ACTIVITY-BASED MODELLING OF HOUSEHOLD TRAVEL

by

Matthew J. Roorda

A thesis submitted in conformity with the requirements
for the degree of Doctor of Philosophy
Graduate Department of Civil Engineering
University of Toronto

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This thesis reports on significant progress in three research areas. First, a major in-depth longitudinal data collection effort has been undertaken which has provided groundbreaking information on various elements of the activity scheduling process. The three year panel survey involved a variety of methodological techniques aimed at capturing different components of the activity scheduling process. Analysis of these new data has significantly improved our understanding of behavioural processes surrounding household activity scheduling. Second, a new rule-based technique for simulating activity schedules has been developed. Third, a tour-based mode choice model that incorporates crucial household interactions including vehicle allocation, ridesharing to joint activities and dropoff/pickup scenarios has been estimated and applied in a large-scale microsimulation framework. The latter two pieces of work have been developed into a modelling software package entitled the Travel Activity Scheduler for Household Agents (TASHA). It is felt that the TASHA modelling system that is more behaviourally valid than current state-of-practice models, provides more precise outputs with no additional input requirements, and has potential for the analysis of contemporary demand-oriented policies. With some additional research, testing and development, it is felt that this approach can evolve to become the “next generation” of travel demand modelling for major urban centres such as the Greater Toronto Area.

Acknowledgements

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I also thank all of the dedicated staff and the respondents that have worked on the Toronto panel survey over the past few years. Without your dedication, hard work, persistence, and sense of humour, the project would long ago have come to a grinding halt. What has often felt like thankless, boring and frustrating work has resulted in some extraordinary new research developments. For that you should all be proud.

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I have been supported financially in my PhD work at various times by SSHRC, NSERC, the City of Toronto, and the Neptis foundation. For this funding I am grateful.

Finally, I thank my wife Linda and my children Calvin, Joshua and Nathan. To you I am thankful for perspective, for laughs and for love. I hereby invite you to decorate this thesis with crayons, just like you did with my Masters!

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1. Introduction

Travel demand models have been providing decision-support for transportation infrastructure planning over the past half-century. The four-stage model has been the “workhorse” analysis tool for transportation planning since it was originally developed in the 1950’s. This modelling framework, if done well, was able to provide travel demand forecasts with an appropriate level of precision for the context in which it was developed. Decision support for large highway and transit infrastructure projects required relatively crude modelling efforts, particularly when the goals of providing the infrastructure were largely to increase mobility. Since the 1960’s, however, the development of major freeway systems and mass transit infrastructure has slowed dramatically. In the Greater Toronto Area, there are few corridors remaining in which new freeways can be built without severe impacts. There has also been a realization in planning circles that the provision of new roadway capacity quickly leads to new development in newly accessible parts of the city, often causing the new capacity to be filled in a matter of years.

Travel demand management (TDM), Intelligent Transportation Systems (ITS) technology, and high occupancy vehicle (HOV) lanes, are some policy instruments that have been used to make better use of existing roadway capacity. Each of these measures, however, requires more precise decision support tools than the traditional four-stage modelling approach. This thesis presents a new operational prototype microsimulation model of Travel and Activity Scheduling for Household Agents (TASHA) that provides more precise and behaviourally sound model outputs than current state-of-practice models, with little increase in the supporting data requirements.

One primary motivation for the development of TASHA was the need for a model that provided a closer representation of the actual human behaviour in making travel and activity decisions. The prevailing notion in most travel demand models, that humans choose activity/travel patterns and modes of transportation to optimize their own individual self-interest, was not entirely satisfying. We felt that the household context in which individuals operate has a very strong influence on individuals’ decisions, particularly when household resources are shared, there are shared household responsibilities (such as the care of children), and there are decisions that are made jointly by multiple household members (such as the decision of what activities to do together and when to do them). By viewing the decisions of individuals within the context of the household, it became clear that sometimes an individual would make sacrifices if it would enhance the opportunities for other household members. Furthermore, we felt that for some decisions, an "optimizing" strategy was not appropriate at all. For example, the choice of an activity pattern is more realistically represented as a process of adding activities to a schedule and modifying that schedule as new opportunities and constraints arise, than as an optimal selection from among thousands of possible alternative activity patterns.

Our motivation to more realistically represent individual behaviour, and at the same time to incorporate household interactions explicitly, led to the choice of an agent-based microsimulation framework for the modelling effort. In microsimulation the behaviour of individual agents, and their interactions with other agents is simulated explicitly (i.e. there is a one-to-one computer representation of individuals in reality). The cumulative effects of these individual behaviours form the overall behaviour of the system. Microsimulation modelling is becoming increasingly recognized as an improved method over conventional "zone-based" systems, which have biases due to aggregation, computational inefficiencies, and are less sensitive to "demand-oriented" policies.

The microsimulation approach is also consistent with a much broader research program under development at University of Toronto, named ILUTE (Integrated Land Use Transportation Environment), in which decisions about activities and travel are one of several linked long- and short-term decisions that influence the urban system and its evolution over time. As shown in Figure 1.1, travel and activities are directly influenced by longer-term household location choice and automobile ownership decisions. Conversely, the travel and activities undertaken by members of a household affect strategic long term decisions if, for example, commute times are too long or accessibility to other activities is poor.

Activity and travel decisions also have a direct impact on the short-term performance of the transportation network. Trips are realized on road and transit networks. With recent advances in the microscopic simulation of traffic on regional scale networks, there is a rising need for travel demand models to produce outputs that are at the right level of precision (in time and in space) to form appropriate inputs for the microscopic traffic assignment models.

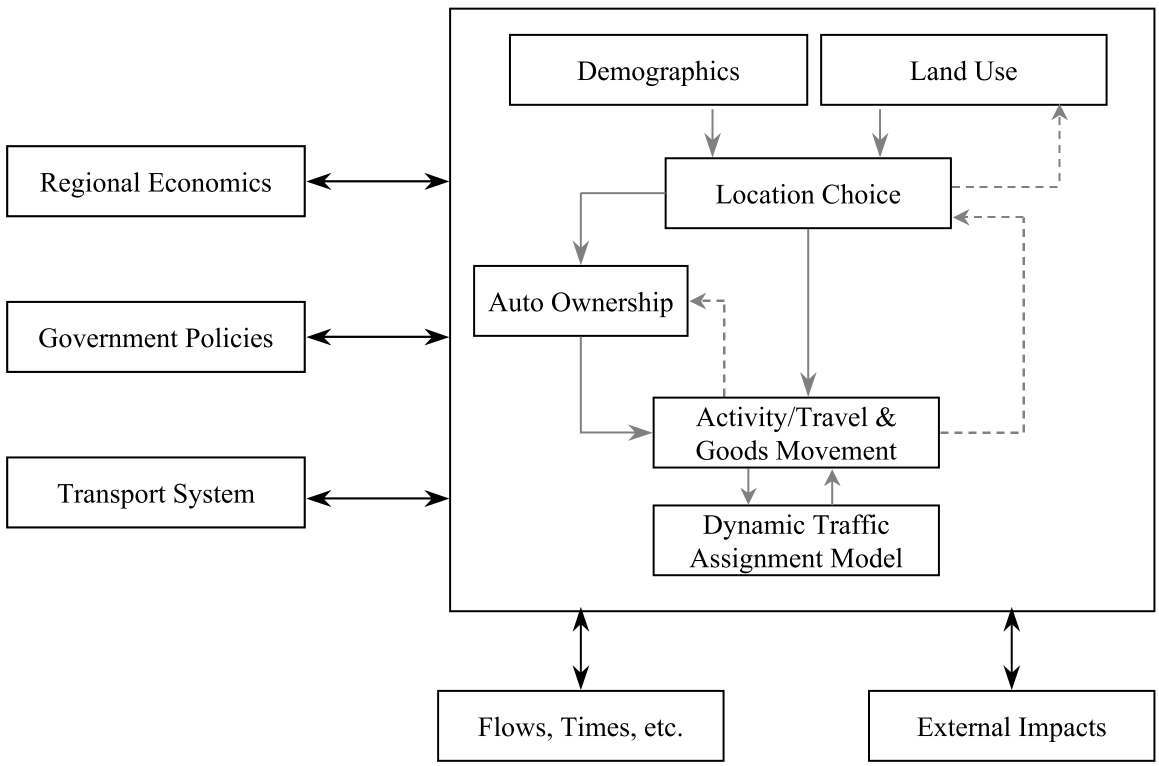

Figure 1.1 – The ILUTE Modelling Framework

The TASHA model, however, does not require the full ILUTE model to be useful. It is also designed as a stand-alone piece of software that can replace the conventional 4-stage model with a more behavioural and more precise model that requires no additional input data. This is a critical design feature that is intended to facilitate the uptake of the approach amongst transportation planning practitioners. Figure 1.2 compares the conceptual designs of the 4-stage model and the TASHA model. Clearly, a very different approach has been taken at each stage of the decision-making process, and the information passed from one stage to the next is also quite different. In the subsequent chapters of this thesis, the rationale and the benefits for each of the improvements is described in more detail.

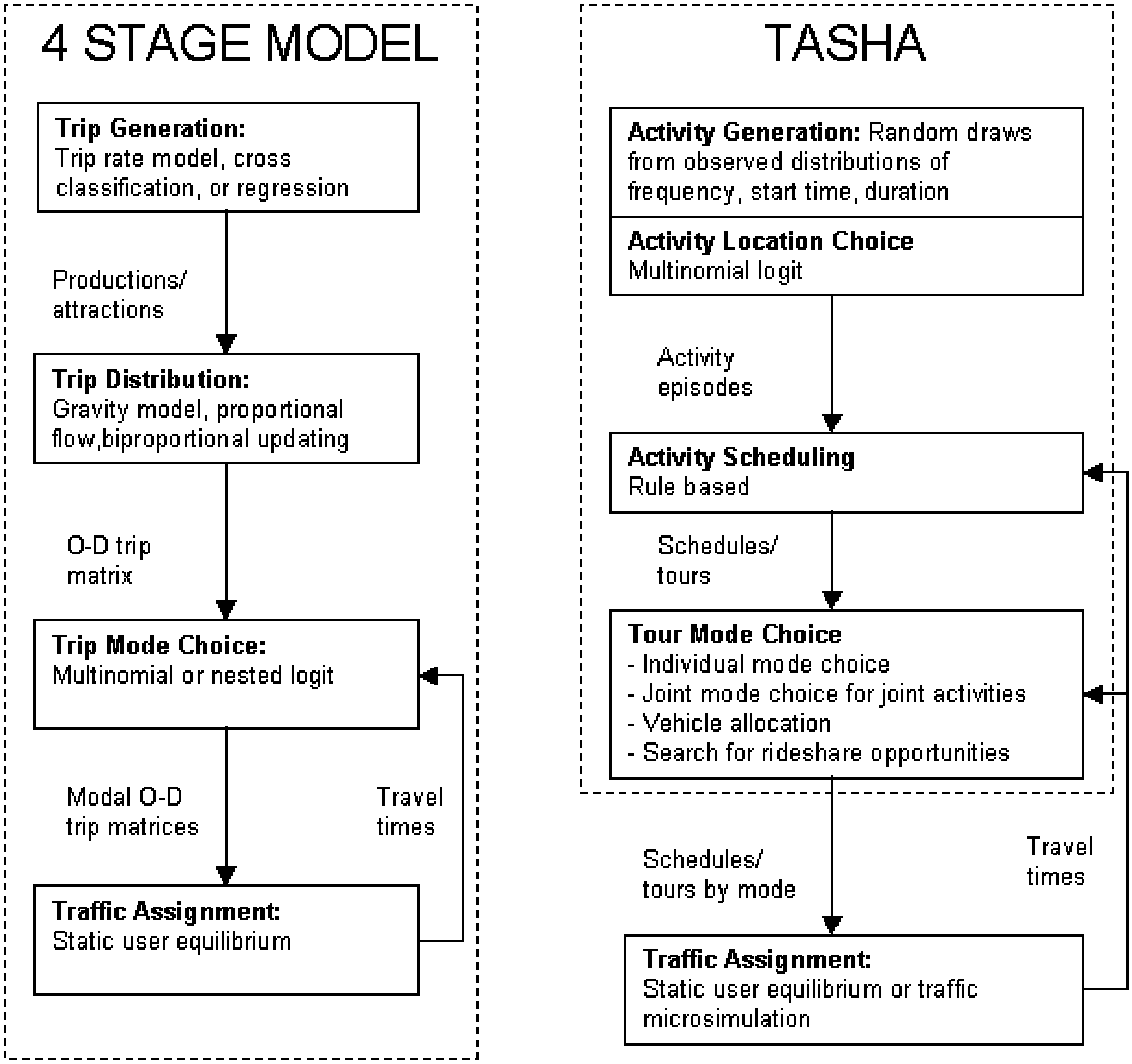

Figure 1.2 – Conceptual designs of the four-stage model and TASHA

Overall, three major contributions have been made in this thesis. First, a 3 wave in-depth panel survey of activity scheduling behaviour has been undertaken in Toronto on 270 households. This was a major long-term effort spanning a period of three years, involving an interviewing staff of up to four interviewers and a geocoder. The purpose of the survey was to collect data on the *process* of activity scheduling for a medium-sized random sample of households. Very little data collection of this type has been reported in the literature to date, and the combination of an in-depth survey on the activity scheduling process within a panel framework is, to this author's knowledge, unprecedented. Preliminary analysis of the data from this survey has been used to inform the structure of the models presented in this thesis. However, the data from first wave of the survey, using the CHASE survey instrument (Doherty and Miller, 2000), is already being used extensively for other behavioural and methodological research (Buliung and Roorda, 2005; Doherty *et al.,* 2004; Doherty, 2004; Doherty, 2003; Doherty, 2005; Doherty and Mohammadian, 2003; Mohammadian and Doherty, 2005; Mohammadian and Doherty, submitted; Roorda and Miller, 2004; Roorda and Miller, 2005; Joh *et al.*, 2005; Doherty and Papinski, 2004).

The second major contribution is the development of the activity scheduling model within TASHA. This prototype activity scheduling microsimulation model generates activity schedules and travel patterns for a twenty-four hour typical weekday for all persons in a household. As noted above, the model is based solely on conventional trip diary data, and therefore is applicable in many urban areas where activity data may not be available. A heuristic (rule-based) method is used to organize activities into projects, and then to form schedules for interacting household members. The TASHA model has been fully operationalised for the Greater Toronto Area and has been used to forecast emissions (Miller and Roorda, 2002) and to assess impacts of alternative development scenarios (Weldon, 2005).

The third major contribution is an innovative household tour-based mode choice model, within TASHA. This mode choice model makes a serious attempt to capture the explicit interactions within the household influence and constrain the mode choices of individual members. The explicit incorporation of joint mode decisions for joint travel, vehicle allocation, and assessment of drop-off and pick-up scenarios in a tour-based model is unprecedented in the literature. Part of the reason this has not been done is that the resulting model structure is unconventional and parameter estimation cannot be done using typical gradient search techniques. An evolutionary algorithm was used in a distributed computing environment to overcome this difficulty. The experience gained in parameter estimation for the TASHA mode choice model is expected to bear fruit in other components of the ILUTE modelling framework in which parameter estimation is similarly non-trivial.

It is very important not to overstate the predictive capabilities of the models presented in this thesis. It is always tempting to believe that a well-specified model that fits the observed data from the current year well will necessarily predict the future with reasonably good accuracy and precision. I argue that this is an unrealistic and inappropriate expectation for models that involve human behaviour.

One precondition to good forecasts is that inputs are accurate. Inputs to TASHA include, for example, the price of fuel and the demographic makeup of the population, both of which are very difficult to predict with precision. But perhaps more importantly, human patterns of behaviour can change in unpredictable ways. Cultural shifts, new technologies and world events such as wars or major economic changes have had dramatic unexpected effects on human activities and travel in the past and are likely to do so in the future. Our hope is that by drilling deeper to understand more fundamental behaviour of individuals, for example by finding simple rules and constraints from which more complex patterns of behaviour emerge, we will end up with a more robust model that can better withstand cultural, technological, political and economic changes.

Clearly, policy decisions are being made in complex situations based on imperfect information every day. The strength of models such as TASHA is that they approach very complicated problems in a systematic, understandable and transparent way. They can provide a framework for experimentation and discussion, and they are appropriate for analysing scenarios based on clear, transparent assumptions. In this spirit, this thesis attempts to document model assumptions as clearly as possible in an effort to best inform policy analysis.

The remainder of the thesis is organized as follows. Chapter 2 provides a literature review. Chapters 3 and 4 present the Travel Activity Panel Survey and a preliminary analysis of these data, respectively. Chapters 5 and 6 present the methods, assumptions and parameter estimation results of the activity scheduling and mode choice components of the TASHA model. Chapter 7 provides results of the models to a large scale sample of the GTA population, and Chapters 8 through 10 discuss potential policy applications, future work and conclusions, respectively.

2. Literature Review

2.1 Activity Based Modelling and its Antecedents

The current state of the art in activity-based modelling has a history of development that has spanned over at least 50 years.

2.1.1 The Social Physics Approach & the Urban Transportation Modelling System

The Urban Transportation Modelling System (UTMS) was developed from the 1950s to the early 1970s and is still used extensively in practice today (e.g. Meyer and Miller, 2001). The UTMS is a four-stage approach to predicting travel demand, including trip generation, trip distribution, mode choice, and transportation network assignment. Early UTMS frameworks are based on a modelling approach that used physical analogies, such as the gravity model in the case of trip distribution, for determining human trip making behaviour. These models are aggregate in nature. They include no representation of the individual person or household and there is no direct attempt to explicitly model their individual behaviour. Rather aggregate trip totals from origin zones to destination zones are the travel demand outcomes of interest, and they are modelled directly. No behavioural understanding of interactions among household members is present in such models.

2.1.2 The Econometric Approach

Econometric models of travel demand began to be developed in the late 1960s. The critical development in this era was a move to represent individual choices based on disaggregate data. These models incorporate the concept of utility (a measure of satisfaction or benefit) in human decision-making. These models usually take the form of discrete choice models, where individuals are assumed to make choices that result in a maximization of their utility (see Ben-Akiva and Lerman, 1985 for a comprehensive description of the theory and application of discrete choice models). Utility is generally described as a linear function of attributes of the decision-maker and attributes of the alternatives that a decision-maker chooses from. Thus, research in this era generally attempted to model choices without adequately taking into account the individual's social context. Constraints in behaviour due to the complexities of an individual's interactions with other people could not be understood because the context was not provided in the modelling framework. Furthermore, models developed in this era generally tried to model individual trips without trying to understand the context of the trip in terms of other trips made during the day, or the underlying participation of activities that formed the rationale for making the trip in the first place. Kitamura notes that models in this era were primarily concerned with "improved statistical economy in data collection, and versatile policy applicability" (1988). And Pas (1990) notes that many researchers have strongly argued that these models have little behavioural content (Heggie, 1978; Burnett and Thrift, 1979; as cited in Pas 1990).

2.1.3 The Activity-Based Approach

Activity-based analysis of travel recognizes that travel is a "derived demand based on individuals' needs and desires to participate in activities at spatially separated locations" (Pas, 1990). Jones *et al*. (1990) outline an additional six features of the activity paradigm as follows:

- Focus on sequences or patterns of behaviour rather than an analysis of discrete trips;
- Emphasis on decision making in a household context, taking explicit account of linkages and interactions among household members;
- Emphasis on detailed timing as well as the duration of activity and travel, rather than using the simple categorization of 'peak' and 'off peak' events;
- Recognition of the interdependency among events which occur at different times, involve different people, and occur at different places; and
- Use of household and person classification schemes (e.g. stage in family life-cycle), based on differences in activity needs, commitments and constraints.

(Jones *et al*. 1990, p.34-35)

One of the primary conceptual frameworks that has been used to explain an individual's actions in time and space is Hagerstrand's concept of space-time prisms (1970). Hagerstrand's "space-time prisms" indicate the freedom of a person to move in time and space in relation to constraints. He has theorized that there exist 3 kinds of constraints on human activity:

- *capability constraints* – those which limit the activities of the individual because of his biological construction and/or the tools he can command
- *coupling constraints* – "define where, when and for how long, the individual has to join other individuals, tools, and materials in order to produce, consume and transact" (p. 14) (e.g. meetings, supporting children's schedules, etc.)
- *authority constraints* – e.g. property constraints, sites available only upon invitation or some kind of payment

There has been a wealth of applications of the activity paradigm including activity-time allocation models (e.g. Kitamura *et al.*, 1996; Golob and McNally, 1997; Bhat and Misra, 1997), econometric (discrete choice) models of activity participation (e.g. Bowman and Ben-Akiva, 2001; Wen and Koppelman, 1999) and computational process models (e.g. Arentze and Timmermans, 2000; Ettema *et al.*, 1993; Kitamura and Fujii, 1998).

2.2 Within Household Interactions

Although Hagerstrand's 'coupling constraints' point to the behavioural importance of interactions with other people, and Jones *et al.* (1990) point out directly the emphasis of household interactions in the activity paradigm, research on household interactions has not yet fully matured.

There are four key dimensions of household interaction:

- Time allocation / allocation of activities among household members;
- Car allocation among household members;
- Ridesharing within the household;
- Participation in joint activities

Most published research to date has focused on one or two dimensions of household interaction. For example:

Golob and McNally (1997) consider interactions between husbands and wives by finding correlations between total time spent on different classes of activities. However, they do not model the number of activities, their time, their location, the mode of transportation, or how the activities are scheduled. The work of a number of other researchers similarly focuses on time allocation, activity allocation and/or joint activity participation among household members including Borgers *et al*. (2002) Ettema *et al.* (2004), Srinivasan and Athuru (2005), Srinivasan and Bhat (2005), and Scott and Kanaroglou (2002).

Gliebe and Koppelman (2002) have analyzed both joint activity participation and ridesharing. They classify tours by the presence of joint activities, ridesharing and dropoff/pickup and proceed to model joint travel outcomes of multiple household members.

Scott and Kanaraglou (2000) present a conceptual framework for a model that incorporates activity generation, activity scheduling, mode choice and tour generation for two adults in the household. Their approach incorporates joint activity participation, correlations in activity generation between multiple household members, but does not include children in the model. The activity generation component of the model is the only part that has been implemented to date (Scott, 2000).

Computational process models (e.g. Arentze and Timmermans, 2000; Ettema *et al.*, 1993; Kitamura and Fujii, 1998) use heuristics (rules) to develop the activity schedules given an activity agenda. As Scott and Kanaraglou (2000) point out, they "are unable to generate activities, but can incorporate household interaction in the form of an agenda [i.e. a list of activities in which a person would like to participate] provided *a priori*". Schedule formation, however, is done in these models by an individual without including household constraints on behaviour.

Wen and Koppelman (1999) also provide a fairly comprehensive treatment of household interactions by developing a discrete choice model that includes household maintenance stop generation, stop allocation to household members, auto allocation to household members and the sequence of activities in the activity patterns of the husband and wife. However, it does not consider joint activities, and it does not attempt to model the times, durations, or locations of various activities.

Perhaps the most comprehensive representation of intrahousehold interactions has been incorporated into operational activity-based travel demand models. Vovsha *et al.* (2003) recently developed a tour based modelling system for the Mid-Ohio Regional Planning Commission (MORPC) that incorporates joint activity participation, and the associated ridesharing using a set of three choice models: (a) joint tour frequency, (b) travel party composition and (c) person participation in each tour for each of the household members. The MORPC model also explicitly models within household allocation of maintenance activities to household members (Vovsha *et al.*, 2004b). More recently, Vovsha and Petersen (2005) have developed and estimated a model of ridesharing and escorting of children to school, that is designed for possible inclusion in the regional travel model system for the Atlanta Regional Commission (ARC). The major interaction that appears to be missing from this modelling effort is that of vehicle allocation.

2.3 Models of the Activity Scheduling Process

Another recent development in the activity-based modelling literature is a focus on the modelling of the *process* of activity scheduling. It has been recognized for some time by travel behaviour researchers that in order to model activities and travel, it is necessary to gain an understanding of the underlying behaviour, or process, that leads to travel and activity patterns (e.g. Pas, 1985; Jones *et al.*, 1990; Axhausen and Gärling, 1992; Lee-Gosselin, 1996; Axhausen, 1998; Bhat and Lawton, 2000).

Activity-based models of travel demand seek to replicate the final activity travel patterns including what activities to conduct, by whom, with whom, at what time, for how long, at what location and by what mode. Process models seek to utilize an enhanced understanding of “how?” and “why?” questions to more realistically replicate the sequence of decisions and events that lead to these observed patterns.

Bradley (2004) and Axhausen (1998) have both developed lists of these types of questions we would wish to have answered to enhance our understanding of the "how" and "why" behind travel decisions. Bradley's list is shown as follows:

- What other alternatives did a person consider?
- What other alternatives were possible?
- Was the decision planned in advance or made on the spur of the moment?
- If planned in advance, how far in advance, and did the plans change over time?
- Was the decision dependent on other decisions that were made?
- Which decision factors were most important?
- What information did the person have regarding those factors?
- How and when did the person acquire that information?
- What other information would have been useful?
- Why did the person not have that information?
- How would the person go about getting that information?
- Had the person made that decision before?
- If so, did the person tend to make the same choice each time, or did it vary?
- If it varied, why would the person choose differently at different times?
- Was the decision made jointly with other(s)?
- If so, how did the different people enter into the decision?
- If so, was there a negotiation or a tradeoff of priorities?
- Did other people (employers, etc.) indirectly influence the decision?
- If so, what was their influence?
- How did past experiences influence expectations regarding that decision?
- Were there any recent major changes that influenced the decision?
- Were there any future expected changes that influenced the decision?
- What roles did variability, uncertainty and risk play?
- Did the person have any strong attitudes about the choice alternatives?
- If so, when and how did those attitudes develop?
- Does the person have any strong unconscious feelings or associations regarding the alternatives?

Understanding the answers to these questions is crucial in developing a dynamic model of scheduling behaviour that can represent the sequence of these decisions and the way people reschedule over time in response to changing opportunities and constraints.

There have been two basic approaches in the literature that deal with the modelling of the activity scheduling process. The first approach assumes that an individual chooses from a set of activity/travel patterns, usually under a utility maximization framework (e.g. Jones *et al.,* 1983; Recker *et al.*, 1986a and 1986b; Kawakami and Isobe, 1990; Bowman and Ben Akiva, 2001). Gärling (1994) has criticized such models, drawing on a body of research in the behavioural sciences to suggest that micro-economic theory is not an accurate description of how people make decisions (see Abelson and Levy, 1985). Gärling *et al.* (1994) advocated that a computational process model of activity scheduling, in which a set of rules in the form of condition-action pairs are used to specify how a scheduling task is solved.

Several computational process models have been developed to model the activities and travel. SCHEDULER was developed conceptually by Gärling *et al.* (1989) and partially operationalized (Gärling *et al.* 1998). The model uses a heuristic approach to choose activities from an individual's long term memory, to partially sequence the activities on the basis of identified temporal constraints, and then to re-sequence the activities to minimize total travel distance. In SMASH (Ettema *et al.*, 1994), a scheduling process is modelled, in which sequential scheduling steps lead to the final schedule. SMASH recognizes that the disutility of the scheduling effort needed for complex tours may be greater than the utility of combining multiple trips into one tour. A satisficing (rather than an optimizing) approach is assumed in which an acceptable schedule is created with acceptable effort.

Doherty *et al.* (2002) have proposed an activity scheduling model based on the Computerized Household Activity Scheduling Elicitor (CHASE). This model begins with an activity agenda common to the entire household. Individuals develop their activity schedules simultaneously by choosing to add activities during the current day (spontaneous activities) or at future time periods (preplanned activities). The addition of activities can invoke a conflict resolution module, which may result in modification or deletion of activities in the schedule. Random events are generated in the model to reflect unexpected events such as "emergency" activities, changes in travel or activity duration. The model is probably the most ambitious of all computational process models in its attempt to represent the longer term planning horizon explicitly. However, no attempt to operationalize this model has been made to date.

The ALBATROSS (Arentze and Timmermans, 2000) is perhaps the most comprehensively implemented computational process model. The core of the ALBATROSS system is the scheduler engine. This engine assumes that a sequence of longer term commitments and constraints are given as input, resulting in a schedule skeleton. The scheduling engine sequentially selects activities to add to the schedule, determines the persons involved and the activity duration, positions those activities in the schedule, chooses the mode of transportation, and selects activity location. All of these decisions are made through the use of probabilistic decision tables induced from diary data (see Arentze and Timmermans, 2004). Given a set of condition variables describing the decision context, a probabilistic distribution is used to determine decision outcomes, and ultimately the makeup of the individual's schedule.

2.4 Process and Panel Data

There exists a well-developed theoretical basis for scheduling process models. Part of the problem in their implementation has been the difficulty associated with collecting data in which the scheduling process is observed. Indeed, operational models have generally been developed using trip or activity diary data, which include little or no information on the underlying process (e.g. Arentze and Timmermans, 2000). Thus, assumptions must be made about the sequence in which decisions are made, the inclusion of activities in a pre-planned skeleton schedule, the degree of optimization in schedule, the amount of information available to the decision-maker, etc.

The difficulty is that the development of behavioural models of activity scheduling and travel requires an abundance of data. As pointed out by Axhausen (1998), we not only need to know the more typical descriptors of an activity, such as activity type, time, duration, mode and location. We also need to answer questions about the more subtle attributes of activity scheduling, such as "*When was the activity was first conceived?*", "*What could have replaced it and achieved the same aim?*", "*How important was it in comparison to the other activities performed and still planned for the day?*", and "*What was the earliest/latest time for the performance of the activity today?*". With answers to these kinds of questions about the scheduling of activities, we can attempt to develop rule-bases for better behavioural models of the activity scheduling process.

Some elements of the process of activity scheduling have been observed in activity scheduling surveys. Ettema *et al.*, (1994), for example, developed an interactive computer experiment for assessing scheduling rules (MAGIC). In this survey, respondents were asked to develop activity schedules for the next day, allowing for the addition and deletion of activities and the modification of activity attributes such as start/end time, location and mode. They found that fairly simple scheduling heuristics were used. Usually activities were found to be scheduled in order of execution, and relatively few deletions or modifications were made. One problem with the technique was that it observed the scheduling procedure only at a single point in time for a single person, with little qualitative probing asking questions of "why" people scheduled the way they did.

Similar in some respects to MAGIC, the CHASE survey instrument has been used to collect activity scheduling process data (Doherty and Miller, 2000). CHASE builds upon previous laboratory-based methods (e.g. Hayes-Roth and Hayes-Roth, 1979; Ettema *et al.*, 1994) by providing a means to observe the scheduling process as it occurs in reality in a household setting over a week-long period. It is able to capture both routine and complex scheduling processes and observe those scheduling decisions made during the actual execution of the schedule. CHASE uses a computerized software environment that traces the timing of data entry. CHASE does begin to address the questions of "why" scheduling decisions are made, by prompting for additional information given the scheduling decisions that are made. CHASE has been used in a variety of technological settings, including an internet version (Lee and McNally, 2001), and a version on a hand-held, GPS linked PDA (Rindsfüser and Doherty, 2003).

There are well-recognized difficulties associated with response burden when asking a large number of complex questions. As suggested by Axhausen (1998), it is impossible to obtain the vast amount of information we need for activity process modelling from one person. Clearly, none of the above surveys of the activity scheduling process is, by itself, able to systematically address the many behavioural process questions that have been outlined by Bradley or Axhausen. As suggested by Axhausen, it is necessary to divide the data collection using more than one survey instrument (1998).

Panel surveys are one way of achieving the objective of maximizing the data retrieved from individual respondents or households. Panel surveys involve contact with respondents at multiple points over time. Hence, they provide an opportunity to manage the response burden issue by spreading the burden over several years. This is in addition to the more typical benefits derived from observing a sample of households at multiple points in time, such as the ability to observe changes in behaviour, to capture the effects of changes to the household such as employment, residential location, or family structure. These typical benefits and challenges of panel surveys have been well documented (see, for example, Paaswell, 1997; Raimond and Hensher, 1997; Kitamura, 1990; and Cambridge Systematics, 1996).

While major panel surveys have been used to collect longitudinal activity travel data in the past two decades, these panel surveys have in general used a single instrument in multiple waves to elicit changes in behaviour over time. This includes two major general purpose activity panel surveys to date, the Dutch National Mobility Panel (Baanders and Slootman, 1983; Golob *et al*., 1986; van Wissen and Meurs, 1989) and the Puget Sound Transportation Panel (Murakami and Ulberg, 1997). The reasons for using a single unmodified instrument in all waves of a panel survey are sound, especially if the primary purpose of the survey is to provide estimates of change in behaviour that are not obscured by differences due to the bias introduced by each instrument (see Goulias *et al.*, 1992). If, however, clear unobscured trend analysis is not the *primary* purpose of the panel survey then a range of other benefits arise from using multiple instruments. These benefits include:

- An increase in the breadth and depth of data that can be retrieved from a single set of respondents. More questions can be asked about different aspects of the activity scheduling process and a greater number of observations can be obtained at different points in time.

- The potential to evaluate bias associated with different survey instruments. Systematic differences in the responses of the same people to similar questions by different retrieval methods (e.g. face-to-face interview, telephone retrieval, self-administered computer entry) can be attributed to instrument bias, if there is evidence that no systematic change in behaviour has occurred over time.

At least three other practical reasons exist for using panels to elicit in-depth activity scheduling data:

- By allowing survey methods to change from wave to wave, the inevitable conditioning of panel members in earlier waves can be embraced. Respondents' experience of the survey exercise in one wave can lead to improved quality of response, lower respondent training time, and increased flexibility for instrument design[1] in subsequent waves that is responsive to comments made by survey respondents.
- The ability to vary the kinds of questions posed to respondents to help maintain their level of interest, and ultimately to result in greater participant motivation and reduced rates of panel attrition.
- Survey design for each wave can be informed by the results of data analysis from previous waves.

A review of the literature revealed no studies of activity/travel behaviour that used a flexible instrument design in a panel survey context to take advantage of these benefits. Furthermore, the author is aware of no studies that have administered an in-depth survey of the activity scheduling process within a panel survey framework.

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[1] As discussed in Chapter 3, the second wave of the Toronto Activity Panel Survey was administered using a mail-out-mail back questionnaire, and telephone retrieval. This would not likely have been successful without the training provided in face-to-face interviews in the first wave.

2.5 Tour-based Mode Choice Modelling

Clearly associated with activity scheduling decisions are those of travel mode choice. Activity scheduling influences mode choice because the choice of time of day and the arrangement activities into chains can influence the origins, destinations and travel times of individual trips. Similarly, the travel times associated with different modes of transportation has an impact on the time needed within the schedule to accommodate those trips.

There is a vast literature on disaggregate mode choice models. The majority of these models are trip-based, and focus on a specific purpose (e.g. Miller, 2001; Ortúzar, 1983; Asensio, 2002), rely heavily on traditional *random utility maximization* (RUM) theory, and incorporate trip-based assumptions of conventional four-stage models. The lack of behavioural realism of trip-based models, however, has been criticized by several authors (e.g., Ben-Akiva, *et al.*, 1998), who emphasize the importance of a more comprehensive tour-based approach.

Some of the problems associated with individual trip-based models are as follows:

- There is no consistency at the level of the tour. An individual can drive to work and travel home by transit, with no penalty for "stranding" the car at work;
- Vehicle allocation cannot incorporated in the model. More than one household member may engage on drive trips to different locations at the same time, even though only one household vehicle is available;
- Passenger mode is included as an alternative, regardless of the availability of a household vehicle and a driver to give the person a ride;
- People engaging in joint activities may choose different modes of transportation; and
- Trip-based models are often estimated at the disaggregate level, but are applied at the aggregate level. This often means that limited socioeconomic variables can be appropriately used in the model specification (which would require reliance on average values for the zone of interest).

Tour-based models have been developed to address at minimum the first of these problems. Most of the tour-based models have been developed either within the context of European national models in countries such as The Netherlands (HCG, 1992), Italy (Cascetta, *et al.*, 1993), Sweden (Algers, *et al.*, 1997; Beser and Algers, 2002) and Denmark (Fosgerau, 2002), or US cities and regions such as San Francisco (Bradley, *et al.*, 2001; Jonnalagadda, *et al.*, 2001), New York (Vovsha *et al.*, 2002), Ohio (Vovsha *et al.*, 2003), Atlanta (Vovsha and Petersen, 2005), Boston (Bowman and Ben-Akiva, 2001), and Portland (Bowman, *et al.*, 1998). Although differences exist among them, these models share several important features:

- Reliance on some "tree logit" form;
- Simplification in the definition and construction of tours;
- Assumption of a "main" mode;
- Separate calibration by purpose; and
- Use of explicit assumptions about car availability rather than car allocation *per se*.

Of note is the recent trend in tour-based modelling toward incorporating intra-household interactions in models of mode choice as described earlier in this chapter. (e.g. Algers et al. 1997, Vovsha *et al.*, 2002, 2003, 2004a and Vovsha and Petersen, 2005). This improvement in behavioural realism has largely been made possible by the implementation of the models in a microsimulation framework. Good descriptions of the benefits of microsimulation framework for modelling household travel and mode choice are given by Vovsha *et al.* (2002) and Miller (1996).

Nested logit (NL) models are most commonly used for tour-based mode choice models[2]. For example, the Stockholm model uses three NL substructures for (a) "long-term" decisions (car ownership and destination), (b) primary destinations, and (c) secondary destinations. These three substructures are connected by *inclusive values* or "logsums" of utilities that carry information about the decisions made on the lower levels to upper levels, in a sequential procedure. Similarly, in the San Francisco model, mode choice is modelled as a *multinomial logit* (MNL) that "informs" the upper destination decision level through logsums. Bowman, *et*

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[2] The nested logit model is a relaxation of the multinomial logit model, which has the independence from irrelevant alternatives (IIA) property. This property assumes that the introduction of a new alternative will have an equal proportional impact on all other alternatives. Other relaxations have been applied to the mode choice problem, including the multinomial probit model (Daganzo, 1979), the mixed logit model (Bhat, 1998) the paired combinatorial logit (Koppelman and Wen 1997), the cross-nested logit (Vovsha, 1997) the heteroscedastic extreme value (Bhat 1995) and the hybrid choice model (Walker and Ben-Akiva, 2001). Due to computational difficulties for large nesting structures, the nested logit model has been preferred over such other, more general, models (Wen and Koppelman, 1999).

al. (1998), assume five types of models in a hierarchy of activity patterns, and primary and secondary destination-mode choices. Finally, Wen and Koppelman (1999) use a series of linked NL models for (a) stop generation and stop/auto allocation, (b) tour generation and assignment of stops to tours, and (c) travel/activity patterns.

In several mode choice models, the assumption of a single mode choice for all trips on the chain is made. This implies that no switching between modes within a tour can be made by travellers, and the detailed consideration of mode preferences is made only with respect to the main mode. In other cases this assumption is partially relaxed. In the Portland model, for example, a set of rules is used to aggregate all the possible combinations of modes into a manageable number; in the San Francisco model the trip mode choice is applied for each stop of the tour, conditional on the predicted “main” mode and the origin, destination, and time of day.

Treatment of car allocation varies among models. For example, the Danish model directly incorporates household car availability in the tree structure; the Stockholm model considers a level for the car allocation process that defines the possible mode choice options; and the San Francisco model consider vehicle availability at higher levels, above tour and trip generation. Finally in Wen and Koppelman’s model (1999), auto allocation is done at the third level of a NL structure, with “stop generation” and “stop allocation to household members” as the upper levels. These models do not allow for more complex car allocation behaviour, such as the use of a single car by different members of the household at different times within the day.

Some computational process models also include mode choice. In the ALBATROSS model (Arentze and Timmermans, 2000), mode choice enters into the rule-based activity scheduling framework in two places. First, in step one, the “main” mode choice for primary work activities is chosen using context-dependent decision rules. By allowing the decisions of one household member to subsequently condition the alternatives available to other household members, a car allocation model is incorporated into the framework. However, it appears that the order in which persons in the household are processed in the model may unduly influence the outcome of the car allocation. Second, in step five, the choice of transport mode for nonprimary work tours is made at the tour level. The authors recognize that people can change modes within a tour, but ignore this in the model structure since their data contain very few such cases.

2.6 Summary

The state-of-the-art in activity based modelling of travel demand has progressed significantly over the past 20 years, including major advances made in the following relevant areas:

- Observation of the process of the activity scheduling process and its influence on travel behaviour;
- Modelling of the activity scheduling process using both econometric and rule-based methods;
- Development of tour-based mode choice models as part of more comprehensive models of travel demand;
- Incorporation of household interactions into both mode choice and activity scheduling models, leading to an improved behavioural realism in the development of the schedules of household members and the modes of transportation chosen;
- Many of the above models have been developed to the point where they are of operational status, and ready for use in practical policy settings.

However, none of these research thrusts has progressed to full maturity. All models either partially cover the scope of relevant activity travel decisions, are missing key interactions, attempt to represent only observed outcomes and little of the behavioural process and/or are forced to make theoretical compromises to achieve operational status. The following chapters outline the contribution that has been made in this doctoral work to advance the maturity of each of the above areas of research.

3. The Travel Activity Panel Survey

3.1 Introduction and Background

Our aim to develop an improved activity-based travel demand model in the Greater Toronto Area has underscored the need for data collection techniques that allow us to observe the activity scheduling process as directly as possible. Qualitative and quantitative observations are needed to improve our understanding of the factors that influence activity / travel behaviour, to help inform model structure, and to form the basis for formulating behavioural rule sets within the models. To address this need, in-depth longitudinal surveys are being conducted on panels of participants in two Canadian urban areas: Toronto and Quebec City. A total of 520 responding households from the two areas complete in-depth surveys at one-year intervals. The panel surveys use a variety of instruments, each emphasizing different, but complementary, aspects of the scheduling process. This chapter describes the overall data collection philosophy for the two urban areas and the detailed design of the instruments used in each wave in Toronto.

The remainder of this chapter is organized as follows. Section 3.2 describes the overall design strategy for the three-wave activity panel survey. A detailed description of the design of Waves 1, 2 and 3 in Toronto follows in Section 3.3. Section 3.4 describes the implementation of the survey, Section 3.5 provides preliminary analysis of a few key data elements of the survey and Section 3.6 lists additional analysis being done by other researchers. Finally, a discussion of the benefits and challenges associated with the data collection approach are discussed in Section 3.7.

3.2 Overall Design Strategy for Data Collection in the Two Regions

The substantive objectives of the travel activity panel survey are:

a) To understand a variety of aspects of the *process* by which people schedule and reschedule activities and travel within the context of the household;

b) To observe how activities, travel and the underlying scheduling process change or remain stable over time, particularly in response to major changes in the household;
c) To compare decision processes in two different study areas, Quebec City and Toronto; and
d) To provide an empirical basis for the modelling of activity and travel scheduling and rescheduling.

In addition, a number of methodological objectives were a focus of the research, including:

e) To assess the feasibility of using an in-depth but relatively onerous computer-aided, self-administered instruments on a wide spectrum of households, including the CHASE survey package and some limited testing of personal GPS units;
f) To compare the feasibility and perceived burden of computerised versus non-computerised methods to study decision processes;
g) To develop new measures of data quality specific to activity scheduling process data;
h) To test the feasibility of interactive home-interview methods to engage respondents in classifying the way they went about deciding to do the activities that were recorded during an observation period;
i) To test the usefulness of a semi-structured sub-interview about linked activities, household decision dynamics, issues of satisfaction, and anticipated changes during the life of the survey and beyond; and
j) To test the feasibility of using a telephone interview method to conduct stated adaptation surveys of scheduling conflict resolution.

To achieve both the substantive objectives (a) and (d) and to achieve all of the methodological goals (e) to (j), the decision was made to use a "reflexive" approach in which the survey methods would be allowed to change from wave to wave, as researchers learned about the feasibility of previously untried methods, refined research questions for subsequent waves based on the results of previous waves, and sought to test new survey techniques. It was recognized at the outset that panel conditioning would be inevitable given the depth of probing into the scheduling process. We decided, using the "cumulative experience" design principle, that panel conditioning could be used to our advantage. For example, we would not have successfully been able to use a telephone interview survey in Wave 2 to conduct a detailed and qualitative stated response survey of activity scheduling conflicts had the respondents not already had some face-to-face experience in Wave 1 with developing activity repertoires, and creating and updating an activity schedule. The evolving design also served to test new survey techniques, as researchers learned about the feasibility of previously untried methods, and refined research questions for subsequent waves based on the results of previous waves.

To use a multi-instrument approach in a panel survey context counters conventional wisdom that instruments should remain unchanged through all waves of a panel survey (see, for example, Goulias *et al.*, 1992). Two consequences of choosing a multi-instrument design were that (1) panel refreshment would not be possible and (2) any behaviour trends inferred from the panel data could not be distinguished from changes in instrument bias. The first of these consequences was addressed by making panel retention a high priority through the use of incentives, frequent respondent contacts, and persistent recruiting. To address the second, we attempted to design the surveys with a common set of data elements to be collected using similar collection instruments. In all survey waves, at minimum a two-day "executed" activity diary was collected, as shown in the upper-left cell of Table 3.1. Table 3.1 also summarizes the data collected and the methods used that are specific to each wave and to each region. We were partially successful in presenting an unchanging instrument for the core set of data elements. In waves 2 and 3, a 2-day paper diary was developed that only incorporated very minor changes between waves. However, the nature of these two diaries was significantly different from more "process-driven" diaries used in Wave 1 in Toronto (CHASE) and Quebec City (OPFAST). A detailed list of "core" variables collected in every wave in both regions is shown in detail in Table 3.2.

Table 3.1: Summary of data and methods used in each wave in each region

Wave	Data and methods common to Toronto and Quebec City	Data and methods specific to Toronto	Data and methods specific to Quebec City
Data and methods common to all waves	• Socioeconomic information including residence location, household structure, personal information (e.g. work location, personal income), vehicle information • 2-day "executed" activity schedule, including in-home and out-of-home activities with start-time, duration, location, purpose, mode(s) of transportation, number of passengers, other persons involved in the activity and, children under the care of the respondent at the time	• Interviews conducted in English • Computer aids used *on-line* to speed data entry during the interviews	• Interviews conducted in French • Computer aids used *after* the interview period for data entry
Wave 1	• 7-day activity/travel schedule with activity description, time, duration, location, mode and participants • Activity agenda: a set of activities that the respondent is likely to participate in over the 7-day survey period • Detailed planning process for all activities in the 7-day schedule • Flexibility of activities in time, space, mode, and participants	• CHASE instrument • Computerized self-administered survey • Automated prompts ask for detailed information on every schedule addition/change including when it was conceived, the reason for the change, and the type of co-ordination involved. • In-depth End-of-Week review concerning spatial/temporal/interpersonal flexibility, and the frequency and durations of major classes of activity • An add-on pilot study on a subset of 12 individuals outfitted with portable GPS units while doing the survey • An add-on study of 30 households to assess data quality of the CHASE survey • Surveys conducted between March 2002 and May 2003	• OPFAST instrument • Paper and pencil survey with fax-back on a daily basis • In-depth post-interview on spatial/temporal fixity, planning horizons and interdependence, holistic interpretations, "projects", activity negotiation, telecommunications, expectations about the future, and unsatisfied demand • An add-on study of 34 low income women • Surveys conducted between May 2002 and December 2003
Wave 2	• Stated adaptation to hypothetical "perturbations" to randomly selected activities from the 2-day activity survey • Qualitative scheduling responses to conflict	• Surveys conducted between July 2003 and May 2004	• Surveys conducted between March 2004 and May 2005
Wave 3	• Assessment of the "routine weekly schedule", the activities that the respondent normally does every week. • Route tracking throughout the survey period using a small personal GPS unit (on a subset of respondents only)	• Routine activities for a week entered on a single 17x22 sheet of paper • Surveys began in August 2004 and are in progress	• Routine activities for a week entered on a memory jogger mailed in with the diary and explored in the telephone interview • Surveys planned for July to December 2005

Table 3.2 - Core Survey Elements

Data Category	Data Collected
Residence Information	• Current address (and previous address for Wave 1) • Tenure • Length of time at that home • TV and internet availability
Household Structure	• Changes to people in the household over the past year, including new children born • Reason that household member(s) joined or left
Person Information	• Name • Household role • Age • Marital status • Drivers license, transit pass • Cell phone usage • Level of education • Children under regular care • Child care arrangements (for children) • Employment status, job type(s), employer(s), duration of employment • School status, type of degree/diploma/certificate • Gross income
Modes of Transportation	• Vehicles available to household members, make, model, vintage, ownership, length of ownership, principle driver(s), people that ride in the vehicle • Vehicles disposed of between waves, date of disposal
Executed 2-day Activity Schedule	• All activities completed for all participating household members (minimum age of 16 years) • Activity description, • Start time, • Duration, • Location, • Mode(s) of transportation, • Estimated travel time, • Passengers in the vehicle, • Other people involved in the activity, • Children under the respondent's care at the time of the activity

The choice of a medium-sized initial sample of 250 to 270 households per region was dictated by the available resources, and the desire to have a large enough sample to cover a wide variety of household types and locations. Within the life of the survey, it was only possible to implement three waves for the panel.

Each wave of the panel in each of the two regions was undertaken over the period of approximately a year. This arrangement was chosen to prevent the need for assembling a large-scale survey centre and training a large number of staff to complete all interviews over a short period. An effort was made, however, to survey households at about the same time of year in each wave. Efforts were also made to coordinate the timing of the corresponding waves in Quebec City and Toronto, however, because of additional design work and pilots necessary for the previously untested OPFAST survey, the Quebec City waves of the panel were operational some months later than the Toronto survey in each wave.

Toronto and Quebec City were chosen as study regions for the panel, in part, because both regions regularly undertake major travel surveys (over 100,000 households sampled in Toronto and over 27,000 in Quebec City) which provide benchmark trends in activity and travel behaviour that complement the in-depth behavioural data collected in the panel survey. The characteristics of physical infrastructure and population in Toronto and Quebec City are substantially different from each other. Toronto has a high growth rate, a high level of transit usage, and a highly congested road network compared to Quebec City, whose population is nearly stagnant and predominantly auto-dependent, with a far less congested roadway network. Such differences provide interesting opportunities for regional comparisons.

3.3 Detailed Survey Design

3.3.1 Wave 1: CHASE

The first wave of the panel was completed in the Toronto Area using CHASE (**C**omputerized **H**ousehold **A**ctivity **S**chedule **E**licitor) (Doherty and Miller, 2000; Doherty, 2002; Doherty *et al*., 2004). CHASE is a week-long survey in which the activity scheduling *process* is observed as it occurs in reality, along with observed activity-travel patterns. The CHASE survey process, as shown in Figure 3.1, begins with an up-front face-to-face interview in which a notebook computer with the CHASE software is loaned to the household; socio-demographic, transportation mode and residence information is retrieved; and the software is customized with an "agenda" of activities that the respondent(s) might conduct over the week-long period.

At the beginning of the week, respondents enter activities that have already been planned for the upcoming week in a computerized schedule resembling a daytimer (an example partially complete schedule, and the dialogue box that appears for every schedule addition/modification are shown in Appendix A). Over the course of a week, respondents are instructed to log in at least once a day to enter newly planned activities and activities that have been executed since the last login time. All changes the respondents make to their plans over the course of the week, including activity additions, activity deletions and the modification of activity attributes such as timing, mode of transportation or location are recorded. Reasons for all of these changes are also recorded through a series of automated prompts in the CHASE software. Once the week is completed, respondents are asked to complete an "End of Week Review" (EWR), in which the respondent is asked a systematic set of automated questions about the temporal, spatial and interpersonal flexibility, and the normal durations and frequencies of the activities they have conducted throughout the week (See an example prompt in Appendix A). The notebook computer is retrieved after one week and a follow-up interview is conducted in which data are checked by the interviewer for omissions and problematic data.

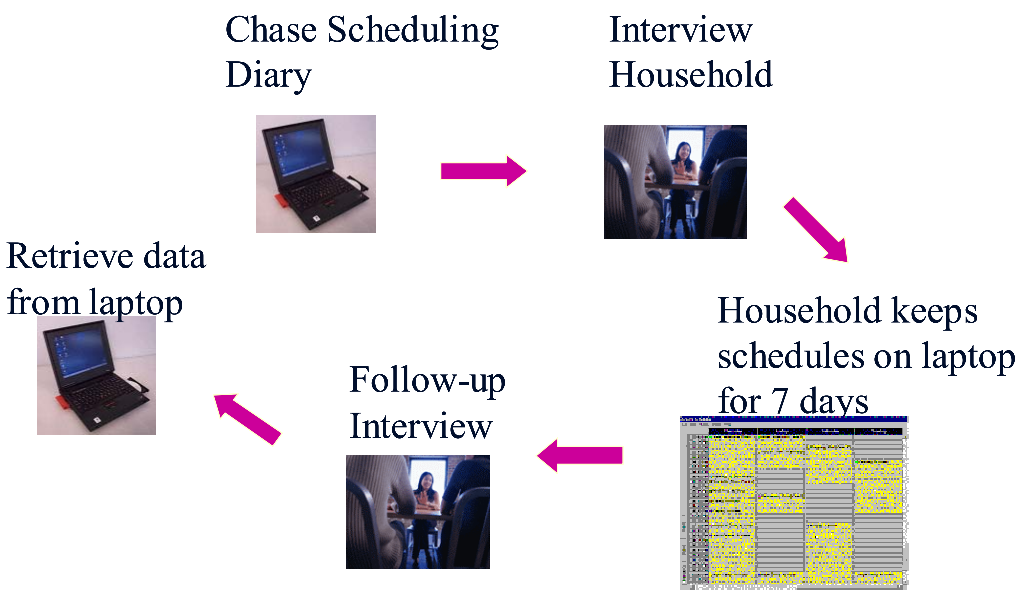

Figure 3.1 - CHASE Survey Process

In Wave 1, two add-on surveys were implemented on sub-samples of households in Toronto. The first Toronto add-on involved a follow-up quality assessment of the CHASE survey process on a sub-sample of 30 respondents. It involved asking respondents questions about their experience of the survey including the specific types of problems that were encountered, whether they would do another similar survey, the necessity of an incentive, etc. This follow-up survey is described in more detail by Doherty *et al.* (2004).

A second add-on involved giving personal GPS tracking device to 12 individuals during the Wave 1 study period in Toronto. The original objectives of this research were to explore the development of algorithms to automatically detect a person's activity patterns from GPS data, and how such information could be incorporated into activity scheduling process surveys in the future to offset respondent burden and improve accuracy. Other uses have been found for the GPS data, for instance, a method was discovered to *automatically* detect elements of a person's underlying scheduling decisions in addition to their observed travel patterns (Doherty and Papinski, 2004).

3.3.2 Wave 2: Stated adaptation survey of activity scheduling conflicts

The second wave of the panel survey is a telephone interview survey. Respondents are first sent a two-day paper and pencil "memory jogger" diary (See Appendix B), on which they are asked to record some basic information about all executed in- and out-of-home activities as they occur over a two-day period. After the two day period is complete, a telephone interview is conducted in which a) changes to the household and personal information, residence location, employment status and location, and available vehicles are retrieved for the past year for all household members; b) the basic information about the two-day activity diary is retrieved over the telephone and more detailed questions about the activity location, participants, auto passengers and children under care are asked; and c) a stated adaptation survey is conducted on each participant in the household.

The entire survey was conducted with the aid of custom-designed CATI software. The use of a CATI is invaluable in that it streamlines the telephone interview process significantly. First, it provides a way to have Wave 1 data from the household be quickly viewed on screen as a reference for entering Wave 2 data. Second, it allows for some simple real-time error checking. Third, the data are immediately entered into a Microsoft ACCESS database, eliminating to a large extent the need for manual coding after the interview is complete. Finally, the CATI helps the interviewer navigate through the interview and, in particular, makes the random selections from the two-day diary that are necessary for the stated adaptation component of the Wave 2 survey.

A stated adaptation survey conducted on respondents after the two-day diary is retrieved is the additional survey element added for Wave 2. Hypothetical situations are framed in which activities from the respondent's two-day schedule are "perturbed" so as to cause conflicts in the schedule. Respondents are asked open-ended questions about how they would have modified their plans and how other household members would have been affected in response to the perturbations in their schedule. First, an activity (other than "basic needs" activities such as night sleep, washing and eating meals) that involved travel is randomly selected from the core 2-day activity schedule. The following three open-ended questions are then asked of the respondent regarding that activity:

Q1: *What would have happened if you had an unexpected one-hour delay in getting to this activity?*
Q2: *What would you have done if the ______ mode were not available to get to that activity?*
Q3: (For parents of children in school or child care only) *What would you have done if you got a call while you were (doing the activity) that your child was sick and would need to be brought home?*

After these questions were complete, a *pair* of adjacent activities from the two day schedule are selected randomly such that a) neither activity is a "basic needs" activity, b) activities are either different activity types, or they are at different locations, and c) activities are not both conducted at home. The following question is asked for this pair of activities:

Q4: *Imagine that* [description of activity 1] *was going to take longer than planned. If you decided to spend more time at* [description of activity 1] *it would have caused you to be one hour later than planned for* [description of activity 2]. *What would you have done?*

In each of the four open-ended questions above, efforts are made to start a conversation with the respondent to have them describe in some detail the alternative plans that would be made. In particular, four probing questions are used, for each of the above questions, to help the respondent articulate the full range of impacts on their household:

- *How would it have affected the other activities you did that day?*
- *Please estimate the times of the revisions to your plans.* (This question was customized depending on the types of revisions that were suggested by the respondent)
- *Would this have affected the plans of other members of your household?*
- *Would this have affected your plans on other days?*

Responses to these questions were entered in the words of the respondent to the greatest extent possible, and were classified into standard responses after the interview was complete.

3.3.3 Wave 3: Routine Weekly Schedule

The design of the core 2-day diary for Wave 3 in Toronto is almost identical to that of Wave 2[3], with a memory jogger for which the data are retrieved by telephone interview. In addition to the core 2-day diary, a large single-page paper and pencil "routine weekly schedule" is completed by the respondent (see Appendix C). On the routine weekly schedule, activities are entered that are "normally done every week", and a system of wavy lines and coloured symbols entered on the schedule are used to indicate the extent to which particular activity attributes (including start and end time, location, mode of transport and the involved persons) are routine or not, as shown in Figure 3.2.

Both the 2-day diary and the routine weekly schedule are mailed to the interviewer after they are completed (a carbon copy of the routine weekly schedule is retained by the respondent). A telephone interview is then completed with each member of the household, in which further details on the 2-day activity diary (including specific location information for activities, people with whom activities were done) and on the routine weekly schedule (including details on the spatial and temporal flexibility of routine activities) are retrieved.

[3] Slight modifications were made to the paper instrument to speed the telephone retrieval process. Three additional questions were asked, including "Was the activity done at home?", "Was the activity done alone?", "Were children under your care?".

Instructions for the Routine Weekly Schedule

Your routine schedule consists of **activities and trips that you normally do every week.**

Please enter all routine activities and trips on the attached schedule, following the instructions on this sheet.

You **do not** need to fill all of the time. Please **do not** enter any activities or trips that are **not** normally done every week.

Please use the pencil and markers provided to complete the following 5 steps.

STEP 1:
Begin by entering routine activities as shown below:
With the **PENCIL**, write in a description of the activity and the most frequent location. If the start or end times change from week to week by more than 15 minutes, use a wavy line.

STEP 2:
Please enter trips you normally make every week. Include the normal mode of transportation, the usual travel time and the origin and destination of travel (e.g. home to work).

STEP 3:
Some activities may be routine in time, but do not have a single routine location. With a red marker, draw for each activity either:

RED O: The activity is normally done at the same location
RED X: The location is not normally the same.

STEP 4:
Some routine activities may not always be accessed using the same mode of transport (e.g. car, TTC, GO train, walk). With a blue marker, draw for each activity either:

BLUE –: No transportation is required (same location as previous activity)
BLUE O: Same mode of transport is normally used to get there
BLUE X: Different modes of transport are used

STEP 5:
Some routine activities are not always done with the same people. With a green marker, draw for each activity (except for sleeping) either:

GREEN –: Activity is normally done alone
GREEN O: Activity is normally done with the same people.
GREEN X: The activity is done with different people.

When all members of your household have filled out their routine weekly schedule, please mail them back to us in the enclosed self-addressed envelope. Thanks!

Example

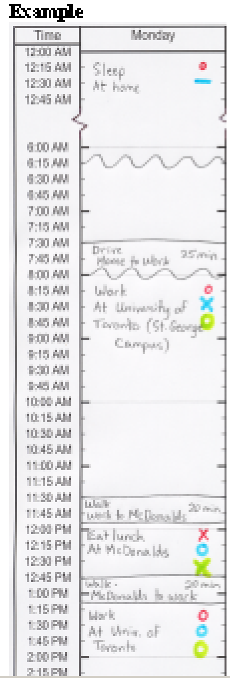

Figure 3.2 – Instructions for Routine Weekly Schedule (given to respondent)

3.4 Survey Implementation

3.4.1 Wave 1

Study Area

Samples of household telephone numbers and addresses were selected randomly from the telephone directory for the Toronto study area shown in Figure 3.3. In Toronto, the study area includes the entire City of Toronto and the surrounding (more suburban) municipalities of Vaughan, Richmond Hill, Markham, Mississauga and Pickering. In total, the study area covers about 74% of all households in the Toronto Census Metropolitan Area and represents an excellent diversity of urban forms, population densities, and levels of transportation accessibility.

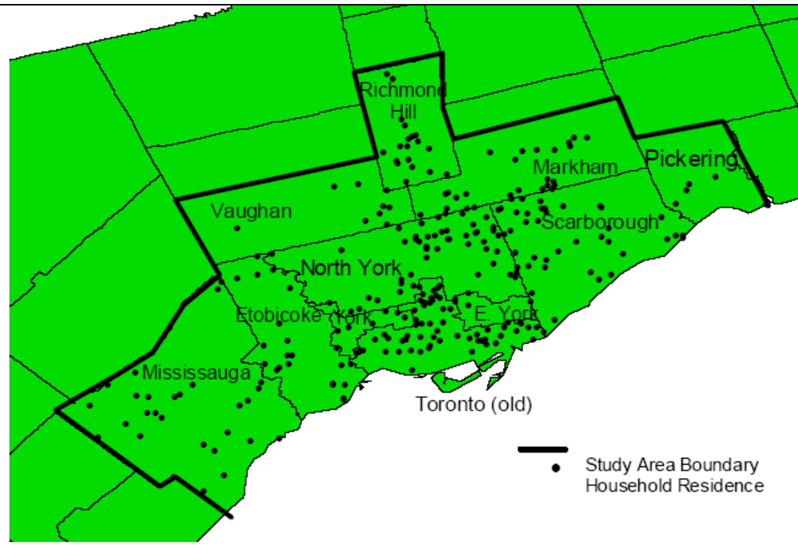

Figure 3.3 – Geographic Distribution of Wave 1 Respondents

(Note: Residence locations are randomly adjusted slightly to preserve respondent anonymity)

Survey Staff

Due to the nature of the Toronto Wave 1 survey, which included 2 face-to-face interviews in the home of the respondent, a field staff of four interviewers was hired to complete the surveys. These interviewers lived in the vicinity of the region for which they were responsible, greatly reducing the travel times (often during the evening peak) to reach the homes of the respondents. While efforts were made to train interviewers as consistently as possible, make use of a detailed interviewer manual (Roorda, 2002) and to maintain open discussion between interviewers and the survey manager throughout the survey period, there is undoubtedly some interviewer bias embedded in the database. This is somewhat mitigated by the "computerized" nature of the CHASE instrument which operates entirely consistently regardless of the interviewing style.

Contacts with the household

Households were contacted at numerous points before, during and after the initial wave of the survey, as recommended by Dillman (1978) and Stopher *et al.* (2004). A letter of introduction was initially sent out to each household, in which the purpose and a description of the survey were given. Shortly thereafter, a telephone recruiting call was made, with reference to the letter of introduction, to attempt to arrange an interview date. A reminder/confirmation phone call was made on the day of the start-up interview. Most households were contacted by the interviewer at least once during the week of the survey in order to identify any problems/difficulties in filling out the survey and to continue to build rapport with the respondent. Respondents were also given the cellular telephone numbers of the interviewer and the survey director to allow for questions to be asked. Thank-you notes were given to the household, including an incentive valued at approximately $20 CAN per household, during the follow up interview.

Initial Response Rates

Respondents were recruited using an introductory mail-out / telephone call in the Toronto Area using an initial sample of 1935 households randomly selected from the telephone directory. Of this initial total, successful contact was made with 1637 Toronto households, and members of 271 households agreed to complete the initial wave of the panel survey, representing an effective response rate of 16.6% (see Table 2). An effort was made to recruit as many household members as possible from these households, resulting in a total of 453 individual respondents, of whom 423 (on average, 1.6 per household) provided usable data[4]. In 75% of households, all adult members completed the Toronto Wave 1 survey.

The initial response rates are low compared with other general-purpose travel surveys, such as the Dutch National Mobility Panel. This is likely due to the large and on-going time commitment required of the respondent, in comparison with the relatively small time commitment associated with the completion of conventional activity-based panel surveys.

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[4] See Doherty et. al (2004) for a detailed discussion of Wave 1 response rates, sample representativeness and data quality.

Table 3.3 - Recruiting Results

Recruiting Result	Number of Households	Response Rate	
		Raw Sample	Contacted Households
Contact made			
Survey completed	271	14.0%	16.6%
Survey started but not completed	19	1.0%	1.2%
Refusal	1,076	55.6%	65.7%
Language barrier	114	5.9%	7.0%
Other	157	8.1%	9.6%
Subtotal	***1,637***	***84.6%***	***100.0%***
No contact made			
6+ calls with no response	179	9.3%	
Number not in service	91	4.7%	
Number not in the study area	17	0.9%	
Fax machine 3 times	11	0.6%	
Subtotal	***298***	***15.4%***	
Total	**1,935**	**100.0%**	

Respondent burden

The response burden for Wave 1 was heavy. An examination of time-stamps stored with every entry in the CHASE survey in Toronto indicated that the average login duration for CHASE was 139 minutes (or about 20 minutes per survey day), with some respondents logging in for up to 380 minutes. This was in addition to a start-up interview of approximately 1 hour and a follow-up interview of about 20 minutes. Impressions from field staff indicated that parts of the survey were tedious to answer, notably, the end of week review involved a highly repetitive line of questioning. A follow-up interview conducted on a sub-sample of 30 Toronto households after the CHASE survey indicated that the majority of households (58%) enjoyed completing the survey, 23% were indifferent, and 19% did not enjoy the survey. 48% of households found that the survey took too long and 74% reported that they had taken some shortcuts in filling out the survey, such as skipping activities and avoiding the entry of activity preplanning. A more complete discussion of the follow up interview is given by Doherty *et al.* (2004).

Incentives

The role of incentives in facilitating recruitment remains unclear. Non-cash incentives valued from $20 CAN per household were provided after the entire survey was complete. Reports from field staff in Toronto indicated that these incentives were very important in encouraging respondents to undertake and complete the survey. However, in a post-survey follow up interview, 94% of a sample of 30 respondents stated that they would have done the survey without an incentive.

Geocoding

In all waves in both regions, significant effort was placed on obtaining location information that was specific enough to attach an x, y coordinate. Home addresses and postal codes were provided with the survey sample, however, this information was verified with the respondent, because in some cases the respondent had moved since the sample was drawn. All activity locations were obtained with a detailed description (e.g. “Yorkdale Shopping Centre”), an address or nearest intersection, and the municipality.

Geocoding of activity, home and work locations was done using GIS databases after the surveys were complete. In Toronto, GeoPinpoint software was used with a DMTI street network file. In Wave 1, a geocoding “hit rate” of 98.2% was achieved for out of home locations, and 100% of home locations were successfully geocoded. This very high rate of geocoding success was attributed to a careful review undertaken by the interviewer and with the respondent when the computer was retrieved from the household. Because interviewers were geographically based, they had a high degree of familiarity with the geographical area in the vicinity of the households they interviewed and so were effective in identifying incorrect addresses. Furthermore, an experienced geocoder used a combination of automated geocoding and manual map-based searches. No callbacks were made to households to clarify location information.

3.4.2 Waves 2 and 3

Attrition

Our concern over the fairly low initial effective response rate prompted us to design the second wave of both the Quebec and Toronto panels to be less burdensome to the respondent. Wave 2 interviews typically lasted less than 45 minutes for the initial respondent (who reported changes to the household socio-demographic information) and less than 35 minutes for additional respondents from the same household. The rate of attrition from Wave 1 to Wave 2 was kept quite low. A total of 84% of households in Toronto that completed Wave 1 also completed the Wave 2 survey. Furthermore, the number of participants per household in Toronto actually increased from 1.6 members per household in Wave 1 to 1.8 members per household in Wave 2, for the 227 households that participated in both surveys.

A number of strategies were used to maintain a high retention rate. In Toronto, since the Wave 2 survey required less interviewing effort (especially, no travel), the entire survey could be most cost-effectively implemented with a single surveyor. The most successful interviewer from Wave 1 (who completed over half of the interviews, and had the highest recruiting success rate) was selected to complete all Wave 2 interviews in Toronto. Much of the success in panel retention can be attributed to the efforts of a dedicated and persistent interviewer.

Second, careful attention was paid to the recruiting method. Well in advance of the package being sent out, a telephone call was made to the household to reacquaint them with the panel and to (re)-recruit. As done in Wave 1, a formal letter on University letterhead was later sent to the household with a summary of results from the Wave 1 survey. Reminder telephone calls were made and additional survey packages were sent where necessary.

Third, we believe based on the reports of field workers that the variety in survey tasks has contributed to respondent motivation in the panel. It is likely that a much lower retention rate would have been achieved had the CHASE survey been implemented again in Wave 2 or 3. As indicated in the follow-up survey of 30 survey respondents, 81% stated that they would participate in another study such as CHASE in the near future, 16% reported not being sure, or did not know, and 1 respondent said they would not do the survey again.

3.5 Preliminary Results of the First Two Waves

There is clear value in using an in-depth panel design for the assessment of activity schedules. First, a comparison of mean activity and travel behaviour over the entire sample can help us to identify instrument bias, when we have evidence to show that macro changes or trends have not occurred between survey waves. Second, individual respondents' changes in travel and activity behaviour can be assessed over time to determine the extent to which behaviour is habitual. Comparisons between the core two-day activity diaries from first two waves are used in this section to demonstrate these two ways of using multi-instrument panel data. Beyond the analysis of executed activity diaries, it is also possible to make use of the data that is unique to each wave. Such analyses of wave 1 data (activity pre-planning) and wave 2 data (responses to hypothetical "stated adaptation" questions) are also given in this section.

3.5.1 "Executed" activity and trip rates

Table 3.4 shows a comparison of average daily activity duration for Wave 1 and Wave 2. The analysis is limited to 189 respondents for whom the core two-day activity diary was completed in both waves for two weekdays. The mean activity duration for the major activity types does not vary significantly between waves. Basic needs (including night sleep), work/school, household obligations, recreation/ entertainment, and travel are five activity types with the greatest average duration and none of these activity types show differences between waves that are statistically significant at the 95% level. However, the mean duration of some of the other minor activity types, including drop-off/pick-up, services, social and other activities do differ significantly between waves. This has led us to re-assess the consistency of our survey procedures in each of the waves. In particular, we felt that there was probably some subjectivity in the classification of activities into activity types that can be rectified. For example, picking-up one or two items from a corner store can be classified as drop-off/pick-up, shopping, or perhaps household obligations. Since different interviewers were involved in different waves, there is potential that some systematic biases were introduced into the coding of data. Perhaps of greater concern is that the mean daily duration of travel also increased significantly between waves by about 10 minutes (10%). This corresponds with an increase in the mean number of daily trips from 3.88 to 4.37 (13%) from Wave 1 to Wave 2, as shown in Table 3.5. Noticing this difference early on in the survey prompted us to convey renewed emphasis to respondents for *precision* and *accuracy* in their reporting of travel times in Wave 2. In addition to instrument bias, it is noted that the differences in activity and travel duration between waves may also be due to real changes in behaviour over time for this particular sub-sample of respondents.

Table 3.4: Average Weekday Activity Duration

Activity Type	Mean duration of weekday activities (hrs)		t-statistic on the difference in means
	Wave 1	Wave 2	
Basic Needs	10.11	9.81	1.60
Work/School	6.05	6.17	-0.32
Household Obligations	1.56	1.71	-0.78
Drop-off / Pick-up	0.17	0.07	3.40
Shopping	0.34	0.40	-0.93
Services	0.20	0.41	-3.65
Recreation/Entertainment	3.18	3.31	-0.56
Social	0.65	0.37	2.72
Other	0.35	0.00	6.05
Travel	1.55	1.71	-1.59
Total	**24**	**24**	

Means based on 189 respondents that participated in both waves and for whom the core survey days were both weekday

Table 3.5 shows similar results for the number of trips by primary mode of transportation. The total number of trips is significantly higher in Wave 2 as compared to Wave 1. This increase is mostly due to a large increase in trips by "other" modes (including walk, cycle and taxi).

Table 3.5: Average Daily Number of Trips by Mode

Mode	Mean number of weekday trips		t-statistic on the difference in means
	Wave 1	Wave 2	
Car (driver or passenger)	2.783	2.974	-0.85
Public Transit	0.534	0.426	1.28
Other	0.561	0.974	-2.96
Total	3.878	4.373	-2.31

Means based on 189 respondents that participated in both waves and for whom the core survey days were both weekday

In general, we are encouraged by these results. At this stage of analysis, it appears that there is no evidence of *major* sources of bias in the survey instruments for Waves 1 and 2 of the panel, as pertain to the variables we have tested. However, the process has enlightened us to potential problems with some of the minor activity types, reported travel duration, and the number of trips by "other" modes of transportation that do show significant differences between waves. Clearly, comparing data from multiple instruments on the same sample allows us to be aware of potential problems with each of the instruments.

3.5.2 Assessment of Habitual Behaviour

By observing the activities people do for multiple days of the week and for consecutive years, it is possible to analyze habitual behaviour and changing behaviour over short and long periods of time. Figure 3.4 illustrates the occurrence of habitual behaviour for an example respondent. In this case, the core two-day diary was completed on Thursday and Friday in both Waves 1 and 2. A number of observations can be made about these schedules. First, there is clear similarity in all of the four daily activity schedules. This individual tends to leave for work at 6:00am (or shortly before), tends to finish work at about 2:30 – 3:00pm, and tends to do errands on the way home. However, there are also notable similarities within waves that are not observed between waves. In both days for Wave 2, there is at least one additional out-of-home activity, in which the respondent drops off and picks up his wife. In Wave 2, a more complex workday is observed with 2 work locations and a coffee break at a different location.

The simplest method for measuring the similarity between activity schedules is to choose statistics that describe the schedules, and to attempt to find correlation among these statistics between waves (holding day of week constant) and between days (within the same wave). Two statistics are used in this analysis: activity duration by activity type and number of trips by mode. The correlations between days within the same wave, and between waves holding day of week constant are shown for these two statistics in Tables 3.6 and 3.7, respectively.

In Table 3.6, it is evident that all correlations are positive in sign. This shows that regardless of the day of week or the year, an individual respondent shows routine, or habit, in the amount of time they devote to different activity types that cannot be observed to the same extent between different individuals. This is an obvious observation that reflects the opportunities, interests and on-going commitments of individuals. However, for all activity types, the correlation is greater between 2 days *within* a wave than it is for the same weekday in two different years. This clearly shows there exist short-term routines or habits that do not extend over a year-long period. The drop-off and pick-up activities for the example respondent in Figure 3.4 would illustrate a short-term routine activity that does not extend over the long-term.

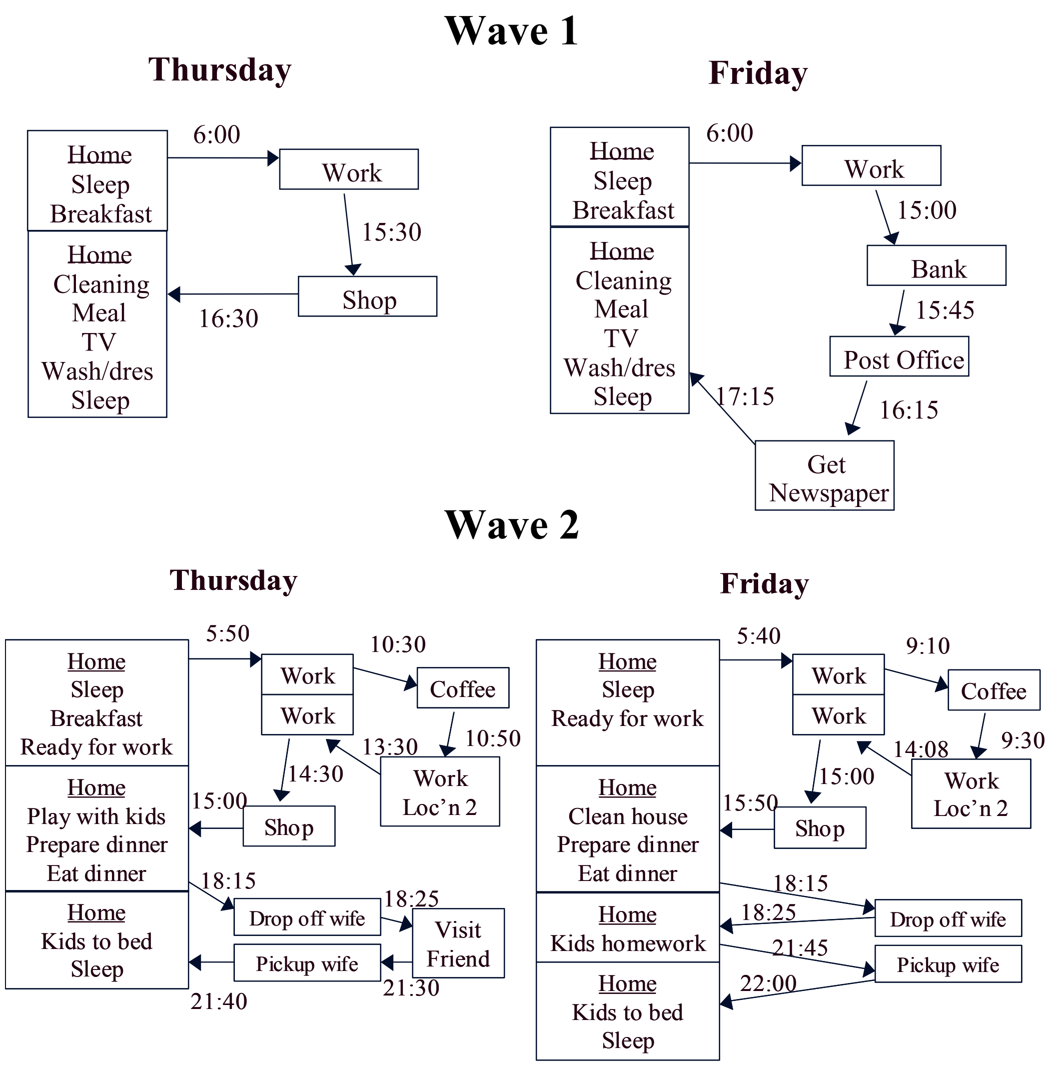


Figure 3.4 - Core Activity Schedules for an Example Respondent

The corresponding correlations for the number of trips by mode are shown in Table 3.7. The same pattern emerges. There exist short-term routines in behaviour, with respect to the number of trips by mode, that are stronger than long-term routines.

Table 3.6 - Correlation of Activity Duration – Within Waves and Between Waves

Activity Type	Correlation Between 2 Days Within Waves		Correlation Between Waves	
	Wave 1	Wave 2	Day 1	Day 2
Basic Needs	0.559	0.493	0.390	0.113
Work/School	0.722	0.742	0.522	0.491
Household Obligations	0.749	0.625	0.382	0.390
Drop-off/Pick-up	0.264	0.256	0.142	0.148
Shopping	0.085	0.200	0.077	0.146
Services	0.252	0.260	0.037	0.078
Recreation/Entertainment	0.589	0.508	0.505	0.328
Social	0.447	0.269	0.118	0.062
Travel	0.618	0.497	0.297	0.158

Correlations based on 189 respondents that participated in both waves and for whom the core survey days were both weekdays

Table 3.7 - Correlation of Number of Trips – Within Waves and Between Waves

Mode	Correlation Between 2 Days Within Waves		Correlation Between Waves	
	Wave 1	Wave 2	Day 1	Day 2
Car (driver or passenger)	0.517	0.617	0.515	0.409
Public Transit	0.567	0.694	0.585	0.530
Other	0.534	0.683	0.246	0.185
Total	0.505	0.492	0.401	0.244

Correlations based on 189 respondents that participated in both waves and for whom the core survey days were both weekdays

3.5.3 Wave 1 activity pre-planning

Further analysis of wave 1 data was done to assess the preplanning of activities. On average, approximately 1/4 of all activities are planned impulsively, about 1/4 are planned the same day or within a week, and about 1/4 are routine activities or were planned more than a week in advance, as shown in Table 3.8. For 22.5% of activities, the respondent did not respond to the question of when the activity was planned. In such cases, the activity is more likely to be routine, or planned a long time ago. Clearly, the activity types most impulsively planned are "other", entertainment, social, household obligations, and shopping. Those most often planned a week or more in advance are night sleep and other basic needs, and work/school.

Table 3.8 – Activity preplanning by activity type

Activity Type	When planned (5 categories, non-merged routine)						Total
	Impulsive	Same day	Days before	Weeks/months/years ago	Routine	Unknown/can't recall/missing	
Night sleep & other basic needs	18.2%	7.5%	11.6%	22.6%	16.8%	23.3%	100.0%
Meals	26.2%	14.6%	9.3%	14.1%	13.0%	22.8%	100.0%
Work/School	10.2%	12.0%	17.6%	23.0%	10.6%	26.5%	100.0%
Household Obligations	29.0%	16.0%	9.7%	11.4%	10.9%	23.0%	100.0%
Drop-off/Pick-up	17.7%	16.4%	16.0%	17.8%	9.6%	22.4%	100.0%
Shopping	28.9%	34.4%	15.3%	3.0%	2.4%	16.0%	100.0%
Services	18.2%	19.2%	23.1%	15.8%	4.8%	18.9%	100.0%
Active recreation	19.5%	15.6%	18.1%	15.9%	7.2%	23.7%	100.0%
Entertainment	36.9%	14.6%	9.0%	9.1%	8.2%	22.1%	100.0%
Social	32.7%	19.2%	17.7%	7.7%	4.4%	18.4%	100.0%
Other	47.6%	24.6%	10.2%	1.1%	2.6%	13.9%	100.0%
Total	24.7%	14.0%	12.3%	15.3%	11.1%	22.5%	100.0%

3.5.4 Wave 2 categorized responses to hypothetical questions

Responses to the questions outlined in Section 3.3.2 were entered into the CATI and later classified into standard responses. Partial responses for the first two open-ended questions for 400 Wave 2 respondents in Toronto are summarized in Table 3.9 and Table 3.10, respectively. In these tables the primary effect of a one-hour delay and of mode unavailability on the respondent's next activity and the mode of transportation are shown. A more comprehensive summary of secondary effects on other activities in the same day, on other days, and on other household members is presented in Appendix D.

From Table 3.9, we can see that in response to a one-hour delay in getting to an activity, most changes (approximately 78%) made to the activity in question involved a change in timing (including a shortening of the activity, a shift of the activity to another part of the day, or to another day). Another 17% decided they would skip the activity outright. Very few respondents (less than 3%) suggested a change in activity location or mode of transportation would solve the scheduling problem, which is not surprising given the wording of the question.

As shown in Appendix D, a wide range of different responses was observed for other activities in the same day. For 44% there was no effect at all. In cases where other activities were affected, about 63% of the time only in-home activities were affected, 32% of the time only out-of-home activities were affected and about 5% of the time, both in- and out-of-home activities were affected. Other days were impacted in less than 20% of cases, usually with the rescheduling of an affected activity. In 70% of cases there was no effect on any other household members; when there was, most often it was other members participating with the respondent on the "joint" activity who were affected.

Table 3.10 summarizes all of the responses to the second hypothetical scenario (Question 2), in which the mode of transportation was not available to get to the activity. An examination of the change to the mode of transportation showed that 61% chose to change their mode of transportation, 21% decided not to travel, and 15% chose to use the same mode, but a different vehicle, a different time or a different activity location. In 50% of cases, the change in mode of transportation was sufficient and the activity was not affected. However, for those activities that were affected, the timing was changed in 50% of the cases, the location was changed in 10%, and the activity was skipped, or someone else was found to do the activity in 40% of cases.

As described in Appendix D, other activities in the day were affected by mode unavailability 44% of the time, and the effects varied widely among activity timing changes, mode changes, and activity cancellations. Approximately half of these effects were timing changes to in-home activities. Finally, in response to mode unavailability, 15% of cases involved a change to the schedule for another day. Only about 37% involved an effect to another household member, and these effects were most often other members that were doing the same activity with the respondent, or who were asked to give the respondent a ride.

Table 3.9 - Hypothetical Scenario 1: A one-hour delay getting to an activity
a) Effect of a one-hour delay on the respondent's next activity

Description	Number of observations	Percent
Modify activity timing within the same day	**263**	**65.8%**
Shorten duration of activity	101	25.3%
Shift activity to another part of the day	142	35.5%
Shift and shorten duration	17	4.3%
Shift and lengthen duration	1	0.3%
Split the activity	2	0.5%
Move activity to another day	**47**	**11.8%**
Skip or replace activity	**67**	**16.8%**
Change mode of transportation	**3**	**0.8%**
Change activity location	**7**	**1.8%**
No effect or unknown	**13**	**3.3%**
Total	**400**	**100.0%**

Table 3.10: Hypothetical Scenario 2: Unavailability of mode to get to the activity
a) Effect of mode unavailability on the mode of transportation to the next activity

Description	Number of Observations	Percent
Use a different mode - transit	74	18.5%
Use a different mode - auto drive	12	3.0%
Use a different mode - passenger	78	19.5%
Use a different mode - walk	33	8.3%
Use a different mode – taxi	34	8.5%
Use a different mode – other	11	2.8%
Same mode - use a different vehicle	42	10.5%
Same mode - go to a different location	3	0.8%
Same mode - wait until mode is available	16	4.0%
Would not travel	85	21.3%
No or unknown effect	12	3.0%
Total	**400**	**100.0%**

b) Effect of mode unavailability on the respondent's next activity

Description	Number of Observations	Percent
Modify activity timing within the same day	**57**	**14.3%**
Shorten duration of activity	30	7.5%
Shift activity to another part of the day	22	5.5%
Shift and shorten duration	3	0.8%
Shift and lengthen duration	1	0.3%
Split the activity	1	0.3%
Move activity to another day	**42**	**10.5%**
Skip or replace activity	**79**	**19.8%**
Change activity location	**20**	**5.0%**
No effect or unknown	**202**	**50.5%**
Total	**400**	**100.0%**

3.5.5 Changes in household attributes between wave 1 and wave 2

Part of the benefit of a panel survey is the ability to correlate changes in activity/travel behaviour to changes in lifecycle stage, vehicle ownership, residential location, and other socioeconomic variables. Yet such analyses are possible only if enough observations are made of such changes in these variables. Of the 227 Toronto households that completed the first two waves, 28 (12%) changed their residential location. 96 (42%) households made at least one vehicle transaction, including 49 who obtained one or more vehicles, 7 households that disposed of one or more vehicles, and 40 who made a combination of purchase and disposals. 65 Toronto households (29%) experienced a change in household structure[5], including 37 households in which an adult joined, 6 in which senior(s) joined, 12 households in which an adult left, 3 new babies, and 6 households in which children grew to be teenagers. Finally, 32 people (out of 406 that were observed in both waves), experienced a change in employment status, 60 changed their primary job, 13 changed their secondary job and 29 changed school status or started taking new educational courses.

3.6 Additional Research on Panel Survey Data

Aside from the brief analysis provided in this chapter, and the more in-depth analysis in Chapter 4, panel survey data have been utilized to analyze several elements of the activity scheduling process. In particular, the CHASE data from Toronto have been most extensively used to date. Doherty *et al.* (2004) and Doherty (2004) have developed new quality indicators for activity scheduling data. Activity flexibility and activity repertoires have been studied by Doherty (2003). Planning horizons of activities have been measured and analysed by Doherty (2005), and planning horizons have been modelled using neural networks (Doherty and Mohammadian, 2003), hazard models and mixed logit models (Mohammadian and Doherty, 2005). Joh *et al*. (2005) have modelled the frequency and type of scheduling modifications. Finally, Buliung and Roorda (2005) have developed measures of spatial stability of activity patterns and assessed their relationship to temporal elements of the activity scheduling process.

[5] These households do not include all changes to household membership, but only those that changed the household structure, for example, from a 2 adult household with no children to a two adult household with children.

3.7 Discussion

A number of benefits and challenges of using a variety of in-depth survey instruments in a panel framework have come to light in this investigation. Benefits are that:

- A large variety and quantity of questions can be asked of the respondents without imposing too great a burden at one point in time. In addition to the core 2-day activity diary collected in all waves, we are able to obtain for each respondent a very detailed record of the planning process for a week long activity/travel plan, a stated adaptation survey of reactions to perturbations made to the two-day schedule, and a record of routine activities. These in-depth surveys are supporting new understanding of that activity scheduling process. However, it is only reasonable to collect this volume of data by "spreading the burden" over the three waves of the panel.
- By comparing the schedules of individual respondents for multiple days of the week and over multiple years, we can observe habits and differences in behaviour, both over the short-term and the long-term.
- Different instruments are applied to the same persons with the intention of obtaining a common *core* two-day activity schedule for each year. This provides us with an opportunity to evaluate our instruments empirically, while controlling for the unobservable attributes of the respondent.
- The use of multiple instruments helps to keep respondents interested and engaged in the panel. We expect that this has contributed to the relatively low rates of panel attrition thus far.

We also see a number of challenges that arise due to the chosen design:

- It is impossible to differentiate between instrument bias and real trends in travel and activity behaviour. Therefore, if we do not have evidence from a separate data source of what the trends in behaviour are, it becomes difficult to evaluate our survey instruments properly.
- For the same reason, a multi-instrument panel survey is not ideal for evaluation of overall trends in the behaviour of the population.

- The cost savings for design, pretesting, interviewer training, software and equipment that are associated with a single instrument panel are not fully realized in a multi- instrument panel.

Overall we have found that the in-depth panel survey approach is appropriate and useful, given the objectives and motivations for the data collection effort in Toronto. It is providing a rich data source to support the development of better behavioural rule-bases for activity-based models. The next chapter builds on the preliminary analysis provided in this chapter with a more detailed analysis of activity scheduling conflicts, that is specifically intended to inform the TASHA activity scheduling model discussed in the subsequent chapter.

4. Strategies for Resolving Activity Scheduling Conflicts: An Empirical Analysis

4.1 Introduction

Modelling the process of activity scheduling has been difficult to do because there have been relatively few reliable data sources through which the day-to-day scheduling decision making process has been observed. Conflict resolution, the process of deciding what to do when multiple activity opportunities are available at the same time, requires information about the activity schedule before and after the conflicting opportunities arose. With data from the Travel Activity Panel Survey, we now have an opportunity to better understand conflict resolution outcomes, and use that understanding to inform models of this process.

This chapter reports on an attempt to use data from the first wave of the Travel Activity Panel Survey in Toronto to assess rules for activity rescheduling in response to scheduling conflicts. The CHASE survey instrument employed in the first wave (see Doherty *et al.,* 2004) resulted in revealed activity rescheduling scenarios.

Two types of rules are considered in the analysis. First, the concept of activity precedence is defined and analyzed; does activity precedence play an important role in resolving conflicts, is activity type a valid measure for activity precedence, and if so, what kinds of activities are more likely to be modified or deleted when a scheduling conflict occurs? Second, strategies for rescheduling of the activities are assessed. Given that a conflict has occurred, is the activity moved to another time in the same day, is it moved to another day, or is the activity skipped altogether? The intention of this analysis is to provide an empirical basis for enhancing the system of rules used in the prototype TASHA model of activity and travel scheduling.

4.2 Concepts of Activity Priority, Precedence and Conflict Resolution for TASHA

As will be shown in detail in Chapter 5, TASHA models the process of schedule building by:

1. Generating activities with attributes based on empirical distributions,
2. Inserting those activities into project agendas, and
3. Constructing person schedules by moving activities from project agendas to be inserted into person schedules

The process of insertion in steps 2 and 3, above, can result in scheduling conflicts when two activities are generated at overlapping times. Conflicts arise when a “competing” activity, which is a new activity being inserted into the schedule, overlaps in time with an “original” activity, which already exists in the schedule. Three different classes of conflict arise, as shown in Figure 4.1:

Class 1 – A competing activity being added to the schedule is added within an original activity
Class 2 – A competing activity being added to the schedule partially overlaps one or two original activities
Class 3 – A competing activity completely overlaps one or more shorter original activities

The concepts of “activity priority” and “activity precedence” play a large role in the current implementation of TASHA. Activities are moved from project agendas to form person schedules in order of priority/precedence, by broad activity type. The order in which activities are added to the schedule clearly has an influence on the predicted activity schedule; the process is path-dependent.

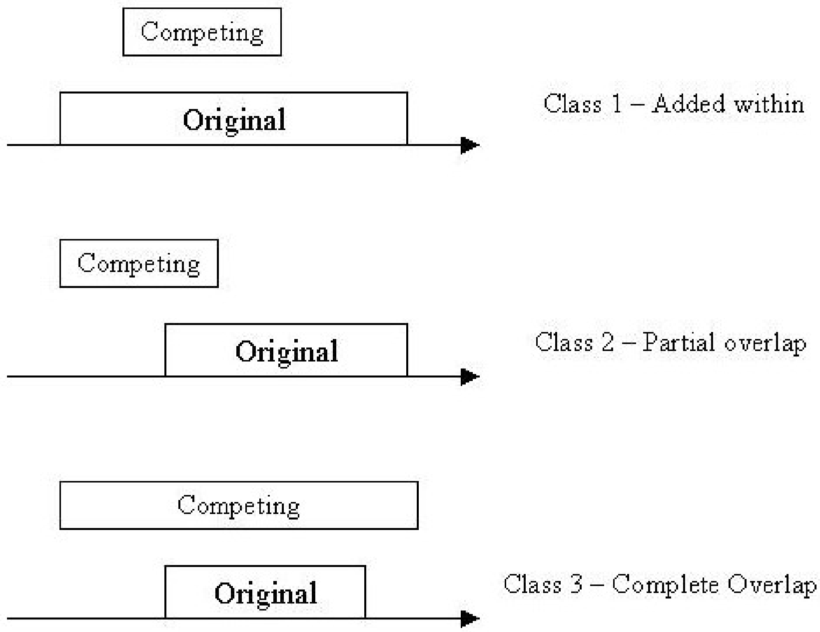


Figure 4.1 – Classes of activity conflict

Given our current goal of testing the assumptions made in TASHA, it is important to clarify our conceptualizations of priority and precedence. Priority is a term that holds connotations of importance, of "utility" (the satisfaction or benefit one obtains by participating in an activity) and of the degree of commitment to other parties. Precedence, on the other hand, is the degree to which an activity is planned at an earlier point in time than other activities. An activity's precedence may be related to its place in a "normal routine" (activities that are usually done at around the same time and place without thinking too much about their planning), and its "fixity" (the extent to which the attributes of the activity may not be changed, once they are planned), in addition to any influence of the activity's utility/importance.

Examples of activities with high and low levels of priority and precedence are shown in Table 4.1.

Table 4.1 – A typology of priority and preference

	High Precedence	Low Precedence
High Priority	Preplanned, high utility activities, especially with commitment to others (e.g. doctors appointment)	Spontaneously planned, high utility activities, especially with commitment to others (e.g. pick up sick child from school)
Low Priority	Routine or preplanned activities with less utility, and less commitment to others (e.g. watch favourite TV show)	Spontaneously planned activities with less utility and less commitment to others (e.g. shopping at cornerstore for a magazine)

It is noted that the fixity of an activity in time and space (i.e. the extent to which an activity is non-flexible) is **not** considered here to be an element of priority. In fact, high priority activities may be very flexible. Work might be have a high priority (important, involving commitment), yet one may indeed have the option to work at times and locations of one's choosing. A highly non-flexible activity might register very low in terms of priority if the activity is considered unimportant (for example, a one-time showing of a boring movie at 7:00pm at the theatre). Clearly flexibility can be related to commitments and contracts one has with another party regarding a particular activity, but it is not fixity *per se* that determines the priority of the activity.

Similarly, the flexibility of an activity can be distinguished from its precedence, although the two may be related. One might have, as part of one's regular routine, a stop at the coffee shop on the way home from work. Yet, this may be an entirely flexible activity; one could just as easily go for coffee at a different time or location, with little consequence.

When activities conflict, elements of priority, precedence and flexibility all play a part in determining the scheduling outcome. Intuitively, activities that have lower priority and higher flexibility are more likely to be adjusted than fixed, high priority activities. Furthermore, those activities that have higher precedence are more likely to be modified simply because they are already part of a schedule into which more spontaneous activities must fit. *Ceteris paribus,* activities with high precedence are more likely to be planned in advance, they are more likely to be the “original” activity in a scheduling conflict, and they are more likely to be modified or skipped, particularly if they are flexible or low priority activities.

Priority of an activity is a latent variable. It is very difficult, if not impossible, to measure and no empirical analysis of activity priority can be provided in this analysis. Precedence is measurable using CHASE: we observe the time when each activity was entered into the schedule. However measures of precedence are not available in traditional activity- or trip-based surveys, on which models such as TASHA are based. Therefore, we need to assess whether another activity attribute, such as broad activity type is a sufficient measure of precedence to explain the outcomes of scheduling conflicts (and thus is appropriate as a clear rule for scheduling), or whether a more complex treatment is required.

TASHA, or any rule-based model which attempts to predict scheduling/rescheduling behaviour, must also represent the process of conflict resolution. Once it is decided which of two conflicting activities is displaced, a course of action must be chosen. Should the activity be moved to another time in the same day, should it be moved to another day, should the duration be shortened, should the activity be split, or should it be skipped altogether? The rules for activity rescheduling in the prototype implementation of TASHA are numerous and depend on the conflict class and the availability of nearby “gaps” in the schedule. In cases of conflict, the lower priority activity is shifted to an adjacent gap in the schedule, if one exists. If a gap does not exist, then one is created by shifting the adjacent activity provided there is sufficient “room” in the schedule to take place without significantly reducing activity durations. Once an activity is successfully added to a schedule in TASHA, it is never subsequently deleted or moved to another day.

4.3 Analysis of Rescheduling Rules

4.3.1 Summary of Activity Scheduling

The first wave of the Travel Activity Panel Survey in Toronto was designed to assess the mechanics of schedule building with particular focus on how scheduling conflicts are resolved as they arise.

The CHASE data can be summarized as follows:

Number of responding households:	264*	
Number of responding persons:	423*	
Total activity operations in 7-day schedule:	40756	(13.8 operations/person-day)
Total number of activity additions	35644	(87.5%)
Total number of activity deletions	753	(1.8%)
Total number of activity modifications	4359	(10.7%)
Total number of executed activities	34880	(11.8 activities/person-day)

* 6 households and 30 persons were eliminated from this analysis due to poor data quality

Of the deleted activities, 465 (62%) could be linked with an activity of the same type at the same location that was "added" to the schedule. If the addition was entered into the computer within one hour of "deletion" operation, the two activities are considered to be linked (and is treated as a modification).

One of the drawbacks of the CHASE data is that only a subset of possible activity conflicts and the resulting modifications and deletions are observed. Consider the following example. A friend calls to go for dinner with a CHASE respondent on Friday evening, but she had already planned to go to a movie with her brother at that time. Several solutions to this scheduling conflict exist, only some of which would be observed in the CHASE database. If the respondent decided not to go for dinner with the friend, then the activity would not have been entered into the CHASE database. If she decided to have dinner earlier than suggested, then the activity would have been entered into the CHASE database at a different time (likely into a gap in her schedule), but would not have been captured as a conflict. The conflict would only have been captured in CHASE if the movie was rescheduled or skipped completely because of the conflict and the dinner plan was entered into the schedule. Indeed, it would be very difficult to try to model all potential activity conflicts, since one is arguably screening a constant stream of possible opportunities subconsciously.

It is also important to note that not all activity modifications are made as the result of a conflict with another higher priority activity. Activities can be modified because of traffic delays, changes to plans made by other people, or simple adjustments in the attributes of the activity (e.g. "I had nothing else planned so I spent an extra hour studying econometrics at the library"). Yet, the concern for this research is on how scheduling conflicts are handled.

The identification of activity conflicts in the CHASE database is not straightforward, and requires some assumptions about what constitutes a conflict. For the purposes of this analysis, the following criteria are used to define a conflict:

- The competing activity overlaps in time with the original activity in a manner described by one of the conflict classes shown in Figure 4.1,
- The competing activity is entered by the respondent at a point in time after the initial entry of the original activity,
- A valid adjustment was made to the original activity such that the conflict was resolved. Valid adjustments included: moving the activity to another day, shifting the activity to another part of the day such that there was no overlap with the competing activity, or deleting the activity outright.
- The adjustment to the original activity is entered by the respondent not more than one hour before the entry of the competing activity.

The total number of conflicts discovered in the CHASE database is as follows:

Class 1 – (added within)	1023
Class 2 – (partial overlap)	445
Class 3 – (complete overlap)	449
Total	1917

Of these 1917 conflicts, there were cases where a competing activity conflicted with more than one original activity and cases where more than one competing activity conflicted with one original activity. The total number of activities represented in our database of conflicts is shown below:

Total number of competing activities	1678
Total number of original activities	1279
Total number of conflicts	1917

Table 4.2 shows the proportion of "original" activities that are displaced by another activity with which it is in conflict. From Table 4.2 it is possible to see that work/school, drop-off/pickup and recreation/entertainment are the activities that are most likely to be displaced. Overall, 3.6% of activities were displaced by another activity (recognizing that this is an underestimate of all possible conflicts, as described on the previous page). These activity modifications or deletions represent about 1/3 of all activities that are modified at least once, which indicates that many modifications are made due to changing opportunities or constraints that do not relate to other conflicting activities.

Table 4.2 – Original activities ordered by probability of modification / deletion

Activity Group	Total Activity Additions		Total number of conflicts		Total number of original activities		Prob. of displacement
Work/School	3390	9.5%	423	22.1%	225	17.6%	6.6%
Drop-off/Pick-up	1726	4.8%	91	4.7%	73	5.7%	4.2%
Recreation/Entertainment	7079	19.9%	402	21.0%	277	21.7%	3.9%
Household Obligations	4985	14.0%	227	11.8%	168	13.1%	3.4%
Social	1818	5.1%	115	6.0%	58	4.5%	3.2%
Services	805	2.3%	39	2.0%	25	2.0%	3.1%
Basic Needs	13906	39.0%	555	29.0%	405	31.7%	2.9%
Shopping	1240	3.5%	48	2.5%	35	2.7%	2.8%
Other	695	1.9%	17	0.9%	13	1.0%	1.9%
Total	35644	100.0%	1917	100.0%	1279	100.0%	3.6%

4.3.2 Assessment of Activity Precedence

One way of assessing the precedence of an activity is to compare the number of conflicts in which activities of the same type are the competing activity (i.e. doing the displacing) to the number where they are the original activity (i.e. being displaced). Table 4.3 shows the number of scheduling conflicts that occur between competing and original activities, grouped by broad activity type. If activities are ordered from highest to lowest precedence in this matrix, then the entries above the main diagonal are conflicts where the lower precedence activity (which are entered later) displaces a higher precedence activity (which is entered earlier). Those elements below the main diagonal are conflicts where a higher precedence activity displaces one with lower precedence.

If activity type was a perfect descriptor of precedence, then the activities types could be arranged such that the lower half of the matrix would be zeros. In this case, a simple rule could be developed for the order that activities are added into the schedule. In Table 4.3, activities are ordered optimally, to maximize the sum of the elements above the diagonal. Yet, 531 (28%) of conflicting activities remain below the main diagonal, indicating that there is significant room for improvement in assessing precedence. We also recognize that for the 428 (22%) of conflicting activities on the diagonal, with two activities of the same type in conflict, we would need additional rules, using attributes other than activity type to specify which activity has higher precedence.

Table 4.3 – Optimal precedence ranking for conflicting activities

Precedence Ranking	Activity Group - Original Activity	Activity Group - Competing Activity									
		Work/ School	Basic Needs	Recreation/ Entertainment	Drop-off/ Pick-up	Social	Household Obligations	Services	Other	Shopping	Total
1	Work/School	49	113	92	57	22	33	23	6	28	423
2	Basic Needs	43	215	115	13	48	68	24	20	9	555
3	Recreation/Entertainment	39	108	82	25	33	46	22	23	24	402
4	Drop-off/Pick-up	24	18	8	4	5	17	3	4	8	91
5	Social	9	30	24	2	18	22	2	4	4	115
6	Household Obligations	32	43	38	13	18	48	13	6	16	227
7	Services	4	5	3	2	2	8	6	1	8	39
8	Other	1	6	6		1	1	0	1	1	17
9	Shopping	6	7	14	1	3	8	3	1	5	48
	Total	207	545	382	117	150	251	96	66	103	1917

Shading indicates for each pair of activity groups, the "competing"/"original" ordering that is observed more frequently

Total number of entries where the lower precedence activity displaces the higher precedence activity	958	50.0%
Total number on the diagonal (same activity group)	428	22.3%
Total number of entries where the higher precedence activity displaces the lower precedence activity	531	27.7%

In an attempt to improve this result, the matrix was cross-classified with sex, and subsequently with income. For each classification, optimal precedence rankings were developed and the number of "violations" was assessed, as shown in Table 4.4. Two observations can be made about this table. First, the precedence rankings change slightly for different groups of people, but major differences are not evident. Work/school does appear as the highest precedence activity for all groups of people regardless of income or gender. On the other hand, more "discretionary" activities such as shopping, services and other activities are consistently found to have low precedence. As the number of observations decreases within a particular group of persons the data within the matrix become more sparse, leading to less confidence in the resulting ranking. Some of the results that look somewhat anomalous for low-income groups (note the positions of household obligations and other activities) are partially explained by the low number of total conflict observations for low-income households (36 and 17 for these two activity types, respectively). Overall, evidence in Table 4.4 shows that, in terms of activity precedence rankings, the differences between people of different genders and incomes are minor and that the use of a single rule base for different people may be an appropriate simplification.

Second, with a single rule base for activity precedence, we observe violations at a rate of 27.7%. Yet, by disaggregating by sex or income, we can only obtain marginal improvements in this violation rate (to 27.4% and 25.7%, respectively). While the optimal rule base does explain the majority of choices, it is clear that precedence lists based only on broad activity type are not sufficient to fully predict the order in which activities are added to the schedule. To fully explain the outcome of scheduling conflicts, a more sophisticated measure for activity precedence is required.

Table 4.4 - Optimal precedence rankings by age and household income

	All Conflicts	Males	Females	Low Income (<=$35K CAN)	Medium Income ($35-60K CAN)	High Income (>60K CAN)
Optimal Precedence Rankings (Rule: If activities higher in the list conflict with activities lower in the list, those lower in the list are modified or deleted)	Work/School	Work/School	Work/School	Work/School	Work/School	Work/School
	Basic Needs	Basic Needs	Recreation/ Entertainment	Recreation/ Entertainment	Recreation/ Entertainment	Basic Needs
	Recreation/ Entertainment	Recreation/ Entertainment	Drop-off/ Pick-up	Other	Drop-off/ Pick-up	Recreation/ Entertainment
	Drop-off/ Pick-up	Household Obligations	Basic Needs	Basic Needs	Basic Needs	Drop-off/ Pick-up
	Social	Drop-off/ Pick-up	Social	Drop-off/ Pick-up	Household Obligations	Social
	Household Obligations	Social	Household Obligations	Shopping	Social	Household Obligations
	Services	Shopping	Services	Social	Services	Other
	Other	Other	Shopping	Services	Shopping	Shopping
	Shopping	Services	Other	Household Obligations	Other	Services
Total Conflicts	1917	644	1228	327	573	950
Total Rule Violations	531	148	365	77	145	254
% Rule Violations	27.7%	23.0%	29.7%	23.5%	25.3%	26.7%
Overall % Rule Violations	**27.7%**	**27.4%**			**25.7%**	

Two methods are suggested for further research based on these results.

a) An improved measure of activity precedence could be developed that is a function of activity type and other key attributes that are elements of precedence. These elements could include the level of commitment to other people, the degree of pre-planning associated with this activity, the difficulty associated with rescheduling the activity, and so on. Such an improved measure could be used to develop better rules for predicting the outcome of scheduling conflicts.

b) There are some attributes of activities that have an influence on the activity's precedence that cannot be observed. Currently, with a simple specification of precedence based only on broad activity type, we are able to explain precedence with a rule violation rate of 27.7% (although we recognize that when two activities of the same type are in conflict, our rule base does not make any prediction about precedence). While the violation rate could be improved with a better specification of precedence, uncertainty will always exist. This uncertainty could be incorporated into the measure of precedence by means of an error term, such that the rule base for activity scheduling/rescheduling becomes more stochastic in nature.

4.3.3 Strategies Employed to Resolve Scheduling Conflicts

In the CHASE database, conflict resolution strategies could be determined by observing the modification or deletion of the original activity that was displaced by the competing activity. A summary of the strategies used to resolve each of the conflicts is shown in Table 4.5. It is noted that in some cases, some judgement was required to properly classify the conflict. The first source of ambiguity existed when a respondent deleted an activity, and some time later added another activity of the same type at the same location. If the respondent made the addition within one hour of the deletion, the two operations were considered a single modification; otherwise, the deletion and addition were assumed unrelated. Similarly, an activity was assumed to be "split" into two activities if the original activity was shortened, and a new activity of the same type was added at the same location such that the result resembled a split activity.

Most conflicts are resolved by shifting activities within the same day (68%). 12% are resolved by moving the activity to another day and the remaining 20% are resolved by deleting the activity altogether. Skipped activities do not imply that the activity never gets done. In fact, such an activity could possibly be done by the same person in a different week (which we do not observe in a one week survey), by another household or non-household member, or could be replaced by another type of activity that meets the same goal. A skipped activity, here, is defined as an activity that is not immediately replaced by another activity of the same type at the same location by the same person within the same week.

Table 4.5 – Strategies used to resolve conflicts

Description of Strategy	Total Number of Conflicts		Total Number of Original Activities	
Modify activity within the same day	**1297**	**67.7%**	**888**	**69.4%**
Shorten duration of activity	493	25.7%	330	25.8%
Shift activity to another part of the day	90	4.7%	75	5.9%
Shift and shorten duration of activity	204	10.6%	118	9.2%
Shift and lengthen duration of activity	110	5.7%	85	6.6%
Split the activity	400	20.9%	280	21.9%
Move activity to another day	**233**	**12.2%**	**157**	**12.3%**
Skip activity	**387**	**20.2%**	**234**	**18.3%**
Other	**0**	**0.0%**	**0**	**0.0%**
Total	**1917**	**100%**	**1279**	**100%**

The resolution of a conflict is related to the conflict class, as shown in Table 4.6. If a complete overlap (i.e. class 3) occurs, then the activity is moved to another day or skipped outright over 60% of the time. However, if the "competing activity" falls within the original activity, then the activity is shortened or moved within the same day over 80% of the time.

Table 4.6 – Conflict resolution strategies by conflict class

Description of Strategy	Wave 1 (Revealed Response)							
	Class 1 - (added within)		Class 2 - (partial overlap)		Class 3 - (complete overlap)		Total	
Modify activity within the same day	**831**	**81.2%**	**292**	**65.6%**	**174**	**38.8%**	**1297**	**67.7%**
Shorten duration of activity	337	32.9%	156	35.1%	0	0.0%	493	25.7%
Shift activity to another part of the day	8	0.8%	24	5.4%	58	12.9%	90	4.7%
Shift and shorten duration of activity	95	9.3%	57	12.8%	52	11.6%	204	10.6%
Shift and lengthen duration of activity	23	2.2%	26	5.8%	61	13.6%	110	5.7%
Split the activity	368	36.0%	29	6.5%	3	0.7%	400	20.9%
Move activity to another day	**63**	**6.2%**	**58**	**13.0%**	**112**	**24.9%**	**233**	**12.2%**
Skip activity	**129**	**12.6%**	**95**	**21.3%**	**163**	**36.3%**	**387**	**20.2%**
Other	**0**	**0.0%**	**0**	**0.0%**	**0**	**0.0%**	**0**	**0.0%**
Total	**1023**	**100%**	**445**	**100%**	**449**	**100%**	**1917**	**100%**

Some differences are also noticeable between resolution strategies for different activity types, as shown in Table 4.7. Activities that are most likely to be skipped include drop-off/pickup activities, shopping, social and other activities. These activities are largely discretionary activities, with the exception, perhaps, of the drop-off and pick up of children. Drop-off/pick-up of children are generally very inflexible activities in time and location and are a very high priority. As such they are not susceptible to being rescheduled. Therefore these tasks are almost certainly transferred to another person or otherwise accommodated, but are not reschedulable within the "conflicted" person's schedule. With the exception of social activities, these discretionary activities are also highly likely to be moved to another day and somewhat less likely to be shifted around in the same day. Those activities that were more likely to have timing and/or duration changed within the same day included work/school, services and basic needs. Work/school and basic needs are more preplanned in nature and tend to form the basic, routine skeleton for the schedule. Thus, fine-tuning, as more spontaneous activities are added to the schedule, would reasonably cause these changes.

Table 4.7 – Conflict resolution strategies by activity type

Activity Group - Original Activity	Move activity within the same day		Move activity to another day		Skip Activity		Total
Basic Needs	423	76.1%	68	12.2%	65	11.7%	556
Drop-off/Pick-up	25	31.6%	19	24.1%	35	44.3%	79
Household Obligations	147	63.6%	37	16.0%	47	20.3%	231
Other	19	48.7%	8	20.5%	12	30.8%	39
Recreation/Entertainment	258	64.7%	61	15.3%	80	20.1%	399
Services	19	70.4%	1	3.7%	7	25.9%	27
Shopping	27	55.1%	10	20.4%	12	24.5%	49
Social	83	67.5%	8	6.5%	32	26.0%	123
Work/School	296	71.5%	21	5.1%	97	23.4%	414
Total	1297	67.7%	233	12.2%	387	20.2%	1917

Clearly, duration of the activity must play a role in how activities are rescheduled. First, the duration of an activity affects the kinds of conflicts that occur with the activity. Figure 4.2 shows how short duration "original" activities are far more likely to be involved in conflicts with other activities that overlap them completely (i.e. Class 3 conflicts). As duration increases, the incidence of partial overlaps increases (i.e. Class 2 conflicts), and for "original" activities that are longer than 2 hours in duration, the majority of conflicts are with competing activities that fall entirely within the original activity (i.e. Class 1 conflicts).

The conflict resolution strategy is also related to the duration of the activity, as shown in Figure 4.3. As duration increases, opportunities to shorten the duration of or split the activity increase notably. Opportunities to shift the activity within the same day tend to decrease with increasing activity duration, especially when the activity's duration is not simultaneously shortened.

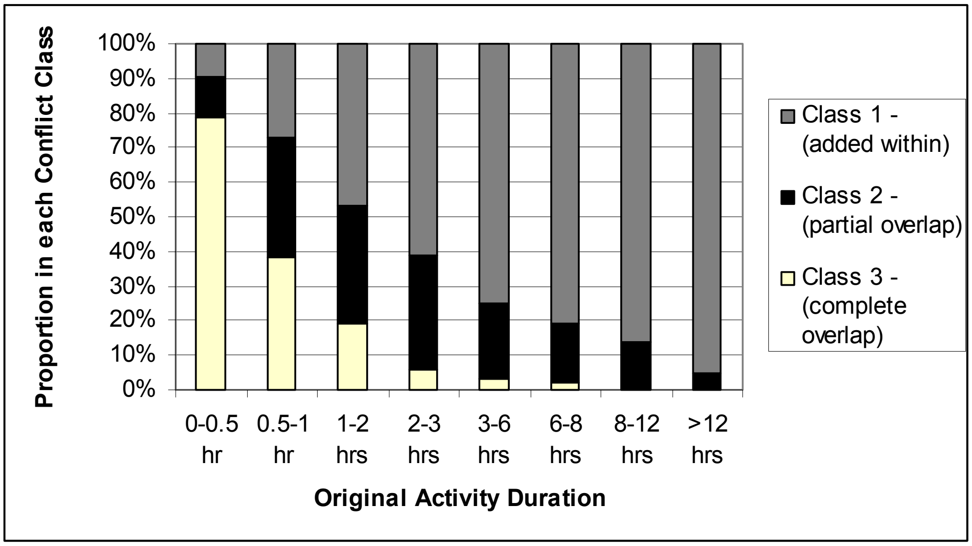


Figure 4.2 – The proportion of conflict classes by original activity duration

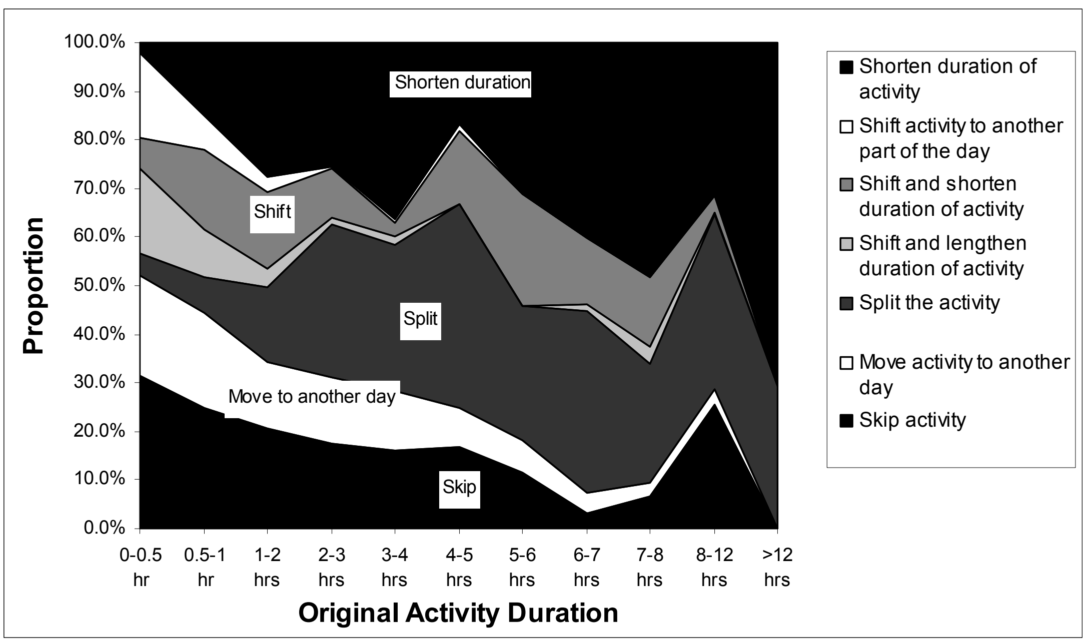


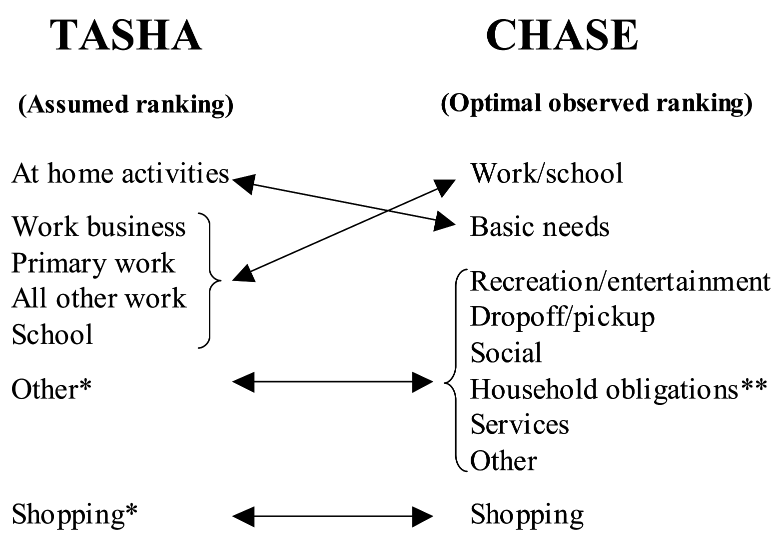
Figure 4.3 – Conflict resolution strategies by original activity duration

The way that a conflict is resolved appears to be related, at least, to the kind of conflict, and characteristics of the activity, including its duration and the activity type. Yet each of these attributes are related to each other, which makes it difficult to sort out the true causal factors behind the choice of a conflict resolution strategy without a multivariate analysis. Furthermore, there are clearly other influences on the kinds of strategies chosen including the characteristics of the schedule (where are there “gaps” in the schedule that might accommodate a shifted activity?), and characteristics of the person (are certain persons more prone to fill their schedule, while others are more likely to reject opportunities that arise?). These influences are potential subjects for further research.

While analysis continues to sort out potential influences on rescheduling behaviour, it is certain is that no single attribute of the activity, the conflict, the schedule or the person can, by itself, explain the resolution strategy chosen.

4.4 Implications for the TASHA Scheduling Process Model

The prototype version of the Travel and Activity Scheduler for Household Agents (TASHA) requires a set of rules for activity rescheduling in response to scheduling conflicts (see Chapter 5 for details). Some observations can be made to inform these assumptions, in light of the empirical analysis provided in this paper. First, optimal precedence rankings found in the CHASE data can be used to specify the order in which activities are added to the schedule in CHASE. A comparison is shown in Figure 4.4. First, it is to be noted that the activity classifications used in TASHA are limited by what is available in the travel survey data upon which it is based, therefore, the activity classifications are not as precise as those found in CHASE, in particular for the “other” category. Second, the precedence rankings in TASHA can be made to correspond reasonably well to those found in the CHASE survey data. One exception is that of basic needs activities, which are most often done at home. In CHASE it is found that basic needs activities have lower precedence than work/school. However, the data on which TASHA is based do not include an articulation of at-home activities, therefore, we are forced to assume that at-home activities are the default. This is similar, but not equivalent, to giving at-home activities the highest precedence.



* In TASHA, a further differentiation is assumed between individual and joint shopping and other activities, with joint activities being assigned a higher precedence

** In CHASE, some household obligations done at home better correspond to "At home activities" in TASHA

Figure 4.4 – Precedence rankings assumed in TASHA vs. those observed in CHASE

Of the many scheduling strategies found in CHASE, the TASHA model is designed to simulate some of the most common. Conflicts in TASHA are resolved by a) shortening the duration of the activity, b) shifting the activity to another part of the day, c) shifting and shortening the activity or d) splitting the activity. Once they have been added to the schedule, TASHA *does not* allow activities to be shifted and lengthened, skipped, moved to another day, moved to another week, or shifted to another person's schedule. The latter three resolution strategies would require representing schedules with a time period greater than one day, and would require an understanding of "household level tasks". The conventional trip diary data upon which TASHA is based are not sufficiently detailed to support such representation.

4.5 Conclusions

Several conclusions can be made through the analysis of CHASE data from the first wave of the Toronto Area Panel Survey:

- It is feasible to observe conflict resolution strategies using revealed response data from the CHASE survey instrument.
- About one third of all activity modifications are made because of an activity conflict. Once an activity is entered into the schedule there is, overall, at least a 3.6% chance that it is subsequently modified or deleted because of a conflicting activity.
- Precedence, the degree to which an activity is routine or pre-planned, can be simply approximated using broad activity groups, yielding the following "optimal" precedence ranking: work/school, basic needs, recreation/ entertainment, drop-off/pickup, social, household obligations, services, other, shopping. This ranking is violated 27.7% of the time in the CHASE data.
- The precedence ranking is difficult to improve significantly by cross-classifying the data by sex or income, and the rankings themselves do not change very much across groups. Therefore, a single activity precedence ranking for all individuals may be an appropriate simplification.
- Assessment of the strategies used to resolve the conflict (once the displaced activity is chosen) shows that most conflicts (68%) are resolved by moving the activity within the same day. 12% are moved to another day and 20% are skipped, moved to another day outside the survey week or done by another person.
- Systematic differences in conflict resolution strategy can be found for different kinds of conflicts, for different activity types and for different activity durations. No single attribute of the activity, the conflict, the schedule or the person can, by itself, explain the resolution strategy chosen.
- Activity precedence rankings found in CHASE data can be used to inform precedence assumptions in TASHA with the exception of in-home activities, which are not observed in the dataset underlying TASHA.
- Of the many scheduling strategies found in CHASE, the TASHA model is designed to simulate the majority of the most common, including a) shortening the duration of the activity, b) shifting the activity to another part of the day, c) shifting and shortening the activity or d) splitting the activity. However, a significant proportion of conflicts are resolved by moving activities to another day (12%), skipping activities (or shifting them to another week or another person's schedule) (20%), and shifting and

lengthening activities (6%). The prototype version of TASHA does not allow for these responses, largely because of data limitations.

The following suggestions are provided for further research based on these results.

- An improved measure of activity precedence could be developed that is a function of activity type and other key attributes that are elements of precedence (e.g. level of commitment to other people, the degree of pre-planning, etc.). Such an improved measure could be used to develop better rules for predicting the outcome of scheduling conflicts.
- There are some attributes of activities that have an influence on the activity's precedence that cannot be observed, hence uncertainty will always exist in our measure of precedence. This uncertainty could be incorporated into the measure of precedence by means of an error term, such that the rule base for activity scheduling/rescheduling becomes more stochastic in nature.
- This analysis of conflict resolution strategies has focussed on the influence of attributes of the activity and the nature of the scheduling conflict. Other influences include the characteristics of the schedule (where are there "gaps" in the schedule that might accommodate a shifted activity?), and characteristics of the person (are certain persons more prone to fill their schedule, while others are more likely to reject opportunities that arise?). These should be further explored.
- The time horizon of the TASHA model should be extended from 24 hours to one week and the representation of household interactions in the model should be improved to allow for a full range of rescheduling responses.

5. Travel Activity Scheduler for Household Agents

5.1 Introduction

A central motivation for collecting and analyzing detailed activity scheduling data is to help inform new activity-based models of travel demand with an improved behavioural base. The Travel Activity Scheduler for Household Agents (TASHA) is one such activity-based model that has been operationalised for the Toronto Area. Because the Travel Activity Panel Survey was conducted in parallel with the development of the model, only some of the insights have been incorporated into the modelling framework, namely, those discussed in Chapters 3 and 4. Furthermore, most of these insights were used to validate TASHA after the simulation framework had been developed, rather than at the stage of model design.

Nevertheless, in its current form, TASHA is considered to be a significant advance in behavioural modelling of travel demand and it has been developed in a versatile microsimulation framework which allows for the testing of alternative behavioural assumptions without reconstruction of the model. New analysis on the data available from the panel survey can not only serve to provide additional validation opportunities, but can help to set the research agenda for future model development in the TASHA environment (see Chapter 10).

The TASHA model is based on a conventional origin-destination (OD) trip dataset. This was an intentional design consideration. If such an activity-based model is to be used in practice in the near future, it should not require that an expensive activity scheduling survey like CHASE be conducted for parameter estimation. In the development of TASHA, CHASE data is used to assess fundamental behavioural rules underlying the scheduling process (which are less likely to vary dramatically from city to city over time). However, the main OD data set for defining the population and their activity types, times and locations are more context dependent. Thus TASHA could be implemented with reasonably low expense in any city with a large enough conventional OD survey dataset.

5.2 The Travel Activity Scheduling Model for Household Agents

The major features of the operational TASHA model are as follows:

The model makes use of the concept of the project to organize activity episodes into the schedules of persons in a household. Activity episodes are the basic unit of analysis in the formation of a schedule. Each activity episode has a start time, a duration, a location and an activity type. A project is defined as a group of logically connected set of activity episodes that contribute towards a common objective. Projects may involve one or more household members as well as differing activity types. Projects have project agendas, which are a list of activity episodes that are associated with the project. The concept of the project, as discussed in depth by Miller (2005a,b), can be used to combine short-term decisions (such as activity scheduling) with long-term decisions (such as residential location choice) in a unified conceptual framework. One of the other key advantages of using the concept of the project in an operational model is that it allows household interactions between household members to be handled cleanly and realistically, particularly with activities that involve joint participation (e.g. going to a movie together) or joint responsibility (e.g. taking care of children).

The model features interactive household agents. The schedules of the persons within the household are generated simultaneously to allow for interaction between family members that normally occurs within a household. The primary way that household members interact in the current model is through the generation of joint activity episodes as part of household level projects. Joint activity episodes are activities where more than one person in the household takes part in an activity. The participation in joint activities requires that, in general, the activity takes place at the same time, for the same length of time at the same location. Therefore a “window” of opportunity must exist or be created in the schedules of all of the household members taking part in that activity for it to be a feasible joint activity. There are many other ways in which household members interact to “coordinate” their schedules. One example is the coordination necessary for the care of children and other “dependents” in the household. Such coordination can involve the need to care for a child directly (e.g. put the child to bed or play with the child), accompany the child while they do an activity (e.g. watch their soccer game), or to have the child “tag along” while doing some other activities. The model treats the care of children in a limited way. Out-of-home activities done with children are included in the model, but in-home activities with children are not, and other out-of-home child accompaniment is only incorporated to the extent that the activities of child and adult are identically classified in the base data. Modelling other aspects of the care of children is not currently possible given the limited data available on children in the TTS. Another point of household interaction is the allocation of household maintenance tasks such as grocery shopping. The activity classification in the base data are not detailed enough to distinguish such tasks, therefore, they are not modelled as household activities. Household interactions concerning joint travel, sharing of household vehicles and chauffeuring are handled in detail in the mode choice model discussed in Chapter 6.

The model is a microsimulation of a 5% sample of households in the Greater Toronto Area. A total of approximately 89,000 households and 243,000 persons are represented as individual entities in the computer model. Activity/travel schedules are generated for each person individually.

The model was designed using an object oriented programming technique. Object orientation is a modelling paradigm that attempts to mirror real life objects relevant to the scheduling process directly as “classes” in the program code. The class design for the travel activity scheduling model is shown in Figure 5.1. As shown in Figure 5.1, households, persons, projects, activity episodes and travel episodes are each represented as explicit entities in the model. Each household has persons, and each person has a person schedule which contains all activity episodes and travel undertaken by that person. Both households and persons have projects, each of which has an agenda consisting of all activity episodes relevant to that project. The model also contains a spatial representation of the Greater Toronto Area, as well as a series of probability distributions for activity episode frequency, start time and duration.

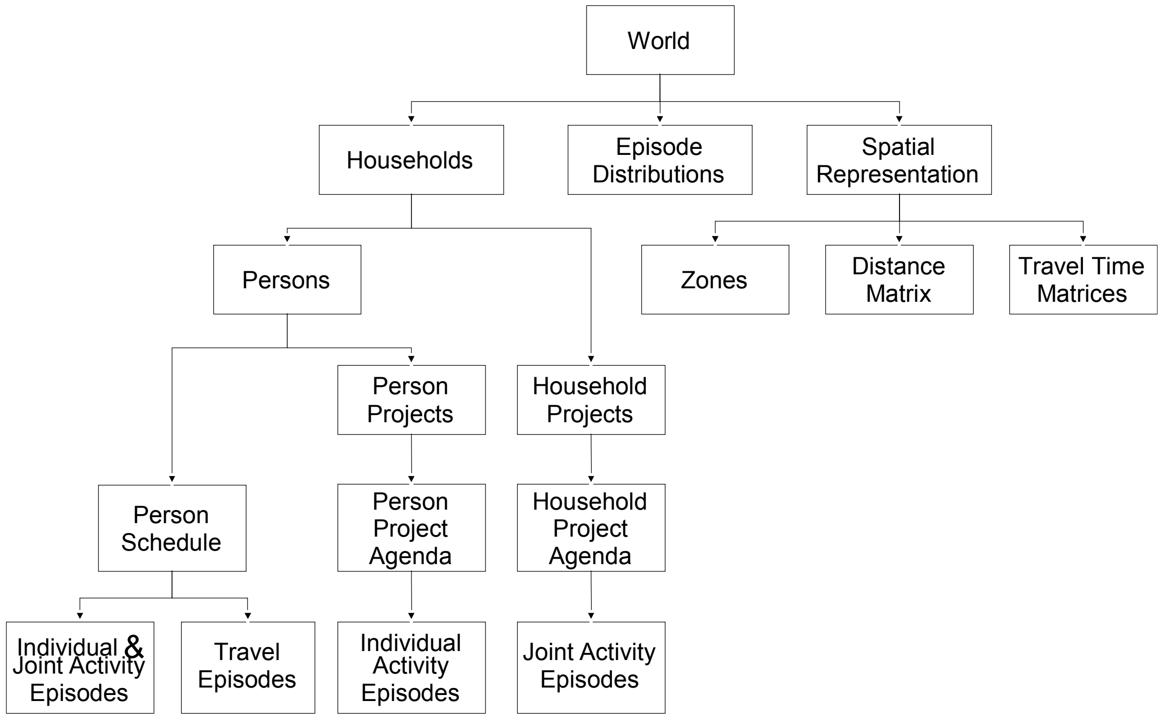


Figure 5.1 – Object Oriented Class Structure

The model assumes broad project and episode types. Projects are assigned as either person-level or as household-level projects. Broad project types are assigned to each household and to each person as shown in Figure 5.2. The serve-dependent household-level project has not been explicitly incorporated into the working version of the operational model but has been implicitly incorporated as discussed previously. The household mobility project represents the household interactions associated with the sharing of vehicles, the sharing of rides and chauffeuring in order to fulfill the mobility needs of the household. This project results from the need for household members to do activities, and functionally resides in the mode choice model in Chapter 6.

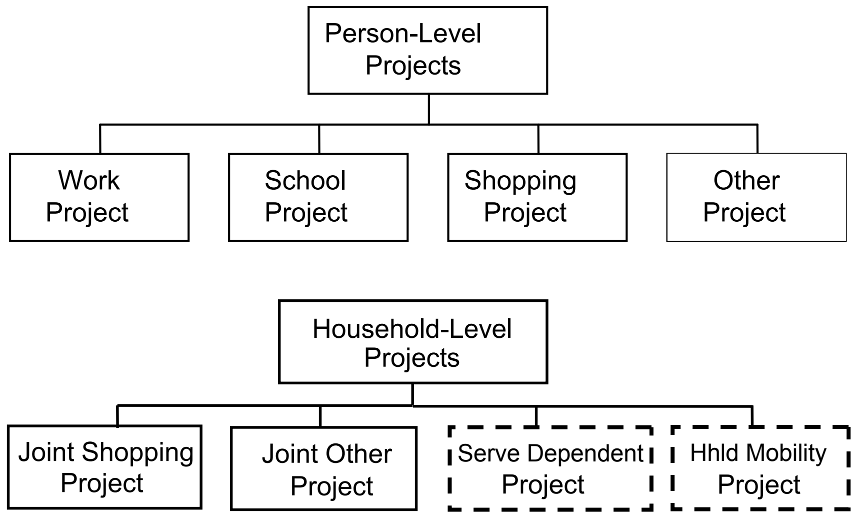


Figure 5.2 - Project Types

Within each project, one or more episodes types are incorporated. The work project is the most complex project as it houses several activity episode types. These episode types include:

- *Primary work* – the first work episode of the day and all subsequent work episodes, occurring at the usual place of work, and beginning before 3:00p.m. ,
- *Secondary work* – subsequent work episodes occurring at the usual place of work that start after 3:00 p.m.,
- *Work business* – work episodes that occur at a location other than the usual place of work, for a person that normally works at a location other than their home,
- *Work-at-home business* - work episodes that occur at a location other than home, for a person that normally works at home, and
- *Return home from work* – at-home episodes that are embedded within the primary work event. These episodes can be thought of as lunch trips but may include other at-home activities, in the midst of the workday.

Each of the other projects contains only a single episode type, which is of the same name as the project.

The model assumes sequential household decisions. It is recognized that households and household members make decisions simultaneously on many different aspects of their lives. Mode choice, for example, is a decision that is very strongly integrated with decisions about where and when to undertake activities. In the current operational model, however, the numerous household decisions are assumed to be made sequentially. That is, residential location, work location and auto ownership are assumed to be exogenous inputs into the model. The schedule formation process then provides trips and tours, which are the inputs for a mode choice model. Currently, modelled auto drive travel times are assumed in the schedule formation procedure to determine how much time must be allocated for travel in a person's schedule.[6]

5.3 The Current Data Source – Uses and Limitations

The Travel Activity scheduling model is based on trip diary data from the 1996 Transportation Tomorrow Survey (TTS). The TTS is a traditional household-based trip diary survey in which attributes of the household, of all household members, and of all trips made by household members over a 24 hour time period are collected. The 1996 TTS is an extremely valuable data source because it has a very large sample size (5%), allowing for a very good level of confidence that it is representative of the entire population.

The 1996 TTS data are used for the generation and validation of activity schedules in three ways. First, the database provides the base population on which the schedule model is run. Attributes of the households (e.g. number of vehicles, residence location) and person attributes (age, sex, employment status and location, etc.) from the TTS are considered to be exogenous inputs into the scheduling model. For a base year model run, schedules for each person in the base population are regenerated.

[6] A future improvement to the model will be to incorporate a mode choice/vehicle allocation module within the scheduling model so that travel times reflect the chosen mode.

Second, the TTS trip data are used as the basis for generating activity episode attributes including their frequency, start times, durations, the number of people involved and the location of the activity. Some manipulation is necessary to extract activity attributes from the trip database. Activity durations, for example, are determined by comparing the start times of two consecutive trips and subtracting an estimated travel time for the first trip.

For the current model a set of observed probability distributions for each activity episode attribute are developed based on TTS data. Joint probability distributions for frequency-start time and for start time-duration are used to reflect the correlation between these inter-related activity attributes. The probability distributions are developed for different classifications of household and person attributes. For example, distributions for individual shopping activity episodes are developed using classifications of age group, gender and employment status. The classifications for each episode type are shown in Table 5.1.

Table 5.1 – Classifications for Activity Episode Generation

Activity Type	Explanatory Variables used for Classification
Primary work	Age, occupation, employment status
Secondary work	Occupation, employment status
Work-business	Age, occupation employment status
Work-at-home business	Age, occupation employment status
Return home from work	Occupation, employment status
School	Age, student status
Independent other	Age, possession of drivers license, employment status
Joint other	Presence of children, number of adults, number of vehicles
Independent shopping	Age, employment status, gender
Joint market	Presence of children, number of adults, number of vehicles

The third use of TTS data is for validation of modelled activity scheduling outcomes against observed schedules. Preliminary model validation results are shown in Chapter 7.

The major limitations of the 1996 Transportation Tomorrow Survey for the purpose of modelling activity scheduling are as follows:

First, only the executed trips are observed, from which executed activity schedules are derived. Since the executed activity schedule is the product of a large number of scheduling decisions prior to execution, it only provides a limited understanding of how a person's schedule is derived. Thus, creating a fully dynamic scheduling model is near to impossible based on TTS data alone.

Second, the survey is limited to a 24-hour window on each person's schedule. The decisions that are made about the frequency with which a person conducts certain types of activities, however, are closely intertwined with the decisions made for prior and subsequent days. It is clear that many activities are planned on a weekly basis. For example, events such as grocery shopping, organized sports, and university courses, most often occur at the same time each week. The scheduling implications of such events cannot be adequately examined with a 24-hour survey.

Third, activities can only be classified to a very aggregate set of activity types. The activity classifications are limited to home, work, school, shopping, and other. Since the attributes of activities within each of these classifications can vary widely, it is difficult to determine scheduling rules that are appropriate for each classification. For example, social visits and doctor's appointments are both considered to be in the "other" activity category. However, doctor's appointments are usually planned well before the day, have relatively inflexible start times and durations, usually occur during the day and are high priority compared with most other activities. Social visits, however, can be much more loosely planned, flexible and are much more likely to occur in the evening. An aggregate activity classification forces very heterogeneous activities to be scheduled in the same way.

Fourth, the activities of children under the age of 11 are not recorded in the TTS survey. To partially account for this deficiency, elementary school trips are synthesized for all school age children.

Finally, TTS data does not provide any information about how individual episodes are organized into projects. Activity episode attributes including location, start time, duration, mode, activity type and the number of household members involved are observed. However, no additional information is available to determine whether activities of different types are linked to each other logically to fulfill a common objective. Therefore, it is necessary to implement the project concept based only on activity type. It is noted that some information about the formation of projects has been collected in the Quebec City version of the Wave 1 panel survey, and when available, can be used to improve the definition of projects in the model.

5.4 The Scheduling Model Method

In the current operational model, person schedules are constructed from scratch based on the following steps:

1) Activity episodes are generated for insertion into each project agenda based on 1996 TTS distributions of activity attributes
2) These activity episodes are inserted into project agendas where they are placed into a preliminary time sequence with other activity episodes that are connected by a common purpose
3) Once the project agendas have been formed, person schedules are constructed by taking activity episodes from the project agendas and adding them to the person schedule. Activity attributes are modified and travel is added as necessary to result in a coherent consistent schedule
4) A "clean up" algorithm is applied to reflect final scheduling / fine tuning just before or during execution of the schedule.

As such, the procedure is a "bottom up" approach to activity scheduling, which is in contrast to the "top-down" approach used in a variety of other scheduling models in which "patterns of activities" are chosen from a large, but finite set of observed activity patterns (Jones *et al.*, 1983; Recker *et al.*, 1986a, 1986b; Kawakami and Isobe, 1990). It is felt that the "bottom up approach" is more conducive to dynamic scheduling in which schedules are constantly changing due to new opportunities and constraints that a person encounters prior to the execution of his/her schedule.

In order to develop realistic activity patterns, a fairly large number of assumptions are made throughout the process of generating schedules. The following section outlines the procedure for generating schedules for members of a household and the underlying assumptions for each of the schedule formation steps that are necessary to ensure reasonable schedules.

1) Activity episodes are generated for insertion into each project agenda. At the outset, the project agenda is blank for each project. Out-of-home activity episodes are then generated based on 1996 TTS probability distributions for frequency, start time and duration along with reasonable rules to ensure that the resulting agendas are logical. Joint probability distributions for frequency-start time and for start time-duration are used to reflect the correlation between these inter-related activity attributes.

The generation of activity episodes for the work project is particularly complex given the number of activity types that are included in this project. In general, the following principles are adhered to when generating work project episodes:

- No work episodes are generated for children under 11 years old, or for people whose employment status is “not employed”. No work-at-home episodes are generated for people under 19 years of age.
- Episodes are generated and inserted in the following order: primary work episode (W), work business episodes for people with a usual place of work (B), secondary work episodes (R), return home from work (L), work business for people with no usual place of work (B), work-at-home business (A)
- Frequency of episodes of each type is randomly chosen from the appropriate frequency distribution for that person/episode type (a maximum of 1 episode is allowed for episode types W, R, and L).
- Given the frequency, start time is then chosen randomly from the joint frequency-start time distribution so that:
    - Work business episodes fall within the primary work event

- Secondary work episodes must start at least one hour after the end of the primary work event and after 3:00 p.m.
- Return home from work (i.e. lunch) must conclude before 3:00 p.m. and must result in at least 30 minutes of work before and after the returning home episode. Return home from work episodes are not generated if the start time of the primary work event is later than 12:00 p.m.

- Given start time, duration is then chosen randomly from the joint start time-duration distribution within appropriate constraints, as follows:
  - Work-business episodes must be less than the duration of the primary work event
  - Secondary work episodes must start at least one hour after the end of the primary work event and must conclude by the end of the day
  - Return home from work (i.e. lunch) episodes must be at least one hour less than the duration of the primary work event
- For primary work and return to work episodes for people with a usual place of work, the employment zone is assigned to the primary work episode. For all other episodes, other than the return home from work, a location choice model based on 1996 TTS data is used to generate a random zone for that episode.

Other person-level activity episodes are generated by simply assessing the frequency, duration and start time from the appropriate probability distributions for that person/episode type. The complexities of the work project do not apply because only a single episode type is assumed to be included in each of these projects.

2) Activity episodes are inserted into person-level and household-level project agendas. Once activity episodes are generated, they are added to project agendas along with other activity episodes with a common purpose. Activity episodes are inserted into the appropriate project one by one such that each project is internally consistent, or in other words, there are no activities within a project agenda that overlap in time. As such, construction of the project agendas represents the first step that a person takes to begin to organize their desired activities into a preliminary sequence. A project agenda does contain "gaps" with no planned activities.

It is also noted that a project agenda does not include travel, which is only accounted for when a person constructs their actual schedule.

There are four different cases that occur when a "new" activity episode is being inserted into a project agenda that already contains "existing" activity episodes that were previously inserted. The cases include splitting an episode (Case 1), inserting an episode between "prior" and "posterior" existing episodes (Cases 2 and 3) and overlapping an existing episode completely (Case 4). These cases are described in Figure 5.3.

The process of inserting episodes into project agendas involves the application of the following rules/assumptions:

- When the new episode being inserted overlaps with part of at least one existing activity episode, the following steps are followed to attempt to create an appropriately sized "gap" for the new activity.
  - If either of the prior or posterior existing episodes is a "gap" in the project agenda then the new episode is shifted to replace all or part of the "gap",
  - The prior episode is shifted if a "gap" exists in the project agenda immediately before the prior activity,
  - The posterior episode is shifted if a "gap" exists in the project agenda immediately after the posterior activity,
  - The durations of the new episode and the existing episodes are reduced in proportion to their existing durations to a minimum of 50% of their original duration, and
  - If all of the above fail, the insertion is considered to be infeasible and the new episode is rejected.
- The insertion of work-business episodes into a primary work event is a special case in which the primary work episode is not shifted, but rather is partially replaced by the work business activity episode. This is allowed because work business episodes are included in the duration of the primary work duration distribution.
- If activities are rejected due to scheduling conflicts, they are regenerated with a new randomly generated start time and duration up to a maximum of 10 attempts.

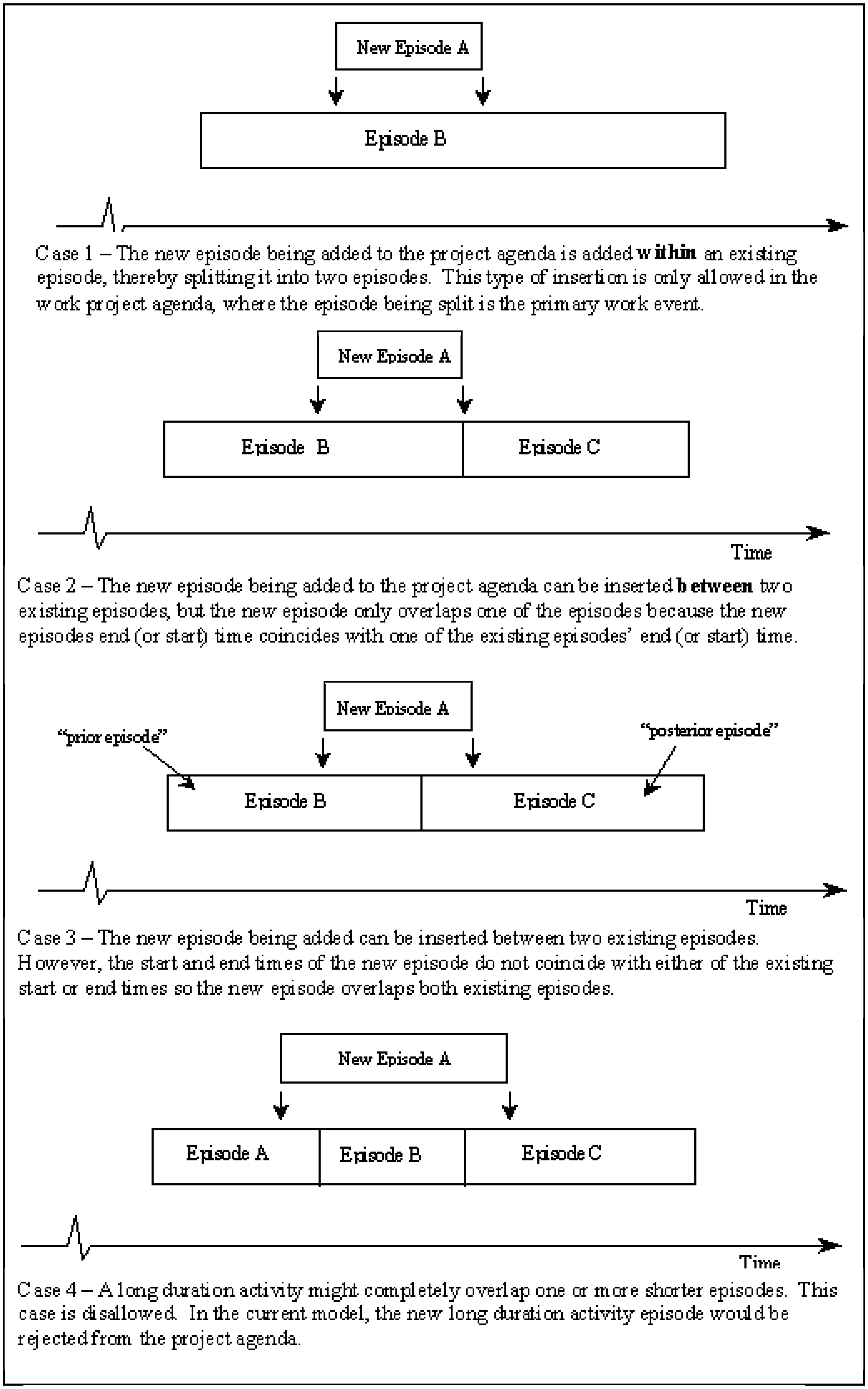


Figure 5.3 - Inserting Activity Episodes into Project Agendas

3) Person schedules are constructed by taking activity episodes from the project agendas and adding them to the person schedule. While projects are used to organize partially elaborated activities into sequence with other activities with a common purpose, the final timing of the activities must be coordinated with activities from other projects. The process of generating a person's schedule, therefore, involves taking episodes one-by-one from the project agendas and adding them to the person schedule in order of precedence.

The order of precedence is chosen to reflect the precedence rankings observed in CHASE, as analyzed in Chapter 4 (see Figure 4.4). The order used in the current operational model is as follows:

- Work-business episodes,
- Primary work episodes,
- All other work episodes,
- School episodes,
- Joint other episodes,
- Joint shopping episodes,
- Individual other episodes, and
- Individual shopping episodes.

The construction of the person schedule proceeds in a manner similar to that of the project agendas. The major differences are that, in the person schedule, travel episodes are added to account for the time necessary for trips between activities with different locations, and that the person schedule does not include "gaps" or areas with no planned activities. It is noted that at the beginning of the scheduling process, a person's schedule consists of a single "at-home" activity, which is the default if no other activities are added to the schedule.

An example of an episode insertion into a person schedule is shown in Figure 5.4. As shown in this diagram, a number of steps are followed to properly insert an episode into a person schedule.

- The travel episode from episode 1 to episode 2 is deleted,
- New travel episodes are defined from existing episode 1 to the new episode and from the new episode to existing episode 2.
- Episodes 1 and 2 are shifted forward and backward, respectively, to allow for the necessary room to insert the new episode and the two new travel episodes.
- If "non-home" episodes exist directly before episode 1 and directly after episode 2, then there is assumed to be no room for shifting of episodes. In this case, episodes 1, 2 and the new episode are truncated in proportion to their durations to a maximum of a 50% reduction in duration.
- If all of the above steps are unsuccessful then the insertion is considered to be infeasible.

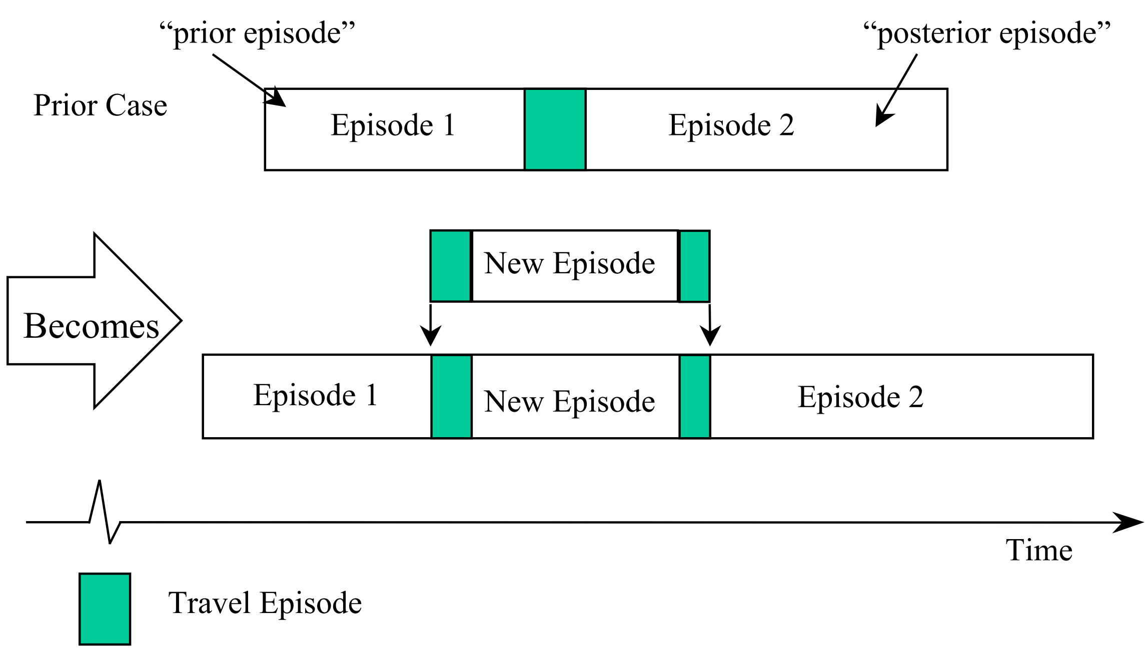


Figure 5.4 – Inserting an Activity into a Person Schedule with Travel

4) A "clean up" algorithm is applied to reflect final scheduling / fine tuning just before or during execution of the schedule. Once a skeleton or preliminary 24-hour schedule is derived based on steps 1, 2 and 3 above, further scheduling changes can be made to reflect decisions made just before or during the execution of a person's schedule. These may include cleanup or optimization algorithms, but also may allow for the introduction of random events, impulsive changes, and further modification, revisions, re-sorting and planning.

This stage of the scheduling process is limited to a single cleanup algorithm that is applied to rearrange the schedule to remove work episodes with duration less than or equal to a 30 minute duration.

An unrealistically high number of "short" work episodes are generated by the model because start times are generated randomly. We believe that schedules are constructed according to a rational process, although it is recognized that not all schedules are arranged optimally. It is felt that using a 30 minute threshold is an appropriate compromise that improves the schedules without fully optimizing them. An example of the schedule clean-up procedure is shown in Figure 5.5.

In this example a number of steps are undertaken to "clean" short work episodes in the schedule.

- The "short" work episode and its associated travel episodes are deleted,
- The primary work episode is extended forward to include the duration of the "short" work episode, and thereby retain the total work duration
- Travel episodes are regenerated appropriately
- The start time of the work business episode is adjusted to account for the reduced total amount of travel time

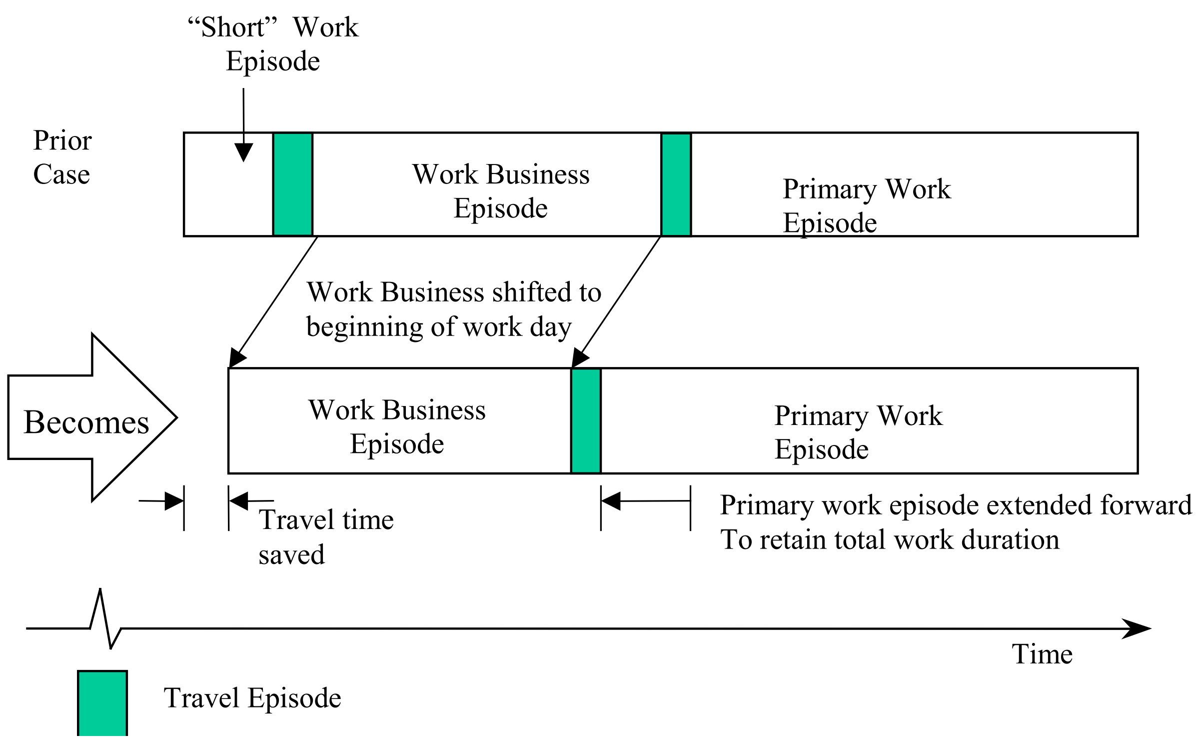


Figure 5.5 – Example of Cleaning a Schedule that has a Short Work Episode

5.5 Behavioural Assumption Summary and Assessment

It is important that the underlying assumptions embedded in current models be fully understood, and that strategies be developed to improve the behavioural validity of the models. Such information provides a more definite objective for future data collection efforts and helps to set priorities for empirical analysis and model development. The major assumptions that have been made in the current operational model are summarized in Table 5.2.

For each assumption, an attempt has been made to outline an alternative modelling approach that would result in a more behaviourally appropriate model. The data sources available or required for the new developments have been outlined and some preliminary qualitative judgements have been made regarding the ease of analysis or development of the model formulation and the ease with which the modification could be integrated into the current modelling framework. It is noted that the improvements to the behavioural assumptions in Table 5.2 have been ordered (roughly) in order of their priority for implementation in future versions of the activity scheduling model, as will be discussed in the next section.

5.6 Conclusion

The Travel Activity Scheduling Model for Household Agents (TASHA) represents a very successful attempt to microsimulate the formation of 24 hour activity schedules for a large sample of people, based on trip diary data provided in the 1996 Transportation Tomorrow Survey. However, it is clear that the further model improvements to effect the desired behavioural basis of the model will require data sources beyond the Transportation Tomorrow Survey. The CHASE survey, which is a high quality data source soon to be available for modelling purposes, has been designed to provide much of the necessary information to further improve the model in a number of key ways. However, there is also a need for continued development of new survey techniques to analyze several of the important concepts underlying the current modelling effort and to address and improve on the assumptions made in the model.

The second component of the TASHA model is the tour-based model of mode choice. This model is discussed in detail in Chapter 6.

Table 5.2 – Behavioural Assumption Summary and Assessment

Behavioural Assumption Made in the Current Model	**Alternative Modelling Approach to Improve Behavioural Validity**	**Existing or Potential Data Source to Support the Alternative Modelling Approach**	**Ease of Development/ Analysis of the Alternative Approach**	**Ease of Integration of the Alternative Approach into the Current Modelling Framework**
Mode choice is a decision that is assumed to occur in sequence after the schedule is formed.	Mode choice decisions should be incorporated as part of the schedule formation procedure since mode has an impact on travel time and therefore affects the schedule.	CHASE can provide only limited insights on the sequence of mode choice in context of other activity attributes.	Moderate (Adequate data exists. Models of scheduling and mode choice exist, but need to be evaluated in their integrated form)	Moderate (Requires addition of a new mode choice model within the scheduling framework. Possible computation issues.)
Activity location is generated based on household, person and zone characteristics only, and may not be modified during the scheduling procedure	Activity location should be sensitive to the activity's position in the person's schedule and the locations of activities before and after the activity.	Trip-based Transportation Tomorrow Survey data could be further analyzed to provide this linkage. CHASE data will provide insight into location changes as the schedule develops over time	Moderate (Data exists and a more elaborate location choice model could be readily re-specified)	Less Difficult (Little program restructuring, relatively simple function modification)
Joint household scheduling decisions are limited to the generation of joint activities (i.e. activities that include more than 1 household member)	Additional joint household decisions / interaction should be incorporated including the care of children and who does other tasks for the household such as grocery shopping.	CHASE data from households can provide detailed information on joint activities, such as what activities in the household are applicable to household members, how spouses may differentially plan and conduct joint activities, and the difference between adult activities that involve children vs. serve the children vs. take place when children are present. The decision of who should do household tasks requires new survey data that targets the differentiation between household and person activities.	Difficult (Household interactions are complex and are likely to vary greatly from household to household)	Moderate (The current model is structured to allow for household interactions if clear rules/ methodology are discovered

Behavioural Assumption Made in the Current Model	**Alternative Modelling Approach to Improve Behavioural Validity**	**Existing or Potential Data Source to Support the Alternative Modelling Approach**	**Ease of Development/ Analysis of the Alternative Approach**	**Ease of Integration of the Alternative Approach into the Current Modelling Framework**
A single set of schedule formation decision rules apply to all people	Different strategies for scheduling behaviour could apply to different people	CHASE data from the Travel Activity Panel Survey will provide much more information on how and when people plan different activities. Other smaller focussed surveys have been developed to capture the planning of different activity attributes. Some combination of such data sources may provide guidance in attempts to derive different sets of rules for different types of people.	Difficult (Rules are difficult to derive since each person is unique and many act in idiosyncratic ways)	Difficult (If drastically different rules apply to different people, significant model restructuring may be required)
Schedules are planned over a 24 hour period	Schedules of at least 7 days (and possibly longer) in length would capture more fully the dynamic nature of the scheduling process	CHASE data from the first wave of the Travel Activity Panel Survey will provide 7 day schedule data.	Moderate (Similar method to that used currently could be addressed using 7 day activity generation)	Moderate (Straightforward model extension, provided that computational burden can be overcome)
Projects are based on very broad activity types (work, school, shopping and other) and only include activities of that type	More detailed project definitions could be developed that more closely reflect the true concept of the project, which allows for different activity types, provided that there is a common overall objective for those activities	In CHASE, user defined definitions of activity type are used that allow for a highly detailed assessment of activity types. Therefore, the potential exists to more precisely redefine activity and project classifications. Neither CHASE nor TTS have information about whether activities are logically linked as part of a project. In the complementary panel survey run in Quebec City, quantitative questions were asked about the project. Analysis of this data source may give insights into the linking of activities.	Difficult (New data required. Necessary to merge insights from several data sources. There exists no proof that the project is a valid concept in all cases)	Less Difficult (Given clear conclusions regarding the classification of projects and activities, the model could be readily extended to incorporate them)
The "execution" stage of schedule formation includes only a single algorithm to "clean-up" short work episodes	The "execution" stage of the scheduling process could be extended to include "impulsive decisions" to add/modify/delete activities and "random event" such as unexpected delays, cancellations, changes in duration, etc.	CHASE data provides a detailed tracing of information on impulsive additions and modifications to schedules as they occur leading up to and during execution. The reasons for these changes are also probed (for instance, to distinguish modifications due to random events versus user-initiated changes. New or follow-up surveys to CHASE could also be considered in order to examine re-scheduling processes in more depth.	Difficult (The "execution stage" is not well-researched and new data may be required)	Moderate (If clear rules can be deduced, they could be relatively straightforward to implement)

Behavioural Assumption Made in the Current Model	**Alternative Modelling Approach to Improve Behavioural Validity**	**Existing or Potential Data Source to Support the Alternative Modelling Approach**	**Ease of Development/ Analysis of the Alternative Approach**	**Ease of Integration of the Alternative Approach into the Current Modelling Framework**
Activities are scheduled in order of precedence based only on activity type. There is no explicit time dimension describing when an activity is planned.	Activities could be added to a person's schedule in a fully dynamic way, whereby some activities of different types are planned well in advance to form a "skeleton" schedule, while others are planned spontaneously, very close to the time of execution.	CHASE data from the first wave of the Travel Activity Panel Survey captures the point in time when an activity is first planned and inserted into the schedule. Data is also systematically collected on a wide range of attributes of activities (spatial fixity, temporal fixity, normal frequency and duration, interpersonal fixity). Therefore, it would be possible to develop a precedence as a function of the attributes of activities, the person, and key situational factors in the schedule (e.g. time to next event; time available on schedule) making it possible to dynamically predict the scheduling of an activity.	Moderate (The CHASE survey is specifically designed to capture such dynamic planning)	Moderate (Straightforward replacement of "hard-wired" precedence to a "precedence function")
The model generates a single schedule at one point in time, without regard to a person's history of schedule formation	We have observed some resemblance between a person's schedule from one year to the next. Therefore, schedule formation should be placed in the context of a person's scheduling history.	The Travel Activity Panel Survey allows for the observation of the schedule formation procedure for the same households at one-year intervals.	Difficult (Significant research required to understand long term scheduling dynamics)	Difficult (Would require storage/retrieval of scheduling history)
No learning or habit formation is incorporated	Learning could be applied by implementing modifications to the episode generation routine, such that attributes of generated activities reflect past experiences	CHASE provides some information on the historical formulation of habitual activities, but no information on new habit formation over the course of the weekly data collection. The Travel Activity Panel Survey data will be needed at minimum to observe changes in scheduling behaviour over time. An in-depth survey would probably be needed to fully explore learning and habit formation	Difficult (Learning/habit formation is not well-understood and would require an innovative new approach and data collection effort)	Difficult (Significant changes would be required to existing activity generation procedures)

Behavioural Assumption Made in the Current Model	**Alternative Modelling Approach to Improve Behavioural Validity**	**Existing or Potential Data Source to Support the Alternative Modelling Approach**	**Ease of Development/ Analysis of the Alternative Approach**	**Ease of Integration of the Alternative Approach into the Current Modelling Framework**
Activity attributes are initially generated based on the final executed schedules observed in the TTS data	Activity episodes should be initially generated based on their "desired" attributes and then modified to reflect the time and resource constraints a person is faced with in the scheduling procedure	CHASE data will provide some insight into "normal" activity attributes prior to execution, such as normal frequency and durations. A new in-depth survey would be useful to fully understand how and why "desired" activities differ from "executed" activities.	Difficult (New data required. Difficult to define and capture "desired attributes" reliably)	Less Difficult (Would require modification to model inputs only)
A limited set of resolution strategies are assumed for handling conflicts that arise during the insertion of activities into project agendas and person schedules	An assessment of CHASE data has shown that conflict resolution strategies may involve additional solutions as discussed in Chapter 4.	Further analysis of CHASE data is required to understand the factors that influence the choice of a resolution strategy.	Moderate (The CHASE survey is specifically designed to capture modifications to the schedule over time)	Unknown

6. A Tour Based Mode Choice Model

6.1 Introduction

The second major component of TASHA is a tour-based model of household mode choice decisions. The mode choice model presented in this chapter was developed to complement the rule-based activity scheduling model discussed in Chapter 5. The mode choice model is both tour-based and trip-based. It is tour-based in that consistent choices must be made to result in a feasible set of mode choices for the tour. For example, if an automobile is taken for the first trip in a tour, it must be returned to the home by the end of the tour. The model is trip-based for non-vehicle tours, for example, it is feasible to take transit on the trip to a destination, but then return home by walking. The model has been developed to be consistent with the conceptual framework outlined by Miller *et al.* (2005), but with some advances to improve the behavioural underpinnings of the model and its operational status.

The model presented here also improves upon other limitations that have been noted in mode choice models found in the literature (see literature review in Chapter 2). First, vehicle allocation should be treated explicitly in the model to prevent unrealistic situations where more than one household member chooses to drive the same household vehicle at the same time. Second, the passenger mode should only be available if there are both a vehicle available and a driver available to offer a ride. The choice to be dropped off or picked up by someone else should consider not only the utility that the passenger derives from the ride, but also the disutility that the driver experiences from having to go out of their way to make the drop-off. Third, people traveling together to participate in joint activities should be constrained to make the same mode choice.

Overall, the mode choice model is developed to be consistent with the TASHA model of household activity scheduling. That is, the activity schedules and tours output from the TASHA model are sufficient to form the inputs for the application of the mode choice model.

6.2 Background Theory

Mode choice modelling has a rich history in econometric decision analysis. It is one of the classic decisions for which new model structures and theoretical concepts are tested. Ben Akiva and Lerman (1985), for example, use mode choice as the primary example to describe the theories of discrete choice analysis.

Multinomial logit, nested logit, mixed logit and probit models are perhaps the most common econometric methods for modelling mode choice. These theories are based on random utility theory, which assumes that people make rational decisions in order to maximize their level of satisfaction (utility). Utility U(m,t,p) of mode m for trip t on tour (chain) c by person p, as shown in Equation [6.1], is assumed to consist of a systematic component V(m,t,p) which is formulated as a linear function of explanatory variables x and parameters β, and an error term, which is assumed to be randomly distributed.

$$U(m,t,p) = V(m,t,p) + \varepsilon(m,t,p) \qquad t \in T(c,p);\ m \in f(t,p) \qquad [6.1]$$

where:

V(m,t,p)=	systematic utility component of mode m for trip t for person p
ε(m,t,p)=	random utility component of mode m for trip t for person p
T(c,p) =	set of trips on tour c for person p
f(t,p) =	set of feasible modes for trip t for person p

Under the assumption of random utility maximization, each person p is assumed to choose the mode m that results in the highest U(m,t,p). The distribution of the error term ε(m,t,p) is the difference between the logit model and the probit model. The logit model assumes that ε(m,t,p) has a Gumbel distribution. With this distribution, the probability of choosing a specific alternative m can be written using the following simple analytical expression.

$$P(m) = e^{V(m,t,p)} / \Sigma_{m'}\, e^{V(m',t,p)} \qquad [6.2]$$

The probit model, on the other hand, assumes a multivariate normal distribution for the error term, resulting in a much more flexible error structure. To solve for the choice probabilities, it is necessary to solve a J-1 dimensional integral, where J is the number of alternatives in the choice set. Clearly, this is computationally difficult.

Parameter estimation is typically done by choosing the maximum likelihood set of parameters, (the set of parameters that is most likely to result in the model prediction of observed choices). The log-likelihood function L for a particular set of parameters β is written in Equation [6.3].

$$L(\beta) = \Sigma_h \Sigma_{p\in H(h)} \Sigma_{c\in C(p)} \Sigma_{t\in T(c,p)} \log(P(m^*,t,p|\beta)) \qquad [6.3]$$

where:

H(h) = set of persons observed in household h

C(p) = set of home-based tours for person p

β = vector of model parameters (including parameters of the error distribution) to be estimated

P(m*,t,p|β) = simulated probability of person p choosing the observed mode m* for trip t on tour c, given the model parameters β.

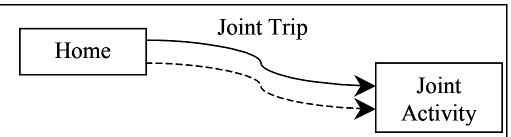
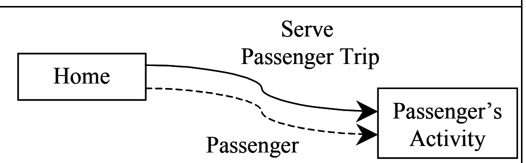
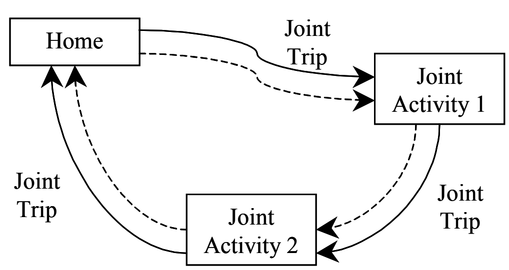
Neither the multinomial logit nor the multinomial probit models, however, are suitable for choice situations where the choice tree structure is non-trivial. Incorporation of vehicle allocation, ridesharing and tour logic in the choice structure results in a level of complexity that does not lend itself well to an analytical solution.

However, simulation is available as a computationally expensive but flexible tool for maximum likelihood parameter estimation (see Lerman and Manski, 1981). In this technique, the error term is simulated directly, resulting in specific, discrete mode choices being made in the model, rather than an integration of the error terms resulting in a probability for each mode being chosen. The mode choice decision must be replicated in this way many times to achieve a statistically valid representation of the choice process.

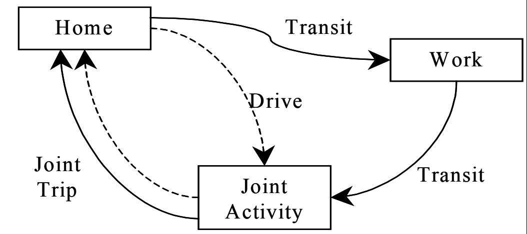
The use of a simulation approach allows for the use of virtually any error structure without adding new layers of complexity to the model estimation process. It also means that the decision process need not be constrained to mathematical formulations that have a simple closed-form solution. For these two reasons it is chosen for use in this modelling effort.

6.3 Definitions

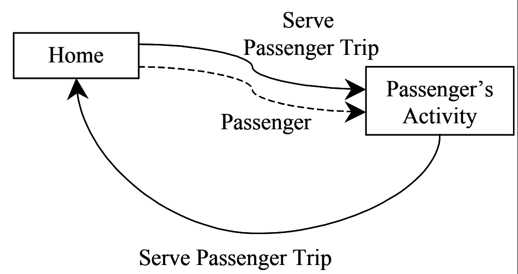
The mode choice model handles different trip and tour types in different ways. In particular, in addition to single-traveller tours, there are different scenarios in which household members travel together. To understand the method for handling these scenarios we first present how we define the different scenarios, in Figure 6.1.

Joint Trip **-** A joint trip is a trip in which more than one household member travel together to or from a joint activity. This can either be a rideshare trip (by car), taking transit together, walking together, etc.	
Serve Passenger Trip - A trip made by one member of a household for the purpose of transporting another member to their desired activity. A serve passenger trip may include a passenger (e.g. the trip to drop someone off), or may not include a passenger (e.g. the return trip home after dropping someone off).	
Pure Joint Tour - A joint tour is a tour in which more than one household member travel together to or from at least one joint activity. A pure joint tour occurs when all of the activities on the tours of multiple household members are joint activities. These household members travel together to and from joint activit(ies), and all of these household members make the same trips on the entire tour, at the same times to the same locations. Mode choice for pure joint tours is assumed to be a joint decision, simultaneously determined for all joint activity participants.	

Partial Joint Tour - A partial joint tour is possible when some but not all of the activities on the tours of multiple household members are joint activities. A partial joint tour occurs when some but not all of the trips in each of these household members' tours, accessing or egressing from the joint activity, are at the same time, have the same origin and destination, and are by a shared mode.



Pure Serve Passenger Tour - A tour made by one household member solely for the purpose of picking up or dropping off another household member. No activities other than "dropping off" or "picking up" are conducted on a pure serve passenger tour.



En route Serve Passenger Tour - A tour made by one household member that includes at least one serve passenger trip, but also includes other activities before or after the serve passenger trip. For example, a tour in which a parent drops off a child at school on the way to work would be considered an en route serve passenger tour.

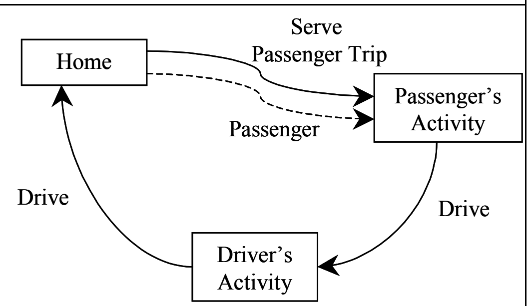


Figure 6.1 – Trip and Tour Definitions

6.4 Method

The mode choice model method can be summarized as follows:

Step 1 Individual tour mode choice

- Mode choice for individual trip-maker is determined based on a random utility maximization framework that incorporates a tour-based decision tree structure.
- Trip-level and tour-level rules for mode availability are enforced.
- For pure joint tours (tours that involve more than one person for all activities on the tour) mode choice is determined simultaneously by all tour participants.

Step 2 Vehicle allocation

- Allocation decisions are made at the household level to maximize household utility.

Step 3 Serve passenger matching procedure

- Compatible individual tours are considered for *en route* serve passenger tours and partial joint tours. Shared rides are chosen for compatible individual tours if it improves total household travel utility.

Step 4 Pure serve passenger tours

- If *en route* serve passenger opportunities are not available, then pure serve passenger tours are considered if a driver is available at home. Such arrangements are chosen if it improves total household utility.

A clear conceptual description of the mode choice model presented in this chapter has been described in Miller *et al*. (2005). However, the prototype implementation of this model was incomplete. It did not include the implementation of joint tours, within household ridesharing, drop-offs and pick-ups. The mode choice model presented here includes the following modes: auto drive, auto passenger (serve passenger tours), rideshare (for pure joint tours), transit all-way, and walk. Bicycle, taxi, drive access transit, commuter rail and school bus are excluded because they represent a very small proportion of total reported trips in the Greater Toronto Area. Carpool (inter-household) trips are excluded from the model and reserved for future study because they require understanding of inter-household interactions. The remainder of this section will give a brief summary of steps 1 and 2 above, and will introduce a more detailed description of the method used for implementation of mode choice for joint tours, ridesharing, drop-offs and pick-ups.

6.4.1 Individual Trip-maker Tour Mode Choice

The objective of the mode choice model is to select a mode of transportation for each trip made by each member of the household such that trip and tour level rules are satisfied, vehicle allocation constraints are not violated and the total utility of the household is maximized.

Consider first the case where an individual chooses the modes of transportation for trips within a tour. Figure 6.2 shows the basic trip tour-level decision that is made, within which a number of sub-decisions are made for individual trips within the tour. Clearly, the choice of whether to take an automobile along on the tour has very strong implications for all trips on that tour and for the decision making of other household members. First, it is necessary that the vehicle be returned back home at the end of the tour. Second, the vehicle must be used for every trip on the tour unless the driver plans to return to the same location to "pick up the vehicle" before returning home. Finally, if the vehicle is being used by one household member, it is unavailable for other members to use as long as it is out of the driveway.

Conceptually, bicycles could be treated in exactly the same way as automobiles, as shown in Figure 6.2. However, the bicycle mode is not included in the model specification presented in this chapter.

For the "non-vehicle" tour alternative, the mode choice decision for each individual trip is assumed to be independent of the decisions for the other trips within that tour. The maximum utility non-personal vehicle mode is chosen for each trip in the tour.

Sub-tours (sub-chains) add an additional level of complexity to the choice structure. For example, an individual can drive to work, walk to a restaurant for lunch, walk back to work, and return home by car at the end of the workday. Generally, if a sub-tour exists, then non-vehicle modes are available for trips on that sub-tour even if the main part of the tour is made using a car or a bicycle.

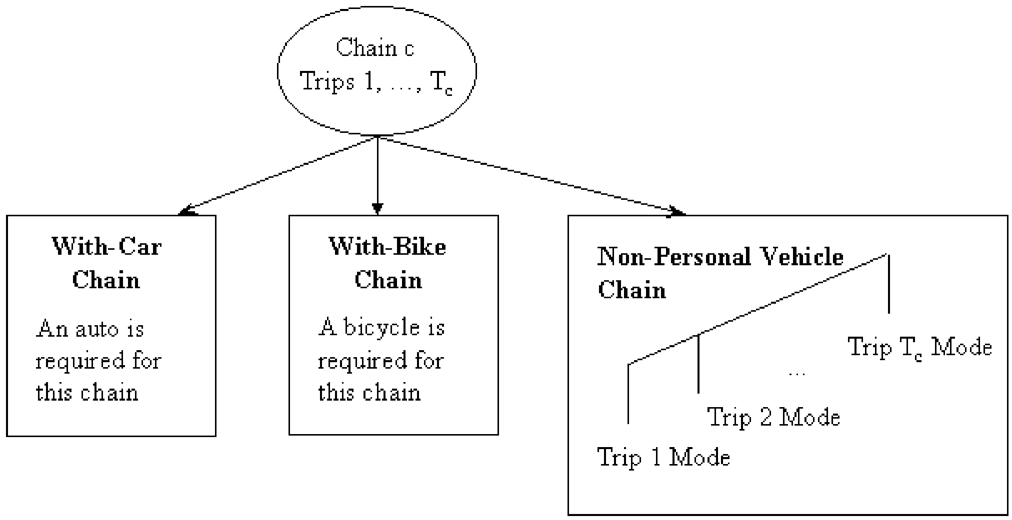


Figure 6.2 – Mode Choice Tour-Level Decision Tree

There are a number of sub-choices within the with-car tour alternative. A car may be used to access a GO rail station or a park-and-ride subway station. The car may be used to get to work but may be left in the work parking lot while the owner walks or takes a taxi to go for lunch (or in other words, to participate in a work-based sub-tour), only to return to work and drive back home again. These complex tour types are handled in the model using the concept of a "tour mode set", defined as a feasible set of modes for the trips in the tour that satisfy the constraint that an automobile must be returned home at the end of the tour without being left stranded at any point in the tour.

Figure 6.3 shows an example of two "with-car" alternatives for a work tour that includes a mid-day lunch and a business meeting. In this example, the work-lunch-meeting-work portion of the tour is considered to be a sub-tour, because the person is returns to an "anchor point" in the tour (in this case the anchor point is work) where the car can be left and other modes taken if desired. The first alternative shown in Figure 6.3 is to drive to work. If the car is taken to work then the car is also available for use in the sub-tour. If however, the car is used to drive to the GO station (the other alternative shown), then non-drive modes must be used for all trips in the sub-tour, and a drive egress GO train trip must be used on the way home. Other similarly complex alternatives beyond these two exist in the model, but are not shown in Figure 6.3.

This fairly complex decision structure allows for logic in the mode choice decisions that simply could not be incorporated within a conventional trip-based decision-tree structure.

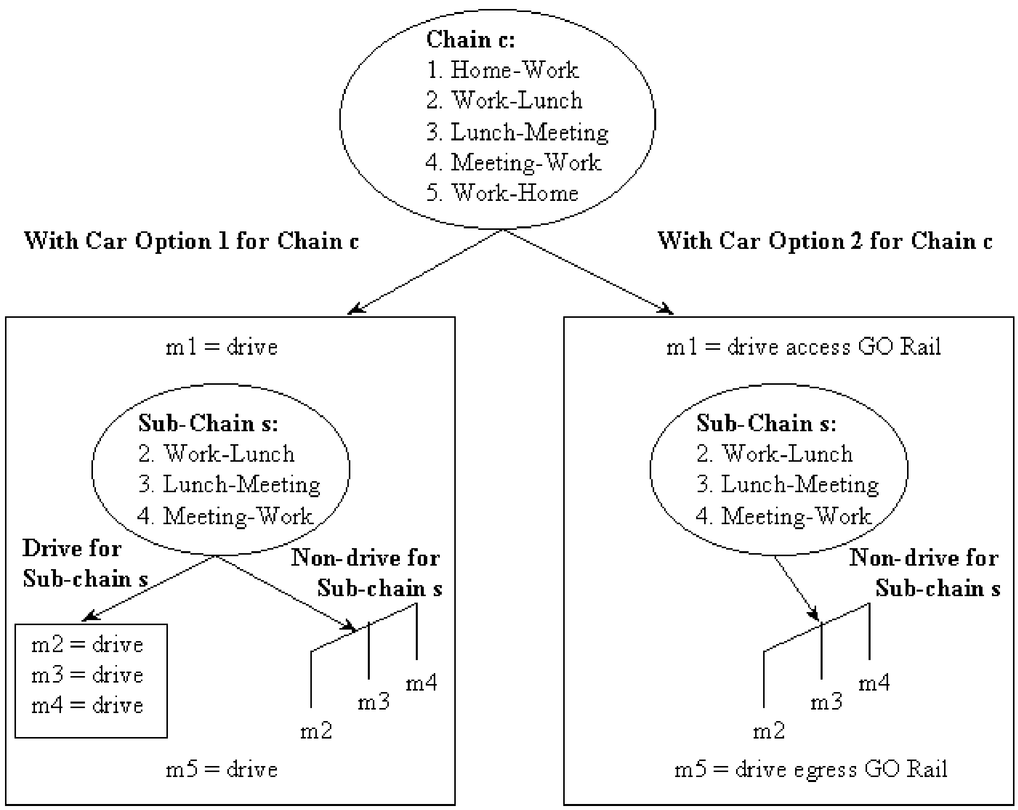


Figure 6.3 - Example of 2 "with-car" alternatives for a complex work tour

As discussed in Miller *et al.* (2005), a random utility approach is adopted in this model to determine the choice among these options. The utility of person p choosing mode m for trip t on tour c, U(m,t,p), is formulated in the usual way as shown in Equation [6.1].

Further, we assume that the utility for a specific combination of modes for the entire tour c, U(M,p) is simply the sum of the individual trip utilities:

$$U(M,p) = \sum_{t \in T(c,p)} V(m(t),t,p) + \sum_{t \in T(c,p)} \varepsilon(m(t),t,p) \qquad M \in F(c,p) \qquad [6.4]$$

where:

M = one set of specific feasible modes for the trips on tour c for person p (the *tour mode set*)

F(c,p)=set of tour mode sets for tour c for person p; this set is defined by both *a priori* trip constraints (e.g., trip distance too long to walk) and tour-based "contextual" constraints (e.g., can't use auto-drive on return trip if it was not used on the outbound trip)

Equation [6.4] is a key assumption in the model design, although it is not clear that attractive, practical alternatives to this assumption exist. It is essential to provide a consistent comparison between tour-based and trip-based modes, as well as to deal with ridesharing and joint-travel mode choices. Also note that this linear additive assumption is implicit in conventional trip-based models.

The standard random utility assumption is made that the tour mode set chosen is M* for which:

$$U(M^*,p) \geq U(M,p) \qquad \forall\, M,M^* \in F(c,p);\ M^* \neq M \qquad [6.5]$$

That is, the drive or (optimal) non-vehicle tour mode set will be chosen for the given tour, depending on which provides the maximum utility to the trip-maker.

We use a microsimulation approach to evaluate Equation [6.5] directly. For each trip, the $\varepsilon(m,t,p)$ term is generated randomly, assuming a normal error distribution. Given the randomly generated ε's, and the systematic utility $V(m,t,p)$ the highest utility tour mode set can be identified and chosen. To determine the maximum likelihood parameters, it is necessary to compute $P(M^*,p)$ by replicating the process many times and determining the frequency with which the observed tour mode set is chosen. This is discussed in more detail in Section 6.5.

6.4.2 Pure joint tours

If multiple household members engage in tours that consist only of joint activities, then the tour is labelled a pure joint tour and mode choice is considered to be a joint decision. For pure joint tours, it is assumed that the total utility for all persons involved on the joint tour is equal to the sum of the utilities of the joint tour mode set (M_j) for each person:

$$U(M_j,P)= \sum_{p\in P(c)} U(M_j,p) \qquad M_j\in F_j(c,P(c)) \qquad [6.6]$$

where:

M_j = one set of specific feasible modes for the trips on pure joint tour (chain) c for person p (a *joint tour mode set)*

$F_j(c,P(c))$ = set of joint tour mode sets for tour c for persons P(c); this set is defined by both *a priori* trip constraints (e.g., trip distance too long to walk), tour-based "contextual" constraints (e.g., can't use auto-drive on return trip if it was not used on the outbound trip) and rideshare constraints (e.g. more than one person will not be driving the car at the same time, rather the "rideshare" mode will be used)

P(c) = set of persons participating on the joint tour c

It is noted that if the automobile is used, the drive mode and the passenger mode are replaced by the "rideshare" mode for trips in joint tour mode sets. This is simply done because, for a shared ride, it is not important for our modelling purposes to know which of the people in the vehicle is driving. The utility for the "rideshare" mode, however, is different from that of the drive mode in the following ways:

- The travel cost for rideshare = travel cost for drive * 1/N(t)
- The parking cost for rideshare = parking cost for drive * 1/N(t)
- The rideshare mode specific constant ≠ drive mode specific constant
- Destination purpose dummy variables for rideshare ≠ those for drive

- The error term ε(rideshare,t,p) ≠ ε(drive,t,p)

where N(t) = the number of persons ridesharing (and thus sharing the costs) on trip t

All other variables and the coefficients on those variables are assumed to be the same for the drive and rideshare modes, including that of auto in-vehicle travel time.

6.4.3 Vehicle allocation

Initially, the mode choices for individual tours and for pure joint tours are made without regard for the availability of household vehicles at particular times of day. However, in many instances the tours in a household overlap in time. If the number of vehicles available to the household is less than the number of overlapping with-car tours, then a decision must be made as to which household member uses the vehicle. In such cases, all possible vehicle allocations are evaluated and the allocation that results in the highest overall household utility is chosen. Those household members that are not allocated a vehicle as a result of this evaluation are assumed to choose the highest utility non-vehicle tour mode set. Figure 6.4 shows an example of the vehicle allocations that are evaluated for three conflicting with-car tours in a 2-vehicle household.

In subsequent mode choice steps, opportunities for ridesharing are considered for conflicting tours.

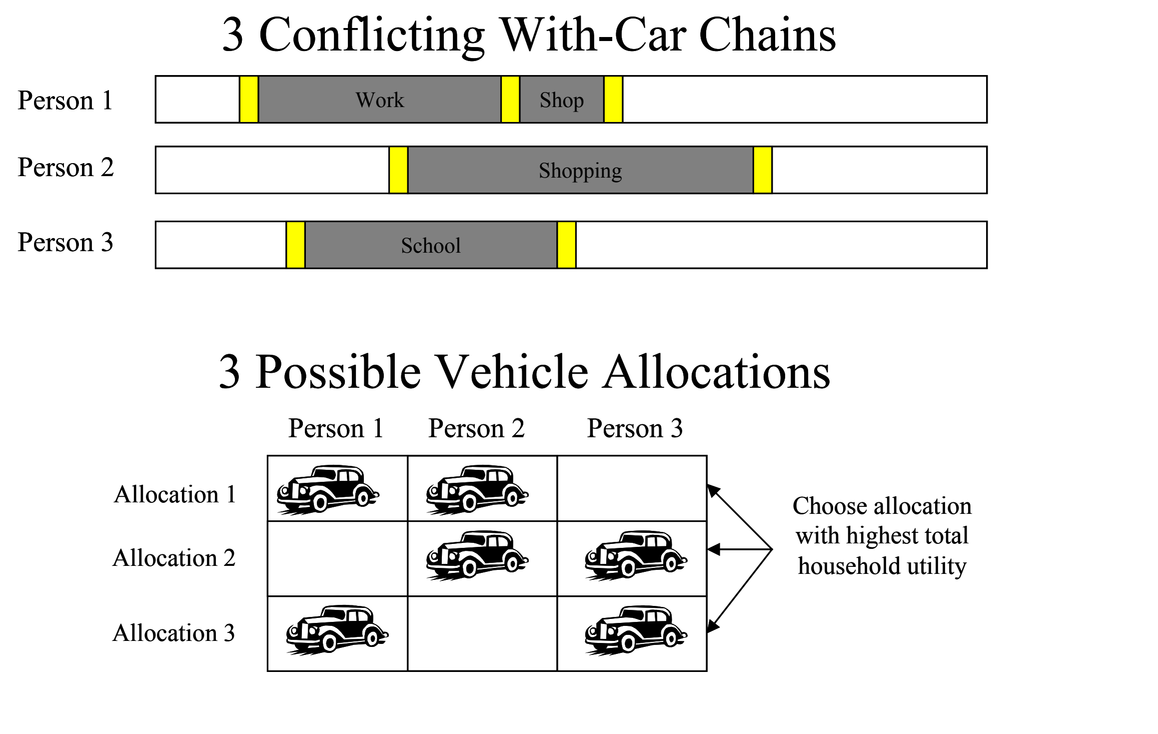


Figure 6.4 - Example of conflicting tours and vehicle allocation in a 2-car household

6.4.4 En-route serve-passenger tours

Opportunities exist within the household for ridesharing, even when activities are not done together. One common example is that of parents dropping-off or picking-up children at school *en-route* to work or other activities. In such situations, the person that serves the passenger (i.e. gives them a ride) experiences an increase in travel time and inconvenience, in order to chauffeur another household member, who as a result experiences an improvement in travel utility. Our model approach assumes that household members first consider their tour mode choices individually. Serve passenger opportunities are then evaluated in terms of total household utility, that is, if the increase in utility experienced by the passenger exceeds the decrease in utility experienced by the driver, then the serve passenger arrangement is chosen. Otherwise, the driver drives alone, and the would-be passenger chooses the best alternative available mode.

Serve passenger opportunities are considered on a trip-by-trip level if the would-be passenger had chosen a non-vehicle tour mode set. For example, consider a household with two work tours where person 1 chose to drive (in Steps 1 and 2 of the mode choice algorithm) and person 2 chose transit both ways. There may be opportunities for person 1 to give person 2 a ride to work, **and/or** to give person 2 a ride home from work. However, if person 2 was given a ride to work it is still equally possible for person 2 to take transit home. In other words, the rideshare to work can be considered independently from the rideshare home from work, since neither decision acts to constrain the mode options of either party for the other trip.

Conversely, if person 2 had chosen a with-car mode set for the tour, then his entire tour would need to be reconsidered if he were to accept a ride. To accept a ride **to** work, the person 2 would have to leave the car at home for the entire tour. It would be necessary for him to find non-personal vehicle modes, such as transit, walk or auto passenger, for all other trips on the tour.

Formally, the travel utility gain for the serve passenger alternative $\Delta U_{s,p}$ for person p involved on the serve passenger trip can be written as follows:

$$\Delta U_{s,p} = \Sigma_{t_s \in T_s(c,p)} U(m_s,t_s,p) - \Sigma_{t \in T(c,p)} U(m,t,p) \qquad [6.7]$$

t = the trip made without serve passenger

t_s = the trip made with serve passenger

m = the mode for trip t without serve passenger

m_s = the mode for trip t_s with serve passenger

T(c,p) = the set of trips t on tour c for person p, without serve passenger

$T_s(c,p)$ = the set of trips t_s on tour c for person p, with serve passenger

The total household travel utility[7] gain for the serve passenger alternative ΔU_s is:

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[7] We note that, in addition to the change in travel utility, there may also be changes to activity utility (the utility that one derives from participating in an activity at some time, at some location, for some duration) because activities can change when those wanting to serve a passenger need to modify their schedules. In this model of mode choice, as with other mode choice models in the literature, this utility is ignored.

$$\Delta U_s = \Sigma_{p \in P_s(c)} \Delta U_{s,p} \quad [6.8]$$

where

$P_s(c)$ = the set of persons involved in the serve passenger alternative for tour c.

The shared ride alternative is chosen if $\Delta U_s > 0$.

An *en route* pick-up or drop-off is generally only feasible if the trips by driver and passenger occur at about the same time of day. There may be some willingness for either the driver or the passenger to leave early from their origin activity or arrive late at their destination activity to share a ride, but there is an associated inconvenience with doing so. This inconvenience may be tolerable, depending on the type of activity that one is doing before or after the trip and the degree to which the start or end times of these activities must be changed to accommodate a serve passenger.

Since we do not have the necessary data to develop an adequate representation of activity utility, a simple set of rules is assumed to govern the feasibility of the serve passenger alternative.

Using notation:

ΔD^o_{driv} = decrease in duration of driver's origin activity due to serve passenger

ΔD^d_{driv} = decrease in duration of driver's destination activity due to serve passenger

ΔD^o_{pass} = decrease in duration of passenger's origin activity due to accepting a ride

ΔD^d_{pass} = decrease in duration of passenger's destination activity due to accepting a ride

Thresholds are chosen for reductions in activity duration that are a result of the serve passenger arrangement. If we assume that utility loss only occurs when activities are shortened in duration, then four threshold parameters would be required to specify such a complete rule-base.

τ^{o}_{driv} = maximum decrease in duration of driver's origin activity

τ^{d}_{driv} = maximum decrease in duration of driver's destination activity

τ^{o}_{pass} = maximum decrease in duration of passenger's origin activity

τ^{d}_{pass} = maximum decrease in duration of passenger's destination activity

If a serve passenger arrangement results in a violation of one or more of those thresholds, as follows:

If $\Delta D^{o}_{driv} > \tau^{o}_{driv}$

Or $\Delta D^{d}_{driv} > \tau^{d}_{driv}$

Or $\Delta D^{o}_{pass} > \tau^{o}_{pass}$

Or $\Delta D^{d}_{pass} > \tau^{d}_{pass}$ [6.9]

then the serve passenger alternative is considered to be infeasible.

Different thresholds are specified for the driver and the passenger because the passenger would presumably be more willing to modify his or her activity schedule to suit that of the driver of the vehicle. Thresholds could be further differentiated by activity type (i.e. one experiences more utility loss for showing up late at work than for showing up late at home to watch TV), or at least for in-home vs. out-of-home activities.

6.4.5 Partial Joint Tours

A tour is a candidate to be a partial joint tour if at least one but not all of the out-of-home activities on the tours of multiple persons in the household are joint activities. The procedure for assessing partial joint tours is a special case of the more general procedure described for serve passenger trips. By definition, tours that are candidates to be partial joint tours include trips that have common origin, destination and timing for multiple people. For these trips, therefore, it is not necessary for one person to make adjustments to their tour to include a "drop-off / pick-up" activity. Hence, the rideshare feasibility rules need not be applied in this case; the rideshare mode will always be feasible provided there is a vehicle available. Equations [5] and [6] can therefore be applied directly to determine whether a partial joint tour is formed.

6.4.6 Combined Pure and Partial Joint Tours

In some instances, a pure joint tour may occur in a household in combination with a partial joint tour. Such an example is shown in Figure 6.5. In such cases, the joint mode would be chosen in Step 1 for those involved in the pure joint tour (in Figure 6.5, the pure joint tour is made by persons 2 and 3). Then, in Step 3 after the vehicle allocation is done, an assessment would be made of the change in total household utility if the person that is partially involved in the joint tour (in Figure 6.5 this is person 1) would also share a ride. Hence no additional special procedures or model complexity is required to handle combined pure and partial joint tours.

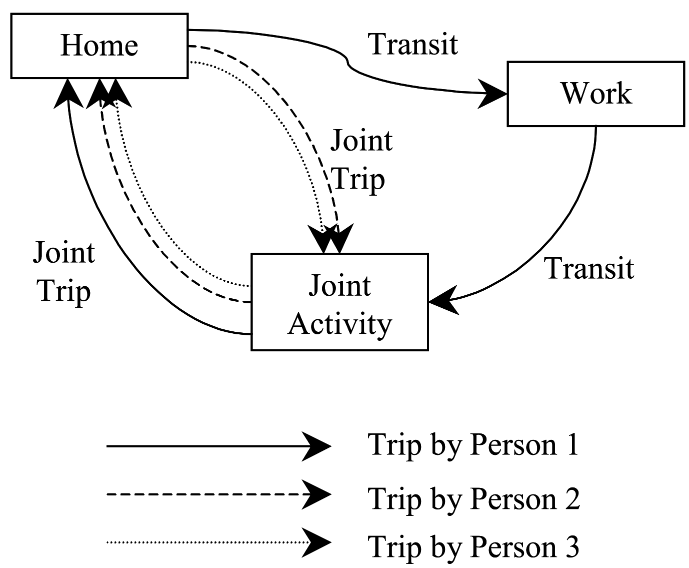

Figure 6.5 – Example of a combined pure and partial joint tour

6.5 Data

The mode choice model is based on data from the 1996 Transportation Tomorrow Survey (TTS) (DMG, 1997). While 2001 data are currently available, a complete set of level of service data, estimates of parking costs, and transit fares for all time periods in the day are not yet available for 2001. In order to support a household tour-based model, a significant effort was made to clean the data, to identify tours, to identify and classify joint trips and serve passenger tours, and to attach level of service information not included in the TTS database. The following steps were done for all TTS survey records:

- Households containing problematic data (i.e. records with missing data, illogical trips) were removed from the dataset (Eberhard, 2003);
- Trips were processed to identify associated activity attributes including start time, activity location and activity duration. Joint activities (activities involving more than one household member) were identified based on these data. (Eberhard, 2003);
- Trip level-of-service attributes were attached to each trip record. Auto-drive travel times were obtained by assignment of origin-destination trips from the 1996 TTS to an EMME2 model of the road network (see Guan *et al.*, 2003). Travel cost and transit travel times (including transit in-vehicle travel time and transit access walk and wait time) for the AM peak hour were obtained from the GTA model (Miller, 2001). Walk times were estimated using the straight-line distance, a multiplier of 1.4 (to approximate network distance), and a walking speed of 4 km/hr;
- Tours and sub-tours were identified in the TTS database. A tour begins with a trip that originates at home, and terminates when a subsequent trip ends at home. A sub-tour occurs within a tour when a person returns to an “anchor point” (a point that has already been visited on the tour) before returning home (Eberhard, 2003);
- Rideshare trips (drive trips made by multiple household members to joint activities were identified) were distinguished from passenger trips (in drop-off / pick-up scenarios), and carpool trips (drive trips made with non-household members); and

- Households with people making carpool trips or trips using minor modes were removed from the database.

For model estimation purposes, a sample of households was drawn randomly from the full TTS dataset. Additional processing steps were done as follows:

- The tour mode choice model incorporates trip-level, tour-level rules, and household-level rules to ensure that all modes included in the individual's choice set are indeed feasible. However, there are a small number of cases in the observed data that violate these rules. For example some people do drive without a license (violating a trip-level rule), others drive to work and leave their car there to walk back home (violating a tour-level rule), and some households claim to take the same car to two different places at the same time (violating a household-level rule). In all of these cases, the entire household was removed from the estimation dataset.
- Serve passenger trips are intended to be an output of the mode choice model. Serve passenger trips only occur when the rideshare mode is chosen in a dropoff/pickup scenario. A serve passenger trip and a dropoff (or pickup) activity are added to the driver's travel pattern as a result of the decision to give someone a ride. The TTS database, however, *includes* dropoff/pickup activities and serve passenger trips because the data are collected after mode choices are made. To generate an estimation database that reflects a "prior condition" before mode choices are made, serve passenger trips must be removed. An example of how a TTS tour is modified for a rideshare scenario is shown in Figure 6.6. The adjusted TTS trip dataset on the bottom reflects the prior condition. The mode choice model would attempt to predict the child dropoff activity and the associated serve passenger trip shown in the original TTS trip dataset. The adjusted TTS trip dataset is generated as follows: If the serve passenger trip is made *en route* to another activity, the trip is removed and the origin of the next trip on the tour is adjusted. Pure serve passenger tours are removed from the estimation dataset entirely, since the driver would stay at home if rideshare arrangements were not made.

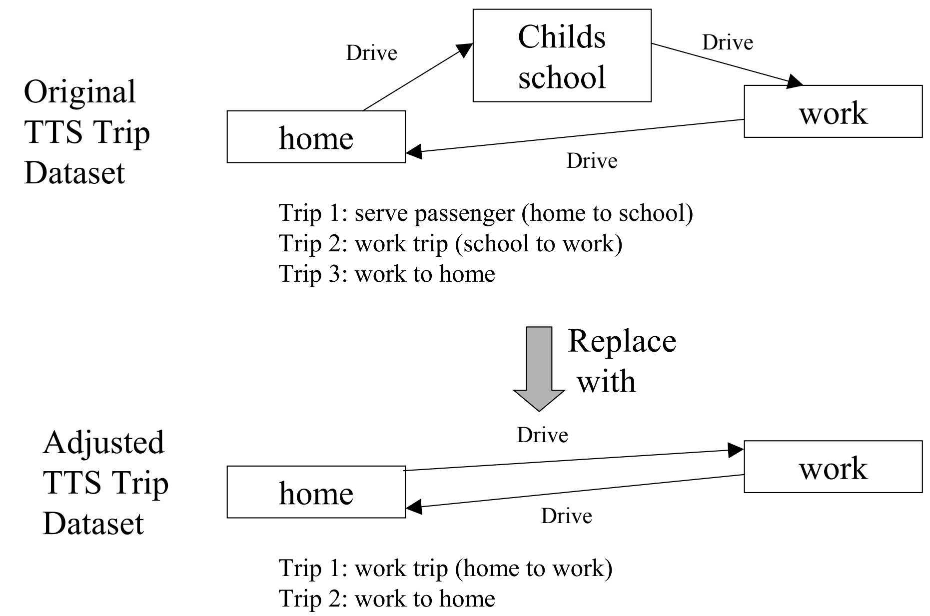

Figure 6.6 – Removal of serve passenger trips from the base data set

Table 6.1 - 1996 TTS Total Sample & Estimation Sub-Sample Summary Statistics

	TTS				Estimation Sample			
	Total Households (Raw)		Processed Households with major modes only (carpool removed)		Initial Estimation Set		Final Estimation Set[1]	
Households	88898		45565		4465		4049	
Persons	243286		117404		11446		7154[2]	
Tours	N/A		100706		9073		8603	
Trips	500313		229178		20442		19335	
Drive[3]	311502[4]	62.3%	139819	61.0%	12199	59.7%	11702	60.5%
Transit All-way	59760	11.9%	35846	15.6%	3297	16.1%	3118	16.1%
Walk	29250	5.8%	16128	7.0%	1395	6.8%	1299	6.7%
Passenger (dropoff / pickup)	78768[5]	15.7%	8012	3.5%	650	3.2%	399	2.1%
Rideshare (to joint activities)	N/A		29373	12.8%	2901	14.2%	2817	14.6%
Drive Acc Subway	863	0.2%	0	0.0%	0	0.0%	0	0.0%
Drive Egr Subway	798	0.2%	0	0.0%	0	0.0%	0	0.0%
Drive Acc Go Rail	1241	0.2%	0	0.0%	0	0.0%	0	0.0%
Drive Egr Go Rail	1161	0.2%	0	0.0%	0	0.0%	0	0.0%
Non-drive Go Rail[6]	2216	0.4%	0	0.0%	0	0.0%	0	0.0%
Taxi	2386	0.5%	0	0.0%	0	0.0%	0	0.0%
Schoolbus	7684	1.5%	0	0.0%	0	0.0%	0	0.0%
Bicycle	3891	0.8%	0	0.0%	0	0.0%	0	0.0%
Other/Unknown	793	0.2%	0	0.0%	0	0.0%	0	0.0%

Notes: *(1) Trips by modelled modes complying with all choice set rules.*
(2) Only includes persons making a trip. Other columns include all persons in the households.
(3) Drive includes motorcycle trips.
(4) In the raw TTS data, rideshare to joint activities is not identified as a separate mode. Rideshare drivers are included in this number
(5) In the raw TTS data, rideshare to joint activities is not identified as a separate mode. Rideshare passengers are included in this number
(6) "GO Rail" is the GTA commuter rail system. "Non-drive GO" indicates transit, walk, auto passenger and taxi commuter rail station access modes.

6.6 Parameter estimation

6.6.1 Calculating the log likelihood

Model parameter values were estimated by maximizing the log-likelihood function shown in Equation 6.3:

Because of the complex error structure, the non-standard tour "nesting" structure shown in Figures 6.2 and 6.3, and the complexities of vehicle allocation, no analytical expression could be found for the choice probability P. Thus, P is simulated through a Monte Carlo process in which N sets of random utilities U are drawn for each trip for each person for each tour for a given β, Equation [6.5] is evaluated for each draw, and the frequency with which m* is predicted to be chosen is accumulated. In order to account for the possibility that m* is never chosen within the N draws, P is defined as (Ortúzar and Willumsen, 2001):

$$P(m^*,t,p|\beta) \quad = \quad [F(m^*,t,p|\beta) + 1] / [N + n_t] \qquad [6.10]$$

where $F(m^*,t,p|\beta)$ is the number of times m* was selected for trip t out of the N draws, and n_t is the number of feasible modes for trip t.

The routine for calculating the log likelihood function, mode choice model estimation routine is implemented in a C++ program, and is built using an object-oriented programming framework, consistent with that of the activity scheduling component of TASHA

6.6.2 Evolutionary algorithm for maximum likelihood parameter estimation

The search for a parameter set that resulted in the maximization of the log-likelihood function was done using an evolutionary algorithm (EA). Simply put, evolutionary algorithms are a method of searching multi-dimensional space to, according to some criteria (Back, 1996). The method is based on an analogy to the evolutionary process in nature, in which populations of organisms adapt and change over time through processes of selection, reproduction, and mutation. Those organisms with the genetic makeup that is most well adapted to the environment are most likely to survive and reproduce, resulting in a population that is increasingly "fit".

As applied to the problem of mode choice parameter estimation, the evolutionary algorithm analogy is developed as follows. Each vector of parameters β is considered a *chromosome*, and each individual parameter within that vector is a *gene* within that chromosome. The *fitness* of the chromosome is the value of the log-likelihood function in [6.3], thus, the chromosome with the highest fitness is the maximum likelihood parameter set.

The EA begins by initializing a *population* of chromosomes, that is, a group of feasible parameter sets (β). This initial population forms the first generation of the evolutionary process. The fitness ($L(\beta)$) of each of those chromosomes is then evaluated. Based on the fitness of each of the chromosomes in the population, a process of *selection* takes place in which chromosomes with higher fitness *survive* and unfit chromosomes are discarded. *Reproduction* involves the selection and the mixing of the genes of two *parent* chromosomes (that have survived the selection process) to result in *child* chromosomes. The process of reproduction involves both *recombination*, the mixing of genetic information from the two parents, and *mutation*, the introduction of slight modifications to individual genes in the chromosome. The next generation is then built using an *assembly* step, in which a subset of the parent and child populations are chosen through the process of selection. This evolutionary process repeats itself over many generations, and the overall fitness of the population improves in each generation.

The design of an EA for a particular application involves the choice of methods for each of the processes as described above. Significant testing was undertaken to find the combination of methods that was feasible given our computing resources, converged reasonably quickly to a solution, was able to find the maximum likelihood parameter set with a good degree of consistency. Table 6.2 shows the EA methods chosen based on these tests. While this EA configuration is not necessarily the most efficient, it was sufficient to solve the maximum likelihood parameters for our mode choice application with reasonable efficiency. The choice of an appropriate population size was a critical decision because it directly influenced the computing resources required and the speed of convergence. This setting was tested by applying the evolutionary algorithm multiple times with different random number streams. To obtain stable estimation results we found that it was necessary to use a population size of approximately twice the number of parameters to be estimated. However, further increasing the population size achieved limited benefits in the consistency of the solution. Hence, for most model runs, a population size of 50 was used, however, in the final set of model runs the population size was increased to 70.

Table 6.2 – Evolutionary algorithm methods and settings

Evolutionary Algorithm Element	**Chosen Method or Setting**	**Description**
Population size	70	
Initial population	Random selection	Genes for each chromosome in the initial population are randomly generated within the defined search space.
Selection (for assembly)	Best Selector	Selects chromosomes with the highest fitness.
Selection (for recombination)	Rank-based Selector	Chromosomes are ranked in order of fitness. Chromosome a is selected with a probability defined by: P[a] = (popsize-rank(a))/(popsize).
Assembly	Crowding Assembler	Pools the parent and child chromosomes and selects those with the highest fitness (Best Selector)
Recombination	Real Multi-Crossover	Parents are chosen using the Rank-based selector. Each of the genes of the child is set to the value of that gene in one or the other of the parents, with equal probability.
Mutation	Percentage Gene Mutator	All parameters were mutated within a range of +/-7%
Stopping Criterion	Number of generations with no increase in maximum likelihood	15

The GALAPAGOS software (Kruchten, 2003) was used to apply the evolutionary algorithm to the problem of mode choice parameter estimation. GALAPAGOS is built upon the LIGHTGRID grid-computing engine, which allows calculations to be run in a distributed computing environment. Given that an available grid of computers is linked to a common network, LIGHTGRID manages the process of setting up client computers and dispatching computing tasks to those clients. By parallelizing the computing using GALAPAGOS and LIGHTGRID, the speed with which a model could be estimated was dramatically improved. As noted by Kruchten (2003), the optimal usage of the client computers could be made when:

$$\text{Population size / number of client computers = integer value} \qquad [6.11]$$

The minimum model run time was therefore obtained by allowing the number of client computers to match the population size. This was feasible for this project, because a large networked computing grid of moderately powerful 1.4 GHz single-processor desktop machines was available for use during off-hours. Time to convergence for the model runs ranged from 1.5 to 2.5 hours using the distributed computing environment.

6.7 Model Results

Table 6.3 shows the definition of the explanatory variables included in the model utility function.

Table 6.3 Definition of Explanatory Variables

Parameter	Description
c-tr_n_dr	Mode specific constant for transit all-way
c-walk	Mode specific constant for walk
c-ridesh	Mode specific constant for rideshare (joint trips)
c-pass	Mode specific constant for auto passenger
Atime	Auto in-vehicle travel time (min)
Tivtt	Transit in-vehicle travel time (min)
Twalk	Walk travel time including walk access to/from transit (min)
Twait	Transit wait time (min)
travelcost	Travel cost ($1996)
pkcost	Parking cost ($1996)
dpurp_shop_d	=1 if trip purpose = shopping (drive mode); = 0 otherwise
dpurp_sch_d	=1 if trip purpose = school (drive mode); = 0 otherwise
dpurp_oth_d	=1 if trip purpose = other (drive mode); = 0 otherwise
dest_pd1_w	=1 for walk trips destined for downtown Toronto; = 0 otherwise
intrazonal_t	=1 for an intrazonal trip for the transit all-way mode; = 0 otherwise
adjzone_t	=1 for an adjacent zone for the transit all-way mode; = 0 otherwise
age11_15_p	=1 if age 11-15 (passenger mode); =0 otherwise
Etrip_par	Scaled variance for the trip specific error η_{pmt}

Table 6.4 Mean and Standard Deviation of Explanatory Variables in the final estimation dataset

Variable	Average	Std.Dev.	Variable	Average	Std.Dev.
atime	12.3	11.3	dpurp_shop_d	0.174	0.379
Tivtt	25.0	21.7	dpurp_sch_d	0.088	0.284
twalk	21.9	21.4	dpurp_oth_d	0.243	0.429
Twait	7.4	5.0	dest_pd1_w	0.077	0.267
travelcost	1.6	1.5	intrazonal_t	0.075	0.263
pkcost	0.76	1.97	adjzone_t	0.033	0.180

Table 6.5 presents parameter estimates, likelihood ratio tests for these parameters, and goodness-of-fit statistics for the model.

Table 6.5 Model Estimation Results

Parameter	Description	Coeff-icient	Lik. Ratio
c-tr_n_dr	Mode specific constant for transit all-way	-0.166	18.46
c-walk	Mode specific constant for walk	-0.304	28.96
c-ridesh	Mode specific constant for rideshare (for joint trips)	0.835	72.40
c-pass	Mode specific constant for auto passenger	-2.385	527.0
atime	Auto in-vehicle travel time (min)	-0.075	167.2
Tivtt	Transit in-vehicle travel time (min)	-0.029	94.7
twalk	Walk travel time including walk access to/from transit (min)	-0.064	1263.5
Twait	Transit wait time (min)	-0.145	267.8
travelcost	Travel cost ($1996)	-0.065	28.7
pkcost	Parking cost ($1996)	-0.302	314.2
dpurp_shop_d	=1 if trip purpose = shopping (drive mode); = 0 otherwise	0.993	174.0
dpurp_sch_d	=1 if trip purpose = school (drive mode); = 0 otherwise	-1.181	302.1
dpurp_oth_d	=1 if trip purpose = other (drive mode); = 0 otherwise	0.593	116.7
Dest_pd1_w	=1 for walk trips destined for downtown Toronto; = 0 otherwise	0.897	114.3
intrazonal_t	=1 for an intrazonal trip for the transit all-way mode; = 0 otherwise	-2.962	299.9
adjzone_t	=1 for an adjacent zone for the transit all-way mode; = 0 otherwise	-1.016	142.2
age11_15_p	=1 if age 11-15 (passenger mode); =0 otherwise	0.954	61.3
Etrip_par	Scaled variance for the trip specific error η_{pmt}	1	
Num Observations		19335	
Num Parameters		17	
Log Likelihood L(beta)		-5035.87	
Log Likelihood No Parameters L(0)		-17434.8	
-2[L(0)-L(beta)]		24797.8	
rho2		0.7112	
Adjusted rho2		0.7102	
Number of Observations in which observed mode never chosen		166	

The following results are notable from Table 6.5:

- All parameters have expected signs.
- Given the parameter estimation procedure used, asymptotic t-statistics cannot be readily computed. Instead, likelihood ratio tests were performed for each parameter by deleting the parameter and re-estimating the model. Using that test, all parameters are strongly significant. One of the least significant variables was that of *travelcost*. We note that the coefficient for this parameter showed some variability between model runs, yet it was retained as a key policy variable.
- All parameters are of plausible magnitude. However, the *travelcost* parameter, which, combined with the parameter values for *atime* and *tivtt*, implies values of time of $69/hr for auto users and $27/hr for transit users. These values of time are somewhat higher than expected.

- The mode choice model fits the data very well and produces a fairly high overall goodness of fit (an adjusted ρ^2 of 0.710).
- An important concern in simulated log-likelihood calculations is the possibility that an observed mode for a given observation is never chosen within the Monte Carlo simulation. In this analysis, 100 random draws were generated per trip. As shown in Table 6.5, 166 of the 19,335 trips (0.86%) did not have the observed chosen mode selected at least once during the simulation. While ideally this number should be driven to zero as the estimation proceeds, such a small number of "never chosen" trips is not likely to be having a large impact on the model estimation results.
- Of the 166 trips never correctly predicted, 72 were auto passenger trips, comprising 18% of total auto passenger trips. For other modes, less than 2% of total trips were never correctly chosen. A manual review of the base data for these trips uncovered no obvious reason to explain why they were not chosen. However, this result indicates that passenger mode is clearly the most difficult mode of transport to predict correctly. This is not surprising, because the passenger mode (for dropoffs and pickups), involves a negotiation among household members for which we only have a limited understanding. Furthermore, it impacts not only the trip attributes of the driver and passenger but also the activity schedule of the driver (a dropoff activity is added).

Table 6.6 presents prediction-success tables for both models. Again, the good fit of the model is indicated in this table, with over 88% of observed modes being chosen on average. In addition, each mode except for the passenger mode is well predicted with prediction success rates in the order of 95%, 74% and 67%, and 99% for the auto-drive, transit, walk, and rideshare modes, respectively. For these modes, relatively little "confusion" exists within the model, with off-diagonal elements being generally small and "well balanced" (approximately as many transit trips are incorrectly assigned to walk as walk trips are assigned to transit, and so on). However, the prediction success rate of passenger trips is a relatively low value of 21%. Attempts were made to improve this result by including additional model parameters (for example, destination purpose, and additional dummy variables for different age categories, and sex). All of these additional variables were found to be insignificant.

It is also noted in Table 6.6 that the aggregate predicted mode shares for the auto-drive, transit, walk and rideshare modes very closely match the observed mode shares. However, the total predicted mode share for the passenger mode was found to be 75% of the observed mode share. Unlike a conventional logit model estimation procedure, for example, in which predicted and observed mode shares are forced to match through the selection of the alternative-specific parameter values, no such constraint is imposed within this model's estimation. Thus, the ability to reproduce the observed shares for all but one of the modes is a reasonably strong test of the model's overall performance.

Table 6.6 Prediction Success Tables for the Estimated Model

Trips	Predicted Mode					Total
Obs Mode	Drive	Transit	Walk	Rideshare	Passenger	
Drive	11054	448	139	0	59	11699
Transit	487	2313	216	28	73	3117
Walk	122	252	863	2	60	1299
Rideshare	0	0	3	2814	14	2831
Passenger	109	125	70	0	81	385
Total	11771	3139	1291	2844	287	19331

% of Tot Trips	Predicted Mode					Total
Obs Mode	Drive	Transit	Walk	Rideshare	Passenger	
Drive	57.2%	2.3%	0.7%	0.0%	0.3%	60.5%
Transit	2.5%	12.0%	1.1%	0.1%	0.4%	16.1%
Walk	0.6%	1.3%	4.5%	0.0%	0.3%	6.7%
Rideshare	0.0%	0.0%	0.0%	14.6%	0.1%	14.6%
Passenger	0.6%	0.6%	0.4%	0.0%	0.4%	2.0%
Total	60.9%	16.2%	6.7%	14.7%	1.5%	100.0%

% of Obs Mode	Predicted Mode					Total
Obs Mode	Drive	Transit	Walk	Rideshare	Passenger	
Drive	94.5%	3.8%	1.2%	0.0%	0.5%	100.0%
Transit	15.6%	74.2%	6.9%	0.9%	2.3%	100.0%
Walk	9.4%	19.4%	66.5%	0.2%	4.6%	100.0%
Rideshare	0.0%	0.0%	0.1%	99.4%	0.5%	100.0%
Passenger	28.3%	32.5%	18.1%	0.0%	21.0%	100.0%
Total	60.9%	16.2%	6.7%	14.7%	1.5%	100.0%

The model specification shown in Table 6.5 includes a variety of trip level of service characteristics. However, in contrast to most mode choice models in the literature, only one variable describing the person or household (age=11-15 dummy for the passenger mode) is included. Several other person variables were tested but were found to be insignificant. We believe that this result occurs because of the improved representation of household negotiation and trip making behaviour. In fact, we are encouraged by the results because they indicate that the microsimulation method for mode choice behaviour represents conflicts and constraints with sufficient detail to preclude the need for a wide range of additional socio-economic variables. The following are examples of household or person variables that do not show up as significant parameters in the model, presumably, because they are incorporated in the household interaction structure.

Household size and number of household vehicles: These variables have been used in conventional mode choice models to account for vehicle availability. In the current model formulation, the number of vehicles is known, vehicle availability is calculated and vehicle allocation is explicitly represented.

Sex: In conventional model formulations, a sex variable may be used to represent differing propensities to travel by different modes. We believe based on our results that most of the important differences in travel behaviour attributed to gender can be explained by vehicle availability and the specific competing travel needs of various household members. Also, our model distinguishes between the rideshare mode (for travel to joint activities) and the passenger mode (for drop-off / pick-up scenarios). In the rideshare mode, which is more frequent than the passenger mode for drop-offs/pick-ups, we do not attempt to model which of the rideshare participants is driving and which is the passenger. Thus, gender differences that may exist between driver and passenger do not show up for these trips.

Drivers License: In our model, the auto mode is only available to individuals with drivers' licenses. For the rideshare mode, at least one person must have a drivers' license. Thus the parameter does not enter into the utility function.

6.8 Conclusions

The household tour-based mode choice model developed for the Greater Toronto Area is a significant improvement on the existing models in that it represents household level interactions explicitly, including vehicle allocation within the household, joint travel decisions, and negotiations over ridesharing in the household. Such explicit representation of household-level constraints results in more limited choice sets available for individual mode choice, thereby improving the chance of predicting mode choice for individual trips correctly. It also ensures logical combinations of mode choices for trips within a tour, and for tours within a household.

Preliminary evidence from this research indicates that several socio-economic variables that are typically included in a mode choice model specification become insignificant when household interactions and constraints are explicitly modelled at the micro level. In this way, the modelling approach may arguably be considered more “behavioural” than other approaches. Further research is required to fully substantiate this claim.

While the method is rather complicated, all of the decisions are modelled within a consistent theoretical framework of household random utility maximization. The simulation technique used for estimating the likelihood and the genetic algorithm used for parameter estimation are well suited to accommodate the complicated choice structure, and we feel they have significant potential for the handling of other similarly complex household decisions affecting travel demand.

7. Model Results

7.1 Introduction

The TASHA scheduling and mode choice models were applied to a 5% sample of the population of the Greater Toronto Area and then weighted to represent the full population. This test application was undertaken for a number of reasons. First, the motivation for model development was not only to further our understanding of activity scheduling and mode choice behaviour, but also to provide a practical modelling tool as an alternative to the four-stage modelling approach. For such a tool to be used in practice, application to a large urban area is essential. The purposes of the test application are as follows:

- Demonstrate the functionality of the model;
- Provide a preliminary validation of model results; and
- Identify strengths and weaknesses in aggregate model outputs; and
- Provide a description of the model shortcomings that lead to weaknesses in aggregate model outputs, and a plan for addressing those shortcomings.

7.2 Trip Comparison by Time Period and Destination Purpose

The prototype model replicates 1996 trip-making characteristics in the Greater Toronto Area reasonably well. Table 7.1 compares the TASHA model trip totals to observed trip totals by time period, by trip destination purpose. The following observations are made based on the results in this table.

- Overall, the model underestimates daily trips by approximately 311,000 trips (-3.3%).
- Total daily trips by destination purpose are slightly overestimated for work trips (1.7%) slightly underestimated for school trips (-1.7%) and home trips (-2.7%) and significantly underestimated for shopping (-10.0%) and other trips (-10.2%). The model underestimates trips, in general, because of scheduling conflicts that result in the rejection of activity episodes. Rejections occur more often for shopping and other activities because they are assumed to be lower priority activities that are scheduled last.

- Total trips in the PM Peak Period (3:00 p.m. to 6:59 p.m.) and the night time period (7:00 p.m. to 5:59 a.m.) are slightly over-estimated (2.4% and 2.9% respectively), whereas the trips in the AM Peak Period and the Midday Period are significantly underestimated (-12.1% and –8.3%, respectively). Underestimation of trips in the AM and Midday Periods is a result of scheduling conflicts that occur more often in these time periods. In the TASHA model, such scheduling conflicts result in a shift in trip start times out of the desired time period into adjacent time periods or in an outright rejection of conflicting activities.

In addition, the number of trips per home-based chain is accurately modeled. The model predicts, on average, 2.18 trips per chain, while the TTS data indicates 2.19 trips per chain (calculated as the total number of trips divided by the number of trips destined for home). This is encouraging since trip chains are an “emergent” outcome of the modeled scheduling process.

Overall, the model replicates observed trip making within what are considered to be acceptable limits for a prototype model. However, there is significant room for refinement in the model as our understanding of activity scheduling rules improves, new data sources become available, and alternative assumptions about such elements of scheduling such as mode choice, location choice, learning and habit formation are tested in the microsimulation framework.

Table 7.1 - Comparison of Modelled to Observed Trips

Trip Destination Type		Trip Comparison by Time Period (1,000's of trips)				Total Daily
		AM Peak Period 6:00am–8:59am	Midday Period 9:00am-2:59pm	PM Peak Period 3:00pm-6:59pm	Night-time Period 7:00pm-5:00am	
Work	Modeled Trips	1187.1	651.9	223.6	222.6	2285.1
	Observed Trips	1366.0	533.7	193.7	153.7	2247.1
	Model +/- Trips	-179.0	118.3	29.9	68.9	38.0
	Model +/- %	-13.1%	22.2%	15.4%	44.8%	1.7%
School	Modeled Trips	533.3	102.9	20.7	8.8	665.8
	Observed Trips	551.5	99.5	22.3	3.9	677.2
	Model +/- Trips	-18.2	3.5	-1.5	4.9	-11.4
	Model +/- %	-3.3%	3.5%	-6.9%	123.3%	-1.7%
Shopping	Modeled Trips	25.7	287.3	287.6	112.5	713.1
	Observed Trips	15.6	411.3	247.4	118.5	792.8
	Model +/- Trips	10.1	-124.0	40.2	-6.0	-79.6
	Model +/- %	65.0%	-30.2%	16.3%	-5.0%	-10.0%
Other	Modeled Trips	86.3	365.7	473.1	333.3	1258.4
	Observed Trips	95.2	507.9	453.1	344.4	1400.6
	Model +/- Trips	-8.9	-142.3	20.0	-11.1	-142.3
	Model +/- %	-9.4%	-28.0%	4.4%	-3.2%	-10.2%
Home	Modeled Trips	27.3	645.4	2247.5	1251.5	4171.6
	Observed Trips	87.2	687.4	2259.8	1253.0	4287.3
	Model +/- Trips	-59.9	-42.0	-12.3	-1.5	-115.7
	Model +/- %	-68.7%	-6.1%	-0.5%	-0.1%	-2.7%
Total	Modeled Trips	1859.6	2053.2	3252.6	1928.7	9094.0
	Observed Trips	2115.5	2239.7	3176.2	1873.5	9405.0
	Model +/- Trips	-255.9	-186.6	76.3	55.1	-311.0
	Model +/- %	-12.1%	-8.3%	2.4%	2.9%	-3.3%

* Facilitate passenger trips collected in the TTS survey (i.e. giving someone a ride) are not included in the TASHA model, but are to be generated in the mode choice model. Conversely, school trips for children under 11 years were not collected in the TTS survey, but are generated in the model. This table only includes trip categories that are included in both the TASHA model and the TTS survey data.

7.3 Trip Comparison by Origin and Destination

Table 7.2 shows a comparison of total daily trips by all modes for all purposes for districts within the Greater Toronto Area. The definition of the districts for this analysis are shown in Figure 7.1. This comparison reflects the quality of the location choice models that have been used in the prototype model. As shown by the row and column sums in Table 7.2, there is a good degree of correspondence between modelled and observed total trips originating and destined for each of the districts. All City of Toronto districts, and the Regions of Durham, York, Peel and Hamilton are modelled within 5% of observed trip totals. The Region of Halton, which is the least populated region in the Greater Toronto Area, is undersimulated at a rate of 7.6% for both total origins and destinations. Most of this undersimulation can be attributed to a lack of modelled trips internal to the region.

External trips are also strongly undersimulated. This is due to the lack of spatial detail for external zones in the model. Since the location of activities in external zones is represented by the centroid of large external zones, the distances to opportunities at the "inner edge" of external zones are overestimated, making those locations less attractive in general. This deficiency could be addressed by developing a more detailed external zone system. Other model validation results by origin, destination and time of day are shown in Appendix E.

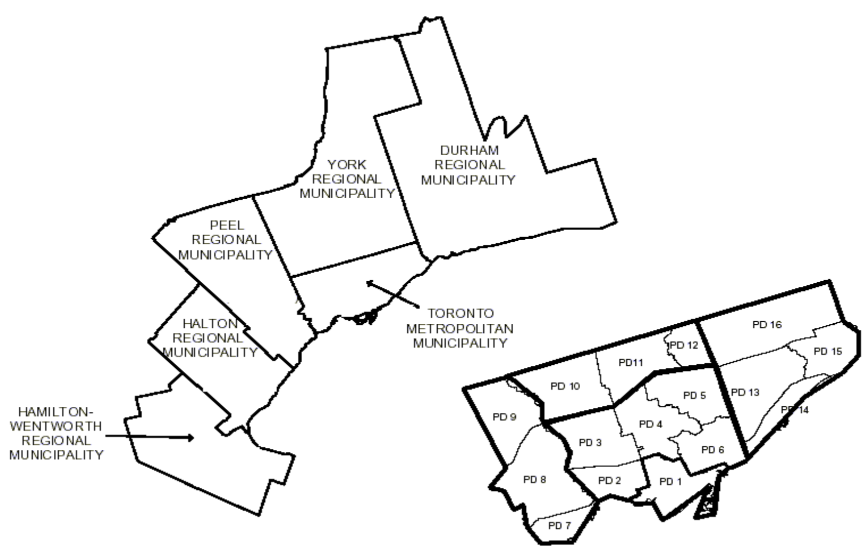

Figure 7.1 – District system used for Origin-Destination Comparison

Table 7.2: Trip Comparison by Origin and Destination, TASHA vs. TTS

Modelled Trips (1,000s)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	210.2	263.7	40.9	45.7	64.6	18.3	40.2	52.3	15.5	3.6	0.7	755.6
2 Toronto PD2-6	262.7	802.4	84.5	139.3	120	15.7	74.1	62	6.7	1.6	2.9	1571.9
3 Toronto PD7-9	40.3	84.9	255.1	43.4	9.5	2.4	27.5	116.2	9.8	2.3	0.8	592.1
4 Toronto PD10-12	46.4	137.6	44.1	286.7	60.8	9.8	106.7	37.2	4.1	1.1	1.3	735.7
5 Toronto PD13-16	64	121.1	9.1	60.5	518.2	42.3	79.5	12.5	1.6	0.4	1.5	910.7
6 Durham	18.3	15.3	2.6	9.8	42.7	665	24.1	4.3	0.4	0.4	2.8	785.7
7 York	40.5	74.2	27.3	106.2	79.2	24.3	678.1	37.7	2.9	0.6	3.3	1074.5
8 Peel	52.9	61.5	116.1	37.8	12.5	4.4	37.3	1110.6	74.9	9.6	4.9	1522.5
9 Halton	16	6.7	9.5	4.1	1.5	0.4	2.9	75	425	62.1	4	607.2
10 Hamilton	3.4	1.7	2.1	1.2	0.3	0.3	0.7	9.5	62.3	736	9	826.6
11 External	0.7	2.8	0.8	1.3	1.4	2.8	3.3	5.1	4	8.9	0.1	31.3
Total	755.6	1571.9	592.1	735.7	910.7	785.7	1074.5	1522.5	607.2	826.6	31.3	9413.8

Observed Trips (1,000s)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	209.5	262.2	37.8	45.1	60.9	19.4	42.7	53.1	16.8	4.8	1.9	754.3
2 Toronto PD2-6	254.7	772.3	73.8	132.5	110.9	17.7	70.9	60.7	8.2	2.7	6.2	1510.6
3 Toronto PD7-9	36.7	72.8	312.1	33.5	9.8	3.2	24.2	103.1	10.5	2.4	3.5	612
4 Toronto PD10-12	45.1	131	34.1	290.9	54.6	10.3	99.7	35.6	4.2	1.3	2.9	709.7
5 Toronto PD13-16	60.8	110.2	9.9	54.4	524.7	41.1	66.2	15.4	2.2	0.6	2.7	888.3
6 Durham	20	17.1	3.4	10.6	39.6	658.1	23.3	5.8	1.1	0.6	8.2	787.7
7 York	43.1	68.9	23.9	95.4	65.6	23.5	693	36.4	3.5	1.3	10.2	1064.9
8 Peel	53.8	61.5	100.3	35.4	16	5.9	37.2	1078.9	67.1	10.8	12.7	1479.4
9 Halton	17.2	7.9	10.2	4.2	2.2	1.1	3.7	67.2	477.5	56.1	9.8	657
10 Hamilton	4.7	2.5	2.4	1.3	0.7	0.5	1.4	10.3	56	748.1	18.9	847.1
11 External	1.2	6.5	3.2	2.4	3.1	8.4	9.4	12.4	9.8	19.6	16	92.1
Total	746.9	1512.9	611.2	705.8	888.2	789.2	1071.7	1478.9	656.9	848.3	93.1	9403.1

Model +/- Trips (1,000s)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	0.7	1.5	3	0.6	3.6	-1.2	-2.5	-0.8	-1.3	-1.2	-1.3	1.3
2 Toronto PD2-6	8	30.1	10.7	6.8	9.1	-2	3.2	1.2	-1.5	-1.1	-3.3	61.3
3 Toronto PD7-9	3.6	12.1	-57	9.8	-0.4	-0.8	3.3	13.1	-0.7	-0.1	-2.7	-19.9
4 Toronto PD10-12	1.3	6.6	10	-4.2	6.2	-0.5	7	1.6	-0.2	-0.2	-1.5	26.1
5 Toronto PD13-16	3.1	10.9	-0.8	6	-6.5	1.3	13.3	-2.8	-0.6	-0.3	-1.3	22.4
6 Durham	-1.7	-1.8	-0.8	-0.8	3.1	6.9	0.8	-1.5	-0.7	-0.2	-5.5	-2.1
7 York	-2.6	5.3	3.4	10.8	13.6	0.8	-14.8	1.3	-0.6	-0.7	-6.9	9.6
8 Peel	-0.8	0	15.7	2.4	-3.5	-1.5	0.2	31.7	7.9	-1.1	-7.7	43.1
9 Halton	-1.1	-1.2	-0.7	-0.1	-0.7	-0.7	-0.8	7.9	-52.5	5.9	-5.8	-49.9
10 Hamilton	-1.3	-0.8	-0.3	-0.2	-0.4	-0.2	-0.7	-0.8	6.3	-12.2	-9.9	-20.5
11 External	-0.6	-3.6	-2.4	-1.2	-1.7	-5.6	-6.1	-7.3	-5.8	-10.7	-15.9	-60.8
Total	8.7	59	-19.1	30	22.5	-3.5	2.8	43.6	-49.8	-21.8	-61.8	10.7

Model +/- Percent

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	0.3%	0.6%	7.9%	1.3%	6.0%	-5.9%	-5.8%	-1.5%	-7.8%	-24.2%	-65.7%	0.2%
2 Toronto PD2-6	3.2%	3.9%	14.5%	5.1%	8.2%	-11.3%	4.5%	2.0%	-18.7%	-39.5%	-53.7%	4.1%
3 Toronto PD7-9	9.7%	16.6%	-18.3%	29.4%	-4.0%	-26.1%	13.5%	12.7%	-6.9%	-3.3%	-76.6%	-3.2%
4 Toronto PD10-12	2.8%	5.0%	29.5%	-1.5%	11.3%	-4.9%	7.1%	4.6%	-3.9%	-18.8%	-53.6%	3.7%
5 Toronto PD13-16	5.2%	9.9%	-8.1%	11.1%	-1.2%	3.1%	20.1%	-18.5%	-28.1%	-39.1%	-46.4%	2.5%
6 Durham	-8.3%	-10.2%	-23.1%	-7.8%	8.0%	1.1%	3.3%	-25.6%	-65.5%	-35.9%	-66.4%	-0.3%
7 York	-6.0%	7.6%	14.3%	11.4%	20.7%	3.3%	-2.1%	3.5%	-16.9%	-50.7%	-67.3%	0.9%
8 Peel	-1.6%	0.0%	15.7%	6.7%	-21.9%	-26.1%	0.4%	2.9%	11.7%	-10.5%	-61.1%	2.9%
9 Halton	-6.5%	-15.1%	-7.2%	-3.4%	-31.1%	-65.1%	-22.7%	11.7%	-11.0%	10.5%	-59.3%	-7.6%
10 Hamilton	-27.8%	-33.0%	-11.2%	-12.9%	-54.1%	-37.0%	-51.6%	-7.7%	11.3%	-1.6%	-52.4%	-2.4%
11 External	-44.3%	-56.0%	-74.2%	-47.5%	-55.2%	-66.3%	-64.5%	-59.0%	-59.1%	-54.6%	-99.3%	-66.0%
Total	1.2%	3.9%	-3.1%	4.2%	2.5%	-0.4%	0.3%	2.9%	-7.6%	-2.6%	-66.4%	0.1%

7.4 Mode Share Comparison

The evaluation of aggregate mode shares that are output from TASHA are an assessment of all components of the TASHA model. If an individual's activity schedule is incorrectly simulated, then the tour configurations may be inappropriate, resulting in incorrect tour mode choices. If the tours of multiple household members are not timed properly in the scheduling model, then car allocation may not be realistic and ridesharing opportunities may not be found. If location choice is improperly simulated, then mode choices will obviously be affected. Since mode choice is the last sequential component of the model to be simulated, all errors from previous modules are incorporated in the mode choice results. This is the case with the four-stage model, and any other model that sequentially simulates multiple travel behaviour components. For this reason, the comparison of mode shares is a strong test of overall model performance.

Table 7.3a shows the aggregate modelled and observed mode shares for all trips for all time periods for all trip purposes. The aggregate mode shares show some important differences:

- For 2.6% of total trips, no feasible mode could be predicted by the TASHA model. This is due to the sequential nature of the TASHA approach. In these cases, an activity schedule was developed for an individual that could not be supported with the modes available to that person. One example that would lead to such a result would be if multiple household members simultaneously needed the sole household vehicle for tours to different locations. If transit was not available, the distance was too far to walk and trips were at significantly different times to prevent a reasonable dropoff/pickup, then no alternatives would exist for the individual. Another example would be if a location were chosen for someone with no vehicle that was not accessible by transit and too far to walk. The fact that such a small proportion of trips are infeasible by any mode is encouraging.

Table 7.3 – Aggregate Mode Share Comparison, TASHA vs. TTS

(a) Mode Shares for All Trips

	TASHA Model		TTS Processed households[1]	
Mode of Transport	Weighted Trips[2]	Mode Share	Weighted Trips[2]	Mode Share
No modes available[3]	227000	2.6%	0	0.0%
Drive	4977000	56.8%	2828000	60.9%
Transit all-way	1841000	21.0%	732000	15.8%
Walk	904000	10.3%	325000	7.0%
Rideshare (to joint activities)	568000	6.5%	594000	12.8%
Passenger (dropoff/pickup)	239000	2.7%	161000	3.5%
Total	8756000	100.0%	4640000	100.0%

(b) Mode Shares for Pure Joint Tours

	TASHA Model		TTS Processed households[1]	
Mode of Transport	Weighted Trips[2]	Mode Share	Weighted Trips[2]	Mode Share
No modes available[3]	2000	0.3%	0	0.0%
Drive	0	0.0%	0	0.0%
Transit all-way	27000	4.3%	32000	5.0%
Walk	25000	4.1%	1000	0.2%
Rideshare (to joint activities)	568000	90.7%	594000	94.8%
Passenger (dropoff/pickup)	4000	0.6%	0	0.0%
Total	626000	100.0%	626000	100.0%

(c) Mode Shares for Tours Not Including Pure Joint Tours

	TASHA Model		TTS Processed households[1]	
Mode of Transport	Weighted Trips[2]	Mode Share	Weighted Trips[2]	Mode Share
No modes available[3]	225000	2.8%	0	0.0%
Drive	4977000	61.2%	2828000	70.5%
Transit all-way	1814000	22.3%	700000	17.5%
Walk	878000	10.8%	324000	8.1%
Rideshare (to joint activities)	0	0.0%	0	0.0%
Passenger (dropoff/pickup)	235000	2.9%	161000	4.0%
Total	8130000	100.0%	4014000	100.0%

1 All households with problematic data or that used minor modes including bicycle, schoolbus, taxi, carpool are removed for this comparison
2 Weighting factors are calculated for the TTS survey to allow the full population to be represented by a 5% sample The same weighting factors are applied to TASHA model results for this comparison
3 Because activity schedules are calculated sequentially before the mode choices are made, some schedules are infeasible by any mode of transportation
4 Trips made by children under 11 years old are not included in the TTS data and therefore are also removed from the mode share analysis of the TASHA model. Such trips are most often made by the walk and passenger modes.

- The overall share of modelled trips made by rideshare (6.5%) is only about half of the observed rate (12.8%). This is a product of the "bottom up" nature of schedule development assumed in TASHA. Rideshare, by definition, is only available for pure joint tours (tours that involve only joint activities and joint travel for multiple household members on all trips in the tour). The proportion of simulated trips on pure joint tours is 7.1%, whereas the observed proportion of trips on pure joint tours is 13.5%. Other joint activities in the TASHA model are clearly being accessed from different locations. For example, for TASHA is likely overpredicting joint shopping activities where one person arrives directly from work, and another participant arrives from home. Scenarios such as this would explain the overall oversimulation in transit and walk modes, since one person would likely be simulated to walk or take transit to meet at the joint activity and catch a ride home. Breaking the mode shares into those for pure joint tours, and non-pure joint tours (in Tables 7.3b and c, respectively) leads to more encouraging results. Table 7.3b shows that mode share attributed to rideshare (90.7%) for pure joint tours is close to the observed value of 94.8%.

- Table 7.3b also shows that walk mode is chosen for very few (0.2%) observed pure joint tours. Pure joint tours only include those trips to joint shopping and joint other activities. Yet it is noted that the TTS does not collect information on short walk trips except for school and work destination purposes. Hence the modelled walk mode share of 4.1% is more realistic than the very low corresponding observed mode share.

The differences in aggregate mode shares are reasonable given the number of model components that can lead to deficiencies. The main conclusion to be drawn from this analysis is that the sequential nature of TASHA makes it very difficult to predict travel by mode correctly. Clearly a high priority for model development should be to incorporate mode feasibility into scheduling decisions more directly. For example, if the two processes were integrated, it would be possible to revisit a scheduling decision (perhaps change the timing or location of an activity) such that there would always be a feasible means of getting to and from that activity. Such improvements are further discussed in Chapter 9.

8. Policy Applications

8.1 Introduction

TASHA was designed to improve upon current four-stage modelling systems used in the Toronto Area in several ways, most importantly, the behavioural representation of human decision making, the spatial and temporal precision of outputs, and the sensitivity to demand oriented policies. This chapter begins in Section 8.2 with a summary of the major differences between TASHA and the four-stage modelling system. This comparison sets the context for a discussion of new potential policy applications of TASHA in Section 8.3.

8.2 Comparison of TASHA and the Four-Stage Model

The conceptual designs of the currently used four-stage model and the TASHA model are outlined in Figure 8.1 and a comparative summary of the basic features is shown in Table 8.1. As noted in previous chapters, one of the most profound differences between TASHA and the four-stage model is that TASHA is a fully disaggregate microsimulation model. In other words, TASHA assesses choices at the individual level, and passes the outcomes of those individual decisions to subsequent stages of the model. This is in contrast to the four-stage model, which performs most calculations at the more aggregate level of the traffic zone and passes Origin Destination (OD) trip tables from stage to stage. Microsimulation is the key design principle that makes possible numerous methodological improvements shown in Table 8.2.

A series of discussion and workshops with potential users of the TASHA modelling system indicated that increased data requirements are a barrier to the infusion of new methods into practice (Roorda and Lee-Gosselin, 2005). TASHA was deliberately designed to improve behavioural realism, precision and policy sensitivity without requiring more data inputs than the four-stage model. Both require data from a conventional trip diary survey, and for forecasting, both require future year zonal population estimates, zonal occupational employment estimates and future year transportation networks.

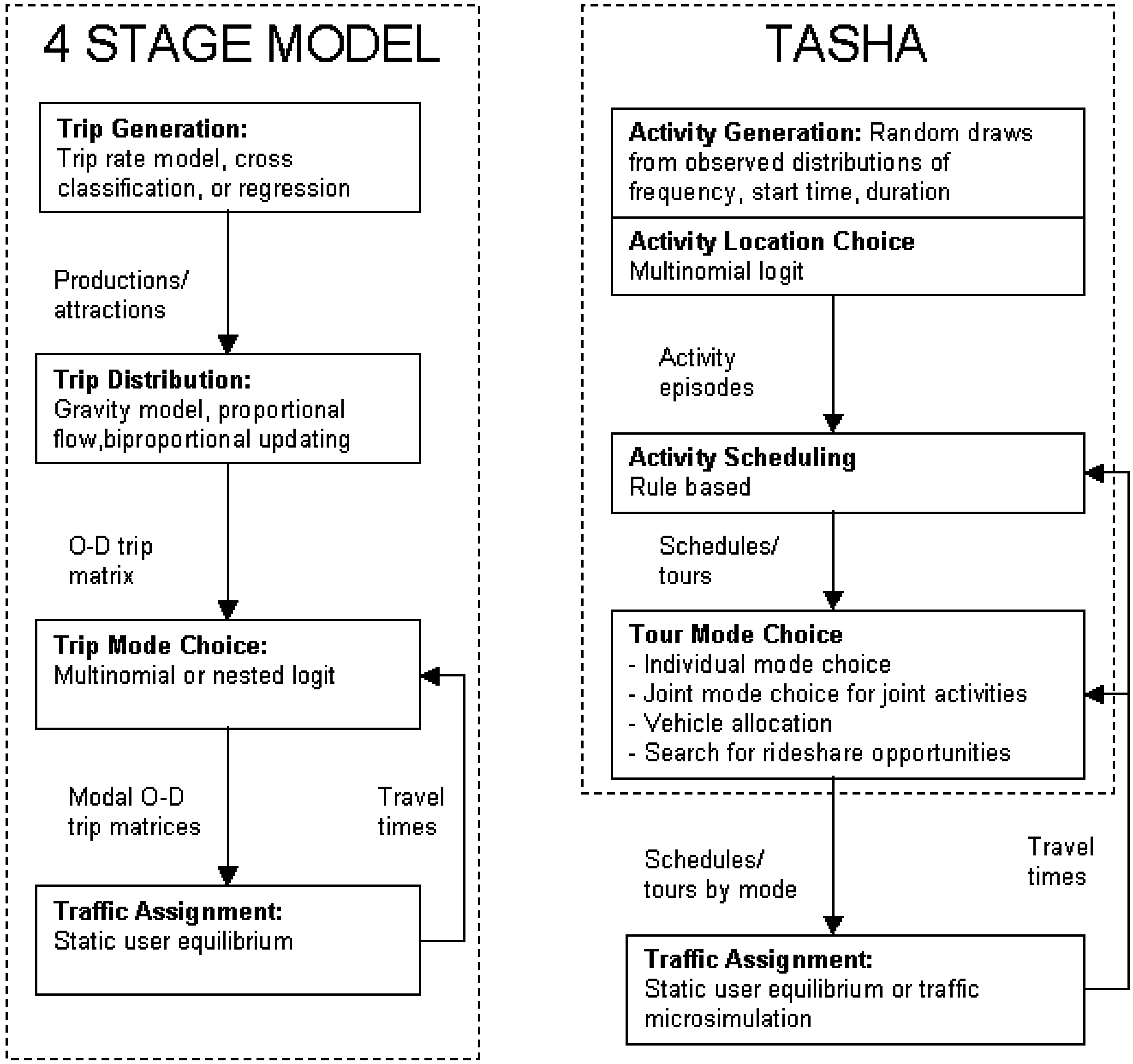

Figure 8.1 - Conceptual designs of the four-stage model and TASHA

Table 8.1 - Comparison of features of the four-stage model and TASHA

Model Feature	**Four stage model**	**TASHA**
Level of disaggregation	Household / zone	Person / household
Unit of analysis	Trip	Activity episode
Inputs requirements	Conventional trip diary data Population, employment forecasts	Conventional trip diary data Population, employment forecasts
Outputs	Zonal origin-destination trip tables Assigned transit and traffic flows	Tours, activity schedules Assigned transit and traffic flows
Period of analysis	Peak hour	24 hour period
Temporal aggregation	1 hour	5 minutes
Spatial aggregation	Traffic zone level	The prototype version is developed at the zonal level of detail. However, this could be disaggregated to specific locations if such spatially disaggregate information is available.
Computational requirements	Trip generation, distribution and mode choice require fairly minimal computational resources. Trip assignments in EMME/2 require moderate computation.	TASHA runs quickly, but requires substantial RAM memory. Parameter estimation for the tour based mode choice model requires heavy computation (including parallel processing). Trip assignments in EMME/2 require moderate computation.
Parameter Estimation	Conventional methods and software are used.	A genetic algorithm is required to estimate the parameters of the mode choice component

Table 8.2 - Comparison of methods of the four-stage model and TASHA

Model Component	**Four-stage model method**	**TASHA method**
Population synthesis	The four-stage model is aggregate in nature. Therefore no population synthesis is required.	Population synthesis is currently done for future years applying a biproportional updating method to base year occupational place-of-residence place-of-work tables to match future zonal population and employment totals.
Trip / activity generation	Trips are generated using linear regression, cross-classification, or trip rate models	Activities are simulated based on observed distributions available from TTS data. Tours are an outcome of the activity scheduling process.
Trip / activity distribution	Trip distribution is done either using gravity model, a proportional flow model, or biproportional updating. These methods are all at the zonal level of analysis.	Multinomial logit location choice models are used to choose the location of non-work out-of-home activities. Location choice is a function of the attributes of the person, the household, and zonal attributes such as employment or retail floor space.
Mode Choice	Multinomial or nested logit models are used to predict mode choice. These models are at the zone or the individual level of analysis. Choices are typically made for individual trips, without a tour logic, and without enforcing an overall household logic.	A tour-based mode choice model operates at the person and the household level. Mode choices are made at the individual level, but are subject to household vehicle constraints via an explicit vehicle allocation model. The mode choice algorithm treats ridesharing as a utility-based negotiation between household members.
Trip Assignment	Trip assignment is done for total O-D peak hour trips using EMME/2, TransCAD, or other static user equilibrium models	Trip assignment is currently done using EMME/2. However, because individual tours are generated by TASHA with a 5-minute temporal precision, a micro- or meso-scopic traffic simulation with dynamic traffic assignment is feasible.
Incorporation of *intra*-household interactions	Since there is no disaggregation to a level lower than the household, within household interactions cannot be represented	Explicitly represents joint activities, sharing of household vehicles, and within-household ridesharing. Does not incorporate task allocation of maintenance activities within the household.
Incorporation of *inter*-household interactions	No inter-household interactions (aside from trip assignment) such as carpooling between households can be represented	No inter-household interactions are represented. However, the agent-based microsimulation framework provides a laboratory for testing interactions such as carpooling

8.3 Policy Applications of TASHA

The first application of the prototype version of TASHA was in the policy context of travel and emissions estimation for alternative land use scenarios in the Greater Toronto Area (Miller and Roorda, 2002). Clearly, more conventional four-stage models can also be used to evaluate land use scenarios by altering population and employment inputs. The primary advantages associated with TASHA forecasts in this context were the reduction of aggregation biases associated with the use of zone based modelling, the provision of emissions estimates for a 24-hour period (compared to peak period estimates only for the four-stage model), and an improved behavioural realism associated with the method for estimating travel.

However, perhaps the most critical advantage of the TASHA model is its sensitivity to demand oriented policy instruments. The TASHA model was designed to overcome the inability of current state-of-practice models to adequately assess demand oriented policy solutions to transportation problems. The following sections describe in detail three particular policy questions for which the TASHA model is considered to provide insights that are not provided by the four-stage model.

- Alternative hours (flexible working hours, compressed work weeks, staggered shifts, and telecommunications substitution for travel)
- High occupancy vehicle lanes
- ITS initiatives

8.3.1 Alternative hours

The goal of alternative hours is to allow individuals a greater freedom in their choice of when to travel. Such strategies allow individuals to avoid recurring congestion by travelling during off-peak times, and in some cases reducing total travel. Forms of alternative work hours include staggered work shifts (employees shifts begin and end at various times selected by the employer), flexible work hours (employees are given some choice over arrival and departure times from work), compressed work weeks (employees work longer hours in fewer days to achieve the same total work hours) and telecommunications substitution for travel (including telework, conference calls, online shopping, schooling and recreation).

Alternative hours strategies are a popular policy tool by government and public institutions since they generally require no investment in transportation infrastructure, but are intended to encourage better use of existing transportation capacity. For example, the Smart Commute Initiative was recently formed in the Greater Toronto Area to develop transportation management associations (TMAs) that will promote TDM measures including alternative hours strategies (Smart Commute Initiative, 2003). However, such strategies can be less successful than anticipated if the constraints and opportunities available to a household are not fully considered. For example:

- A worker on a compressed work week may opportunistically use available time on their additional day off to make additional recreation or shopping trips.
- Worker acceptance of flexible work hours may be constrained by the schedules of other household members such as children that must be dropped off at or picked up from day care, or other household members that would like to use the family vehicle.
- Telecommunications may substitute for some work or leisure trips, but may result in a more dispersed social or business network, resulting in a greater distance trips when they do occur.

Current state-of-practice models used in the Toronto Area are basically insensitive to alternative hours policy scenarios and the resulting secondary effects, because:

- They are trip-based, therefore, substitution of activities for travel cannot be represented
- They do not represent interactions and negotiations within a household, and therefore cannot properly represent the circumstances that constrain the effect of alternative work hours.

- They typically model the peak period only, and cannot easily be used to assess impacts in off peak travel or on the "shoulders" of the peak hour and the associated congestion and pollution effects.

TASHA is a modelling framework in which activity scheduling constraints and negotiations between household members are explicitly modelled. Thus, household circumstances that may reduce the effectiveness of alternative hours policies can be accounted for and better estimates of the transportation impact can be made.

8.3.2 High occupancy vehicles – HOV (ride-sharing, car-pooling).

The effective use of scarce roadway capacity through encouraging higher average auto occupancies (including the allocation of dedicated lanes to HOVs) is an issue of concern to urban communities across Canada. In the Toronto Area, there are currently over 60 km of HOV lanes in operation in the Greater Toronto Area (MRC, 2005), and the first HOV lanes on Ontario highways were scheduled to open in the Fall of 2005 (CNW, 2004). HOV lanes provide a travel time incentive to transit users and to individuals that share a ride with another person. Such incentives have the potential to reduce the number of vehicles in HOV corridors, if drivers take advantage of HOV lanes by either carpooling, ridesharing with family members. However, HOV lanes can result in increased congestion if they take the place of regular lanes of traffic and single occupancy vehicle traffic does not decrease substantially. It is therefore critical to assess the ability and willingness of individual drivers to share rides or take transit and take advantage of HOV lanes.

Four-stage models can be used to evaluate mode choice between automobile, transit and auto passenger modes, thus they can be used to evaluate HOV initiatives in a crude manner. However, the typical mode choice models used are developed, at best, for an individual only. Ridesharing, however, inherently involves communication and negotiation between two or more persons. The process of finding a "match" between individuals travelling approximately from the same origin to the same destination at the same time is critical to the availability of ridesharing as a feasible mode.

As a household-based activity/travel model, TASHA is unique in its ability to model within-household ridesharing. Ridesharing results from the scheduling process in one of three ways in the TASHA model. Activity schedules of all household members are first developed, with joint activities being added simultaneously into the schedules of those people. Hence, ridesharing to joint activities is an inherent part of the scheduling process. Second, ridesharing opportunities are also found for people accessing different activities in compatible locations at compatible times. The underlying principle of the model is that a person will drop off or pick up another household member en route to his/her own destination if the utility gain for the passenger of the trip exceeds the utility loss for the driver. Finally, home-based trips that are made solely for purpose of dropping off or picking up another passenger, are allowed for, if there are no other transportation options for the passenger or the utility gain of the passenger exceeds the utility loss of the driver. The three modes of ridesharing are discussed in detail in Chapter 6.

Clearly the complete assessment of an HOV initiative would require the capability to model carpooling. The current version of TASHA does not model inter-household carpooling. Modelling carpooling in a credible, "behavioural" fashion is an extremely difficult, unsolved problem that should be the focus of dedicated research efforts. There is no model comparable to TASHA worldwide at this time that adequately handles the inter-household car-pool problem.

8.3.3 Intelligent Transportation Systems (ITS)

ITS involve such technologies as:

a) En-route route guidance: Automated traffic information systems (ATIS), including variable message signs (VMS), and in-vehicle navigation tools.
b) Pre-trip route guidance: Real time internet traffic information, real time transit scheduling
c) Real-time system control (e.g. traffic responsive ramp metering and signal control)
d) Incident detection

Investment in ITS infrastructure can be one of the most cost-effective ways to improve the performance of transportation systems. Generally, ITS improves the capacity of highway and transit infrastructure while avoiding many of the social and environmental impacts associated with new highway lanes, such as traffic delays due to construction and the use of agricultural, environmentally sensitive or residential land. It is critical that both short- and long-term planning models be able to assess the impacts of ITS investment policies.

ITS technologies affect transportation systems in two fundamental ways. First, real-time system control and incident detection affects transportation system performance from the supply side. In general, incidents can be cleared more quickly and freeway and arterial queuing can be reduced, making travel times shorter and more reliable. Second, en-route and pre-trip guidance provided to travellers affects their behaviour. Information provided to individuals can influence the routes and modes chosen, and occasionally the location of, or the participation in activities of individuals.

Static macroscopic traffic assignment models currently used in practice, such as EMME/2 and TransCAD, are unable to adequately assess such impacts of ITS. Rather, micro- or meso-scopic simulation models with dynamic traffic assignment are becoming increasing used (e.g. Mahmassani *et al.*, 2004; Ben-Akiva *et al.*, 1997; de Palma and Marchal, 2002; TRANSIMS, 2004). These models require time varying inputs. For example, a microscopic traffic simulation loads individual vehicles onto a traffic network at specific points in time at specific locations. Yet typical planning level models only provide total origin destination flows that are aggregated to a one-hour period and to a coarse traffic zone system. To use such matrices as input to a microsimulation model requires assumptions about the temporal profile and the exact location of vehicle entries into the traffic network. These are crude assumptions and can have adverse effects on the accuracy of microscopic simulation models.

Currently, TASHA interfaces with a macroscopic static user equilibrium traffic assignment model, as does the four-stage model. However, the precision of TASHA outputs is appropriate for micro-or meso-scopic simulations. Trips and activities are output at a precision of five minutes and disaggregate work and home location data at the block face or even the individual building level can be used if the data are available.

There exists the possibility of developing a feedback mechanism that allows the experiences of the traveller on the traffic network to impact their activity schedule. For example, if a traveler experiences recurring congestion on the drive to work, they may adjust their departure time appropriately or find alternative strategies to improve their commute. Such learning mechanisms have been studied (e.g. Chang and Mahmassani, 1988; Sun *et al*., 2005) but are not a current feature of the prototype version of the TASHA model. The object-oriented nature of TASHA and the fact that it is a microsimulation model with explicit representation of individuals facilitate such extensions.

The ability to assess long- and short-range planning impacts of ITS technologies should be a key feature of a planning model. Currently, neither the traditional 4-stage model nor the TASHA activity-based microsimulation model is sensitive to ITS-related policy. However, TASHA clearly is capable of providing the necessary temporal and spatial precision to make use of the capabilities of dynamic traffic assignment and traffic microsimulation methods, and is ideally set up to incorporate learning mechanisms and other behavioural responses to ITS information.

8.4 Conclusions

There is a clearly a need for improved modelling methods to assess demand oriented transportation policies. This chapter has argued that the TASHA modelling system, whose first prototype version has been developed for the Greater Toronto Area, is a successful example of such a method. This model is particularly well-suited to assess:

- Alternative hours (flexible working hours, compressed work weeks, staggered shifts, and telecommunications substitution for travel)
- High occupancy vehicle lanes
- ITS initiatives

TASHA has been designed for streamlined infusion into practice. In particular, it does not require any additional input requirements for model application beyond those of the four-stage model. With some additional validation, testing, and software engineering, it is hoped that TASHA will become a "next generation" of travel demand modelling tool for transportation planners in the GTA.

9. Future Work

Abundant opportunities for future research emerge from the work presented in this thesis. The models that have been described in previous chapters are a significant improvement upon the current state-of-practice in travel demand modelling, and comprise a unique combination of features not found in other modelling efforts reported on in the literature. But as with any good research, as some problems are solved an even greater number of questions and research opportunities bubble to the surface. Improvements to the models developed so far can be categorized as shown in Figure 9.1. Each category of model development is discussed in the

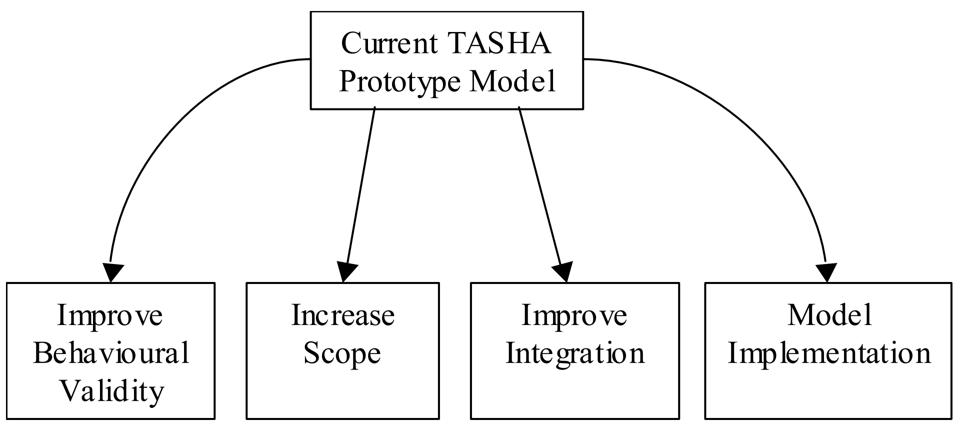

Figure 9.1 – Categories of future work

9.1 Improvements in Behavioural Validity

In Chapters 5 and 6, the behavioural assumptions of the activity scheduling and mode choice components of TASHA are outlined in detail. As noted in Table 5.2, there are significant challenges to validate or improve upon on these assumptions. Probably the principal challenge, one that largely dictates priorities for further model development, is the availability of data. Given that the appropriate data are available, improvements to the model would logically be done by addressing those assumptions that would yield the greatest improvement in behavioural validity for the least effort in both development / analysis of the new approach and in the integration of the new approach into the current operational modelling framework.

One of the major objectives of this thesis, as described in Chapter 3, was to collect the data necessary for future validation and improvement of the behavioural assumptions in the model.

The highest priority model improvements for the time being, therefore, are those that require no additional data (i.e. can be done using TTS data or data from the Travel Activity Panel Survey).

Those behavioural improvements that require TTS data include:

- Improving the activity location choice model within TASHA
- Developing an activity generation model to generalize the current use of activity attribute distributions currently used in TASHA,

Those that require data from the Travel Activity Panel Survey include:

- Incorporation of additional joint household decisions such as the care of children
- Applying different strategies for scheduling to different people
- A much more detailed representation of episodes and projects
- A more detailed representation of the "execution stage" of schedule formation

Further behavioural improvements will require new data, as follows:

There is a need for a Toronto based survey that attempts to capture directly how a person's activities of different types are linked together with a common purpose or objective[8]. This is crucial since the scheduling model is built upon the concept of the project and it would be much better to fully elaborate the concept with observed data. One possibility for collecting such information would be through an "add-on" to the core CHASE survey instrument being used in the Travel Activity Panel Survey. A series of probing questions could be asked of respondents to establish links between activities that they have entered into the week-long

[8] The first wave of the Travel Activity Panel Survey in Quebec has collected some information on the organization of activities into projects. This data is qualitative in nature, and had not yet been compiled at the time this thesis was written. An attempt was also made to implement a systematic set of questions about the organization of activities into projects for the 3rd wave in Toronto. However, this initiative was abandoned after extensive pretesting indicated that the questioning was confusing for respondents and was not yielding useful results.

schedule diary. This could work effectively, but it risks overly burdening CHASE participants, which would also have implications for data quality. Another possibility would be to design a "targeted" face-to-face survey asking respondents about a general activity or event that they are planning for the near future (such as a home maintenance project, a family outing or a dinner party). Respondents would then be asked probing questions to determine all of the activities that they have already done or will do that are related to that event.

The ways in which attributes of activities may be differentially decided is an important concern – for example, when planning activities, people often only partially plan (or do not plan at all) certain activity attributes such as location, exact timing, the travel mode, or involved persons. Assuming that all attributes are decided at once, in the same sequence, will certainly not hold all the time. Investigating these sequences is key to future model development.

Another area of important concern is that of "decision rules" utilized throughout the scheduling process. Although the application of rule-based approach to travel behaviour modelling has been taken up in the literature (e.g. Gärling *et al.*, 1986; Lundberg, 1988), very little direct empirical evidence has been published on the nature of the decision rules utilized during the activity scheduling process. One technique for investigating the actual rules used to is to ask people to "think aloud" during a problem solving exercise (see also Ericsson and Simon, 1993). An alternative would be to provide some means to query people live during a scheduling survey, perhaps via telephone or other recording device. Such data could lead to the development of alternative rule-based modelling structures.

A new in-depth survey would be useful to fully understand how and why "desired" activity attributes (before any scheduling has taken place) differ from "executed" activity attributes (after time and resource constraints are realized in the scheduling process). The design of such a survey would not be straightforward. Nonetheless, the concept should be further explored because the current model implementation, which uses "executed" activity data from TTS to generate "desired" activity attributes is not entirely satisfactory in a behavioural sense.

9.2 Improvements in Scope

To successfully develop and validate an operational model of activity scheduling and mode choice, it was necessary to initially limit the model's scope. This has allowed us to focus our attention and energy on the elements of travel behaviour that we felt to be the most critical, without being overwhelmed by the size and complexity of the problem. We "walked before we ran". Furthermore, many decisions of scope were made because of data limitations and our desire to base our method on the same data currently being used for transportation demand modelling in practice. That said, the model could be improved behaviourally and in terms of policy sensitivity by increasing its scope, as follows:

Extend from a 24 hour model to a week-long model - The primary benefit of this would be at the activity generation stage. Some activities (such as grocery shopping, swimming lessons, university courses, etc.) have a weekly cycle and their timing depends greatly on the time since the activity was last done. There is better potential to capture the dynamic nature of the scheduling process in a weeklong model.

Implement a 100% microsimulation of all people in the urban area – Our current microsimulation is of the 5% population sample that was surveyed in the 1996 TTS, and each microsimulation person is assigned an expansion factor to result in representative total population behaviour. Expansion to a 100% microsimulation would require development of a population synthesis technique to generate households that represent the full heterogeneity of the population.

Extend the mode choice model to include minor modes of transportation – Currently the major transportation modes of drive, transit (not including transit trips with drive access or egress), walk and rideshare/passenger are available as options for a trip-maker. Minor modes such as schoolbus, bicycle, taxi, commuter rail, park 'n' ride and kiss 'n' ride amount to less than 5% of total trips in the GTA, but are extremely important from a policy standpoint.

Fully elaborate the children's schedules and the "serve dependent" project – Since children under the age of 11 years old were not covered in the TTS survey, they are poorly represented in the activity scheduling process. Yet we know that the need to care for and support children can strongly constrain an adult's propensity to do different types of activity and can influence their need to travel. Data from the Travel Activity Panel Survey does not directly capture the schedules of children. However, all adults in the household are asked, for each activity, the names of the children that were under their care at the time. This could allow for much improvement in the representation of childrens' schedules.

9.3 Improvements in Integration

Decisions are not made in isolation from each other. Although each decision is separated out into distinct modules within a larger modelling framework (with appropriate information passing from one decision to another), we must remember that all of these decisions are made in the single person's mind. Although people do not make all decisions simultaneously, some decisions are closely integrated with each other. The challenge we have as modellers is to decide on the appropriate level of integration and how that integration should be best implemented into a model. For simplicity, the current TASHA model assumes sequential decisions:

- Auto ownership, residential and work location are considered to be inputs into the TASHA activity scheduling model,
- The activity scheduling model builds schedules assuming auto-drive travel times, and passes tours to the mode choice model,
- The TASHA mode choice model determines the modes chosen for each trip on each tour, and passes the tours to a traffic assignment model to calculate travel times.
- The capability exists to allow revised travel times to then be fed back into the activity scheduling and mode choice models for consistency.

However, improved integration is a future research objective in the following ways:

The decisions of activity scheduling and mode choice within TASHA should be more closely integrated with mode specific travel times – People without access to a car would not build a schedule based on auto-drive travel times (as is currently assumed) if they fully expected to use transit or walk modes. Although people don't always make the final decision for their mode of transportation at the time when they decide to do activities, we feel that it is probably better to assume that people evaluate the mode of transportation as activities are added to the schedule, rather than after the entire activity schedule is complete.

There is an opportunity to fully exploit the richness of the activity-based modelling approach by integrating TASHA with a microscopic traffic assignment model - Clearly microscopic traffic simulation provides more precision, as well as more accuracy compared to static user equilibrium models, which is of interest in the development of models of activity scheduling. Some of the major problems with static user equilibrium assignments are that 1) they assume equilibrium, which is argued by some to be a fundamentally flawed concept (Goodwin, 1998), 2) they are not dynamic and cannot handle changes in demand over short periods of time, and 3) since traffic congestion cannot pass from link to link, queuing buildup, discharge, and shockwaves cannot be accounted for, therefore control strategies and information systems cannot be assessed with any kind of precision.

There is a strong feedback relationship between congestion and activity scheduling decisions. Activities that involve travel must have an estimate of the travel time in order to be scheduled. For scheduling purposes, the level of precision with which the travel time is known depends on the variability in traffic conditions and the familiarity that the person has with the route. A proper model of activity scheduling would require some representation of the learning process that a person has with regard to the variability of a particular route at a particular time of day (see Arentze and Timmermans (2000) for an example of how learning can be incorporated into a decision-making framework). This variability could be assessed in a traffic microsimulation model.

TASHA can provide the necessary inputs for microsimulation models of traffic congestion, both for current and forecast years. Traffic microsimulation models require minute-to-minute estimates of entries into a network, preferably at a detailed level of spatial disaggregation. Thus, integration between TASHA and a traffic microsimulation model would not only improve activity scheduling model performance but would provide much better inputs for microscopic traffic models.

Finally, integration with an activity-based model would allow traffic microsimulations to be demand responsive beyond the typical route-choice. As cited by Stern (1998), one study of executives in the Netherlands found that the most likely responses to congestion were "earlier departure from home" and "changing work hours", while "changing route to/from work", was only the third most likely response.

The principal barrier to integrating TASHA with a traffic microsimulation model is that the computational effort is currently too large to effectively simulate traffic microscopically using standard packages at the regional level. However, TRANSIMS has made significant strides in developing regional scale traffic microsimulators (Nagel *et al*., 1998), and with improvements in computing power, such integration may be feasible in the near future.

TASHA was designed to be integrated with long-term decisions such as location choice and automobile ownership within the ILUTE modelling framework, shown in Figure 1.1 – Aside from technical difficulty of merging TASHA code into the ILUTE program, the key points of integration requiring elaboration are the feedbacks *from* TASHA *to* longer term decisions of location choice and automobile ownership (shown in dotted lines in Figure 1.1). Significant conceptual thought has been put into the nature of this feedback (Salvini, 2003; Miller, 2005a; Litwin and Miller, 2004). In particular, the concept of the "stressor" has been incorporated into the ILUTE modelling framework as a form of feedback between recurring short term events and long term decisions (see Salvini, 2003 and Miller, 2005a for more details). Application of the stressor concept to activity scheduling would involve the development of measures of "scheduling stress". Households that repeatedly experience long travel times to regular activities, an inability to find the time to execute all desired activities, or regular household conflicts over usage of vehicles, have a level of "scheduling stress" that may "trigger" a longer term decision to purchase a new household vehicle or change job or residence location. Development of behaviourally appropriate measures of scheduling stress will require careful research.

9.4 Model Implementation

There is a great deal of research that must be done before the TASHA system is ready for implementation in real transportation planning policy analysis. The following work needs to be done to prepare TASHA for use in practice:

Extensive model verification and validation is required beyond that discussed in Chapter 7 – Model verification and validation discussed in Chapter 7 include the aggregate assessment of key system-wide travel demand characteristics, including activity participation and trip making by purpose, by time of day, by location and by mode.

Additional tests have yet to be done to test the need for model replications to obtain statistically reliable simulation results, and the need for feedback iterations to ensure that assigned travel times are consistent with those assumed in the activity scheduling and mode choice processes. Analysis should be done to assess the sensitivity of the model to a limited number of policy scenarios. Finally, analysis should be done to test the ability of TASHA to forecast future year conditions. Fortunately, the Transportation Tomorrow Survey is undertaken every five years in the Greater Toronto Area. This provides an opportunity to test forecasts of the models calibrated on 1996 base year data for a five-year forecast. Such a forecasting test should be done in parallel with that of a conventional model, to allow for a direct comparison of forecasting performance.

Demonstration projects are necessary to test TASHA's ability to provide better travel forecasts, and increased policy sensitivity than conventional methods - Most practitioners are unlikely to risk the investment in a new modelling approach unless it has been successfully applied to real projects with credible results, within a reasonable budget. Thus, the research programme should place priority on the development of a set of test projects that demonstrate the range of capabilities of the model. This includes test projects that can be analyze using more conventional methods (such as major improvements to highway or transit infrastructure, alternative land use scenarios) and those that cannot be adequately modelled using conventional methods (such as HOV lanes, alternative hours policies, ITS initiatives, etc.)

TASHA needs to be reprogrammed as "production-grade software" – Priorities for reprogramming are to develop a graphical user interface, increase running speed and reduce the need for CPU and memory. Formal testing of the program in a wide range of modelling scenarios would eliminate the potential for minor software bugs.

10. Conclusions

The research presented in this thesis represents significant progress in three research areas. First, a major in-depth longitudinal data collection effort has been undertaken which has provided groundbreaking information on various elements of the activity scheduling process. Analysis of these new data, both within this thesis and by other analysts, has significantly improved our understanding of behavioural processes surrounding household activity scheduling. Second, a new rule-based technique for simulating activity schedules has been developed. Third, a tour-based mode choice model that incorporates crucial household interactions including vehicle allocation, ridesharing to joint activities and dropoff/pickup scenarios has been estimated and applied in a large-scale microsimulation framework. It is felt that the coordinated efforts on these three research projects has led to a modelling system that is more behaviourally valid than current state-of-practice models, provides more precise outputs with no additional input requirements, and has potential for the analysis of contemporary demand-oriented policies. With some additional research, testing and development, it is felt that this approach can evolve to become the “next generation” of travel demand modelling for major urban centres such as the Greater Toronto Area.

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Appendix A: Travel Activity Panel Survey, Wave 1: CHASE

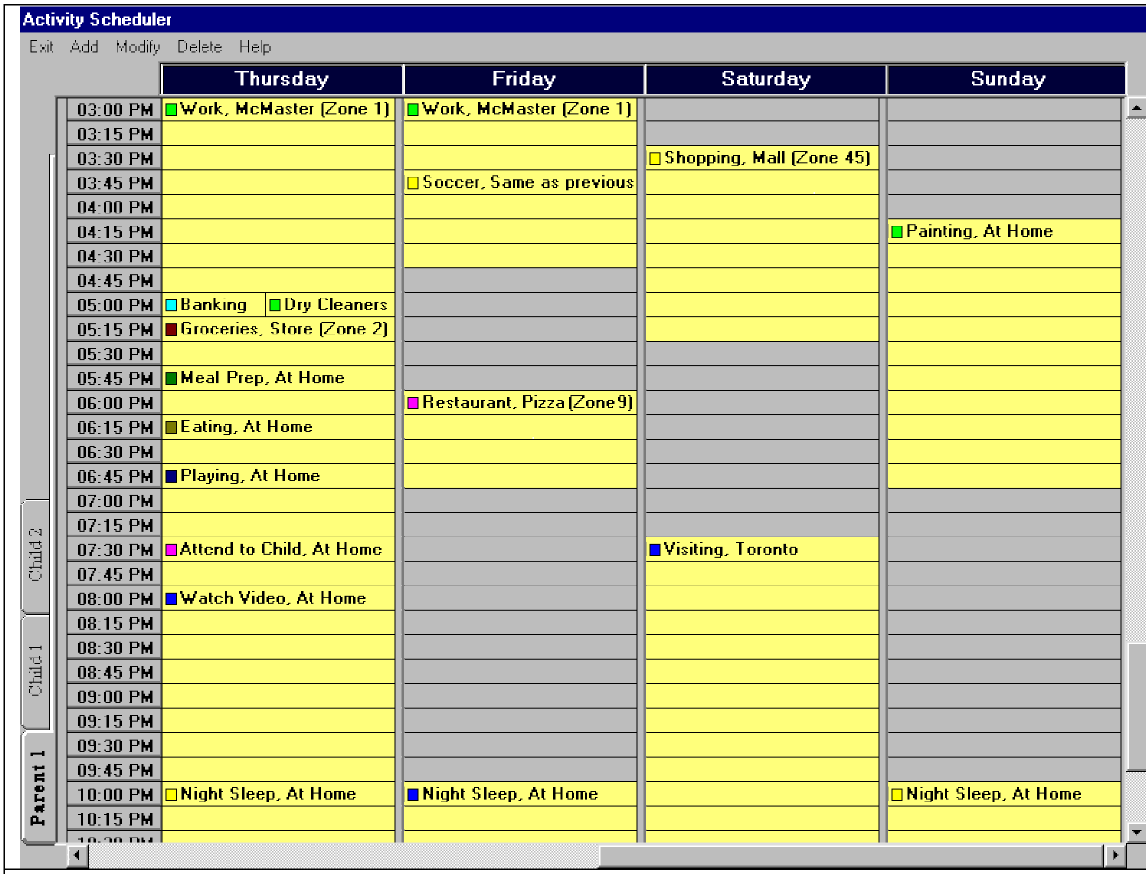

Figure A1 - CHASE - Example Partial Schedule

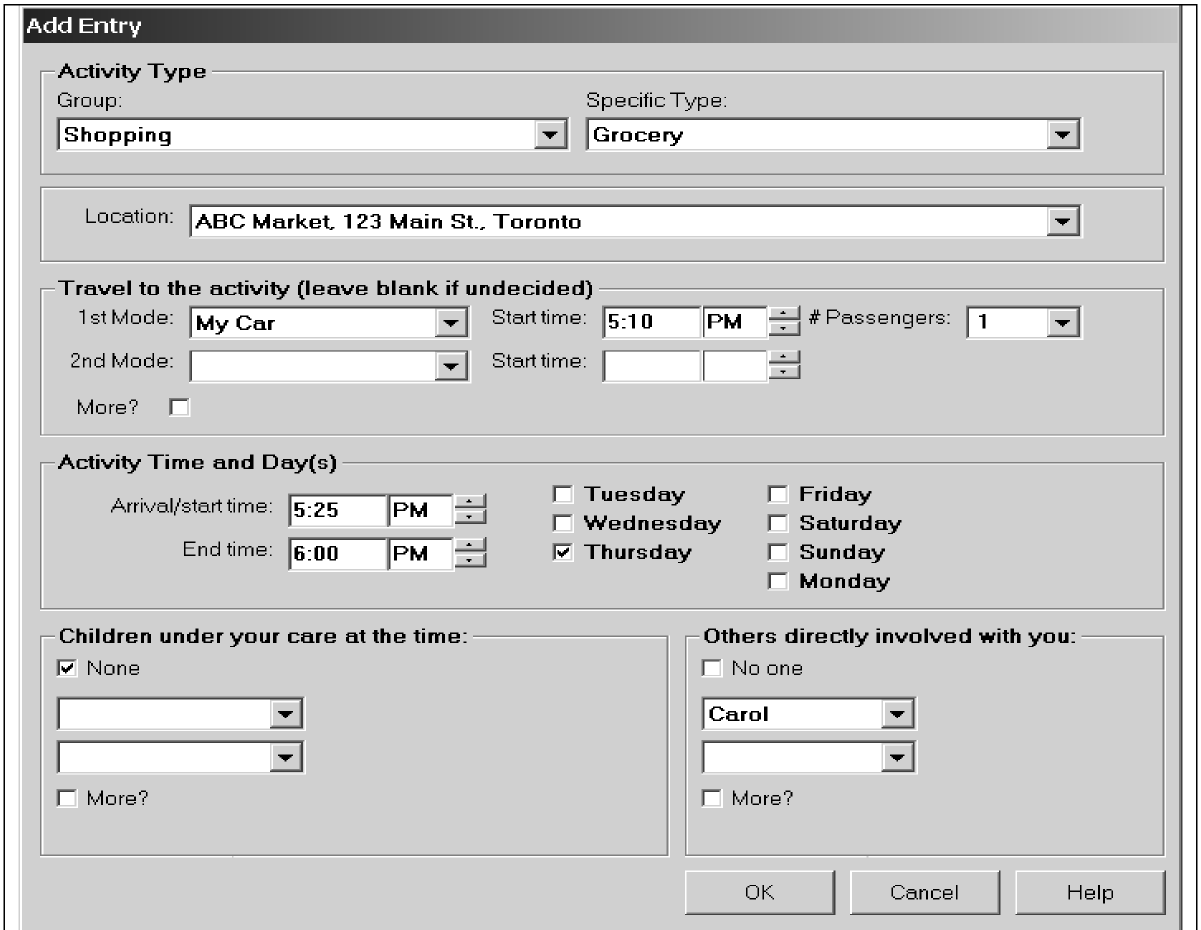

Figure A2 – CHASE: Add/Modify Dialogue Box

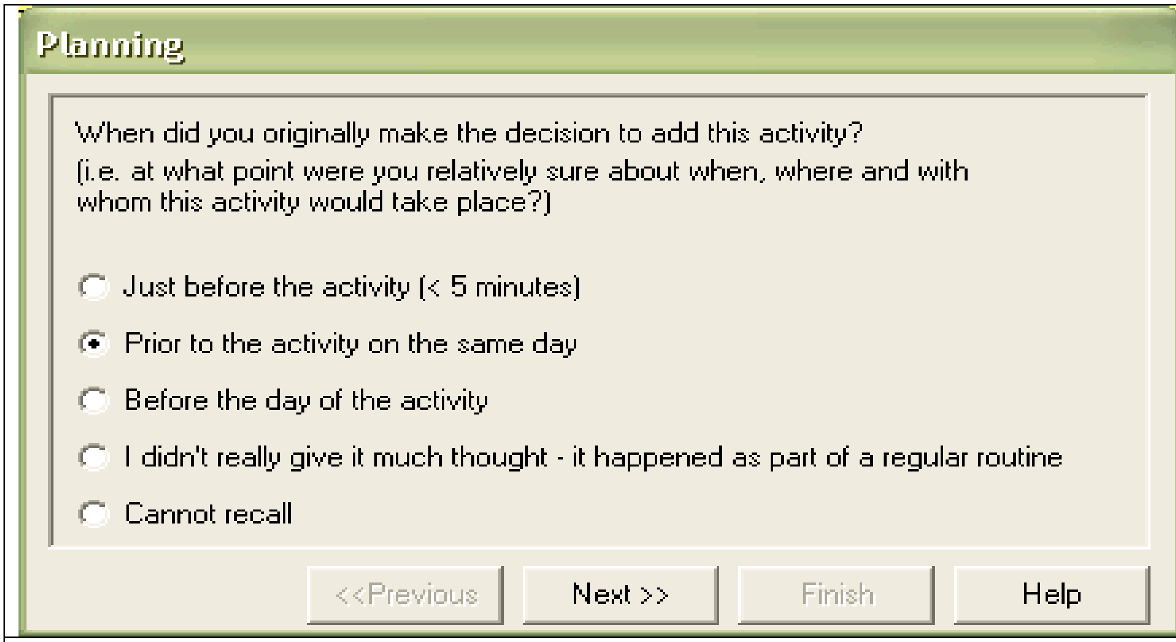

Figure A3 – CHASE: Example End of Week Review Prompt

Appendix B: Travel Activity Panel Survey, Wave 2: Stated Adaptation

Activity Diary - EXAMPLE

Name: JANE DOE

Date: APRIL 3, 2003

DAY 1:

Activity Description	Travel Start Time	Activity Start Time	Activity End Time	Mode of Transport Used to Get to Activity
NIGHT SLEEP	NO TRAVEL	12:00 AM	7:30 AM	NO TRAVEL
EAT BREAKFAST	NO TRAVEL	7:30 AM	8:00 AM	NO TRAVEL
GET READY FOR WORK	NO TRAVEL	8:00 AM	8:15 AM	NO TRAVEL
WORK	8:15 AM	8:55 AM	12:00 PM	DRIVE
GO OUT FOR LUNCH	12:00 PM	12:08 PM	12:50 PM	WALK
WORK	12:50 PM	12:58 PM	4:45 PM	WALK
PICK UP KIDS (DAYCARE)	4:45 PM	5:00 PM	5:15 PM	DRIVE
PREPARE DINNER	5:15 PM	5:35 PM	6:00 PM	DRIVE
EAT DINNER	NO TRAVEL	6:00 PM	6:40 PM	NO TRAVEL
PICK UP MOVIE	6:40 PM	6:45 PM	7:00 PM	WALK
CLEAN UP HOUSE	7:00 PM	7:05 PM	7:30 PM	WALK
PUT KIDS TO BED	NO TRAVEL	7:30 PM	8:00 PM	NO TRAVEL
WATCH MOVIE	NO TRAVEL	8:00 PM	10:30 PM	NO TRAVEL
NIGHT SLEEP	NO TRAVEL	10:30 PM	12:00 AM	NO TRAVEL

Figure B1 – Wave2: Example completed day from the 2-day memory jogger diary

Appendix C: Travel Activity Panel Survey, Wave 3: Routine Weekly Schedule

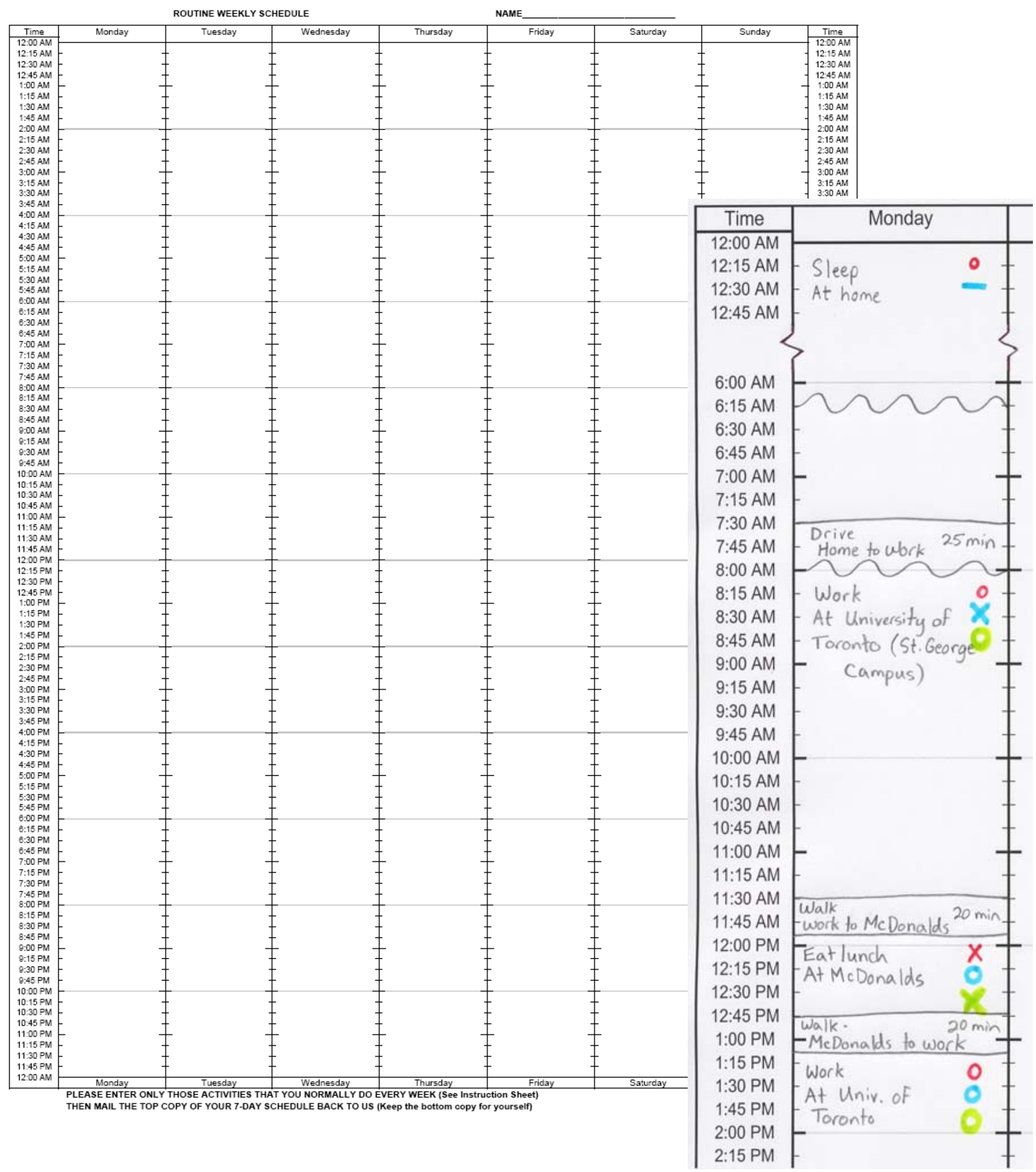

Figure C1 – Wave 3: Routine weekly schedule form (with blow up of a completed Monday)

Appendix D: Detailed Results of Panel Survey Wave 2

Table D1 - Hypothetical Scenario 1: A one-hour delay getting to an activity

a) Effect of a one hour delay on the respondent's next activity

Description	Number of observations	Percent
Modify activity timing within the same day	**263**	**65.8%**
Shorten duration of activity	101	25.3%
Shift activity to another part of the day	142	35.5%
Shift and shorten duration	17	4.3%
Shift and lengthen duration	1	0.3%
Split the activity	2	0.5%
Move activity to another day	**47**	**11.8%**
Skip or replace activity	**67**	**16.8%**
Change mode of transportation	**3**	**0.8%**
Change activity location	**7**	**1.8%**
No effect or unknown	**13**	**3.3%**
Total	**400**	**100.0%**

b) Effect of a one-hour delay on respondent's other activities in the same day

Description	Activities Modified						Total Scenarios	
	In-home activities		Out-of-home activities		Total Modifications			
	Obs	%	Obs	%	Obs	%	Obs	%
Modify timing of other activities within the same day	**111**	**49.1%**	**56**	**24.8%**	**167**	**73.9%**	**167**	**41.8%**
Shorten duration of activit(ies)	32	14.2%	20	8.8%	52	23.0%	52	13.0%
Shift and/or shorten other activit(ies)	53	23.5%	28	12.4%	81	35.8%	81	20.3%
Add and/or lengthen other activit(ies)	26	11.5%	8	3.5%	34	15.0%	34	8.5%
Move other activit(ies) to another day	**2**	**0.9%**	**8**	**3.5%**	**10**	**4.4%**	**10**	**2.5%**
Skip or replace other activit(ies)	**27**	**11.9%**	**13**	**5.8%**	**40**	**17.7%**	**40**	**10.0%**
Ask someone else to do the other activit(ies)	**0**	**0.0%**	**4**	**1.8%**	**4**	**1.8%**	**4**	**1.0%**
Other rescheduling of other activit(ies)	**2**	**0.9%**	**3**	**1.3%**	**5**	**2.2%**	**5**	**1.3%**
Total - Modifications to other activities	**142**	**62.8%**	**84**	**37.2%**	**226**	**100.0%**	**226**	**56.5%**
Total - No or unknown effect on other activities							**174**	**43.5%**
Total							**400**	**100.0%**

Includes 12 Scenarios where both in-home and out-of-home activities were modified

c) Effect of a one-hour delay on respondent's activities on other days

Description	Number of observations	Percent
Activity would be rescheduled for another day	57	14.3%
Activit(ies) on another day would be skipped	3	0.8%
Activit(ies) would be added on another day	8	2.0%
Activit(ies) would be lengthened on another day	4	1.0%
No or unknown effect on other days	328	82.0%
Total	**400**	**100.0%**

d) Effect of a one-hour delay on other household members

Description	Number of observations	Percent
Another member would do the activity for the respondent	14	3.5%
Affects schedule(s) of other member(s) on the joint activity	51	12.8%
Affects schedule(s) of children under care at the time	13	3.3%
Other member(s) would be delayed	25	6.3%
Another member would give a ride	2	0.5%
Other members would change mode of transport	6	1.5%
Another member would skip out-of-home activit(ies)	1	0.3%
Another member would add an in-home activity	1	0.3%
Other member(s) would be upset or otherwised inconvenienced	2	0.5%
Affects multiple people in different ways	4	1.0%
No or unknown effect on other people	281	70.3%
Total	**400**	**100.0%**

Table D2 - Hypothetical Scenario 2: Unavailability of mode used to get to the activity

a) Effect of a mode unavailability on the mode of transportation to the activity

Description	Number of Observations	Percent
Use a different mode - transit	74	18.5%
Use a different mode - auto drive	12	3.0%
Use a different mode - passenger	78	19.5%
Use a different mode - walk	33	8.3%
Use a different mode - taxi	34	8.5%
Use a different mode - other	11	2.8%
Same mode - use a different vehicle	42	10.5%
Same mode - go to a different location	3	0.8%
Same mode - wait until mode is available	16	4.0%
Would not travel	85	21.3%
No or unknown effect	12	3.0%
Total	**400**	**100.0%**

b) Effect of a mode unavailability on the respondent's next activity

Description	Number of Observations	Percent
Modify activity timing within the same day	**57**	**14.3%**
Shorten duration of activity	30	7.5%
Shift activity to another part of the day	22	5.5%
Shift and shorten duration	3	0.8%
Shift and lengthen duration	1	0.3%
Split the activity	1	0.3%
Move activity to another day	**42**	**10.5%**
Skip or replace activity	**79**	**19.8%**
Change activity location	**20**	**5.0%**
No effect or unknown	**202**	**50.5%**
Total	**400**	**100.0%**

c) Effect of a one-hour delay on other activities in the same day

Description	Activities Modified						Total Scenarios	
	In-home activities		Out-of-home activities		Total Modifications			
	Obs	%	Obs	%	Obs	%	Obs	%
Modify timing of other activities within the same day	**74**	**42.3%**	**24**	**13.7%**	**98**	**56.0%**	**98**	**24.5%**
Shorten duration of activit(ies)	17	9.7%	3	1.7%	20	11.4%	20	5.0%
Shift and/or shorten other activit(ies)	13	7.4%	6	3.4%	19	10.9%	19	4.8%
Add and/or lengthen other activit(ies)	44	25.1%	15	8.6%	59	33.7%	59	14.8%
Move other activit(ies) to another day	**0**	**0.0%**	**14**	**8.0%**	**14**	**8.0%**	**14**	**3.5%**
Skip or replace other activit(ies)	**7**	**4.0%**	**22**	**12.6%**	**29**	**16.6%**	**29**	**7.3%**
Ask someone else to do the other activit(ies)	**2**	**1.1%**	**5**	**2.9%**	**7**	**4.0%**	**7**	**1.8%**
Change mode of other activities	**0**	**0.0%**	**17**	**9.7%**	**17**	**9.7%**	**17**	**4.3%**
Other rescheduling of other activit(ies)	**2**	**1.1%**	**8**	**4.6%**	**10**	**5.7%**	**10**	**2.5%**
Total - Modifications to other activities	**85**	**48.6%**	**90**	**51.4%**	**175**	**100.0%**	**175**	**43.8%**
Total - No or unknown effect on other activities							**225**	**56.3%**
Total							**400**	**100.0%**

Includes 4 scenarios where in-home and out-of home activities are modified

Includes 1 scenario where in-home and out-of home activities are modified

d) Effect of a one-hour delay on respondent's activities on other days

Description	Number of observations	Percent
Activity would be rescheduled for another day	54	13.5%
Activit(ies) on another day would be skipped	3	0.8%
Activit(ies) would be added on another day	3	0.8%
No or unknown effect on other days	340	85.0%
Total	**400**	**100.0%**

e) Effect of a one-hour delay on other household members

Description	Number of observations	Percent
Another member would do the activity for the respondent	16	4.0%
Affects schedule(s) of other member(s) on the joint activity	29	7.3%
Affects schedule(s) of children under care at the time	9	2.3%
Other member(s) would be delayed	1	0.3%
Another member would give a ride	45	11.3%
Other members would change mode of transport	30	7.5%
Another member would skip out-of-home activit(ies)	11	2.8%
Another member would add an in-home activity	0	0.0%
Other member(s) would be upset or otherwised inconvenien	1	0.3%
Affects multiple people in different ways	7	1.8%
No or unknown effect on other people	251	62.8%
Total	**400**	**100.0%**

Appendix E: Model Validation Results: OD Trip Summaries by Time of Day

Table E1 - Model Trips

Night Time (19h00 - 5h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	383.2	716.3	102.6	94.4	146.4	34.3	80.9	110.5	27.7	6.9	1	1704.2
2 Toronto PD2-6	402.4	1563.1	216.9	321.5	308.6	29.6	157.1	130	10.1	3.5	4.6	3147.4
3 Toronto PD7-9	54.9	208	436.1	88.8	15.8	6.4	61.5	291.5	20.8	6.6	1.5	1192
4 Toronto PD10-12	59.1	309.3	106.5	506.6	156.4	20.5	266.7	80.8	7.8	3.4	1.4	1518.5
5 Toronto PD13-16	82.9	272.7	15.5	130.5	1018.3	104.6	201.9	18.6	2.9	1.5	3.1	1852.6
6 Durham	25.2	20.2	4.8	13.2	75.9	1414.1	44.8	8.8	1.5	0.4	2.9	1611.8
7 York	41	159.3	57.7	233.9	205.3	58.9	1304	78.9	5.7	1	4.5	2150.1
8 Peel	62.8	123.3	248.3	67	20.9	9.3	72.3	2341.2	192.1	18	7.6	3162.7
9 Halton	15.8	10.3	18.5	5.2	3.6	0.4	4.6	174.2	885.7	141.6	4.8	1264.6
10 Hamilton	3.7	2.9	3.7	1.9	0.8	0.4	1.5	12.1	143.7	1532.8	9.3	1712.9
11 External	1.2	5.9	1.9	2.4	1.8	8.1	7.4	12.7	8.5	19.2	0.2	69.3
Total	1132.2	3391.4	1212.4	1465.4	1953.8	1686.7	2202.6	3259.3	1306.5	1734.9	40.8	19386.1

AM Peak (06h00 - 08h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	429.4	144.5	19.4	36.1	29.8	4.4	18.2	25.3	4	0.8	3.4	715.3
2 Toronto PD2-6	962.9	1925.5	159.1	296	178.3	16.2	167.8	146.6	12.5	2.4	16.1	3883.3
3 Toronto PD7-9	158.8	134	688.2	90.4	17.5	2.7	53.4	155.3	11.1	1.9	4.6	1317.8
4 Toronto PD10-12	168.4	222.9	74.3	751.6	71.9	8.1	149.9	66	4.7	0.8	7.9	1526.3
5 Toronto PD13-16	296.5	273.6	28.1	161.5	1274.5	35.5	160.3	47.6	2.6	0.4	8.3	2288.9
6 Durham	111.3	78.3	12.5	47.8	163.6	1546.8	92.2	21.5	1.2	0.8	16.9	2092.9
7 York	209	171.9	63.5	241.5	127.7	23.6	1776.1	81.9	3.8	1.6	20.2	2720.9
8 Peel	254.3	144.3	296.7	114.1	29	4.3	99.2	2725.8	104.1	13.3	26.4	3811.6
9 Halton	101.3	26.2	38.2	18.5	5.8	0.8	11.9	205.2	1007.9	89.2	24.3	1529.4
10 Hamilton	17.5	6.2	8.8	4.7	1.2	1.9	2.4	38.8	150.7	1622	51.1	1905.3
11 External	0.2	0	0	0	0	0.4	1	0.2	1.2	0.6	0	3.6
Total	2709.7	3127.3	1388.7	1762.1	1899.3	1644.9	2532.2	3514.1	1303.9	1733.8	179.2	21795.1

Midday (09h00 - 14h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	570.4	556.4	89.7	111.9	128.7	26.1	75.4	103.9	25.6	6.3	1.3	1695.8
2 Toronto PD2-6	734.1	1716.4	209.2	377.8	299.6	24.8	176.6	138.4	15.2	4	5.7	3701.8
3 Toronto PD7-9	114.1	209.8	507.8	115.5	21.4	2	67	276	19.3	4	1.2	1338.2
4 Toronto PD10-12	140.5	366.4	109.6	589.4	146.6	15.8	251	79.8	6.4	1	3.6	1710.2
5 Toronto PD13-16	166.6	294.2	25.8	169.4	1068.1	85.7	187.2	25.5	2.4	1	2.4	2028.2
6 Durham	36	30.8	5.8	21.6	99.1	1353.2	55.9	6.4	0.4	0.4	5.1	1614.8
7 York	98.9	161.9	63.1	268.7	190.3	45.4	1265.3	87.8	6.9	0.9	5.8	2194.9
8 Peel	139.4	133.5	297.4	89.6	23.2	4.6	85	2070	162.8	22.7	11.7	3039.9
9 Halton	32.8	13.4	19.1	9.3	2.4	0.5	5.9	174	848.1	152.9	8.5	1266.8
10 Hamilton	9.9	3.8	5.1	2.3	0.4	0.2	1.2	23.4	166.7	1677.4	22.3	1912.8
11 External	1.4	4.2	2	1.7	2.5	6.8	6.5	8.5	6.3	15	0.4	55.4
Total	2044.1	3490.9	1334.8	1757.4	1982.3	1565	2176.9	2993.6	1260.1	1885.6	68	20558.8

PM Peak (15h00 - 18h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	719.2	1219.8	196.8	214.3	340.7	117.9	227.3	283.6	97.7	22.2	0.8	3440.4
2 Toronto PD2-6	528	2819.3	260.3	397.9	413.3	86.2	239.7	204.7	28.8	6.5	2.4	4986.9
3 Toronto PD7-9	75	296.8	919	138.9	39.8	12.6	93.1	439.6	46.9	10.4	1	2073.1
4 Toronto PD10-12	96.2	477.5	150.7	1019	233.2	53.2	399.8	145.3	21.9	5.4	0.4	2602.4
5 Toronto PD13-16	93.6	370.2	21.9	143.4	1821.5	197.6	245.4	33.7	8.2	1	0.8	2937.5
6 Durham	11	24.2	2.7	15	88.6	2335.9	48.1	6.2	0.8	1.9	2.7	2537.1
7 York	56.4	248.7	88.7	317.9	268.8	115.3	2436	128.6	12.5	3	3	3678.9
8 Peel	72.6	213.8	318.2	107.2	51.7	25.3	117	3969.1	290.4	42.5	3.6	5211.2
9 Halton	10.5	17.3	19	7.6	3.6	2	6.6	197.1	1508.1	236.8	2.2	2010.9
10 Hamilton	2.9	4	3.7	2.8	0.9	0.8	1.8	21.1	161.9	2527.3	7.6	2734.8
11 External	4.1	18.2	4.4	8.6	9.7	13	18.4	29.5	24	54.3	0.6	184.8
Total	1669.6	5709.7	1985.4	2372.6	3271.8	2960	3833.1	5458.4	2201.3	2911.3	25	32398.1

Table E2 – Observed Trips

Night Time (19h00 - 5h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	405.7	757.4	98.3	98.3	152.7	39.5	99.8	120.6	34.7	15.2	3.2	1825.3
2 Toronto PD2-6	303.1	1567.7	158.2	243.4	230.9	37.9	154.2	130.5	20.1	7.5	6.7	2860.1
3 Toronto PD7-9	39	168.4	584.2	66.7	25.1	9.1	43.2	233.2	24.6	4.7	6.7	1205.1
4 Toronto PD10-12	48	277.1	67	481.9	118.6	22	204.3	72.6	9.8	4.9	3.8	1309.9
5 Toronto PD13-16	54.7	231.5	17.3	95.9	1022.4	94.2	131.3	33.5	3.6	1	2.6	1688
6 Durham	22.5	35.1	9.2	16.8	79.6	1328.8	32.3	17.1	3.2	2.1	11.2	1557.8
7 York	38.6	142.1	45.9	192.4	149.6	52	1334.9	66.1	5.6	4.6	13.9	2045.8
8 Peel	48.7	138.4	185.7	64.2	39.8	16.8	77.8	2218.6	147	25	18	2979.9
9 Halton	12.6	18.3	16	5	5.3	2.4	7.6	127.1	974.3	132.8	11.2	1312.6
10 Hamilton	7.2	4.2	5	2	3.2	2	5	23.5	114.5	1501.3	25.3	1693.1
11 External	2.9	18.1	11.5	6.7	8.6	22.8	31.6	35.3	30.1	62.6	24.2	254.3
Total	983.1	3358.3	1198.3	1273.2	1835.6	1627.6	2121.9	3078.1	1367.4	1761.7	126.8	18732.6

AM Peak (06h00 - 08h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	390.8	168	22	41.8	26.3	5.9	22.4	32.7	4.8	1.8	2.8	719.4
2 Toronto PD2-6	1083.3	1558.2	184.4	350.1	209.8	26.2	205.8	177	14.5	4	18.4	3831.7
3 Toronto PD7-9	184.9	144.9	580.6	99.2	20.8	2	71.2	189.1	16.1	3.3	8.1	1320.3
4 Toronto PD10-12	199.6	255	78	621.8	78.9	9.9	192.7	72.4	5.1	0.4	9.5	1523.3
5 Toronto PD13-16	348.9	302.3	35.3	175.3	1054.4	38.2	177.7	49.7	5.4	1	5.8	2194
6 Durham	133.1	74.1	13.5	55.1	162	1303.1	107	18.8	2.5	1.6	27.5	1898.5
7 York	255.4	190	66.8	281.4	147.6	25.9	1514.6	94.6	6	1.4	29.7	2613.3
8 Peel	314.5	163.4	337.5	139.8	29.6	7	127.5	2434.9	123.3	15.8	44.9	3738
9 Halton	125.1	27.4	43	21.5	7.1	1.2	14.5	238.7	897.3	96.5	39.2	1511.6
10 Hamilton	23.4	7.5	10.3	3.9	1.4	0.8	2.7	38	165.7	1444.6	69.5	1767.8
11 External	0.2	2.1	1.1	0.7	0.8	3.6	1.7	3.2	3	5.2	12	33.5
Total	3059.1	2892.8	1372.5	1790.7	1738.7	1423.9	2437.7	3349.1	1243.9	1575.6	267.3	21151.9

Midday (09h00 - 14h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	587.8	399.4	56.3	75.8	63.2	15.6	50.7	62.3	11.2	8	7	1337.2
2 Toronto PD2-6	740.9	1988.6	168	329.7	258	27.4	117.1	101.7	13.2	5.7	24.6	3775
3 Toronto PD7-9	87.3	159	897.3	69.2	13.9	3.5	43.9	190.4	16.2	4.8	13.8	1499.1
4 Toronto PD10-12	124.5	306.6	68.2	779.4	122.2	13.2	210	54.4	6.7	2	12.5	1699.7
5 Toronto PD13-16	130.5	247.4	22.4	135.2	1385.2	74.3	147.5	28.3	5.6	1.7	12.8	2190.9
6 Durham	27.8	28.8	6	18.7	82.2	1725.1	52.2	11.8	2.6	1	25.9	1982.1
7 York	88.6	127.3	42	219.7	125.6	36	1779.8	60.4	5.7	3.3	37.2	2525.5
8 Peel	106.4	100.7	200.3	60.1	32.5	11.1	58.5	2478.1	116.9	18.1	40.7	3223.4
9 Halton	20.6	12.1	22.1	8.2	4.4	2.3	5.4	129.9	1301.7	100.4	29.3	1636.4
10 Hamilton	9.7	6.5	5	4.4	1.9	1.6	3.5	21.5	123.6	2046.3	55.8	2279.8
11 External	3.8	16.7	8.6	6.3	9.1	20.8	22.3	24.6	17.2	35.5	77.5	242.6
Total	1927.8	3393	1496.2	1706.6	2098.2	1930.9	2490.9	3163.5	1620.6	2226.8	337.1	22392.3

PM Peak (15h00 - 18h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	710.7	1297.3	201.9	234.9	366.9	133.3	253.7	315.9	117.4	22.8	6.2	3660.9
2 Toronto PD2-6	419.8	2608.5	227.8	401.8	409.9	85.3	232	198.1	34.1	9.9	12.4	4639.6
3 Toronto PD7-9	56.1	255.5	1059.2	100.1	38.7	17.4	84	418.6	48.4	10.8	6.8	2095.6
4 Toronto PD10-12	79.4	471.6	127.4	1025.7	226.6	57.5	389.9	156.1	20.8	5.8	2.8	2563.8
5 Toronto PD13-16	74	320.8	24.3	138.1	1785.1	204.3	205.1	42.2	7.8	2.7	6.2	2810.5
6 Durham	16.7	33	4.9	15.2	71.8	2223.8	41.8	9.9	3	1	17.7	2438.7
7 York	48.5	229.8	84.3	260.1	233.5	121.4	2300.5	143.2	17.5	3.9	21.4	3464.1
8 Peel	67.9	212.4	279.7	90.1	57.8	24	108	3657.5	283.7	48.8	23.1	4853.1
9 Halton	13.4	21.1	21	7.3	5.6	4.8	9.9	175.9	1601.2	231.7	17.8	2109.8
10 Hamilton	6.9	7.2	3.7	3.1	0.7	1	3	20.4	155.9	2489.1	38.9	2729.9
11 External	5.6	27.7	11.2	10.5	12.7	36.7	38.3	60.7	47.6	92.6	46.8	390.3
Total	1498.9	5485	2045.3	2287	3209.3	2909.5	3666.2	5198.6	2337.5	2919.2	200.1	31757.2

Table E3 – Model +/- Trips

Night Time (19h00 - 5h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	-22.6	-41.1	4.3	-3.9	-6.2	-5.2	-18.8	-10.1	-7	-8.3	-2.2	-121.1
2 Toronto PD2-6	99.3	-4.6	58.7	78.1	77.7	-8.2	2.9	-0.5	-10	-3.9	-2.1	287.2
3 Toronto PD7-9	15.9	39.6	-148.1	22.1	-9.3	-2.8	18.3	58.4	-3.8	1.9	-5.3	-13.1
4 Toronto PD10-12	11.1	32.1	39.5	24.7	37.8	-1.4	62.4	8.2	-2	-1.5	-2.4	208.6
5 Toronto PD13-16	28.2	41.2	-1.8	34.6	-4.1	10.5	70.6	-14.9	-0.6	0.4	0.6	164.7
6 Durham	2.7	-14.9	-4.3	-3.6	-3.6	85.3	12.4	-8.3	-1.8	-1.6	-8.3	54
7 York	2.3	17.2	11.8	41.5	55.8	6.8	-30.9	12.8	0.1	-3.6	-9.4	104.4
8 Peel	14.1	-15	62.5	2.8	-18.9	-7.5	-5.5	122.6	45.1	-7	-10.4	182.8
9 Halton	3.2	-8	2.4	0.2	-1.6	-2	-3	47.1	-88.6	8.9	-6.5	-48
10 Hamilton	-3.4	-1.3	-1.3	-0.1	-2.4	-1.6	-3.5	-11.4	29.2	31.5	-16	19.7
11 External	-1.7	-12.1	-9.6	-4.2	-6.8	-14.8	-24.2	-22.6	-21.6	-43.5	-23.9	-185.1
Total	149.1	33.1	14.1	192.1	118.2	59.1	80.8	181.2	-60.9	-26.8	-86	653.4

AM Peak (06h00 - 08h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	38.6	-23.5	-2.6	-5.7	3.4	-1.5	-4.2	-7.4	-0.8	-1	0.6	-4.1
2 Toronto PD2-6	-120.4	367.3	-25.3	-54.2	-31.5	-10	-38	-30.4	-2	-1.6	-2.3	51.6
3 Toronto PD7-9	-26.1	-11	107.6	-8.8	-3.3	0.7	-17.8	-33.8	-5	-1.5	-3.5	-2.5
4 Toronto PD10-12	-31.2	-32.1	-3.8	129.8	-7	-1.8	-42.8	-6.5	-0.5	0.4	-1.6	3
5 Toronto PD13-16	-52.4	-28.7	-7.2	-13.9	220.1	-2.7	-17.4	-2.1	-2.9	-0.6	2.5	94.9
6 Durham	-21.8	4.2	-1	-7.4	1.5	243.7	-14.8	2.7	-1.3	-0.8	-10.6	194.4
7 York	-46.4	-18.1	-3.3	-39.9	-19.8	-2.3	261.5	-12.7	-2.1	0.2	-9.4	107.6
8 Peel	-60.1	-19.1	-40.8	-25.7	-0.6	-2.7	-28.3	290.9	-19.2	-2.5	-18.5	73.5
9 Halton	-23.8	-1.2	-4.8	-3	-1.3	-0.4	-2.6	-33.5	110.6	-7.2	-14.9	17.8
10 Hamilton	-5.9	-1.3	-1.5	0.8	-0.1	1.2	-0.3	0.8	-15	177.4	-18.4	137.5
11 External	0	-2.1	-1.1	-0.7	-0.8	-3.2	-0.7	-3	-1.8	-4.6	-12	-29.9
Total	-349.4	234.5	16.1	-28.7	160.6	221	94.6	165	60	158.2	-88.1	643.2

Midday (09h00 - 14h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	-17.3	157	33.4	36.2	65.4	10.6	24.7	41.6	14.4	-1.7	-5.7	358.5
2 Toronto PD2-6	-6.8	-272.3	41.2	48.2	41.6	-2.6	59.4	36.6	2	-1.7	-18.9	-73.3
3 Toronto PD7-9	26.8	50.9	-389.5	46.3	7.6	-1.5	23.1	85.6	3.1	-0.7	-12.6	-160.9
4 Toronto PD10-12	16.1	59.9	41.4	-190	24.4	2.5	41	25.3	-0.3	-0.9	-8.9	10.5
5 Toronto PD13-16	36	46.8	3.4	34.3	-317.1	11.4	39.7	-2.9	-3.2	-0.7	-10.4	-162.7
6 Durham	8.2	2	-0.2	3	16.8	-371.9	3.7	-5.4	-2.2	-0.6	-20.7	-367.3
7 York	10.3	34.6	21.1	49	64.8	9.4	-514.5	27.4	1.2	-2.4	-31.4	-330.5
8 Peel	33	32.9	97.2	29.5	-9.2	-6.5	26.5	-408	45.8	4.5	-29	-183.4
9 Halton	12.2	1.2	-3	1.1	-2	-1.8	0.4	44	-453.5	52.5	-20.8	-369.6
10 Hamilton	0.2	-2.6	0.1	-2.1	-1.5	-1.4	-2.3	1.9	43.1	-368.9	-33.5	-367
11 External	-2.4	-12.5	-6.6	-4.6	-6.6	-14	-15.8	-16.2	-10.9	-20.5	-77.1	-187.2
Total	116.3	97.9	-161.4	50.8	-115.9	-365.8	-314	-169.9	-360.5	-341.1	-269	-1833.5

PM Peak (15h00 - 18h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	8.5	-77.5	-5	-20.6	-26.1	-15.4	-26.4	-32.3	-19.7	-0.6	-5.3	-220.5
2 Toronto PD2-6	108.3	210.7	32.5	-3.9	3.4	0.9	7.7	6.6	-5.4	-3.4	-10.1	347.3
3 Toronto PD7-9	18.9	41.3	-140.2	38.8	1.1	-4.8	9.1	21	-1.6	-0.4	-5.8	-22.4
4 Toronto PD10-12	16.8	5.8	23.3	-6.8	6.5	-4.3	9.9	-10.8	1.1	-0.5	-2.4	38.6
5 Toronto PD13-16	19.6	49.5	-2.4	5.3	36.4	-6.7	40.4	-8.5	0.4	-1.7	-5.4	127
6 Durham	-5.7	-8.9	-2.2	-0.2	16.8	112.1	6.3	-3.7	-2.1	1	-15	98.4
7 York	7.9	18.9	4.5	57.8	35.4	-6.1	135.5	-14.7	-4.9	-0.9	-18.4	214.8
8 Peel	4.6	1.4	38.4	17.1	-6.2	1.3	8.9	311.6	6.7	-6.3	-19.5	358.1
9 Halton	-2.8	-3.9	-2	0.3	-2	-2.7	-3.3	21.2	-93.1	5.1	-15.7	-98.9
10 Hamilton	-4	-3.1	0	-0.4	0.2	-0.2	-1.2	0.7	6	38.2	-31.3	4.9
11 External	-1.4	-9.5	-6.8	-1.9	-3	-23.7	-19.9	-31.3	-23.6	-38.3	-46.2	-205.5
Total	170.7	224.7	-59.9	85.6	62.5	50.5	166.9	259.9	-136.3	-7.8	-175.1	641

Table E4 – Model +/- Percent

Night Time (19h00 - 5h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	-5.6%	-5.4%	4.4%	-4.0%	-4.1%	-13.1%	-18.9%	-8.4%	-20.2%	-54.5%	-69.1%	-6.6%
2 Toronto PD2-6	32.7%	-0.3%	37.1%	32.1%	33.6%	-21.8%	1.9%	-0.4%	-49.6%	-52.7%	-31.4%	10.0%
3 Toronto PD7-9	40.8%	23.5%	-25.3%	33.1%	-37.0%	-30.5%	42.4%	25.0%	-15.4%	39.3%	-78.3%	-1.1%
4 Toronto PD10-12	23.0%	11.6%	59.0%	5.1%	31.9%	-6.6%	30.6%	11.3%	-20.1%	-30.0%	-63.1%	15.9%
5 Toronto PD13-16	51.5%	17.8%	-10.6%	36.1%	-0.4%	11.1%	53.8%	-44.6%	-18.0%	42.9%	22.1%	9.8%
6 Durham	12.2%	-42.4%	-47.4%	-21.6%	-4.6%	6.4%	38.5%	-48.8%	-54.6%	-79.1%	-74.0%	3.5%
7 York	6.0%	12.1%	25.8%	21.6%	37.3%	13.1%	-2.3%	19.4%	1.2%	-78.6%	-67.8%	5.1%
8 Peel	29.0%	-10.9%	33.7%	4.4%	-47.5%	-44.8%	-7.1%	5.5%	30.7%	-27.9%	-58.0%	6.1%
9 Halton	25.8%	-43.9%	15.2%	3.7%	-30.9%	-83.6%	-39.5%	37.0%	-9.1%	6.7%	-57.5%	-3.7%
10 Hamilton	-48.0%	-30.7%	-25.7%	-2.9%	-75.2%	-77.8%	-70.5%	-48.5%	25.5%	2.1%	-63.2%	1.2%
11 External	-57.9%	-67.1%	-83.6%	-63.7%	-79.4%	-64.6%	-76.6%	-64.1%	-71.8%	-69.4%	-99.1%	-72.8%
Total	15.2%	1.0%	1.2%	15.1%	6.4%	3.6%	3.8%	5.9%	-4.5%	-1.5%	-67.8%	3.5%

AM Peak (06h00 - 08h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	9.9%	-14.0%	-12.0%	-13.7%	13.0%	-25.3%	-18.9%	-22.6%	-17.2%	-55.7%	22.0%	-0.6%
2 Toronto PD2-6	-11.1%	23.6%	-13.7%	-15.5%	-15.0%	-38.2%	-18.5%	-17.2%	-13.8%	-40.7%	-12.6%	1.3%
3 Toronto PD7-9	-14.1%	-7.6%	18.5%	-8.9%	-16.0%	34.7%	-25.0%	-17.9%	-31.0%	-44.6%	-42.7%	-0.2%
4 Toronto PD10-12	-15.6%	-12.6%	-4.8%	20.9%	-8.9%	-17.8%	-22.2%	-8.9%	-9.5%	89.9%	-17.0%	0.2%
5 Toronto PD13-16	-15.0%	-9.5%	-20.3%	-7.9%	20.9%	-7.0%	-9.8%	-4.3%	-52.6%	-60.4%	43.8%	4.3%
6 Durham	-16.4%	5.7%	-7.6%	-13.4%	0.9%	18.7%	-13.8%	14.4%	-52.2%	-49.1%	-38.5%	10.2%
7 York	-18.2%	-9.5%	-5.0%	-14.2%	-13.4%	-8.9%	17.3%	-13.4%	-36.0%	17.5%	-31.8%	4.1%
8 Peel	-19.1%	-11.7%	-12.1%	-18.4%	-2.0%	-38.1%	-22.2%	11.9%	-15.6%	-16.0%	-41.2%	2.0%
9 Halton	-19.0%	-4.5%	-11.2%	-14.0%	-18.5%	-33.4%	-17.9%	-14.0%	12.3%	-7.5%	-38.1%	1.2%
10 Hamilton	-25.1%	-17.8%	-15.0%	20.6%	-10.5%	155.9%	-12.5%	2.2%	-9.1%	12.3%	-26.5%	7.8%
11 External	23.5%	-100.0%	-100.0%	-100.0%	-100.0%	-89.7%	-40.1%	-94.1%	-58.9%	-88.5%	-100.0%	-89.2%
Total	-11.4%	8.1%	1.2%	-1.6%	9.2%	15.5%	3.9%	4.9%	4.8%	10.0%	-32.9%	3.0%

Midday (09h00 - 14h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	-2.9%	39.3%	59.3%	47.7%	103.4%	67.9%	48.6%	66.8%	128.3%	-21.2%	-80.9%	26.8%
2 Toronto PD2-6	-0.9%	-13.7%	24.5%	14.6%	16.1%	-9.5%	50.7%	36.0%	14.8%	-29.8%	-76.8%	-1.9%
3 Toronto PD7-9	30.7%	32.0%	-43.4%	66.9%	54.8%	-42.4%	52.7%	45.0%	19.3%	-15.3%	-91.3%	-10.7%
4 Toronto PD10-12	12.9%	19.5%	60.7%	-24.4%	20.0%	19.2%	19.5%	46.5%	-3.9%	-47.6%	-71.1%	0.6%
5 Toronto PD13-16	27.6%	18.9%	15.0%	25.4%	-22.9%	15.4%	26.9%	-10.2%	-56.9%	-41.2%	-81.6%	-7.4%
6 Durham	29.5%	6.9%	-2.9%	16.0%	20.5%	-21.6%	7.1%	-45.5%	-84.7%	-57.0%	-80.2%	-18.5%
7 York	11.6%	27.2%	50.3%	22.3%	51.6%	26.2%	-28.9%	45.4%	20.3%	-73.3%	-84.5%	-13.1%
8 Peel	31.0%	32.6%	48.5%	49.2%	-28.5%	-58.6%	45.3%	-16.5%	39.2%	24.9%	-71.2%	-5.7%
9 Halton	59.4%	10.3%	-13.4%	13.0%	-45.8%	-79.8%	8.0%	33.9%	-34.8%	52.3%	-70.9%	-22.6%
10 Hamilton	2.6%	-40.6%	2.8%	-47.7%	-79.7%	-87.5%	-65.4%	8.6%	34.9%	-18.0%	-60.1%	-16.1%
11 External	-64.2%	-74.7%	-76.2%	-73.4%	-72.3%	-67.2%	-70.7%	-65.6%	-63.3%	-57.8%	-99.5%	-77.2%
Total	6.0%	2.9%	-10.8%	3.0%	-5.5%	-18.9%	-12.6%	-5.4%	-22.2%	-15.3%	-79.8%	-8.2%

PM Peak (15h00 - 18h59)

O\D	1 Toronto PD1	2 Toronto PD2-6	3 Toronto PD7-9	4 Toronto PD10-12	5 Toronto PD13-16	6 Durham	7 York	8 Peel	9 Halton	10 Hamilton	11 External	Total
1 Toronto PD1	1.2%	-6.0%	-2.5%	-8.8%	-7.1%	-11.6%	-10.4%	-10.2%	-16.8%	-2.7%	-86.3%	-6.0%
2 Toronto PD2-6	25.8%	8.1%	14.3%	-1.0%	0.8%	1.1%	3.3%	3.3%	-15.7%	-34.6%	-81.0%	7.5%
3 Toronto PD7-9	33.7%	16.2%	-13.2%	38.7%	3.0%	-27.4%	10.8%	5.0%	-3.2%	-3.9%	-85.7%	-1.1%
4 Toronto PD10-12	21.1%	1.2%	18.3%	-0.7%	2.9%	-7.5%	2.5%	-7.0%	5.1%	-7.8%	-85.8%	1.5%
5 Toronto PD13-16	26.5%	15.4%	-10.0%	3.8%	2.0%	-3.3%	19.7%	-20.1%	5.0%	-61.6%	-87.0%	4.5%
6 Durham	-34.1%	-26.8%	-45.2%	-1.4%	23.4%	5.0%	15.2%	-37.8%	-71.8%	99.0%	-84.8%	4.0%
7 York	16.2%	8.2%	5.3%	22.2%	15.1%	-5.0%	5.9%	-10.2%	-28.3%	-22.6%	-86.1%	6.2%
8 Peel	6.8%	0.7%	13.7%	19.0%	-10.7%	5.5%	8.3%	8.5%	2.4%	-13.0%	-84.5%	7.4%
9 Halton	-21.1%	-18.4%	-9.5%	4.6%	-35.6%	-57.1%	-33.6%	12.1%	-5.8%	2.2%	-87.8%	-4.7%
10 Hamilton	-58.3%	-43.6%	0.0%	-12.1%	26.3%	-19.0%	-39.3%	3.6%	3.8%	1.5%	-80.5%	0.2%
11 External	-25.7%	-34.2%	-60.6%	-18.0%	-23.8%	-64.5%	-52.0%	-51.5%	-49.5%	-41.4%	-98.7%	-52.7%
Total	11.4%	4.1%	-2.9%	3.7%	1.9%	1.7%	4.6%	5.0%	-5.8%	-0.3%	-87.5%	2.0%