

Assessing Potential Energy Savings in Household Travel:
Methodological and Empirical Considerations of Vehicle
Capability Constraints and Multi-day Activity Patterns

by

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For Angela.

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ABSTRACT

The lack of multi-day data for household travel and vehicle capability requirements is an impediment to evaluations of energy savings strategies, since 1) travel requirements vary from day-to-day, and 2) energy-saving transportation options often have reduced capability. This work demonstrates a survey methodology and modeling system for evaluating the energy-savings potential of household travel, considering multi-day travel requirements and capability constraints imposed by the available transportation resources.

A stochastic scheduling model is introduced – the multi-day Household Activity Schedule Estimator (mPHASE) – which generates synthetic daily schedules based on “fuzzy” descriptions of activity characteristics using a finite-element representation of activity flexibility, coordination among household members, and scheduling conflict resolution.

Results of a thirty-household pilot study are presented in which responses to an interactive computer assisted personal interview were used as inputs to the mPHASE model in order to illustrate the feasibility of generating complex, realistic multi-day household schedules. Study vehicles were equipped with digital cameras and GPS data acquisition equipment to validate the model results. The synthetically generated schedules captured an average of 60 percent of household travel distance, and exhibited many of the characteristics of complex household travel, including day-to-day travel variation, and schedule coordination among household members. Future advances in the methodology may improve the model results, such as encouraging more detailed and accurate responses by providing a selection of generated schedules during the interview.

Finally, the Constraints-based Transportation Resource Assignment Model (CTRAM) is introduced. Using an enumerative optimization approach, CTRAM determines the energy-minimizing vehicle-to-trip assignment decisions, considering trip schedules, occupancy, and vehicle capability. Designed to accept either actual or synthetic schedules, results of an application of the optimization model to the 2001 and 2009 National Household Travel Survey data show that U.S. households can reduce energy use by 10

percent, on average, by modifying the assignment of existing vehicles to trips. Households in 2009 show a higher tendency to assign vehicles optimally than in 2001, and multi-vehicle households with diverse fleets have greater savings potential, indicating that fleet modification strategies may be effective, particularly under higher energy price conditions.

Introduction

1.1. Overview

Light-duty vehicles used for personal travel accounted for 65 percent of U.S. transportation sector greenhouse gas emissions (GHG) emissions in 2009, and 18 percent of emissions from all sectors (U.S. EPA 2011). In addition to the negative environmental impacts, providing energy to these vehicles results in significant economic costs and a dependence on unstable regions for a steady supply of petroleum. The response of auto manufacturers to more stringent fuel economy regulation and increased consumer interest in efficiency has been to accelerate the deployment of technological innovations such as direct injection (DI), hybrid-electric (HEV), plug-in hybrid-electric (PHEV), and electric vehicles (EV), while also expanding the selection of smaller vehicles. However, widespread adoption of more efficient vehicles will be limited to some extent by the higher cost of these technologies, the capacity limitations of smaller vehicles, and the range limitations of EV's and PHEV's.

A wide range of factors influence vehicle choice and its use, not least of which are cost, personal preference, convenience and perceived safety. But at a minimum, a feasible vehicle choice must be able to satisfy the physical capability requirements of the trips for which it will be used. Because these requirements vary, vehicles may operate much of the time with underutilized capacity. In the case of passenger capacity, the average occupancy for trips in 2009 was 1.7, while the average capacity of personal vehicles, was 5 occupants (Santos et al. 2011). Underutilized capacity represents an opportunity for energy savings, since at any given level of technology, a decrease in capacity is invariably tied to a decrease in energy intensity (in terms of energy used per unit of distance traveled) as smaller vehicle size and power requirements result in decreased

inertial mass and frictional losses. However, without information about a household's multi-day patterns of travel requirements, it is not possible to know whether the composition or use of their vehicle fleet can be modified without making major changes in activity participation.

Household travel surveys often collect detailed information about vehicle utilization and activity schedules, but almost without exception are limited to one or two days because of the significant costs of administering the survey, and the high burden placed on participants. The results of recent studies using in-vehicle Global Positioning System (GPS) receivers to collect trip path data offer some promise for reducing these costs, especially over long survey periods. However, this GPS data by itself is insufficient for determining the vehicle capability requirements of trips. Additional information about travel party size and carried items is also needed. The primary goal of this research is to develop and demonstrate a survey methodology and modeling system for evaluating the energy-savings potential of household travel, considering multi-day travel requirements and the constraints imposed by the available transportation resources.

1.2. Activity-based approach to travel behavior analysis

In the last few decades, significant progress has been made towards the goal of understanding travel from the standpoint of the activities that are conducted, rather than the trips themselves. With a shift in focus to the underlying reasons for travel, it becomes possible to capture many of complex individual, interpersonal and environmental factors that motivate and constrain decisions. Yet despite the theoretical advantages of an activity-based approach, the realization of an operational model of household travel remains an elusive goal, in large part due to the difficulty of collecting data which can be used to explain complex travel behavior.

Before the activity-based approach: The four step model

The modern era of transportation planning began in the 1950's in the United States. The need for a more integrated and systematic approach for planning infrastructure arose from the goal of connecting major population centers with a national network of highways, and the widespread diffusion of the automobile for personal use. The four-step model (FSM) (Table 1.1) was developed to achieve this goal, and with its widespread use

by transportation planners around the world, became known as the *conventional* method (McNally 2000).

Table 1.1 The Four Step Model

Step	Description
Trip Generation	Propensity to travel for a population is represented by frequencies of trip end productions and attractions
Trip Distribution	Spatially defined origin-destination pairs are estimated from trip productions and attractions, considering the transportation network and travel times
Mode Choice	Transportation network and demographic information is used to divide trips between public transit and personal vehicles
Route Choice	Trips are assigned to paths on the transportation network according to a minimization objective, often travel time

A typical application of the FSM would be to aid in the decision of whether or not to fund a transportation project, such as the addition of a road to a network, or the expansion of an existing road. Based on the network traffic predicted by the model, the cost-effectiveness of various proposals could be compared in terms level-of-service or capacity, using metrics such as average speed or flow rate.

The major drawback of the conventional method is that its theoretical foundation lacks any consideration of the underlying behavioral determinants of travel. All trips are assumed to exist in isolation, and no distinction is made between trips conducted by members of the same household and those of strangers. So there is no possibility for an individual to chain trips together or reassign trips among household members. Perhaps more significantly, the FSM assumes that travel demand is fixed, as a model input, and does not account for the possibility that people adjust their schedules and agendas to adapt to new conditions. As a result, conventional transportation modeling is not well-suited to analyze Travel Demand Management (TDM) policies, which are intended to reduce travel demand in order to meet goals for reducing energy consumption, air pollution, congestion, or capital expenditures on new infrastructure projects (Kitamura et al. 1997).

Origins of the activity-based approach

While transportation studies will naturally include a locational component, the consideration of the spatial dimension in behavioral research is a relatively recent development. It wasn't until the seminal work on household activity systems by urban planners Chapin and Hightower (1966) that a framework was defined for describing both

the temporal and spatial aspects of an individual's behavior, using the concept of activity patterns. At about the same time, in the late 1960's, geographers at the University of Lund, Sweden took similar steps to place the individual in spatial models, with an emphasis on the movement from one point to another (Hägerstrand 1970).

Whereas previous spatial models of human behavior had predominantly aggregated individuals into mass probabilistic representations, these new efforts recognized that individuals are not simply data points, isolated in time and space to be consolidated or subdivided to suit the needs of the analyst. In reality, individuals exist in a continuum of time and space, with their decisions influenced by other people, and the events and conditions both in the past and the future. Torsten Hägerstrand (1970), a leading proponent of the disaggregate approach, observed, "*on the continuum between biography and aggregate statistics, there is a twilight zone to be explored, an area where the fundamental notion is that people retain their identity over time, where the life of an individual is his foremost project, and where aggregate behavior cannot escape these facts.*"

In the 1970's, some in the transportation research community adopted the disaggregate modeling concept from this early work, believing it to be the best approach for dealing with the contemporary issues of energy shortages, air quality and environmental degradation, and urban decline in an environment of reduced public funding for infrastructure and a shift from large-scale, long-term strategic planning to local, community-level solutions (Jones 1983a). The term *activity-based approach* was coined during this period to describe the incorporation of individual behavioral considerations into efforts to explain, and predict transportation behavior. However, in practice, although the many studies classified as activity-based are loosely related by their disaggregate approach, the field has been characterized throughout its four-decade existence by a lack of, and the search for, a unifying methodology (Goodwin 1983; Pas 1990). Despite the diversity in methods, some recurring themes have emerged that can be used to tie together the broad range techniques used. Various lists of attributes have been compiled, but the one presented by Jones et al. (1990) is particularly complete and concise, defining the activity-based approach as a framework which considers:

- (i) that demand for travel is derived from the desire to partake in activities;

- (ii) behavioral patterns and sequences, rather than discrete trips;
- (iii) decisions in a household context, considering interactions among its members;
- (iv) both the timing and duration of activities and travel;
- (v) spatial, temporal, and inter-personal constraints;
- (vi) interdependency among events across time, location, and participants;
- (vii) household and person classifications based on activity needs, commitments, and constraints.

At this point, it is instructive to review some of the important travel analyses and modeling that have been conducted using the activity-based approach from the inception of field, until today. The techniques used can be generally classified into those based on empirical analysis using econometric and statistical methods, and those employing rules-based simulations of travel behavior. With a focus on the significant achievements, as well as the shortcomings of these techniques, the following discussion is intended to place the contributions of this dissertation in the context of a field that has become reasonably well established, but has yet to coalesce around a set of methodologies that can fulfill the ambitious goals of the activity-based approach.

Econometric and statistical techniques

The increased focus on the individual decision maker in travel research occurred at the same time that significant advancements in discrete choice methodology in econometrics were being made. Some of the first attempts to include behavioral considerations in travel models involved the use of consumer choice models from economics to improve the estimation of mode choice in the conventional four-step model (Quandt and Baumol 1966; Reichman and Stopher 1971; Rassam et al. 1971). The major breakthrough came with the Nobel-prize winning work of Daniel McFadden, who while working as a consultant for California's Bay Area Rapid Transit (BART) authority conceived of linking discrete choice theory from the field of psychology with the method of logistic regression used in biostatistics to create what is now known as the multinomial logit (MNL) model (McFadden 1974; 2001). The method was initially promoted as complementary to the existing, conventional aggregate model, for its ability to facilitate calibration and improve forecasting accuracy (McFadden and Reid 1975). The mode

choice module of the four step model was one promising application, and continuing along the lines of McFadden's BART study, MNL models were used to link levels of auto ownership and use of public transportation to demographic characteristics (Ben-Akiva and Lerman 1976; Train 1980a). Yet some of the most significant contributions of discrete choice methods have come from the applications outside of the conventional, aggregate framework. The following decades have seen disaggregate, discrete choice methods used on their own so frequently as to create an entire sub-discipline within activity-based travel research.

Many early applications of the discrete choice model were motivated by an increased focus on energy conservation and regulatory initiatives to improve the efficiency of the personal automobile that arose from the oil crisis of the late '70's. These included studies of household vehicle holdings and response to fuel economy regulations (Lave and Train 1979; Boyd and Mellman 1980; Manski and Sherman 1980), the market for electric vehicles (Beggs and Cardell 1980; Train 1980b), usage in multivehicle households (Mannering 1983; Hensher 1985), and joint discrete-continuous models of vehicle choice and usage (Mannering and Winston 1985; Hensher 1986).

As complex as vehicle and travel mode choice decisions are, applications of discrete choice methods to the questions of activity participation, frequency, duration, and timing face an additional challenge. Because the number of discrete choice alternatives which encompass all combinations of activity characteristics is exceedingly large, econometric analyses are often focused on one or two particular aspects of an activity, such as its duration (Kitamura 1984), start time (Abkowitz 1981), period between occurrences, or joint participation with other household members.

More recent developments have extended the capabilities of discrete choice methodology. When combined with the hazard model used more commonly in engineering and biology, discrete choice models have incorporated continuous values for activity and inter-episode durations (Ettema et al. 1995; Bhat et al. 2004; Cirillo and Axhausen 2009). Modeling of agenda setting and daily schedules generation has been achieved by aggregating the durations of activities of the same type (Munshi 1993), or by classifying schedules into predefined activity patterns (Adler and Ben-Akiva 1974; Bowman and Ben-Akiva 2000). Multi-dimensional discrete choice modeling can avoid

this simplifying aggregation step, while simultaneously addressing activity timing, duration, frequency, and location through the use of multi-stage and nested logit models (Wen and Koppelman 1999). Genetic Algorithms, with a capability for handling large numbers of choice combinations, have been used to specify discrete choice models of activity scheduling considering interaction among household members (Meister et al. 2005; Charypar and Nagel 2005; Roorda et al. 2006).

Similar questions have been answered without discrete choice models using other statistical techniques. For example, structural equations modeling (SEM) has been used to investigate the relationship between vehicle type and usage in multivehicle households (Golob et al. 1996), and interactions among household members (Golob and McNally 1997; Fujii et al. 1999). Data reduction of large travel survey data sets has been achieved using statistical methods for the identification of relationships among variables, recurring patterns, and causal factors. Techniques have included multi-dimensional contingency tables (Kostyniuk and Kitamura 1983), Principal Components Analysis (Cullen and Godson 1975; Hanson and Huff 1986; Doherty 2006), pattern recognition and sequence alignment methods (Wilson 1998; Joh et al. 2002), and data mining algorithms (Wets et al. 2000).

A discussion of the weaknesses of discrete choice methodology is well-documented, with the greatest criticisms aimed at the theory of utility maximization, and the limited cognitive capacity of humans (Simon 1955). The theory of bounded rationality maintains that humans make sub-optimal decisions in situations where the number of choices becomes large, or some uncertainty exists about the outcome of a choice (Simon 1957; Kahneman and Tversky 1979). The process of decision making itself has some disutility so that considering every possible combination of choices, if that were even possible, may be undesirable. As a result, people are believed to approach complex decisions by employing heuristics, and selecting an option that is “good enough” though a process of satisficing (Simon 1956). Discrete choice models and data reducing statistical techniques in activity-based research have proven themselves to be operationally practical, and will continue to provide useful insights into travel behavior. At the same time, recognition of the weaknesses of these statistical techniques has led to development of alternative

methodologies involving rules-based simulations, which model the specific decision making steps of individuals.

Rules-based simulations

Whereas discrete choice models are based on choice outcomes in the form of either revealed preference or stated preference data, rules-based simulations begin with a representation of the choice process itself. It has been argued that the simulation approach provides a more behaviorally sound basis for a theory of decision making (Heggie 1978), although not without its own significant drawbacks of complex rule definitions, and data collection challenges, to be discussed further below.

Computational Process Models

One type of rules-based simulation, the Computational Process Model (CPM), is based on the concept of the production system developed by Newell and Simon (1972), and attempts to replicate the problem solving process using a series of IF-THEN decision rules. In early applications to travel analysis, CPM techniques were used to account for limitations in human ability to perceive and recall spatial relationships. The TOUR (Kuipers 1978), NAVIGATOR (Gopal et al. 1989), and TRAVELLER (Leiser and Zilbershatz 1989) models simulate an individual's cognitive map of her environment in order to more realistically represent way-finding and spatial learning. The SCHEDULER model (Golledge et al. 1994) combines spatial learning with an activity scheduling component, and considers both long and short term calendars to simulate human memory and account for habitual behavior.

Even under the assumptions of bounded rationality, utility considerations still play a major role in many decisions, and utility theory is often incorporated into rules-based simulations. Recker et. al (1986a;1986b) developed the STARCHILD model, which incorporates an MNL choice module for selecting a final activity program from all feasible combinations of activities. In the SMASH scheduling model (Ettema et al. 1993), activities are sequentially added, removed, or modified to produce a final schedule when further steps fail to increase the total utility.

One of the major obstacles preventing more widespread adoption of CPM's is difficulty collecting data in a useful form for defining the complex decision rules.

Approaches for addressing this challenge include the use of computer learning to improve rule definitions over repeated iterations of the model (Arentze and Timmermans 2004) and the use of *fuzzy* rules to accommodate more qualitative descriptions of the decision process in the model (Vause 1997).

Constraints-based models

The concept of constraints on the movement of individuals (Hägerstrand 1970) has been widely accepted in activity-based research, and is incorporated into many of the techniques described above. Constraints-based simulation models typically address constraints in terms of the spatial and temporal limitations they impose on individuals, such as the infeasibility of being in two places at the same time, or the requirement that two or more people participate in an activity together. Without any consideration of the decision process, a purely constraints-based model cannot claim to forecast responses to policy actions. Nevertheless, these models can be useful as planning tools by providing insight into the upper limits of the effectiveness of various policy proposals. In particular, if the objective is to reduce energy consumption, a best-case study would compare the competing proposals assuming that resources are used optimally.

Despite the strong influence of transportation mode and vehicle choice on energy use, the limitations imposed by vehicle capability constraints are often ignored, even in constraints-based simulations. This dissertation was motivated in part by the lack of previous work on the important topic of vehicle capability constraints.

Comprehensive modeling systems

None of the activity-based techniques discussed up to this point are capable of performing all the functions of the conventional four-step model, nor are they intended to. For this purpose, complex modeling systems have been developed which integrate many concepts of the activity-based approach, including discrete choice modeling, constraints, intra-household interactions, activity characteristics, and scheduling algorithms, in addition to transportation network and land use data. Notable among these integrative modeling systems are SMART (Stopher et al. 1996) and TRANSIMS (Rilett 2001). While activity-based techniques can potentially be incorporated into comprehensive

models like these, it's important to remember that more focused applications have been proven to provide useful insights into travel behavior, and will continue to do so.

1.3. Research questions

The need to develop new survey methods capable of providing data for disaggregate models of travel behavior was identified at an early stage in the development of the activity-based approach (Clarke, Dix, and Jones 1981; Brög and Erl 1983; Goodwin 1983). In particular, the development of improved methods for multi-day data collection has been cited as an important topic in activity-based research (Kitamura 1988; Jones and Clarke 1988; Madre 2003). Yet despite methodological and technical advances in data collection techniques, the overwhelming majority of travel behavior analyses are still based on data from single-day travel-activity diaries.

The lack of multi-day data creates a particular challenge for any analysis of the potential for households to reduce transportation energy use. Since travel requirements vary over time, it is not possible to use a single-day of data to determine the feasibility of household fleets modified with more efficient, but less capable, vehicles. Even if travel requirements can be satisfied on one particular day by a vehicle with reduced capability, the vehicle may fail to meet the requirements of another day. Any judgment about the overall feasibility of a reduced capability fleet requires knowledge of travel patterns over multi-day time periods.

To restate from the beginning of this chapter, the main goal of this research is to develop and demonstrate a model system which can be used to evaluate the energy-savings potential of modifications to household vehicle fleet composition and use, considering multi-day travel requirements and the constraints imposed by the available transportation resources. This goal is approached through five specific research questions. [Q1], [Q2], and [Q3] are questions about the methodology for collecting multi-day data for household travel and vehicle capability requirements. [Q4] and [Q5] are empirical questions intended to illustrate how the consideration of vehicle capability constraints in an activity-based analysis can provide useful insights into travel behavior and the potential effectiveness of energy-saving strategies.

- | |
|--|
| <p>[Q1]. Is it feasible to collect multi-day data for household activities using an interactive survey approach?</p> <p>[Q2]. Is it feasible to generate complex and realistic household schedules using activity characteristics reported as probabilities and ranges?</p> <p>[Q3]. Is it feasible to use passive in-vehicle data acquisition equipment to observe trip capacity requirements over extended time periods?</p> <p>[Q4]. What was the average energy savings potential for U.S. households in 2001 and 2009 if existing vehicle fleets were utilized optimally?</p> <p>[Q5]. Did multi-vehicle households in 2009 utilize their fleets more optimally than in 2001?</p> |
|--|

The reporting of multi-day data using a travel-activity diary places a high burden on participants. Interactive survey techniques can accommodate flexibility of responses, encourage discussion among household participants, and facilitate the identification of inconsistencies and missed responses. [Q1] is intended as an initial investigation to determine if the approach merits further attention. [Q2] addresses the format of the survey questions, and the potential for integrating probabilistic, “fuzzy” responses into a schedule generating model for household activities. [Q3] addresses the method of validating survey responses, and the use of passive data acquisition equipment to make observations of the physical requirements of trips.

Although there are many ways in which households can reduce their transportation energy consumption, changes in travel behavior are more likely to be adopted if they do not require major changes in activity participation. [Q4] addresses one of the simplest ways that households with multi-vehicle fleets can achieve immediate energy savings, which is to optimally assign existing vehicles to trips. Optimal assignment is defined as the matching of vehicles to trips which minimizes total household transportation energy consumption while satisfying the requirements of the given travel-activity schedule. Because of differences in vehicle capability, the requirements of each trip must be considered separately in order to determine if vehicle reassignment is feasible. In addition

to vehicle capability constraints, coupling constraints enforce the requirement that trip schedules and vehicle availability coincide for feasible assignments. Because of increases in energy prices and the ongoing economic recession in 2009, households would have a greater incentive to make optimal assignment decisions than in 2001, a hypothesis that is tested in [Q5].

1.4. Organization of this dissertation

In chapter 2, a model is introduced which generates household schedules using a method of characterizing activities in terms of their likelihood of occurrence, range of potential times, and other “fuzzy” descriptors. The multi-day Probabilistic Household Activity Schedule Estimator (mPHASE) employs a novel finite element approach for assigning activity times and durations based on a physical representation of the household schedule. Examples are provided for how considering the intra-household coordination of activities can produce complex schedules ([Q2]).

Chapter 3 describes the Household Travel Patterns Study, a pilot investigation of 30 households to test an interactive survey method ([Q1]). The original aspect of the survey approach is the reporting of typical activity frequencies, locations, places, times, and participants in terms of probabilities and ranges. Responses from the survey are used as inputs to the mPHASE model, which generates synthetic multi-day activity schedules. Also described is an electronic data acquisition device developed for this work, the Vehicle Utilization Survey Equipment (VUSE) with GPS and digital image capture capability ([Q3]). The generated schedules from the mPHASE model are compared to the travel observed using VUSE units to provide additional insights into the feasibility of the survey method ([Q1]), and the realism of the mPHASE-generated schedules ([Q3]).

Chapter 4 introduces the Constraints-based Transportation Resource Assignment Model (CTRAM), providing a computationally efficient enumerative optimization of household vehicle assignments. The model is applied to the 2001 and 2009 National Household Travel Survey data, and a discussion of the results is provided for [Q4] and [Q5].

Finally, the research questions are reviewed in the Conclusion, along with a discussion of empirical findings, potential applications, and limitations of the methods introduced in this work.

A multi-day probabilistic scheduling model for household activities

After several decades of advancement, activity-based methods have been successfully shown to provide useful insights into real-world questions about travel demand. These efforts were largely motivated by a desire to study travel in ways more firmly grounded in fundamental theories of human decision making and spatio-temporal relations than were the previously available methods. By extension, a richer set of questions about the influence of such factors as demographic and land use changes, transportation policies, and infrastructure investment could be explored with an expectation of more realistic results. The significant number of existing activity-based travel demand models is evidence of the attraction of activity-based methods. But the continuing development of new models and methods shows that no single model has achieved preeminence, and as is likely, no model will ever be perfectly suited to every purpose.

This chapter presents a model which generates household activity schedules for the purpose of evaluating the potential effectiveness of various strategies for reducing personal travel energy consumption. The model, referred to hereafter as the multi-day Probabilistic Household Activity Schedule Estimator (mPHASE), borrows elements from existing techniques and also adopts a novel finite element approach for assigning activity times and durations based on a physical representation of the household schedule. The generated schedules output by mPHASE have three important characteristics which are critical for the model's designed purpose. Namely, the schedules: 1) reflect the day-to-day variability inherent in household travel; 2) ensure that time conflicts are avoided by considering the inter-personal and intra-personal coordination of household members' activity times and locations; 3) account for the activity characteristics which constrain

travel options and thus influence energy use. It is useful to begin by placing the mPHASE model in the context of existing schedule generation models, focusing particularly on those which exhibit one or two of the characteristics above.

2.1. Background

Activities and their classification

In the most basic sense, an activity describes what one is doing at a particular time. Yet while an individual may have a good sense of ‘what they are doing’, the researcher has a difficult task quantifying the use of time in a consistent and useful way. The subjective nature of time itself has been revealed in previous work (Ampt and West 1983) and described by Scheuch (1972) “...*the perception of how one’s time is spent as a socially-relevant derivative of the physical property time varies with the type of society.*” Classification attempts are further complicated by the fact that in reality our time is occupied by a continuous stream of behaviors, sometimes simultaneous, than cannot always be broken down into discrete activities (Dagfinn 1978).

These difficulties notwithstanding, researchers have a strong motivation to define activity characteristics, in particular their priority and flexibility – two features of great importance in scheduling decisions. These features are illustrated by the *activity-peg* theory of scheduling, where high-priority activities with limited space and time flexibility act as pegs about which other, more flexible activities are positioned (Cullen and Godson 1975). This intuitive concept has been supported empirically (Lee and McNally 2006), and underlies a common practice of characterizing activities as either *mandatory* or *discretionary*. While mandatory implies higher priority and might clearly be used to describe work or school activities, the degree of flexibility for many activities cannot be defined along a single dimension. Even the most rigidly constrained activity has some variation in its characteristics while the most flexible activities still have some constraints on who can conduct them, and when and where they can take place. Stopher et al. (1996) proposed that in addition to highly fixed mandatory activities, discretionary activities which vary in frequency, time and space should be considered as *optional*, and a third category of *flexible* should be added to describe activities with a combination of fixed and variable characteristics.

The focus on the household as the unit of analysis has led others to identify the importance of flexibility in the participants of an activity. The addition of a *maintenance* category has been used to describe required activities which are not assigned to a particular household member (Reichman 1976; Wen and Koppelman 2000; Vovsha et al. 2005; Srinivasan and Bhat 2005), while an *individual* or *joint* specification has been used to clarify the interpersonal coordination required for discretionary and mandatory activities (Kang and Scott 2009).

More detailed classifications have been proposed, such as by the need underlying the activity (Nijland et al. 2010), but any attempt to assign strict categories will result in some ambiguity because of the multi-dimensional nature of activities.

An alternative to a rigid classification system is to describe the characteristics of activities across multiple dimensions. Doherty (2006) recognized that different activities of the same type (work, school, etc.) often have varying flexibilities, and proposed instead to define activities according to the features that can better explain the complex processes of activity scheduling and tour formation. Using Principal Component Analysis on one week data from the CHASE survey, he identified seven “salient attributes” of an activity: frequency, duration, involved persons, travel time, temporal flexibility, spatial flexibility, interpersonal flexibility.

Review of existing activity scheduling models

While household schedule data is readily available for single-day periods, the availability of multi-day schedules is limited by the difficulty in conducting long-term surveys – an issue that is addressed in detail in chapter 3. This lack of multi-day schedule data has led to an interest in the generation of synthetic schedules using models which attempt to reproduce the results of actual scheduling decision processes. What follows is a review of some of the most relevant existing models, which are listed in Table 2.1.

Table 2.1 Existing Scheduling Models

Model type and name	Generated schedules consider:			Input data source
	Multi-day variation	Inter-personal Coordination	Activity Constraints	
Rules-based				
CARLA (Clarke, Dix, Jones, et al. 1981)	✗	△	○	Single day activity diary
STARCHILD (Recker, McNally, and Root 1986b)	✗	○	△	Single day activity diary and constraints
SCHEDULER2 (Gärling et al. 1998)	✗	✗	○	Fictitious activity descriptions
SMASH (Ettema et al. 1995)	○	○	✗	
TASHA (Miller and Roorda 2003)	✗	○	✗	One-day activity diary
Albatross (Arentze and Timmermans 2004)	△	○	△	Two-day activity diary
Random Utility Maximizing				
van Der Hoorn (1983)	○	✗	△	One-week time table and activity diary
Bowman and Ben-Akiva (2000)	✗	○	✗	Single-day travel diary
Cirillo and Axhausen (2009)	○	✗	✗	Six-week MOBIDRIVE survey

○: full consideration, ×: no consideration, △: partial consideration (see text for details)

In activity-based analysis, existing models for generating trip schedules can be generally classified as either econometric choice models or rules-based simulations. Econometric, or random utility maximizing (RUM) models, are based on the principle of utility maximization and require the definition of discrete choice sets of travel options (McFadden 1981). These models estimate choice probabilities by fitting regression models to empirical data in which the observed choices have been characterized according to predefined attributes. In contrast, rules-based models build up choice probabilities from the perspective of individuals using a series of IF-THEN steps that attempt to replicate the decision making process.

Econometric (RUM) scheduling models

In general RUM techniques, which require a priori definition of choice sets, are not particularly well-suited to the scheduling problem since even relatively coarse increments on the time scale result in an exponentially large number of possible choice combinations. Still, several RUM models are worth mentioning here, although they cannot all truly be considered scheduling models. Bowman and Ben-Akiva (2000) demonstrated an

econometric model using single-day diary data from a Boston travel survey which defined choice sets in terms of tours, or combinations of trips. These tours were characterized by the number, sequence, and purpose of the primary and secondary activities conducted on that tour. While the sequencing of activities is considered, this can only marginally be described as a scheduling model, since the time of day is coarsely divided into four periods in order to reduce the number of choice combinations. More recently, Cirillo and Axhausen (2009) introduced an application of discrete choice methods to what they termed “dynamic” multiday activity modeling. Based on the six-week MOBIDRIVE data from 1999, theirs is the first example of an RUM model which considers the dependence of activity generation decisions on past occurrences. RUM methods are becoming well-established in operational models, although the definition of choice sets presents a challenge for a fine-grained analysis of multi-day travel behavior which has a very large number of choice combinations.

Rules-based scheduling models

Rules-based models can be constructed based on the fundamental factors underlying actual decision behavior, and would therefore seem to be a natural fit for activity-based analysis. Constraints on activities can be explicitly defined, as well as the interaction between members of the household - both important factors when determining which activities will be undertaken and when. However, despite the apparent advantages, rules-based methods do not yet have the well-established methodology that RUM methods enjoy (Wets et al. 2000).

One of the earliest examples of a rules-based scheduling model, CARLA (Jones et al. 1983), was developed to evaluate potential reactions to a disturbance to an existing household schedule such as might occur with a change in school hours. CARLA is actually a re-scheduling, rather than a scheduling model, since it takes an existing one-day set of activities, and rearranges them with the goals of minimizing travel disutility and/or maximizing free time according to various definitions. A mathematical programming approach is used which considers all combinations of activity sequences and time placements. In order to limit the total combinations to a computationally feasible level, the range of possible adjustments is restricted to 15 minute increments for activity starting time, and a fixed duration reduction of 25 percent.

The STARCHILD modeling framework (Recker, McNally, and Root 1986a) is more ambitious than CARLA in its approach to simulating the selection of activities from an agenda to include in a daily schedule. Like CARLA, every possible combination of activities is reduced to the feasible set, considering the constraints on time, location, and shared resources such as vehicles. Detailed schedules would then be constructed using utility maximizing principles. STARCHILD was not implemented using real-world data, but a mathematical programming approach to the framework was later defined in the Household Activity Pattern Problem (HAPP) (Recker 1995), for which an optimal schedule solution could be found using techniques of Mixed Integer Linear Programming (MILP). This approach provides the benefits of a continuous time scale, and the ability to specify windows for the earliest and latest activity times. In addition to minimizing travel disutility, other proposed objective functions included the minimization of the risk of not returning home in time, or the risk of not being able to complete an activity due to stochastic variations in travel times and activity durations. The HARP model (Gan and Recker 2008) focused the HAPP model towards the solution of a single-day activity rescheduling problem, as demonstrated by example of the cancellation of a car-pooling agreement to pick up a child from school. An interesting feature of all of these models is their ability to consider the allocation of household vehicles to trips, reflecting the suitability of mathematical programming techniques towards solving logistical and fleet assignment problems.

The SCHEDULER and SCHEDULER2 models (Gärling et al. 1998) activities are added into open time slots in the schedule in a priority determined by a utility for conducting a particular type of activity, the cost to travel to the activity location, and the state of readiness to perform any activity. Activity durations are assumed to be fixed, and gaps between activities are considered waiting time. The required model inputs include characteristics of potential activities such as type, duration, and utility by hour of day, and characteristics of potential locations such as spatial coordinates, opening and closing hours, and aversion to visiting. The model has been tested with fictitious activity descriptions, but does not appear to have been validated with real-world data.

The Toronto Area Scheduling Model for Household Agents (TASHA) uses single-day activity diary data to generate a detailed 24 hour schedule for synthetic households

(Miller and Roorda 2003). The daily activity agenda is constructed by applying the survey data distributions for frequency, start times, durations, and number of people involved. Conflicts between activity episodes that overlap on the schedule are resolved using rules to shift or remove activities depending on their priority, precedence, and the available gaps. When available gaps are insufficient, activity durations can be shortened by up to 50 percent. Using seven-day survey data, the original TASHA model was adapted to use a utility maximizing approach to generate daily activity programs for flexible activities using, but this iteration of the model stops short of producing daily schedules (Habib and Miller 2008).

The Albatross model (Arentze and Timmermans 2003;2004) creates schedules in a two-step process, first adding fixed activities along a continuous time scale, and then filling in flexible activities into available openings in six discrete time-of-day segments according to probabilistic decision trees created from two-day activity diary data. The boundaries of each time segment act as constraints, limiting how much an activity can be shifted in time by its earliest start time, or latest end time. Unless two activities are explicitly linked, gaps in the schedule are left undefined. As a result, the model does not fully define start and end times for each activity.

As a subset of the rules-based model, a computational process model (CPM) is an explicit attempt to simulate the cognitive decision making process. This includes realistic limitations to perception, memory, and logic which lead to sub-optimal results in real-world decision heuristics (Gärling et al. 1994). SMASH (Ettema et al. 1993) is an early example of a CPM scheduling model which builds the schedule incrementally through the addition, deletion and modification of activities. The suboptimal nature of decision making is exhibited by the heuristic of selecting the best next step in the sequential process rather than a global maximum. Similar to the HARP model, an output variable is proposed which measures the chance of successfully completing the schedule, given the statistical distribution of activity duration and travel time.

As scheduling problems become more complex, it becomes untenable to construct rules based simply on expert knowledge and intuition. Attempts to develop a standard methodology for constructing rules based on travel dairy data have made use of inductive learning techniques such as a CHAID-based algorithm in Albatross (Arentze and

Timmermans 2004), and data mining techniques such as the C4 algorithm (Wets et al. 2000).

2.2. mPHASE model overview

Despite the theoretical attractiveness of rules-based models, their actual applications have been limited by the difficulties involved with specifying rules and collecting the required model input data. The multi-day Probabilistic Household Activity Schedule Estimator (mPHASE) has been developed to realize some of the benefits of a rules-based model, while ensuring that required input data can still be reasonably supplied by households using a companion survey such as the one described in detail in chapter 3.

It is useful to first clarify the definitions of some familiar terms as they are applied to the following description of the mPHASE model. An *activity* is considered to be the set of actions that occur contiguously (possibly simultaneously) at a single location which satisfy one or more needs of the individuals involved or of the household as a whole. This set of satisfied needs together define the *activity purpose*. A particular occurrence of an activity is referred to as an *activity episode*¹.

Activity purpose as the central organizing theme

In a trip-based approach to travel analysis, the purpose of a trip may be just one of many details recorded in a diary along with travel party members, mode, destination, trip start and end time, etc. In the approach described here for the multi-day Probabilistic Household Activity Scheduling Estimator (mPHASE), the purpose is central so that all activity episodes which serve to meet a particular need are considered to be mutually exclusive, and are considered together, even though the particular characteristics of the episodes may vary.

To illustrate the interchangeability of episodes with a common purpose, consider how a couple shopping for groceries together satisfies the need for a particular type of household maintenance. Shopping trips by either person alone would replace the need for a mutual trip unless the companionship they receive while shopping together is a requirement for the activity.

¹ This distinction between an activity 'episode' and 'purpose' is consistent with the definitions used by Chapin and Hightower (1966).

Templates and probabilistic multi-dimensional descriptions of activities

In order to avoid the ambiguous and subjective classification of activities to pre-defined categories, the approach of a multi-dimensional description of activities by their salient attributes proposed by Doherty (2006) is used. Of the five dimensions selected for use in mPHASE – day, time, location, household participants, and items carried – the first four are considered in some manner by nearly all existing scheduling models. The last, items carried, is included to help achieve the model’s goal of accounting for activity characteristics which constrain travel mode options and thus influence energy use. The five dimensions and their relationship to this goal are summarized in Table 2.2.

Table 2.2 Five Dimensions of mPHASE Activity Templates

Activity dimension	Related to energy consumption through:
1: Day	Mode and vehicle availability
2: Time	Mode and vehicle availability
3: Location	Distance traveled, mode access, and vehicle range capability
4: Household participants	Vehicle capacity limitations (passenger capacity)
5: Items carried	Vehicle capacity limitations (cargo volume and weight capacities)

A description of an activity across all five dimensions is called an activity template, and defines the ranges of values that activity episodes fitting within the template can exhibit. A unique template is created if it differs from existing templates in the values assigned to one or more dimensions. To illustrate, a young company employee is given the responsibility of providing donuts for his co-workers once a month, on a Friday of his choice. Although most many aspects of this new Friday work activity remain the same, a new template would be required to describe the dimensional changes in the day (Fridays), the time (following a “pick-up donuts” activity), and items carried (donuts), while the dimensions of household member and location would remain unchanged. The new “work with donuts” template would still serve the same purpose as the “work without donuts” template, such that the two templates are prohibited from both contributing to a work episode on the same day. The five dimensions of mPHASE activity templates are described in more detail below.

Dimension 1: Day

The week is an important organizing structure for many activities, and the operation of nearly all institutions is tied in some way to the day of the week. As a result, household

schedules tend to exhibit weekly patterns, making it critical to include the day of the week in any scheduling model. In addition, some institutions also reflect seasonal or monthly constraints, with school being an obvious example.

The mPHASE model represents these day of the week constraints as ratios of probable occurrence on each day relative to the other days of the week. Table 2.3 shows examples of three different activity templates. An activity in template A has an equal chance of occurring on any day of the week, while those in template B are restricted to the weekend. An activity in template C is also restricted to the weekend, but more likely to occur on Saturday. Seasonal and monthly constraints are incorporated in mPHASE using a binary value to indicate if the activity can be conducted all year (template A), in the school year (template B), or only in July (template C) as shown in Table 2.4.

Table 2.3 Examples of Weekday Occurrence Ratios

Activity template	Mon	Tue	Wed	Thu	Fri	Sat	Sun
A	0.14	0.14	0.14	0.14	0.14	0.14	0.14
B	0	0	0	0	0	0.5	0.5
C	0	0	0	0	0	0.75	0.25

Table 2.4 Examples of Month Occurrence Constraints

Activity template	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	1	1	1	1	1	1	1	1	1	1	1	1
B	1	1	1	1	1	0	0	0	1	1	1	1
C	0	0	0	0	0	1	1	1	0	0	0	0

Dimension 2: Time

Many activities have some limitations on the times of day when they can occur. Activities such as meetings which involve interpersonal coordination, and activities that take place at institutions with limited operating hours provide two examples. The mPHASE activity templates accommodate a flexible specification of activity time limits, allowing hard constraints to be defined for the earliest and latest possible start and end times, and the longest and shortest possible durations. Within those limits, target times and durations are also specified. The time constraints and targets are used in the mPHASE activity scheduling and conflict resolution module described in detail in Section 2.4.

Dimension 3: Location

The accessibility of a potential location is a function of the distance from the prior activity location and the average travel speed. The spatial relationships between a

potential activity episode and the prior and subsequent episodes are accounted for in the mPHASE scheduling module by an estimate of travel times between each location pair.

It is not uncommon that an activity can be performed at a variety of locations while still fulfilling the same need. Shopping is an obvious example, but other recreational and entertainment activities are also often not restricted to any single place. A household may have a favorite movie theater, but when the preferred showing time is not available, they might visit the theater across town. Multiple potential activity locations are defined in mPHASE templates by their relative likelihoods. As shown in Table 2.5, an activity in templates A or C might be restricted to one work or school location, a softball game in template D might be equally likely to be scheduled at one of three fields, and template B could describe a shopping activity that is more likely to occur at one store than another.

Table 2.5 Examples of Location Probabilities

Activity template	Location 1	Location 2	Location 3	Location 4	Location 5	Location 5
A (work)	1	0	0	0	0	0
B (shopping)	0	0	0.90	0.10	0	0
C (school)	0	1	0	0	0	0
D (softball)	0	0.33	0	0	0.33	0.33

Dimension 4: Household participants

Household maintenance activities are defined by the characteristic that they are not specific to any one member of the household. Activities may include individuals in the travel party whose presence is not essential for the primary purpose to be fulfilled. Instead they may join the activity to satisfy a desire for companionship, or because their presence is required for another activity in the trip chain. In the case of children, activity participation may be the result of need to be in the presence of a caregiver throughout the day.

For these reasons, the composition and number of household participants may vary between activity episodes in the same template. In the mPHASE model, each activity template is required to have at least one primary participant defined, without whom the activity would not be possible. If the primary role can only be filled by particular household members, their presence is categorized as mandatory. In other cases, the primary participant(s) could be any combination of household members authorized to fill an optional, primary role. Individuals whose presence is not central to the activity are assigned a secondary, optional role, or for children, a follow-caregiver role if they are not

permitted to remain alone. Household members who do not fulfill mandatory, optional, or follow-caregiver roles are considered to be prohibited from participating in activities in that template. This includes members who are assigned a drop off/pickup only role. Examples of household member participation roles are given in Table 2.6. Template A might define a work activity which has only one possible participant. Template B would be representative of a shopping activity which could be conducted by either, or both, individuals with optional roles. A school activity for a young child could be described by template C, which has only one possible participant, but involves other household members in drop off/pickup roles. Finally, template D could be used to describe a recreational softball game which has one mandatory participant, but might optionally involve other household members as supporters.

Table 2.6 Examples of Household Member Participation Roles

Activity template	Household member X	Household member Y	Household member Z (child)
A (work)	1	0	0
B (shopping)	2	2	4
C (school)	5	5	1
D (softball)	3	1	4

Primary participation categories: 1=Mandatory, 2=Optional
Secondary participation categories: 3=Optional, 4=Follow caregiver
Prohibited participation categories: 0=Prohibited, 5=Drop off/Pickup

Dimension 5: Items carried and non-household members

The size and weight of items that need to be carried to or from an activity are important factors because they influence the potential of using a particular mode of transportation or type of vehicle for a trip. The feasibility of walking to the store is constrained not only by the distance, but also by one's ability to carry the purchased items home. When personal vehicles are used, the number of people in the travel party, including non-household members, may exceed the capacity of some vehicle types.

The mPHASE model accounts for variation in the items carried and travel party size by the specification of minimum, maximum and average values for item mass, item volume, and accompanying non-household members as shown in Table 2.7. The work activity in template A doesn't require any additional items, while the shopping activity in template B will require that groceries be carried from the store, and remain with the participants until they return home. The other example templates involve non-household

members, with car-pooling for dropping off at school in template C, and taking up to three softball teammates to and from the game, along with their equipment, in template D.

Table 2.7 Examples of Items Carried and Non-household Member Ranges

Activity template	Item mass (kg)			Item volume (m3)			Non-household members		
	min	avg	max	min	avg	max	min	avg	max
Carried to									
A (work)	0	0	0	0	0	0	0	0	0
B (shopping)	0	0	0	0	0	0	0	0	0
C (school)	0	0	0	0	0	0	0	1	1
D (softball)	8.2	8.2	8.2	0.11	0.11	0.11	0	2	3
Carried from									
A (work)	0	0	0	0	0	0	0	0	0
B (shopping)	0.2	5.5	10.1	0.010	0.025	0.040	0	0	0
C (school)	0	0	0	0	0	0	0	0	0
D (softball)	8.2	8.2	8.2	0.11	0.15	0.11	0	2	3

Occurrence rules and accounting for day-to-day variability

From an individual's perspective, the variation in schedules is the result of both intentional choices that reflect the degree of flexibility in activities, and those factors that are outside of their control. Some highly variable activities are quite flexible, like going out for ice cream, while others are not, such as a doctor on-call being asked to see a patient, or a school closing which causes a parent to stay at home with their child. In these cases, the activity is highly irregular but there is little flexibility in the individual's choice of activities.

In the mPHASE model, the reasons for the day-to-day differences in an activity are of less importance than the resulting variation itself. This is by design, since the model specification relies on the responses of individuals who may not even be able to easily identify the underlying cause of the differences. For example, it would be difficult to report whether some shopping trips take longer than others because the store is crowded or because they spent more time browsing. Variability, whether by choice or externally imposed, is expressed by a single probabilistic representation for each of the various activity characteristics.

Day-to-day variation in occurrence is defined in mPHASE by rules which specify whether episodes occur periodically, with a certain frequency or likelihood, or a combination of these. These rules also are used to describe relationships between all the activity templates sharing a common purpose. The probability of occurrence of an

activity on any given day is calculated using these rules in the mPHASE agenda setting module, as described in detail in Section 2.3. The characteristics of periodicity, frequency, and likelihood are introduced below.

Variability in periodic activities

Periodicity is a trait of activities for which the utility derived is related to the time elapsed since it was last performed (Kraan 1997). The desire to return to the park may be low immediately after a visit, but is likely to grow as the week progresses. Similarly, the need to buy groceries increases as supplies dwindle, so that one may try to shop for groceries every three days, but on some occasions shop two days in a row and at other times wait a full seven days. This variation can be defined by a cumulative distribution function which represents the cumulative probability of occurrence as a function of the time since the last occurrence (the inverse of a survival function), as shown in Figure 2.1. If the distribution is known, the survival function can be estimated for this model by fitting a curve through points which are defined as the minimum, median, and maximum time between two occurrences. In this example, one goes shopping at least every seven days ($\Pr(t_{max})=\Pr(7)=1$), typically every three days ($\Pr(t_{median})=\Pr(3)=0.5$), but never more frequently than every two days ($\Pr(t_{min})=\Pr(2)=0$).

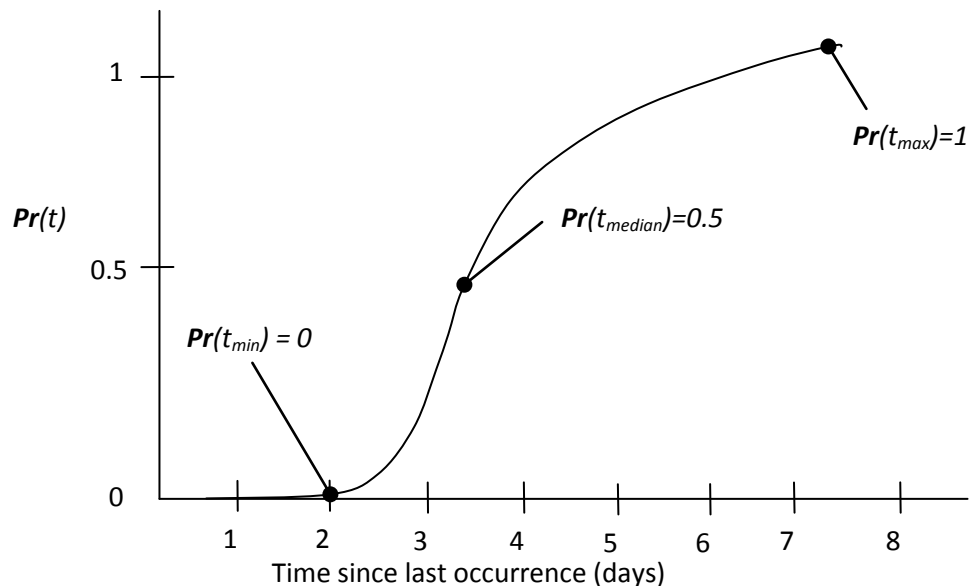


Figure 2.1 Example of cumulative distribution function for periodic activities

Variability in activity frequency

Frequency is an appropriate measure for activities that occur a certain number of times in a period, with no regularity in the time elapsed between episodes. This might be the case for the work activity of a substitute teacher who is restricted to 10 days a month, but has no idea of which days they might be. Activity frequency variability in mPHASE is defined as the minimum, maximum, and average number of episodes per week, per month, or per year.

Variability in activity likelihood

Other activities occur neither at regular periods or a set frequency, but instead tend to occur at fixed calendar dates and times. Often these are activities which involve coordination with institutions and people outside of the household, such as a Monday through Friday school week, or a meeting on the first Tuesday of the month. In these cases, the uncertainty is most easily represented by a percentage probability of conducting the activity on that day. For example, one might know that they have used three sick days in the last year, and can therefore estimate that they attend 99% of the days in their weekday job. While it would also be possible to assign a frequency for number of workdays in a year, it is simpler in this case to report the percentage likelihood.

Defining occurrence rules

The probability of occurrence for some activities cannot be defined completely using only one of the characteristics of periodicity, frequency, or likelihood. As an example, some work rules may limit the number of consecutive days (the period) yet require a certain number of days per week or month (the frequency). Furthermore, activity templates which share a common purpose may place different restrictions on episode occurrence. For example, an eight hour work shift might occur two or three times a week, while a twelve hour shift might be limited to one time per week. The mPHASE model uses flexible definitions of occurrence rules, and allows as many rules as necessary to define occurrence variability for every template of an activity purpose.

Model structure

The overall flow of the mPHASE model is shown in Figure 2.2. The model takes as inputs a set of potential activities for a household, defined by the templates for each activity purpose, and outputs the detailed schedules for each day in the study period. Alternatively, multiple iterations of the model over the study period can produce a distribution of multi-day schedules. Internally, the model consists of two main components 1) the activity agenda-setting module, and 2) the scheduling and conflict resolution module.

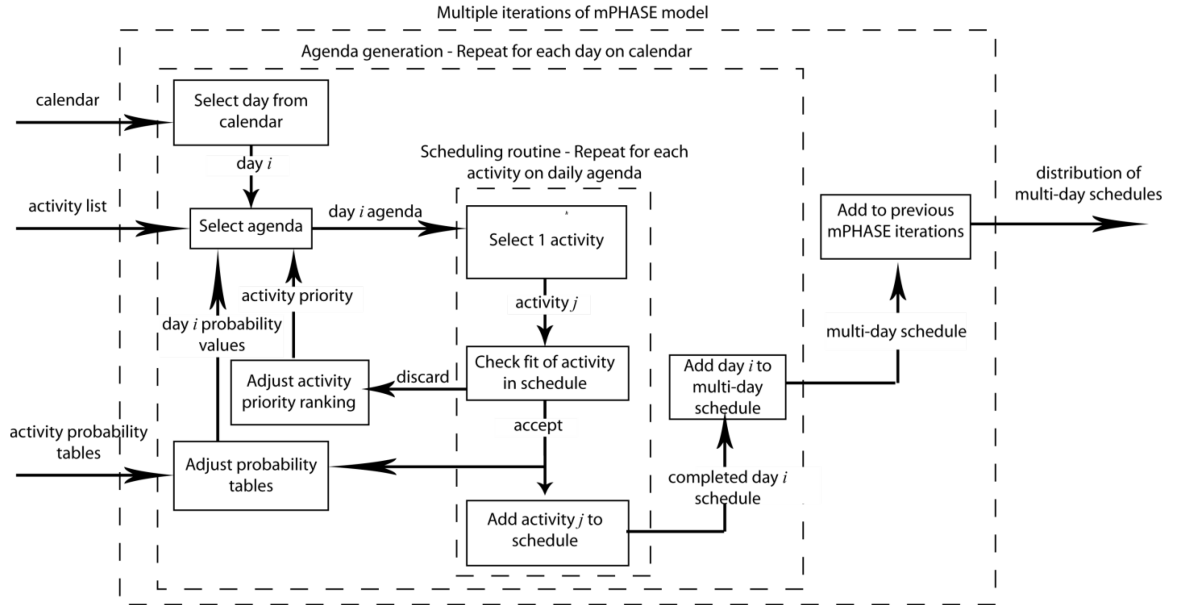


Figure 2.2 mPHASE model flow diagram.

2.3. Activity priority and the daily agenda

For the i th day, the probability of activity pattern j occurring can be represented by $Pr_{OCCURi,j}$. Some activities on the complete activity list will be automatically excluded from consideration, either because institutional constraints make them infeasible, e.g. operating schedules, or because they are not part of the household routine so that $Pr_{OCCUR} = 0$. All other activities will have a non-zero chance of appearing on the daily agenda. The first step of the mPHASE model process, shown in figure 1, is to generate an activity agenda for a randomly selected day on the calendar by drawing from the complete activity list according to values of Pr_{OCCUR} .

An activity's presence on the agenda does not guarantee that it can be performed, because there may be scheduling constraints or a lack of required resources to travel to and conduct the activity.

The method proposed for the mPHASE model is to 1) initially assign a priority ranking randomly to all activities, 2) generate a random agenda for the i th day based on the values of \mathbf{Pr}_{OCCUR} , 3) order the activities on the agenda according to their priority ranking, 4) starting with the highest priority activities, add activities from the agenda to the schedule one at a time until a conflict occurs, or the time pressure reaches a predetermined level, 5) if any activities were excluded from the schedule, increase their priority by readjusting the activity rankings according to values of $\mathbf{Pr}_{OCCUR,j} \times Q_j$, where Q_j is the cumulative number of times that activity j has been excluded from a schedule over all model iterations. In this way, activities which have been disproportionately excluded from the schedule previously are less likely to be excluded in future iterations. As a result, over many iterations the fraction of days in which activity j occurs will approach $\mathbf{Pr}_{OCCUR,j}$.

2.4. A finite element approach to activity scheduling and conflict resolution

The activity scheduling problem has much in common with the physical systems that engineers encounter in structural design. The beams of a truss can be thought of as analogous to individual activities. The primary difference between the two is that the coordinates of the physical structure are defined in 3-dimensional space, while a schedule is defined along a temporal axis. Scheduling conflicts prevent activities at different locations from overlapping in time in the same way that elements of a physical structure cannot occupy the same space. The beams of a truss deform when external forces are applied, while activities in a schedule are shortened or extended to accommodate pressure applied by the preceding and following activities. Finally, the movement of activities can be limited by external scheduling constraint. For example, the operating hours of a business might define the feasible limits of an activity just as a rigid barrier can define the maximum displacement of the physical structure.

Beyond the similarities between the scheduling and structural engineering problems, the Finite Element Method (FEM) used here is particularly well-suited to aspects of

activity scheduling that are difficult to handle with rules-based methods. First, the activity schedule is both discrete, in terms of the individual activities, and continuous, in the potential placement of activities in time. This description corresponds to the discrete elements in FEM which can be displaced continuously in space. Second, the schedules of individual household members are often linked together in complex ways through joint participation in activities, and the allocation of shared responsibilities and resources (like household vehicles). These relationships can be readily represented in FEM by defining connections at each element node to one or more adjoining elements.

Description of the Finite Element Method

The Finite Element Method encompasses a set of numerical techniques for finding a solution to differential equations which define the behavior of an idealized representation of a physical system. Implementations of the FEM include engineering analysis of heat transfer, fluid dynamics, and vibration of structures, in addition to static structural analysis. In the field of classical mechanics, a system is defined to be in static equilibrium when it is at rest and the sum of forces acting on each particle within the system is zero. For simple structures, this means that displacements resulting from an external force can be calculated by solving a system of simultaneous equations for force balance and displacement continuity at each node. However, the class of problems in which the structure is subject to redundant constraints, known as “statically indeterminate”, cannot be solved by manipulating these equations using methods of elimination and substitution. The direct stiffness method (DSM) was developed initially to solve a statically indeterminate problem in aircraft wing design (Levy 1953; Turner et al. 1956). The method’s use of matrix algebra to represent elements makes it particularly well-suited for the digital computation of large problems, while its generality has extended its usefulness from its original applications in aeronautical engineering.

The direct stiffness method continues to serve as the basis for many FEM implementations, in addition to other, calculus-based approaches. What follows is a brief overview of the DSM, which consists of three steps: breakdown, assembly, and solution.

The starting point is an idealized representation of the real-world structure as bar elements, each connected at their end nodes to one or more adjoining elements. In the *breakdown* step, these elements are each considered separately as individual springs, with

a stiffness that depends on the material properties and cross-sectional dimensions of the actual truss. In mechanics, Hooke's law (equation 2.1) provides the relationship between the force on a spring and its displacement, where F is the net force, δ is the displacement, and k is the spring constant, or stiffness.

$$F = k\delta \quad (2.1)$$

In order to account for forces and displacements in any direction and at either end node of an element, force and displacement relationships in Hooke's law are expressed as member stiffness relations (equation 2.2) where \mathbf{K}_e is the member stiffness matrix (equation 2.3). \mathbf{K}_e is a square matrix, with a row and column for every degree of translational and rotational freedom for each of the element's two nodes, i and j . Most engineering applications of FEM are applied to 2-D or 3-D systems, but for simplicity a system constrained to move along a single dimension, the x axis, is presented here.

$$\begin{bmatrix} f_{x,i} \\ f_{x,j} \end{bmatrix} = \mathbf{K}_e \begin{bmatrix} u_{x,i} \\ u_{x,j} \end{bmatrix} \quad (2.2)$$

$$\mathbf{K}_e = \begin{bmatrix} \mathbf{K}_{e,i=1,j=1} & \mathbf{K}_{e,i=1,j=2} \\ \mathbf{K}_{e,i=2,j=1} & \mathbf{K}_{e,i=2,j=2} \end{bmatrix} = k \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \quad (2.3)$$

Simple 1-D systems can be easily represented by a single element with an equivalent spring constant calculated from the individual spring constants based on whether they are configured in parallel or in series. For more complex systems where multiple sets of springs in series and parallel are nested within each other, a general solution for finding the equivalent stiffness combinations of springs is desirable. This is achieved by the second step of the direct stiffness method, *assembly*, where member stiffness matrices are aggregated into a single master stiffness matrix, \mathbf{K} . The connectivity of any n spring elements can be described by an Element Freedom Table (EFT) which maps i and j end nodes of each element to a global nomenclature. Figure 2.3 shows an example of a six element spring system and the associated EFT.

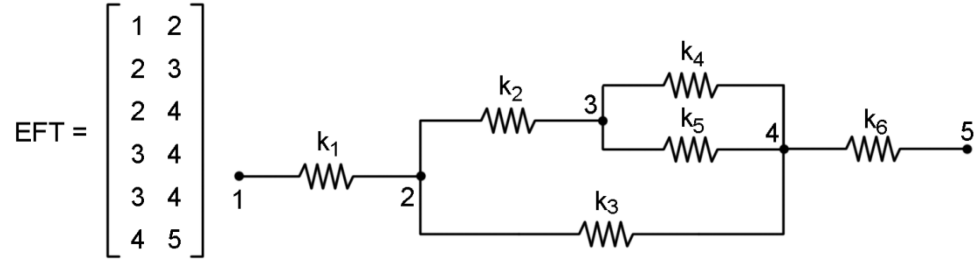


Figure 2.3 1-D System of springs.

The master stiffness matrix, \mathbf{K} , is constructed by summing the contributions of the member stiffness matrices at each node, according to the EFT (equation 2.4). Note that the summations for each element 1 thru n are performed over nested loops over i , then j . The force-displacement relations for the all of the m nodes of the entire system can then be expressed by the master stiffness equation (equation 2.5).

$$\mathbf{K}_{pq} = \sum_{e=1}^n \mathbf{K}_{e,ij} \quad \text{for } i = 1 \text{ to } 2, j = 1 \text{ to } 2, p = \text{EFT}(e,i), q = \text{EFT}(e,j) \quad (2.4)$$

$$\begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ \dots \\ f_m \end{bmatrix} = \mathbf{K} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ \dots \\ u_m \end{bmatrix} \quad (2.5)$$

The *solution* step is the third and final phase of the DSM. Without any external constraints or boundary conditions, the rows and columns of the master stiffness matrix are linear combinations of each other so that \mathbf{K} is singular in equation 2.5. Therefore, the node displacements resulting from an applied external force cannot be solved. Physically, this would be as if the spring system in Figure 2.3 were “floating” in space. Either the displacement of a node, or the external force may be prescribed for any node, but not both. By rearranging the row ordering of \mathbf{f} and \mathbf{u} in equation 2.5, \mathbf{K} can be split into four sub matrices depending on whether the force or displacements are known for each particular node (equation 2.6).

$$\begin{bmatrix} \mathbf{f}_{\text{known}} \\ \mathbf{f}_{\text{unknown}} \end{bmatrix} = \begin{bmatrix} \mathbf{K}_{11} & \mathbf{K}_{12} \\ \mathbf{K}_{21} & \mathbf{K}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{u}_{\text{unknown}} \\ \mathbf{u}_{\text{known}} \end{bmatrix} \quad (2.6)$$

Since the goal is to determine node displacements, the first matrix equation of 2.6 can be used to express the unknown node displacements as a function of the known forces and displacements (equation 2.7). Displacements can be solved for most efficiently

using the Gaussian elimination method, thus eliminating the computationally expensive step of calculating the inverse of the \mathbf{K}_{11} matrix.

$$\mathbf{u}_{\text{unknown}} = \mathbf{K}_{11}^{-1}(\mathbf{f}_{\text{known}} - \mathbf{K}_{12}\mathbf{u}_{\text{known}}) \quad (2.7)$$

Representing activities as elements

An activity's position in a daily schedule can be defined simply by a combination of any two of its start time, end time, and duration. In the mPHASE model, individual activities are defined by three-elements referred to as start anchor, end anchor, and activity elements (Figure 2.4). The start and end anchor elements join fixed nodes (3 and 4) to the activity start and end nodes (1 and 2), respectively. The anchor points represent “target” or neutral times for the activity's beginning and end, such that it requires more effort to schedule an activity at undesirable times. The activity element itself provides resistance to departure from a neutral activity duration, independent of the start and end anchor elements. As a result, there will be more resistance to shifting start and end nodes each 10 minutes in opposite directions away from the neutral times than to shifting them by 10 minutes in the same direction away from the neutral times. The relative stiffness of the three elements is set independently so that start time, end time, and duration can have different values of flexibility for deviation from their neutral values. For example, an activity might have very little flexibility in its duration, but significant flexibility in its start time or vice versa.

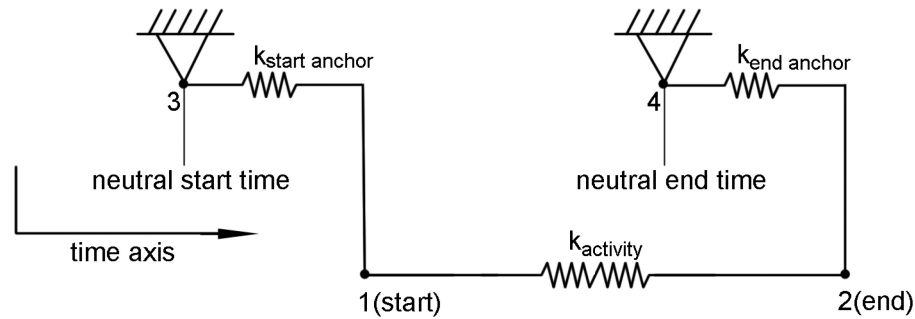


Figure 2.4 Representation of an activity in mPHASE.

In addition to the resistance provided by the start and end elements, an attempt to shift an activity too far from its neutral time can be limited by hard constraints on earliest and latest times, and duration (Figure 2.5).

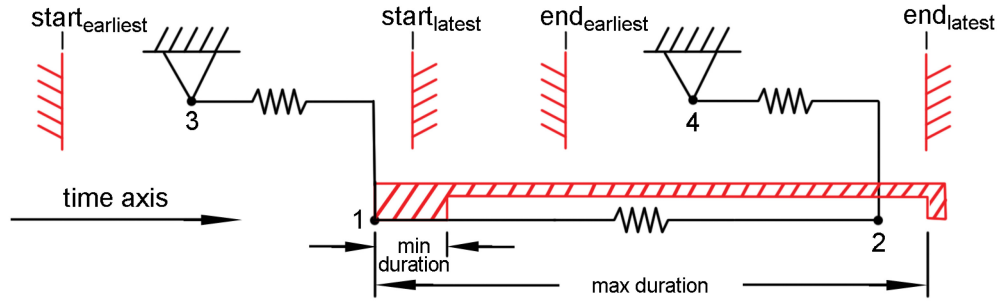


Figure 2.5 Constraints on activity duration, and start and end times.

Activity schedules at the household level

By joining together individual activity elements at their start and end nodes, a daily schedule can be created with node positions determined using the finite element method. To illustrate, consider the after-dinner activities of a three-person household consisting of a mother ($p1$), father ($p2$) and their son ($p3$). The final portion of the household's activity agenda for day i is shown in Table 2.8. All three members of the household are mandatory participants in the dinner activity at home ($L1$). The son is the sole participant in the study group at a classmates house ($L4$). The travel times between every pair of locations $L1$ through $L5$ can be estimated from the relative distance between the locations, and an assumption about average travel times as shown in Table 2.9 and Figure 2.6. In this example, it's a 15 minute trip from home to the study group activity. In the finite element model, travel time is represented using travel elements with a length equal to the time needed to travel between adjoining activities which occur at different locations. Travel time is assumed to be inflexible, and elements are assigned a high spring constant².

² FEM cannot accept spring constant values of zero or infinity, since either will result in division by a determinate of zero when computing the inverse of the K matrix. For very large values, mPHASE assigns $k_{inf} = 9 \times 10^7$, and for very small values, $k_{zero} = 1 \times 10^{-7}$.

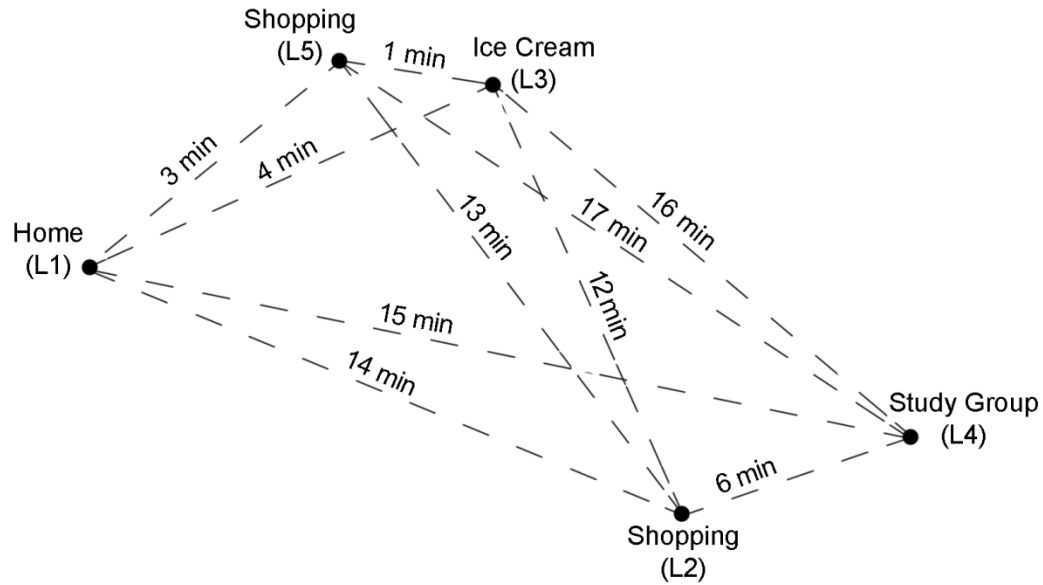
Table 2.8 Activity Agenda Example 1: After Dinner Study Group Only

<i>j</i>	Activity	Participation			t_{start}			t_{end}			duration(<i>d</i>),(minutes)		
		<i>p</i> 1	<i>p</i> 2	<i>p</i> 3	earliest	neutral	latest	earliest	neutral	latest	min	neutral	max
13	Dinner	1	1	1	17:00	17:45	18:30	-	-	-	15	30	45
14	Study group	0	0	1	18:00	18:30	-	19:30	20:00	20:05	60	-	-

Table 2.9 Location Probabilities by Activity and Location Pair Travel Times

		$Pr_{LOCATION}$			
Activity (j)		Dinner at home (13)	Son's study group (14)	Shopping (15)	Ice cream (16)
Location					
..	
L1		1	0	0	0
L2		0	0	0.4	0
L3		0	0	0	1
L4		0	1	0	0
L5		0	0	0.6	0

		1 travel time (minutes)				
Location		L1	L2	L3	L4	L5
...	
L1		-	14	4	15	3
L2			-	12	6	13
L3				-	16	1
L4					-	17
L5						-

**Figure 2.6 Spatial map of activity locations with travel times.**

As shown in Figure 2.7, the entire day's activities are defined from 00:00 to 04:00 (12:00am to 4:00am the following day). A day in real life is not composed of a continuous stream of distinct activities. This is not to say that the time between activities is spent idly, yet a certain amount of time is inevitably spent waiting for the next activity, especially if the available time is too short to engage in anything else. At home in particular, a significant amount of time may be spent doing small chores, such as tidying up. This is certainly time well spent, but it would be too difficult to categorize each of

these highly flexible and brief tasks as a distinct activity. In the mPHASE model, the unspecified time between defined activities is classified as *slack time*, and is represented by elements with spring constants of near zero, in accordance with the great degree of flexibility involved.

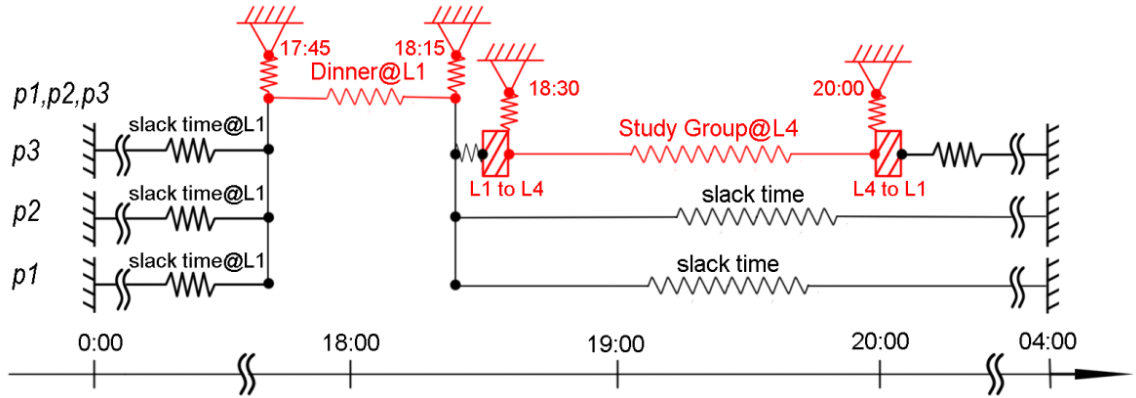


Figure 2.7 Finite element representation of activity agenda example 1. ($p1$ = mom; $p2$ = dad, $p3$ = son)

Minimizing time pressure and finding equilibrium in schedules

In the previous example, the travel time of 15 minutes was equal to the difference between the neutral end time of the dinner activity at 18:15, and the neutral start time of the study group activity at 18:30. Since no forces will be applied to disturb the activities from their neutral positions, a displacement of zero for each node is the trivial FEM solution. Consider instead the activity agenda for example 2, shown in Table 2.10, which now has a shopping activity with a neutral duration of 30 minutes. Any member of the household can conduct the activity, but for purpose of illustration, Figure 2.8 focuses on the son. The store is open until 20:30, so he could choose to go shopping either on the way to the study group, or on his way home. If he chose to go before, one or more of the following adjustments would need to be made: 1) move the dinner end time earlier, 2) begin the study group activity later, or 3) shorten the shopping activity. If the son chose to go shopping after his study group, there would be more flexibility, although he might decide to leave the study group earlier in order to finish shopping before the store closes. A number of various combinations of activity sequencing, location, and participants are possible, although some will require greater effort to fit within the given constraints. The degree of effort can be considered to represent a ‘time pressure’ of that schedule, which

household members would recognize as being too busy to conduct activities as they normally would. A heuristic for excluding activities on the generated agenda from the final schedule would ideally consider the time pressure of the schedule by removing activities which cause excessive pressure, or shifting time pressure across multiple days to match some predetermined distribution. At the same time, a decision rule which simply minimized time pressure would consistently reject the most demanding activities, causing the resulting activity distributions to deviate from the targeted Pr_{OCCUR} values.

Table 2.10 Activity Agenda Example 2: After Dinner Shopping and Study Group

<i>j</i>	Activity	Participation*			t_{start}			t_{end}			duration(<i>d</i>), (minutes)		
		<i>p1</i>	<i>p2</i>	<i>p3</i>	<i>earliest</i>	<i>neutral</i>	<i>latest</i>	<i>earliest</i>	<i>neutral</i>	<i>latest</i>	<i>min</i>	<i>neutral</i>	<i>max</i>
13	Dinner	1	1	1	17:00	17:45	18:30	-	-	-	15	30	45
14	Study group	0	0	1	18:00	18:30	-	19:30	20:00	20:05	60	-	-
15	Shopping	2	2	2	08:00	19:45	-	-	-	20:30	20	30	60

* Participation codes are defined in Table 2.6 as 0: prohibited, 1: mandatory, 2: optional/independent, 3: optional/non-independent, 5: drop-off/pick-up

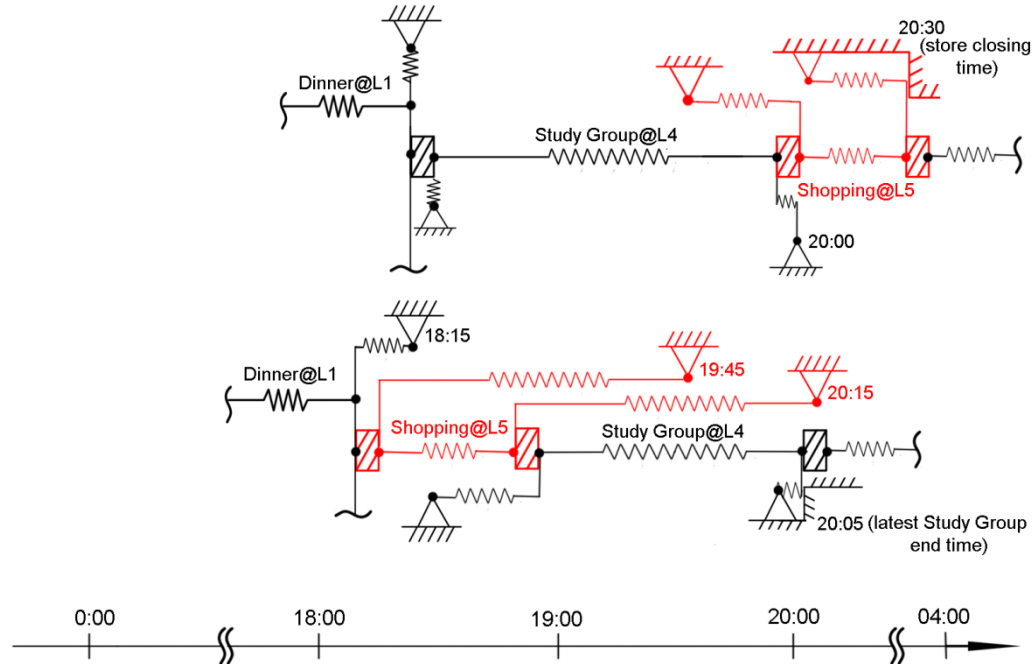


Figure 2.8 Finite element representation of activity agenda example 2:
a) shopping before study group; and b) shopping after study group.

In the mPHASE model, the energy stored in the system of finite elements is used to measure time pressure. This energy value is calculated after each attempt to insert an activity on the agenda in order to determine which combination of activity sequence, location, and participants will be selected for inclusion in the final schedule. The decision

rule used in the model is to select the option which minimizes time pressure. In real-world terms, time pressure is a measure of how far activity start/end times and durations are moved from their ideal values, and how flexible these values are. In the FEM representation, time pressure depends on the degree to which activity element nodes have been shifted from their neutral positions, and the level of rigidity of the activity and anchor elements (i.e., their spring constants). More precisely, the mPHASE model calculates time pressure as the potential energy (PE) of all elements for the m activities in the finite element schedule (equation 2.8).

$$\begin{aligned} \text{time pressure} &= PE \\ &= \sum_{e=1}^m \frac{1}{2} \left((k_e \delta_e^2)_{\text{activity element}} + (k_e \delta_e^2)_{\text{end anchor element}} + (k_e \delta_e^2)_{\text{start anchor element}} \right) \quad (2.8) \end{aligned}$$

In the previous shopping example, it seems likely that there would be less time pressure induced by placing the shopping activity at the end of the day (Figure 2.8b), where it is displacing the son's highly flexible slack time. Shopping earlier in the day (Figure 2.8a) would require large displacements in the more rigidly constrained dinner and study group activities. Also, the son had two options for the location of the shopping activity, L2 and L5. It might seem that either location choice would result in the same time pressure, since the total travel time returning home (L4→L5→L1 or L4→L2→L1) is 20 minutes in each case. However, the travel time from L4 to L2 is less than the time from L4 to L5, so selecting L2 would allow more time for shopping before the store closed. The exact time pressure value for each option, however, would be determined in mPHASE using the spring constant values unique to each activity.

When adding a new activity to an existing schedule, the static equilibrium must be found for the revised finite element system. As defined earlier, a system is said to be in static equilibrium when it is at rest and the sum of forces acting on each particle within the system is zero. The algorithm used in mPHASE performs a search for equilibrium by splitting the schedule in two parts where the new activity will be inserted, and displacing the schedule's right hand side (RHS) and left hand side (LHS) in steps. The force balance requirement is achieved when the force applied to the LHS is equal and opposite to the force RHS. The equilibrium algorithm is shown graphically in Figure 2.9, and consists of five steps: 1) at the insertion point for the new activity, disconnect original nodes and

remove travel element if it exists; 2) join the open node of the schedule LHS with a travel element (to the new activity) and the new activity element; 3) shift the open nodes of the RHS and modified LHS in opposite directions, until the gap is equal to the travel time duration (from the new activity); 4) shift the LHS and RHS together in the direction which minimizes the difference in forces, until they are balanced; and 5) join the open nodes on the LHS and RHS with the travel element.

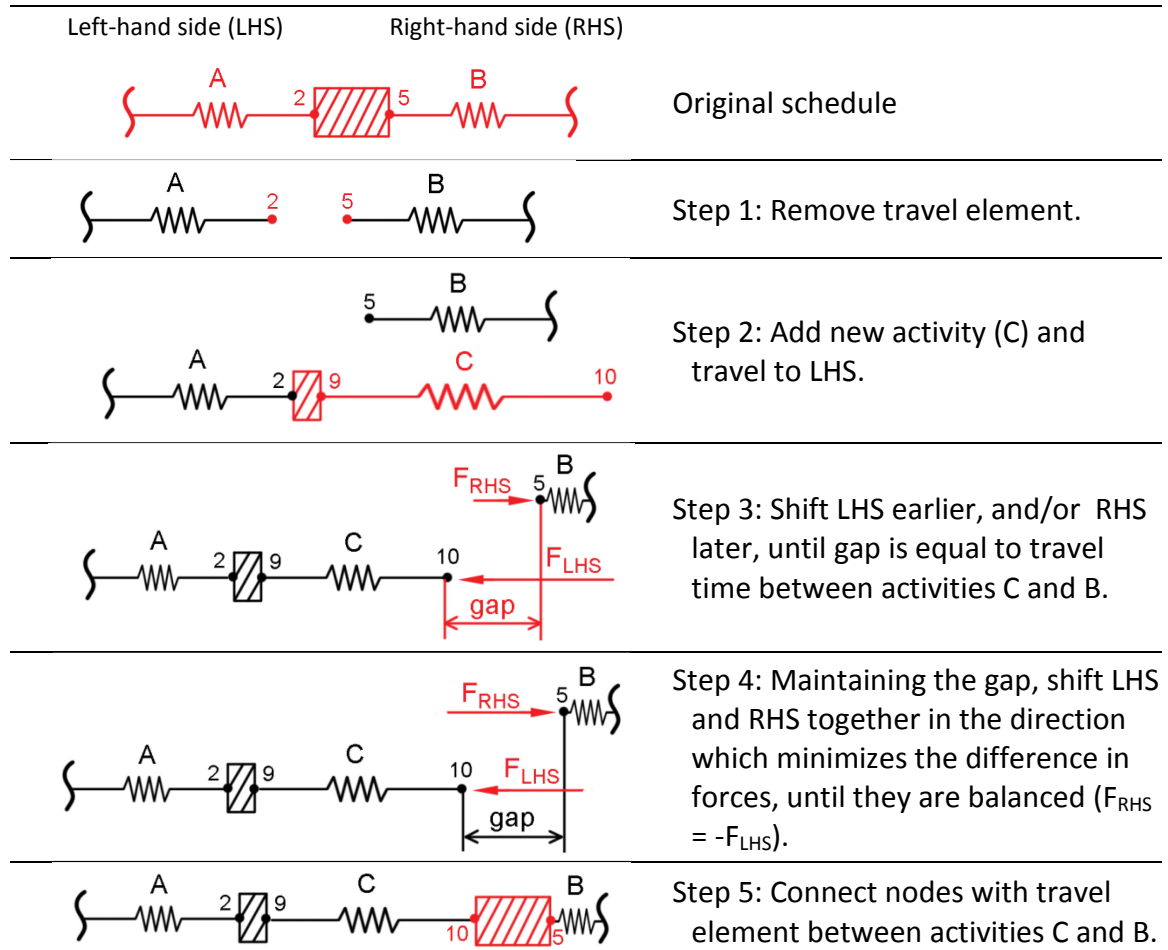


Figure 2.9 Search algorithm for schedule equilibrium when adding new activity.
(anchor elements not shown for clarity)

Coordinating schedules among multiple household members

When multiple household members participate jointly in an activity, the schedule must be arranged so that every member is simultaneously present at a common location both before and after the joint activity. This requirement arises from the assumption in the mPHASE model that participating household members travel together to and from any non-home based joint activities, and do not arrive at a location by independent travel.

In the current implementation of mPHASE, the gathering of individuals before and after a joint activity is limited to the home location, but it could conceivably include any location. As a result, unless the exact travel party is already gathered at a common location, members will return home before departing for the new joint activity.

Table 2.11 Activity Agenda Example 3: Ice Cream Outing

<i>j</i>	Activity	Participation			t_{start}			t_{end}			duration(<i>d</i>),(minutes)		
		<i>p1</i>	<i>p2</i>	<i>p3</i>	<i>earliest</i>	<i>neutral</i>	<i>latest</i>	<i>earliest</i>	<i>neutral</i>	<i>latest</i>	<i>min</i>	<i>neutral</i>	<i>max</i>
..
13	Dinner	1	1	1	17:00	17:45	18:30	-	-	-	15	30	45
14	Study group	0	0	1	18:00	18:30	-	19:30	20:00	20:05	60	-	-
15	Shopping	2	2	2	08:00	19:45	-	-	-	20:30	20	30	60
16	Ice cream	1	1	1	18:30	19:00	-	-	-	22:00	15	20	30

In example 3, the family decides to go out for ice cream that evening (Table 2.11). The algorithm used in mPHASE for adding joint activities is similar to that of finding schedule equilibrium for an individual (Figure 2.9). The primary difference is that multiple nodes must now be joined on the schedule right and left hand sides. Additionally, the number of possible insertion points increases as the new activity can occur at any one of the various sequence combinations for each participant. The sequencing process is shown as Step 1 in Figure 2.10, and is simplified in this example since the parents' schedules have only one possible insertion point after dinner. The son, for purpose of illustration, will conduct the new activity after shopping. In Step 2, nodes are separated at each insertion point, and travel elements are removed, if present. In Step 3, slack time and travel elements for a return trip home are added for individuals who are not already at home either before or after the new activity. Because the shopping activity includes only the son, he will need to return home after shopping to pick-up his parents, even though he would have traveled less if he had driven to the ice cream shop directly from the store. For individuals who are already at home, slack time elements are added so that in Step 4, open nodes can be aligned. This is achieved by extending the earliest open nodes on the LHS later, so that all LHS nodes are coincident. Similarly, the latest open nodes on the RHS are extended earlier until all RHS nodes are aligned. Finally, in Step 5, the new activity is added and equilibrium is found by applying the schedule equilibrium search algorithm.

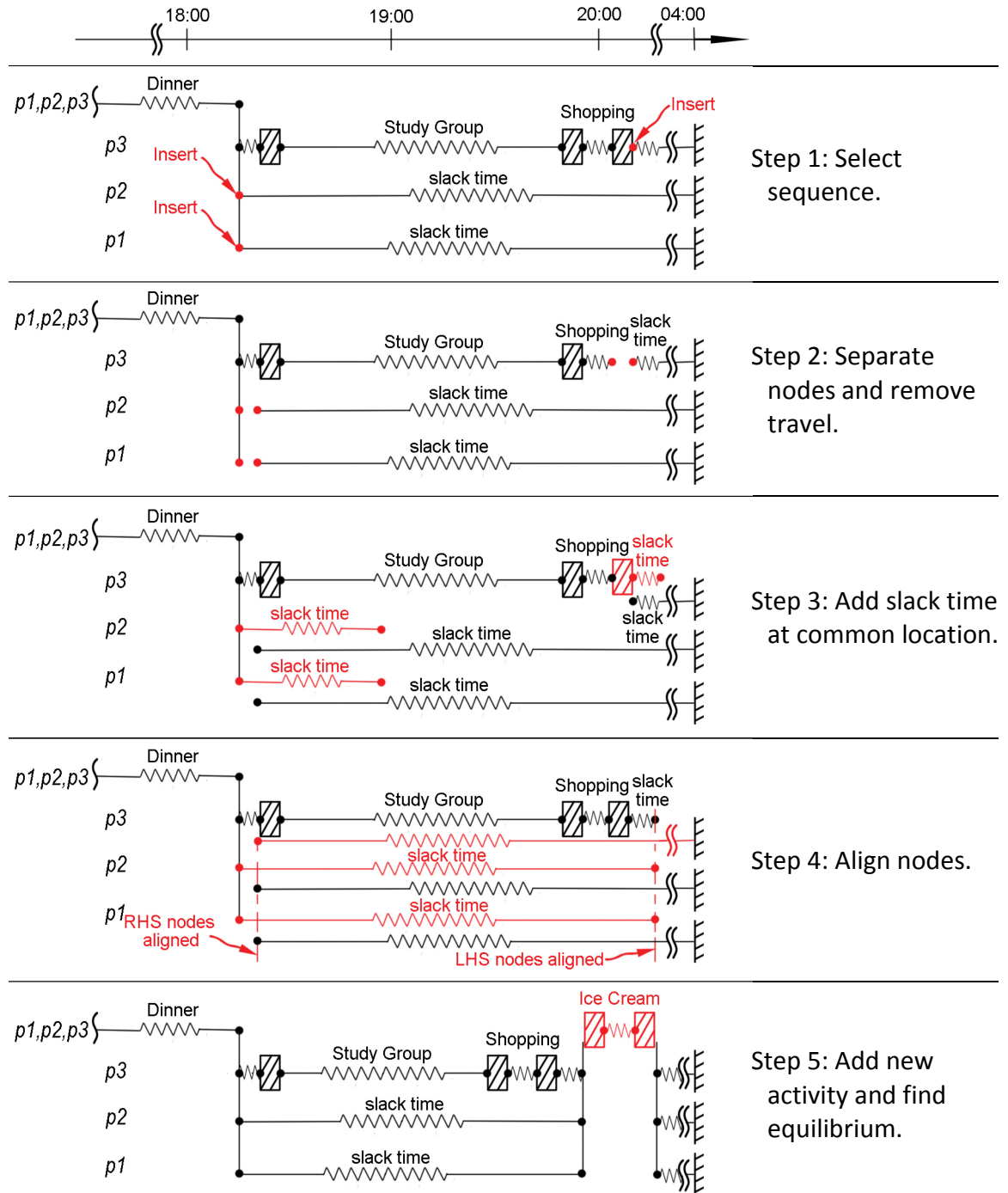


Figure 2.10 Multi-participant coordination algorithm for new activity, as Example 3, Ice Cream Outing. ($p1$ = mom; $p2$ = dad, $p3$ = son, anchor elements not shown for clarity)

The Household Travel Patterns Study: A pilot demonstration

The trip diary has been an indispensable tool for transportation researchers, providing data that have been used to illuminate many aspects of household travel behavior. The popularity of the methodology is due in large part to its simplicity and general applicability, yet despite its advantages there remain some questions that cannot be answered using data from existing trip diaries. Among the method's most significant weaknesses is the difficulty of collecting data over periods longer than one or two days. Alternatives like GPS technology can be used to reduce respondent burden for multi-day studies, but by itself cannot provide information about the trip purpose and other important activity details which influence the decision making process.

This chapter begins with an overview of existing techniques, and then introduces an activity-based method for collecting travel data over multi-week time periods. Unlike trip diaries which rely on the accurate reporting of specific trips, the proposed methodology asks respondents to describe the range of values for each dimension of a possible activity: time, day of week, place, participants, and items carried. The combination of these dimensional descriptions forms an activity template, with a probability of occurrence defined by rules relating the frequency, periodicity, or daily likelihood for all the templates which satisfy a common activity purpose. Responses are intended to be used as inputs to the mPHASE model for generating multi-day travel-activity schedules, potentially offering an alternative to the conventional trip diary data collection method. The chapter concludes by presenting the results of the Household Travel Patterns Study (HTPS), a thirty household pilot demonstration conducted in 2011 in the Ann Arbor, Michigan area. Descriptions of typical travel were collected during home visits using a computer-assisted personal interview (CAPI) with involvement from all household

members. The household's two vehicles were each equipped with digital cameras and GPS data acquisition equipment to observe usage for two weeks. The goal of the HTPS was to determine if the mPHASE model and its companion web survey are capable of producing complex and realistic multi-day travel-activity schedules.

3.1. A review of methods for multi-day data collection

Travel behavior studies rely heavily on written diaries recording one or two days of travel as the primary source of data. The self-reported activity timelines commonly used in cross-sectional analyses today evolved from time-use studies going back nearly one century, including a 1924 study of the daily lives of workers in Moscow (Hedges 1972). These early time budget surveys were not specifically intended for travel analysis, and as the field of activity-based travel research took shape in the late 1960's and early 1970's, geographers and urban planners were motivated to extend the methodology to include spatial information (Bullock et al. 1975). Even at this early stage, the weaknesses of the diary as a survey instrument were recognized. In a pre-test comparison of contemporary methods (Scheuch 1972), it was noted *"the various shortcomings of a particular technique tended to have a stronger influence on time-budget figures than on other objects of research."*

Among the most significant shortcomings of the diary as a survey instrument is the subjective nature of classifying and cataloging activities which occur in a constant stream of behavior (Dagfinn 1978) and often simultaneously (Scheuch 1972). Another is the considerable amount of effort required of respondents to produce diaries which provide reliable information at the level of detail necessary to be useful. To make this burden manageable, diaries are normally limited to short time periods. The resulting single-day data is sufficient for cross-sectional analyses of aggregate travel tendencies and inter-personal variations, but cannot provide any insights into intra-personal travel variation and patterns at the household level (Hanson and Huff 1982).

The desire to employ a new technique for data collection is summarized nicely by Jones and Clarke (1988) who wrote, *"As we move in the urban policy arena increasingly away from transport investments designed to cater for unrestricted demand, to some form of management of travel behaviour, it becomes necessary to understand more about the*

processes of travel. We argue that some of the issues being addressed cannot be answered using one-day data, regardless of the sample size, because by their nature they are questions about variations in behaviour over time.”

Over the last few decades, a great deal of effort has been applied towards developing methods for collecting travel-activity data over extended time periods. The most straightforward examples have simply extended the diary methodology to a period of one week in the German Mobility Panel, U.K. National Travel Survey, and Dutch Mobility Panel (Sharp and Murakami 2005; Golob and Meurs 1986), a period of two weeks for the German KONTIV survey and in Belgium (Brög et al. 1983; Bellemans et al. 2009), and up to six weeks in the case of the German Mobidrive study (Axhausen et al. 2002). These long-term diaries can be less costly per day of data collected compared to single-day diaries, but this comes at the expense of a larger sample size and the estimation power for small population subgroups (Sharp and Murakami 2005). Perhaps more importantly, the phenomenon of reporting fatigue has been shown to cause significant underreporting of trips as the study period grows longer, particularly for short trips and those which may be perceived by the respondent as unimportant or incidental (Barnard 1983; Golob and Meurs 1986).

Alternatives to the travel diary have emerged which offer the potential to not only extend the time-period, but also provide some insight into the activity scheduling and travel decision making processes not possible with purely observational methods. At the same time, technological advancements like GPS equipment have made multi-day observation of travel an increasingly realistic alternative to travel diaries, especially when combined with supplemental details from participant survey responses (Giaimo et al. 2010).

Alternative survey techniques

In the absence of reliable multi-day schedules from travel diaries, alternative approaches attempt to identify the underlying determinants of travel behavior, as influenced by a wide variety of factors including individual opinions, preferences, social norms, available options, and the real and perceived constraints imposed by the material environment and interpersonal commitments (Brög and Erl 1980). Considering the complex interplay between these factors, it would seem an impossible task to create any

standardized survey instrument that provides insight into travel decisions, particularly when combined with the challenge of activity and time-use classification discussed in chapter 2. The alternatives that have been proposed include interactive interviews, gaming simulations, dynamic scheduling, qualitative surveys and web-based instruments. While these techniques are wide-ranging, they share in common a great degree of flexibility in capturing diverse responses, and the rejection of a rigid, standardized questioning format.

Interactive and situational surveys

As a survey procedure moves away from a rigid structure towards a less-well defined format, the interaction between the respondent and the interviewer plays an increasingly important role in the quality of the results. While observer effects are normally to be avoided in behavioral research, the interactive interviewing technique seeks to “*exploit the dynamics of the personal interview in order to probe the attitudes, motivations, perceptions and behaviour of respondents at a deeper level than is possible using the structured questionnaire*” (Jones 1983b). In practice, this requires that a skilled interviewer engages respondents in a dialogue which allows relevant comments to be pursued and inconsistencies identified. Placing individuals in the situational context of actual decision making is likely to improve the accuracy of the responses, and can be simulated by conducting interviews in a group setting with all household members present.

The pioneering work using interactive techniques in travel behaviour research was conducted by researchers at Oxford University’s Transport Studies Unit, and focused on small-scale demonstrations of the Household Activity Travel Simulator (HATS) developed there (Jones 1979). The three critical elements of the technique are: 1) the interactions with the interviewer and among participants; 2) the use of visual aids as a structuring device; and 3) the gaming simulation approach. Employing a game-like display board, the HATS procedure begins with participants representing their activities by placing markers on the map and filling in timelines with colored blocks to indicate travel and activity types and durations. The interviewer encourages a discussion about activity constraints and linkages among household members, and then asks participants to explore potential adaptations to a proposed change. In addition to serving as a device

around which to structure the interview, the novelty of the game board as a visual-aid was found to maintain respondent interest throughout the interview, and engage individuals who might otherwise be reluctant to share information with the interviewer. This HATS technique has been used to study household adaptations to changes in school hours, shift scheduling for city bus drivers, rural bus service level, and rail service frequency (Jones 1979;1980;1983b). The approach has been adopted by other research agencies, and used to address the question of how households adapt their vehicle use to energy shortages and gasoline rationing (Phifer et al. 1980).

Dynamic scheduling surveys

Interactive techniques attempt to collect information about the scheduling process by conducting the interview in a manner that resembles the situational context of real decision making. Another approach is to collect information about actual scheduling decisions in real time (or as close to real time as possible), allowing researchers to observe the dynamics of scheduling as activities are planned, modified or removed from the agenda, and added or canceled spontaneously.

One of the first of these dynamic scheduling surveys was the Computerized Household Activity Scheduling Elicitor (CHASE) which prompted each individual in the household to enter a planned schedule for the one week study period, and then revisit those responses at least daily, adding, deleting, or modifying activities as necessary (Doherty et al. 1997). Respondents were also instructed to report when the decision was made, and the reason for a modification, making it possible to investigate the process of decision making in scheduling.

Building on this approach, the REACT! software (Lee and McNally 2001) improved the data input interface, and allowed for gaps to remain in the planning schedule, avoiding the tendency for respondents to complete all the unplanned portions of the time table. More recently, the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model was developed which adds more resolution to the scheduling process, allowing individual attributes of the activities to be planned in advance, independently of other attributes and in an order that is not fixed a priori (Auld and Mohammadian 2009).

One difficulty with dynamic scheduling surveys is that a very large number of alternatives may be available which are evaluated and screened continuously, sometimes subconsciously, as new opportunities arise in a constant stream (Roorda and Miller 2005).

Responses as ranges and probabilities

Variation is an important aspect of multi-day schedules, and not properly considered by methods which ask respondents to strictly define activity start times, durations, and frequencies. Vause (1997) argued that our real life conception of time is “*fuzzy and adaptable*”, and would be better represented by *fuzzy times* in surveys. The example given would define activity episode start times in quadruples (t_1, t_2, t_3, t_4) where t_2-t_3 is the ideal start time range, and t_1-t_2 and t_3-t_4 are the allowable time ranges.

The French National Institute for Transport and Safety Research (INRETS) developed a telephone survey which used this approach to capture 4-weeks of travel behavior by asking respondents how frequently they conducted activities in each of eight categories over the past month (Madre 2003).

Qualitative approaches

The difficulty in using quantitative methods to understand complex travel behavior has motivated some researchers to increase the flexibility of their methods through the incorporation of open-ended responses. Focusing on the issue of activity re-scheduling, Clark and Doherty found that using qualitative techniques allowed them to identify significantly more rescheduling decisions and conflicts than the CHASE dynamic scheduling survey (Clark and Doherty 2009).

GPS and passive location-finding technologies

The constellation of Global Positioning System (GPS) satellites launched and maintained by the U.S. Government since the late 1970's were originally intended solely for defense purposes. It eventually became clear, however, that general population would also benefit from a wide range of civilian uses. In the year 2000, the Selective Availability feature which intentionally reduced accuracy was disabled, allowing non-military users to utilize the full capability of the system (Clinton 1996). The advancements in GPS when combined with the steady progress in consumer electronics towards smaller and more

inexpensive devices created the opportunity in the last decade for passive-location finding technology to be used in travel behavior research.

The high cost and power requirements of the earliest commercial GPS units restricted their use in travel studies to in-vehicle units. Personal data collection units are better suited for general travel studies for their ability to record an individual's movements regardless of travel mode, but the first demonstrations involved cumbersome units with large battery packs. Significant effort was directed at making the devices more convenient to carry (Stopher et al. 2005), and more recently, GPS receivers have been incorporated into increasingly smaller devices such as mobile phones which have reduced power requirements for extended battery life. The trend towards even less expensive and smaller devices is likely to further accelerate the use of the technology in travel research.

With just over a decade passed since the first applications in small-scale pilot studies, the role of GPS in travel behavior research is still evolving. The potential uses of the technology offer many benefits over traditional data collection methods, but the cost of GPS units remains an obstacle to its adoption in large scale studies. As shown in Table 3.1, most studies involving GPS are conducted at a small scale.

Table 3.1 Applications of GPS Technology in Travel Behavior Studies

Study	Sample size, period, and method	Purpose
1997 Lexington	100 vehicle, six day, vehicle GPS + PDA input	Feasibility, route choice
	200 vehicles w/GPS + paper diary	Feasibility, validation of paper survey, trip end identification
1997 Austin	117 household/186 vehicle,	
2000 Atlanta (Wolf et al. 2001)	30 vehicles w/GPS + PDA input	Potential to replace trip diary
2002 Lexington (Du and Aultmanhall 2007)	276 vehicles w/GPS	Automatic trip end identification
2007 Waterloo (Clark and Doherty 2008)	40 individuals, 2 day, personal GPS units, preplanning and prompted recall CASE, open-ended interview	Test data collection method for dynamic scheduling process
2009 Cincinnati HTS pilot (Giaimo et al. 2010)	100 households, 3 day, personal GPS units, prompted recall CASI	Test response rates of different demographics and incentive levels
2009 Chicago UTRACS (Frignani et al. 2010)	112 people, 2 week, personal GPS units, prompted recall CASI	Test data collection method for dynamic scheduling process
2009-2010 Cincinnati HTS (Stopher et al. 2011)	3500 households, personal GPS units	First GPS-only full scale survey

Despite the unique capability of GPS equipment to accurately identify travel trajectories, studies which have considered the stand-alone potential for the technology

have found that major obstacles remain in the identification of precise destinations for individual trips and their purposes (Wolf 2000). The problem of identifying trip start and endpoints has been addressed with the use of a minimum stop time, such as used by Wolf et al. (2001), where a trip end point was defined for stops of longer than 120 seconds. However, the short stops to pick-up and drop-off passengers might be missed. More involved methods use a combination of dwell time, vehicle heading change, and distance from the road network. Using these techniques, trip end points have been successfully identified with an error rate of around 5 percent (Du and Aultmanhall 2007).

Even more challenging than the automatic identification of trips from GPS data is the assignment of purposes to these trips. Wolf et al. (2001) conducted a pilot study using 30 vehicles in Atlanta for the purpose of determining if trip diaries could be replaced with GPS data by assigning trip purposes automatically using geocoded addresses. They found that most trip purposes could be correctly identified, but 22 percent would require some clarification. Similarly, Stopher et al. (2007) concluded that if additional information about the addresses for home, work, and the two most frequented grocery stores were collected, both mode and purpose could be deduced from geocoded GPS traces for about 70 percent of trips.

Reflecting the challenges in extracting activity details from observed travel paths, most studies of the use of GPS in travel surveys have not been intended to show that the technology can entirely replace the active participation of respondents. Instead, GPS technology has been more often investigated for its role as a supplement to other survey instruments, since the information required for many travel studies goes beyond an accounting of where individuals are located throughout the day. One approach has been to incorporate the observed GPS paths into web-based prompted recall surveys to provide more details about the activities which underlie the observed trips (Clark and Doherty 2009; Frignani et al. 2010; Stopher et al. 2011). By eliminating the need for respondents to recall exact times and locations, interviews can then focus on capturing other details about activities, and identify trips that would have otherwise been missed.

3.2. A proposed companion survey for mPHASE

The multi-day Probabilistic Household Activity Schedule Estimator (mPHASE) presented in chapter 2 provides a technique for placing activity episodes on a continuous time scale considering the linkages among household members and constraints imposed by activity time limits and travel time between activity locations. The goals of the proposed companion survey are to produce the input data for the mPHASE model 1) in a single session of household interviewing, and 2) of sufficient detail and quality for the generation of realistic and complex multi-day schedules. The key aspects of the survey share similarities with previous data collection efforts, and many of the techniques described in Section 3.1 are applied. What is unique is the method's achievement of flexible activity definitions through the use of probabilities and value ranges to describe every dimension of an activity. While a probabilistic description of activities is, by design, a requirement of the mPHASE model, it is also believed that respondents can reasonably be expected to report variable, multi-day activities in terms of probabilities and value ranges – a hypothesis that is tested in the HTPS pilot investigation.

Key aspects of the survey approach

Flexible activity definitions

The classification of activities into rigid categories is a difficult and ambiguous task, as discussed in chapter 2, and does little to illuminate the properties relevant to the scheduling problem. Instead of forcing the classification of activities into predefined categories, such as work and shopping, this approach requires that respondents describe activities by their salient attributes, as proposed by Doherty (2006).

Fuzzy responses

Activity characteristics are defined using fuzzy responses in this approach. A description of activity variation in terms of probabilities and ranges is potentially an intuitive method for respondents, and one that directly satisfies the input requirements of the mPHASE model.

Interactive interviewing

In contrast to the highly-structured format of surveys utilizing travel-activity diaries, this approach is more open-ended, by design, to allow flexibility of responses. Interactive interviewing, by engaging all household members in a two-way dialogue, is a method of improving the accuracy and completeness of open-ended responses.

Feedback and iterative input

Although not implemented for the pilot study, synthetic schedules generated by mPHASE are intended to be shown to participants as they are providing responses. As one element of the interactive interview approach, the purpose of this feedback is to increase the identification of inconsistencies, to facilitate discussion, and to encourage greater engagement of participants in an iterative process of adding and revising activity characteristics when unrealistic schedules are displayed.

Description of the web-based survey instrument

The companion web survey to the mPHASE model is intended to be interactive, and be completed by the household members together as a group. First, household members are asked to select the locations they typically might visit. Next, they are asked to describe the activities that might be performed at these locations. Finally, a series of schedules generated by the mPHASE model are presented, and the household members are asked to review them, and if necessary make revisions to their responses for activity locations and detail.

Selection of locations

Identifying activity locations with the level of accuracy required for computing travel distances is a potentially time consuming task. The web survey provides respondents with several options for adding location marker icons to a Google Maps™ panel on the activity location data input page (Figure 3.1). The available methods are 1) a marker icon can be dragged directly onto the map, and positioned visually, 2) an address, if known, can be typed into search box, or 3) a place name can be typed into a search box. If the address or place name text searches return multiple results, the correct location can be

selected from a list, and the marker will be automatically placed in the correct location on the map. Regardless of the method used, when a location is added, an information window appears, prompting the user to input a place name, and select a place type. Respondents can continue to add markers in this manner, while the added locations are summarized as a list of place names alongside the map.

HTPS
Household Travel Patterns Study

[Main Page](#) [Take the Survey](#) [View Demo Survey](#) [About](#) [Contact](#) [Logout](#)

Activity locations

Place markers on the map at locations that might be visited by household members over the next 12 months. [?](#)

Click a marker symbol to place it on the map [?](#)

Show locations by purpose, (click marker to add to map):

• all

Auto Zoom


Name: Kroger
Type: shopping/errands
Address: 400 South Maple Road
[save](#) [cancel](#) [Delete Location](#)

Type	ID	Location
	1513	Bates Elementary School
	1549	Charlottesville VA
	1518	Country Market
	1509	Courtney Work
	1542	Courtneys Parents
	1515	Dancers Edge
	1528	Dexter Arts Center
	1527	Dexter District Library
	1522	Dexter Gardens LLC
	1529	Dexter Senior Citizens

Figure 3.1 Web survey input page: Activity locations .

Description of activity characteristics











After a sufficient number of markers have been added to the location page, the interview proceeds to the activity details page (Figure 3.2). Participants are encouraged to add as many activities as they can, with an emphasis on those which 1) occur regularly, 2) require long travel distances, or 3) require transporting bulky or heavy items, or a large number of passengers.



[Main Page](#)
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[View Demo Survey](#)
[About](#)
[Contact](#)
[Logout](#)

Activity details

Show activities by purpose:

• all



















Purpose	Activity pattern details
<div>  <div> <div>Clothes and HH items Shopping</div> <div>Category: shopping/errands</div> </div> </div>	<div> <div>Clothes and HH items - Meijer</div> <div>Clothes and HH items - Target</div> <div>Clothes and HH items - Salvation Army</div> <div>Clothes and HH items - Value World</div> </div>
<div>  <div> <div>Cub Scouts</div> <div>Category: social/recreational</div> </div> </div>	<div> <div>Cub Scouts</div> </div>
<div>  <div> <div>Softball</div> <div>Category: social/recreational</div> </div> </div>	<div> <div>Softball</div> </div>
<div>  <div> <div>Baseball</div> <div>Category: social/recreational</div> </div> </div>	<div> <div>Baseball</div> </div>
<div>  <div> <div>Hockey</div> <div>Category: social/recreational</div> </div> </div>	<div> <div>Hockey</div> </div>
<div>  <div> <div>Hudson Mills</div> <div>Category: social/recreational</div> </div> </div>	<div> <div>Hudson Mills - Summer biking</div> <div>Hudson Mills - Winter Skiing</div> </div>
<div>  <div> <div>Visit Courtneys Parents</div> <div>Category: family personal business</div> </div> </div>	<div> <div>Visit Courtneys Parents 7 to 10 days</div> </div>
<div>  <div> <div>Visit Mikes Mom</div> <div>Category: family personal business</div> </div> </div>	<div> <div>Visit Mikes Mom</div> </div>

Figure 3.2 Web survey input page: Activity details.

For each activity purpose, one or more activity templates must be defined, as described in chapter 2. The mPHASE model requires that probabilistic descriptions be provided in each of an activity template's five dimensions – day, location, time, household participants, and items carried. Within each displayed row of an activity template, the five dimensions are represented by icons, the selection of which causes the appropriate detail popup window to appear (Figures 3.3, 3.4, 3.5, 3.6, and 3.7). The responses entered in these popup windows are used directly in the mPHASE model as the probability and range values defining the activity characteristics.

The markers added previously to the locations page are made available in the activity places detail popup window (Figure 3.4). Multiple potential locations can be selected for each activity template, and a relative likelihood value assigned to each location.

Day

Select the days and the months

Select All

Weekdays

Weekend

Clear All

Mon	Tue	Wed	Thu	Fri	Sat	Sun
<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
50	100	100	50	0	0	0

Jan

☐

1

Feb

☐

1

Mar

☐

1

Apr

☐

1

May

☐

1

Jun

☐

1

Jul

☐

1

Aug

☐

1

Sep

☐

1

Oct

☐

1

Nov

☐

1

Dec

☐

1

All Year

School Year

Spring

Summer

Fall

Winter

Clear

ok

close

cancel

Figure 3.3 Web survey input popup window: Day details.

Places

add location

Place name	Likelihood		
1889 - Lucky 7 Chinese Food ▼	24 %		✗
1890 - Benitos Pizza ▼	26 %		✗
1892 - Jets Pizza ▼	26 %		✗
1893 - Subway - Oakwood ▼	13 %		✗
1893 - Subway - Oakwood ▼	11 %		✗

Total likelihood: 100 %

ok

close

cancel

Figure 3.4 Web survey input popup window: Locations.

Figure 3.5 Web survey input popup window: Time.

	Dropping off	Activity Participation	Picking up	Follow Caregiver
Katie	<input type="checkbox"/> 0	<input type="radio"/> Prohibited <input type="radio"/> Optional-Secondary <input type="radio"/> Optional-Primary <input checked="" type="radio"/> Mandatory	<input type="checkbox"/> 0	<input type="checkbox"/>
Adam	<input type="checkbox"/> 0	<input type="radio"/> Prohibited <input type="radio"/> Optional-Secondary <input type="radio"/> Optional-Primary <input checked="" type="radio"/> Mandatory	<input type="checkbox"/> 0	<input type="checkbox"/>

Figure 3.6 Web survey input popup window: Household participants.

Carried To Activity	Item Description	Min Qty	Usual Qty	Max Qty	Carried From Activity
<input type="checkbox"/> 1	Recreational tent - 4 person 0.180 w x 0.180 h x 0.580 l (m), 5.700 (kg)	1	1	1	<input type="checkbox"/> 1
<input type="checkbox"/> 1	Recreational air mattress - full size 0.310 w x 0.120 h x 0.420 l (m), 4.300 (kg)	2	2	2	<input type="checkbox"/> 1
<input type="checkbox"/> 1	Recreational oil lantern 0.180 w x 0.400 h x 0.200 l (m), 2.040 (kg)	1	1	1	<input type="checkbox"/> 1
<input type="checkbox"/> 1	Shopping paper - grocery 0.140 w x 0.330 h x 0.406 l (m), 4.536 (kg)	4	4	5	<input type="checkbox"/> 1
<input type="checkbox"/> 1	Recreational bike - adult 1.702 w x 0.940 h x 0.584 l (m), 17.055 (kg)	2	2	2	<input type="checkbox"/> 1
<input type="checkbox"/> 1	Luggage suitcase - duffle 0.508 w x 0.254 h x 0.254 l (m), 4.536 (kg)	2	2	2	<input type="checkbox"/> 1
<input type="checkbox"/> 1	Recreational cooler - full size 0.695 w x 0.625 h x 0.323 l (m), 25.000 (kg)	1	1	1	<input type="checkbox"/> 1

Figure 3.7 Web survey input popup window: Carried items.

When multiple activity templates have been created within a single activity purpose, flexible rules can be created to define the relationships among the templates (Figure 3.8). Using these rules, any combination of an activity template's occurrence likelihood,

frequency, or period can be defined, either independently, or in conjunction with other templates. This highly flexible use of rules allows many different activity patterns to be considered. For example, it's possible to define rules which specify that an activity occurs at least three times a month, but never more than two days in a row.

Rules			
	Rule Name and Type		
486	<div>3 stop Big Grocery Shc</div> <div> <input checked="" type="radio"/> Likelihood <input type="radio"/> Frequency <input type="radio"/> Period </div>	<div>50</div>	<input type="checkbox"/> 0 1321 Big Grocery Shopping - Kroger 2nd <input type="checkbox"/> 1 1322 Big Grocery Shopping - TJ 3rd <input type="checkbox"/> 0 1320 Big Grocery Shopping - Meijer 1st
420	<div>2 stop Big Grocery Shc</div> <div> <input checked="" type="radio"/> Likelihood <input type="radio"/> Frequency <input type="radio"/> Period </div>	<div>100</div>	<input type="checkbox"/> 1 1321 Big Grocery Shopping - Kroger 2nd <input type="checkbox"/> 0 1322 Big Grocery Shopping - TJ 3rd <input type="checkbox"/> 0 1320 Big Grocery Shopping - Meijer 1st
487	<div>Any Big Grocery Shop</div> <div> <input type="radio"/> Likelihood <input checked="" type="radio"/> Frequency <input type="radio"/> Period </div>	<div> at least usually at most <input type="text" value="1"/> <input type="text" value="1"/> <input type="text" value="1"/> time(s) time(s) time(s) per <input checked="" type="radio"/> week <input type="radio"/> month <input type="radio"/> year </div>	<input type="checkbox"/> 1 1321 Big Grocery Shopping - Kroger 2nd <input type="checkbox"/> 1 1322 Big Grocery Shopping - TJ 3rd <input type="checkbox"/> 0 1320 Big Grocery Shopping - Meijer 1st

add rule

ok close cancel

Figure 3.8 Web survey input popup window: Rule definitions.

Iterative review of generated schedules

After several activity templates and their occurrence rules have been defined, it is possible to begin generating schedules using the mPHASE model. Even if participants have not yet fully described their common activities, a review of some sample daily schedules at this point can help to identify inconsistencies in the reporting of activity characteristics and rules. In addition to potentially improving the quality of the responses, an interactive process of reviewing generated schedules can help maintain participant interest throughout the survey.

3.3. Custom in-vehicle data acquisition equipment

Overview

The purpose of the VUSE equipment is to record trip start time, trip end time, and route taken for every trip made by a household vehicle, along with images of the vehicle interior which show vehicle occupants and items carried. Furthermore because of the multi-week data collection period, the units should be capable of operating continuously without any action required by participants.

There are a number of existing inexpensive GPS vehicle positioning devices which are capable of sensing vehicle location, heading, and speed. This information is either recorded to an on-board data logger, or transmitted in real-time to a data center via satellite or cellular phone networks. GPS units are also available which have been paired with video surveillance, consisting of a rearward facing camera mounted inside the vehicle near the top of the windshield, and a data recording or transmitting device. These video-capable units are intended for improving safety by offering parents of young drivers and managers of vehicle fleets the ability to remotely monitor driver behavior (McGehee et al. 2007; Richtel 2011). However, the field-of-view of these single-camera units misses much of the vehicle interior and cargo areas, making them unsuitable for this study.

The custom-designed VUSE equipment used in this research was developed by Micro-Basics, a small embedded electronics design firm, according to the specifications provided. A summary of the basic equipment specifications is given in Table 3.2. The production of 50 printed circuit boards was sourced to a firm specializing in low-volume prototyping, and 20 complete units were fabricated by the principal investigator and a research assistant.

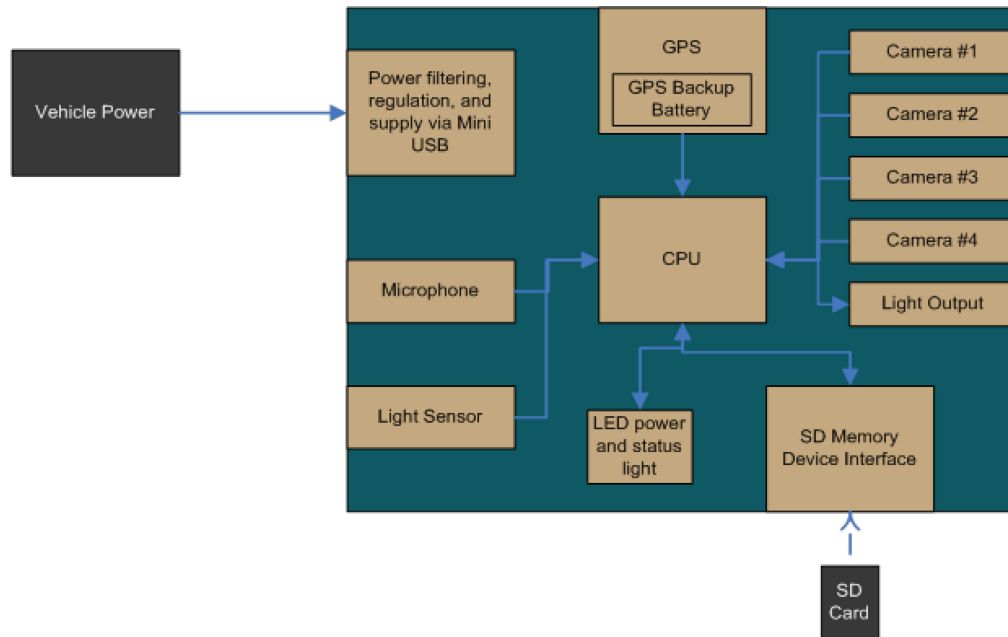


Figure 3.9 Hardware block diagram of VUSE units.

Table 3.2 Summary of VUSE Specifications

<u>General</u>	
Unit size:	14 x 9 x 3 cm
Power input (at unit):	5 volt mini-USB
Image resolution (max):	640x480 pixels
Camera connections (max):	4
GPS:	External receiver
Cost/unit:	\$200 (approx, w/2 cameras + GPS)
<u>Vehicle electrical connections</u>	
Connection location:	Vehicle cabin or engine fuse box
Unit power supply:	12 volt constant power circuit
Ignition signal input:	12 volt ignition-powered circuit
Vehicle circuit protection:	2 amp fuse
<u>Data storage</u>	
Storage media:	SD card
Data capacity (max):	2GB (approx 125 weeks)
File format:	Comma separated value (csv)
Output file fields:	GPS signal status, Date, Time, Lat, Long, Speed, Heading, Elapsed Time, Event Description, Event
<u>Configurable settings</u>	
GPS:	Time interval, stop speed threshold, stop time threshold
Camera:	Image resolution, image capture logic
Light Sensor:	Trigger light level threshold
Microphone:	Trigger sound level threshold

Trip detection and image capture logic

A *trip* is defined here as travel from the location of one activity (the origin) to the location of another activity (the destination). For vehicular trips, this definition often coincides with occupants entering or exiting the vehicle. A stop at a bank or restaurant drive-thru window where the occupants remain in the vehicle would be an exception, and still considered a trip for this study. Cases when individuals exit the vehicle for some reason other than to conduct an activity are not considered trips. Examples include

returning to the trip origin to retrieve a forgotten item, stopping to ask for directions, or moving a vehicle because of parking restrictions.

The task of GPS-based trip detection has been accomplished in previous studies using dwell time to automatically identify potential stops, followed by a manual inspection using GIS software to confirm the validity of the stop (Wolf et al. 2001). The use of dwell time as the sole means of instant trip identification will result in some improperly identified trips. Some very brief stops, such as dropping off a passenger, may only require several seconds. However, setting the dwell time threshold this low would result in many erroneous trip destinations at traffic signals and in congested areas. It is particularly important that the VUSE equipment minimize the number of misidentified trips in order to reduce unnecessary image processing time and storage requirements. By adding vehicle door open and close event sensing to vehicle speed sensing, the VUSE equipment allows a zero second dwell time threshold without generating false trips in traffic.

The VUSE trip identification and image capture algorithms, using a configurable combination of events and system state rules, determine the occurrence of *capture events* which trigger one or more cameras and the associated time and GPS location. The *trip start event* is defined as the last door closing before the vehicle starts moving, while the *trip stop event* is the first door opening after the vehicle stops. The *trip period* is the time between the trip start and stop events during which the state of vehicle occupants and items carried, together the *capacity state*, are assumed to be fixed.

Ideally, there will be one and only one capture event during each trip period, so that the capacity state can be assigned to the trip without ambiguity. This could be done by capturing an image just after the last door closing at the start of a new trip period. Two issues that arise are 1) it is not possible to know at the time a door closes if it is the last closing, and 2) without a supplemental light source, there will often be insufficient lighting to capture an image after last door has closed. This is also true, even in the daytime, for vehicles which have a cargo area in the trunk that is separate from the cabin. The configuration of the VUSE software allows capture event rules, shown in Table 3.3, to be defined separately for each camera. Multiple capture event rules can also be

assigned to a single camera to reduce the potential for missing images by causing capture at different points in the trip period.

Table 3.3 VUSE System States and Capture Event Rules

System States

Movement state:	Set to 1(on) when speed threshold is exceeded Set to 0 (off) when speed falls below threshold
Sound state:	Set to 1(on) when threshold of peak sound relative to the average is exceeded while vehicle is stopped Set to 0 (off) when vehicle starts moving
Light state:	Set to 1(on) when threshold of peak light is exceeded while vehicle is stopped. Set to 0 (off) when vehicle starts moving
Powerup state:	Set to 1 when the unit is powered on (no 0 value, since unit is inoperable without power)
Ignition state:	Set to 1(on) when ignition-switched vehicle circuit is supplied with 12 volts. Set to 0 (off) when vehicle starts moving

Capture Event Rules

- Rule 1: Image capture in moving vehicle at trip beginning
Occurs when movement state changes from 0 to 1 while sound state = 1
- Rules 2.x : Image capture in moving vehicle at trip beginning
Occurs when movement state changes from 0 to 1 while light sensor x light state = 1
- Rules 3.x : Image capture in stopped vehicle at trip completion, or previous parked state
Occurs when light sensor x light state changes from 0 to 1
- Rule 4: Image capture at unit configuration.
Occurs when powerup state is set to 1
- Rule 5: Image capture in moving vehicle at trip beginning
Occurs when movement state changes from 0 to 1 while ignition state = 1

To illustrate how capture event rules are used to produce images of every capacity state, consider the example of a vehicle with two cameras, A and B. The timeline in Figure 3.10 shows the use of the vehicle for three separate trips. In the first trip, the driver takes a passenger, who places something in the trunk before leaving. The driver drops off the passenger without turning off the ignition. The second trip is the driver's return home, where she turns off the ignition, opens the door, exits, and closes the door. In the third trip, the driver opens the door, turns on the car, and then places something in the trunk before closing the door. Another passenger then gets in, and after traveling to their destination, the ignition is turned off and both driver and passenger exit the vehicle.

Camera A is located in the passenger area, and is configured to take an image according to rules 1, 2.1, 3.1, and 5. The last digit of rules 2.x and 3.x identifies which of four light sensors are associated with a camera. In this example, light sensor 1 is located near the cabin dome light, and serves to trigger camera A on rule 3.1 the first time the dome light turns on while the vehicle is stopped. This is intended to provide an image of

the capacity state for the trip just completed, and because the interior is illuminated, can be used in low-light conditions. Rules 1, 2.1, and 5 are intended to take an image just after the vehicle starts moving for the first time after a sound event, a light event, or an ignition event, respectively. These events often occur together at the start of a trip, and some redundancy in rule definitions can increase reliability against incorrect sensor readings. Multiple simultaneous triggers for a camera are reduced to a single image capture event.

Camera B in this example is located in the trunk, and will take an image according to capture event rule 3.2. Because there is usually no light in the trunk when the vehicle starts moving, the other rules are not appropriate. Light sensor 2 is located on the trunk illumination light, and serves to trigger camera B as soon as the trunk is open, the first time after the vehicle is stopped. The resulting image will represent the capacity state of all the previous trips since the trunk was last opened.

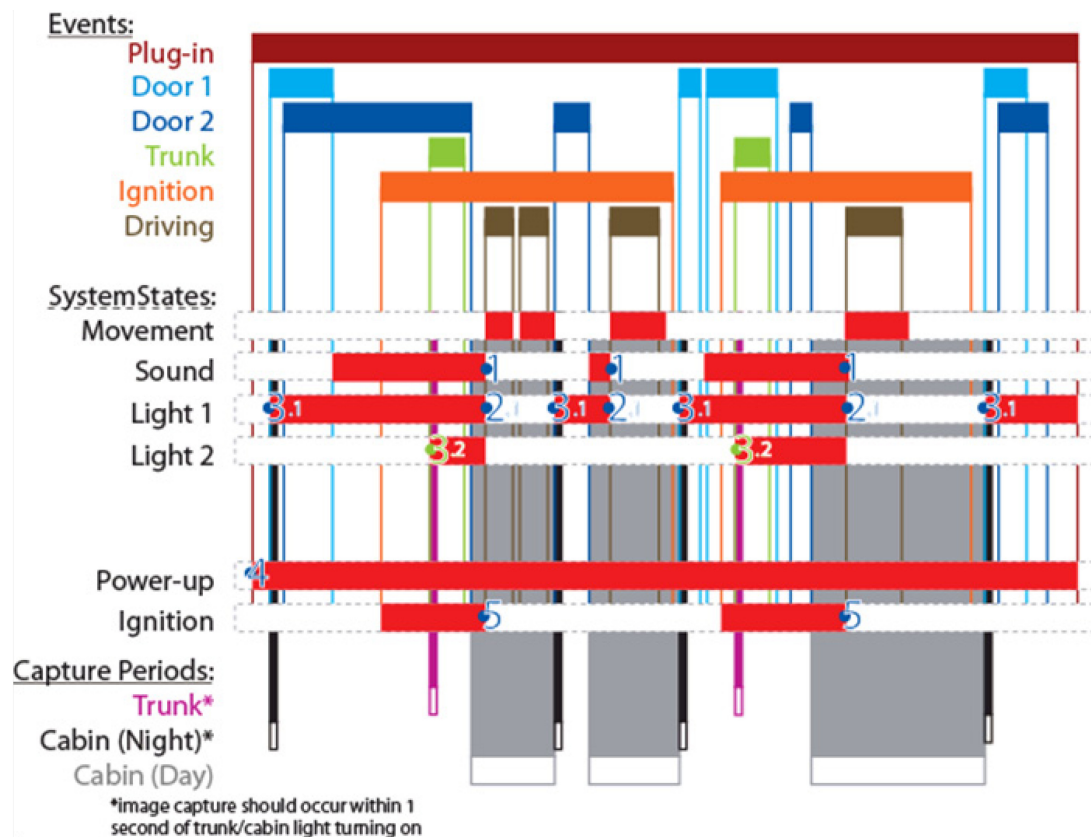


Figure 3.10 Sample timeline of VUSE system state changes and image capture events.

3.4. Household Travel Patterns Study protocol

While the mPHASE model and the companion web survey share many elements in common with existing travel behavior research techniques, some new concepts are unproven. In particular, the application of FEM to solve the scheduling problem and the web survey's probabilistic description of activity characteristics are two ideas that require some evidence of their effectiveness in order to merit further attention. Small scale pilot studies are often used in travel behavior research to demonstrate new techniques (Ampt and West 1983). The purpose of these studies is not to draw any general conclusions about the population being studied, but instead to identify the strengths and weaknesses of the methodology.

The goal of the Household Travel Patterns Study (HTPS) was to test the feasibility of using a web survey to 1) collect long-term travel pattern data, and 2) generate realistic multi-day schedules using mPHASE. A sample size of 30 households is sufficiently large to meet these objectives, and achievable within the five month study period by the HTPS team which consisted of the author and three undergraduate assistants.

Participant recruitment

Eligible households for this study were required to have two regularly-used vehicles, at least two registered drivers, and a home internet connection. Some complexity in travel patterns was required to adequately test the methodology, so single-vehicle and single-driver households were excluded. The limited number of data acquisition units prevented the inclusion of households with a large number of vehicles, so only households with two vehicles were considered. Additionally, applicants who made a significant number of trips by means other than their personal vehicles were not accepted, since it would not have been possible to observe their travel. The research team was required to make two home visits to each participant, so households were required to be within a one hour driving radius from the University of Michigan's Ann Arbor campus.

Study subjects were recruited primarily through a call for participants posted on a website for local part-time job openings (Figure A.2). A financial incentive of \$100 cash was provided to each household after completion of the web survey to compensate for their time and to alleviate any concerns about the installation of VUSE units in their

personal vehicles. A carry-out meal was also provided at the time of the first home visit, with a value of \$8 - \$15 per person, depending on their meal choice (Figure A.3). Aside from the purpose of assisting in recruitment, the meal was also intended to encourage all members of the household to take an interest in the study, and to actively contribute towards the completion of the web survey.

Respondents to the call for participants were instructed to provide a contact phone number and other basic information using an online form (Figure A.4). Applicants were then contacted by phone by the author and given a brief description of the study purpose and what they would be expected to do as participants. After confirming their eligibility for the study, respondents were given a chance to ask questions. Those still expressing an interest were then asked if they would like to participate, and if so, an appointment was scheduled for the first home visit.

First home visit

Arrival and informed consent

Initial home visits were scheduled for a time when all household members would be present, to the extent possible, and when all household vehicles would be available for equipment installation. The home visit team consisted of the author and one or two research assistants. After introducing the visit team and providing a verbal overview of the research, each licensed driver in the household was asked to sign an individual consent form, in paper format (Figure A.5 and Figure A.6).

At this point, participants were given the option of either taking the web survey immediately, or waiting until all household members were available to gather. In either case, a research assistant began installing the in-vehicle data acquisition equipment as soon as the consent forms had been signed.

Administering the web-based survey

To conduct the survey, described in Section 3.2., a location in the participant's home was selected where everyone could be seated to view an enlarged image of the laptop computer screen, projected on a blank wall. After establishing a connection to the household's internet service, the author initiated a session on the study website with a user id and password specific to that household. After briefly introducing the survey, the

four sections were completed sequentially, with the responses recorded by the author. Participants were informed that the target time required to complete the survey was between 60 and 90 minutes.

Installing the in-vehicle data acquisition equipment

Observations of actual travel activity episodes over the study period were recorded using the in-vehicle data acquisition units designed and fabricated for use in this study. The Vehicle Utilization Survey Equipment (VUSE), described in detail in Section 3.3, combines the GPS receiver and position logging capability available in many off-the-shelf units with the ability to capture digital images of the vehicle interior from up to four cameras. These images can then be used to document the travel party members without burdening participants with the requirement of recording household and non-household members in a written log. The images also show any cargo items carried, which would be difficult to note in a detailed and consistent manner using a log.

The VUSE in-vehicle data acquisition units, described in detail in Section 3.3, were installed in the two household vehicles by the research assistants while participants were taking the web survey. The installation process required between 1.5 and 2 hours per vehicle, and did not require any permanent modification to the vehicles. The main module was placed under the driver's seat, with 12 volt power provided by a wire connected to the vehicle's fuse box. The cameras and GPS antenna were affixed to the interior plastic trim panels using removable double-sided adhesive tape. After completing the installation, a test was performed to confirm that the vehicle position and image data were being recorded properly.

Wrap-up and departure

After completing the VUSE unit installation and survey, drivers were shown the equipment in their vehicles, and given instructions to not unplug the units during the data collection period. They were also asked to call the author immediately if they noticed any problems with the equipment such as cameras becoming detached, or a loss of power to the units. Participants were asked to select a time and date between two and three weeks later for a second home visit when the equipment could be recovered. Finally, the home visit team thanked the participating individuals, and departed.

Second home visit

Prior to removing the VUSE equipment, the collected data was checked for completeness. In cases where a correctable equipment malfunction in either of the vehicles resulted in missed data, households were asked to extend their participation to ensure a total of at least two weeks of data in both vehicles, concurrently. After confirming the units had functioned properly, photographs of the installation were taken for later reference and the equipment was removed, concluding the household's participation in the study.

Data post processing

A web-based tool was developed to improve the consistency and speed of data post-processing VUSE data (Figure B.1). The main steps required for post-processing are 1) automatic identification of trip ends based on the recorded vehicle events, 2) visual inspection of identified trip segments, and correction with split and join operations, 3) flagging of erroneous trip segments, and 4) visual inspection of digital images and coding of passengers and items, and their locations in the vehicle for each trip segment.

Manual trip identification

The VUSE equipment is well-suited for the automatic identification of trip ends, because it is capable of recording both vehicle ignition and door closing events. However, events such as an interruption in the gps signal, stopping to ask for directions after getting lost, or returning to a location to retrieve a forgotten item may result in the misidentification of trip ends. A post-processing tool was developed for the purpose of reviewing the automatically generated trip data. By visually inspecting the trip segment data on a map, incorrectly identified trips were corrected by joining or splitting segments, as necessary (Figure B.1).

In other cases poor GPS reception, a power supply issue or other equipment failure resulted in a gap in the trip segment path. In these cases, error codes were assigned to the trip segment based on a visual inspection of the suspect path, and those before and after (Table 3.4).

Table 3.4 Segment Post Processing Error Codes

Error code	Description
0 Parked	Events recorded while vehicle parked
1 Missing start	Path does not contain identifiable start
2 Missing middle	Path has gap between segment start and end
3 Missing end	Path does not contain identifiable end
4 Shuffled	Segment consists of movement to another parking location
5 Configured	Segment begins with unit power-up
6 GPS jump after	Path has gap between segment end and next segment start
7 Missing start and end	Path does not contain identifiable start or end

Digital image inspection and coding

The post-processing of digital images was conducted through a process of visual inspection. The web-based post-processing tool simultaneously displays all the images captured during a trip segment, allowing the items carried and vehicle occupant information to be input with some consideration of the context of the particular trip (Figure B.1).

3.5. Results of pilot study

Sample description

The Household Travel Patterns Study (HTPS) pilot investigation described in chapter 3 was conducted in 2011 using thirty households in the Ann Arbor, Michigan area (Figure 3.11). Study requirements stipulated two-household vehicles, although the types of those vehicles varied widely from compact 4-passenger cars to 8-passenger, full-size SUV's (Figure 3.13). The largest household size was five members, while multiple households had two members. Half of the households had one or more minors (Figure 3.12).

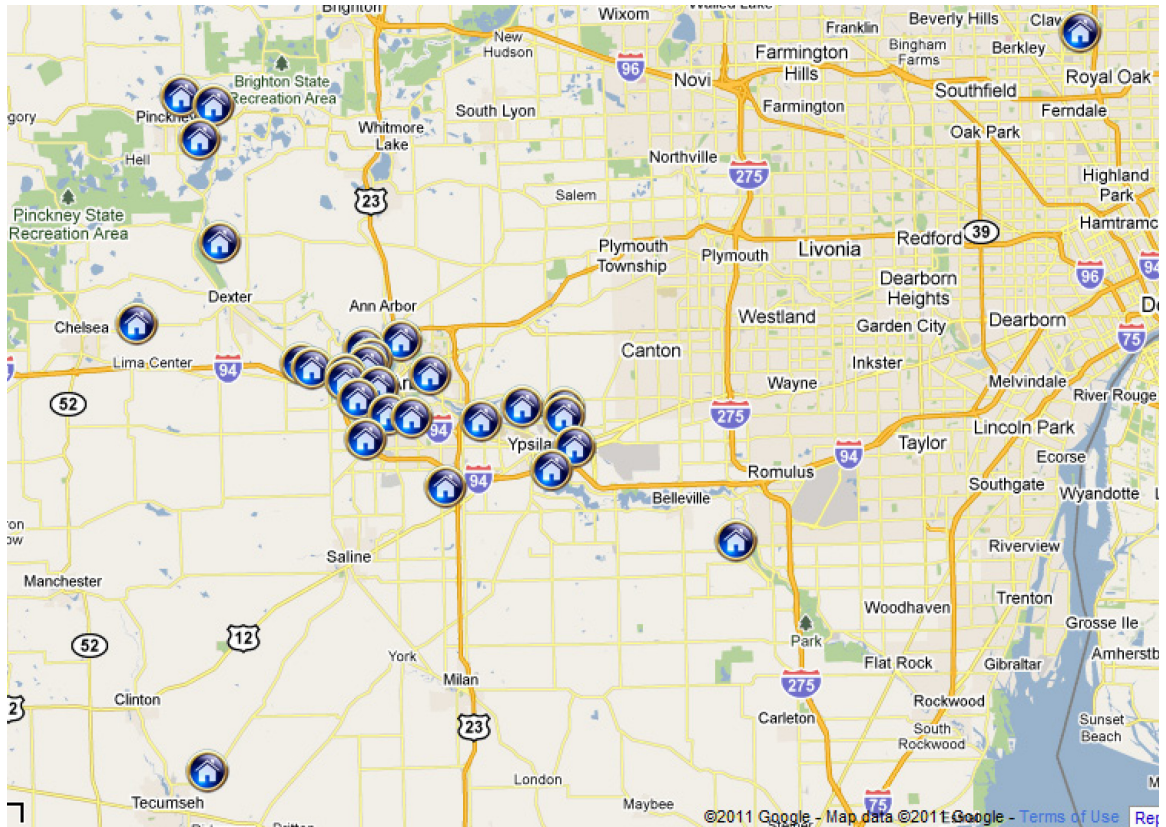


Figure 3.11 Location of participant households in southeast Michigan.

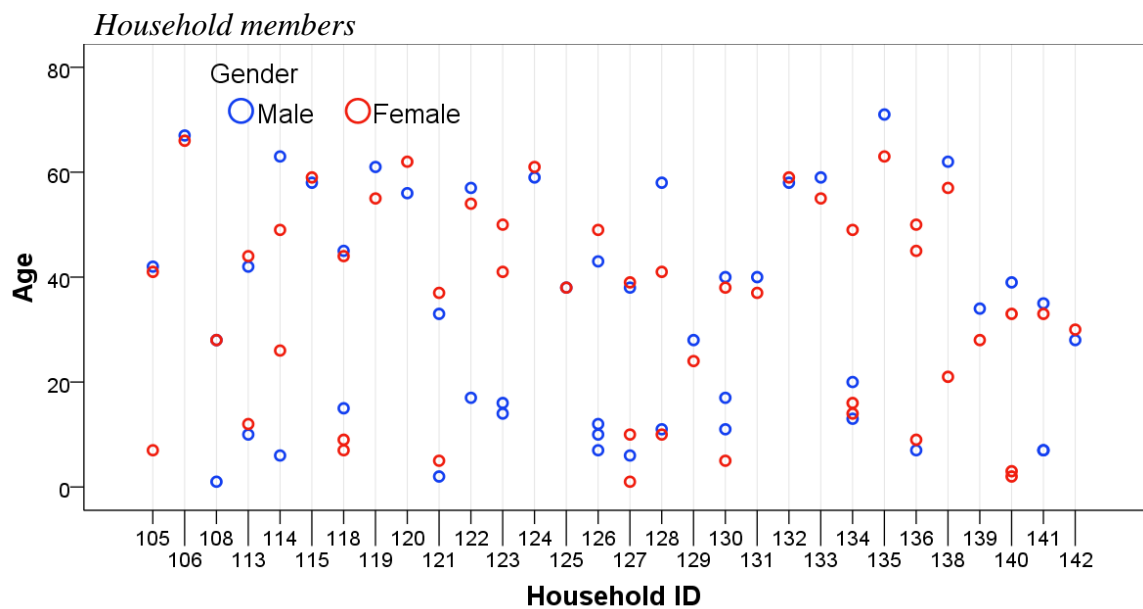


Figure 3.12 Age and gender of household members.

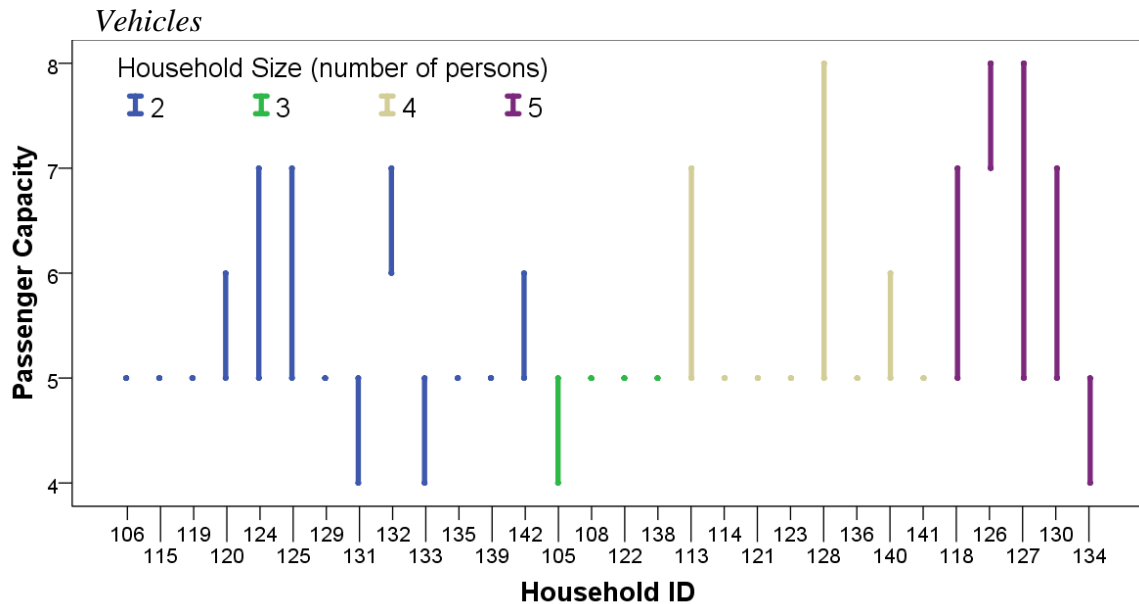


Figure 3.13 Passenger capacity range of vehicles in household – Max and Min

Interactive web survey experience

The group interview process was, in nearly every case, found to be an effective method for encouraging discussion among participants. Arranging the interviews at a meal time, and providing a carry-out meal as an incentive was likely an important factor in the success of this approach. In only two households was it necessary for the primary contact person in the household to provide activity information on behalf of another adult household member. In both of these cases, the non-participation was due to scheduling conflicts, and not, apparently, due to lack of interest.

For the thirty households, the interactive survey required an average of 90 minutes, to complete, ranging from as short as 30 minutes to as long as 140 minutes. Some improvements in the web survey instrument allowed more activity details to be collected in a given time for the later households. Throughout the study period, longer survey durations were correlated with greater details in terms of the number of reported activity purposes, templates, and locations (Figure 3.14), and in general, the survey improvements did not reduce the time to complete the interview.

All participants seemed able to easily conceptualize the reporting of activities in terms of ranges and probabilities for frequency, time, location, participants. The reporting of items carried was unproblematic for common shopping activities. However, for less

frequent activities requiring the transport of large or heavy items, reporting was complicated by the lack of pre-coded items in the survey instrument.

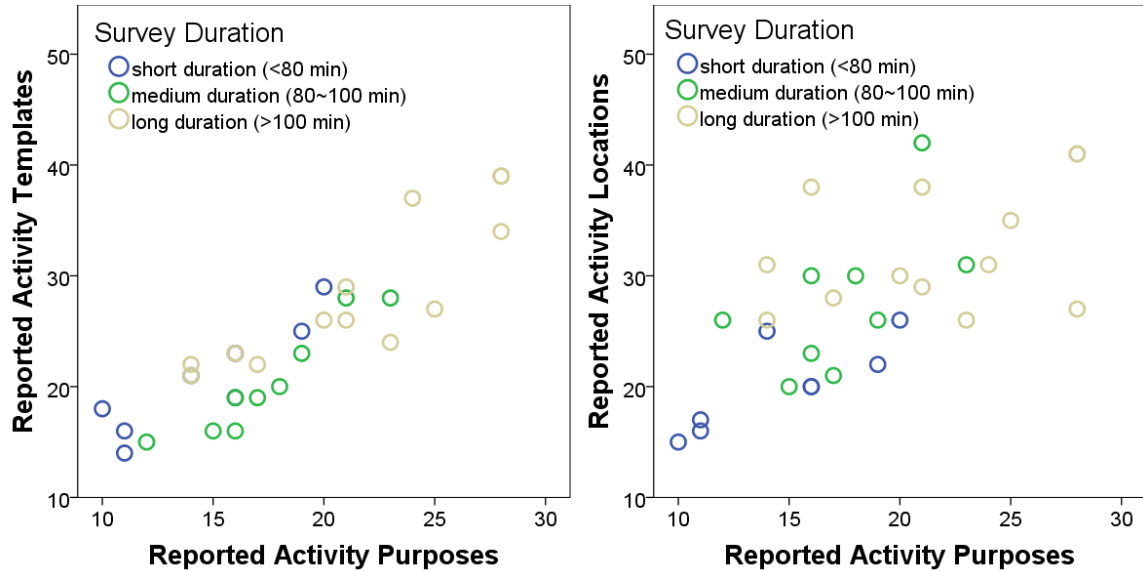


Figure 3.14 Activity response detail for a) templates, and b) locations.

Multi-day schedules generated using mPHASE

Based on the responses generated by the HTPS pilot investigation, the mPHASE model was able to generate synthetic schedules which exhibited many of the characteristics of complex household travel. Total daily travel distances were found to exhibit 1) distinct patterns of weekday and weekend travel, 2) occasional non-travel days, and 3) occasional high-travel days (Figure 3.15).

Complex household interactions were evident in the generated schedules, including 1) the assignment of activities to designated household members according to their availability, and 2) the coordination of picking up and dropping off other household members at their activities.

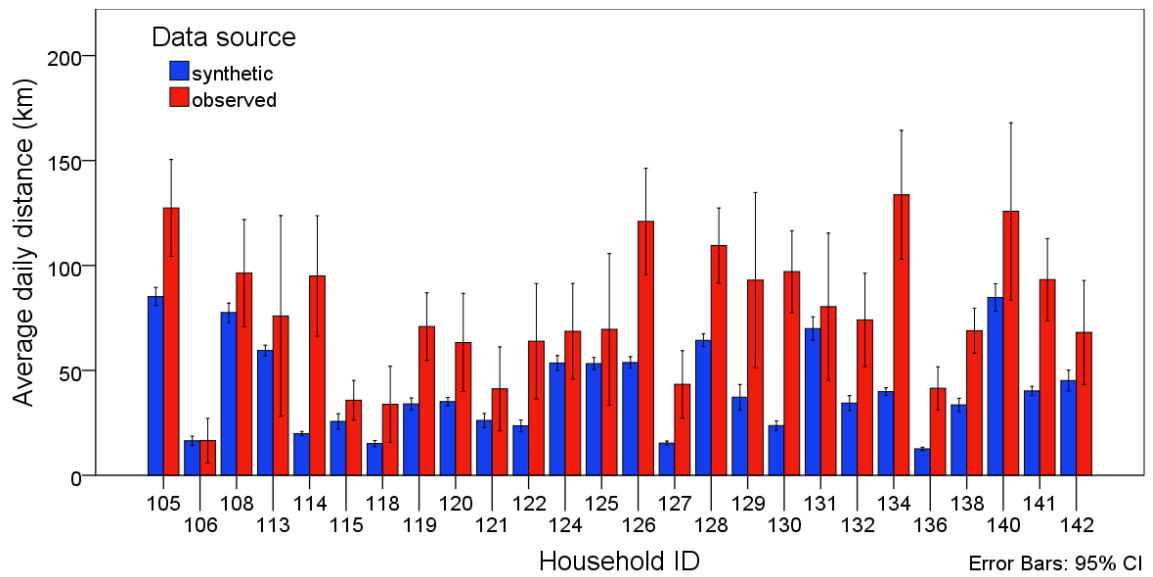


Figure 3.15 Average daily household distance - Synthetic vs. observed travel.

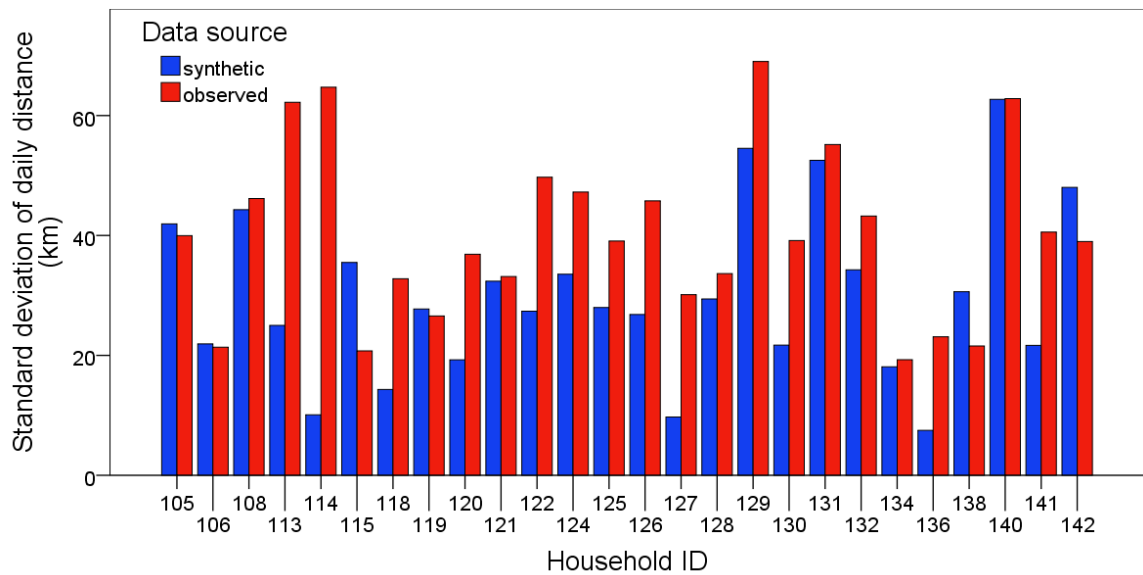


Figure 3.16 Variation in daily travel distance - Synthetic vs. observed travel.

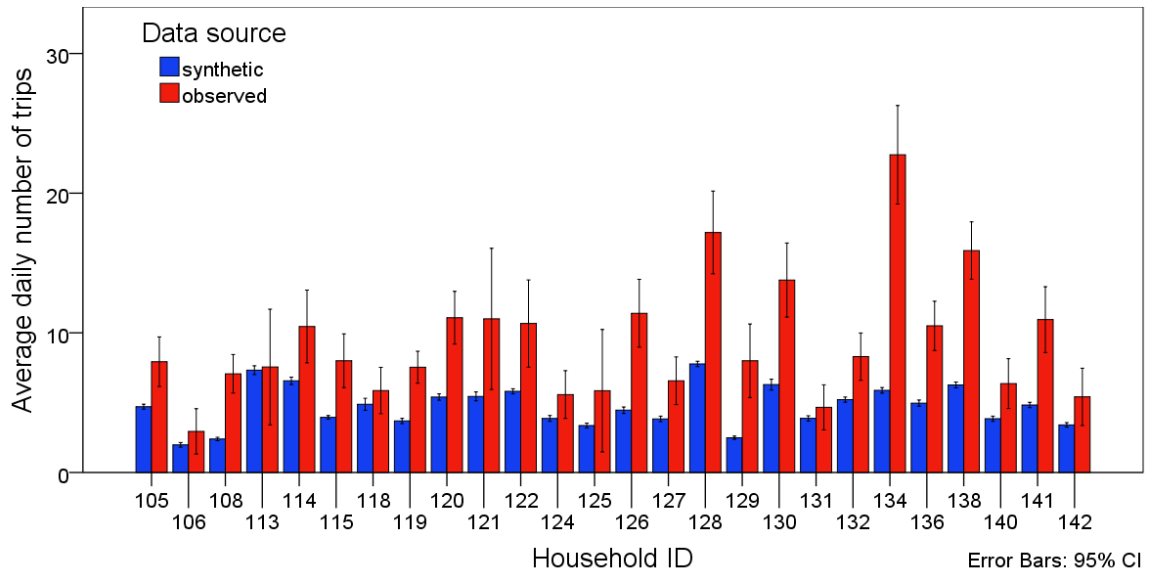


Figure 3.17 Average daily number of trips - Synthetic vs. observed travel.

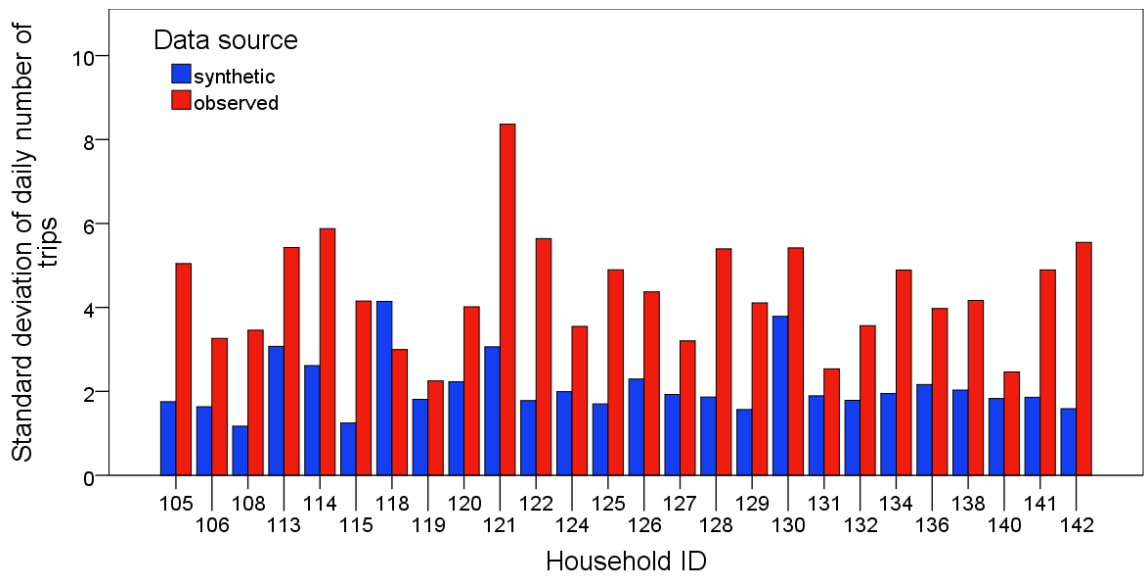


Figure 3.18 Variation in daily number of trips - Synthetic vs. observed travel.

Capability constraints and the optimal assignment of vehicles to trips

Transportation energy use for households with access to multiple vehicles can be heavily influenced by decisions regarding which vehicles should be used to conduct the desired travel-activity schedule. While these vehicle-to-trip assignment decisions may be influenced by a variety of factors, at a minimum the vehicles selected must be capable of meeting the physical requirements of the trips. The number of people in the travel party, the items carried, and the distance to an activity location are examples of trip requirements that cannot exceed the constraints imposed by the capability of the selected vehicle.

This chapter begins with a review of existing constraints-based techniques, and previous work on the household vehicle assignment problem. The Constraints-based Transportation Resource Assignment Model (CTRAM) is then introduced which determines the fuel-use minimizing vehicle assignments for a given travel schedule and vehicle fleet. This original enumerative optimization model is unique in its ability to consider any number of vehicle attributes related to an activity's physical travel requirements in a computationally efficient manner. One of the most common vehicle constraints, passenger capacity, is considered here in some detail, although the model can also account for vehicle range and cargo carrying capability, among others.

An analysis of the 2001 and 2009 National Household Travel Survey (NHTS) is then presented. By supplementing this publicly available survey data with detailed vehicle specification data, the CTRAM model is able to explore the influence of vehicle capability constraints on potential energy saving strategies more thoroughly than was possible using previously existing methods. Questions investigated in this chapter include

the potential fuel savings with optimal assignments, the influence of fuel prices, and differences in assignment decisions between 2001 and 2009.

A constraints-based approach to the problem of vehicle assignment is appropriate for exploring the boundaries of behavioral reaction to a given scenario, but is not intended to predict what an actual response might be. Nevertheless, based on single-day travel survey data, the CTRAM model can provide useful insights into the energy savings that can be achieved using existing household fleets. When provided with the hypothetical, multi-day activity schedules generated using the methodology described in chapter 2, the CTRAM model can be used to investigate a wider range of strategies, including changes in household fleet composition and size, the adoption of range-limited electric vehicles, and the use of alternatives to personal vehicles, such as public transportation, walking, biking, and car sharing.

4.1. Background

The explicit consideration of constraints in travel analysis was an important contribution made by geographers at the University of Lund in the late 1960's. The time-space prism framework they developed integrates various types of constraints (Hägerstrand 1970), and defines how an individual's spatial boundaries of potential movement change as he progresses through time (Lenntorp 1976). An individual's range of travel is defined by the type of transportation, or more generally, by the *capability constraints* imposed by the available technology, and may be expanded with the availability of faster transportation. An individual's path in space and time within a prism is governed by *coupling constraints* that define when and where the individual has to join other individuals, tools, and materials and *authority constraints* that arise from the various rules that are observed in work, home, public, and other domains. Of these three types of constraints identified by Hägerstrand, coupling and capability constraints are particularly relevant to vehicle assignment decisions and household transportation energy use, and are the focus of the constraints-based methodology introduced in this chapter.

Household fleet capability and coupling constraints

The actual decision of which vehicle to use for a trip will be based on a wide range of factors that include personal preference, convenience, habit, and household rules

restricting drivers from particular vehicles. But at a minimum, the selected vehicle must be capable of meeting the physical requirements of the trip, and be available when the travel party embarks.

The availability of a vehicle at the correct time and place is dependent on the coupling constraints which govern not only how household members coordinate activities with others, but also how common resources like vehicles are scheduled and shared. The need to coordinate vehicle use is evident in households with more drivers than vehicles. But even in households with one or more vehicles per driver, scheduling conflicts may result in the preferred vehicle being unavailable at the required time.

Availability is not by itself sufficient for trip assignment since the vehicle used must also have the ability to reach the destination in the required time, and to carry the people and cargo that need to be carried to and from the activity location. Capability constraints may reduce the number of feasible options, leaving only those vehicles with sufficient capacity, range, and average speed (given the available refueling infrastructure, traffic congestion, and weather conditions).

Capability constraints are particularly relevant when considering energy use, since at a given level of technology, a decrease in capability is invariably tied to a decrease in a vehicle's *fuel consumption* rating (defined in terms of the amount of fuel consumed per unit of distance traveled) as reduced vehicle size and power requirements leads to reduced inertial mass and frictional losses. One measure of the potential to reduce capacity is the *load factor*, which is expressed as the ratio of the carried load to the vehicle capacity. For passenger travel in the U.S., average load factors of 0.83 for domestic air travel (BTS 2011), 0.49 for passenger rail (Amtrak 2011), and 0.33³ for automobiles (Santos et al. 2011) indicate that there is an opportunity to save energy by either reducing vehicle size, or increasing the number of passengers per vehicle. However, eliminating excess capacity is complicated by the variability in transportation needs, and the uncertainty of accurately projecting future needs. As McCarthy (1984) noted, "*the larger capacity expected to be needed for some trips, however infrequently, induces households to purchase vehicles with enough room to meet these contingencies. Similar considerations apply to other features, including load carrying and performance. As a*

³ Based on the reported average of 1.67 occupants per trip, and an assumed passenger capacity of 5.

result, there occurs, on average, a mismatch between a household's trip requirements and the characteristics embodied.”

When a fleet is composed of a diverse range of vehicles, some level of *capacity matching* can be achieved by assigning the vehicle with capabilities just sufficient to satisfy the trip requirements. This practice is common for businesses and institutions that manage large fleets, and is the topic of many studies in the branch of operations research dealing with logistics. On a smaller scale, households with multiple vehicles can also realize some energy savings through vehicle assignment decisions.

Constraints-based methods and vehicle assignment in previous work

Many of the earliest constraints-based disaggregate travel studies were strongly influenced by the space-time prism concept pioneered by the Lund School. Studies of *accessibility* – the range of destinations that can be reached by an individual – were a natural application of this approach. Lenntorp (1976) investigated accessibility, and the effects of varying average travel speeds, connection schedules, and wait times that characterize multi-modal, public transportation journeys. Burns (1979) used a similar approach to argue that greater highway travel speeds of personal automobile trips had objectively increased accessibility, despite the longer travel distances associated with low-density suburban development. Forer and Kivell (1981) used space-time prisms to investigate the accessibility of urban destinations for women in single-vehicle households.

Following the fuel shortages of the 1970's, constraints-based methods were applied to answer questions regarding household vehicle usage and energy conservation. An initial step in this direction was the recognition that when considering the energy efficiency of travel, passenger miles traveled (PMT) is a more meaningful measure of vehicle utilization than commonly used measure of vehicle miles traveled (VMT) (Lee-Gosselin 1983).

One approach to investigating the role of constraints in household travel decisions is the use of gaming simulations in an interactive household interview, as conceived by the pioneering work done at Oxford University's Transport Studies Unit on the Household Activity Travel Simulator (HATS) (Jones 1979). The HATS methodology employs a game board, where scheduled vehicle use is represented with colored blocks which provide an intuitive, physical representation of scheduling conflicts and coupling

constraints. New York state transportation planners adapted the HATS methodology to create the Response to Energy and Activity Constraints on Travel (REACT) game, to investigate how one and two-vehicle households would react to public policies for energy conservation such as gasoline rationing, and vehicle-specific no-drive days (Phifer et al. 1980). The Car-Use Patterns Interview Game (CUPIG) modifies the HATS approach to include a fuel budget allocation dimension (Lee-Gosselin 1990). Respondents are given a limited number of tokens, representing units of fuel, which they can use to indicate their household vehicle assignment decisions as they attempt to modify their activity schedules to adapt to various fuel shortage and energy conservation scenarios.

Vehicle assignment decisions have been incorporated into predictive models of travel behavior using econometric, random utility maximizing (RUM) methods. This approach has been adopted in analyses of mode choice to address the question of whether *any*, rather than *which*, household vehicle will be used (Bhat and Koppelman 1993; Roorda et al. 2006). However, for an analysis of energy use, an understanding of how particular vehicles are used is vital. Econometric methods which require that choice sets be defined in advance are not well-suited for the complete analysis of assignment decisions in multi-vehicle households, where the number of possible combinations can be exponentially large. To make the assignment problem more tractable, statistical methods like structural equation modeling and RUM have been used to quantify how the characteristics of vehicles in the household fleet are related to their utilization, defined not by a vehicle's use on an individual trip assignment, but by its proportion of total household travel distance (Mannering 1983; Hensher 1985; Golob et al. 1996). The disadvantage of this aggregate approach is its inability to identify scheduling conflicts and specific activity requirements that may limit vehicle choices.

Simulation techniques offer the potential for considering disaggregated vehicle assignment decisions in a manner that is computationally manageable. Following nearly two decades with little advancement in methodology, aspects of the Lund School's space-time prisms have begun to appear in more comprehensive simulation models of travel-activity behavior. The Prism-Constrained Activity-Travel Simulator (PCATS), which was designed as a more complete modeling system to predict behavioral responses to such disturbances as increased traffic congestion, and changes in work schedules (Kitamura

and Fujii 1998). Another simulation incorporated the range limitations of walking and biking to study potential reductions of automobile dependency in French cities (Massot et al. 2006).

4.2. CTRAM - Constraints-based Transportation Resource Assignment Model

Constraints-based methods allow researchers to explore the boundaries of potential behavioral responses, without the uncertainties involved with predictive behavioral models (Recker and Parimi 1999). This advantage is particularly beneficial if one wishes to investigate scenarios that are dramatically different from the existing conditions, when the empirical specification of a predictive model would be difficult to justify. For example, efficient vehicles available now and in the future are likely to have different, and sometimes reduced, capabilities from the vehicles they replace. Electric vehicles with range limitations cannot be used in the same way as conventionally fueled vehicles, and the consideration of range and other capability constraints to remove infeasible choices can improve the realism of any model of vehicle utilization, regardless of the methodology used. The Constraints-based Transportation Resource Assignment Model (CTRAM) presented below is intended to provide insight into the potential for household transportation energy savings through the optimal assignment of transportation resources. The focus here is on household fleets of personal vehicles, but *transportation resources* in the model might include any mode of transportation, public or private, motorized or non-motorized.

Model Overview

The goal of the optimal vehicle assignment problem can be summarized as finding the combination of vehicle to trip assignments which minimizes total cost while satisfying the requirements of the travel schedule. The term “cost” is used in the general sense, and might include any of the negative effects of travel, including emissions of greenhouse gases, fuel consumption, or monetary expenditures. The flow diagram shown in Figure 4.1 illustrates the inputs required for CTRAM’s household vehicle assignment algorithm to produce optimal vehicle assignments. The schedule and trip requirement inputs can be provided by household travel diary data, as demonstrated in section 4.3, or by synthetic schedules like those generated using the methodology described in chapter 2.

The household vehicle fleet can be the actual vehicles, in which case the model output can be used to gauge the degree of optimality of the actual vehicle assignment decisions. Or, various hypothetical fleets can be compared to determine the combination of vehicle characteristics which provide the greatest potential for savings.

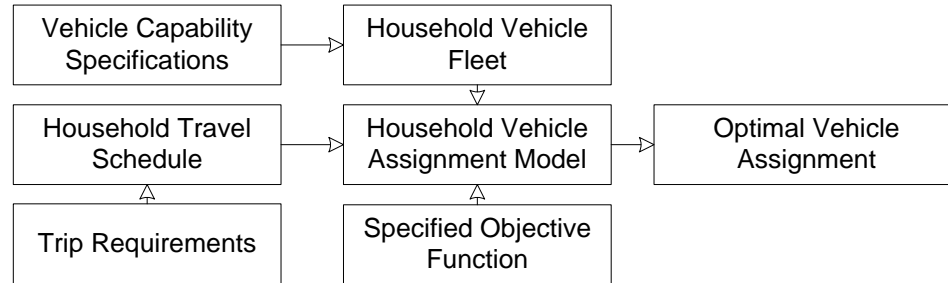


Figure 4.1 CTRAM flow of model inputs and output.

Travel blocks and scheduling conflicts

The model is structured around the household as the basic unit of analysis, within which individuals are likely to share resources and conduct some activities jointly. The travel-activity schedules of every household member are combined into a single schedule which includes information about trip origin, destination, start time, and end time. A *tour* is defined as the combination of trips which start and end at a common location. Work-based tours would be common for an employee who conducts errands on her lunch hour, although any location might serve as a tour origin, as in the case of a parent who goes shopping between dropping off and picking up his child at an activity. Home-based tours are of particular interest in the vehicle assignment problem, because it offers the only opportunity under normal circumstances to exchange vehicles with other drivers in the household. For clarity, a home-based tour is hereafter referred to as a *travel block*, and defines the time period when the vehicle is unavailable for other trips (Figure 4.2).

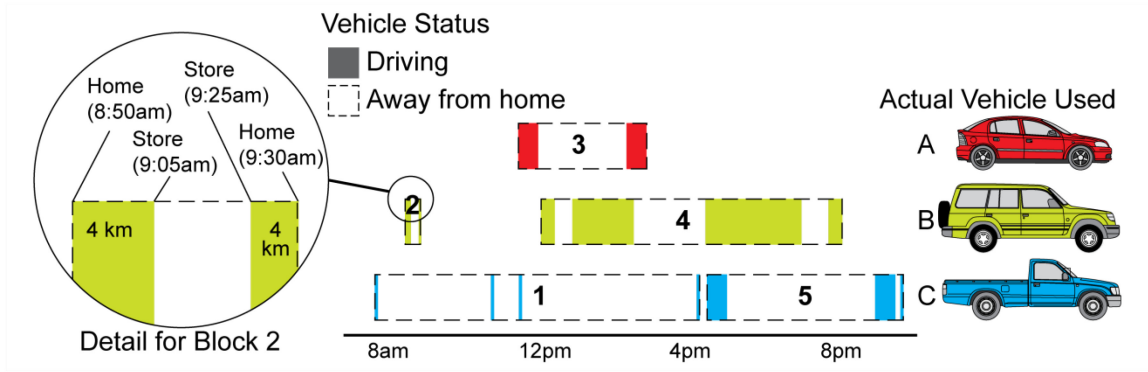





Figure 4.2 Household vehicle use schedule with trips grouped by travel blocks.

When a single vehicle is used for multiple trips with varying requirements, the assigned vehicle must satisfy the most demanding requirements for all trips in the block (Table 4.1, Figure 4.3). For example, if a travel block includes shopping or picking-up passengers, the capacity requirements for cargo and passengers must be satisfied for the entire travel block, even if the vehicle capacity in some trip segments is underutilized. Excluding the identical trips for multiple household members travelling jointly, sets of blocks which overlap in time represent conflicts for the shared vehicles. If the travel schedule is to be successfully completed, the number of feasible vehicle choices (i.e., satisfying both vehicle capability and availability requirements) must be no less than the total number of conflicting blocks at any time.

Table 4.1 Vehicle Specifications for Sample Household Fleet

Vehicle ID	Fuel consumption (L/100km)	Passenger Capacity	Cargo Capacity (10 ³ Liters)	Maximum Range (km)
A 	7.8	0.6	∞	∞
B 	9.8	0.9	∞	∞
C 	15.7	1.9	∞	∞

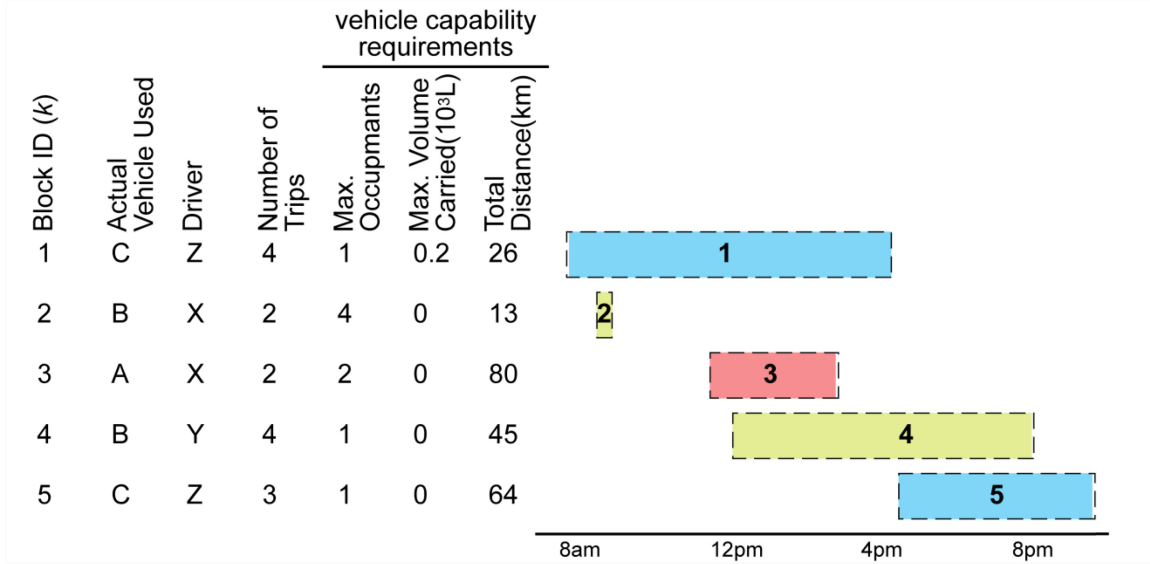


Figure 4.3 Vehicle capability requirements of ordered travel blocks.

Enumeration of assignment combinations

The task of assigning the vehicles in a fleet to travel blocks in order to optimize some objective function is not a trivial one. For example, if the objective is to minimize fuel consumption, one strategy is to always select the most efficient vehicle available for the next travel block. This decision making algorithm is known as *greedy*, and does not always yield optimal results because there is no consideration of how a current decision will influence the available choices in the future. In the example shown in Figure 4.3, the greedy algorithm applied to the first travel block would make the most efficient vehicle unavailable for subsequent blocks of greater distance, and therefore not result in the lowest possible total fuel consumption. A more rigorous approach requires the simultaneous consideration of conflicting blocks. Even when two blocks do not directly conflict, a choice made in one block may affect the set of choices available for a later one through a cascading effect. These *conflict cascades* are defined here as sets of travel blocks which can be identified by sorting all the blocks by starting time, and including each block which overlaps any of the previous blocks. The first block which does not overlap any of the earlier blocks will form the start of the next conflict cascade set. Analyzing choices by dividing schedules in this way can reduce the computational requirements of the model considerably, since the number of assignment combinations, m ,

increases dramatically with the number of travel blocks in the conflict cascade, p (equation 4.1).

$$m = \prod_{k=1}^p a_k \quad (4.1)$$

The elements of the vector a represent the number of vehicles available to choose from at the start of each travel block. The values of a can be determined by subtracting the number of vehicles in use at that time from the number of vehicles available at the start of the conflict cascade, a_1 , which would normally be equal to the size of the household fleet (equations 4.2, 4.3).

$$a_k = a_1 - \text{number of vehicles in use} \quad (4.2)$$

$$\text{number of vehicles in use} = \sum \text{blocks started} - \sum \text{blocks ended} \quad (4.3)$$

Continuing the example in Figure 4.3, for a household with a fleet of three vehicles, $a = [3 \ 2 \ 2 \ 1 \ 2]$, and $m = 24$.

The vector a can be used to generate the *ranked choice matrix*, C with each column representing one of the m unique possible assignment combinations. The 24 possible assignment combinations for the five travel blocks in this example are represented by the $p \times m$ (5×24) matrix in equation 4.4.

$$a = \begin{bmatrix} 3 \\ 2 \\ 2 \\ 1 \\ 2 \end{bmatrix} \Rightarrow C = \begin{array}{c} \begin{array}{c} \text{greedy choice} \\ \text{combination} \\ j=1 \\ \downarrow \end{array} \quad \begin{array}{c} \text{actual choice} \\ \text{combination} \\ j=22 \\ \downarrow \end{array} \end{array} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 \\ 1 & 1 & 1 & 1 & 2 & 2 & 2 & 2 & 1 & 1 & 1 & 1 & 2 & 2 & 2 & 2 & 2 & 1 & 1 & 1 & 1 & 2 & 2 & 2 & 2 \\ 1 & 1 & 2 & 2 & 1 & 1 & 2 & 2 & 1 & 1 & 2 & 2 & 1 & 1 & 2 & 2 & 1 & 1 & 2 & 2 & 1 & 1 & 2 & 2 \\ 1 & 1 \\ 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & 2 & 1 & \boxed{2} & 1 & 2 \end{bmatrix} \leftarrow k=5 \quad (4.4)$$

The values of the ranked choice matrix, C , represent the ordinal position of the chosen vehicle within the set of available vehicles of size a_k . The method of ordering the available vehicle set is not critical, so long as the method is applied consistently. If, as in this example, available vehicles are ranked according to increasing fuel consumption, with the most efficient available vehicle first, a column of all ones in the C matrix represents the greedy choice combination for the objective function of minimizing fuel use. The composition of the available vehicle sets at the start of each block varies for

each of the m combinations because the vehicles in use at any time are a result of choices that were made for previous travel blocks. For example, the chosen vehicle for the fifth travel block of the actual choice combination, $j = 22$, is the second vehicle from a two-vehicle set (see equation 4.4). This corresponds to vehicle C, because vehicle B is still occupied by the fourth travel block. If the travel block schedule is used in this way to translate all the position values from the ranked choice matrix, the result is the *vehicle choice matrix*, U , with a column for each unique assignment combination, whose elements represent vehicle assignments not by rank, but by the particular vehicle identifiers (equation 4.5).

$$U = \begin{bmatrix} A & A & A & A & A & A & A & A & B & B & B & B & B & B & B & C & C & C & C & C & C & C \\ B & B & B & B & C & C & C & C & A & A & A & A & C & C & C & C & A & A & A & A & B & B & B \\ B & B & C & C & B & B & C & C & A & A & C & C & A & A & C & C & A & A & B & B & A & A & B \\ C & C & B & B & C & C & B & B & C & C & A & A & C & C & A & A & B & B & A & A & B & B & A \\ A & B & A & C & A & B & A & C & A & B & B & C & A & B & B & C & A & C & B & C & A & C & B & C \end{bmatrix} \quad (4.5)$$

Capacity constraints and feasible assignments

Availability does not guarantee the feasibility of a choice because a vehicle must also be capable of meeting the requirements of the travel block. For a household with n vehicles, a *capacity utilization matrix*, CU , with dimensions $p \times n$ can be defined for each capacity constraint of interest. Capacity utilization is calculated as the ratio of each travel block's capacity requirements to the maximum capacity of each vehicle. Equation 4.6 shows occupancy and cargo volume capacity utilization matrices for the example household in Figure 4.3. The utilization of range, towing capacity, and other measures of vehicle capability can also be represented in this way.

$$CU_{occ} = \begin{matrix} \leftarrow \text{vehicles} \rightarrow \\ \begin{matrix} A & B & C \end{matrix} \\ \begin{bmatrix} 1/5 & 1/7 & 1/3 \\ 4/5 & 4/7 & \cancel{4/3} \\ 2/5 & 2/7 & 2/3 \\ 1/5 & 1/7 & 1/3 \\ 1/5 & 1/7 & 1/3 \end{bmatrix} \end{matrix} \leftarrow k = 2, CU_{crgvol} = \begin{matrix} \leftarrow \text{vehicles} \rightarrow \\ \begin{matrix} A & B & C \end{matrix} \\ \begin{bmatrix} 0.2/0.6 & 0.2/0.9 & 0.2/1.8 \\ 0/0.6 & 0/0.9 & 0/1.8 \\ 0/0.6 & 0/0.9 & 0/1.8 \\ 0/0.6 & 0/0.9 & 0/1.8 \\ 0/0.6 & 0/0.9 & 0/1.8 \end{bmatrix} \end{matrix} \quad (4.6)$$

Elements of CU with a value greater than one indicate that the vehicle is not capable of meeting the requirements of a travel block, and therefore any choice combinations containing that vehicle and travel block pair are infeasible. In this example, the number of

passengers in the second travel block exceeds the capacity of vehicle C, as indicated with a strikethrough in equation 4.6. Therefore, the choice combination columns 5 thru 8 and 14 thru 17 in U can be excluded from further consideration (equation 4.7).

$$U = \begin{bmatrix} A & A & A & A & A & A & A & A & B & B & B & B & B & B & B & C & C & C & C & C & C & C & C \\ B & B & B & B & \cancel{C} & \cancel{C} & \cancel{C} & \cancel{C} & A & A & A & A & \cancel{C} & \cancel{C} & \cancel{C} & \cancel{C} & A & A & A & A & B & B & B & B \\ B & B & C & C & B & B & C & C & A & A & C & C & A & A & C & C & A & A & B & B & A & A & B & B \\ C & C & B & B & C & C & B & B & C & C & A & A & C & C & A & A & B & B & A & A & B & B & A & A \\ A & B & A & C & A & B & A & C & A & B & B & C & A & B & B & C & A & C & B & C & A & C & B & C \end{bmatrix} \quad (4.7)$$

infeasible
infeasible
choice combinations
choice combinations

Determining the optimal assignment combination

The distances of the travel blocks are represented in this example by a p -length vector, $d = [26 \ 13 \ 80 \ 45 \ 64]km$, while fuel consumption of the household fleet is given by the n -length vector, $f = [7.8 \ 9.8 \ 15.7]L/100km$. The total fuel use by the household, F_j , (for assignment combination j) can be calculated by summing the products of the block distances and the fuel consumption of the assigned vehicle, v (equation 4.8).

$$\text{For fuel use: } F_j = \sum_{k=1}^p (f_v \cdot d_k) \text{ , where } v \text{ is the vehicle assigned to the } k\text{th block} \quad (4.8)$$

and j th choice combination ($v = U_{k,j}$)

Total monetary expenditures, M_j , and greenhouse gas emissions, G_j , can be calculated in the same way using vectors of the relevant cost per unit distance traveled, e and g , respectively (equations 4.9 and 4.10). The elements of g represent the total fuel cycle greenhouse gas emissions in units of $g \cdot CO_2/km$ for each vehicle in the fleet. Elements of the e vector represent operating expenditures, in units of $\$/km$, and include expenditures on fuel, and components of vehicle depreciation, maintenance, and insurance which depend on distance driven.

$$\text{For monetary expenditures: } M_j = \sum_{k=1}^p (e_v \cdot d_k) \quad (4.9)$$

$$\text{For greenhouse gas emissions: } G_j = \sum_{k=1}^p (g_v \cdot d_k) \quad (4.10)$$

The optimal vehicle assignment, j_{opt} , can be determined by finding the minimum total cost from among all j assignment combinations (equations 4.11 thru 4.13). For a fleet composed of single-fuel vehicles, the optimal vehicle assignment combination will

be the same for both the fuel use and greenhouse gas minimizing objective functions. Similarly, the optimal assignment for monetary expenditures will agree with the fuel use objective when fuel costs dominate operating expenditures. This will not be the case if any of the available vehicles are capable of operating on multiple energy sources. For example a plug-in hybrid electric vehicle (PHEV) uses a combination of gasoline and electricity, and the variations in emissions intensity and price for the two energy sources will likely result in different vehicle assignment combinations for optimal greenhouse gas emissions and monetary expenditures.

$$\text{Optimal fuel use:} \quad F_{j,opt} = \min_{j=1:m}(F_j) \quad (4.11)$$

$$\text{Optimal monetary expenditure:} \quad M_{j,opt} = \min_{j=1:m}(M_j) \quad (4.12)$$

$$\text{Optimal greenhouse gas emissions:} \quad G_{j,opt} = \min_{j=1:m}(G_j) \quad (4.13)$$

Concluding the example in this section, for all feasible choice combinations the minimum possible fuel use of 20.8 liters occurs with choice combination $j=17$, which is 20 percent less than the actual fuel consumption ($j=22$, 26.1 liters), and 11 percent less than the greedy choice combination ($j=1$, 23.3 liters).

4.3. Analysis of 2001 and 2009 NHTS data using CTRAM

This section presents an analysis of these two latest versions of the NHTS, 2001 and 2009, based on the results of the CTRAM model. The goals of this application of CTRAM are 1) to quantify the opportunities for reducing fuel use through optimal vehicle assignment, and 2) to investigate any changes in the optimality of assignment decisions that may have occurred over the past decade.

Description of 2001 and 2009 NHTS data sets

Beginning in 1969 when the first Nationwide Personal Transportation Survey (NPTS) was conducted, the U.S. Federal Highway Administration (FHWA) has periodically conducted national surveys to help policy makers and researchers quantify travel behavior by mode, intensity, and purpose, and to identify trends and demographic relationships for various travel characteristics. The surveys in the series are a convenient source of data because they are publicly available, offer generally consistent questions and coding of variables for cross-year-comparisons, and have sample sizes large enough to permit the targeted analysis of households with the particular characteristics of interest.

For use in the CTRAM model, the surveys are especially valuable because they contain information about trips for all members of a household, and for trips using a household vehicle, specify the year, make, and model used and the number of occupants (Table 4.2).

Table 4.2 Minimum Data Requirements for CTRAM

Characteristic	Details
Household	Composition of vehicle fleet (year, make, model)
Vehicle	Fuel consumption rate Capability (max occupancy, cargo volume, other)
Trip	Start/end times Depart/return home flag Distance Occupancy/ other capacity requirements

Households which did not complete any trips on their assigned travel day, or began or ended the day away from home are not suitable for analysis using the CTRAM model. This analysis is focused only on light-duty vehicle utilization, so households without at least one vehicle or with a motorcycle in the fleet were also not considered. After removing samples which displayed one or more of these characteristics, the suitable sample size was 13,347 households in the 2001 NHTS, and 54,785 households in the 2009 NHTS (Table 4.3).

Table 4.3 2001 and 2009 NHTS Sample Sizes

	Survey period	Sample size (households)	Suitable sample size (households)
2001	March 2001 - May 2002	26,038	13,347
2009	March 2008 - May 2009	150,147	54,785

Adding vehicle specifications to NHTS data

The information collected by the NHTS about household vehicles is limited to model year, manufacturer, and model name. Precise values for fuel consumption are unknown since these characteristics may vary according to vehicle trim, engine, and transmission options. The U.S. Energy Information Administration (EIA) provided an augmentation to the 2001 and 2009 NHTS, adding vehicle *fuel economy* values (measured in miles per gallon) based on the EPA test values, adjusted to account for some of the factors which influence the actual, in-use vehicle performance (U.S. EIA 2011). However, the EIA data makes adjustments for real-world driving based on the vehicle distance traveled on the study day, which is one of the dependent variables output by CTRAM. Also, the EIA does not provide separate city and highway fuel consumption rates, thereby eliminating

the possibility of applying more accurate, trip-specific values. Finally, important vehicle capability specifications such as passenger and cargo capacities are not available in either the original NHTS data or the augmented EIA data. For these reasons, a procedure was developed for augmenting the NHTS data with vehicle specifications from other data sources.

Chrome New Vehicle Database

Detailed vehicle specifications have been compiled into proprietary databases for most light-duty vehicles sold in the U.S. over the past two decades. A primary use for this data is to provide information to consumers via commercial websites to assist vehicle purchase decisions (vehix.com 2011; cars.com 2011; edmunds.com 2011). For this study, a data product prepared by Chrome Systems Inc. was obtained for supplementing the NHTS data. The Chrome New Vehicle Data (NVD) contains detailed specifications for every new vehicle sold since 1997, and more limited data for vehicle model years 1983 to 1996.

In-use fuel consumption

Prior to the 2008 model year, EPA methodology for testing new vehicles has tended to underestimate the fuel used in real-world driving conditions. Adjustment factors are applied to correct test results for city fuel consumption, fc_{cty} , (equation 4.14) and highway fuel consumption, fc_{hwy} , (equation 4.15) using the methodology of Mintz et al. (1993). Beginning with 2008 model year vehicles, the EPA testing methodology was revised to account for higher driving speeds, more aggressive driving styles, and air conditioning use in real-world driving, so that corrections are not applied to test values for these newer vehicles.

$$\text{For pre-2008 model year:} \quad fc_{cty} = 0.90 \cdot fc_{cty,test} \text{ L/100km} \quad (4.14)$$

$$\text{For pre-2008 model year:} \quad fc_{hwy} = 0.78 \cdot fc_{hwy,test} \text{ L/100km} \quad (4.15)$$

Fuel consumption values which are not available in the Chrome NVD are estimated using the combined city and highway fuel economy value, fe_{cmb} (measured in miles per gallon) that is available in the NHTS data for most vehicles. The EPA's assumption of a 45 percent city, 55 percent highway driving proportion was used originally to generate the NHTS fe_{cmb} value based on separate city and highway fuel economy values. Using

this knowledge, and the additional assumption that city driving uses 15% more fuel than highway driving, fe_{cmb} can be converted into separate city and highway fuel consumption rates (equations 4.16 and 4.17).

$$f_{c_{cty}} = 235.21 \frac{L/100km}{gal./mi.} / ((0.55 + 0.45 \cdot 0.85) \cdot fe_{cmb} \frac{mi.}{gal.}) \quad (4.16)$$

$$f_{c_{hwy}} = 235.21 \frac{L/100km}{gal./mi.} / ((0.55/0.85 + 0.45) \cdot fe_{cmb} \frac{mi.}{gal.}) \quad (4.17)$$

Characteristics of vehicles in 2001 and 2009

The 2001 and 2009 NHTS surveys were conducted primarily in 2001 and 2008, respectively. However, due to the range of vehicle ages in operation (see Figure 4.4), many vehicles in the 2001 survey are of 1980's vintage, while many in the 2009 survey are from the 1990's. The characteristics of vehicles in household fleets are therefore not necessarily equivalent to those of new models at the time of the survey, but instead reflect vehicle lifespans, and market penetration of the various vehicle classes, designs, and technologies over roughly the two preceding decades.

The average age of vehicles in 2009 was 9.24 years, slightly more than 8.83 years in 2001. Some of this increase may be due to an increase in reliability leading to longer vehicle holding times. A sharp decrease in the proportion of vehicles under two years old in 2009 indicates that the slow-down in vehicle sales that accompanied the 2007–2009 recession was an unusual, possibly temporary, factor in the average age increase.

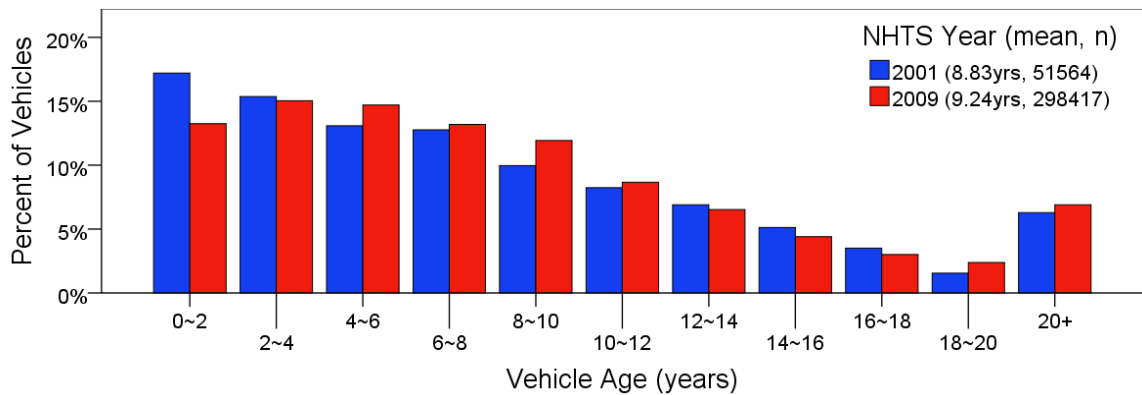


Figure 4.4 Distribution of vehicle ages in 2001 and 2009.

The characteristics of vehicles in operation in 2009 were a reflection of federal fuel efficiency standards that had remained virtually unchanged since 1984, and increased fuel prices had not yet resulted in an industry-wide focus on efficiency. Over the preceding two decades, a variety of technologies such as multi-valve cylinders and high

compression ratio engines had been widely adopted to increase the power output for a given amount of energy embodied in fuel. This new technology was applied towards making more powerful engines for heavier vehicles with more features, while maintaining, rather than reducing fuel consumption. According to the augmented NHTS data, from 2001 to 2009 average engine power increased more than 10 percent, from 179.4hp to 201.1hp, while average curb weight increased almost 80kg (Figure 4.5a and b). Average real-world fuel consumption remained virtually unchanged at 16.3L/100km city, and 10.7L/100km highway (Figure 4.6a and b). Although the averages are unchanged, the variation among vehicles in 2009 ($\sigma = 3.56\text{L}/100\text{km}$) is greater than in 2001 ($\sigma = 3.30\text{L}/100\text{km}$) for city fuel consumption rates, as hybrid electric vehicles (HEV's) became available earlier in the decade with values under 6L/100km, accompanied by an increase in the proportion of vehicles consuming more than 20L/100km.

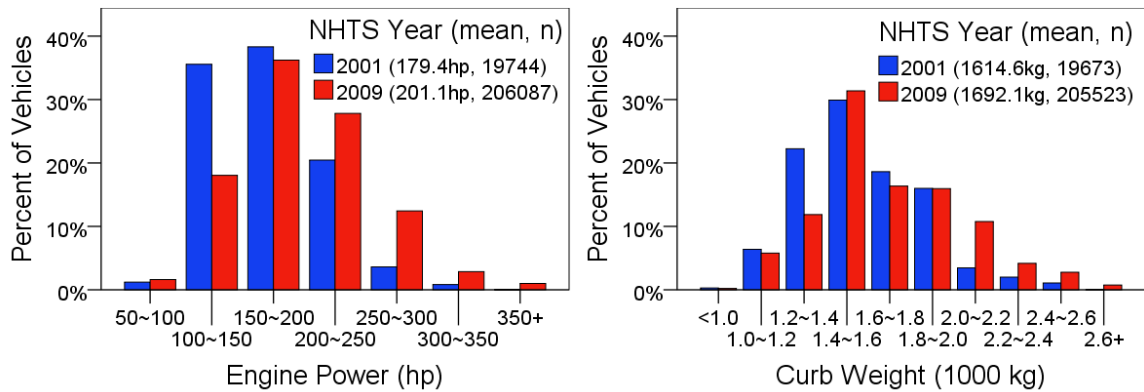


Figure 4.5 Distribution of a) engine power, and b) curb weight in 2001 and 2009.

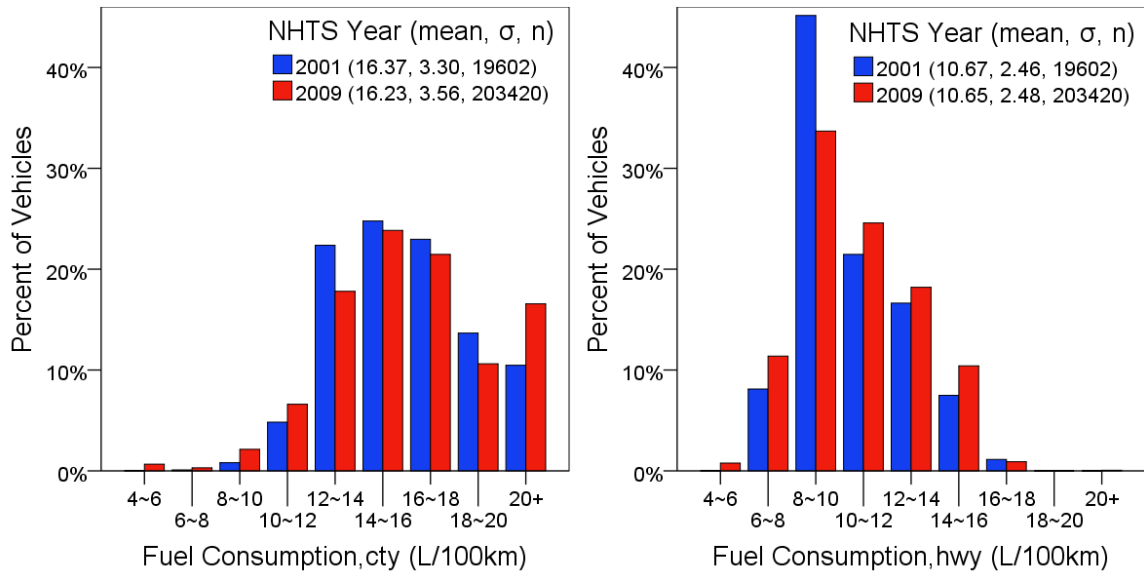


Figure 4.6 Distribution of a) city, and b) highway fuel consumption in 2001 and 2009.

The average passenger capacity increased slightly from 5.04 in 2001, to 5.18 in 2009. A decrease in the number of four-passenger vehicles is offset by an increase in five-passenger vehicles, and the introduction of more eight-passenger mini-vans and SUVs (Figure 4.7a). Despite increases in vehicle power and curb weight, there was little change in average cargo volume capacity between 2001 and 2009. In both years, vehicles follow a bimodal distribution of relatively low-capacity automobiles, and higher capacity mini-vans and SUVs (Figure 4.7b).

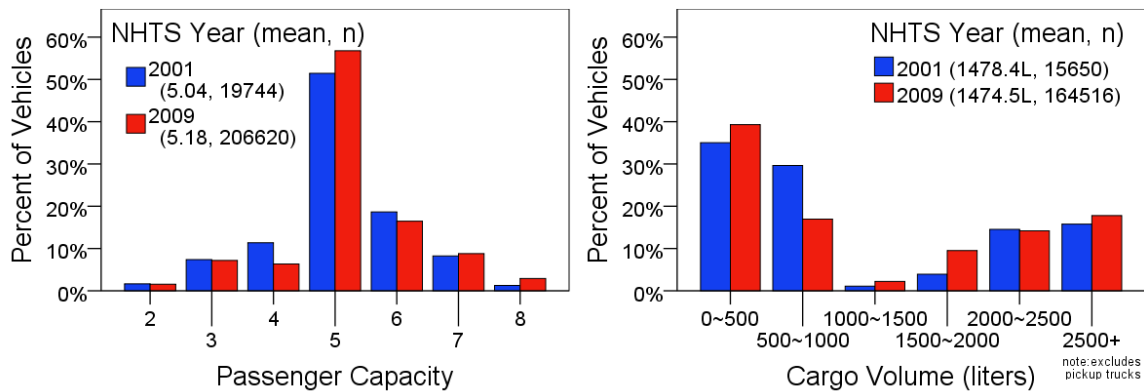


Figure 4.7 Distribution of a) passenger capacity, and b) cargo vol. in 2001 and 2009.

Intra-fleet diversity in multi-vehicle households

In multi-vehicle households, the importance of assignment decisions becomes greater as intra-fleet differences in fuel consumption increase. A household with two identical vehicles would not realize any benefit by changing how they are used, while a household with two different vehicles might.

Households with a larger fleet size can be expected to exhibit greater diversity in vehicle characteristics. This relationship is apparent in both 2001 and 2009, for fuel consumption (Figure 4.8a and b), passenger capacity (Figure 4.9a), and cargo volume (Figure 4.9b). For all household fleet sizes, the intra-fleet diversity in fuel consumption is greater in 2009 than in 2001 (Table 4.4), a finding consistent with the larger variation in 2009 across all vehicles sampled, as noted earlier. There is no significant difference in overall intra-fleet diversity for passenger capacity and cargo volume between the two survey years (Table 4.5).

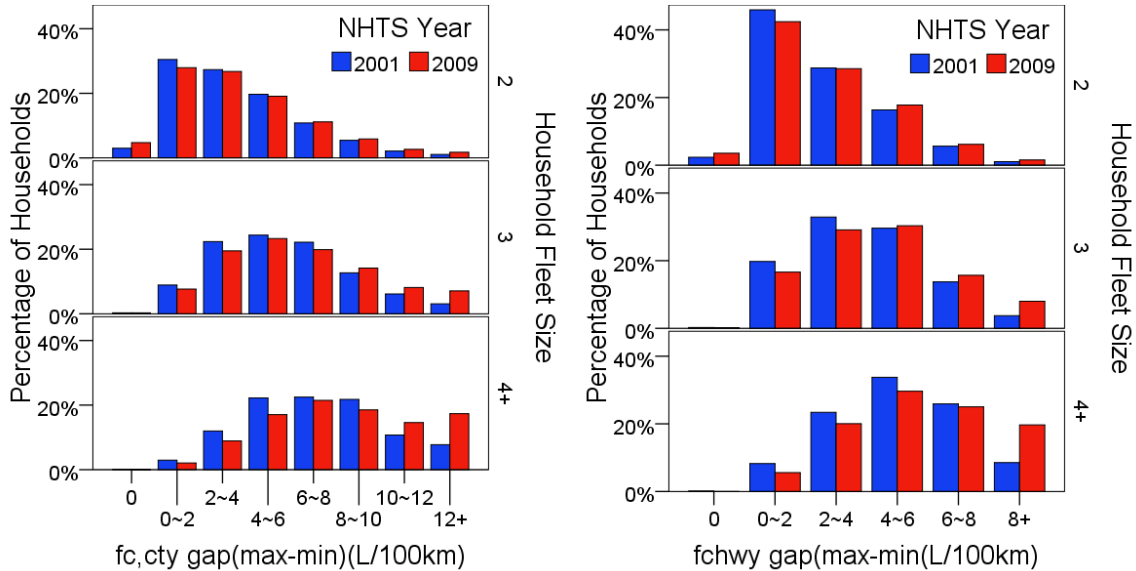


Figure 4.8 Intra-household diversity in a) city, and b) highway fuel consumption.

Table 4.4 Summary Data for Figure 4.8: Diversity of Fuel Consumption

2001	fleet size	N	fc,cty gap (max-min) (L/100km)		fc,hwy gap (max-min) (L/100km)	
			Mean	Std. Deviation	Mean	Std. Deviation
	2	10390	3.70	2.83	2.55	1.98
	3	3683	5.77	2.98	3.96	2.10
	4+	1602	7.28	3.12	5.07	2.20
	Total	15675	4.55	3.16	3.14	2.21
2009						
	2	45276	3.86	3.03	2.68	2.10
	3	16870	6.40	3.51	4.44	2.50
	4+	6294	8.45	3.83	5.94	2.80
	Total	68440	4.91	3.59	3.42	2.53

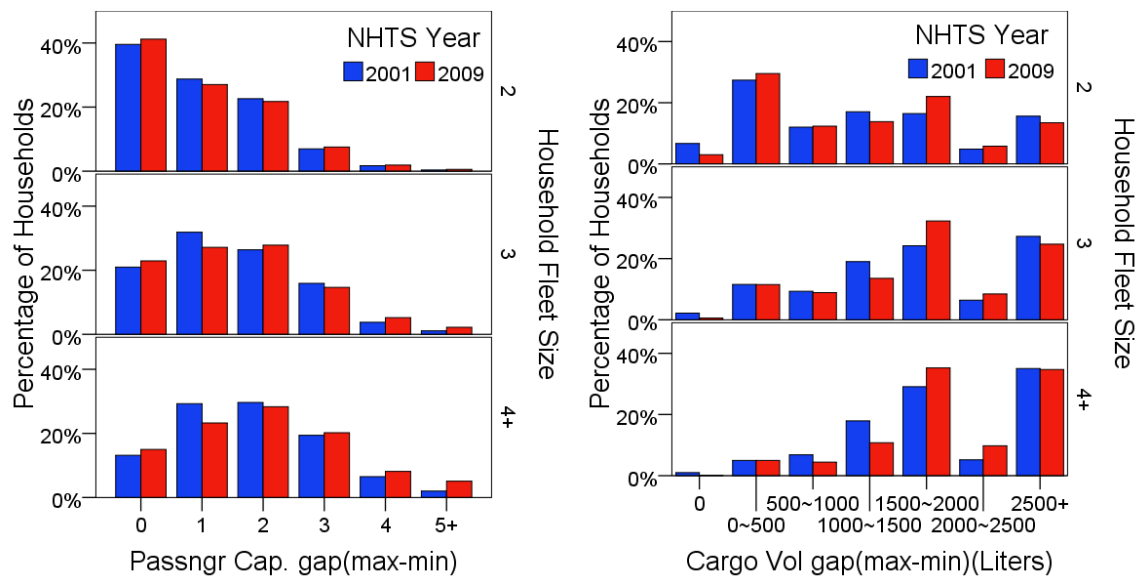


Figure 4.9 Intra-household diversity in a) passenger cap., and b) cargo volume.

Table 4.5 Summary Data for Figure 4.9: Diversity of Vehicle Capability

2001	fleet size	N	Passenger capacity gap (max-min)		Cargo vol. gap (max-min) (Liters)	
			Mean	Std. Deviation	Mean	Std. Deviation
	2	10390	1.04	1.06	1320	1250
	3	3683	1.53	1.16	1950	1360
	4+	1602	1.83	1.20	2290	1460
	Total	15675	1.23	1.13	1580	1340
2009						
	2	45276	1.04	1.10	1304	1130
	3	16870	1.59	1.27	1920	1230
	4+	6294	2.00	1.39	2320	1310
	Total	68440	1.26	1.21	1550	1230

Results and Discussion

By comparing the optimal vehicle assignment decisions output by the CTRAM model to the actual decisions made by NHTS sample households, it possible to determine 1) the maximum potential for reducing trip fuel consumption by selecting a different vehicle, and 2) the degree to which households already make decisions in-line with reducing fuel consumption. Assuming that households do not have access to other modes of transportation or outside vehicles, the choices for any trip are limited to the vehicles within the household fleet. In this analysis, since public transportation and non-motorized modes are not considered, only trips made using a household vehicle are included. Single-vehicle households are assumed to have no opportunity to assign another vehicle, so they are excluded from this analysis, along with any households that reported a motorcycle as part of their fleet.

Optimality of vehicle assignment decisions in 2001 and 2009

The potential reduction in fuel use that can be achieved by optimally allocating vehicles in the existing household fleet is given by equation 4.18, where $F_{j,act}$ is the actual total fuel use, and $F_{j,opt}$ is the optimal total fuel use on the study day.

$$potential\ reduction = \frac{F_{j,act} - F_{j,opt}}{F_{j,act}} \cdot 100\% \quad (4.18)$$

The results of the CTRAM model are summarized in Figure 4.10 for all suitable households. The average potential fuel use reduction in 2009 is 10.13%, less than the 10.91% potential reduction in 2001. It might be logical to expect that given the greater intra-fleet diversity in 2009, that the opportunities for reductions would be greater than in

2001. The contrary result provides an indication that on aggregate, a change in decision making behavior may have occurred between 2001 and 2009 – specifically that households in 2009 placed additional priority on assignment decisions which reduced fuel usage.

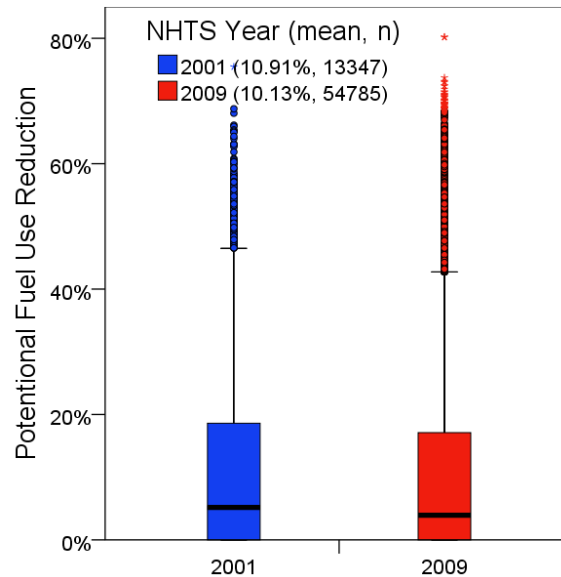


Figure 4.10 Potential fuel use reduction in multi-vehicle households in 2001 and 2009.

To investigate further, households are grouped into short (0-50km) and long (50+km) categories of study day travel distance. In both 2001 and 2009, the potential for savings is less for long travel days than for short travel days (Table 4.6). This result is consistent with the idea that households, at some level, consider fuel use in their vehicle assignment decisions, since households which travel furthest on the study day will benefit most from optimal assignments in terms of the absolute fuel use reduction. Their decisions could occur on short time scales, such as the active switching of vehicles during the day, or on a longer time scale, such as selecting a more efficient vehicle to be used on a regular basis by a driver with a long commute.

Households with greater intra-fleet diversity in fuel consumption have more potential for fuel use reductions in both 2001 and 2009 (Figure 4.11 a and b). However, in 2009, the marginal increase in potential fuel use reduction with increasing fleet diversity is less than in 2001, providing further evidence that households in 2009 were more motivated to reduce fuel use.

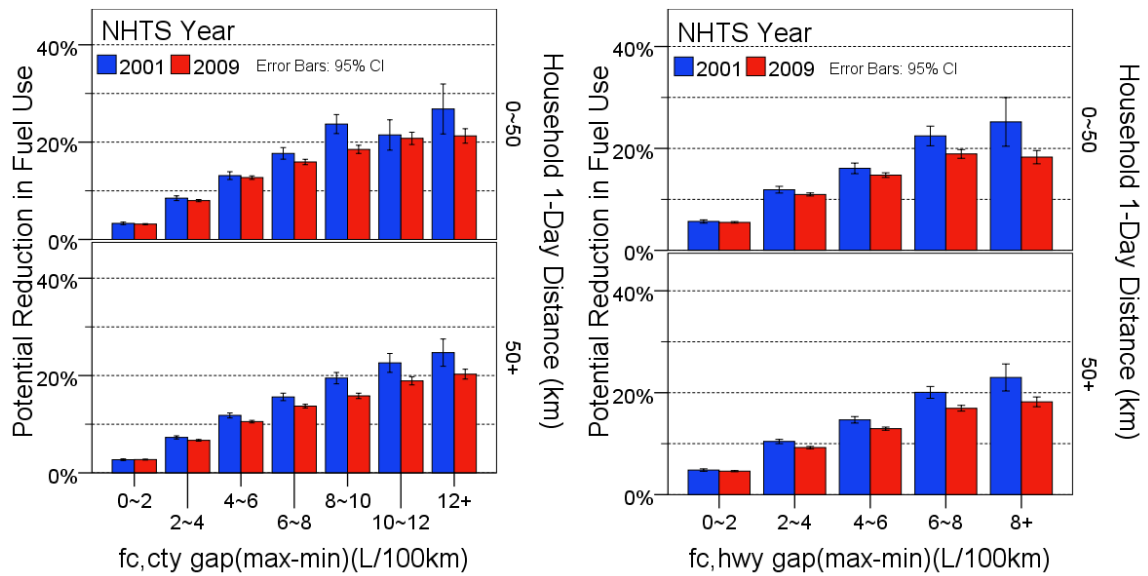


Figure 4.11 Potential fuel use reduction, by fuel consumption gap and 1-day distance.

Table 4.6 Summary Data for Figure 4.11

2001	1-day dist. (km)	N	Potential reduction in fuel use (%)	
			Mean	Std. Deviation
	0to50	4922	11.24	14.13
	50+	8355	10.71	12.85
	Total	13347	10.91	13.35
2009				
	0to50	23403	10.58	13.85
	50+	31382	9.81	12.50
	Total	54785	10.13	13.10

Effect of gasoline price

The 2009 NHTS was conducted at a time of unusual volatility in fuel prices, with gasoline fluctuating in a range from \$1.24/gallon to \$4.25/gallon over the course of the survey. This variation in price provides a unique opportunity to explore how household behavior changes as a result of unusually high fuel prices. Households are grouped into six categories according to the regional fuel prices the week of their study day. Those households in the lower fuel price group exhibited the greatest average potential for fuel savings, 10.60%, while households in the highest fuel price group exhibited lower savings potential, 10.15% (Figure 4.12). This fuel price effect provides evidence that the consideration of monetary expenditures is an important factor in determining the optimality of vehicle assignment decisions.

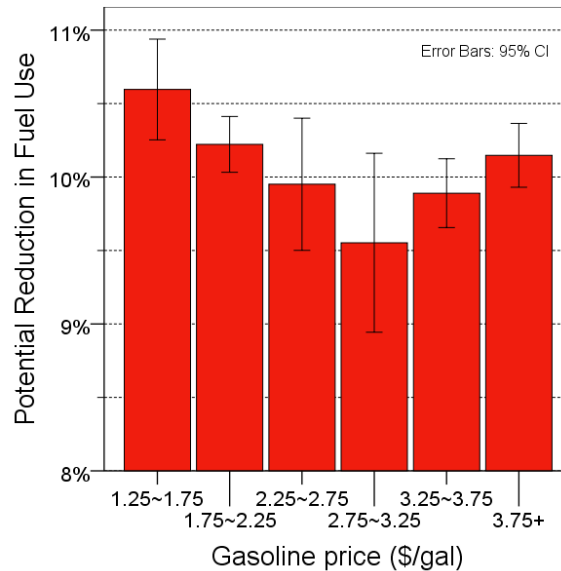


Figure 4.12 Potential fuel use reduction, by gasoline price in 2009.

Table 4.7 Summary Data for Figure 4.12

Gas price (\$/gal)	N	Potential reduction in fuel use (%)	
		Mean	Std. Deviation
\$1.25to\$1.75	5672	10.60	13.17
\$1.75to\$2.25	18473	10.22	13.17
\$2.25to\$2.75	3280	9.95	13.14
\$2.75to\$3.25	1665	9.55	12.67
\$3.25to\$3.75	11679	9.90	12.93
\$3.75+	14016	10.15	13.14
Total	54785	10.13	13.10

4.4. Case study of optimal vehicle replacement

Public policy decisions aimed at reducing the energy consumed by personal vehicles can often have a significant effect on both the characteristics of vehicles, and the composition of the vehicle market. For the past 30 years, the primary approach in the U.S. has been to regulate new vehicles with Corporate Average Fuel Economy (CAFE) requirements. This direct approach has helped to shape the characteristics of the entire U.S. vehicle fleet so that the average fuel economies of vehicles in use now closely matches the minimum required by law. While this demonstrates that CAFE has succeeded in improving vehicle efficiency relative to an unregulated market, the potential of more stringent requirements to quickly provide significant energy savings is limited by the slow rate of penetration of new vehicles in the overall fleet. Furthermore, because drivers often have access to multiple vehicles with a range of fuel economies within a

household fleet, the total energy consumption depends how those vehicles are assigned to trips. The potential of new vehicles to contribute to energy savings could therefore be improved by either discouraging the use of older, less efficient vehicles through higher fuel prices, or encouraging their early retirement or replacement.

The C.A.R.S. accelerated vehicle retirement program

Accelerated vehicle retirement (AVR) schemes have been adopted in the past two decades with the goals of improving air quality through reduced vehicle emissions, and supporting automobile manufactures during economic downturns. More recently, programs have been adopted which have the additional goal of reducing fuel consumption through requirements on improvements in vehicle fuel economy. In July, 2009 the Car Allowance Rebate System (C.A.R.S.) was initiated in the US. A summary of the rules of this program is shown in Table 4.8.

Table 4.8 Summary of C.A.R.S. Program Rules

Replaced Vehicle		Added Vehicle			Incentive
Fuel Economy (mpg)	Age (yrs)	Fuel Economy (mpg)	Price	Age (yrs)	
Car: ≤ 18 Truck-1*: no limit Truck-2*: no limit	≤ 25	Car: $\geq \text{old mpg} + 4$ and ≥ 22 Truck-1*: $\geq \text{old mpg} + 2$ and ≥ 18 Truck-2*: $\geq \text{old mpg} + 1$ and ≥ 15	$\leq \$45,000$	New	\$3,500
“ ”	“ ”	Car: $\geq \text{old mpg} + 10$ and ≥ 22 Truck-1*: $\geq \text{old mpg} + 5$ and ≥ 18 Truck-2*: $\geq \text{old mpg} + 2$ and ≥ 15	“ ”	“ ”	\$4,500

*Category 1 Trucks: SUVs, pickups (wheelbase ≤ 115 in.), minivans, vans (wheelbase ≤ 124 in.), GVWR $\leq 8,500$ lbs.

Category 2 Trucks: Pickups (wheelbase > 115 in.) and vans (wheelbase > 124 in.), GVWR $\leq 8,500$ lbs.

Category 3 Trucks: Work trucks (Program rules not shown), GVWR > 8500 lbs.

The potential vehicle transactions for a household include disposal, addition, or holding. Any analysis of an existing or proposed early retirement program is confounded by the fact that it is difficult to know whether a vehicle transaction would occur, even if the program were not in place. Existing studies generally have not accounted for the difference in vehicle utilization that is likely to occur when a vehicle is replaced with one that is newer, or of a different type. Although programs are often designed to prevent subsidizing the disposal of derelict vehicles, it is very possible that the vehicles being traded in are driven less than other vehicles in the household fleet. Assuming that the added vehicle is more efficient and less polluting than the replaced vehicle, a tendency to

prioritize the use of newer vehicles will tend to increase the positive environmental effects of the program. Conversely environmental benefits may be lessened if a smaller added vehicle has lower capacity than the replaced vehicle, and therefore cannot be utilized on trips with higher capacity requirements.

The purpose of this vehicle replacement case study is to demonstrate how the CTRAM model can be used to evaluate the influence of vehicle-to-trip assignment decisions on the effectiveness of a public policy designed to encourage energy conservation.

Methodology

The National Household Travel Survey (NHTS) provides information about household vehicle fleets and their utilization for daily travel. This study considers the range of potential effects an accelerated vehicle replacement program might have on households in 2002 conditions, using the data from the 2001 NHTS.

Decision-making scenarios for vehicle replacement and use

The specific rules of an AVR program define both the eligible retired and replacement vehicles. However, owners of vehicles eligible for retirement will likely have many options for its replacement, and the program incentive value may vary depending on the characteristics of the selected vehicle. Furthermore, a single household may have multiple eligible vehicles. In order to conduct an analysis of a proposed AVR program without using econometric, utility maximization methods, it is first necessary to establish rules which define different scenarios for household decisions.

In this study, three hypothetical decision-making rule sets are applied separately to the entire household sample. In the first scenario, it is assumed that households minimize total vehicle costs. The retired vehicle will be the one with the highest sum of fixed and variable costs, including fuel expenditures based on the reported annual mileage. The replacement vehicle will have the lowest total costs among all the eligible vehicles, assuming that it is driven the same annual distance as the retired vehicle. The second scenario assumes that households minimize fuel consumption. The vehicle with the lowest fuel economy in the fleet is retired, and replaced with the eligible vehicle with the highest fuel economy. Finally, in the third scenario, the oldest household vehicle is

selected to be replaced with a vehicle of similar inflation-adjusted manufacturer's suggested retail price (MSRP). This is intended to represent business-as-usual rules for household decisions, which are not based on minimizing costs or energy consumption.

Depending on the requirements of the AVR program, households may have an incentive to change to a smaller vehicle. This study considers the case where households keep the same vehicle type, based on market classification, the case where any vehicle which satisfies the decision criteria can be selected, regardless of the vehicle type.

Combining the three decision making scenarios, with the two vehicle type cases results in a total of six scenarios, which are summarized in Table 4.9.

Table 4.9 Vehicle Replacement Decision Scenarios

Decision Type	Replaced Vehicle	Added Vehicle	Replacement Vehicle Type *	Scenario Number *
Cost-minimizing	Highest 5-year avg. cost	Lowest 5-year avg. cost (based on original usage)	Same Type	1
			Any Type	2
Fuel-minimizing	Lowest fuel economy	Highest fuel economy	Same Type	3
			Any Type	4
Non-optimizing (Business as Usual)	Oldest	Same MSRP as retired vehicle (adjusted for inflation)	Same Type	5
			Any Type	6

* Vehicle types based on market classes

Households are assumed to be limited to one vehicle replacement, although in the C.A.R.S. program the condition is placed on one transaction per driver. Some households without any qualifying vehicles will still replace vehicles, but these background transactions are excluded from this analysis. Finally, the household does not receive any money in exchange for the retired vehicle, apart from the program incentive. The vehicle may in fact still have some value derived from scrap material, or recovered parts, but this is assumed to go entirely to offset the costs of administering the program, and is excluded from this analysis.

Description of data sources

The 2001 National Household Travel Survey (NHTS) was conducted between March 2001 and May 2002, and provides detailed information about a single day's travel for each of the 69,817 participating households. Excluding the households that were part of region-specific add-on surveys, 26,400 households in the national sample households

were retained for this study. Individuals were asked to keep a travel diary in which they recorded the start and end times of every trip, as well as the trip purpose and vehicle used.

The NHTS data does not contain the necessary cost and capacity specification information for the 53,275 individual vehicles in the national sample. Using the year, make and model as identifiers resulted in 4,846 unique vehicle models, which were then matched with proprietary data sources from Chrome Systems, Inc., and Automotive Leasing Guide (ALG), Inc. Vehicle specifications and MSRP for 1996 model year and later vehicles were obtained from Chrome System's New Vehicle Database (NVD). Specifications for pre-1996 vehicles were populated using average values for the particular vehicle type. Vehicle depreciation values were obtained from ALG residual value data. These residual values are a projection of future vehicle depreciation, and therefore represent the type of information that would be available to households making decisions about future vehicle ownership costs. Furthermore, these residual value projections are used to set vehicle lease payment amounts, and therefore are directly related to the ownership costs of leased vehicles.

Vehicle ownership costs

This study uses a five-year average of total vehicle costs, which is a rough approximation of the average period that a vehicle is held by a single owner. The total cost of owning and operating a vehicle are a combination of fixed costs and variable costs. Fixed costs are dependent only on the length of time the vehicle is held, and include depreciation, opportunity cost, and insurance. Any decrease in value that might be inflicted by unusually high annual mileage is ignored here. Opportunity cost is a function of the vehicle value, and represents the forgone income from other investments due to the household's wealth being tied-up in vehicles. In this study, a 6 percent discount rate is used. Insurance costs are the third and final fixed cost considered here, not including those policies which charge rates at least partly based on mileage. The insurance rate of \$1,200 per vehicle per year used in this study was assumed to be independent of driver characteristics, or vehicle type and age. Variable costs are composed of maintenance, repair, and fuel costs, each of which is a function of the distance driven. A maintenance and repair rate of \$0.043 per mile is based on the assumption of \$650 per 15,000 miles driven. Fuel costs were calculated based on the CTRAM results.

Vehicle depreciation is one of the most significant costs of vehicle ownership, so for this study as model was developed to estimate vehicle value as a function of age, MSRP, and vehicle type. ALG data for the projected depreciation over the first five years of ownership for new 2002 vehicles consists of the MSRP, and percentage of value retained at 24, 36, 48, and 60 months. For this study, it was necessary to estimate values beyond this period, because existing household vehicles may be older than five years. Figure 4.13 shows the average depreciation of all 2002 model year vehicles, according to vehicle type.

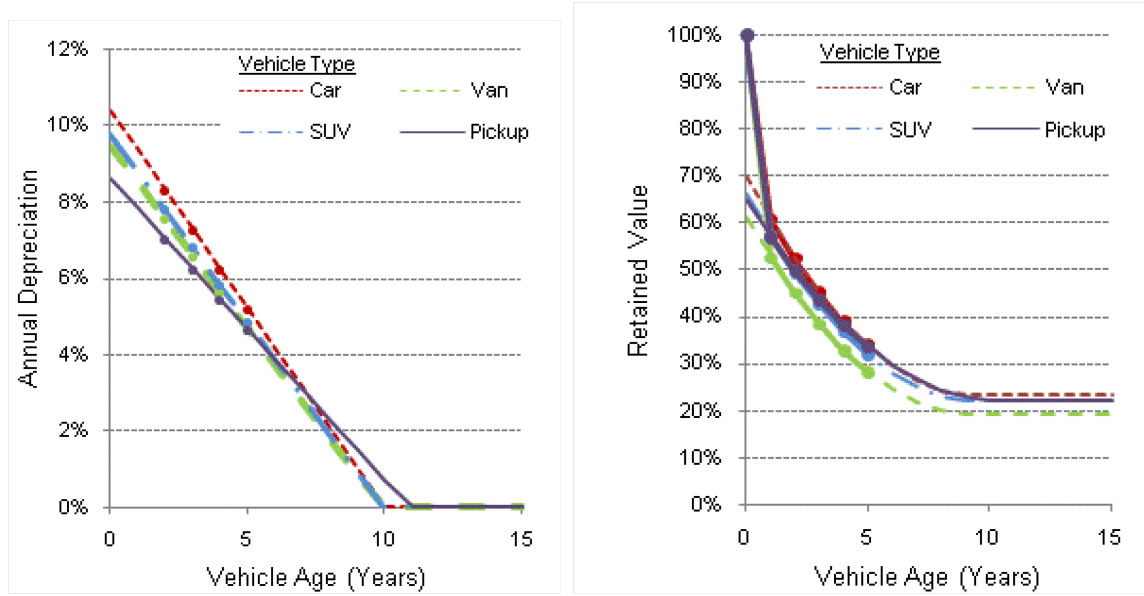


Figure 4.13 Average of 2002 model year vehicles, by type for a) rate of annual depreciation, and b) percent retained value

The data points from the ALG data were extrapolated according to equations 4.19 and 4.20, where d^0 is the initial depreciation that occurs as soon as a new vehicle is purchased, and m and b describe the tendency of the rate of annual depreciation to gradually diminish, until the vehicle reaches a steady-state minimum value.

$$Value_x = msrp \left[1 - d^0 - \sum_{1}^x [\min(mx + b, 0)] \right] \quad (4.19)$$

$$d^0 = 1 - value_{x=2} - \sum_{1}^2 (mx + b) \quad (4.20)$$

Results and Discussion

The initial results of this analysis are shown in Figure 4.14 and Table 4.10 for each of the six replacement scenarios. Out of all sample households, approximately 22 percent are eligible for the program when the replacement can be of any type (scenarios 2, 4, and 6). When the replacement vehicle is restricted to be of the same type as the replaced one, the percentage of eligible households ranges from 10 to 12 percent (scenarios 1, 3, and 5).

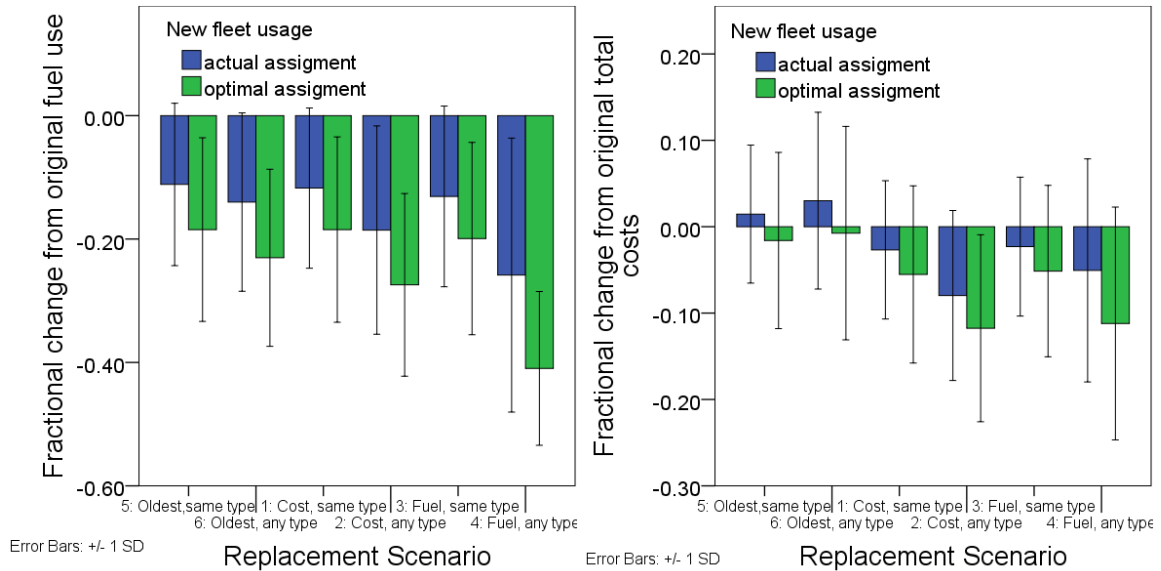


Figure 4.14 Household savings for a) cost, and b) fuel use, by scenario and usage.

Table 4.10 Summary Data for Figure 4.14

Decision Scenarios	Fraction of households eligible	Average change in cost from original. \$ per year (fractional change)		Average change in fuel use from original Gal. per year (fractional change)	
		Actual Use	Optimal Use	Actual Use	Optimal Use
5-Age (Same Type)	0.11	-\$5730 (0.015)	-\$5528 (-0.016)	111 (-0.112)	199 (-0.185)
6 -Age (Any Type)	0.22	-\$5422 (0.030)	-\$5117 (-0.007)	140 (-0.140)	249 (-0.230)
1 -Cost(Same Type)	0.10	-\$6730 (-0.027)	-\$6570 (-0.056)	127 (-0.117)	201 (-0.185)
2 - Cost (Any Type)	0.22	-\$5736 (-0.080)	-\$5505 (-0.118)	205 (-0.186)	294 (-0.274)
3 -Fuel (Same Type)	0.12	-\$6106 (-0.023)	-\$5925 (-0.051)	135 (-0.131)	216 (-0.200)
4 -Fuel (Any Type)	0.22	-\$5739 (-0.051)	-\$5388 (-0.112)	276 (-0.256)	432 (-0.410)

Among households that are eligible for the program, the cost and fuel savings vary widely depending on the replacement decision rule. Assuming the new vehicle is of the same type as the old one, and is used in the same way, the decision rule has only a minor effect on fuel savings, with values ranging from 11 to 13 percent. When the new vehicle can be of any type, average fuel savings increase to over 25 percent when the least fuel efficient vehicle is replaced compared to 14 percent when the oldest vehicle is replaced.

Cost and fuel savings are influenced by not only the replacement decisions, but also by the vehicle to trip allocation decisions made by household members. Optimal vehicle assignments increase fuel savings under every decision rule, but have a particularly large savings of 41 percent in scenario 4, where the least efficient vehicle is replaced and there are no vehicle type restriction on the new vehicle. Overall, it can be concluded that the simultaneous consideration of both the vehicle replacement rule and the usage of the modified household fleet can result in significantly reduced fuel usage (or cost) compared to either factor by itself.

4.5. Potential applications and limitations of constraints-based approach

This application of a constraints-based assignment model to the 2001 and 2009 NHTS data illustrates how additional insights can be gained in activity-based research by including vehicle capability among the set of constraints considered. The intention is not to predict travel behavior, but instead to generate a realistic estimate of the maximum potential for various strategies to reduce energy use and greenhouse gas emissions. For example, it is not realistic to expect that an average fuel use reduction of 10 percent across all households can be achieved by the reassignment of existing vehicles alone. However, an increase in the intra-fleet diversity of vehicles can lead to a significant increase in potential savings. For many households with three or more vehicles, potential savings of greater than 10 percent through fleet reassignment are as significant (and less expensive) as many of the technological options for increasing the fuel economy of internal combustion engines (National Research Council 2002).

This analysis accounted for passenger capacity as a constraint, but not for other vehicle capability constraints, such as those related to carrying cargo. As the set of capability requirements taken into consideration is extended beyond only passenger

capacity, the number of assignment combinations can be expected to decrease as some infeasible vehicle options are eliminated. The lack of detailed data for trip requirements presents an obstacle to the consideration of other trip requirements in future applications of this model. Although vehicle occupancy data is often collected in travel surveys, cargo and towing requirements are particularly important because of the relationship between vehicle capacity and energy intensity. Collecting this data through traditional survey techniques would be costly and overly burdensome for the respondent, so the use of in-vehicle data acquisition equipment and alternative survey techniques can be considered, as explored in chapter 3.

The decision of which vehicle a household member will use for a particular trip is influenced by many factors beyond physical feasibility. Personal preferences for certain vehicle characteristics may override considerations of energy and cost savings for some drivers, even when a more efficient vehicle is available for their use. Household rules might also prohibit some individuals from using a vehicle, as is often the case with young, inexperienced drivers. In other cases, the inconvenience of changing vehicles may be a deterrent, such as when a child seat needs to be moved from one vehicle to another.

Although this analysis considered only the reassignment of vehicles in existing fleets, the model can also be used to compare the energy use and monetary expenditures for various hypothetical household fleets. An application of the CTRAM model to a fleet composition problem is appropriate, since changing a vehicle in the fleet will likely result in changes in utilization for other vehicles in the fleet. The model could then be used to answer questions such as which vehicle should be added to the fleet, which vehicle (if any) should be prioritized for replacement, and what should the characteristics of that new vehicle be in order to satisfy household trip requirements. The capability characteristics of potential vehicles do not need to be limited to passenger and cargo capacities, but could also include range for non-motorized travel and EV's, or operability in inclement weather for biking, mopeds, and motorcycles.

Conclusions

Even though vehicle capability constraints are an important factor in determining the feasibility of energy saving strategies, they have received insufficient attention in previous research. Similarly, although multi-day data collection has been identified for several decades as an important area of improvement for the activity-based approach, the majority of travel behavior research is still based on single-day travel-activity survey data. The combined lack of multi-day data and vehicle capability requirement data is a significant impediment to the ability to evaluate many types of energy savings strategies, since 1) household travel requirements vary from day-to-day, and 2) energy-saving transportation options often have reduced capability, whether in terms of passenger and cargo capacity for compact vehicles, or in terms of range for EV's, PHEV's, and non-motorized transportation modes like walking and biking. The overall goal of this research is to develop and demonstrate a survey methodology and modeling system for evaluating the energy-savings potential of household travel, considering multi-day travel requirements and the constraints imposed by the available transportation resources.

5.1. Key findings

Research questions [Q1], [Q2], and [Q3] address the methodology of collecting multi-day household travel data, with a particular focus on requirements for vehicle capability. Research questions [Q4] and [Q5] are empirical questions intended to illustrate how the consideration of vehicle capability constraints in an activity-based analysis can provide useful insights into travel behavior and the potential effectiveness of energy-saving strategies.

[Q1]. Is it feasible to collect multi-day data for household activities using an interactive survey approach?

The Household Travel Patterns Study (HTPS) pilot investigation described in chapter 3 was conducted in 2011 using thirty households in the Ann Arbor, Michigan area. The interactive survey approach employed a computer assisted personal interview (CAPI), with the simultaneous participation of all household members. The group interview process was, in nearly every case, found to be an effective method for encouraging discussion among participants. Arranging the interviews at a meal time, and providing a carry-out meal as an incentive was likely an important factor in the success of this approach. In only two households was it necessary for the primary contact person in the household to provide activity information on behalf of another adult household member. In both of these cases, the non-participation was due to scheduling conflicts, and not, apparently, due to lack of interest.

The interactive survey required an average of 90 minutes to complete, ranging from 45 minutes for the most brief, to 140 minutes for the most lengthy. Improvements in the web survey instrument for the latter half of the study allowed activity details to be collected more quickly. The improvements in the survey instrument resulted in the reporting of a greater number of activities and locations, and did not reduce the time to complete the interview.

All participants seemed able to easily conceptualize the reporting of activities in terms of ranges and probabilities for frequency, time, location, participants. The reporting of items carried was unproblematic for common shopping activities. However, for less frequent activities requiring the transport of large or heavy items, reporting was complicated by the lack of pre-coded items in the survey instrument.

[Q2]. Is it feasible to generate complex and realistic household schedules using activity characteristics reported as probabilities and ranges?

The multi-day Probabilistic Household Activity Schedule Estimator (mPHASE) introduced in chapter 2 employs a novel physical representation of household activities to account for time constraints, coordination among household members, and resistance to

modifying activity times and durations. The finite element method used in the mPHASE model is well-established in the engineering field for the analysis of physical structures, but this is believed to be the first application in the field of activity-based travel research.

Based on the responses generated by the HTPS pilot investigation, the mPHASE model was able to generate synthetic schedules which exhibited many of the characteristics of complex household travel. Total daily travel distances were found to exhibit 1) distinct patterns of weekday and weekend travel, 2) occasional non-travel days, and 3) occasional high-travel days. Complex household interactions were evident in the generated schedules, including 1) the assignment of activities to designated household members according to their availability, and 2) the coordination of picking up and dropping off other household members at their activities.

[Q3]. Is it feasible to use passive in-vehicle data acquisition equipment to observe trip capacity requirements over extended time periods?

The VUSE in-vehicle data acquisition equipment described in chapter 3 was developed for two purposes. First, the GPS paths collected over two-weeks could be used to validate survey responses. Second, the utilization of vehicle capacity for passengers and cargo could be observed using the captured digital images of the vehicle interior.

In general, the VUSE equipment was found to be capable of providing images with sufficient resolution for the identification of individual household members, and cargo item type. Images in low-light conditions were often difficult to interpret. Of the sixty vehicles in the study, ten had equipment malfunctions that resulted in a partial or total loss of data. Five cases were the result of improper installation, three were caused by software malfunctions, and two were of undetermined cause.

The post-processing of GPS data is an important topic in survey methodology research. A web post-processing tool was developed for this research to reduce the time required, and potential for error. The main steps of the process were 1) automatic identification of trip ends based on the recorded vehicle events, 2) visual inspection of identified trip segments, and correction with split and join operations, 3) flagging of inspected trip segments as complete or incomplete, 4) visual inspection of digital images

and coding of passengers and items, and their locations in the vehicle for each trip segment.

The post-processing tool was highly effective for the enforcement of consistent coding, and the efficient viewing of trip segments and their associated photos. On average, 90 minutes were required for the processing of a single vehicle's two weeks of data, with 50 percent of the time devoted to image inspection.

[Q4]. What was the average energy savings potential for U.S. households in 2001 and 2009 if existing vehicle fleets were utilized optimally?

The Constraints-based Transportation Resource Assignment Model (CTRAM) introduced in chapter 4 was applied to an analysis of the 2001 and 2009 NHTS data to evaluate the fuel-use optimality of vehicle assignment decisions. The CTRAM enumerative optimization model is unique in its ability to consider any number of vehicle attributes related to an activity's physical travel requirements in a computationally efficient manner. In addition to vehicle capability constraints, the model also accounts for coupling constraints, ensuring that vehicle switching only occurs when vehicles and drivers are coincident in time and space.

The lack of a convenient data source for vehicle capability specifications has been one obstacle to the consideration of capability constraints in the past, and was addressed in this work by the augmentation of the publicly available NHTS data with a proprietary vehicle specifications database.

Although there are many ways in which households can reduce their transportation energy consumption, one of simplest, for multi-vehicle households, is to optimally assign existing vehicles to trips. Results of the CTRAM analysis showed that the average potential fuel use reduction in 2009 is 10.13%, less than the 10.91% potential reduction in 2001.

[Q5]. Did multi-vehicle households in 2009 utilize their fleets more optimally than in 2001?

Results of the CTRAM analysis support the hypothesis that households in 2009 were more motivated to make fuel use-minimizing decisions than in 2001. First, from the

finding of [Q4], the overall potential for savings was less in 2009, which is consistent with conscious effort to optimally assign vehicles. Second, households in 2009 with greater intra-fleet diversity in vehicle fuel consumption ratings showed a significantly higher tendency to optimally assign vehicles than similar households in 2001. Finally, in 2009, higher fuel prices are negatively correlated with potential fuel use reductions through optimal assignment, indicating that households are taking monetary expenditures into consideration when making vehicle assignment decisions.

5.2. Limitations

The finite element approach employed by the mPHASE model is analogous to real-world scheduling problems in its consideration of constraints, and interaction among household members. However, the model does not replicate the actual decision-making processes of individuals, which often must be highly dynamic and flexible in order to adapt to changes in conditions and events throughout the day. Dynamic scheduling models have been created which develop schedules continuously as decisions are made about adding, removing, or modifying activities. The approach used by the mPHASE model is quite the opposite, and attempts to create a schedule based on reported activity characteristics, rather than the bottom-up approach used in some models of human decision-making. As a result, the mPHASE model is not well-suited for forecasting the behavioral response changes in conditions that are outside of the individual's frame-of-reference when they are completing the survey.

The constraints-based approach used in this work, both in the mPHASE and CTRAM models, is intended to identify the feasible boundaries of potential decisions. Many factors that play a role in real-world decisions are not included in this proposed modeling system, thus limiting its potential usefulness as a forecasting tool. For example, vehicle assignment decisions are influenced not only by considerations of physical feasibility, but also by factors of convenience, perceived safety, and personal preference.

5.3. Potential applications and future work

While the mPHASE model was developed to work in conjunction with CTRAM to evaluate the energy-savings potential of household fleet modifications, either model could be used independently in a wide range of studies (Table 5.1).

Table 5.1 Potential Applications of mPHASE/CTRAM Modeling System

	without mPHASE	with mPHASE
without CTRAM		<ul style="list-style-type: none"> - scheduling constraint studies - land use studies - flex-time/work-from-home studies
with CTRAM	<ul style="list-style-type: none"> - equivalent-capability fleet studies (within-class technology adoption) - walking/biking studies 	<ul style="list-style-type: none"> - fleet reliability studies - maximum market size studies - reduced-capability fleet studies (EV's, small cars) - car sharing studies

Potential standalone applications of mPHASE

The synthetic schedules generated by the mPHASE model could be used in many studies related to scheduling and travel behavior, apart from the analysis of optimal vehicle assignment with CTRAM. Previous applications of interactive survey methods have studied potential household reactions to changes in scheduling constraints, such as a shift in school opening hours (Jones 1979). Similar investigations could be performed using mPHASE by adjusting the relevant activity time constraints from the original values collected during the interactive survey. Analysis of the effects of flex-time and work-from-home employment policies on household activity scheduling could also be conducted by modifying the mPHASE time and location characteristics for the work activity.

Spatial relationships are represented in the mPHASE scheduling algorithm by the travel times between potential activity locations. The specification of an alternative location could be used to model a change in residential location. Or an entire set of hypothetical locations could be used to model broader land use changes, and their potential impact on household activity schedules.

Potential standalone applications of CTRAM

Even without the availability of multi-day data of travel requirements, the CTRAM model can be applied to an analysis of the potential energy savings from both existing and modified vehicle fleets, as demonstrated in chapter 4. Vehicle assignment decisions in a modified fleet will likely be different from the decisions in the original fleet, and one cannot automatically assume that a new vehicle will be used in exactly the same way as the replaced one. A major advantage of the constraints-based approach used here is that it addresses the boundaries of potential assignments, without attempting to predict actual decisions. With single-day travel data, however, applications of CTRAM must be restricted to analysis of new fleets with equivalent or greater capability than the replaced fleets, since it is unknown if reduced-capability vehicles could satisfy the requirements of the non-observed days. One exception to that could be studies of the potential for options outside of the household fleet, since the opportunities for walking, biking, or public transportation are likely already available for many trips, even with no modification to household vehicle fleets.

Potential applications of mPHASE/CTRAM system

With modified vehicle fleets of reduced capability, CTRAM can identify not only the optimal vehicle assignments, but also the cases where no assignment can satisfy the given travel requirements. When combined with the multi-day activity schedules generated by mPHASE, CTRAM can be used to produce a fleet reliability value, or measure of the risk of unsuccessful schedule completion. For example, potential buyers of EV's might be concerned about being stranded after exceeding the available range of their batteries. A similar risk exists for users of efficient, but limited capacity, two-passenger commuter cars if they occasionally need to transport more passengers or cargo items. Those considering joining a car sharing program while eliminating a personal vehicle from their fleet might worry if the shared vehicle will be in use by another member when they need it. In each of these cases, the mPHASE/CTRAM modeling system can be used to estimate the potential risk that a vehicle will be unavailable, or incapable of satisfying the requirements of their desired trip. Approaching the question from another perspective, if an acceptable risk value is assumed, the modeling system can be used to estimate the

maximum market penetration of new, efficient vehicle technologies and designs with reduced capabilities, or to estimate the number and type of vehicles needed for a car sharing program to meet its members' needs.

Future work


Questions about vehicle downsizing are of particular interest because of the strong relationship between a vehicle's size and mass, and therefore its fuel consumption. Without any information about the requirements for vehicle capability over extended time periods, one and two-passenger commuter vehicles may be too easily dismissed as impractical. Analyses of the tradeoffs between efficiency and capability should be considered in the context of multi-day household travel requirements, and the mPHASE/CTRAM modeling system introduced here is potentially a useful tool as policy makers and auto manufacturers attempt to determine the best vehicle mix for reducing greenhouse-gas emissions while still meeting household travel demands.

During the course of the pilot study, several opportunities were identified for improving upon the proposed methodology. One improvement would be the incorporation of the mPHASE model directly into the interactive web survey, rather than as the currently separate program. By providing immediate feedback for survey responses, in the form of generated, synthetic schedules, participants would be able to identify inconsistencies more easily. Rules for stopping the survey could also be established, for example, after a participant had verified a certain number of generated schedules.

Due to the limited number of VUSE data acquisition units, the HPTS pilot investigation was limited to a 2-week observation period for each household. A longer observation period, preferably 12 months, would allow for validation of any reported seasonal variation in activities, and the capture of infrequent, but important, long-distance trips.


Appendix A

Study recruitment materials


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HTPS
Household Travel Patterns Study

Why participate?
You will receive a summary of your household's travel patterns which describes how efficiently your vehicles are being used, and what options might reduce energy use and travel expenses. Your household will also receive \$100 after completing the web survey.

Requirements for participation
Your household should:

- Have two or more vehicles
- Make most trips using these vehicles
- Have two or more adult drivers
- Have a broadband internet connection

What you will do in study
2 or 3 researchers will make an appointment to visit your home, and install GPS equipment and small still cameras in each of your vehicles. During that visit, all adult drivers in your household will spend about 1 hour to complete a web survey, with the help of a researcher. After 2 weeks, a researcher will return to remove the equipment from your vehicles.

If you are interested in joining this study, please provide the following information. You will be contacted by a member of the research team who will tell you more about the study.

Contact information

First name: *

Last name: *

Email address: *

Phone number:

Home city: *

Home zip code: *

People in household

How many people live at this address?: *

How many drivers 18 or older live at this address?: *

How many drivers under 18 years old live at this address?: *

Vehicles

List the vehicles available for regular use by the people who live in your household. (Both leased and owned) Please include all cars, trucks, and motorcycles.

Vehicle 1: *

Year, make and model (e.g. 2001 Dodge Caravan)

Vehicle 2: *

Year, make and model (e.g. 2001 Dodge Caravan)

Vehicle 3:

Year, make and model (e.g. 2001 Dodge Caravan)

Vehicle 4:

Year, make and model (e.g. 2001 Dodge Caravan)

Vehicle 5:

Year, make and model (e.g. 2001 Dodge Caravan)

Are any of these vehicles used for business purposes? (e.g. delivery, landscaping): *

Are any of these vehicles driven less than 1,000 miles per year?: *

Availability and scheduling

If selected for the study, your household will be assigned a two-week period between January and May, 2011. To help us schedule the necessary equipment and personnel, please select the times when you will be available for this study. For example, do not include times when one or more drivers (or vehicles) will be out of town.

Scheduling:

☐ January 3-17 (1/2011, 1st half)

☐ January 18-31 (1/2011, 2nd half)

☐ February 1-14 (2/2011, 1st half)

☐ February 15-28 (2/2011, 2nd half)

☐ March 1-15 (3/2011, 1st half)

☐ March 16-31 (3/2011, 2nd half)

☐ April 1-15 (4/2011, 1st half)

☐ April 16-30 (4/2011, 2nd half)

☐ May 1-15 (5/2011, 1st half)

☐ May 16-31 (5/2011, 2nd half)


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Figure A.1 Online participant signup form

ann arbor craigslist > jobs > et cetera jobs

2-Vehicle Households Needed for Study

Date: 2011-10-02, 9:51PM EDT

Reply to: *your anonymous craigslist address will appear here*

The University of Michigan is testing a new method for collecting travel data. The goal is to understand what might limit adoption of energy efficient transportation such as an electric vehicle with limited range. Each eligible household will earn \$100.

Please visit <http://www.css.snre.umich.edu/travelpatterns> to learn more and sign up for this study. For more information call 1-734-936-2542.

- Compensation: \$100
- This is a part-time job.
- Principals only. Recruiters, please don't contact this job poster.
- Phone calls about this job are ok.
- Please do not contact job poster about other services, products or commercial interests.

Figure A.2 Call for participants – online posting



Complimentary Meal Options

During your scheduled home visit, you will be asked to complete an online survey with all members of your household present. In order to help conserve your valuable time, the research team will provide a meal of your choice while you complete the survey.

Instructions: Please select one of the four restaurants below. Then select a meal option for each member of your household. Each household may choose only one restaurant but each individual may choose a different option for that restaurant. Please send your selections to kevinb@umich.edu at least 24 hours before your scheduled visit. For example, your email might contain the selections: "A.1 for 2 people and A.3 for 1 person"

A) Jimmy John's sandwiches

- Option #1: Pepe: Smoked ham and provolone cheese garnished with lettuce, tomato, and mayo.
- Option #2: Vegetarian: Layers of provolone cheese separated by real avocado spread, alfalfa sprouts, sliced cucumber, lettuce, tomato, and mayo. (Vegetarian)
- Option #3: Turkey Tom: Fresh sliced turkey breast, topped with lettuce, tomato, alfalfa sprouts, and mayo.

B) Silvio's organic pizza (includes salad, only choose one option)

- Option #1: Margherita: Tomato sauce, fresh mozzarella, olive oil and basil. (Vegetarian and Organic)
- Option #2: Hawaiian: Tomato sauce, mozzarella, ham and pineapple. (Organic)
- Option #3: Zucchini: Zucchini, mozzarella, feta and a touch of onion. (Organic)

C) Earthen Jar (includes salad)

- Option #1: Chana Masala Chick Peas: Chick peas with Indian spices. (Vegan and Spicy)
- Option #2: Scrambled Tofu: Tofu curried with spice and onion. (Vegan and Organic)
- Option #3: Vegan Mac & Cheese (Vegan)

D) Jerusalem Garden (includes a side of hommus and pita bread)

- Option #1: Shish Kabob Sandwich: Grilled marinated beef and vegetables wrapped in hommus.
- Option #2: Falafel with Baba Ghanoug: Roasted eggplant, tahini, tomatoes, garlic, lemon juice and salt. (Vegetarian)
- Option #3: Hommus & Tabbouli Sandwich: Diced vegetables, bulgar wheat, parsley, chick peas, tahini, garlic and lemon juice. (Vegetarian)

v. 1/6/2011

Figure A.3 Complimentary meal options



2-Vehicle Households Needed for Study

Project overview

The University of Michigan is testing a new method for collecting travel data. The goal is to understand what might limit adoption of energy efficient transportation such as an electric vehicle with limited range.

Why participate?

You will receive a summary of your household's travel patterns which describes how efficiently your vehicles are being used, and what options might reduce energy use and travel expenses. Your household will also receive \$100 after completing the web survey.

Requirements for participation

Your household should:

- Have two or more vehicles
- Make most trips using these vehicles
- Have two or more adult drivers
- Have a broadband internet connection

What you will do in study

2 or 3 researchers will make an appointment to visit your home, and install GPS equipment and small still cameras in each of your vehicles. During that visit, all adult drivers in your household will spend about 1 hour to complete a web survey, with the help of a researcher. After 2 weeks, a researcher will return to remove the equipment from your vehicles.

To sign up

Visit www.css.umich.edu/travelpatterns/signup or contact the principal investigator, Kevin Bolon at kevinb@umich.edu or (734) 936-2542 for more information.

[illegible]

Figure A.4 Recruitment flyer

Informed Consent Agreement

Thank you for considering participating in this study. Before you give your consent to volunteer, it is important you read the following information and ask as many questions as necessary to be sure you understand what you will be asked to do.

1. Project title

Measuring patterns of household vehicle use

2. Names of researchers

Principal Investigator: Kevin Bolon, PhD candidate, University of Michigan, School of Natural Resources and Environment (kevinb@umich.edu)

Co-investigator: Lidia Kostyniuk, PhD, University of Michigan Transportation Research Institute, (lidakost@umich.edu)

Faculty Advisor: Greg Keoleian, Professor, University of Michigan, School of Natural Resources and Environment (gregak@umich.edu)

3. Purpose of the research

To study how households which have more than one vehicle can save energy and still meet their day-to-day needs for carrying passengers and cargo. Also, to learn whether or not an internet survey can be used to collect information about a household's travel patterns and vehicle use over a two week period.

4. What you will do in the study

If you agree to be a part of the research study, you will be asked to complete an internet survey, together with the other licensed drivers in your household. The survey will ask you to select locations on a map that you might visit in the next two weeks, and then provide more detail about the trips that you take to those locations. The survey is expected to take about 30 minutes, with an additional 10 minute introduction by one of the researchers.

For the in-vehicle monitoring part of the study, a data collection device will be installed in each household vehicle by the research team. You will be asked to use your vehicles as you normally would for about 2 weeks. Whenever your vehicle is moving, the position will be recorded. When the equipment detects the start or end of a trip, one or more small cameras will be used to take pictures of the passenger and cargo areas. The equipment installed in your car will not affect the operations of your car, or alter its appearance. During the time your car is instrumented, you may not remove, modify, or tamper with any components of the equipment or allow others to do so. We ask that you notify us about any planned mechanical work or maintenance on your car that might affect the equipment.

5. Time required

Members of the research team will come to your home to help explain the web-based survey and to install the data collection equipment. They will also come at the end of your participation to remove the data collection equipment. The first home visit will take about 2 hours, during which the drivers will need to be available for about 1 hour. The second home visit will take about 20 minutes for equipment removal.

6. Potential risks

While driving in this study, you will be subject to all risks that are normally present while driving a passenger car on public roads. At no time during this study will you be asked to perform any unsafe driving actions.

There is a small risk that your vehicle could be damaged as a result of the equipment installation or operation. The researchers have taken steps to minimize this risk though the use fused power connections, and removable double-sided tape for mounting the equipment. The research team is not able to offer financial compensation or to absorb the costs of repairing any damage that may occur as a result of your participation in this research.

Figure A.5 Informed consent agreement – page 1 of 2

The research team may notify the proper authorities if the research team observes or the data collection device records illegal activity that may cause harm to yourself or others.

7. Potential benefits

You will not receive any financial compensation for your participation in this research. Approximately 1 month after participating you will receive a written document that summarizes your vehicle use over the study period, and recommendations for how to reduce travel costs and energy use. Benefits to society may result if the results of this study are applied to household vehicle use decisions, and also to help design more detailed and more accurate surveys to collect transportation information in the future.

8. Confidentiality and data storage and use

We plan to publish the results of this study, but will not include any information that would identify you. There are some reasons why people other than the researchers may need to see information you provided as part of the study. This includes organizations responsible for making sure the research is done safely and properly, including the University of Michigan or government offices.

To keep your information safe, the information in this study will only be used in ways that will not reveal who you are. After your participation has ended, your name is no longer needed for communication and will be removed from all records. You will not be identified in any publication from this study or in any data files shared with other researchers. Digital pictures taken of the vehicle interior will be kept on file at UMTRI for future research, and may include recognizable images of yourself. Your participation in this study is confidential. Federal or state laws may require us to show information to university or government officials, who are responsible for monitoring the safety of this study. It is possible, should you be involved in an accident during testing, that the research team will have to release data on your driving in response to a court order.

9. Voluntary nature of study

Participating in this study is completely voluntary. Even if you decide to participate now, you may change your mind and stop at any time. If you decide to withdraw early, please contact the principal investigator to arrange a time when the equipment can be picked up.

10. Contact information

If you have any questions about the research, please contact Kevin Bolon, 440 Church St., Ann Arbor, MI 48109, (734) 764-1412, e-mail: kevinb@umich.edu

11. Required IRB contact information

If you have questions about your rights as a research participant, or wish to obtain information, ask questions or discuss any concerns about this study with someone other than the researcher(s), please contact the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board, 540 E Liberty St., Ste 202, Ann Arbor, MI 48104-2210, (734) 936-0933 [or toll free, (866) 936-0933], irbhsbs@umich.edu.

12. Documentation of consent for participation in study

By signing this document, you are agreeing to be in the study. You will be given a copy of this document for your records and one copy will be kept with the study records. Be sure that questions you have about the study have been answered and that you understand what you are being asked to do. You may contact the researcher if you think of a question later.

I agree to participate in the study.

Signature: _____ Date: _____

13. Use of images [optional]

Pictures taken by the in-vehicle data acquisition equipment may be used in scholarly publications or by the media to help explain this study to the research community and the public.

Signature: _____ Date: _____

Figure A.6 Informed consent agreement – page 2 of 2

Appendix B

VUSE data post processing

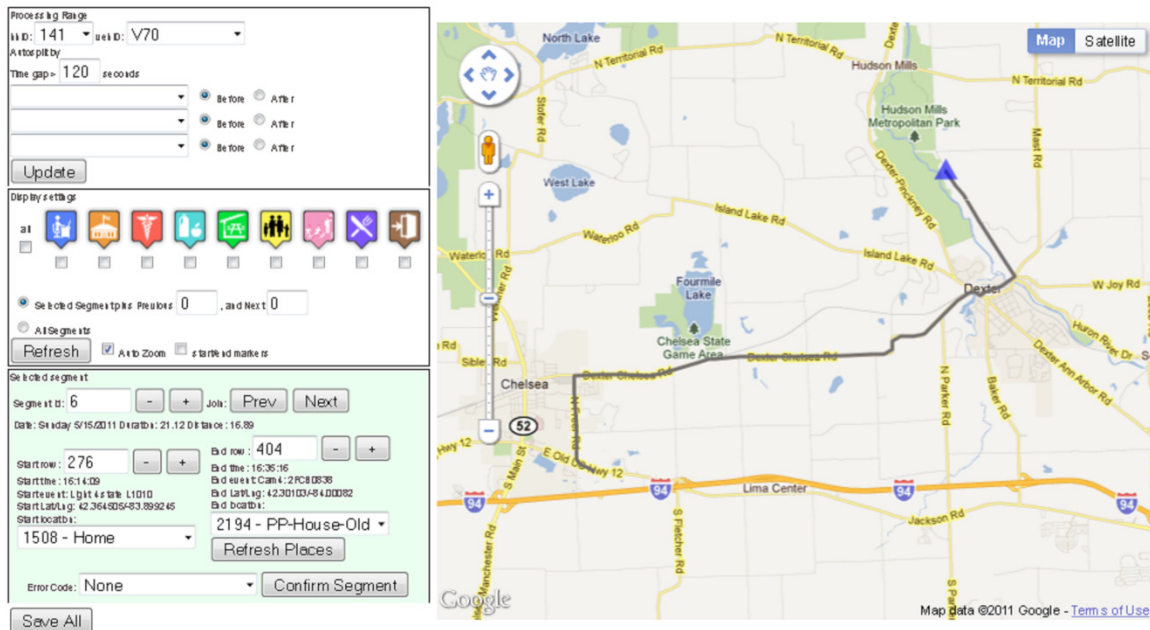


Figure B.1 VUSE data post processing web tool

Appendix C

Web survey screen shots



Figure C.1 Navigation page for the survey.

[Main Page](#)
[Take the Survey](#)
[View Demo Survey](#)
[About](#)
[Contact](#)
[Logout](#)

Household members

Starting with yourself, list all the people who will be living at this address for at least one of the next 12 months. [?](#)

[Add Person](#)

Name ?	Year of Birth	Gender	Relationship	Driver ?	
Mike	1976	Male	Self	Yes	
Courtney	1978	Female	Spouse	Yes	✗
Gabe	2004	Male	Child	No	✗
Sam	2004	Male	Child	No	✗

[Return to Main Page](#)
[Submit Completed Page](#)

Figure C.2 Household member data input page.

[Main Page](#)
[Take the Survey](#)
[View Demo Survey](#)
[About](#)
[Contact](#)
[Logout](#)

Household vehicles

List all the cars and trucks that are kept at or near your home for the exclusive use of household members. [?](#)

[Add Vehicle](#)

Vehicle name ?	Make and model ?		Other information
✗ Vehicle Nickname: <input type="text" value="Accord"/> Can't find my vehicle: <input type="text"/>	Year: <input type="text" value="1999"/> Make: <input type="text" value="Honda"/> Model: <input type="text" value="Accord Sdn"/> Style: <input type="text" value="4dr Sdn LX Manual"/>		Ownership: <input type="text" value="Owned"/> Odometer: <input type="text"/> Annual Miles: <input type="text" value="20000"/>
✗ Vehicle Nickname: <input type="text" value="V70"/> Can't find my vehicle: <input type="text"/>	Year: <input type="text" value="2001"/> Make: <input type="text" value="Volvo"/> Model: <input type="text" value="V70"/> Style: <input type="text" value="T5 A SR 5dr Wgn w/Sunroof"/>		Ownership: <input type="text" value="Owned"/> Odometer: <input type="text"/> Annual Miles: <input type="text" value="20000"/>

[Return to Main Page](#)
[Submit Completed Page](#)

Figure C.3 Household vehicle data input page.

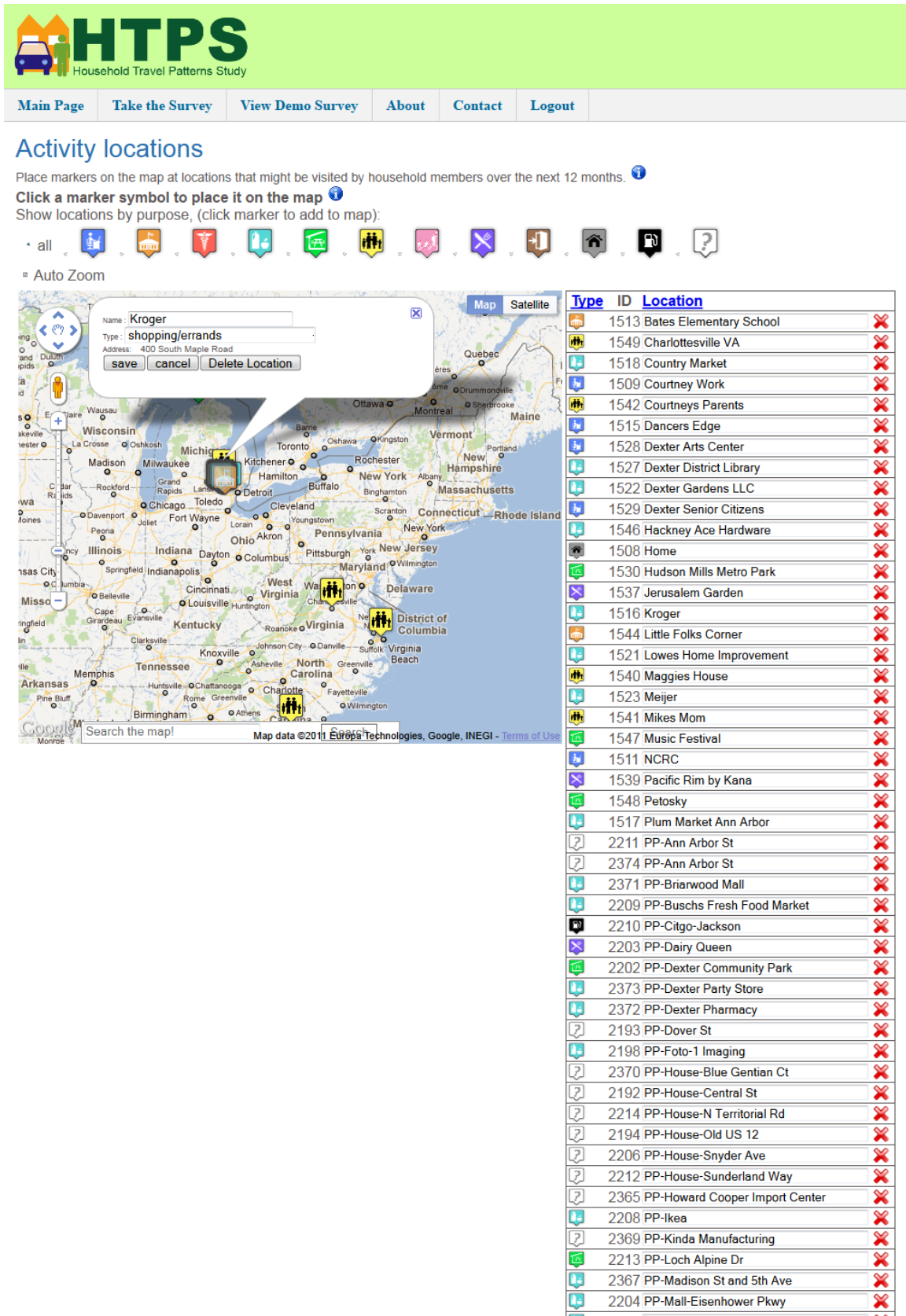



Figure C.4 Activity locations data input page (extended view).



[Main Page](#)
[Take the Survey](#)
[View Demo Survey](#)
[About](#)
[Contact](#)
[Logout](#)

Activity details

Show activities by purpose:

all
shopping/errands
social/recreational
meals
work
family personal business
school/daycare/religious
transportation
healthcare
other

Purpose	Activity pattern details
<div> <div> Clothes and HH items Shopping Category: shopping/errands </div> </div>	<div> <div> Clothes and HH items - Meijer </div> <div> Clothes and HH items - Target </div> <div> Clothes and HH items - Salvation Army </div> <div> Clothes and HH items - Value World </div> </div>
<div> <div> Cub Scouts Category: social/recreational </div> </div>	<div> <div> Cub Scouts </div> </div>
<div> <div> Softball Category: social/recreational </div> </div>	<div> <div> Softball </div> </div>
<div> <div> Baseball Category: social/recreational </div> </div>	<div> <div> Baseball </div> </div>
<div> <div> Hockey Category: social/recreational </div> </div>	<div> <div> Hockey </div> </div>
<div> <div> Hudson Mills Category: social/recreational </div> </div>	<div> <div> Hudson Mills - Summer biking </div> <div> Hudson Mills - Winter Skiing </div> </div>
<div> <div> Visit Courtneys Parents Category: family personal business </div> </div>	<div> <div> Visit Courtneys Parents 7 to 10 days </div> </div>
<div> <div> Visit Mikes Mom Category: family personal business </div> </div>	<div> <div> Visit Mikes Mom </div> </div>
<div> <div> Virginia Beach Category: social/recreational </div> </div>	<div> <div> Virginia Beach 7 to 10 days </div> </div>
<div> <div> Petosky Category: social/recreational </div> </div>	<div> <div> Petosky 2 to 4 days </div> </div>
<div> <div> Dinner out Category: meals </div> </div>	<div> <div> Dinner out </div> </div>
<div> <div> Courtney Weekday Lunch out Category: meals </div> </div>	<div> <div> Courtney Lunch out </div> </div>
<div> <div> Weekend Lunch out Category: meals </div> </div>	<div> <div> Brunch after church </div> <div> Weekend lunch out </div> </div>
<div> <div> Music fest Category: social/recreational </div> </div>	<div> <div> Music fest 3 to 7 days </div> </div>
<div> <div> Boys at Maggies House Category: school/daycare/religious </div> </div>	<div> <div> Boys at Maggies House </div> </div>
<div> <div> Family Reunion - 1x only Category: family personal business </div> </div>	<div> <div> Family Reunion - 1x only </div> </div>
<div> <div> Mike Work Category: work </div> </div>	<div> <div> Mike Work Weekday </div> <div> Mike Work Saturday Winter </div> </div>
<div> <div> Courtney Michigan Radio Category: work </div> </div>	<div> <div> Courtney Work Weekday </div> <div> Courtney Work Weekend </div> </div>
<div> <div> Courtney Yoga Category: work </div> </div>	<div> <div> -Courtney Yoga Turner Center </div> <div> Courtney Yoga NCRC </div> </div>

Figure C.5 Activity details data input page (extended view).

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