Oriented Programming
OOSE	Object-Oriented Software Engineering
PCATS	Prism-Constrained Activity-Travel Simulator
RAP	Representative Activity-travel Pattern
SAMS	Sequenced Activity Mobility Simulator
SMART	Simulation Model for Activities, Resources and Travel
SMASH	Simulation Model of Activity Scheduling Heuristics

STARCHILD	Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions
STC	Short-Term Calendar
STM	Short-Term Memory
TDM	Travel Demand Management
TMIP	Travel Model Improvement Program
UML	Universal Modeling Language
UTMS	Urban Transportation Modeling System
VMT	Vehicle-Miles Traveled

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