Integrated Model of the Urban Continuum

with Dynamic Time-dependent Activity-Travel Microsimulation:

Framework, Prototype, and Implementation

by

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ABSTRACT

The development of microsimulation approaches to urban systems modeling has occurred largely in three parallel streams of research, namely, land use, travel demand and traffic assignment. However, there are important dependencies and inter-relationships between the model systems which need to be accounted to accurately and comprehensively model the urban system. Location choices affect household activity-travel behavior, household activity-travel behavior affects network level of service (performance), and network level of service, in turn, affects land use and activity-travel behavior. The development of conceptual designs and operational frameworks that represent such complex inter-relationships in a consistent fashion across behavioral units, geographical entities, and temporal scales has proven to be a formidable challenge. In this research, an integrated microsimulation modeling framework called SimTRAVEL (Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land) that integrates the component model systems in a behaviorally consistent fashion, is presented. The model system is designed such that the activity-travel behavior model and the dynamic traffic assignment model are able to communicate with one another along continuous time with a view to simulate emergent activity-travel patterns in response to dynamically changing network conditions. The dissertation describes the operational framework, presents the modeling methodologies, and offers an extensive discussion on the advantages that such a framework may provide for analyzing the impacts of severe network disruptions on activity-travel choices. A prototype of the model system is developed and implemented for a portion of the

Greater Phoenix metropolitan area in Arizona to demonstrate the capabilities of the model system.

DEDICATION

To my mother, father and sister who have stood by me through all the ups and downs in my life.

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INTRODUCTION

In the recent past, microsimulation approaches have gained much attention in the field of urban systems modeling. Traditional approaches to modeling the urban systems were aggregate in nature and were based on laws of physics making simplifying assumptions about the processes underlying human decision making behavior. However, human behavior and the decision making processes underlying activity-travel and location choices is complicated and is not adequately represented by the traditional aggregate modeling approaches. Microsimulation approaches on the other hand allow one to realistically represent choice making behavior of individuals while recognizing the interactions, constraints, and underlying decision making mechanisms that they experience (Kitamura et al 2000). The move towards microsimulation approaches for modeling urban systems has been facilitated by advances along four fronts. First, the landscape of policies that planners and policymakers seek to evaluate from the models of urban systems has shifted from highway oriented policies to strategies that manage travel demand by altering decision making behavior of individuals. Limitations of traditional approaches to modeling behaviorally oriented policies are well documented. On the other hand, microsimulation-based approaches allow the realistic representation of individual decision making units and the underlying behaviors and are suited to modeling behaviorally oriented policies. Second, there is rich data available in the form of travel surveys and activity diaries containing information about the individual decision making units and their behavior. The data has allowed researchers to better understand the motivations behind individual activity-travel patterns and incorporate them in models of urban systems. Third, the transportation modeling arena has seen great advances in the statistical and econometric approaches which allow the modeling and analysis of complex decision making behaviors without making any compromises in their representation. Last but not the least, advances in computational technologies allow for efficient estimation of complex model structures, and simulation of millions of agents and their decision making behaviors in reasonable time (Goulias and Kitamura 1992, Pendyala et al. 2008).

A. Components of the Urban System

Research in the field of microsimulation approaches to modeling urban systems has happened mostly independently in three different streams namely, land use, travel demand and traffic assignment. Each of the three streams of research aims to model and represent major components of the urban system that are of interest to transportation planners and policymakers (Waddell 2000).

In the area of land use, microsimulation approaches are applied to model the land use choices of individuals, businesses, governments and developers (Waddell 2002, Waddell et al. 2003). Households in a region make choices about where to locate, individuals within a household make choices about their fixed activity locations including, work place location, school location, and college location (while accounting for the intra-household interactions and constraints).

Businesses make choices about locating their offices, and other related facilities. Developers on the other hand make development (on empty parcels of land) or redevelopment decisions (on parcels of land with existing facilities). The aforementioned land use choices along with the socio-demographic and economic evolutionary process, government land regulations, and zoning policies comprises the urban form in a region. The land use microsimulation models employ principles of market clearance to model the location choices of individuals and businesses (including choices of relocation in simulation for subsequent years), and to capture the real estate decisions of developers. Land use choices are influenced by the existing transportation network. In particular, the land use choices are impacted by the level of accessibility provided by the roadway network. For example, the addition of a new link on the existing roadway network or expansion of an existing roadway facility may impact the investment decisions of developers which in turn may impact the location choices of individuals and businesses. In order to accurately capture the impact of transport accessibility considerations on the land use decisions, one has to incorporate appropriate feedback mechanisms from the transport models (in particular traffic assignment) models to the land use.

In the second stream of urban systems research, namely, travel demand modeling, the field has experienced an increasing use of activity-based microsimulation approaches to modeling the demand for travel. The advent of activity-based approaches was spurred by the recognition of the derived nature of travel. Activity-based approaches explicitly recognize the fact that individuals travel in order to fulfill their need to engage in activities. The primary output from an activity-based travel demand model is the activity-travel patterns of households and individuals that belong to the household along a continuous time axis (Kitamura and Fujii 1998). An activity-travel pattern for an individual contains a detailed account of where, when, for how long, with whom, and the mode used for pursuing activities along a continuous time axis (Arentze and Timmermans 2004). The model system comprises of various sub-models to generate household activity agendas, individual activity schedules, activity linkages, trip chaining, destination and mode choices subject to the different household interactions (including interactions among household members), and temporal, spatial, and monetary constraints. The travel demand model has important linkages with the other two components of the urban system, namely, land use and traffic microsimulation. Firstly, the activity-travel patterns of individuals are affected by the urban land form. Secondly, the activity-travel patterns generated by individuals affect network conditions as trips get routed and simulated. Also, network conditions and transport accessibility measures affect the activity-travel choices including destination choice, mode choice, and activity duration among others. Therefore as with the land use model, appropriate feedback mechanisms need to be incorporated to capture the dependencies between travel demand model and land use/ traffic microsimulation models.

The last stream of research in urban systems deals with traffic assignment. The two main components of a traffic assignment model are route selection and traffic simulation. The inputs for a traffic assignment model include trip tables providing the volume of traffic going between different pairs of origins and destinations, and the transportation network with link attributes, lane configurations and intersection control information. The outputs from a traffic assignment model are the link flows, and transport accessibility measures. These outputs in turn feed into the travel demand model affecting the activity-travel choices and into the land use model to affect the land use choices in the longer term. Typically the inputs that feed into a traffic assignment model are peak hour (AM, PM, or midday peak hour) trip tables. The vehicles are routed assuming peak/ off-peak period transport accessibility measures and also simulated using the same assumption. Models based on this assumption of static travel times on the network are called static traffic assignment models (Beckmann et al. 1956). However, transportation networks evolve continuously over time and the above assumption of static network conditions may lead to results that are not completely representative of dynamic conditions on the actual network. Also, the microsimulation approaches to generate the activity-travel patterns (activity-based approaches) are capable of generating demand at a much finer temporal resolution (1 minute) than the matrices provided by traditional four-step modeling approaches (1 hour). Recognition of the limitations of traditional traffic assignment models and the availability of travel demand at a fine grained resolution has led to the development of dynamic traffic assignment models which can explicitly account for network dynamics (Peeta and Ziliaskopoulos 2001, Friedrich et al. 2000). As a result, the routing of trips, simulation of vehicle movements, and the resulting outputs are more representative of the actual network conditions. Dynamic traffic assignment models also provide the same outputs as static assignment model with an added time dimension, i.e., time dependent link flows, and time dependent transport accessibility measures of the network. The inclusion of temporal dynamics to models of traffic assignment has important detriments to the land use and travel demand models and subsequent planning and policy analysis of urban systems.

B. Need for an Integrated Model of the Urban System

As identified in the previous section, research in the field of urban systems modeling has happened mostly independently in three different streams of research, namely, land use, travel demand and traffic assignment. However, there are inter-relationships and dependencies among these model systems as shown in Figure 1. First, land use choices are affected by the network travel accessibility measures. Land use choices in turn affect the travel demand; one of the major factors affecting the activity-travel choices is the land use decisions of individuals and households choices including home location, work location, and school location. Second, travel demand is also affected by the network travel accessibility measures. Additionally, roadway networks continuously evolve over time (temporal dynamics) and it is important to link these temporal dynamics with the travel demand model in a behaviorally consistent fashion to have a more accurate representation of the production and evolution of activity-travel schedules of individuals over the course of a day. Finally, the network conditions that are simulated for a forecast year affect the land use and travel demand decisions in the subsequent forecast year.

The importance of incorporating these linkages in models of urban systems has been well recognized by researchers (Timmermans 2003, Miller 2006). There have been some conceptual designs and implementations of integrated models which combine two (of three) components of the urban system namely, land use and travel demand or travel demand and traffic assignment. In these integrated models, linkages across component systems are incorporated loosely through feedback processes and data exchange mechanisms. There are very limited if any conceptual designs or operational implementations that have attempted to integrate all the three components of a model system, under a single unifying framework in a seamless fashion across behavioral units, geographical entities and temporal scales.

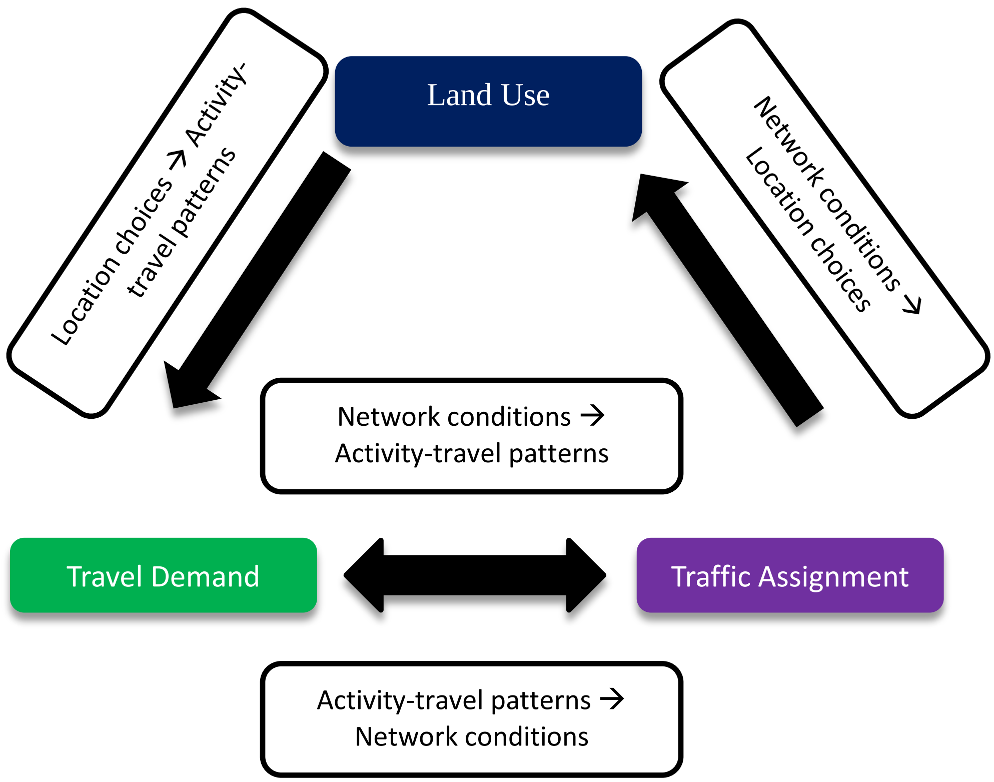

Figure 1: Interrelationships across components of an urban system

C. Beyond Loose Coupling of Component Systems

One of the main focuses of this research effort is to present and implement an integrated modeling framework that goes beyond a loose coupling of the component system through feedback processes and data exchange mechanisms. There is a need for an approach that holistically integrates components of the urban system while accounting for the linkages and dependencies across systems in a behaviorally consistent fashion. The push for the design and development of such an integrated model of the urban system has been motivated by three key considerations as discussed below:

Policy Issues and Planning Applications

In the past, transportation planners used to employ travel demand models primarily for planning and construction of roadway expansions serving major metropolitan areas. However, in the recent past with mounting concerns of sustainability and greenhouse gas emissions, there has been a growing interest in employing models to address a host of new types of issues such as air quality conformity, land use – transportation interaction, transit- and pedestrian-oriented developments, zoning restrictions, mixed use development incentives, implementation of intelligent transportation systems (ITS), impacts of a range of travel demand management (TDM) strategies and transportation control measures (TCM) including variable pricing initiatives, social equity and environmental justice in the context of special populations, transportation and public health (obesity), and the effect of telecommunications on travel behavior (e.g., e-commerce, telecommuting, etc.). These new issues impact choice dimensions across all the facets of the urban continuum including land use (affecting location choices), travel demand (affecting activity engagement decisions) and traffic assignment (route choices). Without an integrated model of the urban system that accurately captures the interrelationships and dependencies across component systems, one cannot conduct accurate policy impact analyses.

Behavioral Representation

The activity-travel engagement decisions and location choice behaviors of individuals are very closely related to each other. There are a number of choice dimensions that characterize these decision processes. These choice dimensions also occur in different time steps and occur across different spatial contexts. In the longer term, individuals make decisions about where to live, work, and go to school. In the medium term people make decisions about automobile ownership, fleet composition and lifestyle. In the shorter term, they make week-to-week and day-to-day activity-travel engagement decisions characterized by activity schedules, destination choices, trip chaining, mode choice and route choices. It can be seen that the location choices (which have typically been modeled in land use models), the activity-travel engagement decisions (which have typically been modeled in travel demand models), and route choice decisions (which have typically been modeled in traffic assignment models) are characterized by choice dimensions which are closely related to each other. It is important to capture the interactions across choice dimensions in a behaviorally consistent fashion because change in the attribute of a choice dimension in one component model system may have impacts on various choice dimension in a different component system(s) across time and space. For example, suppose the travel time for the commute from home to work is increasing for a certain individual. In the short term, the individual may choose an alternative route that is faster (captured in a traffic assignment model) or he may choose to alter his departure time to arrive at work on time (captured in a travel demand model). He may also choose to telecommute or alter his shift hours to travel during less congested periods which in turn could affect his activity-travel engagement decisions for other activities, namely, pick up and drop offs, durations and locations of discretionary and maintenance type activities among others. In the longer term, the individual may choose to relocate closer to his work place or change jobs to make the commute manageable. This may in turn affect medium term choice dimensions namely, vehicle fleet composition (may choose to bike and sell that extra car if moving closer to work or buy an extra car if moving away from work), and lifestyle changes (take the transit if it is accessible as opposed to driving).

In previous implementations of integrated models, the interrelationships were captured by loosely coupling model systems through feedback processes and data exchange mechanisms. For example, a classic approach to integration has been collating results from the travel demand model system and feeding that as an input to a traffic assignment model. However, this approach lacks the behavioral fidelity and fails to accurately capture the cascading impacts of choice dimensions across model systems. There is a need for an integrated modeling framework that not only ensures consistency in representation of time, space, behavioral units, and behavioral processes but also enhances the behavioral fidelity by incorporating additional themes of individual decision making that have been identified by researchers in the recent past. These include:

- Interactions: There are different types of interactions that one needs to consider in the context of modeling the urban continuum. Individuals interact with one another both within the household and outside the household to which they belong. The activity-travel engagement patterns of individuals are closely related to one another and they evolve based on various interactions, dependencies, resource constraints, and household roles. For example, an individual may engage in activities and travel alone or jointly with some other individual from within the household or outside the household. Individuals may be dependent on others for their mobility needs (e.g. children and elderly) and in turn affect the activity-travel engagement decisions of the person who tends to them.

- Constraints: There are different types of constraints that individuals and households are subjected to which affect both their location choices and activity-travel patterns. There are resource constraints (monetary and vehicle fleet composition) which affect the housing arrangement (rent or buy), housing location (urban or rural), the type of activities one can engage in. Also, there are household constraints (that may require an individual be at home to tend to another household member), institutional constraints (work, and school schedules, business hours of establishments), personal constraints (need for sleep), time-space prism constraints (that affect how far people can travel to engage in activities within a given time window). There is a need to account for all these constraints to accurately capture their impacts on the decision making behavior of individuals.
- Heterogeneity: There are differences across individuals in the way they react to the various scenarios, in the way they value and perceive different attributes. Individuals also vary in the attributes they use/evaluate in order to

make a decision about a choice dimension. These differences across individuals are referred to as Heterogeneity. There is observed heterogeneity which can be captured by various land use, network, socio-economic and demographic variables and there is unobserved heterogeneity which is explained by the random term in models of choice dimensions. In the recent past, there have been tremendous advances in econometric approaches which lend themselves to a holistic accounting for heterogeneity. One can use these econometric frameworks to enhance the behavioral representation of various choice dimensions.

- History Dependence: There is history dependency when individual's make decisions about location choices and activity-travel engagement patterns. For example, if a person has engaged in a discretionary activity (grocery shopping) earlier in the day then the probability that he engages in that activity again later in the day is reduced and even if he does engage in the activity the duration is considerably limited. It is important to account for history dependency to avoid the incorrect representation of activity-engagement behavior.

Methodological and Computational Tractability

There have been considerable advances in the methodological and computational capabilities which have motivated the development of integrated urban models. In the past, computational feasibility and tractability were a major hindrance to the development and implementation of integrated models. Urban modelers treated land use, travel demand, and transportation supply models rather independently. They were however loosely coupled to capture the interrelationships by feedback loops and data exchange mechanisms. Land use model outputs served as inputs to travel demand models. Trip tables from the demand models were then loaded onto networks using traffic assignment models. Network level of service measures (usually travel times or other measures of impedance) from the assignment models may be fed back to trip distribution and mode choice models in the demand modeling system to reflect the effects of network performance on these aspects of behavior. Additionally computational tractability and feasibility were major roadblocks to estimating complex model structures of choice dimensions. As a result modelers resorted to making simplifying assumptions about the underlying decision making behaviors, namely, loose coupling across component model systems, and simple model specifications for representing choice dimensions among others.

However, there have been tremendous advances on both methodological fronts and computation fronts that have motivated the development of an integrated model of the urban continuum with strong behavioral representations. On the methodological front, there have been remarkable advances in the field of statistics and econometrics. There are advanced modeling frameworks that allow estimation of multiple choice dimensions simultaneously while also accounting for heterogeneity across individuals and the common unobserved attributes affecting choice processes (by using complex error covariance structures). On the computational front, hardware and software advances allow for accurate representation of the underlying behaviors using complex model structures without having to resort to simplifying assumptions for the sake of computational feasibility and tractability. Also, it is now possible to simulate the choices of millions of agents to mimic their activity-travel and location decisions in reasonable time.

D. Research Outline

This research presented aims to make contributions towards furthering the literature on integrated models and activity-based travel demand models along the following lines of inquiry:

- **Objective:** *Present a framework for integrating land use, travel demand and dynamic traffic assignment components of the urban system that goes beyond traditional loose coupling of component systems through input-output data flows and feedback processes*

  Research Contribution: In this research effort, a unique framework for integrating land use, travel demand and dynamic traffic assignment models is presented that goes beyond loose coupling of component systems. Unlike previous implementations that proceed by running component systems independently and link them through input-output data flows and feedback processes to achieve integration, the approach presented integrates the components under a single unifying framework while holistically identifying and incorporating the interrelationships across component systems in a behaviorally consistent fashion.

- **Objective:** *Demonstrate the feasibility of the integrated model framework by developing a prototype*

  Research Contribution: The research effort adds to the state of practice on integrated models of urban systems by contributing to the development of an integrated model system prototype dubbed Simulator of Transport, Routes, Activities, Vehicles, Emissions and Land (SimTRAVEL) as part of a larger sponsored research effort. In particular, the research contributed to the development of a unique dynamic time-dependent activity travel simulator by combining a travel demand model system implementation - OpenAMOS (Open-source Activity Mobility Simulator) and a dynamic traffic assignment model system implementation - MALTA (Multi-Resolution Assignment and Loading of Traffic Activities). The research effort also makes a contribution to the state of practice by designing and developing an activity-based microsimulation model of travel demand called OpenAMOS (Open-source Activity Mobility Simulator). OpenAMOS builds on an earlier implementation of an activity-based model system called AMOS (Activity Mobility Simulator). However, the whole software system was reengineered and reprogrammed to build a software system that is robust, computationally tractable and feasible. OpenAMOS also includes a child dependency and allocation module that was not included in AMOS.

- **Objective:** *Illustrate differences and implications of the integration framework over traditional approaches to integrated modeling of the urban system*

  Research Contribution: The research effort comprises one of the very first applications of an integrated model of the urban system that combines all the three components including land use, travel demand and traffic assignment with a dynamic time-dependent activity-travel simulator. The study also adds to the empirical literature by conducting a comparative analysis between sequential approach (traditionally used) and the dynamic approach (presented in this effort) to integrated modeling of the urban system.

- **Objective:** *Highlight the behavioral fidelity of new integration framework presented by extending the framework to model network dynamics and understand its implications on activity-travel engagement behavior*

  Research Contribution: Additionally on the empirical front, the research effort comprises one of the limited applications of integrated modeling frameworks for modeling network disruptions and understanding their impact on activity-travel engagement behavior. The dynamic time-dependent activity travel simulator framework presented for integrating the travel demand and traffic assignment components of the urban system was extended to model network perturbations under varying levels of travel information provisions. The research illustrates the implications of network perturbations on activity-travel engagement behavior and thus demonstrates the importance of integrated modeling frameworks for accurately modeling network disruptions.

- **Objective:** Add to the literature on activity-travel engagement behavior for more accurate representation of choice dimensions and decision hierarchies in activity-based microsimulation model systems of travel demand

  Research Contribution: The research effort investigates advanced modeling frameworks to model multiple dimensions of activity-travel engagement simultaneously. The research was conducted with an aim to better understand individual activity-travel engagement patterns and the behavioral processes involved. A probit-based discrete continuous simultaneous equations model was employed to jointly model activity type choice and activity duration choice dimensions while accounting for history dependency of activity engagement. Also using the same modeling framework, the choice of vehicle type and the distance traveled was modeled in the context of tours formed by households with mixed vehicle fleets as they pursue their activity-travel agendas.

In the rest of the document, contributions made along these lines of inquiry are described in detail. In the next chapter a brief literature review of microsimulation approaches to modeling the three components of the urban system is provided. This discussion is followed by a detailed review of integrated modeling frameworks in literature. In Chapter 3, a novel framework for integrating components of the urban system is provided followed by a description of the prototype of an integrated model system in Chapter 4. In Chapter 5, a travel demand model system dubbed OpenAMOS which was used in the development of the integrated model prototype is described. In Chapter 6, two empirical studies are presented that were aimed at advancing the state of research on understanding activity-travel decision making behavior using advanced simultaneous equations framework. In Chapter 7, results from the application of the integrated model prototype for modeling the urban system are presented. The results are also compared against traditional sequential approach to integration and similarities and differences are highlighted. In Chapter 8, the framework for integrating the travel demand and traffic assignment is extended to model network perturbations and the proposed framework was employed to mimic a network disruption under different scenarios of travel information provision. Finally, conclusions and directions for future research are presented in Chapter 9.

CHAPTER 2

MICROSIMULATION MODELING OF THE URBAN SYSTEM

In the last four decades, tremendous progress has been made in the arena of microsimulation approaches to modeling urban systems and the rich body of literature in the field of urban systems is a testament to the progress. In this chapter, a brief review of the literature on the use of microsimulation approaches to modeling the various components of the urban system namely land use, travel demand and traffic assignment is provided. This is followed by a detailed review of literature on integrated modeling of urban systems.

A. Land Use Dynamics

The earliest models of land use were based on principles of spatial interaction (Lowry 1964, Garin 1966, Goldner 1971, Putman 1983, Mackett 1983, Wegener 1982). The models were based on laws of physics and made simplifying assumptions about the underlying processes characterizing urban land form. These models suffered from 7 deadly "sins" as Lee (1973) notes, namely, lack of sound behavioral theory, overly comprehensive, require large amount of data, irresponsive, complicated, mechanical, and expensive to implement. Recognizing these limitations, the next generation of land use models drew their inspiration from the developments in the field of statistical and econometric modeling; the models were based on random utility theory. Two econometric frameworks formed the basis for most of the land use models that are applied in practice today, namely, regional economic models and land market models (Iacono et al.

2008). The regional economic models study the flow of goods and services across zones in a region using spatial input-output models which in turn determine the demand for space. There have been various implementations of the regional economic frameworks to study land use changes including MEPLAN (Echenique et al. 1990), TRANUS (de la Barra 1989), and PECAS (Hunt and Abraham 2005). The land market models on the other hand employ principles of market clearance (Martinez 1992, Waddell 2000, Salvini and Miller 2005). Models based on the principles of land market clearance share the characteristics of a typical microsimulation model as they simulate the choice of each agent (individuals, households, businesses) subject to the various constraints and interactions they experience.

B. Activity-Travel Behavior

In microsimulation approaches to modeling travel demand, activity-based (Arentze et al. 2000, Kitamura et al. 1998, Pinjari et al. 2005) and tour-based (Vovsha et al. 2002, Miller et al. 2005) paradigms are often employed. There are a number of implementations of activity-based model systems in the literature. The model systems differ from each other in the underlying behavioral paradigms assumed to represent activity-travel decision making behavior and in the choice of the decision making unit.

The first step in the employment of a microsimulation model system for travel demand is the generation of a synthetic population for a region. The travel demand model system takes disaggregate household and socio-demographic data of the entire population in a region as input. However, the disaggregate data for the entire population is often not readily available. Instead, disaggregate data for a sample of the population and aggregate distributions of key variables for the entire population are available from sources like the Census or from regional planning agency forecasts. Therefore, synthetic populations are created by sampling households from the sample such that the aggregate distributions for the entire population are matched (Ye et al. 2009, Beckman et al. 1996, Guo and Bhat 2007, Arentze et al. 2007). After the synthetic population is created the activity-travel patterns for the every individual in the synthetic population is generated by employing statistical and econometric models for mimicking the various dimensions of location choices and activity-travel behavior.

In the activity-based approach to modeling travel demand, a number of frameworks are used, namely, utility-maximization principles from econometrics (Bhat et al. 2004, Kitamura and Fujii 1998), rule-based approaches from the cognitive sciences (Arentze and Timmermans 2004, Kwan 1997, Pendyala et al. 1998), and sampling from activity profiles observed in surveys based on certain matching criterion (McNally 1995, Barrett et al. 1999) to model the activity-travel decisions of synthetic households.

The Activity Mobility Simulator (AMOS) comprises a microsimulation model of travel demand that is based on econometric approaches. AMOS comprises a series of submodel systems including Household Activity Generation System (HAGS) and a Prism-Constrained Activity Travel Simulator (PCATS). In addition to generating the household and person-level attributes for the synthetic population, HAGS also generates the location choices of synthetic households and persons and the mandatory activity agendas for all the persons within a household. The mandatory activities define the skeleton around which other flexible activities (including discretionary, and maintenance types of activities) are pursued by individuals. PCATS then generates the flexible activities to generate the full daily activity-travel schedules of every individual in the region. PCATS uses the concept of Hagerstrand time-space prisms to represent the temporal and spatial constraints that individuals are subjected to when making activity-travel decisions. Sub-models within PCATS simulate the activity-travel records within a time-space prism corresponding to each open period (periods where the individual is not engaging in any fixed or mandatory activity) for every individual (Kitamura and Fujii 1998, Pendyala et al. 1998, Kitamura et al. 2000, Pendyala et al. 2008).

The Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns (CEMDAP) is another implementation of an activity-based travel demand modeling system where the choice processes of individual agents are modeled using econometric frameworks. The model system comprises a series of econometric models each representing a particular aspect of individual activity-travel decision making behavior. CEMDAP takes disaggregate household and individual socio-demographic data, land use patterns, and accessibility measures as input and provides activity-travel schedules along the continuous time axis for the entire population in a region. The model can simulate activity-travel patterns for both workers and non-workers (Eluru et al. 2008, Bhat et al. 2004, CEMDAP website). The Integrated Transport and Land-Use Modeling for Environmental Analysis (ILUTE) model system developed at the University of Toronto comprises yet another implementation of a microsimulation model based on econometric principles. ILUTE first simulates the land use choices including the built environment, and the job market which then feed as input into the generation of the activity-travel choices of individuals (Salvini and Miller 2005). The model system was developed with an aim to understand the impacts of different transportation related policies on the emissions and energy use in urban areas of Canada. The travel demand model component of ILUTE is called the Travel Activity Scheduling Model with Household Agents (TASHA). TASHA differs from the other travel demand models in that it uses the concept of projects (Axhausen 1998) to identify and schedule the activities and travel within an individual's daily activity-travel pattern. As the name suggests ILUTE is an integrated modeling system incorporating both land use model and travel demand model in the same framework (ILUTE website).

In contrast to the model systems above that are based on utility-maximization principles, there are other implementations of travel demand models that are based on theories from the cognitive sciences namely that of satisficing and choice heuristics. Albatross: A Learning Based Transportation Oriented Simulation System was developed for the Dutch Ministry of

Transportation. The model system employs decision trees to predict activity-scheduling decisions of individuals and households. Methods from the field of statistics and artificial intelligence are used to create decision tress from activity diary data (Arentze and Timmermans 2004). One of the drawbacks of rule-based approaches is the potential insensitivity of the models to key cost variables like travel-cost and travel-times unlike parametric methods (e.g. econometric model approaches based on utility-maximization principles). Arentze and Timmermans (2005) proposed a hybrid methodology that combines rule-based and parametric modeling approaches called parametric decisions trees to improve the problem of insensitivity to key cost variables. Other travel demand model systems that use rule-based approaches to generate activity-travel patterns include GISICAS (GIS-Interfaced Computational-process-model for Activity Scheduling) that presented a conceptualization of an Advanced Traveler Information System (Kwan 1997), SCHEDULER developed by Garling et al. (1989) was aimed at understanding the activity scheduling and sequencing processes and Vause (1997) was another effort that used rule-based approaches to model travel demand.

A third approach to the generation of activity-travel patterns involves sampling from household travel surveys to generate activity schedules. After sampling activity schedules for every person in the region, econometric methods like nested logit model are used to identify the mode and location attributes of the different activities. Transportation Analysis and Simulation System (TRANSIMS) employs such a travel demand component (Cetin et al. 2002, Barrett et al. 1999, TRANSIMS website) to generate the activity-travel patterns of individuals in a region.

C. Dynamic Traffic Assignment

Traffic assignment is comprised of two main steps namely route selection and traffic simulation. In the route selection step, a route is assigned to a vehicle trip based on an optimization criterion using network link impedances. The link impedances are computed by simulating all vehicle trips through the network along the routes assigned in the route selection step. The techniques used for route selection in the static traffic assignment models include, the classic user and system equilibrium as presented in Wardrop (1952) with different implementations varying in the definitions of the cost functions used to represent link impedances. In user equilibrium, individuals' choose routes to minimize travel times for a particular origin and destination pair. A property of this approach is that the users do not improve their travel time by shifting to alternate routes. On the other hand, route selection models that are based on system optimum principles minimize travel times across all vehicle trips. One of the properties of the system optimum technique is that, individuals' maybe assigned routes which may not be the user optimum (minimum). In other words not all individuals' are assigned routes that offer them the least travel time for the given origin and destination pair. There are different approaches to assigning traffic to the network in a static traffic assignment model. All-or-nothing assignment, incremental-load assignment, incremental-reload assignment, and Frank-Wolfe technique are the most commonly used approaches (Oppenheim 1995). In the dynamic traffic assignment model, similar algorithmic techniques of routing are used to identify paths i.e. user equilibrium and system equilibrium. However, the link impedances are associated with an added time dimension to account for the temporal dynamics that networks experience.

In the traffic simulation step, the vehicle movements are simulated through the transportation network along a continuous time axis. At the end of the simulation, the model component provides the link volumes and link impedances which serve as inputs to the other model components including the routing of trips, land use model, and travel demand model. The different approaches that have been used to simulate traffic flow include macroscopic, microscopic, and cellular automata models. Macroscopic models employ laws of physics by drawing analogies between the systems for which they were developed to simulate vehicular traffic and generate transport accessibility measures. An example of macroscopic models used to represent traffic flow includes Newell (1961) which compares traffic to gases and explains traffic flow using kinetic theory of gases. Other macroscopic approaches to describe traffic flow include those by Lighthill and Witham (1955), Richards (1956), Payne (1979) among others. The microscopic models and cellular automata models fall under category of microsimulation models. In microsimulation models of traffic assignment the agents are the individual vehicles. In cellular automata models of traffic simulation, the links are divided into cells of fixed width and time is discretized.

The movement of vehicles is described by simple rules which dictate how a vehicle moves between cells from one time step to another (Wagner et al. 1997). Microscopic models of traffic simulation on the other hand are based on microscopic traffic models of gap acceptance, car following and lane changing behavior (Mahut et al. 2008, Chandler et al. 1958, Gazis et al. 1959, 1961, Kometani and Sasaki 1959, Gipps 1981). The use of microscopic models for simulation is limited to small networks owing to its high computational requirement. An approach that has gained popularity in the recent past owing to its computational tractability for large networks is the mesoscopic modeling approach to traffic simulation. In this approach, macroscopic theories of traffic flow are used to estimate traffic flow characteristics on the network, the traffic flow characteristics are then used to simulate the individual vehicular movements (Cetin 2002, Chiu and Villalobos 2008, Ramachandran et al. 2008). Other example implementations of microscopic models for traffic assignment include CORSIM (CORSIM website), INTEGRATION (Van Aerde 1999), AIMSUN2 (Barceló et al 1994), VISSIM (VISSIM website). CONTRAM (Taylor 1990), DYNASMART-P (Mahmassani et al. 1992), DynaMIT (Ben-Akiva et al. 1998) are examples of traffic assignment models employing mesoscopic approaches to traffic simulation.

D. Integrated Modeling of the Urban System

There are important linkages across components of the urban system and hence a need to model the components of the urban system using an integrated modeling framework. Miller (2006) defines an integrated model as that which tries to "model the spatial evolution of a given study region system state over time as a function of various socio-economic, demographic, and political processes". The author notes that while the need for integrated models has been recognized for a while, the conceptualization and operationalization of truly integrated model systems has been lacking because the urban system is highly dimensional and usually includes model components that simulate the spatial distribution of residents of the region, the spatial distribution of employment and other out-of-home activity destinations, individual activity-travel decisions described by both spatial and temporal coordinates, the flow of goods and services again described by both spatial and temporal attributes. The author further emphasizes that in truly integrated model systems, the critical dimensions that characterize urban environments namely space, time, networks, socio-economic and demographics are adequately understood and represented.

In the last two decades, there has been considerable progress made in the conceptualization and operationalization of integrated modeling frameworks. Some of the earliest attempts aimed at integrated modeling the urban system were documented in a special issue of the Transportation published in 1996. The integrated modeling frameworks presented in the special issue have shaped the modeling structures and paradigms adopted by more recent integration efforts. Stopher et al (1996), presents an integrated modeling framework dubbed Simulation Model of Activities, Resources, and Travel (SMART). The conceptual framework presented integrates all the components of the urban system including land use, travel demand, and traffic assignment. The framework accounts for land prices, land use policies and constraints, socio-economic and demographic evolution, and the transportation supply in the region while modeling land use. The land use in turn along with the transportation supply and the population characteristics influences the formation of activity-travel patterns while accounting for the resources and constraints that individuals are subjected to. The framework also incorporates appropriate feedback loops to establish the linkages across the components of the urban system, namely, the influence of network conditions on network changes, socio-economic and demographic changes, land use, and activity-travel demand generation.

In the same issue of Transportation, Kitamura et al. (1996) presented Sequenced Activity Mobility Simulator (SAMS) for modeling the urban system. In this framework, a series of model systems are employed to simulate different components of the urban system. The socio-economic and demographic simulator is a stochastic mircosimulator model for generating a synthetic population for the base year. The model system not only simulates the socio-economic and demographic evolutionary life-cycle processes that individuals and households experience, but it also simulates the life-cycle events that firms undergo in the longer term like expansion, relocation, and closure. The urban system simulator is a market-based microsimulation model of the urban built environment. The model system simulates the location choices of households, and firms and development patterns of real estate developers subject to the land use policies, zoning restrictions and network level of service measures. The urban system simulator interfaces with the socio-economic and demographic simulator in generating the location choices. The outputs from these models then feed into the vehicle transactions simulator. The vehicle transactions simulator is a dynamic, stochastic microsimulator of vehicle fleet composition. The simulator also generates the vehicle fleet decisions in the longer run, including, acquiring additional vehicles, disposing already owned vehicles, and type of vehicle acquired or disposed. The Activity-Mobility Simulator (AMOS) simulates the activity-travel decisions of individuals along a continuous time axis. The AMOS component has been enhanced to include time-space constraints when simulating activity-travel engagement decisions (Kitamura et al. 2000). The dynamic network simulator employs a dynamic traffic assignment model for routing trips on the network along a continuous time axis. The network simulator generates the network conditions as outputs and closely interfaces with the urban mobility simulator, vehicle transactions simulator and activity-mobility simulator. Figure 2 shows the design of SAMS along with all the connections and feedback processes between the various model components.

Ben-Akiva et al. (1996) present another framework for integrated model of the urban system. This was one of the earliest frameworks adopting a tour-based approach for modeling the activity-travel engagement patterns. This framework provided the basis for a number of tour-based model systems in practice today. The model structure includes a component for modeling the longer term choice processes like mobility and life styles (including employment, housing, activity skeleton generation, auto ownership, and information technology accessibility). The activity-travel engagement decisions are simulated in the activity and travel scheduling model. The component comprises of deeply nested logit models of primary tour formation, secondary tour formation, tour type, time of day choice, destination choice, and mode choice. The log-sums are fed from the lower levels of the nest into the upper levels to capture the impact of one dimension on the other. In the recent past, tour-based models have grown in complexity with the incorporation of additional attributes affecting activity-travel engagement, including, household interactions in activity engagement and vehicle allocation (Gliebe and Koppelman, 2005; Bradley and Vovsha, 2005). Bradley et al. (2008) present a model structure which combines a tour-based travel demand model with UrbanSim on the land use microsimulation end and a static traffic assignment model on the traffic microsimulation end which can also be replaced with a dynamic traffic assignment model. Network conditions are fed back into the land use microsimulation model to establish the linkages between the traffic assignment component and the land use microsimulation model. The network accessibility measures also affect the travel demand model. The proposed model structure was developed for the Puget Sound Regional Council and utilizes the OPUS software architecture (Waddell 2005).

Salvini and Miller (2005) present an integrated model dubbed ILUTE (Integrated Land Use, Transportation, and Environment). ILUTE comprises of a number of components for simulating various dimensions of the urban system including, land use patterns, location choices, auto ownership, activity-travel patterns and goods movement. Location choice models embody household and business location choice processes while the activity/travel and goods movement entity includes the entire gamut of activity-based travel demand model components and freight transportation models. The choice dimensions within these components are considered endogenous to the system. Appropriate feedback processes are put in place to reflect the dependencies between travel choices and auto ownership, travel choices and location choices, location choices and land use patterns, and location choices and auto ownership. Demographics, regional economics, government policies, transport system attributes, network level-of-service conditions, and external impacts (e.g. air quality) are considered exogenous to the system. However, the exogenous factors are influenced by outcomes of the ILUTE model system for a subsequent year simulation.

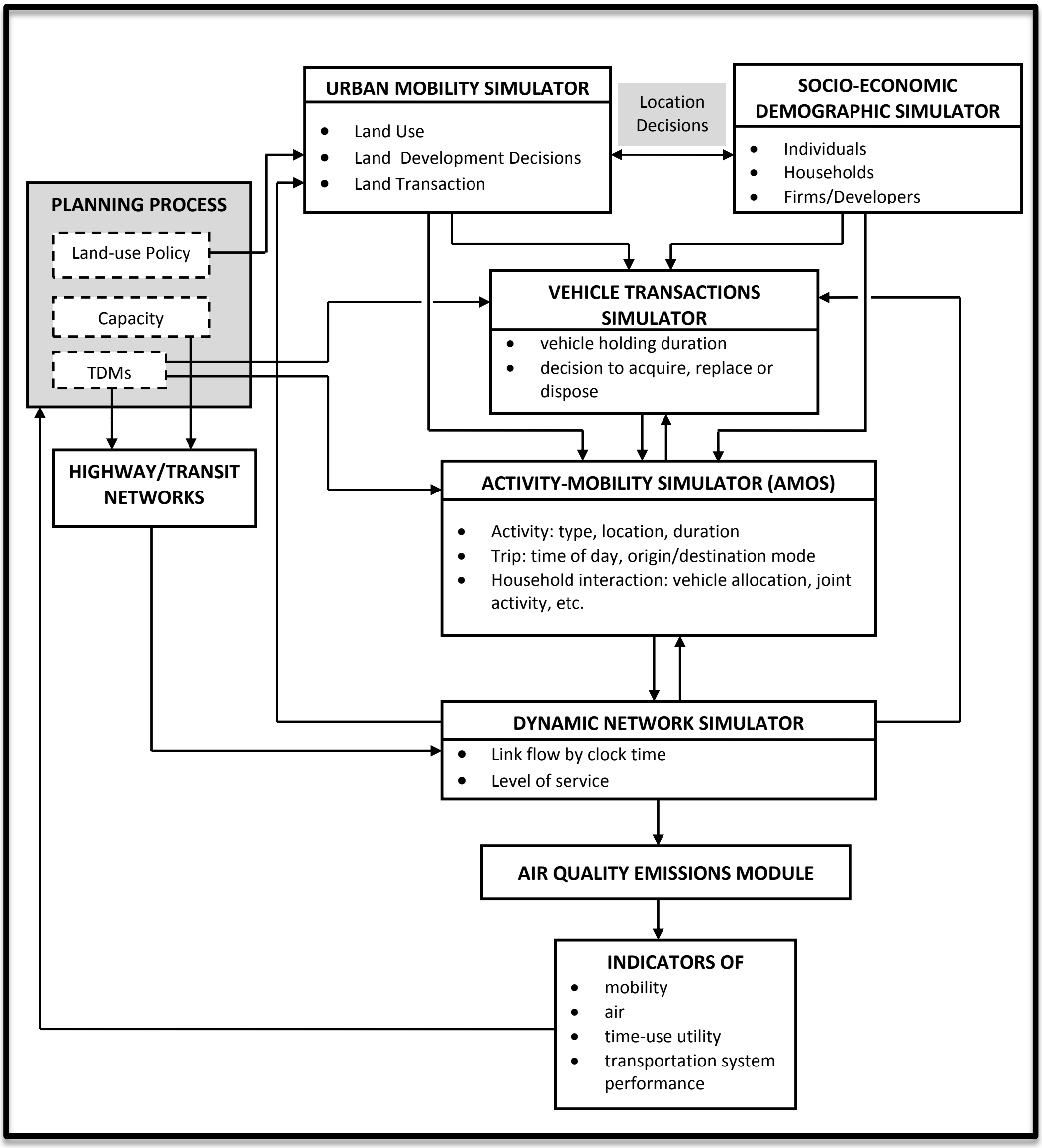

Figure 2: Overview of the Sequenced Activity Mobility Simulator framework (Kitamura et al. 1996)

More recently, Eluru et al (2008) present an integrated modeling framework called the Comprehensive Econometric Microsimulator of Urban Systems (CEMUS). CEMUS comprises of a synthetic population generator, a land use microsimulation model system called CEMSELTS - Comprehensive Econometric Microsimulator of Socio-Economics, Land Use, and Transportation

System and an activity-travel simulator called CEMDAP - Comprehensive Econometric Microsimulator of Daily Activity-travel Patterns (Pinjari et al. 2008). The activity-travel patterns that are generated from the CEMDAP component are then fed into a dynamic traffic assignment model for routing and simulating the trips and network level of service measures are obtained as output. The network level of service outputs from the dynamic traffic assignment model are fed back into CEMSELTS and CEMDAP components in the subsequent iteration. The process is repeated until some convergence in the network conditions is achieved.

In addition to the above integrated modeling structures that aim to integrate all the three components of the urban system, the literature on integrated models is replete with model frameworks that consider only two of the three components with the third component considered exogenous. Waddell et al. (2007) present one such model structure where simple choice models are used to simulate the fixed activity location choices and auto ownership. These dimensions are often simulated in the context of land use microsimulation models. The model structure features a dynamic activity pattern generation system that simulates the tour decisions of individuals including the number of tours, stops within tours, destination locations for each stop, mode on the tour. Trip lists and origin-destination matrices are generated at the end of the dynamic activity pattern generation which is then used to interface with either a static assignment or a dynamic assignment model.

Another model framework that attempts to integrate an activity-based travel demand model with a dynamic traffic assignment model was presented by Lin et al. (2008). The model structure employs CEMDAP (Comprehensive Econometric Microsimulator of Daily Activity-travel Patterns) to simulate the activity-travel patterns and VISTA (Visual Interactive System for Transport Algorithms) for the dynamic traffic assignment. In addition to presenting the conceptual design, the authors also explore issues associated with integrating these model systems, including, technical, computational, and practical issues. The research work presented in the paper throws light on some of the implementation challenges and issues as the authors built a prototype of an integrated model system using Synthetic Population Generator (SPG), CEMSELTS, CEMDAP and VISTA model implementations. The prototype was used on a sample network from Dallas Fort Worth area to explore the convergence properties, and sensitivities.

Another effort in the field of integrated demand-supply model is that of MATSim (Multi Agent Transport Simulation model (Balmer et al. 2005, 2009). The model system links activity schedules derived from a travel demand model with a dynamic traffic assignment model. Within the simulation for a year, the model system proceeds by iteratively adjusting the activity schedules in response to network conditions (feedback loops). A synthetic population is first generated followed by the generation of activity-travel demand for individual agents. In the activity-travel pattern generation, various choice dimensions are considered including activity agendas, activity schedules, location choices and mode decisions. The activity-travel information including other socio-economic information is then fed into the Iterative Demand Optimization Process – Evolutionary Algorithm. The activity-travel schedules are first routed through the network using a dynamic Dijkstra router and travel episodes are included into the activity-travel schedules. The routes are then simulated using a stochastic queue-based agent traffic simulation to obtain network conditions. Travelers then score their experience on the network, they learn from their experience, and then readjust their activity schedules to improve their network experiences. The process is repeated iteratively until individual agents can no longer improve their network experience scores.

TRansportation ANalysis and SIMulation System (TRANSIMS) constitutes another implementation aimed at integrating the travel demand and traffic assignment components of the urban system (Barrett 1999, TRANSIMS website). TRANSIMS has a number of appealing features which has led to a widespread testing and application of the model system. Firstly, TRANSIMS is capable of handling multimodal simulations that pan across various layers of networks namely highway, transit, and walk links. As with any disaggregate model, TRANSIMS proceeds by generating a synthetic population for the entire region. Activity-travel patterns are then generated for all individuals including determination of activity types, destination locations, mode choices, durations, time of day. A classification and regression tree algorithm (CART) is used to generate the activity-travel patterns of the synthetic population. The route plans are then generated for all out-of-home activities that the individuals engage throughout the day using label-constrained, time-dependent shortest path algorithm which is a modification of the classical Dijkstra's algorithm. The route plans are then simulated in the Microsimulator module of TRANSIMS. The Microsimulator module executes the travel plans while accounting for the intra- and inter-modal dynamics across layers of networks. All vehicle movements are simulated in detail second by second including driving on roads, stopping for signals, accelerating, decelerating, and vehicle lane changes. The Microsimulator employs cellular automata principles to simulate the movement of vehicles.

As can be seen there are various examples of integrated model frameworks and implementations in literature. The development of integrated models has partly been motivated by the need to evaluate complex policy scenarios that have cascading impacts across multiple facets of the urban system from land use and location choices in the longer term to routing decisions in the shorter term. The different integrated models discussed thus far do consider the above issues and address them to varying degrees often by making simplifying assumptions. However, there are no model implementations that have holistically considered and accounted for all these issues under a single unifying framework ensuring behavioral consistency. Most of the integrated models involve loose coupling of component model systems, namely, land use, travel demand and traffic microsimulation models through data exchange protocols and feedback processes. Individual model systems are applied often sequentially and results collated before passing them onto the next model system as exogenous inputs. The loose coupling approach lacks the behavioral fidelity and lacks the consistency in behavioral units, geographic entities and temporal scales that are warranted to accurately account for the impacts of complex policies. For example, an approach often used to link demand and supply models is to convert the activity-travel patterns from an activity-based travel demand model into origin-destination trip tables and provide them as inputs to a traffic assignment model. However, during the aggregation process all the behavioral representations are lost and inconsistencies are induced into underlying behaviors. While some of the frameworks from earlier literature do propose a tighter coupling across model systems, they do not describe the operational details necessary to implement the conceptual frameworks. Computational challenges also have limited the progress of truly integrated models. Component model systems are often developed using different programming languages, employing varying software engineering paradigms, and data structures. As a result, a tighter integration of the component model systems in a behaviorally consistent fashion has not been achievable and simplifications are made to represent the behavioral dependencies and inter-relationships across model systems.

In this research work, an integrated modeling framework is proposed that couples all the three component model systems of the urban system, namely, land use, travel demand, and network microsimulation in a behaviorally sound fashion such that consistency in the behavioral units, geographic entities and temporal scales is maintained across all the component systems. A prototype is developed which overcomes the computational challenges that have often hindered the development of truly integrated model systems.

CHAPTER 3

A NOVEL APPROACH TO MODELING THE URBAN SYSTEM WITH DYNAMIC TIME-DEPENDENT ACTIVITY TRAVEL SIMULATION

The discussion in the previous chapter highlights the widespread interest in integrated models of the urban system. This research effort aims to build on these frameworks and develop an integrated model of the urban system that advances the cause of integrated modeling. In the section, first the overall integrated model design is presented. This is then followed by an extended discussion on one of main topics in this research which is the interfacing between the travel demand model and the traffic assignment model. The linkage of the travel demand and traffic assignment components with the land use model and a bootstrapping procedure for generating time-dependent travel time matrices are described in the last two sections.

A. Overall Model Design

Figure 3 presents a high-level overview of the proposed integrated model design. As can be seen from the figure, the process starts with a base year bootstrapping procedure. A base year bootstrapping procedure ensures that link travel times which vary by time of day (consistent with real world network conditions) are obtained to kick start the integrated model system simulation for the base year.

In the base year simulation, first a synthetic population is generated for the region using a synthetic population generator. The land use microsimulation model is then run to simulate the longer term location choices of households, persons, firms and real estate developers. The activity-based travel demand model system then simulates the activity-travel patterns of individuals along a continuous time axis. Both the land use microsimulation model and the activity-based travel demand model utilize the network accessibility measures by time of day in generating the choices. The trips that are generated are then routed and simulated through the network in the dynamic traffic assignment model along a continuous time axis. A detailed discussion on the linkage (representing the dependencies and inter-relationships) between the travel demand and traffic assignment components is presented in the next section. The resulting network conditions, namely, the O-D travel times are then fed back into the activity-based travel demand model. Activity-travel patterns are adjusted in response to the modified network conditions and the trips are re-routed and re-simulated in the dynamic traffic assignment model. This last step is repeated iteratively until convergence is achieved in the network conditions.

The converged base year network conditions are then fed into the land use microsimulation model to simulate the location choices for a future year including the land use development patterns, household and business location choices, and other real-estate market processes (rents, prices). There are two approaches to generating the synthetic population for a future year. The first approach is to generate a synthetic population again for the future year based on the control marginal distributions for a future year. Alternatively one could evolve the base year synthetic population by subjecting them through the various individual, household lifecycle socio-economic and demographic events to create synthetic population for a future year. The activity-travel demand generation and the dynamic traffic assignment steps are then iteratively repeated (with network conditions fed back) until convergence just like the base year. This process is repeated for each horizon year.

As can be seen, the proposed approach is very generic and can be operationalized using any implementations of land use, travel demand and traffic assignment model systems so long as consistency in the treatment of behaviors, and the notions of continuity in time and space are maintained across model systems. Also, it may appear that the integrated modeling framework presented in this section resembles the sequential frameworks proposed by earlier researchers wherein model systems are loosely coupled through data exchange mechanisms and feedback loops. While the proposed approach and other frameworks may share some similarities, an important distinction can be drawn by the approach used to establish the linkages and inter-dependencies between the travel demand and the traffic assignment model systems. This distinction between the proposed model framework and the earlier integrated modeling frameworks will be highlighted in the next section.

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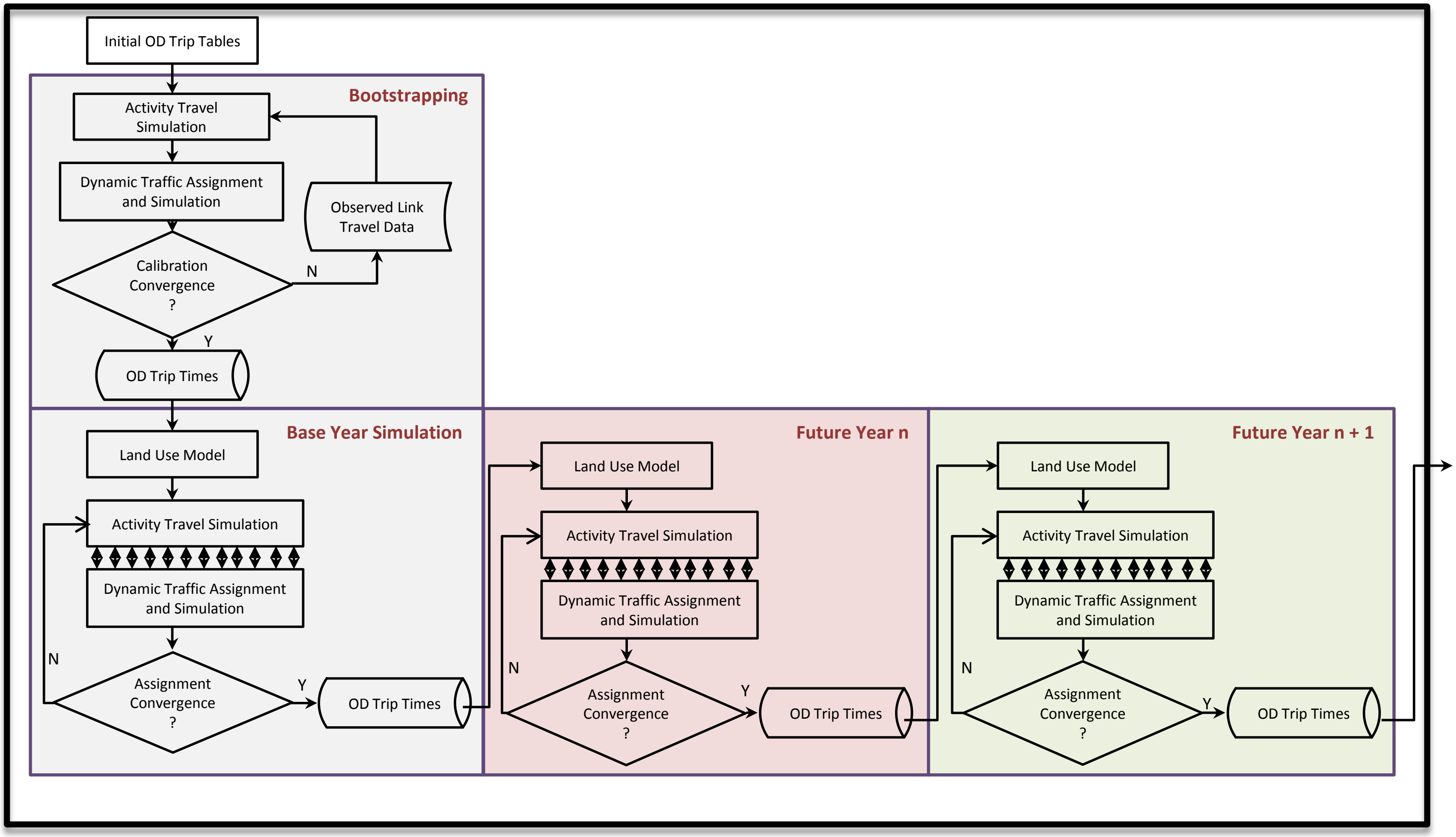

Figure 3: Overview of the Framework for Integrated Model of the Urban System

B. Dynamic Time-Dependent Activity-Travel Simulation

In this section, a detailed description of the linkage between the activity-travel demand model and the dynamic traffic assignment model is presented. While the land use microsimulation model is integral to the integrated model system, it is not as closely linked as the activity-travel demand model and dynamic traffic assignment models. This can be explained by the differing temporal scales at which the choice dimensions in the component systems operate. The land use model deals primarily with longer term choices (location, employment, residential land use) whereas the activity-travel demand model and the dynamic traffic assignment model, deal with medium and shorter term activity-travel choices including where to travel, what mode, and what route among other dimensions which are closely linked together.

An approach often proposed to integrate the demand model and the network supply model was to run the models sequentially with a feedback of the network conditions until convergence is achieved. In this integration approach the individual model systems are run independently and loosely coupled together with input-output data flows. A tighter integration paradigm was proposed by Kitamura et al (2008) to overcome the various challenges associated with sequential approaches. In the tighter paradigm, the travel demand model and the dynamic traffic assignment model are integrated by constantly communicating with each other along a continuous time axis as shown in Figure 4. The resulting activity-travel engagement decisions are truly emergent and the decision to engage in activities and the various activity-travel dimensions including activity type, activity duration, destination, departure time, route, and arrival time are generated and simulated as they happen. The design presented here builds on the event-based approach proposed by Kitamura et al (2008) with major enhancements in the heuristics employed to re-schedule activities in response to arrival time information. Activities and trips are generated along the continuous time axis and they are routed and simulated on the network as they happen.

The demand model needs an initial set of network conditions to start simulating the activity-travel choices. In particular, the mode and destination choice models use the network conditions as inputs to the mode and destination choice dimensions respectively. The mode choice set includes only those alternatives that are available at the given time while the destination choices includes only those destinations that are accessible (by the fastest mode; often this is the auto mode) without violating the time-space prism constraints. These initial travel times can be derived from a traditional four-step travel demand model. However, the network conditions derived from a four-step model are obtained from static traffic assignment procedures and do not reflect the dynamics that real-world transportation networks experience. Therefore a boot-strapping procedure is employed to obtain accessibility measures by time of day that are consistent with real-world network conditions. The bootstrapping procedure is described in a subsequent section.

Once the initial set of network conditions by time of day are available, the framework as shown in Figure 4 is employed to simulate the activity-travel decisions, route the trips, load the trips and simulate their movements on the network. The typical time resolution of an activity-travel demand model is 1 minute. Thus the day can be broken down into 1440 intervals in which activity-travel choices need to be simulated. Within each minute the demand model simulates the activity-travel engagement decisions of all individuals. Trip information is then extracted from the activity-travel engagement decisions, including, origin, destination, mode, and vehicle information and passed on to the dynamic traffic assignment for loading them on the network. It should be noted that not all activity-travel engagement decisions entail travel; only those activities with a destination different from the current location need to be loaded onto the network. The dynamic traffic assignment model in turn routes the trips and simulates them on the network. The routes are generated in the dynamic traffic assignment model based on the Wardrop's principle of user equilibrium (i.e. the trips are assigned to paths between an origin-destination (O-D) pair such that the travel time across all paths between the O-D pair remains the same). The dynamic traffic assignment model is capable of simulating at a finer temporal resolution (less than a minute). Assume that the dynamic traffic assignment model is capable of simulating vehicle movements at a temporal resolution of 6 seconds. In order to avoid lumpy loading of the vehicles onto the network within a 1 minute simulation, the dynamic traffic assignment model uniformly distributes the trips across the 1 minute simulation interval and loads the vehicles on the network every six seconds.

After loading the trips, the dynamic traffic assignment model simulates the movement of vehicles on the network. The vehicle's position is updated at the end of every six seconds. The dynamic traffic assignment stores network level of service conditions (typically the link travel times, volumes, delays among others). It is theoretically possible for the traffic assignment model system to store network level of service measures at a resolution of 6 seconds and then feed those back for the subsequent iteration. However, it becomes computationally burdensome and it may be behaviorally unwarranted to store network conditions at such a fine temporal resolution. Additionally it is hard to imagine that individuals consider network conditions at a resolution of six seconds when they make activity-travel decisions. It may be reasonable to store network conditions at the same resolution as the activity-travel demand model (at a 1 minute resolution or higher). The vehicle movements are executed on the network until the trips arrive at their intended destinations. Once the trips have arrived at their destination, the dynamic traffic assignment model passes back the arrival information to the demand model to make subsequent activity-travel engagement decisions. The activity-travel demand model then allows the individuals to engage in activities before reaching the next activity-travel engagement decision point. Since, the dynamic traffic assignment model operates at a resolution of six seconds; all the trips that have arrived at their destination within any one minute interval are collected and then the arrival information is sent to the demand model. At the end of the simulation for a day, the network conditions by time of day are processed to generate origin-destination travel time matrices by time of day for use in the travel demand model and time-dependent shortest paths between origin-destination pairs for use in the dynamic traffic assignment model in the subsequent iteration.

The steps involved in the proposed integrated framework are summarized below:

1. At time t = 1 minute, an individual who is currently at location O_1 decides to go pursue an activity at destination D_1 using a mode M_1
2. Information about all trips that need to be loaded on the network are extracted, including origin, destination, mode, and vehicle attributes and sent to the dynamic traffic assignment model to be routed and simulated on the network
3. Once the dynamic traffic assignment model receives information about all the trips that need to be loaded onto the network starting at time t = 1 minute, it identifies time-dependent shortest paths for the given origin-destination pairs based on network level of service conditions from a previous iteration
4. The dynamic traffic assignment model then uniformly distributes the trip starting time across interval (t =1 minute, t= 2 minute) and loads them on the network to avoid lumpy loading. For the sample individual considered above, the departure time on the network is t = 1 minute and 36 seconds

5. The trip is then simulated on the network while considering any modal restrictions (such as traffic backup when a transit vehicles stops at a bus station)
6. At time t = 8 minute 48 seconds, the trip was completed and the individual arrived at the destination. However, the dynamic traffic assignment model waits until t = 9 minute to send the arrival information back to the demand model to make subsequent activity-travel engagement decisions because the travel demand model operates at a temporal resolution of 1 minute
7. The individual chooses to stay at location D1 for four minutes before engaging in another trip
8. Steps (1-7) are repeated to simulate activity-travel decisions for a 24 hour period

As noted earlier, the shortest paths are based on network conditions from a previous iteration because link conditions cannot be forecast into the future without actually simulating trips (future period network conditions are needed to calculate time-dependent shortest paths). Similarly, the network conditions from a previous iteration are used to make activity-travel engagement decisions including the destinations, the modes etc. Also, though bicycling and walking are simulated as mode choices in the travel demand model, they are not actually simulated on the network. Their arrival information is estimated based on some assumptions of average bicycling and walking speeds respectively.

The proposed approach to linking the activity-travel demand system and the dynamic traffic assignment model has some very behaviorally appealing features. Firstly, the arrival times are determined by "real-time" conditions on the network along a continuous time axis and are not based on a pre-determined network state from a previous iteration. Secondly, the feedback of network conditions from iteration to iteration mimics a day-to-day learning process wherein individuals make activity-travel engagement decisions and adjustments in response to their travel experience from the previous iteration. This learning behavior is captured by the outer feedback loop shown in Figure 4. Finally, consistent with the notion of dynamic traffic assignment and changing network conditions, the shortest paths that are computed are time-dependent shortest paths. Time-dependent shortest paths explicitly recognize the fact that time elapses when one moves from one link to the next along a path. For example, say that a route comprises of five links. The travel time for the path is not the sum of travel times along the links at an instantaneous moment in time. Instead, the travel time for the path is obtained by considering the travel times across links in a time-dependent manner. For example, suppose the travel time along the first link was 6 minutes, then the travel time for the second link that is added to compute the travel time along the path is measured 6 minutes from the time the trip started. The process continues until the travel time for the entire route/path is computed.

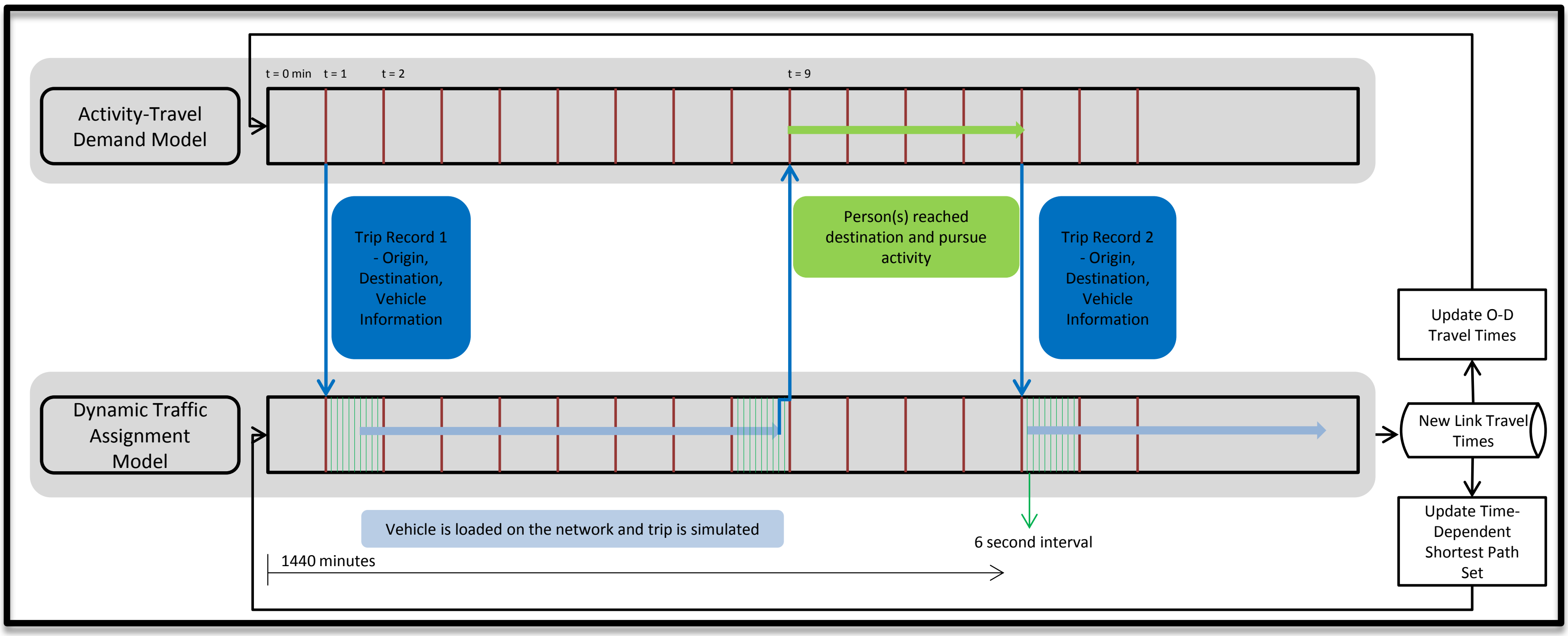

Figure 4: Framework for Integrating Travel Demand and Traffic Assignment Models with Dynamic Time-Dependent Activity Travel Simulation

C. Integration with Land Use

The framework described in the previous two sections constitutes the integration between demand and supply models along a continuous time axis. The connection and integration with the land use model completes the integrated modeling framework. The land use microsimulation model system aims to simulate the residential and work location choices of residents in a region, business and employment location choices, and other longer term processes that capture household and business evolution. The location choices are sensitive to network level of service and accessibility measures. Land use microsimulation models employ a host of network accessibility measures to capture their impact of the location choice decisions of individuals, businesses and developers.

As can be seen from Figure 3 and Figure 4, there is no instantaneous ("real-time") feedback from the traffic assignment model into the land use microsimulation model. This is because land use choices are assumed to be longer term choices whereas activity-travel and routing decisions are considered to be shorter term decisions. The accessibility indicators that people experience in one year are assumed to affect the location choice decisions for a subsequent year. Therefore the land use microsimulation operates at a temporal resolution of one year. The network level of service and accessibility measures from one year affect the location choice decisions of the next year and the location choices in turn then affect the integrated activity-travel demand and supply model system. The network level of service attributes and accessibility measures from convergence of the integrated activity-travel demand and network supply model system then again affects the land use microsimulation and process is repeated.

D. Bootstrapping: Generating Time-Dependent Network Inputs

To get the integrated model started, one needs link travel times by time of day. One approach is to obtain the travel times from a calibrated four-step travel demand model. However, these travel times are based on coarse aggregations of time (the whole day is divided into four or five time periods) and also the origin-destination matrices used are obtained from trip-based modeling approaches. As a result the travel times may not be consistent with the paradigms adopted in the activity-based travel demand and dynamic traffic assignment models. It is proposed that a boot-strapping procedure be employed as shown in Figure 3 to obtain starting values of travel times which are more consistent.

The bootstrapping procedure shown in Figure 3 closely resembles the integrated demand-supply frameworks proposed by earlier researchers wherein the travel demand model and the traffic assignment model systems are applied in sequence with feedback loops until some convergence in the network conditions is achieved. There are variants of bootstrapping procedure to obtain network measures (time-varying travel time matrices for use in the activity-based demand model and time-dependent link travel times for use in the dynamic traffic assignment model) consistent with base year conditions depending on the model system implementation for generating the demand. In the first bootstrapping procedure, a full-scale microsimulation-based demand model is run sequentially with a dynamic traffic assignment model and both model systems are run repeatedly with input-output data exchanges until convergence is achieved. In the second bootstrapping procedure, the demand is kept constant by using origin-destination travel time matrices obtained from a four step model and only the dynamic traffic assignment model is run iteratively to convergence. The choice of the bootstrapping procedure is dictated by application context. A discussion of the bootstrapping procedure employed in this research effort and the rationale for the selected approach are presented in Chapter 6.

CHAPTER 4

PROTOTYPE OF A DYNAMIC INTEGRATED MODEL OF THE URBAN SYSTEM: SIMTRAVEL

The framework presented in the previous chapter was operationalized by building a prototype of an integrated model system dubbed SimTRAVEL – Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land. In this chapter, first the model considerations that went into the development of the prototype are described followed by a discussion of the implementations of component model systems used to build the prototype. In the third section, the behavioral and computational linkages across travel demand and traffic assignment model systems are presented in detail.

A. Prototype Design Considerations

As with the design and development of any model system, there are issues that need to be identified and addressed. This exercise becomes all the more important in the context of integrated model system which aims to link model systems representing the different components of an urban environment, namely, land use models that simulate the longer term location choices, travel demand models that generate the medium and shorter term activity-travel choices, and traffic assignment models that mimic the shorter term route choice decisions. A number of these considerations have been identified in literature earlier and have been addressed to varying degrees in previous implementations of integrated models. The proposed framework and implementation builds on previous literature and attempts to address the various considerations which were either addressed by making simplifying assumptions or in some instances ignored.

Choice of Behavioral Unit

In any microsimulation model system, the first task is to identify the behavioral unit at every choice step and often the behavioral units vary across choice steps. For example, in the land use model, the behavioral unit is a household when making the determination of a household's location whereas in the choice of workplace location, the behavioral unit is the person (individuals within the household). The issue of identifying behavioral units is amplified further in the case of integrated model systems. While it may be a challenge to identify and accommodate different behavioral units for the different models within the integrated model system, it is important to understand that the identification of behavioral units is necessary and desirable so as to accurately establish the behavioral soundness of the models and the choice processes they represent. A secondary issue that arises due to variation in the behavioral units across models is that of book-keeping. Appropriate book-keeping mechanisms need to be implemented within microsimulation model systems to ensure consistency and to keep an accurate tracking of agents and resources including households, persons, vehicles, riders, and other agents throughout the model system. Book-keeping mechanisms also allow one to incorporate additional behaviors like constraints and interactions which are important factors in shaping location choices and activity-travel engagement decisions.

Identification of Choice Dimensions and Representation of Decision Hierarchies

The main aim of an integrated model system is to represent the entire range of choices that represent an urban system including longer term location choices of households, persons, and businesses, medium and shorter term activity-travel choices of households and persons, and routing choices of individuals. A major challenge in this process is to identify the various choices. Further each of the choice dimensions may be characterized by a series of attributes that need to be identified and specified. For example, within the travel demand model, the fixed activity schedule generation will comprise a submodel generating the number of fixed activity episodes including work and school, a series of submodels for identifying the temporal anchors for the fixed activity episodes (both work and school). Also, with recent advances in methodological approaches, availability of richer data on individual decision making behavior and the computational advances combined with the growing need to analyze complex policies has led to a growing interest in incorporating additional choice dimensions in model systems of the urban system. For example, there has been a growing interest in incorporating models of vehicle fleet composition and vehicle type usage so as to evaluate policies aimed at impacting vehicle holding and vehicle usage patterns (e.g. impact of hike in fuel surcharges on VMT - Vehicle Miles Traveled, impact of providing incentives for buying cleaner and greener cars).

In addition to identifying all the choice dimensions that represent an urban system, one also needs to accurately identify and represent the decision hierarchies across choice dimensions. The literature on activity-travel behavior is replete with examples of interaction between choice dimensions. For example, activity type choice affects destination and mode choices, solo versus joint activity engagement, and time of day choice, activity duration affects timing and vice versa, travel duration affects activity duration and vice versa, vehicle ownership affects mode choice and destination choice. In all of these instances, multiple dependent (endogenous) variables affect one another calling for the adoption of simultaneous equations model frameworks that reflect the simultaneity in many choice processes. Even within simultaneous equations model systems, one needs to determine the appropriate model specification, error correlation structure, and dimensionality of the model system (Ye and Pendyala 2009, Konduri et al. 2010). The representation of decision hierarchies is not just limited to choices within the travel demand model system and they permeate across model systems. For example, if one were to consider the classical self-selection problem in residential location choice modeling, residential location choice is endogenous together with vehicle ownership, vehicle fleet composition and vehicle usage patterns (Eluru et al. 2010). It can be seen that the residential location choice is part of the land use model and vehicle fleet and mode choice are part of the travel demand model. Recent work in this area has shed light on appropriate decision hierarchies and highlights the importance of accounting for interactions across choice dimensions and specifying appropriate decision hierarchies.

Representation of Space

Most of the choice dimensions that are considered in integrated models have a spatial attribute attached to them. Traditional models of land use and travel demand have operated at an aggregate resolution of space, namely, traffic analysis zones (TAZ). However, with the advent of microsimulation-based approach to modeling the urban system, there is a growing interest to represent space at a finer scale. Census provides data at the spatial resolution of census tracts, blockgroups, and blocks, local planning agencies now maintain land use data at individual parcel level, with some agencies even keeping stock of buildings within parcels, employment by type within those buildings or real estate by type and occupancy within those buildings.

The choice of the spatial unit and its representation in the integrated model system is constrained by a multitude of factors. First, the availability of data imposes a major constraint on the representation of space. Not all agencies maintain land use data at the most disaggregate level. Therefore it may not always be possible to represent space at the most disaggregate resolution of buildings or parcels. Second, the choice and representation of spatial resolution is affected by the decision making process underlying the choice under consideration. How do people perceive space when making location choices? Is there a hierarchical decision making process involved in making location choice? For example, it may be plausible to assume that when making residential location choice, households first make a choice of a certain area within the region based on some socio-economic and demographic attributes of the area, transport accessibility measures with respect to their fixed activity locations like school and work. Then, after making the choice of an area within the region they may then make the choice of the neighborhood, subdivision, parcel, and finally the individual building unit. The choice of destination locations may also range in choice from zones at one extreme to individual building units at the other extreme. If the individual wishes to go grocery shopping then it may be more appropriate to treat space at the parcel (or building unit) level. However, if an individual wishes to go window shop in area before purchasing something, then a higher spatial resolution like say TAZ may be the appropriate unit of analysis. Third, the disaggregate representation of space is associated with computational overhead (both processing and memory related). The roadway networks associated with a finer spatial resolution are generally larger (exponentially proportional to the number of spatial units) and are difficult to handle. While there are operational land use models that have represented space at the lowest resolution of parcels, such a finer scale representation of space hasn't been carried out in travel demand and traffic assignment models.

Representation of Time

Many of the same issues that are encountered in the representation of space are also encountered in the representation of time. When considering the time dimension in integrated models, on one extreme the location choices like work place location choice, residential location choice, school location choice, real estate development patterns evolve over yearly/multi-yearly time frames. On the other extreme, the simulation of vehicular movements in the traffic assignment models occur in time steps of seconds. And there are other choice processes within the integrated model system that proceed and evolve in time steps that are between these two extreme representations of time. For example, the vehicle fleet choices may be medium-term (yearly) to longer-term (multi-year), activity-travel choice dimensions may vary from longer term to shorter term. The activity-travel choice dimensions of fixed activities may be considered longer term decision processes, the commute level trip attributes like departure time, departure mode, and trip chaining patterns may be considered shorter term choices. Activity-travel dimensions (including the associated trip level attributes) for non-fixed activities like discretionary and maintenance activities may be considered shorter term and assumed to vary from day-to-day. The temporal scale of a choice process also determines the structure of the feedback loops which are established to obtain convergence. For example, the longer term choice processes like location choices, fixed activity schedules may be simulated once for a base year whereas the shorter term day-to-day activity-travel choice processes may be repeated across iterations until some convergence criterion are satisfied. Therefore, it is important to recognize the differences in temporal scales across choice dimensions so that appropriate model structures are used in establishing linkages.

Additionally the accurate representation of space and time is also important to generate location choice sets when generating the activity-travel choices for individuals within any open time-space prism, and representing activity-engagement interactions. Time-space prisms represent the constraints that influence and govern activity-travel patterns that are measured and observed in travel surveys. The explicit consideration of time-space interactions provides the ability to intelligently sample destination choices for modeling activity location choices and allow for simulating activity-engagement decisions.

Representation of Time-Dependent Networks

The representation of networks has gained much attention with the advent of microsimulation models of land use and transport systems. Networks are comprised of nodes (representing intersection elements) and links that connect nodes (representing the roadway elements). In addition to these, networks are also comprised of additional nodes representing generators and attractors (TAZ centroids in a zone based representation of space, individual activity locations in a finer representation of the network). Transit networks are also comprised of nodes and links like roadway network but additionally they also include additional elements to represent the access to transit by walk and auto. In most traffic assignment models, transit is not treated at the same fine grained resolution as roadway users wherein individual agents are tracked across multimodal networks between origin-destination pairs throughout the day.

In this research effort, given the emphasis on microsimulation approaches to land use and transport systems, the network representation will be at a finer resolution with high fidelity. Also, since the dynamic traffic assignment models will be used for routing and simulation of trips, time-dependent network conditions at a temporal resolution consistent with behavior are necessary. In addition to the regular network attributes such as travel times, time-dependent networks will also include cost attributes such as transit fares, parking pricing, and tolls. All the links will include lane configuration, speed limits, and percent trucks information, and nodes that represent intersections will include information regarding turning bays, intersection control and potentially could include signal phasing plans (subject to data availability).

Transit adds a challenging dimension in the microsimulation modeling context. When activity-travel patterns are simulated, there is no guarantee that the time of day choice will be consistent with the availability of transit as dictated by transit schedules. Therefore it is important to have a transit network that includes detailed information on stops, routes, schedules by time of day, transfer points, access and egress opportunities so that transit trips can be accurately modeled. In case of transit modes sharing the roadway network, both networks need to be integrated to reflect the influence of one on the other (transit vehicles on auto and vice-versa). Additionally, transit schedules and routes affect activity timing, destination and mode choices particularly in trip chaining contexts. Microsimulation approaches provide a good avenue to incorporate these behaviors by introducing necessary heuristics at critical decision steps in the transit modeling process to keep track of riders, adjust their activity-travel patterns to be consistent with transit schedules and network performance, and track them through their tours to completion (for example, a traveler should not be left stranded at a time and place when transit is not available).

Representation of Stochasticity

Human behavior is complex and is characterized by considerable randomness. This randomness in the decision making behavior exhibited by individuals is best described as a stochastic process and is modeled using probabilistic model forms and specifications. Also, in traditional surveys, one cannot obtain all attributes contributing to an individual's decision making behavior. Therefore there is a need to account for these unobserved attributes in models to avoid incorrect inferences. Often the randomness exhibited by individuals along with the unobserved attributes is captured by specifying an error term in models and a probabilistic distribution form is assigned to this error term. Additionally error correlation structures are specified to capture the correlation across decision variables or across choice dimensions due to common unobserved variables to avoid incorrect inferences of coefficient estimates (Mannering 1986, Pendyala and Bhat 2004, Konduri et al. 2010).

In a microsimulation model system, the simulation proceeds by first specifying a random seed and then running a series of models and submodels to simulate the choices of individuals. The choices then correspond to one stochastic realization of the human decision making behavior and is dependent on the random seed. If one were to change the random seed, another realization of the human decision making behavior is obtained. As can be seen by changing the random seed one can simulate the stochasticity in human decision making. The issue then is to determine how many times the choices should be simulated to assess the impact of policy on human behavior. There are two approaches that have often been used to study systems that are stochastic. The first option is to perform a number of runs and then average the results across the runs to represent an average outcome or forecast. The second options also entails performing a number of runs but then instead of reporting the outcomes in an aggregate form like the previous option, report the forecasts in a distributional form and report an acceptable range (confidence intervals) as opposed to point estimates for potential outcomes or forecasts. The latter option may be more appropriate in this context as this captures the stochasticity associated with human decision making behavior and provides a range of possible outcomes.

Representation of Activity Types

The representation and classification of activities into activity types (trip purposes) has been a subject of much interest. In the past activities were classified into mandatory activities, flexible activities and discretionary activities based on the temporal and spatial rigidity (or flexibility) of the activities. Mandatory activities are those that were fixed in time and space, flexible activities are those that can be shifted either in time or space or both time and space but cannot be forgone whereas discretionary activities are those that are flexible in time and space and those that can be foregone. Activities such as work and school are generally classified as mandatory activities, shopping and personal business related activities are classified as flexible activities and social recreation and entertainment type of activities are classified as discretionary activities. While this basic activity classification has served well in previous implementations of activity-based models, the classification lacks the richness of information due to the coarser classification and may lead to poor sensitivity of the models. Also, it may be hard to incorporate household interactions in models of activity-travel engagement due to the coarser classification based only on temporal and spatial flexibility (Doherty 2006).

In the activity-based travel demand model that will be employed in the integrated model, it is important to have a robust treatment of activity types because for any base year, first a primary skeleton of activities is constructed for each individual (comprising of mandatory activities followed by flexible activities) and then the activity-travel engagement decisions for discretionary type activities are evolved over the course of a day in response to network conditions. Additionally, the activity-based travel demand model also locks the skeleton of activities of individuals within a household based on intra- household interactions (such as child related activities) and the activity classification should consider the joint activity-travel engagement in addition to the temporal and spatial flexibility. Therefore it is important to have an activity type classification which will allow for accurately constructing the activity-travel skeletons of individuals while recognizing the household interactions.

Feedback Processes: Behavioral and Computational

There is both a behavioral and computational consistency motivation for including feedback processes in integrated models of urban continuum. Network conditions directly impact various dimensions of the activity-travel engagement, namely, activity generation, activity scheduling, time of day choice, destination choice, and activity linking or trip chaining. For example, if it is likely that a time-space prism constraint is going to be violated, an activity may be shifted to another open time-space prism period, thus shifting the activity in time. Alternatively, the activity may be pursued at an alternative destination which is closer to the current location of the traveler thus resulting in savings in travel time and adherence to time-space prism constraints. Another possibility, particularly for those activities where spatial and temporal fixity is quite rigid, includes a modification of the duration of the activity. For example, if one is running late for work, a movie, or a restaurant, the duration of that activity may be shortened by the amount equal to the excess travel time. The converse is also true; when travel times are less than anticipated, then a new activity may be inserted into the agenda, an activity originally scheduled for a different time period may be shifted in time to fill up the excess time available in the current time-space prism, a traveler may visit a more desirable destination that is farther away, or an existing activity may simply be prolonged in duration to fill up the extra available time. Therefore there is a need to incorporate feedback processes that reflect the behavioral adjustments and adaptations that people make to their activity-travel engagement patterns in response to network conditions. Additionally there is a computational consistency motivation for inclusion of feedback loops (Siegel et al, 2006). Network conditions serve as inputs to various dimensions of activity-travel engagement as noted earlier. Once the activity-travel engagement patterns are generated, they are then loaded on the network (trips are routed and simulated) resulting in another set of network conditions. It is desirable to ensure that network conditions that serve as inputs to a travel demand model are consistent with the network conditions that are obtained from the traffic assignment model. Procedures of feedback processes to address consistency of network conditions have been addressed by Boyce and Bar-Gera (2003, 2006). The authors suggest the use of averaging techniques across iterations to avoid oscillations in the convergence criterion and to reach a stable solution efficiently. It should be noted that while the network conditions affect the location choices in a land use model, the linkage represents an evolution of the system over time wherein network conditions of one year affect the location choices and land development patterns of the following year. The linkage does not represent a feedback process as there is no iterative process involved between the land use model and traffic assignment model.

Model Calibration, Validation, and Sensitivity Analysis

Model calibration, validation, and sensitivity analysis are three important aspects of any modeling effort. These issues are of even more significance in the integrated model system which comprises of three different component systems (land use, travel demand and traffic microsimulation) each with their own set of models and submodels. In model calibration, the coefficient estimates are modified to match the model outputs with observed patterns of individual decision making behavior (collected through travel surveys). Model validation on the other hand involves comparing aggregated model outputs with observed ground counts (for example, link traffic volumes, transit route ridership and stop boardings, business and employment characteristics). While model calibration ensures that model systems are able to closely represent the individual's decision making behavior, model validation ensures that the model systems closely represent the real world conditions. In the context of integrated model system, it is necessary to incorporate feedback loops and re-calibrate and re-validate the models as necessary to obtain results that are consistent. In addition to model calibration and model validation, one also needs to establish a series of heuristics to ensure consistency in predicted model behavior at the disaggregate level. For example, household and person activity-travel decisions simulated by a travel demand model have to be logical and consistent. Children that are dependent on adults cannot be abandoned; a person should not engage in multiple activities at the same time, joint activities across household members should be spatially and temporally feasible. Similar heuristics can also be established in the context of land use and traffic assignment components of the integrated model.

A key motivation for a truly integrated model system is the ability to analyze policies and impacts of socio-economic and demographic changes in a modeling environment where the individual behaviors are represented consistently across the wide array of choices that constitute the urban system. A truly integrated model system provides the ability to capture the direct and indirect effects of changes to the system as effects are felt throughout the model continuum. For example, a developer's land use development choices will affect the household and business location choices, which in turn impact the entire range of activity-travel choices, and traffic patterns. Therefore it is important to have a robust model that is responsive to policy changes, including, socio-economic, demographic, land use, network conditions, and travel demand management measures. For example, the model system should be able to respond to land use policies including those that promote transit-oriented development along new major transit routes and light rail lines and zoning policies that promote new mixed use development in an area. The model system should be able to reflect the impacts of corridor or area-wide pricing policies, fuel price shifts, parking pricing, and the entire range of network level of service impacts. These include anything from simple capacity expansion to more sophisticated dynamic tolling methods that can be analyzed using dynamic traffic assignment models embedded within integrated model systems. The model system should be capable of responding to shifts in socio-economic conditions in the area. Shifts in population and employment characteristics bring about shifts in activity-travel demand. All of the changes noted here may happen at the macro- or micro- level and the model system should be able to respond to these changes appropriately.

Software Architecture, Data Structures and Computational Issues

As noted in an earlier discussion, the modeling of components of the urban system has occurred mostly independently in the fields of land use, travel demand and traffic microsimulation. The individual model systems have been developed on different paradigms of software architecture, adopting different data structure designs and are subjected to varying sets of computational issues. The component model systems are often developed using different programming languages. As a result, it is often difficult to establish linkages across models systems in a seamless fashion based on sound behavioral foundations due to the computational limitations. Researchers have often made simplifying assumptions on the linkages by applying the model systems sequentially. While the approach has served well previously, the growing emphasis on more sound representation of individual decision making behavior has called for a tighter coupling between model systems. Secondly, microsimulation approaches to modeling the urban system are subject to large data and memory requirements, and call for huge software and hardware resources to run model systems of this nature. This is particularly true for large urban areas where one is dealing with millions of parcels in land use model systems, millions of persons in activity-travel demand model systems, and tens of millions of trips in dynamic traffic assignment. The problem is only magnified once feedback loops are accounted for. The development of integrated microsimulation model systems has been partly hindered by the software architecture differences, data structure handling, and computational limitations.

Advances in the field of computer hardware and software allow one to address some of the issues highlighted above. There are various programming paradigms and libraries in place which allow one to make functions calls from a model system written in one programming language to a model system written in another programing language (for example, one can make function calls from a dynamic traffic assignment model coded using C++ to a travel demand model developed using Python or vice versa using the concepts of embedding and extending). This however calls for a good Application Passing Interface (API) design so that the necessary function calls across model systems can be facilitated. Advances in the database management systems allow for very efficient way to organize, store, manage, and manipulate large data sets. Additionally, there is need for maintaining consistency and parsimony in data structures in the context of the development of the integrated model system because model systems often share the same data. For example, mode choice and destination choice models use network level of service measures to model choice behavior. Similarly, land use microsimulation models use network level of service measures from one year to model development and location choices of the following year. Socio-economic data is used by the population synthesizer and in modeling location choices in the land use microsimulation model system. The dynamic traffic assignment model and model calibration and validation steps involve the use of traffic volume information. As can be seen, the same data items serve as inputs for modeling different choice behaviors. It is desirable to have parsimony in databases where different model components can access the same information from the same database as needed. This can be facilitated by database management systems which also lend themselves to simultaneous access from different model systems. The computational issues associated with disaggregate representation of agents and their choice processes can be handled by modern day hardware systems. Additionally there are software paradigms in place like parallelization, namely, symmetric multiprocessing (SMP), message passing Interface (MPI) and socket programming, wherein one can distribute the computational load across available computing resources to gain efficiencies in run times.

Model Considerations and Treatment in SimTRAVEL

All of the issues noted above were considered in the development of the SimTRAVEL prototype. The degree to which the different design aspects were considered and addressed was dictated by two key factors. First and the most important factor was availability of data. While the intent was to introduce as much fidelity as possible in the behaviors, the temporal units and spatial scales, the prototype development was limited to a certain extent by the availability of data. Second factor that guided the prototype development effort was computational tractability and feasibility. Though there have been tremendous computational advances, there is still significant overheads associated with simulating millions of agents their behaviors and tracking their movements through the different dimensions of the urban system. Nonetheless the prototype developed comprises a significant contribution that addresses all of the key design considerations that go into models of the urban system. Table 1 and Table 2 provide a summary of the different design considerations and the treatments applied in the initial prototype of the integrated model system – SimTRAVEL. Figure 5 provides a high level overview of the process flows in the integrated model prototype, temporal scales at which the various model systems are operating and the behavioral and computational feedback loops entailed in the integrated model run for a horizon year. The emphasis of this research effort was in the development of the transport component of the prototype and the application of the prototype to simulate activity-travel engagement patterns in the base year. Therefore the discussion in the table and subsequent chapters has a significant emphasis on the integration of the travel demand and traffic assignment components of the urban system; while the integration of the land use component adheres to all of the design considerations noted in this chapter, the discussion is just limited to integration of the transport components of the urban system.

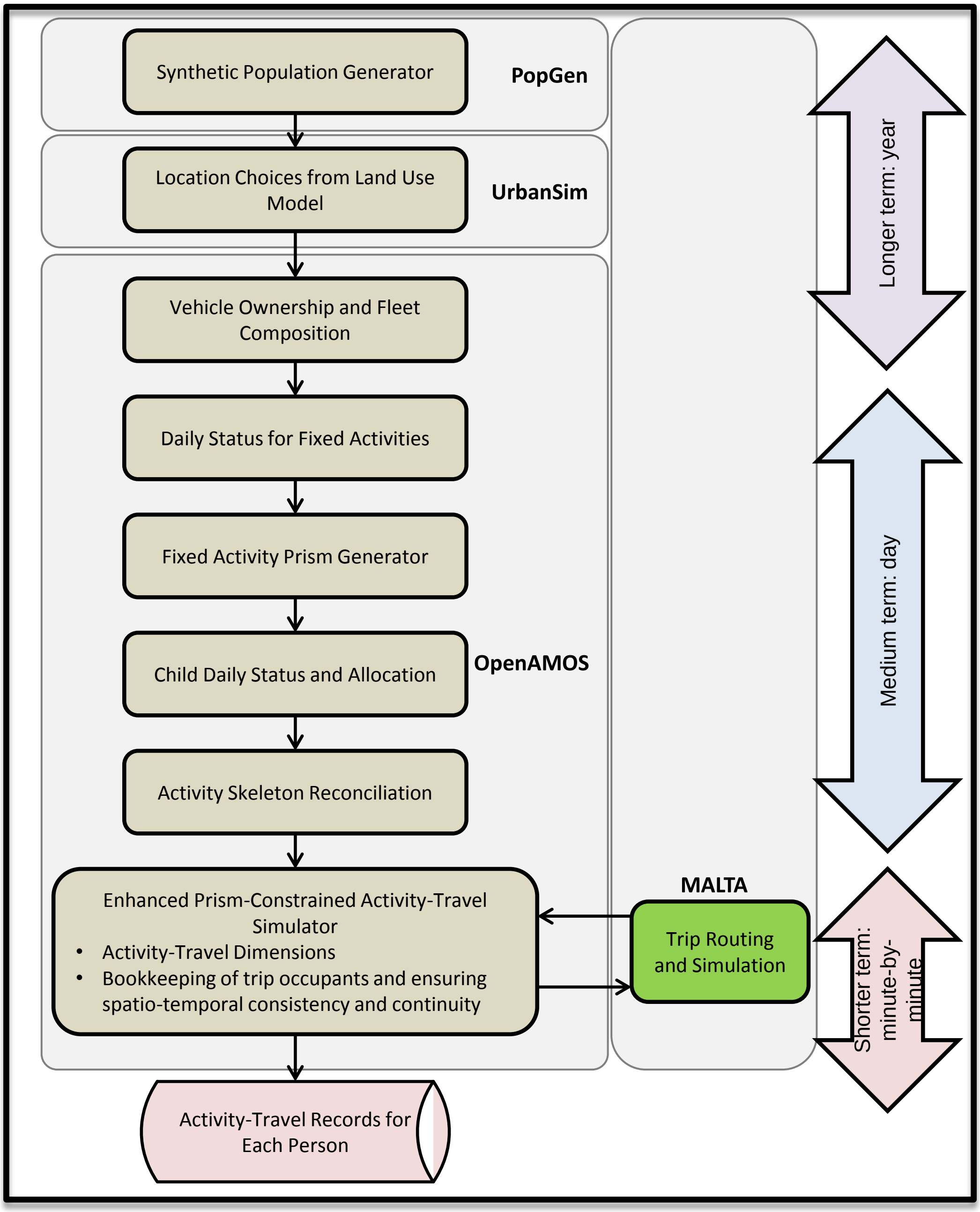

Figure 5: Overview of the SimTRAVEL Integrated Model Prototype

Table 1: Summary of the Model Design Considerations and the Treatments Implemented in SimTRAVEL

	Challenges	*Proposed Treatment*
1.	Choice of Behavioral Unit	Individuals are the basic units of analysis; the activity-travel patterns of individuals are generated while considering the various interactions (child dependency and allocation, joint activity engagement)
2.	Identification of Choice Dimensions and Representation of Decision Hierarchies	Choice dimensions for various attributes of activity-travel engagement were identified, and decision hierarchies were established. In the initial prototype, the choice dimensions were estimated using independent modeling frameworks. Chapter 5 describes the travel demand model system and the enhancements over its legacy implementation. Chapter 6 presents some empirical research looking at choice dimensions simultaneously
3.	Representation of Space	The basic unit of space is traffic analysis zone
4.	Representation of Time	The temporal scales of various choice dimensions have been identified and are indicated in Figure 5. Feedback processes are appropriately incorporated to reflect the dependencies across choice dimensions. Activity-travel patterns are generated at the temporal resolution of 1 minute and traffic simulation is performed at a resolution of 6 seconds
5.	Representation of Time-Dependent Networks	Network level-of-service conditions by time of day are considered using skim matrices for 24 hourly periods in a day
6.	Representation of Stochasticity	Random utility based frameworks are employed and appropriate modeling methodologies are used to model the various choice dimensions and account for stochasticity
7.	Representation of Activity Types	In-home activity engagement patterns are considered in addition to a host of out-of-home activity types (including, work, school, personal business, shopping, eat meal, social, sports and recreation, other, pickup, drop-off) to cover the full range of activities that people participate in during the course of day.
8.	Feedback Processes: Behavioral and Computational	Feedback structures were employed to capture computational and behavioral inter-relationships and dependencies across components of the urban system

Table 2: Summary of the Model Design Considerations and the Treatments Implemented in SimTRAVEL (continued)

	Challenges	*Proposed Treatment*
9.	Model Calibration, Validation and Sensitivity Analysis	Model calibration was performed using a 5 percent sample by trying to replicate weighted survey distributions. While validation was not done in the traditional way by using a hold out sample technique due to the limited sample size. Validation was performed by means of replicating activity-travel characteristics observed from the survey sample. Replication was limited to travel demand characteristics and was performed by comparing a host of activity-travel engagement attributes obtained from full population runs against observed weighted survey distributions.
10.	Software Architecture	Python and C/C++ programming language are used in component model system implementations.
11.	Data Structures	PostgreSQL - a very mature and open source Relational Database Management System (RDBMS) was used for data storage needs in OpenAMOS, UrbanSim utilizes a native data format and MALTA does not employ any database system and uses flat file formats to store and retrieve data
12.	Computational Issues	Instead of approaching the simulation using a purely agent-based paradigm where activity-travel engagement decisions are generated by subjecting the agent through the various activity-travel choice dimensions, a hybrid approach was adopted. In this hybrid approach, for choice dimensions that do not involve rules/heuristics for generating the choice, a matrix approach is used wherein each individual row corresponds to an agent and the calculations proceed by using matrix capabilities. For choice dimensions that do not involve rules/heuristics for generating the choice, the choices are generated one agent at a time.

B. Component Model System Implementations in SimTRAVEL

In this section, the implementations of component model systems that were used to build the integrated model prototype - SimTRAVEL are briefly described.

Synthetic Population Generator

The first input for the application of any microsimulation model system is socio-economic and demographic data about every household and person in the region. This data is generally not readily available. However, disaggregate socio-economic and demographic data about household- and person-level characteristics of interest are available for a sample of the population in the region (e.g. travel surveys, and census decennial survey) and aggregate marginal distributions of key household- and person-level variables of interest (e.g. agency forecasts, census summary files) is available. Synthetic population generators are often used to expand the disaggregate sample so that known aggregate distributions are matched to generate a synthetic population for a region. In the context of generating a synthetic population, it is important to ensure that the synthetic population generator employed can not only match given distributions of household variables of interest but also known distributions of person variables of interest. This will ensure that the synthetic population closely matches the household and individual socio-economic and demographic profiles of region which in turn impact the land use, activity-travel engagement and route choice decisions.

PopGen - a synthetic population generator is used to generate a synthetic population for the region in SimTRAVEL. PopGen implements a heuristic algorithm called Iterative Proportional Updating (IPU) algorithm for generating a synthetic population while ensuring that household- and person-level marginal distributions are matched simultaneously (Ye et al. 2008). PopGen is a stand-alone open-source software package developed using Python and is available to the public under the GNU General Public License (GPL) agreement.

Land Use Microsimulation Model

The land use microsimulation model that will be employed in the development of the SimTRAVEL prototype is UrbanSim. UrbanSim is an open-source land use microsimulation model which comprises of a series of models that simulate the location choices of households, persons, businesses, real-estate agents while explicitly considering the zoning policies and restrictions that built environments experience. UrbanSim is also developed using python and available under the GNU GPL agreement.

Activity-Travel Demand Model

The travel demand microsimulation model system that will be employed is OpenAMOS. OpenAMOS is an open-source activity-based travel demand model system which generates the activity-travel patterns of individuals. OpenAMOS builds on previous work namely, AMOS (Activity-Mobility Simulator) and its implementation for the state of Florida called FAMOS (Florida Activity-Mobility Simulator). AMOS comprises of two major components namely, the Household

Attributes Generation System (HAGS) and Prism-Constrained Activity Travel Simulator (PCATS). Some fundamental behavioral paradigms have been preserved in OpenAMOS from the legacy implementation. However OpenAMOS enhances the model framework to more realistically represent individual activity-travel decision making behaviors and the constraints they experience including child dependency and allocation, intra-household activity-travel engagement interactions, multi-modal trip generation among others which were not adequately addressed in the legacy implementation. OpenAMOS is implemented in Python and is available to public under the GNU GPL agreement.

Dynamic Traffic Assignment Model

The dynamic traffic assignment (DTA) model system that was deployed in the integrated model prototype is MALTA (Multi-Resolution Assignment and Loading of Traffic Activities). The traffic assignment process in MALTA is handled by a new Hierarchical Time Dependent Shortest Path (HTDSP) algorithm for the highway modes. The MALTA model system is primarily written in C++. The model system is also open-source, similar to the other packages that are used in the development of the prototype, and is available to the public under the GNU GPL agreement.

C. Linking Component Model Systems

In order to implement the integrated model framework described in Chapter 3 and build the SimTRAVEL prototype, there was a need to establish a number of linkages across component model systems. While some linkages across component systems required a simple interfacing with input-output data flows (the outputs generated from one system serving as inputs to the other system), there were other linkages that required a tighter coupling in order to ensure consistency in the representation of individual agents, and their behaviors. The choice between interfacing and tighter coupling was driven by the behaviors that needed to be linked across component systems and the temporal resolution at which those behaviors operated. The linkages between the component model system implementations namely, the land use model – UrbanSim, the travel demand model – OpenAMOS, and the dynamic traffic assignment model – MALTA are described in detail below.

Linking UrbanSim and OpenAMOS

As discussed in an earlier chapter, the location choices of individuals, businesses, developers, and governments affect the activity-engagement patterns of households and individuals. The processes underlying location choices operate on a longer-term horizon. Therefore location choices of the urban system are only influenced by the network conditions that are generated at the end of the previous horizon year, and the location choices are assumed to remain fixed when simulating the urban system for a horizon year.

Given the temporal scales at which UrbanSim (land use model) and OpenAMOS (travel demand model) operate, the linkages across the component systems is achieved through input-output-data flows using a common shared database. At the start of the simulation for a horizon year, UrbanSim generates the fixed activity location choices of every household- and person- in a region and writes it to the shared database. OpenAMOS uses the fixed activity location choices to build skeletons of activity-travel schedules.

Linking OpenAMOS and MALTA

As noted earlier one of the main topics of this research effort was to establish the linkage between the travel demand and traffic assignment model in a behaviorally consistent fashion. The framework for integrating the travel demand and traffic assignment model systems described in Chapter 3 calls for a tighter coupling of OpenAMOS (travel demand model) and MALTA (dynamic traffic assignment model) as there is a need for passing information between the model systems along a continuous time axis. At the start of each simulation interval, OpenAMOS generates activity-travel engagement decisions for all individuals that have an open time-space prism and passes information to MALTA about those individuals that are embarking on a trip. MALTA in turn identifies routes for those trips, loads those trips, and simulates them through the network. MALTA also collects and passes back information about trips that have arrived at their destination in the previous simulation interval to OpenAMOS to make subsequent activity-travel scheduling and re-scheduling decisions. This process is repeated for every simulation interval during the day to generate activity-travel engagement patterns for every individual for an entire day. At the end of iteration, convergence measures are computed both on the supply side and demand side. If convergence is achieved both on the supply side and demand side then the process is stopped and the simulation of the urban system for a horizon year is complete. However, if convergence was not achieved then there is a feedback of network conditions to OpenAMOS and MALTA and the process is repeated iteratively until convergence is achieved.

As noted in an earlier section, one of the challenges to the development of truly integrated model of the urban system has been computational challenges. Often component model systems are developed using different programming languages and integrating the software becomes a challenge and is sometimes not possible given the limitations of programming language employed. Even in cases where the integration across programming languages is possible there is need for a well-designed Application Passing Interface (API) to enable communication across component systems. Also, the data storage and retrieval mechanisms employed by the individual model systems make it difficult to interface.

Similar challenges were faced in the context of SimTRAVEL prototype development because OpenAMOS is developed using Python programming language and MALTA is programmed using C++. However, Python is a high-level programming language and is built using C. The built-in C API to the Python interpreter was used to communicate between OpenAMOS (written using Python) and MALTA (written using C/C++) without having to resort to loose coupling of the software and compromising on the underlying behaviors.

In order to implement the integration between OpenAMOS and MALTA with dynamic hand shaking, there was a need to build low level programming code involving the Python interpreter. There were two approaches that one could adopt in order to implement the minute-by-minute handshaking, namely, extending and embedding. In the extending approach, a wrapper is built around the MALTA code which is written in C++ and OpenAMOS interfaces with MALTA through the exposed MALTA API. Alternatively, one can embed OpenAMOS which is written in Python so that the MALTA code can make calls to OpenAMOS to enable the hand shaking. After exploring the underlying data structures and the programming paradigms, the embedding approach was pursued to integrate the model systems consistent with the proposed framework. The embedding approach has a very intuitive appeal with MALTA in the driver's seat and OpenAMOS serving as a decision engine simulating behaviors of agents. MALTA makes calls to OpenAMOS at the start of every simulation interval to make scheduling and re-scheduling decisions for agents and provide information about trips and MALTA in turn routes and simulates the trips, and returns arrival information about trips that have reached their destination.

Linking MALTA and UrbanSim

The location choices of individuals, businesses, developers, and governments are impacted by network conditions. At the end of the simulation of the urban system for a horizon year, the network conditions including travel time matrices and accessibility measures feed as inputs to the location choices of different agents in the subsequent horizon year.

Again owing to the differing temporal scales at which UrbanSim (land use model) and MALTA (traffic assignment model) operate, the linkages across the component systems is achieved through input-output-data flows. At the end of simulation for a horizon year, MALTA generates travel time matrices and other network accessibility measures in the form of text files which are then processed by UrbanSim for generating location choices.

Schedule Adjustment Heuristics in the OpenAMOS-MALTA Interface

A key feature of the framework presented in Chapter 3 is the Dynamic Time-Dependent Activity-Travel Simulation. The dynamic framework goes beyond traditional approach to integrating the travel demand and traffic assignment model systems by adopting an event-based paradigm that ensures consistency and continuity in the representation of individual agents and their behaviors. In order to conform to the framework presented and ensure behavioral consistency, a number of rule-based heuristics were employed in OpenAMOS (travel demand model) to represent the schedule adjustment behavior exhibited by individuals in response to real-time arrival information obtained from MALTA (traffic assignment model).

The literature on schedule adjustment behavior of individuals in response to arrival information is few and far between. As a result some of the heuristics implemented in SimTRAVEL may comprise a strong assumption of underlying activity-travel decision making behavior. Nonetheless the heuristics employed ensure behavioral consistency and continuity and the software infrastructure employed is very robust which can easily be enhanced with more refined heuristics based on observed behaviors as and when data and literature become available. Below is a description of all the heuristics employed in SimTRAVEL to represent the schedule adjustment behavior in response to real-time network arrival information:

- Person arrives earlier than expected: In this case the destination activity is pushed to earlier so that the activity starts as soon as the person arrives at the destination. Also, the person engages in the activity for the full length of the planned episode. In addition to engaging in the destination activity for the full planned duration, the early arrival also impacts the activity-travel engagement downstream of the destination activity. The person now has a wider time-space prism immediately following the destination activity and this could result in new/adjusted activity-travel engagement. For example, the person may engage in another non-fixed activity before heading to his next fixed activity episode without violating time-space prism constraints resulting in a new activity-travel engagement. Alternatively, if the expanded prism is not enough to engage in a new activity then the person will continue to be at the same location until it is time to head to the next fixed activity location resulting in adjusted activity-travel engagement.
- Person arrives as expected: In this case there are no heuristics that need to be employed and subsequent activity-travel engagement decisions are unaffected.

- Person arrives later than expected: There are two situations that may arise when the person arrives later than expected. First, if the person arrives later than expected but the arrival time falls between the start and end time of the destination activity. In this situation, the person shortens the destination activity by adjusting the start time. Second, the person arrives later than expected and the arrival time is later than the end of the destination activity and there is no conflict with planned activities downstream of the destination activity. The person foregoes the destination activity and comes to a decision point to make subsequent activity-travel engagement decision. Third, the person arrives later than expected and the arrival time is later than the end of the destination activity and there is also a conflict with planned activities downstream of the destination activity. If the planned activities downstream of the destination activity (including those that are missed or conflicting) were not children related activities (i.e. dependent children's activities allocated to the person), the person can forego the missed activities. However, if the planned activities downstream were joint episodes that the person was supposed to pursue with a dependent child, the joint activities are rescheduled and pushed downstream of the arrival. This is to ensure that dependent children are not abandoned.

Similar to the early arrival scenario, the late arrival also impacts the activity-travel engagement decisions downstream of the destination activity. The person now has a narrower time-space prism immediately following the destination activity and this could result in fewer non-fixed activities being pursued or adjusted activity-travel engagement. For example, in the second case of late arrival described above, the person has a narrower time-space prism and now the person may not have enough time to engage in another episode and may just head out to the next fixed activity location. Alternatively, he may have to choose a location that is closer or adjust the duration of the non-fixed activity to fit another non-fixed activity in the narrower prism.

It can be seen that the adjustment heuristics entailed in the framework and implemented in the SimTRAVEL prototype serve to ensure consistency and continuity in the representation of individual behaviors. The dynamic time-dependent activity-travel simulation along with the heuristics exhibits some neat capabilities. First, there is a full accounting of activities and travel through a day and the sum of travel and trip budgets add up to 1440 minutes available in a day. Second, the approach ensures consistency in the spatial and temporal representation of agents by ensuring that a person can be at only one location at any instance in time. The approach also ensures that constraints in the form of joint activities and dependencies are respected and individuals are not abandoned. The tight coupling between demand model and the traffic assignment model ensures that there is no need for compromising individual representation (in the form of “magic moves” etc.) entailed in traditional approaches to ensure consistency. Third, the tighter coupling has intuitive appeal and adjustment reflects some real behaviors (i.e. adjusting planned activities, foregoing non-fixed activities, respecting dependencies, altering destination choices etc.) exhibited in response to experienced time-space prism constraints. This last feature is of particular importance when evaluating planning and policy situations involving network interruptions and understanding their impact on activity-travel engagement decisions.

CHAPTER 5

OPEN-SOURCE ACTIVITY MOBILITY SIMULATOR: OPENAMOS

In addition to the development of an integrated model prototype, a key contribution of this research effort was in the development of a microsimulation-based travel demand model system. The research effort led to the development of an open-source travel demand model system dubbed Open Activity Mobility Simulator (OpenAMOS) which builds on legacy implementation called Activity Mobility Simulator (AMOS) (Kitamura et al. 2000 and Pendyala et al. 2005) with a number of enhancements to improve the various activity-travel engagement behaviors and constraints. In the first section, the legacy travel demand implementation AMOS is described. In the next section, the new open-source travel demand model system OpenAMOS is described along with an overview of enhancements in OpenAMOS over the legacy implementation (AMOS).

A. History of the Activity Mobility Simulator (AMOS)

Figure 6 shows an overview of the Activity Mobility Simulator (AMOS). In AMOS, first a synthetic population is generated by expanding a regional travel survey to match known distributions of variables of interest. The synthetic population generator employed in AMOS employs an approach similar to that proposed by Beckman et al. (1996) for generating a synthetic population. After generating a synthetic population, fixed activity skeletons are constructed for all individuals. These two steps are accomplished in the Household Attributes Generation System (HAGS). Fixed activity skeletons are constructed by identifying spatio-temporal coordinates of activities that have little or no flexibility, namely, morning and evening sojourns at home, work episodes for workers and school episodes for students. Once the skeletons are constructed, open time-space prisms (periods when there are no fixed activities that individuals need to pursue) are identified within which individuals engage in other flexible activities like maintenance and discretionary activities. The activity-travel engagement decisions within any open time-space prism are generated in the Prism-Constrained Activity-Travel Simulator (PCATS). Figure 7 provides flowchart of the different steps involved in the PCATS. PCATS comprises a series of models that simulate the various choice dimensions characterizing activity-travel engagement. Within any open time-space prism, first a check is made to see if there is enough time in the open prism to engage in an activity. If there is time then a series of sub models are invoked, namely, activity type choice model, a joint destination-mode choice model and activity duration model to simulate the activity-travel engagement decisions. Once the attributes for an activity-travel episode are generated, then another check is made to see if there is time left in the prism to engage in activities. If there is time available in the open prism, then the process is repeated to generate more activity-travel episodes otherwise the person is moved to the next fixed activity location. However, if there was no time in the prism to engage in an activity to begin with, the person makes a choice of the mode and is sent to the next fixed activity location. Within PCATS, it is possible that the activity-travel episodes that are generated may violate a time-space prism in such a case some adjustments are made to either the flexible activity that was generated or to the fixed activity skeleton subject to some thresholds. At the end of the run, activity-travel patterns are generated for an entire day for every individual in the region.

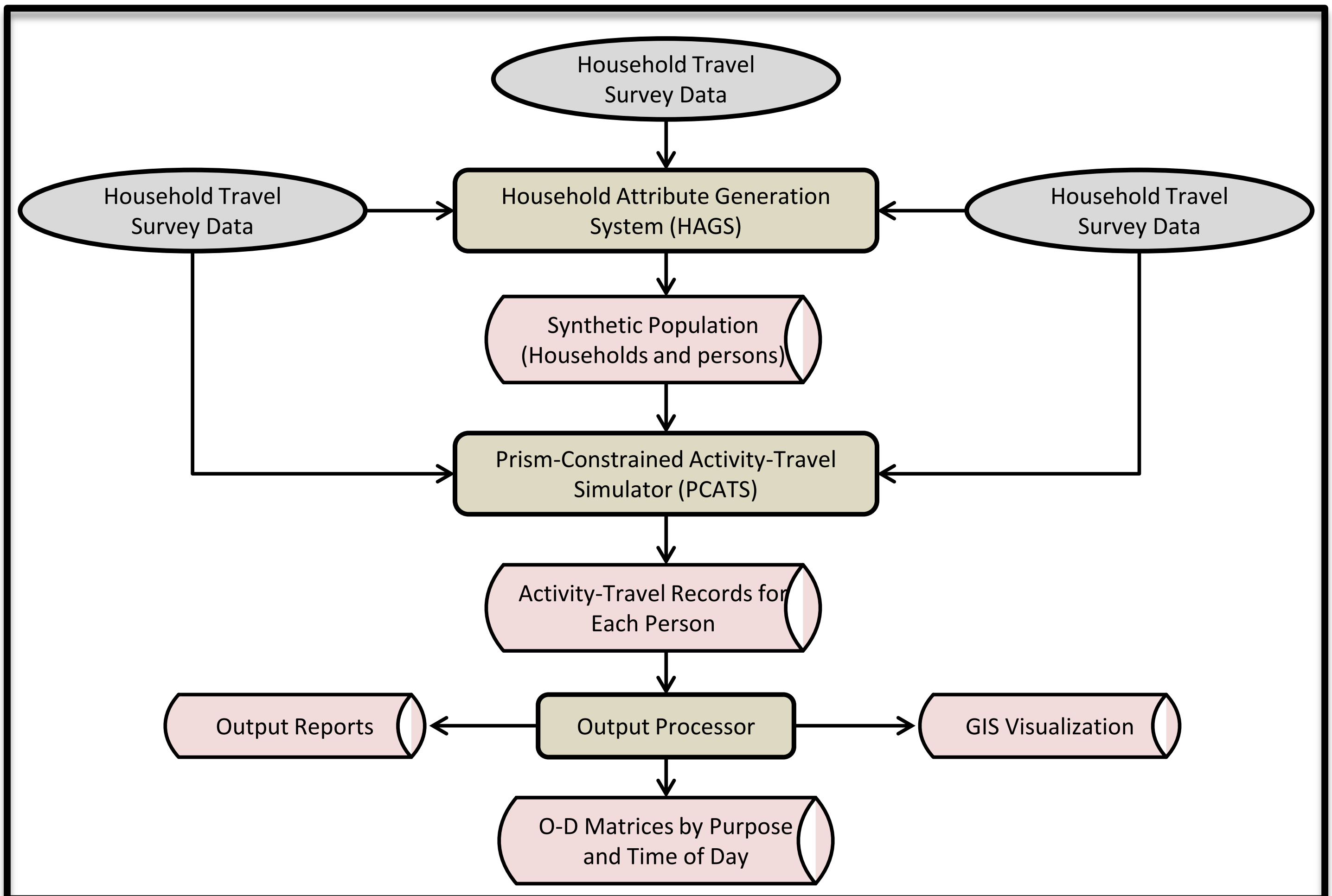

Figure 6: Overview of Activity Mobility Simulator (Kitamura et al. 2000)

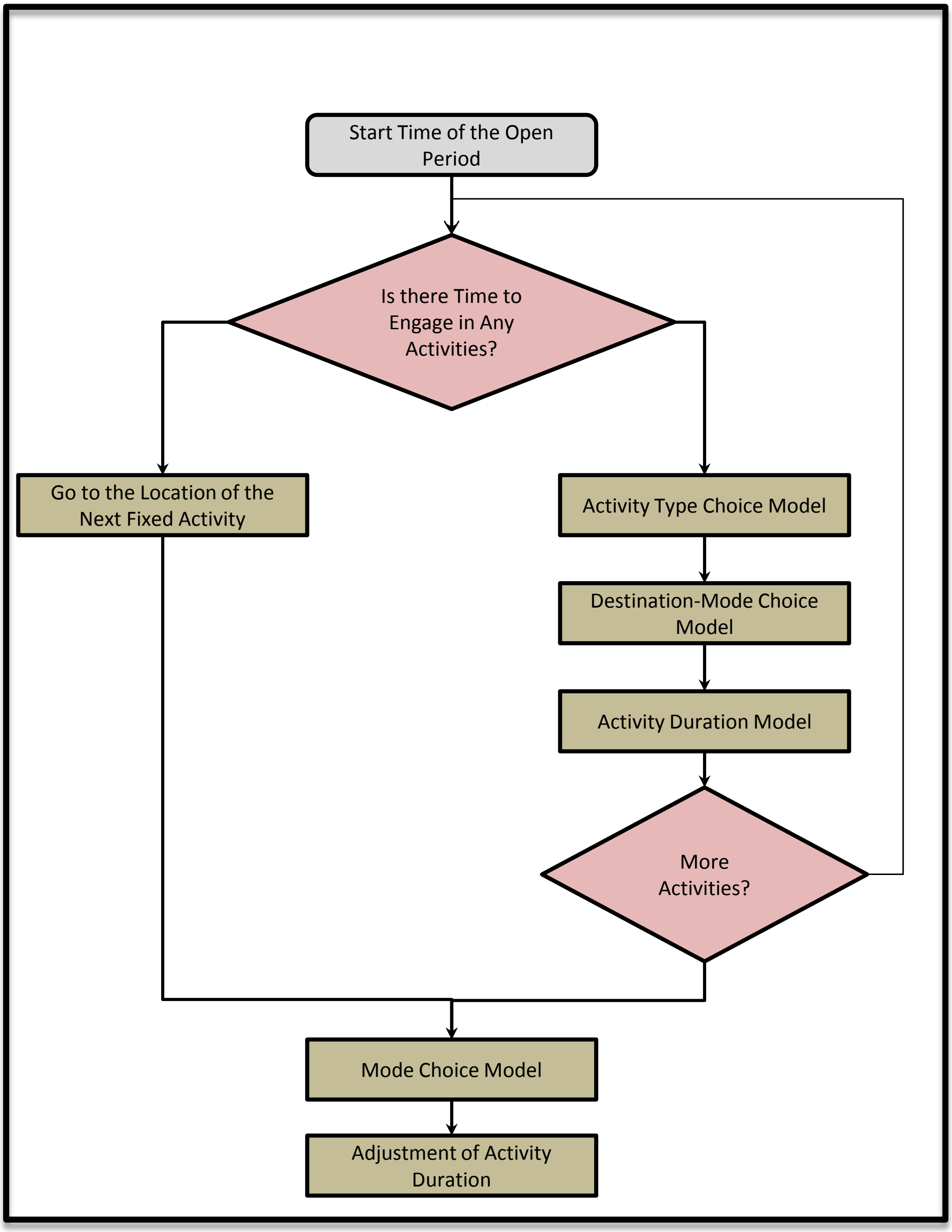

Figure 7: Prism Constrained Activity-Travel Simulator in AMOS (Kitamura et al. 2000)

B. Enhancements in the Open-Source Activity Mobility Simulator

The development of Open-source Activity Mobility Simulator (OpenAMOS) was spurred by two key motivations. First, some of the same design considerations that drove the development of SimTRAVEL (described in Chapter 4) also motivated the development of an enhanced travel demand model system. The key themes being - enhanced representation of behaviors, ensuring consistency and continuity in the spatial units and temporal scales, and accounting for constraints experienced by agents when making activity-travel engagement decisions. Second, there was a need for developing a software infrastructure to model travel demand that was robust and extensible. The software infrastructure needed the capability to operate independently as well as in an integrated modeling environment to generate activity-travel engagement decisions. Additionally, the integration of the travel demand model system with a dynamic traffic assignment model consistent with the design proposed in Chapter 3 called for an alternative software design compared to the software design in AMOS.

The overall framework of OpenAMOS is similar to the framework employed in AMOS. The activity-travel simulation proceeds by first generating a synthetic population followed by generating the skeletons of fixed activities. The open time-space prisms around fixed activity episodes are then filled with non-fixed activities (including discretionary and maintenance type activities). However, there are some differences in how the skeletons are built and how activity-travel engagement decisions are made in open prisms. In the rest of the section, the enhancements included in OpenAMOS over legacy AMOS are described:

Child Dependency and Allocation

In the recent past there has been a growing literature on the role played by intra-household interactions in shaping activity-travel engagement patterns (Kang and Scott 2009, Zhang and Fujiwara 2006, Bhat and Pendyala 2005). Without explicitly accounting for interactions, the activity-travel generation process may not truly reflect the underlying decision making behavior and may potentially lead to incorrect inferences when evaluating policies. For example, there may be a dependent child who may need to pursue an after school activity and needs an adult to chauffer him to the activity location; hence there is an intra- household interaction that one needs to consider in this context.

Recognizing the importance of intra-household interactions, children related intra-household interactions are simulated in OpenAMOS. The process first begins by identifying all children that are dependent on an adult for their travel needs. The full day activity-travel patterns of dependent children are then simulated employing the same Prism Constrained Activity Travel Simulator framework presented in Figure 7. Then a child dependency allocation module is invoked to allocate the dependent children's activities to adults based on their availability. Therefore, in addition to an adult's own fixed activities, activities of dependent children and associated travel episodes also contribute to the formation of activity-travel skeletons for household adults.

The importance of dependent children's activities in the formation of activity-travel agendas of other members of the household is well recognized and recent literature on the subject is a testament to the fact. However, data to conduct a thorough exploratory analysis and model estimation exercise is still lacking. Travel surveys place a lesser emphasis on collection of activity-travel engagement patterns of the children demographic. Often data related to children is not collected and in surveys where the data about children is collected, the data is requiring in quality. As a result a number of assumptions are made when accounting for intra-household interactions in microsimulation-based travel demand models. The child dependency allocation module employed in OpenAMOS employs a simple rule-based module that allocates dependent children's activities to adults within the household based on spatial and temporal availability. The heuristic process employed for allocating children-related activities and trips in OpenAMOS is described below:

- First a dependency status is generated for every child that is younger than 17 years old. Children younger than 6 years are assumed to be dependent by default. For children aged between 5 and 18 years, a binary logit model is run to simulate their dependency status. Everyone 18 and older is assumed to be independent and can engage in activities and trips on their own. All independent persons within the household are assumed to be potential candidates for serving dependent's activity and travel needs.

- Dependent children always engage in activities under the supervision of an adult except for discretionary activities and school episodes where the dependent child can engage in the activity alone. The rationale behind allowing discretionary activities alone is these activities entail episodes such as social activities, sports, and recreation among others where children are assumed to be supervised and therefore no household adult needs to be present. On the other hand all trips associated with out-of-home activities including, school, discretionary, and maintenance type episodes are required to be served by an independent adult.
- In order to avoid dependent activities in a sequence being allocated to multiple individuals within the same household and subsequently constrain their activity-travel engagement behavior, activity-travel trip chains are formed and the activity-travel trip chains are allocated instead of individual activity and trip episodes. Trip chains are formed by building activity and trip sequences that are anchored by either an in-home episode or a discretionary activity episode on both ends. This assumption is pretty reasonable as one adult in a household can travel and engage in a series of out-of-home activities before leaving them at home where they can be catered to by another adult or at a discretionary activity location where they will be supervised. Subsequent trip chains can then be allocated to the same person or other persons within the household based on their spatial and temporal availability. However, the in-

home activities that form anchors of activity-travel chains are allocated individually to persons within the household.

- When allocating activities or trip chains, first persons without fixed activities on the simulation day are scanned to see if they have open time-space prisms to supervise the dependent child. If no adult without fixed activities are found then persons with fixed activities are scanned to see if they have an open-time space prism so that they can cater to the dependent child's activity-travel needs. If no person in the household has an open time-space prism to supervise the child then the child is assumed to be supervised by a non-household member. The rationale behind this heuristic process is that dependent children activities are first consumed by people that do not have to be at a fixed activity that they must pursue and as a result can spend time tending to the needs of the child. In the event that there are no available persons without fixed activities then the persons with fixed activities are assumed to cater to the needs of the child before assigning them to non-household members such as relatives, babysitters etc. While there is no identification of the non-household member in the allocation process, it is assumed that in the universe of people and their activity-travel engagement decisions, the dependent travel and activity episodes with non-household members are represented.

The allocation module in OpenAMOS has a behaviorally intuitive basis i.e. allocate dependent children's activities to adults based on spatial and temporal availability and activities and trips that cannot be allocated are assumed to be pursued with non-household members. The rule-based framework can easily be replaced with advanced frameworks employing statistical and econometric formulations to model and simulate child dependencies and allocate them to household/non-household members. The research on understanding intra-household interactions and simulating the process in travel demand model systems is still growing and provides a great avenue for further research and inquiry.

Software Architecture and Development

As the name suggests OpenAMOS is an open-source software package and is available to public under an open-source licensing agreements. OpenAMOS is developed using Python programming language and uses a number of python modules and extensions. All the libraries, extensions and supplementary software used in the development of OpenAMOS are also available for public under open-source agreements. OpenAMOS uses PostGreSQL – a Relational Database Management System (RDBMS) for data storage and retrieval. PostGreSQL was chosen because it uses standard SQL querying constructs to store and retrieve data. Also, the RDBMS feature of PostGreSQL lends itself to storing and retrieving data that is used and generated by OpenAMOS, namely, socio-economic and demographic data about households and persons, activity profiles and trip records.

As noted earlier OpenAMOS builds on its legacy implementation called AMOS. However, the entire software paradigm underlying AMOS was modified and re-engineered in OpenAMOS. The software architecture and development was motivated by three features. First, develop a software infrastructure that can support rich representation of underlying activity-travel behaviors and that can easily be extended to include additional behaviors as the state of research makes progress. Second, the software infrastructure must be computationally tractable and feasible. Finally, the software framework must be flexible enough to work independently and be coupled with other network simulation model systems depending on the application context. Following is a description of the various elements in the OpenAMOS that support the three features described:

- **Extensibility:** The OpenAMOS software infrastructure comprises of two components. First, a model specification system that can be used to specify a travel demand model system using any paradigm with any number of choice processes employing any structure of the decision hierarchy. Second, the model simulation engine that uses the model system specified to generate choices. OpenAMOS uses an XML (Extensible Markup Language) file for specifying the submodels representing choice dimensions and to specify the decision hierarchies. The model simulation engine parses the XML document to translate the choice hierarchies, decision flows, specifications, and formulations and then uses that information to simulate the various choice dimensions characterizing activity-travel demand. XML configuration files are very simple to construct and are easily readable. The configuration file is built using basic XML constructs and modifying the model specifications and decision hierarchies and extending it to include additional behaviors is an easy process.

- **Computational Tractability:** In most implementations of microsimulation-based model systems of travel demand an agent-based paradigm is applied. The activity-travel generation process proceeds by iterating through households and persons and simulating various dimensions of activity-travel engagement behavior. However, such an approach is not always the computationally tractable and feasible. This approach entails looping which are not always ideal when programming using high-level languages such as Python. The approach also does not adequately leverage data caching often a key feature of computationally efficient software; especially when dealing with thousands of agents that have to use the same set of inputs for making decisions. Alternative implementations especially those that do not require capturing dependencies and interactions across agents employ an array-based approach wherein agent attributes are stacked in the form of arrays and matrix capabilities are used to calculate choices. However, a purely array-based approach cannot be used in OpenAMOS where there is a need for employing rules and heuristics to account for dependencies and interactions. Realizing the advantages and shortcomings of both approaches, OpenAMOS employs a hybrid approach for generating activity-travel engagement decisions. In the hybrid approach, choice dimensions that do not involve rules/heuristics are simulated using an array-based approach. For choice dimensions that do involve rules/heuristics for generating the choice, the choices are simulated one agent at a time recognizing the inter-agent constraints and dependencies.

OpenAMOS also leverages off of a number of low-level constructs of Python including embedding and extending to gain efficiencies in run times. One such example is a C/C++ code for querying skim matrices wrapped around with SWIG so that it can be called as a module from within Python. The implementation resulted in nearly 20 times gain in computational efficiency compared to the same code written in Python.

- **Flexibility:** This was another key feature that drove the design and development of OpenAMOS. Ideally OpenAMOS will always be used in conjunction with a land use and traffic assignment model system as described in Chapter 3. However, it may not always be possible to implement such a system due to a number of reasons. For example, the agency exploring OpenAMOS may already have an operational dynamic traffic assignment model system in place that may not be amenable to integration with the demand model in a tightly coupled manner (Dynamic Time-Dependent Activity Travel Simulation framework described in Chapter 3). Alternatively the agency may just be interested in linking a microsimulation-based travel demand model system with a static traffic assignment model system because they want to transition to disaggregate model systems in steps. In both cases, there is a need for travel demand model software that can work independently as well as in close coordination with other components of an urban system to address the various linkages and dependencies. OpenAMOS is built such that it can work in isolation and can easily be integrated with other components of the urban system. Additionally the OpenAMOS infrastructure is also amenable to integrating other traffic assignment models in traditional manner (applying component model systems sequentially) and also under the dynamic time-dependent activity travel simulation framework (tight coupling of travel demand and traffic assignment model systems) without too many changes.

CHAPTER 6

ADVANCED JOINT DISCRETE-CONTINUOUS MODELS OF ACTIVITY-TRAVEL BEHAVIOR

A. Introduction

In most implementations of microsimulation models of travel demand, the dimensions of activity-travel engagement are modeled separately and the models are applied sequentially to simulate activity-travel decisions made by individuals (Kitamura et al. 1997). The sequential approach of modeling and simulating choice dimensions of activity-travel engagement does not account for potential endogeneity affects. Endogeneity impacts parameter estimates and subsequently influences policy analysis based on the parameter estimates. Recognizing the impacts of endogeneity, there has been a growing body of literature on the use of rigorous econometric frameworks for estimating multiple activity engagement dimensions simultaneously (Hamed and Mannering 1993, Bhat 1998, Misra 1999, Ettema et al. 2007, Anggraini 2009). These statistical frameworks are capable of accommodating endogeneity across choice dimensions due to unobserved individual attributes. For example, when simulating an individual's choice of activity type and the amount of time spent in the activity, a discrete choice model of activity type choice and a regression model of activity duration are typically estimated independently without accounting for potential unobserved attributes influencing both dimensions simultaneously. If an individual is predisposed towards shopping and enjoys the activity, then unobserved individual attributes (predisposition and enjoyment) influence both the choice of activity type (choose shopping more frequently) and the time allocated to shopping episodes (spend more time during shopping episodes). The propensity of this person to engage in this particular activity type and the inclination to participate in that activity for longer activity-durations is not captured by variables in a typical time use survey. As a result, when estimating activity type and activity duration models, the propensity of the individual (which is an unobserved explanatory factor) is captured in the random error term of the models and hence leads to correlations across choice dimensions and thus endogeneity effects. Therefore, there is a need for a rigorous estimation framework that not only allows for simultaneous estimation of choice dimensions but also accommodates error correlations across choice dimensions to account for the effect of common unobserved explanatory variables.

Additionally, there are both continuous and discrete choice dimensions that characterize activity-travel engagement behavior. For example in the context of activity engagement, activity type is a discrete choice and the amount of time spent in the activity is a continuous choice. Similarly in the context of type of vehicle chosen on a particular tour in a household with multiple vehicles, the choice of the vehicle type is a discrete choice and the distance traveled on the tour (a proxy for destinations accessed) is a continuous variable. In order to model the discrete and continuous choice dimension simultaneously, joint discrete-continuous model formulations are used. There are a number of joint discrete-continuous frameworks in literature which are capable of modeling discrete and continuous choice dimensions simultaneously. Conventional discrete-continuous modeling methods have either been two-step limited-information approaches, or have employed distributional transformations to facilitate full-information maximum likelihood estimation of logit-based discrete-continuous model systems (Pendyala and Bhat 2004, Bhat 1998).

In this research effort, two empirical studies aimed at understanding activity-travel engagement behaviors are explored involving a discrete choice and continuous choice dimension. In the first empirical study, the activity engagement behavior of individuals is explored at an episode-level by modeling activity-type choice and the amount of time spent on the activity. In the second study, the choice of the vehicle type in multiple vehicle households and the distance traveled – a proxy for destination choice is modeled. Both independent models of choice dimensions and a joint model of the choice dimensions are estimated in an effort to highlight the differences in parameters and capture impacts on policy analysis. A probit-based joint discrete-continuous modeling framework proposed by Ye and Pendyala (2009) is used for modeling the choice dimensions simultaneously. The probit-based approach uses a multivariate normal distribution to accommodate error correlations across choice dimensions and also across alternatives for the discrete variable. The probit-based discrete-continuous approach also offers a rigorous approach for estimating model parameters without having to impose distributional assumptions that one needs to make in the context of the transformation approach often employed in conventional joint modeling frameworks.

In the next section, the probit-based joint discrete continuous model system is presented. An extension of the model formulation to account for varying choice sets of alternatives for the discrete variable is also presented. Additionally, an extension of the hypothesis test proposed by Ye and Pendyala (2009) is presented to test alternative joint discrete-continuous model structures when the choice set of alternatives for the discrete variable varies across decision makers. In Section C and Section D the two empirical studies along with estimation results and findings are presented. The chapter ends with a discussion of the transferring over this enhanced understanding of activity-travel engagement behavior to microsimulation models of travel demand.

B. Probit-based Joint Discrete Continuous Model Formulation

This section presents the probit-based joint discrete continuous modeling methodology proposed by Ye and Pendyala (2009) and describes the extension to accommodate varying choice sets for the discrete variable in the joint discrete-continuous modeling framework.

Formulation

The probit-based joint discrete continuous formulation is presented here for a discrete variable with three choice alternatives. However, the formulation can easily be extended to accommodate discrete variable with any number of choice alternatives. The system of equations for the discrete-continuous model system may be formulated as:

$$\begin{cases} u_1^{\ *} = x_1\beta_1 + \delta_1 d + \varepsilon_1 \\ u_2^{\ *} = x_2\beta_2 + \delta_2 d + \varepsilon_2 \\ u_3^{\ *} = x_3\beta_3 + \varepsilon_3 \\ d \ = z\theta + \lambda_1 y_1 + \lambda_2 y_2 + \omega \end{cases} \quad (1)$$

where $u_1^{\ *}$, $u_2^{\ *}$, $u_3^{\ *}$ are the latent utility functions for three alternatives corresponding to the discrete choice variable. β_1 , β_2 , β_3 are the coefficient vectors corresponding to the exogenous variables x_1, x_2, x_3 on the right-hand side of the latent utility functions. d is the continuous choice variable and enters the utility functions of the discrete choices with coefficients δ_1, δ_2. z is a vector of explanatory variables influencing d with a coefficient vector θ. y_1 and y_2 are indicator variables corresponding to the first and second discrete choice alternatives and are defined as follows:

$$\begin{aligned} y_1 &= I(u_1^* > u_2^* \ and\ u_1^* > u_3^*) \\ y_2 &= I(u_2^* > u_1^* \ and\ u_2^* > u_3^*) \end{aligned} \quad (2)$$

where y_1 and y_2 assume a value of 1 if the conditions in the parentheses are satisfied and 0 otherwise. λ_1 and λ_2 in Equation (1) are the coefficients corresponding to indicator variables y_1 and y_2. For the above model to be identified, either the λ or the δ parameters must be restricted to zero, and this results in two alternative model specifications: (i) λ_1 and λ_2 equal to zero, corresponding to the joint model specification where the continuous dimension of interest is affecting the choice of the discrete dimension (e.g. tour length affects choice of vehicle type for the tour), and (ii) δ_1 and δ_2 equal to zero corresponding to the joint model specification where discrete dimension affects the continuous dimension (e.g. vehicle type choice affects length of the tour pursued).

The random error terms ε_1, ε_2, ε_3, ω in the model are assumed to be multivariate normally distributed with the variance-covariance matrix as shown below:

$$\Sigma = \begin{bmatrix} 1 & 0 & 0 & \gamma_1 \\ 0 & 1 & 0 & \gamma_2 \\ 0 & 0 & 1 & \gamma_3 \\ \gamma_1 & \gamma_2 & \gamma_3 & \sigma^2 \end{bmatrix} \tag{3}$$

It can be seen from the variance-covariance matrix above that the emphasis in the model formulation is to accommodate the error correlations between the discrete choice alternatives and the continuous choice variable and the variance-covariance components corresponding to the discrete choice alternatives are fixed as shown. The notation in Equation (1) may be simplified as shown in Equation (4):

$$\begin{cases} u_1^* = V_1 + \varepsilon_1 \\ u_2^* = V_2 + \varepsilon_2 \\ u_3^* = V_3 + \varepsilon_3 \\ d \ = U + \gamma_1\varepsilon_1 + \gamma_2\varepsilon_2 + \gamma_3\varepsilon_3 + \sigma'\xi \end{cases} \tag{4}$$

where V_1, V_2, V_3 constitute the deterministic part of the latent utility functions and U represents the deterministic component of the continuous model. The random error term in the continuous model has been parameterized as a linear combination of ε_1, ε_2, ε_3, and ξ, where ξ is a random error term that is standard normally distributed and is independent of ε_1, ε_2, and ε_3. σ'^2 is assumed to be equal to ($\sigma^2 - g_1^2 - g_2^2 - g_3^2$) so that the covariance structure shown in Equation (3) is preserved in the modified notation.

Let V_{12} represent the difference in the deterministic components of the latent utility functions of discrete alternatives 1 and 2, i.e., $V_{12} = V_1 - V_2$. Similarly $V_{13} = V_1 - V_3$. One can then derive a joint discrete-continuous probability function conditional on ε_1, ε_2, ε_3. Equation (5) illustrates the probability formulation for discrete choice alternative 1 ($y_1 = 1$).

$$\begin{aligned}
&\Pr(y_1 = 1, d|\varepsilon_1) \\
&= \Pr(u_1^* > u_2^*, u_1^* > u_3^*, d|\varepsilon_1) \\
&= \Pr(\varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1, d|\varepsilon_1) \\
&= \Pr(\varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1|\varepsilon_1) \times \\
&\qquad \Pr\left[(d|\varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1)|\varepsilon_1\right] \\
&= \left[\Phi(V_{12} + \varepsilon_1)\Phi(V_{13} + \varepsilon_1)\right] \times \\
&\qquad \left\{ \frac{1}{\sigma'} \phi\left(\frac{d - U - \gamma_1\varepsilon_1 - \gamma_2\varepsilon_2 - \gamma_3\varepsilon_3}{\sigma'} \right) \middle| \varepsilon_2 < V_{12} + \varepsilon_1, \varepsilon_3 < V_{13} + \varepsilon_1 \right\}.
\end{aligned} \tag{5}$$

$\phi(.)$ and $\Phi(.)$ in Equation (5) denote the probability density function and the cumulative probability density functions respectively. The unconditional probability for discrete choice alternative 1 may then be derived by integrating the probability function over the distributional domains of ε_1, ε_2, ε_3. As can be seen, the distributional domain of ε_1 extends from $-\infty$ to $+\infty$, ε_2 extends from $-\infty$ to $V_{12} + \varepsilon_1$, and ε_3 extends from $-\infty$ to $V_{13} + \varepsilon_1$. The unconditional probability does not have a closed form solution and simulation based techniques may be employed to evaluate the unconditional probability. In order to simulate the unconditional probability, randomly draw ε_{1r} ($r = 1, 2, \ldots R$) from a standard normal distribution and let $\varepsilon_{2r} = \Phi^{-1}[u_{2r}\Phi(V_{12} + \varepsilon_{1r})]$ and $\varepsilon_{3r} = \Phi^{-1}[u_{3r}\Phi(V_{13} + \varepsilon_{1r})]$, where u_{2r} and u_{3r} are two independent draws from a standard uniform distribution. ε_{2r} and ε_{3r} are now draws from the corresponding truncated normal distributions for ε_2 and ε_3. By repeating this procedure R times, the unconditional probability function may be approximated as:

$$\begin{aligned}&\Pr(y_1 = 1, d)\\ &\approx \left\{\sum_{r=1}^{R} \Phi(V_{12} + \varepsilon_{1r})\Phi(V_{13} + \varepsilon_{1r}) \frac{1}{\sigma'} \phi\left(\frac{d - U - \gamma_1\varepsilon_{1r} - \gamma_2\varepsilon_{2r} - \gamma_3\varepsilon_{3r}}{\sigma'}\right)\right\} \Big/ R\end{aligned} \tag{6}$$

The unconditional probability functions for the other two alternatives of the discrete choice variable may be derived in an analogous manner. The Maximum Simulated Likelihood Estimation (MSLE) procedure can then be applied to estimate the parameters using quasi-random Halton sequences (Bhat 2001).

As with any joint discrete-continuous model system, careful consideration must be given to issues of identification and normalization. To avoid any issues with normalization it is recommended that the γ_j in Equation (3) with the smallest absolute value be normalized to zero. This assumption is consistent with previous literature (Walker 2002) and a detailed discussion on the normalization assumption and its validity is presented in Ye and Pendyala (2009).

The model formulation presented above can be applied to any discrete-continuous type problem where the choice set of alternatives is constant for all decision makers. However, in the study presented in Section D, the discrete variable considered in the analysis – vehicle body type – may vary across decision makers (as different households own different vehicle fleets). Therefore, the methodology described above is modified to accommodate varying choice sets.

Let k_1, k_2, k_3 be three indicator variables denoting the availability of each of three choice alternatives for the decision maker. The indicator variable assumes a value of 1 if a particular choice alternative is available and 0 otherwise. The deterministic component in the original utility expressions may be modified as:

$$\begin{cases} u_1^{\ *} = k_1 x_1 \beta_1 + (1-k_1)(-\infty) + \delta_1 d + \varepsilon_1 \\ u_2^{\ *} = k_2 x_2 \beta_2 + (1-k_2)(-\infty) + \delta_2 d + \varepsilon_2 \\ u_3^{\ *} = k_3 x_3 \beta_3 + (1-k_3)(-\infty) + \varepsilon_3 \\ d = z\theta + \lambda_1 y_1 + \lambda_2 y_2 + \omega \end{cases} \tag{7}$$

It can be seen that whenever an alternative is available, the deterministic component of the utility remains the same as in the earlier formulation. However, if a particular alternative is not available then the alternative is made highly unattractive (by adding a very large negative value). As a result the probability of any missing alternative (vehicle type) being chosen is forced to be zero. Thus the model formulation presented in Equation (7) can accommodate varying choice sets for the discrete choice model component in a joint discrete-continuous problem.

Non-nested Hypothesis Test

As mentioned earlier, based on whether the parameter λ or δ is set to zero, two different specifications of the joint discrete-continuous models arise. It is entirely possible that both specifications of the joint discrete-continuous model will provide behaviorally plausible results with statistical goodness-of-fit measures that are quite similar. Therefore, rigorous statistical hypothesis tests are required to compare and choose the appropriate model specification. The choice of the joint discrete-continuous model specification has an important detriment on understanding of the underlying decision making behavior and subsequently on planning and policy analysis conducted using the specification adopted.

Standard likelihood ratio tests cannot be used when model specifications are non-nested. The earliest test to compare alternative non-nested model specifications was proposed by Cox (1961, 1962). Horowitz (1983) and then Ben-Akiva and Swait (1986) modified the Cox test to compare non-nested specifications of discrete choice models. The test initially proposed to compare single equation model systems (McCarthy and Tay 1998) has also been used to compare simultaneous equations model systems (Pendyala and Bhat 2004, Ye et al. 2007). However, the appropriateness of the test for comparing simultaneous equations model systems is unknown. In order to address this issue, Ye and Pendyala (2009) proposed a new hypothesis test for comparing non-nested joint discrete-continuous model systems. However, the hypothesis test cannot accommodate varying choice sets across decision makers. In this research effort, the hypothesis was extended to accommodate varying choice sets for the discrete variable across decision makers.

According to Horowitz (1983), the probability that the goodness-of-fit statistic for a model *B* is greater than the goodness-of-fit statistic for model *A* by a value $t > 0$ assuming that model *A* is the true model is asymptotically bounded as:

$$\Pr\left[\bar{\rho}_B^2 - \bar{\rho}_A^2 > t\right] \le \Phi\left[-\sqrt{-2L^* t}\right] \quad (8)$$

where

$\bar{\rho}_m^2$ = likelihood ratio index for model m and is calculated as shown in Equation (9)

L_m = log-likelihood function value for model *m* at convergence

K_m = number of parameters being estimated in model *m*

L^* = log-likelihood function value of model *m* when all the parameters are assumed to be zero

$$\bar{\rho}_m^2 = 1 - \frac{L_m - \frac{K_m}{2}}{L^*} \quad (9)$$

In the original formulation of Horowitz (1983), L^* was defined as $N \ln(1/J)$ where N is the number of observations and J is the number of choice alternatives. Ye and Pendyala (2009) proposed a modified L^* for comparing joint discrete-continuous model specifications as shown in Equation (10).

$$L^*(\mathit{Joint\ Model}) = L^*(\mathit{Continuous\ \ Model}) + L^*(\mathit{Discrete\ Model}) \quad (10)$$

The equations for calculating L^* for the continuous and discrete model components are shown in Equation (11) and Equation (12) respectively:

$$L^*(\mathit{Continuous\ \ Model}) = -\frac{N-1}{2} - N \ln\left(\sqrt{2\pi}\,\hat{\sigma}\right) \quad (11)$$

where $\hat{\sigma}$ = standard deviation of the continuous variable

$$L^*(\mathit{Discrete\ \ Model}) = -N \ln(J) \quad (12)$$

As can be seen in Equation (12), the formulation of L^* for the discrete choice assumes that the choice set is the same for all decision makers. In order to accommodate varying choice sets for different decision makers, the following form is proposed for the contribution of the discrete model component to L^*.

$$L^*(Discrete\ Model) = -\sum_{i=1}^{N} \ln(j_i) \tag{13}$$

where j_i is the number of choice alternatives in the choice set for individual observation i. Therefore, the modified L^* value for the joint discrete-continuous model with varying choice sets is given by:

$$L^*(JointModel) = -\frac{N-1}{2} - N\ln\left(\sqrt{2\pi}\,\hat{\sigma}\right) + -\sum_{i=1}^{N} \ln(j_i) \tag{14}$$

Substituting Equation (14) in Equation (8) gives the following form for the probability statistic and its asymptotic bound:

$$\Pr\left[\bar{\rho}_B^2 - \bar{\rho}_A^2 > t\right] \le \Phi\left[-\sqrt{-2\left(-\frac{N-1}{2} - N\ln\left(\sqrt{2\pi}\,\hat{\sigma}\right) + -\sum_{i=1}^{N}\ln(j_1)\right)t}\right] \tag{15}$$

Using this formulation, one can compare non-nested discrete-continuous model specifications with varying choice sets across decision makers.

C. History-Dependent Episode-level Analysis of Activity Type and Duration

Activity engagement patterns of individuals are of much interest in the context of the development and implementation of activity-based travel demand models (Arentze et al. 2000, Miller and Salvini 2005, Pendyala et al. 2005, Pinjari et al. 2008), understanding the motivations for travel, analyzing social networks (Timmermans and Arentze 2006, Axhausen 2007), and modeling time use

(Kitamura et al. 1996, Bhat and Misra 1999, Pendyala and Bhat 2004, Chen and Mokhtarian 2006). Among the dimensions of activity engagement that is less understood is that of activity participation or generation itself. The act of participating in an activity of a certain type constitutes the activity generation process, and it is critical to model this process comprehensively and accurately with an understanding of the factors that contribute to people's activity participation decisions (Pendyala et al. 1997).

The modeling of discretionary and maintenance activity engagement is of particular interest due to its increasing importance and role in the formation of daily activity agendas. Most increases in travel time expenditures and trip-making over the past two decades can be largely attributed to increases in discretionary activity-travel engagement, with participation in mandatory activities such as work and school increasing only marginally (Toole-Holt et al. 2005). In this context, there are three aspects that merit attention in modeling discretionary and maintenance activity engagement, which are briefly discussed below.

First, it is desirable to consider both in-home and out-of-home activity participation when analyzing activity engagement patterns (Bhat and Misra 1999, Yamamoto and Kitamura 1999, Clifton et al. 2007). A good understanding of the inter-relationships and tradeoffs between in-home and out-of-home activity engagement patterns will allow one to accurately represent the entire range of activity engagement in travel demand models (Chen and Mokhtarian 2006, Yamamoto and Kitamura 1999).

Second, there is history dependency in activity engagement. Individuals need to fulfill an activity agenda within a limited amount of time that is available; the type of activity in which an individual participates and the amount of time that is allocated to an activity is dependent on the history of activity engagement up to the current activity (Kitamura and Kermenshah 1983, Kitamura et al. 1997). For example, a person that has already engaged in a shopping activity earlier in the day is less likely to engage in more shopping later in the day (Kasturirangan et al. 2002). Another dimension of activity engagement that is important is the timing of the activity (Pendyala and Bhat 2004, Ettema et al. 1995). Therefore models of activity engagement should consider history dependency and time of day effects to account for these factors.

Third, the notion of time use is inextricably linked with activity participation. Each activity engagement decision generally involves a determination of the type of activity to be pursued, where it is to be pursued (in-home or out-of-home), and the duration of the activity. This gives rise to a discrete-continuous choice process where the activity type is a discrete choice while the time use or time allocation is continuous choice. Also, there are common unobserved factors that affect both the choice dimensions and hence there is a need for employing joint modeling frameworks to model the two dimensions simultaneously.

This empirical study makes a contribution along all three aspects of activity engagement. The study employs data from the 2008 American Time Use

Survey (ATUS) to include consideration of all in-home and out-of-home activities that an individual pursues over the course of a day. Individual discretionary and maintenance activity episodes, together with their attributes of timing, duration, location, and purpose, were extracted to form the dataset for analysis. The inter-dependence among activity episodes over the course of a day was represented through the use of explanatory variables that represent the history of activity engagement up to the activity in question. Discrete-continuous models of activity type choice and activity duration are estimated to account for the simultaneity in these choice dimensions. Models are estimated separately for commuter and non-commuter market segments to recognize the differing constraints that influence the activity participation for these two groups. Within the context of this work, time of day choice and history of activity engagement were treated as exogenous variables, although it is clear that time of day should, strictly speaking, be treated as endogenous to the system (Ettema et al. 2007, Ye and Pendyala 2009). The probit-based discrete continuous modeling methodology presented in Section B is used for estimating the system of equations. In the next subsection, the data used is described. In the following subsection, results are presented and the subsection after includes a discussion of the results and conclusions.

Data Set and Sample Composition

Data from the 2008 American Time Use Survey (ATUS) was used in this study. ATUS is the first federally administered survey that collects detailed time use information of individuals in the United States. ATUS is conducted by the US

Census Bureau for the Bureau of the Labor Statistics. ATUS respondents are selected randomly from among households that have completed the eighth and final month of interviews for the Current Population Survey (CPS). The survey is administered such that it evenly covers all months of the year and all days of the week. From a subset of the CPS households, only one person over the age of 14 years is randomly selected to provide detailed time use information for a 24 hour period. In addition to the time use data for the respondent, ATUS collects information about the location of each activity, information about persons accompanying the respondent during the activity, and other socio-economic and demographic information of the household to which the respondent belongs. Additional information about the survey can be obtained at the ATUS website: http://www.bls.gov/tus/.

In the 2008 data set, there were 12,723 respondents who participated in a total of 253,608 activities. Only adult respondents (age 18 and older) were considered in the analysis resulting in a total of 12,108 respondents. The adult activity sample was divided into a commuter (4162 individuals) and a non-commuter subsample (7946 individuals) to recognize that differing constraints (in terms of mandatory activity engagement) influence individual's activity engagement patterns.

The maintenance and discretionary activities that commuters pursued were further divided into three categories based on the time period in which the activities were performed. The three commuter activity classification groups include (a) activities before the first mandatory activity episode, (b) activities undertaken in between mandatory activity episodes, and (c) activities after the last mandatory activity episode. This activity categorization was done to recognize the distinct time periods surrounding mandatory activity engagement for commuters. On the other hand, for the non-commuter sample, time of day was introduced as an exogenous variable in the activity type and activity duration models to understand the influence of time-of-day on activity engagement. Activity types in the ATUS were aggregated to broader categories using the detailed multi-level activity classification scheme. The aggregated activity categories include:

a. In-home mandatory activities
b. Out-of-home mandatory activities
c. In-home maintenance activities
d. Out-of-home maintenance activities
e. In-home discretionary activities
f. Out-of-home discretionary activities
g. Sleep
h. Travel for mandatory activities
i. Travel for maintenance activities
j. Travel for discretionary activities
k. Other activities

Table 3 and Table 4 provide descriptive statistics of activity engagement and time use for the survey sample stratified by commuter and non-commuter segments and considering the three basic periods of the day for the commuter sample. The tables depict averages across all respondents and for the subset of respondents that actually participated in the activity type in question. As expected, a large percent of maintenance and discretionary activities, whether in-home or out-of-home, are undertaken outside the mandatory activity engagement time window. The lone exception is that of out-of-home discretionary activities, reflecting eat-meal trips undertaken during work and school that are classified as out-of-home discretionary activities. The average activity duration for out-of-home discretionary activities pursued in between mandatory activity episodes is just about 45 minutes for those who participated in such activities, fairly close to the typical one hour length of a lunch period. The time allocated and the activity frequency of in-home and out-of-home maintenance and discretionary activity episodes are generally higher after the last mandatory activity episode compared to the period before the first mandatory activity episode. This observation seems reasonable because commuters are likely to engage in such activities later in the day after work and school activities are completed. For non-commuters, the prevalence of in-home maintenance activity participation is quite high, suggesting that these individuals take on the household responsibilities and obligations. Their average activity duration for these episodes amounts to about four hours over the course of a day. They also engage in higher levels of out-of-home maintenance and in-home discretionary activities, both in terms of rate of participation and total time allocated over the course of a day. In general, the descriptive statistics are quite intuitive and consistent with expectations. As such, the data set was considered appropriate for estimating a joint activity type – duration model system as proposed in this study.

Table 3: Average Daily Activity Duration by Activity Type

Activity type	Commuters (N=4162) All Respondents (min/day) Before Mandatory	Commuters All Respondents Between Mandatory	Commuters All Respondents After Mandatory	Commuters All Respondents Total	Commuters Activity Participants (min/day), Sample sizes in parentheses: Before Mandatory	Commuters Activity Participants Between Mandatory	Commuters Activity Participants After Mandatory	Non-commuters (N=7946) All Respondents	Non-commuters (N=7946) Activity Participants
In-home Mandatory Activities	6.4	1.3	13.1	20.8	95.9 *(279)*	91.1 *(58)*	110.3 *(494)*	24.0	200.7 *(949)*
Out-of-home Mandatory Activities				449.1		449.1 *(4162)*		0.0	0.0 *(0)*
In-home Maintenance Activities	55.2	6.6	68.3	130.1	64.7 *(3551)*	65.1 *(420)*	87.9 *(3231)*	229.8	242.4 *(7532)*
Out-of-home Maintenance Activities	6.9	4.3	18.9	30.1	26.6 *(1078)*	31.4 *(572)*	46.7 *(1687)*	62.8	102.8 *(4858)*
In-home Discretionary Activities	26.3	8.4	137.5	172.2	55.9 *(1961)*	87.2 *(401)*	164.1 *(3487)*	361.6	374.9 *(7663)*
Out-of-home Discretionary Activities	11.9	29.0	41.3	82.2	69.5 *(715)*	46.1 *(2614)*	131.1 *(1311)*	127.1	214.1 *(4716)*
Sleeping	143.9	15.3	308.2	467.4	162.3 *(3689)*	338.0 *(189)*	327.0 *(3923)*	554.2	554.7 *(7938)*
Travel for Mandatory Activities	6.6	2.4	16.3	25.4	25.2 *(1098)*	19.4 *(521)*	40.6 *(1674)*	0.3	86.5 *(28)*
Travel for Maintenance Activities	19.1	5.9	15.1	40.1	23.8 *(3342)*	23.8 *(1033)*	25.9 *(2426)*	35.7	59.3 *(4788)*
Travel for Discretionary Activities	3.5	1.9	10.0	15.5	24.4 *(602)*	13.2 *(610)*	35.6 *(1173)*	29.6	52.9 *(4453)*
Other	2.5	1.0	3.6	7.0	38.6 *(266)*	45.1 *(89)*	51.0 *(294)*	14.9	78.4 *(1513)*

Table 4: Average Daily Episode Frequency by Activity Type

Activity type	Commuters (N=4162)							Non-commuters (N=7946)	
	All Respondents (min/day)				Activity Participants (min/day) Sample sizes in parentheses			All Respondents	Activity Participants
	Before Mandatory	Between Mandatory	After Mandatory	Total	Before Mandatory	Between Mandatory	After Mandatory		
In-home Mandatory Activities	0.1	0.0	0.2	0.3	1.3 *(279)*	1.3 *(58)*	1.4 *(494)*	0.2	1.8 *(949)*
Out-of-home Mandatory Activities				2.3		2.3 *(4162)*		0.0	0.0 *(0)*
In-home Maintenance Activities	1.8	0.2	2.4	4.4	2.2 *(3551)*	2.3 *(420)*	3.1 *(3231)*	5.5	5.8 *(7532)*
Out-of-home Maintenance Activities	0.4	0.2	0.7	1.3	1.5 *(1078)*	1.6 *(572)*	1.8 *(1687)*	1.6	2.6 *(4858)*
In-home Discretionary Activities	0.7	0.2	2.2	3.2	1.6 *(1961)*	2.0 *(401)*	2.7 *(3487)*	4.9	5.1 *(7663)*
Out-of-home Discretionary Activities	0.3	1.1	0.6	1.9	1.5 *(715)*	1.7 *(2614)*	1.8 *(1311)*	1.5	2.5 *(4716)*
Sleeping	0.9	0.1	1.1	2.1	1.0 *(3689)*	1.3 *(189)*	1.2 *(3923)*	2.3	2.3 *(7938)*
Travel for Mandatory Activities	0.5	0.2	1.1	1.8	1.8 *(1098)*	1.8 *(521)*	2.7 *(1674)*	0.0	1.8 *(28)*
Travel for Maintenance Activities	0.9	0.4	0.6	1.9	1.1 *(3342)*	1.7 *(1033)*	1.1 *(2426)*	2.1	3.5 *(4788)*
Travel for Discretionary Activities	0.2	0.2	0.6	1.0	1.5 *(602)*	1.2 *(610)*	2.1 *(1173)*	1.5	2.6 *(4453)*
Other	0.1	0.0	0.1	0.2	1.2 *(266)*	1.2 *(89)*	1.3 *(294)*	0.3	1.4 *(1513)*

Model Estimation Results

In this study, joint models of activity type and activity duration were estimated for commuter and non-commuter samples. Three separate models were estimated for the commuter sample. One model was estimated for non-mandatory activities conducted before the first mandatory activity episode, another for activities undertaken between mandatory activity episodes, and a third model for those activities conducted after the last mandatory activity episode. This breakdown of episodes for commuters was done to reflect time-of-day constraints imposed by mandatory activity episodes on non-mandatory activity engagement choices. The effect of time of day on activity engagement for non-commuters was captured by introducing the timing variable as an explanatory variable in the models. The activity type (discrete variable) was modeled as a multinomial probit model and activity duration (continuous variable) was modeled as a log-linear regression model. Joint models of activity type and activity duration were estimated using the probit-based discrete-continuous methodology which can explicitly accommodate error correlations across the choice dimensions. Independent models of the activity type and activity duration which assume no correlations across the activity choice dimensions were also estimated for comparison purposes.

The model structure adopted in this study assumes that activity type choice affects activity duration, i.e., activity type choice enters as an endogenous variable in the model of activity duration. This assumption is plausible as an individual is likely to determine time allocation to an activity based on the decision to engage in a certain activity type. While it is conceivable that the activity type choice may be influenced by the amount of time available in an open block of time prior to the onset of the next mandatory episode, an exploration of such a relationship is left for a future research exercise. The activity type comprised of four discrete choices, namely, in-home maintenance, out-of-home maintenance, in-home discretionary, and out-of-home discretionary. In-home maintenance activity engagement was assumed as the base alternative in the activity type choice model. All parameter estimates in the activity type choice model are therefore relative to in-home maintenance activity type choice. Table 5 and Table 6 provide independent and joint estimation results respectively for the subsample of activities undertaken by commuters prior to the first mandatory activity episode, while Table 11 and Table 12 provide independent and joint model results for the non-mandatory activity episodes undertaken by non-commuters. Estimation results for commuter activity episodes undertaken in between the first and last mandatory activity episodes of the day (Table 7 and Table 8), or after the last mandatory activity episode of the day (Table 9 and Table 10), are discussed briefly.

Independent models of activity type and activity duration that assume zero error correlations across the activity choice dimensions were estimated first. In addition to providing estimates for comparison purposes, these independent model estimates also served as starting values for the probit-based joint discrete continuous model. The Maximum Simulated Likelihood Estimation (MSLE) methodology was applied to obtain parameter estimates with the aid of quasi-random Halton sequences. One hundred quasi-random Halton draws were used for estimating the simulated likelihood function.

Estimation Results for Commuters

Table 5 presents the independent models and Table 6 show the joint model of activity type and duration for non-mandatory episodes undertaken by commuters before the first mandatory activity episode. In general, the estimation results are consistent with expectations. The magnitudes of the constant term in the activity type model reveals that in-home maintenance type activities are more likely to be undertaken in this period than in-home discretionary and out-of-home activities. This is presumably because individuals are getting ready for work and school. Discretionary activities (both in-home and out-of-home) offer males a greater utility than females, suggesting the presence of traditional gender roles. Time-constrained commuters are likely to engage less in all types of non-mandatory activities prior to work or school on weekdays, and are likely to allocate more time to such activities on weekend days when such constraints are likely to be absent. As expected, the presence of children increases the propensity of commuters to engage in out-of-home maintenance type activities. The presence of children also decreases the amount of time allocated to different activity types as evidenced by the negative sign in the duration model. Age has a positive impact on in-home discretionary activities but has a negative impact for out-of-home activity types, suggesting that younger individuals are more prone to seeking out-of-home activity pursuits.

Of particular interest in this study is the nature and sign of the coefficients of the activity type dummy variables (endogenous variables) on the activity duration. The relative magnitude of the endogenous variable coefficients indicate that time allocated to out-of-home discretionary activities is higher than that for in-home maintenance, which is in turn greater than that for in-home discretionary and out-of-home maintenance activities. This finding is behaviorally intuitive in that activity episodes that are of maintenance in nature are likely to be short activities as commuters get ready for the day. On the other hand, out-of-home discretionary activity episodes (such as an early morning jog or workout) are likely to be longer than maintenance activities and in-home discretionary activities. It is interesting to note that the sign of the in-home discretionary activity coefficient is positive in the independent model, but negative in the joint model that accounts for simultaneity and presence of error correlations across activity type and duration dimensions. It is conceivable that the estimates from the independent model are biased and inconsistent because they do not account for the endogeneity of activity type choice. This observation is corroborated by the significance of the covariance between the random error terms in the utility function of in-home discretionary activity and the activity duration equations (value = 0.768; t = 19.9).

One of the goals of the study was to explore the impact of activity history dependency on both the activity type choice and activity duration dimensions. It is interesting to note that activity history has a complementary effect on activity type choice in the "before mandatory activity episodes" period. This finding is reasonable because the time of the day under consideration here is likely to be the morning period when people have not yet accumulated substantial activity history for various activity types, thus leading to a positive impact of activity history on activity type choice. Activity history for all activity types has a positive impact on activity durations except for in-home maintenance activity. This is again plausible because the accumulation of in-home maintenance activities in this period suggests that commuters have completed their morning "get-ready" activities and allocate decreasing amounts of time to such activities as the history of accumulation increases.

Similarly, models were estimated for non-mandatory activity episodes undertaken by commuters in between mandatory activity episodes, and after the last mandatory activity episode of the day. In general, the two model systems were found to offer behaviorally plausible indications.

Unlike the model for non-mandatory activities pursued before the first mandatory activity episode (presented in Table 5 and Table 6), the model for non-mandatory activities pursued between mandatory activity episodes showed no major differences in coefficient values and signs for right hand side activity type variables in the duration model. Consistent with this finding, error covariances across the two choice dimensions were not statistically significant suggesting that there are no significant common unobserved factors affecting activity type choice and activity episode duration for non-mandatory activities pursued in between mandatory activity episodes. As commuters are likely to be constrained with respect to their non-mandatory activity engagement during the period sandwiched by mandatory activity episodes, it is likely that there are few extraneous unobserved factors that impact non-mandatory activity engagement and time use during this period.

Activity history dependency was found to have an impact on both the activity type choice and activity duration for non-mandatory activities pursued by commuters between mandatory activity episodes. The history of in-home maintenance activities has a negative impact on the out-of-home discretionary activity type choice, possibly because these individuals take on the household maintenance role and engage less in discretionary activities outside home. Out-of-home maintenance activity history has a negative impact on both in-home and out-of-home discretionary activity type choices for much the same reason; the impact of out-of-home maintenance activity history on activity duration is positive, suggesting that individuals who undertake household maintenance activities outside home are likely to allocate greater amounts of time for such activities, even in the middle of the mandatory activity period. In-home discretionary activity engagement shows a positive history dependency, indicating that individuals who generally accumulate a history of these types of activities are likely to prefer to engage in these activities again.

Finally, a model was estimated for non-mandatory activities undertaken by commuters after the last mandatory activity episode of the day. The endogenous variables of activity type that enter the activity duration equation were found to be statistically significant except for the dummy variable indicating in-home discretionary activity type. Out-of-home maintenance activities appear to be shorter in duration relative to out-of-home discretionary activities. The coefficient associated with in-home discretionary activity participation was highly significant and positive in the independent duration model; in the joint model, the coefficient was statistically insignificant. Thus, while the independent model suggested that commuters allocate more time to in-home discretionary activity episodes, the joint model did not. However, in the joint model, the covariance between the random error terms in the in-home discretionary activity type utility equation and the activity duration equation was found to be positive and statistically significant. It appears that there are common unobserved attributes that contribute positively to engaging in and allocating more time to in-home discretionary activities after the last mandatory activity episode of the day.

Once again, history dependency played a significant role in non-mandatory activity engagement and time use. In-home maintenance activity history had a negative impact on out-of-home discretionary activity engagement suggesting that those individuals who take on a greater amount of household responsibilities are constrained with respect to their ability to engage in out-of-home discretionary activities. Those who have a history of completing out-of-home maintenance activities are less likely to do in-home discretionary activities; instead they are more prone to potentially undertaking out-of-home discretionary activities that they may chain to maintenance activity-travel. There is a strong positive history dependency for in-home discretionary activity engagement. These individuals are likely to be "home-bound" individuals who like to engage in pleasurable activities at home. The same positive dependence is found for out-of-home discretionary activity engagement, suggesting that individuals possibly fall into lifestyle categories defined by maintenance or discretionary activity participation. In general, the accumulated history of activity engagement negatively impacts activity duration for subsequent episodes, presumably due to time constraints experienced towards the end of the day.

Estimation Results for Non-commuters

Table 11 and Table 12 present independent model and joint model estimation results respectively for the non-commuter sample. In addition to the variables considered in the commuter models, the non-commuter model includes time of day variables as well. The treatment of time of day as exogenous to the model system is consistent with the continuous time approach to the development of activity-based travel demand models. In such models, non-mandatory activities are generated and time is allocated episode by episode. Starting at the beginning of the day, one can model the first activity that a person is likely to pursue and the time that he or she would allocate to it. When the first activity is completed, the individual reaches a decision point regarding the next activity to be pursued. This process continues along the time axis until the entire activity pattern evolves for the full 24-hour period of a day. At each decision point, the time of day (at which choices are being made) is known, thus making it reasonable to treat time of day as exogenous in a joint model of activity type choice and duration.

The model estimation results are generally consistent with expectations. Non-commuters are likely to carry more of the household obligations and responsibilities, thus contributing to a negative constant for all other activity types. Male non-commuters are more likely to engage in out-of-home activities and in-home discretionary activities, and for longer durations, relative to females suggesting that traditional gender roles exist even among non-commuters. Non-commuters tend not to engage in out-of-home maintenance activities on weekends, perhaps reserving those days for discretionary activities, and presumably because they are able to finish maintenance activities on weekdays. On the other hand, they are less prone to engage in discretionary activities during the weekdays, possibly due to household obligations and constraints. The presence of children has a negative impact on out-of-home activity engagement and on activity duration. Older non-commuters are less likely to engage in out-of-home maintenance activities and tend to allocate shorter time durations to non-mandatory activities. There are significant time-of-day effects. Non-commuters tend to engage in out-of-home maintenance activities between 9:00 AM and 11:00

AM and between 4:00 PM and 7:00 PM. In the late evening hours, non-commuters tend to pursue in-home discretionary activities (7:00 PM – 9:00 PM).

With respect to the endogenous variables that enter the activity duration equation, out-of-home maintenance activities tend to be shorter in duration and discretionary activities tend to be longer in duration, with in-home discretionary activities having the highest positive coefficient among all activity types. It is again noteworthy that, for the specific activity type with a significant random error covariance (out-of-home discretionary), the coefficient in the joint model is quite different from the corresponding value in the independent model. This coefficient takes on the highest positive value and is statistically significant in the independent model. In the joint model, this coefficient is not statistically significant.

Once again activity history dependency effects are observed. In-home maintenance activity history has a negative impact on out-of-home discretionary activity engagement and time allocation, presumably due to household obligations and constraints that these individuals face and household roles that individuals fulfill. It is interesting to note that there is evidence of positive history dependency in non-mandatory activity engagement for non-commuters. For out-of-home maintenance, in-home discretionary, and out-of-home discretionary activity types, the accumulated history of activity engagement positively impacts the likelihood of participating in that activity type again. This finding suggests that people not only fulfill distinct household roles, but also adopt activity patterns consistent with their lifestyle and personality traits. Future research efforts should aim to disentangle history dependency effects from unobserved heterogeneity effects so that these lifestyle effects can be isolated and measured. Finally, it is found that all cumulative history variables have a negative impact on activity episode duration, which is consistent with expectations.

Table 5: Results of Independent Models for Non-mandatory Activity Engagement Behavior of Commuters Before First Fixed Activity

	Independent Activity Type Model						Independent Activity Duration Model	
	Out-of-home Maintenance		In-home Discretionary		Out-of-home Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-1.219	-10.6	-1.229	-12.9	-1.680	-12.5	2.942	120.9
Male			0.510	11.8	0.606	8.9		
Weekend (Sat, Sun)							0.337	14.4
Weekday (Tue, Wed, Thu)	-0.120	-2.1	-0.184	-4.2	-0.407	-5.7	0.031	1.5
Presence of Children	0.149	2.6	-0.387	-8.1	-0.660	-9.0	-0.179	-8.3
Low Income (0 - $14,999)							0.059	2.7
High Income ($75,000 -)			-0.131	-2.8	-0.231	-3.0		
Hispanic							0.055	2.0
African-American			-0.125	-1.9				
Age	-0.011	-4.7	0.007	3.7	-0.008	-3.2		
Household Size							0.014	1.9
Out-of-home Maintenance Activity							-0.945	-34.5
In-home Discretionary Activity							0.130	6.1
Out-of-home Discretionary Activity							0.299	9.1
Cumulative Duration of Out-of-home Mandatory upto the Activity								
Cumulative Duration of In-home Maintenance upto the Activity			0.002	6.1	0.003	5.8	-0.001	-3.3
Cumulative Duration of Out-of-home Maintenance upto the Activity	0.012	12.8			0.008	7.0	0.002	4.2
Cumulative Duration of In-home Discretionary upto the Activity			0.001	1.7			0.001	7.0
Cumulative Duration of Out-of-home Discretionary upto the Activity					0.007	12.4		
Log-likelihood at convergence = -32969.8								

Table 6: Results of Joint Model for Non-mandatory Activity Engagement Behavior of Commuters Before First Fixed Activity

	Joint Activity Type Model						Joint Activity Duration Model	
	Out-of-home Maintenance		In-home Discretionary		Out-of-home Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.888	-11.2	-0.842	-12.3	-1.266	-14.2	3.206	113.0
Male			0.330	11.0	0.416	9.8		
Weekend (Sat, Sun)							0.330	14.2
Weekday (Tue, Wed, Thu)	-0.116	-3.0	-0.144	-4.3	-0.280	-6.3	0.010	0.5
Presence of Children	0.044	1.1	-0.306	-8.5	-0.408	-8.8	-0.239	-10.4
Low Income (0 - $14,999)							0.061	2.8
High Income ($75,000 -)			-0.077	-2.4	-0.140	-3.0		
Hispanic							0.058	2.2
African-American			-0.090	-2.0				
Age	-0.007	-4.7	0.003	2.5	-0.005	-2.7		
Household Size							0.012	1.7
Out-of-home Maintenance Activity							-1.019	-15.4
In-home Discretionary Activity							-0.852	-16.0
Out-of-home Discretionary Activity							0.419	6.0
Cumulative Duration of Out-of-home Mandatory upto the Activity								
Cumulative Duration of In-home Maintenance upto the Activity			0.001	3.8	0.002	5.0	-0.0004	-2.3
Cumulative Duration of Out-of-home Maintenance upto the Activity	0.009	13.2			0.006	7.6	0.001	1.8
Cumulative Duration of In-home Discretionary upto the Activity			0.001	1.8			0.002	7.8
Cumulative Duration of Out-of-home Discretionary upto the Activity					0.005	12.5		

Log-likelihood at convergence = -32946.3; γ_{1N} *= 0.130(3.2);* γ_{2N} *= 0.768(19.9);* γ_{3N} *= -0.001(-0.0);* γ_{4N} *= 0.000(-);* σ'_N *= 0.724(25.6)*

Table 7: Results of Independent Model for Non-mandatory Activity Engagement Behavior of Commuters In Between Fixed Activities

	Independent Activity Type Model						Independent Activity Duration Model	
	Out-of-home Maintenance		In-home Discretionary		Out-of-home Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.085	-1.3	-0.415	-4.8	1.490	18.6	2.802	80.5
Male Dummy	-0.220	-2.3	0.460	4.7	0.276	3.7		
Weekend Dummy (Sat, Sun)							0.120	4.9
Weekday Dummy (Tue, Wed, Thu)								
Children Dummy			-0.191	-2.2	-0.295	-4.3		
Low Income Dummy (0 - $14,999)								
High Income Dummy ($75,000 -)	0.456	5.0			0.211	3.1	0.069	3.1
Hispanic Dummy					0.452	5.8	0.054	1.9
African-American Dummy					0.358	4.6		
Age								
Household Size					0.051	2.4		
Dummy for Out-of-home Maintenance Activity							-0.462	-12.2
Dummy for In-home Discretionary Activity							0.575	14.7
Dummy for Out-of-home Discretionary Activity							0.269	9.2
Cumulative Duration of Out-of-home Mandatory upto the Activity							-0.0001	-1.7
Cumulative Duration of In-home Maintenance upto the Activity					-0.002	-5.1		
Cumulative Duration of Out-of-home Maintenance upto the Activity			-0.006	-4.7	-0.012	-12.0	0.001	2.6
Cumulative Duration of In-home Discretionary upto the Activity			0.004	8.5				
Cumulative Duration of Out-of-home Discretionary upto the Activity								
Log-likelihood at convergence = -7315.97								

Table 8: Results of Joint Model for Non-mandatory Activity Engagement Behavior of Commuters In Between Fixed Activities

	Joint Activity Type Model						Joint Activity Duration Model	
	Out-of-home Maintenance		In-home Discretionary		Out-of-home Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.055	-1.3	-0.270	-4.9	1.148	19.1	2.733	37.8
Male Dummy	-0.149	-2.4	0.290	4.6	0.196	3.7		
Weekend Dummy (Sat, Sun)							0.119	4.9
Weekday Dummy (Tue, Wed, Thu)								
Children Dummy			-0.123	-2.2	-0.224	-4.3		
Low Income Dummy (0 - $14,999)								
High Income Dummy ($75,000 -)	0.303	5.0			0.146	2.9	0.069	3.1
Hispanic Dummy					0.353	6.0	0.053	1.8
African-American Dummy					0.281	4.8		
Age								
Household Size					0.041	2.5		
Dummy for Out-of-home Maintenance Activity							-0.400	-4.5
Dummy for In-home Discretionary Activity							0.702	6.4
Dummy for Out-of-home Discretionary Activity							0.344	3.7
Cumulative Duration of Out-of-home Mandatory upto the Activity							-0.0001	-1.7
Cumulative Duration of In-home Maintenance upto the Activity					-0.002	-5.3		
Cumulative Duration of Out-of-home Maintenance upto the Activity			-0.005	-5.2	-0.008	-12.8	0.001	2.5
Cumulative Duration of In-home Discretionary upto the Activity			0.003	8.1				
Cumulative Duration of Out-of-home Discretionary upto the Activity								

Log-likelihood at convergence = -15844.21; γ_{1N} *= -0.0405(-0.76);*g_{2N} *= -0.0828(-1.26);* γ_{3N} *=-0.0501(-0.75);* γ_{4N} *= 0.0000(-);* σ'_N *= 0.8072(70.62)*

Table 9: Results of Independent Model for Non-mandatory Activity Engagement Behavior of Commuters After Last Fixed Activity

	Independent Activity Type Model						Independent Activity Duration Model	
	Out-of-home Maintenance		In-home Discretionary		Out-of-home Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.927	-11.8	-0.554	-9.6	-0.385	-3.6	3.181	100.3
Male Dummy	-0.092	-2.3					0.091	6.7
Weekend Dummy (Sat, Sun)							0.126	6.9
Weekday Dummy (Tue, Wed, Thu)	-0.166	-4.0	-0.083	-2.8	-0.330	-6.9	0.021	1.4
Children Dummy					-0.458	-7.9	-0.057	-4.4
Low Income Dummy (0 - $14,999)	-0.141	-2.6			-0.161	-2.7	0.029	1.7
High Income Dummy ($75,000 -)								
Hispanic Dummy			0.153	3.7	-0.168	-2.3	0.088	4.6
African-American Dummy	0.241	3.9	0.131	3.0			0.078	3.9
Age	-0.003	-2.0	0.008	6.9	-0.011	-5.7		
Household Size					-0.036	-1.9		
Dummy for Out-of-home Maintenance Activity							-0.400	-19.1
Dummy for In-home Discretionary Activity							0.795	55.3
Dummy for Out-of-home Discretionary Activity							0.967	41.5
Cumulative Duration of Out-of-home Mandatory upto the Activity							-0.0005	-10.7
Cumulative Duration of In-home Maintenance upto the Activity					-0.004	-11.5	-0.0002	-2.2
Cumulative Duration of Out-of-home Maintenance upto the Activity			-0.002	-6.9	0.0005	1.1	-0.001	-7.3
Cumulative Duration of In-home Discretionary upto the Activity			0.003	16.8			-0.0004	-5.5
Cumulative Duration of Out-of-home Discretionary upto the Activity			0.0004	1.8	0.004	14.9	-0.001	-12.4
Log-likelihood at convergence = -29179.97								

Table 10: Results of Joint Model for Non-mandatory Activity Engagement Behavior of Commuters After Last Fixed Activity

	Joint Activity Type Model						Joint Activity Duration Model	
	Out-of-home Maintenance		In-home Discretionary		Out-of-home Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.687	-12.7	-0.385	-8.6	-0.396	-5.5	3.471	95.5
Male Dummy	-0.058	-2.2					0.094	7.0
Weekend Dummy (Sat, Sun)							0.124	6.8
Weekday Dummy (Tue, Wed, Thu)	-0.126	-4.4	-0.066	-2.8	-0.226	-7.3	0.021	1.4
Children Dummy					-0.290	-7.9	-0.050	-3.7
Low Income Dummy (0 - $14,999)	-0.097	-2.8			-0.114	-3.0	0.038	2.3
High Income Dummy ($75,000 -)								
Hispanic Dummy			0.116	3.5	-0.083	-1.8	0.117	5.6
African-American Dummy	0.168	4.0	0.099	2.9			0.092	4.3
Age	-0.002	-1.8	0.005	5.3	-0.006	-5.0		
Household Size					-0.023	-1.9		
Dummy for Out-of-home Maintenance Activity							-0.552	-10.3
Dummy for In-home Discretionary Activity							-0.057	-1.1
Dummy for Out-of-home Discretionary Activity							1.016	16.6
Cumulative Duration of Out-of-home Mandatory upto the Activity							-0.0005	-10.6
Cumulative Duration of In-home Maintenance upto the Activity					-0.002	-10.7	-0.0001	-1.0
Cumulative Duration of Out-of-home Maintenance upto the Activity			-0.002	-6.8	0.0001	0.4	-0.001	-9.2
Cumulative Duration of In-home Discretionary upto the Activity			0.002	18.5			0.0002	1.8
Cumulative Duration of Out-of-home Discretionary upto the Activity			0.0002	1.3	0.003	14.8	-0.001	-12.6

Log-likelihood at convergence = -63539.96; γ_{1N} *= 0.1647(5.11);*γ_{2N} *= 0.6959(16.33);* γ_{3N} *=0.0342(0.94);* γ_{4N} *= 0.0000(-);* σ'_N *= 0.7867(31.13)*

Table 11: Results of Independent Models for Non-mandatory Activity Engagement Behavior of Non-commuters

	Independent Activity Type Model						Independent Activity Duration Model	
	OH Maintenance		IH Discretionary		OH Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.542	-11.7	-0.600	-34.5	-1.267	-46.7	3.274	157.9
Male	0.336	15.2	0.469	30.5	0.440	19.7	0.121	17.3
Weekend (Sat, Sun)	-0.189	-9.3					0.092	10.1
Weekday (Tue, Wed, Thu)			-0.043	-2.6	-0.364	-12.9	-0.032	-3.0
Presence of Children	-0.070	-3.0			-0.113	-5.2	-0.084	-10.1
Low Income (0 - $14,999)	-0.083	-3.5	0.171	11.0			0.017	2.2
High Income ($75,000 -)					0.069	3.0	-0.046	-5.7
Hispanic	-0.056	-1.9					0.105	10.3
African-American			0.151	7.6			0.036	3.6
Age	-0.012	-17.0					-0.001	-4.0
Household Size								
Time of Day (4:00 AM - 6:00 AM)	-1.145	-10.1			-1.151	-10.0	-0.086	-3.1
Time of Day (6:00 AM - 9:00 AM)	-0.773	-22.8	-0.146	-6.4	-0.823	-21.1	-0.158	-11.7
Time of Day (9:00 AM - 11:00 AM)	0.086	2.9	-0.115	-4.7			0.045	3.3
Time of Day (11:00 AM - 2:00 PM)					0.347	12.6	0.062	5.3
Time of Day (4:00 PM - 7:00 PM)	-0.097	-3.5	0.269	13.2	0.226	7.4	0.090	8.3
Time of Day (7:00 PM - 10:00 PM)			0.375	17.1	-0.259	-6.8	0.067	5.8
Out-of-home Maintenance Activity							-0.243	-22.4
In-home Discretionary Activity							0.606	80.4
Out-of-home Discretionary Activity							0.788	70.4
Cumulative Duration of Out-of-home Mandatory upto the Activity								
Cumulative Duration of In-home Maintenance upto the Activity					-0.002	-22.5	-0.0002	-6.1
Cumulative Duration of Out-of-home Maintenance upto the Activity	0.002	13.2	-0.001	-9.1	0.001	6.8	-0.001	-15.0
Cumulative Duration of In-home Discretionary upto the Activity			0.002	36.7				
Cumulative Duration of Out-of-home Discretionary upto the Activity			-0.0001	-1.6	0.003	33.1	-0.001	-20.1

Log-likelihood at convergence = -283256.9

Table 12: Results of Joint Model for Non-mandatory Activity Engagement Behavior of Non-commuters

	Joint Activity Type Model						Joint Activity Duration Model	
	OH Maintenance		IH Discretionary		OH Discretionary			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.464	-4.7	-0.528	-12.2	-0.966	-17.1	3.433	37.4
Male	0.217	4.6	0.313	8.1	0.311	6.5	0.126	5.0
Weekend (Sat, Sun)	-0.108	-2.5					0.042	1.4
Weekday (Tue, Wed, Thu)			0.025	0.6	-0.177	-3.2	-0.086	-2.5
Presence of Children	-0.039	-0.8			-0.094	-2.1	-0.130	-4.7
Low Income (0 - $14,999)	0.018	0.4	0.122	3.1			-0.007	-0.30
High Income ($75,000 -)					0.090	1.9	-0.046	-1.7
Hispanic	-0.029	-0.5					0.134	4.2
African-American			0.032	0.7			0.040	1.2
Age	-0.008	-5.7					-0.002	-2.6
Household Size								
Time of Day (4:00 AM - 6:00 AM)	-0.939	-4.1			-0.888	-4.0	-0.188	-2.0
Time of Day (6:00 AM - 9:00 AM)	-0.533	-7.6	-0.071	-1.2	-0.522	-6.8	-0.188	-4.0
Time of Day (9:00 AM - 11:00 AM)	0.054	0.8	-0.063	-1.0			0.109	2.3
Time of Day (11:00 AM - 2:00 PM)					0.224	3.8	0.127	3.1
Time of Day (4:00 PM - 7:00 PM)	0.131	2.2	0.334	6.5	0.198	3.0	0.042	1.1
Time of Day (7:00 PM - 10:00 PM)			0.436	8.0	-0.045	-0.6	0.022	0.5
Out-of-home Maintenance Activity							-0.291	-2.3
In-home Discretionary Activity							0.740	5.2
Out-of-home Discretionary Activity							0.074	0.5
Cumulative Duration of Out-of-home Mandatory upto the Activity								
Cumulative Duration of In-home Maintenance upto the Activity					-0.001	-6.4	-0.0003	-3.2
Cumulative Duration of Out-of-home Maintenance upto the Activity	0.001	2.6	-0.001	-2.9	0.0003	1.0	-0.0003	-1.5
Cumulative Duration of In-home Discretionary upto the Activity			0.002	12.4				
Cumulative Duration of Out-of-home Discretionary upto the Activity			-0.0004	-2.3	0.002	9.7	-0.0004	-2.7

Log-likelihood at convergence = -28407.3; γ_{1N} *= 0.044(0.5);* γ_{2N} *= -.098(-0.9);* γ_{3N} *= 0.467(4.4);* γ_{4N} *= 0.000(-);* σ'_N *=0.978(24.5*

Discussion and Conclusions

Activity engagement patterns of individuals are of much interest in the context of the development of activity-based travel demand models, understanding the motivations for travel, analyzing social networks, and modeling time use. Activity type choice and activity episode duration are two important dimensions of activity participation that are critical to the specification of any activity based model system. Beyond mandatory activities that offer little flexibility in the formation of an activity agenda, discretionary and maintenance activities are of interest because of the role they play in forming an individual's activity engagement pattern. A probit-based joint discrete-continuous modeling methodology was used to model the activity type choice and activity episode duration jointly using data from the 2008 American Time Use Survey dataset. In addition to socioeconomic variables, the history of activity engagement (history dependency) and timing of the activity were used as explanatory variables. Separate models were estimated for commuters and non-commuters.

Covariances between the random error terms of the activity type choice utility equations and activity duration equation were found to be statistically significant for all joint model systems with the exception of that for commuter non-mandatory activities pursued between mandatory activity episodes. Comparisons of the coefficients of endogenous variables where the error correlations were significant against estimates from the independent model specification revealed that there are substantive differences in coefficient estimates and significance that can result from ignoring error correlations. The study confirms the importance of considering the endogeneity of activity type and duration decisions to avoid inconsistent and biased estimates which could subsequently lead to erroneous activity-travel forecasts and policy impact assessments.

One of the interesting findings in this study is that there appears to be a significant degree of positive history dependency in activity engagement. It was found that individuals who undertook or accumulated a history of activity engagement in a certain type of non-mandatory activity were more likely to continue pursuing that activity type again later in the day, subject to shorter durations that arise from increasing levels of time constraints that come into play as the day progresses. This finding potentially points to the possibility that individuals have different lifestyle preferences (in addition to rather well-defined household roles). This finding has key implications for the specification of activity based model systems that aim to capture inter-dependencies among household members that arise from household roles, while simultaneously reflecting personality traits and lifestyle preferences that influence individual activity engagement patterns.

D. A Tour-level Model of Vehicle Type Choice and Usage Decision

In microsimulation modeling of travel demand, two approaches are commonly used, namely, activity- (Arentze et al. 2000, Kitamura and Fujji 1998, Pendyala et al. 2005, Pinjari et al. 2004) and tour- (Bowman and Ben-Akiva 2000, Vovsha et al. 2002, Miller et al. 2005, Bradley et al. 2009) based. In the tour-based approaches, the basic unit of analysis is a trip chain or tour to explicitly recognize the inter-dependency of trips within a tour. There have been a number of successful implementations of tour-based model systems both in the US and elsewhere (Vovsha et al. 2002, Algers et al. 1995, Bradley et al. 2009). Most of the tour-based models consider (to differing degrees) some basic dimensions that characterize tours including primary activity type, location, number of stops and identification of stop locations on the tour, sequencing and scheduling of stops, and mode choice at both the tour- and individual trip- level. There is virtually no tour-based model, however, that explicitly models the type of vehicle used to undertake the tour. Given that the type of vehicle used (in terms of body type, fuel type, and/or vintage) and total distance traveled on a tour are two critical factors determining energy consumption and greenhouse gas (GHG) emissions (Hensher 2008, Spissu et al. 2009), this study focuses on understanding the relationship between these two tour-level dimensions of interest.

Household vehicle ownership (and utilization) by type of vehicle has been the focus of several recent research efforts (Mohmmadian and Miller 2003, Bhat and Sen 2006, Cao et al. 2006, Eluru et al. 2010). However, much of this work is aimed at examining the household vehicle type holdings, the mix of vehicle types in a household fleet, and the overall utilization (mileage) of vehicles. There are no research efforts that have studied the vehicle type choice and usage at the individual tour level in households with multiple vehicle types. This level of disaggregate detail is important to understand the usage patterns of different vehicle types and then accurately assess the associated environmental impacts.

In most of the tour-based model implementations, a number of models are estimated to mimic the different choice dimensions of individual's tour making behavior. The models are often implemented sequentially (with logsum feedback loops) to simulate the different tour characteristics. However, in reality, people make decisions about different tour attributes jointly and there are common unobserved factors affecting these decisions (Pendyala and Bhat 2004, Ye and Pendyala 2009). It is of considerable interest then to adopt modeling approaches that allow one to consider choice dimensions jointly while also accommodating the presence of common unobserved factors by specifying error correlation structures (Mannering 1986).

This study presents a joint model of vehicle type choice and tour length for automobile tours undertaken by individuals in households that have a mix of vehicle body types. In this context, there are interesting questions regarding the relationship between vehicle type choice and tour length that arise. Does vehicle type choice affect tour length, or does tour length affect vehicle type choice? Or is there a more contemporaneous relationship between these two choice dimensions that makes it impossible to choose one specification over the other? Interesting policy outcomes arise in the context of these questions. Consider the situation where tour length affects vehicle type choice, wherein shorter tour lengths are associated with the use of larger vehicle types that consume more energy and pollute more. In that situation, policies that promote land use density may actually have a counter-intuitive effect of not providing the intended environmental benefits if enhanced land use density results in shorter vehicle tours that households can monetarily afford to undertake using large utility vehicles. Similar policy implication arguments can be made for the reverse situation where vehicle type choice impacts tour length. Say, one provides tax incentives for the purchase of a fuel efficient automobile that motivates households to purchase such vehicles. Individuals can now monetarily afford to drive more miles using the fuel efficient vehicles, thus negating at least some of the potential benefits of incentives provided to households to acquire fuel efficient vehicles.

The research effort uses a sample of tours undertaken by individuals in households that own a mix of vehicle types drawn from the 2009 National Household Travel Survey (NHTS) dataset of the United States. A probit-based discrete-continuous model specification presented in Section B was employed to jointly model vehicle type choice (discrete choice variable), and tour length (continuous choice variable).

The remainder of the research study is organized as follows. The data utilized in this study is presented in the next subsection followed by model estimation and hypothesis test results. In the last subsection, conclusions are presented.

Data Set and Sample Composition

In this study, data from the 2009 National Household Travel Survey (NHTS) of the United States is used. Only home and work-based tours are considered as these two locations are often considered anchors of trip making. The subsample employed for analysis in this effort includes only those tours made by individuals residing in households that own multiple vehicles of different body types. In addition, the analysis is limited to the modeling of automobile-only tours undertaken by individuals of driving age (15 years or above) on regular weekdays (Monday through Thursday). This resulted in a total of 102,352 tours performed by 64,568 respondents residing in 37,938 households. The average number of tours per person was about 1.6 and that per household was nearly 2.7. Nearly 29.4 percent of all tours were home-based work (HBW) tours, 64.5 percent were home-based non-work tours (HBNW), and about 6.1 percent were work-based tours mostly comprising of eat-lunch activities pursued by employed individuals between work episodes.

The HBNW tours are of particular interest in this study because people potentially have greater flexibility in the choice of destinations (and therefore distance traveled) and vehicle type for these tours as opposed to home-based work tours and work-based tours which are more temporally and spatially constrained. Also, in order to avoid the inflation of t-statistics resulting from the use of a very large sample dataset that may lead to erroneous inferences, a random sample of a little less than 10 percent (6,478 out of 66,030) home-based non-work tours was selected. Table 13 provides descriptive statistics for the subsample of HBNW tours. Each HBNW tour involved an average of 1.7 stops with average travel duration of 37 minutes and average tour length of 15.7 miles. On an average, there were about 1.7 persons on each tour. Each household in the subsample comprised of nearly three persons with one child. Most of the households in the sample (68 percent) reside in urban areas. There is a slightly higher percentage (56 percent) of females than males. This may be due to the higher number of non-work (e.g. household maintenance, serve-child) activities that women generally participate in compared to men.

Table 14 provides a distribution of tour characteristics by vehicle type chosen. As expected, larger vehicle body types (van, sports utility vehicle) are typically associated with larger vehicle occupancy compared to other vehicle types. Households probably like to use larger vehicles for trips involving multiple individuals in the traveling group. It is interesting to note that, when the vehicle fleet composition of the household is ignored, car appears to be the preferred body type, being chosen for nearly 42 percent of the HBNW tours. The car vehicle type is followed in preferential order by sports utility vehicle (SUV), pickup truck and van. It is also found that the difference in tour lengths across vehicle types chosen for the tour appears to be only marginal. These statistics might give one the impression that vehicle type choice and tour length have no relationship. However, the differences in tour length across vehicle types are more pronounced when one controls for vehicle fleet composition. Whenever van is part of the household vehicle fleet, it appears to be the preferred alternative. In households where both a car and a SUV are present, SUV is chosen for more tours than car. The pickup truck appears to be the least preferred vehicle type. Pickup trucks may not be used as commonly as other vehicle types for routine HBNW tours. Tours where SUV is the chosen body type have the highest occupancy, followed in order by van, car and pickup truck. These findings show that one needs to consider the vehicle availability (fleet composition) choice set when attempting to model the relationships between vehicle type choice and other tour attributes.

Table 13: Descriptive Statistics of the Sample

Variable Description	Mean	Std. Deviation
Tour-level		
Number of passengers/tour	1.7	0.9
Number of trips/tour	2.7	1.2
Number of stops/tour	1.7	1.2
Travel duration/tour	37.0	29.7
Travel distance/tour	15.7	14.4
Household-level		
Household size	3.1	1.3
Household vehicle ownership	2.8	1.1
Number of adults	2.3	0.7
Number of children	0.8	1.1
Percentage of households in non-urban area	30%	0.5
Percentage of households with income less than $40K	20%	0.4
Person-level		
Percentage of males	50%	0.5
Percentage of people less than 18 years old	10%	0.2
Percentage of people 65 or older	30%	0.4
Percentage of people with some college education	70%	0.5

Table 14: Tour Characteristics by Vehicle Type Choice for the Tour

Household Vehicle Fleet Composition by Body Type	Freq.	Body Type Selected for Tour	Tour Dist.	Tour Travel Time	Pax on Tour	Stops on Tour
Average Tour Attributes (Not Considering Vehicle Fleet Composition)						
	2716	Car	16.0	37.7	1.6	1.6
	911	Van	15.2	37.0	2.1	1.8
	1647	SUV	15.4	36.0	1.8	1.7
	1204	Pickup	15.6	36.5	1.5	1.6
Average Tour Attributes (Considering Vehicle Fleet Composition)						
SUV, Pickup	412	SUV	17.0	37.4	1.9	1.8
SUV, Pickup	221	Pickup	15.6	37.4	1.5	1.6
Van, Pickup	169	Van	14.4	35.9	2.0	1.8
Van, Pickup	111	Pickup	15.9	37.5	1.4	1.7
Van, SUV	100	Van	17.2	39.6	2.1	1.7
Van, SUV	76	SUV	16.4	40.3	1.7	1.7
Van, SUV, Pickup	28	Van	15.4	31.9	1.9	1.3
Van, SUV, Pickup	31	SUV	17.9	38.4	1.9	1.6
Van, SUV, Pickup	12	Pickup	17.4	61.4	1.3	1.3
Car, Pickup	1204	Car	17.1	39.3	1.6	1.7
Car, Pickup	662	Pickup	15.4	35.8	1.5	1.6
Car, SUV	767	Car	14.3	36.1	1.5	1.6
Car, SUV	824	SUV	14.1	34.3	1.7	1.6
Car, SUV, Pickup	196	Car	16.6	36.9	1.6	1.6
Car, SUV, Pickup	241	SUV	16.0	37.4	1.7	1.7
Car, SUV, Pickup	137	Pickup	16.9	36.9	1.4	1.6
Car, Van	392	Car	15.2	36.5	1.7	1.6
Car, Van	450	Van	15.0	37.5	2.1	1.8
Car, Van, Pickup	99	Car	15.8	35.6	1.6	1.5
Car, Van, Pickup	102	Van	17.0	38.9	2.1	1.9
Car, Van, Pickup	51	Pickup	14.0	33.5	1.6	1.4
Car, Van, SUV	47	Car	17.2	41.2	1.5	1.6
Car, Van, SUV	50	Van	11.1	28.8	1.8	1.6
Car, Van, SUV	46	SUV	15.4	36.4	1.5	1.9
Car, Van, SUV, Pickup	11	Car	20.3	42.4	1.6	1.6
Car, Van, SUV, Pickup	12	Van	21.7	43.8	2.3	1.8
Car, Van, SUV, Pickup	17	SUV	18.3	40.4	2.1	1.9
Car, Van, SUV, Pickup	10	Pickup	15.0	33.6	1.4	1.6

Model Estimation Results

Joint discrete-continuous models of vehicle type choice and distance traveled were estimated for HBNW tours using the modified formulation presented in Equation (7) of Section B. The vehicle type choice is modeled as a multinomial probit model and the tour length is modeled as a log-linear regression model. The vehicle type choice included four discrete choices, namely, car, van, SUV, and pickup truck, with pickup truck considered the base alternative. Independent models with no error correlations across the choice dimensions were also estimated for assessing the benefits of joint modeling frameworks in this context. The coefficient estimates from the independent models served as the starting values for estimating the joint models. The MSLE procedure was used for estimating the coefficients in the joint model using 100 quasi-random Halton sequences (Bhat 2001).

In this study, two alternative joint discrete-continuous model specifications were explored. Table 15 and Table 16 present independent and joint model estimation results respectively for the first model specification where tour length was assumed to affect vehicle type choice and Table 17 and Table 18 present independent and joint model results respectively for the specification where vehicle type choice was assumed to affect tour length. The two model specifications are behaviorally plausible and could potentially provide a way to evaluate some interesting policy outcomes. According to the first specification, an individual may choose a set of destinations to visit during a tour – in other words he or she determines the distance to travel, and then chooses the type of vehicle dependent on the distance. For longer distances, an individual may choose to use the more fuel efficient vehicle for monetary benefits or the larger less fuel efficient vehicle for comfort and capacity. For shorter distances, the individual may be indifferent to the type of vehicle. In the second model specification, one is postulating that individuals within a household probably have a car assigned to them based on their household roles. For example, in a household with a car and van, if the female head in the household is responsible for chauffeuring kids, then she may be allocated the larger vehicle (van), whereas the car may be assigned to the male head of the household. If that is the case, then the choice of tour length (destinations) may depend on the type of vehicle that the person is assigned (and drives primarily). The male head of the household may choose to travel farther because he is driving the smaller more fuel efficient vehicle (and it is monetarily affordable to do so), or may choose to drive short distances because the small car is not as comfortable as the large vehicle.

Non-nested Hypothesis Test

It is found that both joint model specifications presented in Table 16 and Table 18 offer plausible results. In order to select an appropriate model specification that best fits the data, the non-nested hypothesis test presented earlier was applied. The model with higher likelihood ratio index is generally selected as the appropriate one. The test then gives bounds on the probability that the model selected is incorrect. In this study, the joint model where vehicle type choice affects tour length produces a higher likelihood ratio index. The non-nested test indicates that the probability with which this model will be an incorrect model is less than 0.007. Therefore the model specification is more appropriate and supports the notion that households probably allocate vehicles among household members a priori at a higher longer-term choice dimension level, and then individual tour destinations and travel distance are dependent on the type of vehicle the person is allocated, other tour attributes such as accompaniment type and number of stops on the tour, and usual socioeconomic characteristics. This model specification also has significant error correlations (discussed further later) pointing to the need for modeling the choice dimensions using a simultaneous equations framework that can explicitly accommodate error correlations across choice dimensions. As this model specification is best supported by the data, the remaining discussion focuses on findings reported in Table 18.

Influence of Tour Attributes

The constant terms in the joint model reveal that SUV and van vehicle types are preferred over cars for HBNW tours. This result is reasonably consistent with what was observed in the descriptive analysis where SUV and van were chosen more frequently compared to other body types when these vehicle types existed in the fleet. Note that the other model specification where length affects vehicle type provides results that are different and inconsistent with those found in the specification of Table 18. The results in Table 18 show a slight baseline preference for SUV over van, whereas the results in Table 16 show a baseline preference for van over SUV. Thus, the choice of model specification can have an important impact on inferences.

In addition to the impact of vehicle type choice on tour length, the effect of other tour attributes, namely, number of stops and accompaniment type were also explored. One may contend that accompaniment and number of stops are also endogenous tour attributes and that they should be modeled jointly along with vehicle type choice and tour length. However, the modeling methodology employed in this study effort can only accommodate one continuous variable and one discrete choice variable in its current form. The exploration of all four choice dimensions in an integrated joint modeling framework is left for a future exercise. The number of stops on the tour appears to have a positive influence on the use of van, presumably because these are more complex trip chains involving multiple passengers. The number of stops also has a positive impact on tour length. Solo tours are more likely undertaken by car, consistent with the notion that larger vehicle type may not be needed in the absence of multiple passengers. Solo tours are also likely to be shorter tours in comparison to joint tours. This result is reasonable given that joint tours may involve visiting destinations (that could be farther away, but more preferred) that satisfy the preferences of multiple individuals on the journey. All three vehicle types have a positive impact on tour length compared to the pickup truck (omitted base alternative). Among the three vehicle types included in the model, the car and van are associated with longer tour lengths than the SUV. Thus it appears that, whereas the SUV is more preferred for tour-making (see vehicle type choice model component), the SUV is utilized (mileage driven) less – perhaps because drivers are making a conscious decision to conserve on driving expense. As van tours tend to be more complex (multi-stop) and multi-passenger in nature, it is not surprising that this vehicle type has the largest positive impact on tour length. However, it should be noted that the vehicle type choice has an impact on tour length even after controlling for other tour attributes.

It is also interesting to note the difference in the significance of the variables between the independent models and the joint models. One can see that if the error correlations across choice dimensions are ignored as is the case of the independent model, incorrect inferences may be drawn. For example, the impact of van vehicle type on tour length is insignificant in the independent model, while the same variable has a statistically significant impact on tour length after accounting for potential error correlations. Not only is it statistically significant, but it is also the highest in magnitude. In general, parameter estimates between the independent and joint model specifications are quite different. These observations lend credence to the need for jointly modeling activity-travel choices by accommodating error correlations across choice dimensions.

Influence of Socioeconomic Attributes

A host of household and person level socioeconomic characteristics were included to account for their impacts on vehicle type choice and tour length. The ratio of household size to vehicle count has a negative impact on tour length, presumably because households with a greater ratio have a deficit of vehicles. Individuals in such households may have to choose destinations that are closer to home (small travel distances) so that they can return quickly and make the vehicle available to other members of the household. Van is the least preferred vehicle type for males and the pickup truck (when it is in the fleet of vehicles of a household) is the most preferred vehicle type. Males also have a tendency to engage in longer tours compared to females. It is possible that females take care of household maintenance and serve-child activities that are closer to home, contributing to shorter tour lengths as a whole. Older individuals prefer using a van and engage in shorter tours. It is possible that these individuals prefer the comfort and smooth drive of a van. In addition, these individuals may include grandparents who undertake tours with family members. As the number of children in the household increases, people have a propensity to use a larger vehicle (van) compared to the car. It is interesting to note that the number of children has a negative effect on tour length. There are two plausible explanations for this result. First, if the parents choose to leave a child at home, they may engage in shorter tours so that they can be back home relatively quickly and tend to their kids. Alternatively, if the parents choose to take their kids with them, they may still choose to engage in shorter tours for purposes of efficiency and for avoiding long tours that can be tough on children. Households in non-urban areas are less likely to use large vehicle types, but undertake tours of longer length. While the latter result is quite consistent with expectations in that such households are probably farther away from desirable destinations, the former result is somewhat surprising. It appears that these households prefer to use the car, possibly for trips that do not involve hauling goods or people, or the pick-up truck, possibly for trips that do involve hauling goods and/or people. People with flexible work start times engage in shorter tours suggesting that they may be engaging in more frequent and shorter tours, consistent with the notion that they are less time constrained than workers who do not have temporal flexibility in work start times. The latter group must probably engage in fewer, but more efficient, multi-stop tours that are inevitably longer in length.

In the case of the impact of socio-economic attributes on the endogenous variables, it is found that there are substantive differences in coefficient estimates between the independent and joint model specifications. Thus, accounting for error correlations is clearly important in the joint modeling of vehicle type choice and tour length. However, differences in coefficient estimates between the two joint model specifications are less pronounced.

Table 15: Independent Model Estimation Results for the Model Specification where Tour Length Affects Vehicle Type Choice

	Independent Vehicle Type Choice Model[a]						Independent Tour Length Model	
	Car		Car		Car			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	1.686	13.3	2.077	10.8	1.957	13.7	1.913	36.3
Tour Attributes								
Log of tour length in miles	0.076	2.0	-0.054	-0.9	0.052	1.1		
More than one stop			0.294	2.6			0.793	32.4
Solo tour	-0.381	-4.5	-0.921	-7.2	-0.670	-6.8	-0.063	-1.8
Joint tour							0.235	6.7
Socio-economic Attributes								
Ratio of household to number of vehicles							-0.061	-1.8
Male	-1.825	-21.1	-2.287	-18.3	-1.910	-18.9	0.047	2.0
Age 65 years or older			0.221	1.6			-0.061	-2.1
Number of children	-0.089	-2.7	0.141	2.9			-0.058	-3.4
Household in non-urban area					-0.197	-2.4	0.452	17.8
Education level (atleast college)							0.048	1.9
Can change start time of fixed activities							-0.103	-3.1
Household income less than 40k per year							-0.066	-2.2

[a] Log-likelihood at convergence = -13141.4

Table 16: Joint Model Estimation Results for the Model Specification where Tour Length Affects Vehicle Type Choice

	Joint Vehicle Type Choice Model[b]						Joint Tour Length Model	
	Car		Car		Car			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	1.259	6.5	1.960	4.6	1.456	6.5	1.921	35.9
Tour Attributes								
Log of tour length in miles	0.093	1.3	-0.191	-1.0	0.089	1.0		
More than one stop			0.390	2.3			0.793	32.5
Solo tour	-0.267	-3.7	-0.763	-6.8	-0.510	-6.1	-0.065	-1.8
Joint tour							0.232	6.6
Socio-economic Attributes								
Ratio of household to number of vehicles							-0.067	-2.0
Male	-1.474	-21.4	-1.839	-17.8	-1.538	-18.9	0.047	2.0
Age 65 years or older			0.170	1.5			-0.061	-2.1
Number of children	-0.073	-2.5	0.104	2.4			-0.056	-3.2
Household in non-urban area					-0.192	-2.4	0.452	17.8
Education level (atleast college)							0.046	1.8
Can change start time of fixed activities							-0.099	-3.0
Household income less than 40k per year							-0.066	-2.2

[b] Log-likelihood at convergence = -13151.8; γ_{1N}=-0.040(-0.6); γ_{2N} = 0.120(0.7); γ_{3N}=-0.057(-0.7); γ_{4N}= 0(-); σ'_N= 0.925 (40.2)

Table 17: Independent Model Estimation Results for the Model Specification where Vehicle Type Choice Affects Tour Length

	Independent Vehicle Type Choice Model[a]						Independent Tour Length Model	
	Car		Car		Car			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	1.876	22.2	2.045	14.5	2.091	22.3	1.853	30.8
Tour Attributes								
Vehicle Type is Car							0.079	2.3
Vehicle Type is Van							0.042	1.0
Vehicle Type is SUV							0.044	1.2
More than one stop			0.200	1.9			0.793	32.4
Solo tour	-0.400	-4.8	-0.917	-7.2	-0.684	-7.0	-0.061	-1.7
Joint tour							0.234	6.7
Socio-economic Attributes								
Ratio of household to number of vehicles							-0.058	-1.7
Male	-1.821	-21.1	-2.289	-18.3	-1.905	-18.9	0.060	2.4
Age 65 years or older			0.231	1.7			-0.061	-2.1
Number of children	-0.092	-2.8	0.146	3.0			-0.058	-3.3
Household in non-urban area			-0.227	-2.0	-0.214	-2.6	0.456	17.9
Education level (atleast college)							0.047	1.8
Can change start time of fixed activities							-0.105	-3.1
Household income less than $40k per year							-0.066	-2.2

[a] Log-likelihood at convergence = -13140.5

Table 18: Joint Model Estimation Results for the Model Specification where Vehicle Type Choice Affects Tour Length

	Independent Vehicle Type Choice Model[a]						Independent Tour Length Model	
	Car		Car		Car			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	1.491	23.3	1.625	14.2	1.674	23.2	1.794	24.2
Tour Attributes								
Vehicle Type is Car							0.143	2.1
Vehicle Type is Van							0.174	2.5
Vehicle Type is SUV							0.099	1.6
More than one stop			0.186	2.1			0.792	32.4
Solo tour	-0.290	-4.2	-0.728	-6.9	-0.533	-6.6	-0.055	-1.5
Joint tour							0.234	6.7
Socio-economic Attributes								
Ratio of household to number of vehicles							-0.064	-1.9
Male	-1.474	-21.4	-1.858	-18.2	-1.537	-18.9	0.077	2.8
Age 65 years or older			0.185	1.6			-0.064	-2.2
Number of children	-0.077	-2.8	0.125	3.1			-0.061	-3.5
Household in non-urban area			-0.179	-1.9	-0.190	-2.7	0.461	18.0
Education level (atleast college)							0.045	1.8
Can change start time of fixed activities							-0.108	-3.2
Household income less than $40k per year							-0.064	-2.1

[b] Log-likelihood at convergence = -13148.3; γ_{1N}=-0.068(-1.1); γ_{2N} = -0.180(-2.6); γ_{3N}=-0.051(-0.8); γ_{4N}= 0(-); σ'_N= 0.914 (46.9)

Discussion and Conclusions

With growing concerns about energy sustainability and greenhouse gas (GHG) emissions transportation modelers are increasingly interested in understanding vehicular usage patterns at a disaggregate level of detail (trip chains or tours). In this context, two choice dimensions of particular interest are the choice of vehicle (body type) and the distance traveled to undertake activities. This study presents a joint model of vehicle body type and distance traveled at the individual tour level. A joint probit-based discrete-continuous modeling framework was employed which can also accommodate the influence of common unobserved variables on the choice dimensions by specifying multivariate normal error correlation structure. Two alternative model specifications, namely, vehicle type choice affecting tour length, and tour length affecting vehicle type choice were explored. A modified non-nested hypothesis test was used to select an appropriate model specification that best fits the data.

Model estimation was conducted on a random sample of about 6,500 tours constructed from the 2009 NHTS. Tour level models relating tour length and vehicle body type choice were estimated. The application of the non-nested test showed that the model specification in which vehicle type choice influenced tour length (as opposed to the one where tour length affected vehicle type choice) performed statistically significantly better. This model specification lends credence to the behavioral paradigm wherein vehicle ownership and vehicle allocation to individuals is a longer term choice decision that occurs at the household level and the length of tours undertaken by individuals is a shorter term choice dimension that occurs at the individual tour level and is affected by the vehicle allocated and other tour attributes.

In general, it appears that vans are associated with longer trip lengths, followed respectively by cars, SUVs, and pick-up trucks. This significance is found even after accounting for the fact that van trips may be multi-passenger multi-stop journeys that are likely to be longer. As expected, it is found that the preferences with respect to choice of vehicle body type vary according to the household vehicle fleet composition. In households where a SUV is present, it tends to be the most preferred vehicle type; however, the tour length for this vehicle type tends to be less than that of other vehicle types, suggesting that there is an important relationship between vehicle type choice and tour length that should be modeled while accounting for variable choice sets across observations.

A comparison of coefficients across model specifications shows that the independent models which do not account for error correlations across choice dimensions offer substantively different coefficient estimates and statistical significance than the joint model specifications that account for error correlations. Among the three error correlations estimated, the one representing error covariance between van choice and tour length choice is found to be statistically significant. The correlation is found to be negative. What this means is that the unobserved attributes that make one positively inclined to choose the van as the vehicle type choice negatively impact tour length. This is consistent with expectations. Suppose an individual in a household has more household maintenance and serve-child obligations than another household member. Then, this household member may be more inclined to choose the van as their vehicle of choice as it is convenient to haul people and goods and is comfortable. However, this individual may also be inclined to choose destinations close to home for non-work activities, thus choosing to undertake tours of shorter length. This is because the same factors that made an individual choose the van (household obligations, serve children, desire for comfort) also contribute to the individual choosing to undertake shorter tours because such an individual is time-constrained. Such considerations are critical to the correct specification of multi-dimensional choice models of activity-travel demand.

From a policy perspective, the finding that vehicle type choice affects tour length has important implications. Suppose the government offers rebates, tax incentives, and other price breaks that induce individuals to purchase smaller fuel efficient vehicles. The idea behind offering such incentives is that energy consumption and greenhouse gas (GHG) emissions can be reduced by motivating people to acquire and drive such vehicles. However, the joint model considered most appropriate in this study shows that tours undertaken by cars are likely to be of longer length than tours undertaken by SUV and pick-up trucks and only marginally shorter than van tours. In other words, any gains in energy and environmental sustainability garnered through the increased acquisition of smaller cars may, at least in part, be negated or offset by the longer tour lengths (and therefore miles of travel) undertaken by these vehicles. It appears that individuals, even after controlling for a range of other attributes, may be consciously exercising trade-offs in their utilization of vehicles. Thus, joint models of the type presented in this study can have important implications in terms of the policy impacts estimated for a variety of public policy scenarios. Future research in this area should attempt to treat other tour attributes such as accompaniment type and number of stops as endogenous variables in a multidimensional integrated choice modeling framework.

E. Joint Modeling of Choice Dimensions in OpenAMOS

The two empirical studies demonstrate the need for joint modeling frameworks to accurately model activity-travel engagement decisions. Though there has been tremendous progress in the joint methodologies for modeling choice dimensions simultaneously, there have been very limited applications of the advanced frameworks for simulating activity-travel engagement decisions in microsimulation models. The limited use of joint modeling frameworks for simulating choice dimensions has partly been due to complexity of the error structures, the associated computational overhead, and mathematical rigor involved for incorporating them in microsimulation software. OpenAMOS comprises a very robust simulation framework that can be extended to support joint modeling formulations like the one presented in Section B and subsequently use the joint frameworks to simulate dimensions of activity-travel engagement simultaneously.

CHAPTER 7

AN EXAMINATION OF ALTERNATIVE PARADIGMS FOR DEMAND-SUPPLY INTEGRATION

A. Introduction

As noted in Chapter 2, research into the development of integrated demand-supply models has identified two alternative approaches for achieving model integration. In the first approach, which may be referred to as the sequential approach, models of activity-travel demand and dynamic network assignment are run independently and sequentially using input-output data flows. At the end of iteration, network conditions from the supply model are fed back to the demand model and the process is repeated until convergence is achieved (Lin et al. 2008). An alternative approach, which may be referred to as the dynamic approach was proposed by Kitamura et al. (2008), and has more recently been operationalized by Pendyala et al. (2011) and presented in Chapter 3 and Chapter 4. The dynamic approach adopts an event-based paradigm for integrating the two components of the transport system namely, the demand model and the supply model. In the dynamic approach, there is a constant handshaking between the demand and supply model along the continuous time axis. Within any time interval (say, one minute), the demand model simulates trips that need to be loaded on the network and passes the set of trips to the network model. The network model, in turn, routes and simulates these trips through the network and returns information about trips that have reached their destination in each time interval. Thus, in each time interval of the simulation, the demand model is providing the set of trips that are departing in that interval to the network model, and the network model is returning the set of trips that have arrived at their destination in that interval. In the next simulation interval, the demand model simulates activity-travel choices for individuals that have reached a decision point within the interval and for those that have arrived at their destination in the previous interval. At the end of a simulation iteration (say, for an entire day), network conditions by time of day are saved and subsequently used in both the demand and supply models for making activity-travel and routing decisions in the subsequent iteration. This process is repeated until convergence is achieved. The continuous minute-by-minute communication and handshaking between the demand and supply models along the continuous time axis is intended to mimic the activity generation and scheduling behaviors more closely while accounting for network conditions experienced by individuals through the course of a day. When compared with the sequential approach, the dynamic approach presumably provides tighter coupling while maintaining consistency in the representation of individual behaviors, temporal units, and spatial scales – thus providing a rigorous behavioral framework for modeling alternative network and policy scenarios.

While the tighter model integration implemented in the dynamic approach is appealing from an intuitive standpoint, it is not yet clear as to how this presumably more complex approach differs from the simpler sequential approach to model integration with respect to various performance metrics of interest. This research effort focuses on three specific aspects of performance in order to provide insights into the implications of adopting these alternative approaches to model integration.

- First, the research effort addresses convergence properties of the alternative approaches. In both approaches, the model components (demand and supply models) are run iteratively until convergence is achieved. The convergence properties of the two approaches, and the number of iterations needed to achieve convergence in each of the two approaches are not well understood. Additionally, while convergence processes are generally well understood and formulated on the dynamic network modeling front, such processes are less established on the demand side of the integrated modeling enterprise. As each iteration of the activity-travel demand model constitutes one possible stochastic realization of an underlying probabilistic behavioral process, the variability in activity-travel schedules simulated from one iteration to the next may present convergence challenges that are worthy of investigation. This study conducts a thorough examination of the convergence properties of the alternative modeling approaches.
- Second, the research effort includes a comparison of the simulation results that the two alternative approaches yield. Although both approaches constitute an integration of activity-travel demand and dynamic network models, it is not clear if both approaches converge to the same estimates of activity-travel demand and network conditions for different types of scenario analyses. The

study conducted a thorough comparative examination of the predictions emanating from the alternative approaches to see how they might (or might not) differ with respect to forecasts of behavior and network performance. Both approaches were implemented for base year conditions to see if one is able to better replicate ground-truth conditions when compared with the other. Such a comparison would help establish the contexts or applications in which one approach may be preferred over the other.

- Third, the study examined the implications of adopting different model integration approaches on computational run times and performance. As the dynamic integrated modeling approach involves a greater level of communication between the demand and supply models, one would surmise that this approach would be computationally more burdensome than the sequential approach. However, the extent of the differences in computational run times and burden is not well understood and is worthy of close examination.

B. Study Area

In this study, the SimTRAVEL (Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land) prototype was used to run the sequential and dynamic approaches for demand-supply model integration. The model system is applied to a portion of the Maricopa (Greater Phoenix) region in the United States. A small region was carved out from Maricopa County model region for this prototype implementation and to conduct subsequent comparative analysis.

The subarea comprises of three cities, namely, City of Chandler, Town of Gilbert and Town of Queen Creek. There are about half a million people (505350) in this subarea residing in 167738 households. The spatial resolution of analysis for the implementation was Traffic Analysis Zone (TAZ). All models in SimTRAVEL, were estimated using local data. However, some assumptions had to be made due to data limitations and other issues as noted below:

- In UrbanSim (the land-use model), all the models were estimated using local data. However, the fixed activity locations i.e. school and work locations of students and workers respectively were limited to the three city region because of unavailability of data for the entire Maricopa metropolitan area. This data limitation to run the land-use model contributed to the choice of the three city subarea for the prototype testing instead of the entire region.
- There were no major assumptions in the demand model except for the mode choice dimension of the travel demand. A mode choice model was not implemented in the study and all trips generated were assumed to be pursued using an automobile. This assumption maybe reasonable because the subarea is suburban in nature and there is a lack of alternative modal options.
- The demand generated by the three city region by itself will not generate enough traffic to simulate congestion on the network. In order to model the network conditions as closely as possible to observed travel conditions, background traffic is introduced for the rest of the region using Origin-Destination (OD) tables from a traditional four-step model run. In order to be

consistent with the assumptions of microsimulation-based model and the continuous representation of time, the Origin-Destination tables were discretized into trip lists by using trip start time distributions from the latest wave of the National Household Travel Survey.

- Before running the SimTRAVEL prototype to model the sequential and dynamic approaches, a bootstrapping step was performed to obtain time-dependent link travel times and skim matrices that closely reflect base year network conditions. A bootstrapping step is often employed in stochastic iterative processes to potentially reduce/avoid oscillations across iterations. In the bootstrapping procedure, first Origin-Destination demand matrices from a 4-step model were discretized into trip lists and fed to the network model iteratively until stable network conditions were obtained. Stability in network conditions is assumed to be achieved when change/improvement in network convergence measures across iterations is smaller than a predefined threshold. In order to start the bootstrapping process, free flow conditions were assumed along all links. In the first iteration, MALTA identified paths for trips assuming free flow travel conditions along links and simulated their movement on the network. Origin-Destination travel time matrices generated using the free flow link conditions were used on the demand side to get an expectation of the travel time for each trip that was passed to MALTA. At the end of iteration, the link conditions were updated with simulated network conditions and new time varying OD travel time matrices based on updated network conditions are generated. Network measures are computed and compared across iterations and the process is repeated until stable network conditions are obtained.

It can be seen that a microsimulation-based model was not used to generate the demand in the bootstrapping procedure. Instead the discretized OD demand matrix from a 4 step model run was used successively until stable network conditions were obtained.

C. Metrics for Comparing Sequential and Dynamic Approaches to Model Integration

As noted earlier in the chapter, the comparative analyses was aimed at analyzing the differences/similarities in activity-travel behavior, convergence properties, and computational overheads between the dynamic and sequential approaches and understand the impact of observed differences/similarities for planning and policy analysis. In the following subsections, the metrics used for comparing the alternative approaches are described.

Convergence Characterization

In any integrated modeling framework, the demand and supply models are run iteratively with feedback loops until convergence is achieved. Therefore, convergence criteria need to be established to stop the iterative process. While the concept of convergence and stopping criterion are well established in the field of traffic assignment models, the concept is relatively foreign in the field of travel demand model. In the travel demand modeling arena, the concept of convergence is not considered, every simulation result is accepted as one stochastic realization of the underlying activity-travel behavior.

Traditionally in traffic assignment models, origin-destination travel time matrices are compared across iterations and iterative process is stopped once the difference between the travel time matrices across iterations is small. Boyce and Bar-Gera (2003, 2006) suggest the use of averaging travel time matrices across iterations in order to avoid oscillations in the travel time matrices across iterations observed by a naïve feedback and also to approach convergence more efficiently. Given the tight coupling between travel demand model and traffic assignment model in the proposed framework, the number of iterations required to achieve convergence in the traffic assignment model will be a direct function of how different activity-travel patterns are across iterations. One could argue that it may take more number of iterations to reach convergence in the proposed framework because there are more moving parts in this framework. On the contrary, one could also argue that the traditional sequential approach may be less efficient because the daily activity-travel patterns generated do not fully account for 1440 minutes because activity-travel patterns are not consistent with the actual arrival time information simulated. As a result, more number of iterations may be necessary to reach convergence such that expected and experienced network conditions are same.

In this research effort, on the supply side travel time matrices and gap measures (expected travel time – experienced travel time) were primarily used to monitor and characterize convergence on the supply side. Additionally given the tight coupling between the demand and supply model in the dynamic approach and its potential implications for convergence, the research effort also studied the convergence properties of demand model system to gain a better understanding of the convergence properties of the integrated model system under alternative paradigms. To characterize convergence on the demand side, trip counts, aggregated origin destination matrices, and trip length distributions are monitored from iteration to iteration.

Activity-Travel Behavior

The activity-travel engagement patterns generated from the two approaches were compared against each other. The results from the alternative approaches were also compared against weighted observations from the latest wave of National Household Travel Survey (NHTS 2008) to illustrate the validity of the prototype. A number of activity-travel behavior metrics including time-of-day distributions, trip purpose distributions, and trip rates, were compared to understand the impact of integrated modeling approach adopted on activity-travel engagement patterns generated.

Computational Overhead

Traditional metrics for benchmarking software processes such as processing time and memory overhead were used to compare the alternative approaches.

D. Results

SimTRAVEL prototype is a robust system that can be used to run different configurations of the travel demand and network model systems including, the bootstrapping procedure, the integrated model using the sequential approach and the integrated model using the dynamic approach.

As noted earlier, in the bootstrapping step, the demand model is replaced with discretized trip lists obtained from traditional 4-step OD demand matrices and run in conjunction with MALTA (dynamic network model) for obtaining time-dependent travel time matrices and link travel times. The time-varying network conditions obtained at the end of a bootstrapping procedure were then used to launch SimTRAVEL to mimic sequential and dynamic approaches to integrating the activity-based travel demand model (OpenAMOS) and the dynamic network supply model (MALTA).

Ideally, it is advisable to run the model systems iteratively until stability in the convergence measures are obtained. However, owing to the enormity of the simulations and the associated run times, the bootstrapping procedure was run for 10 iterations and the sequential and dynamic integrated models were run for 5 iterations. As discussed later in this section, these iteration counts seem to produce reasonably stable conditions both on the demand and supply side. The task of characterizing convergence beyond the iteration counts noted above is left for a future exercise.

The convergence characteristics of bootstrapping step and the sequential and dynamic approach to integration are presented in the next subsection followed by comparison of the activity-travel engagement characteristics generated at the end of five iterations. In addition to comparing results from between the sequential and dynamic approaches, results from the two approaches are also compared against weighted observations from the latest wave of the National Household Travel Survey for the model region to test the validity of the SimTRAVEL prototype to replicate known distributions. Finally differences in computational overheads for the alternative integration approaches are presented in the last subsection.

Convergence Characterization

As noted earlier, typically in integrated models, convergence is only characterized on the supply side and convergence properties of the demand models are generally ignored. However, given the tight coupling of the demand and supply models entailed in the dynamic approach, the supply model proceeds to convergence only if the demand also proceeds to some stabile state. Therefore, both demand and supply side convergence measures are monitored in this study in an effort to understand the convergence characteristics across iterations of the component systems and also the integrated model as a whole. On the supply side the deviation in travel time matrices and the gap value measured as a difference between experienced and expected travel times are monitored. On the demand side, aggregate trip counts, trip counts disaggregated by Origin-Destination pairs and trip length distributions are monitored.

Average Skim Deviation

The average skim deviation measure is calculated by taking the average absolute deviation in travel time values between all Origin-Destination pairs. In SimTRAVEL, 24 hourly time of day matrices were generated to represent the changing network conditions throughout the day. A single average deviation value calculated across all 24 hourly matrices was used to generate the chart presented in Figure 8 whereas time varying average deviation value was used to create the chart presented in Figure 9. The average skim deviation measure was monitored across the ten iterations employed in the bootstrapping procedure and across the five iterations of the integrated model thereafter according to sequential and dynamic approaches.

The convergence characteristics of the bootstrapping process highlight the ability of the network model alone to proceed towards stable network conditions. Because the demand is kept constant across iterations in the bootstrapping procedure and network conditions generated at the end of the iteration are fed back to only update routes and simulate trips in the subsequent iteration. The bootstrapping procedure also provided a good benchmark for the network conditions at the end of ten iterations against which results from the sequential and dynamic model runs can be compared to assess their convergence properties.

Ideally during the bootstrapping run the average deviation measure must move closer to zero as SimTRAVEL proceeds through iterations. In other words at the end of bootstrapping run, stable network conditions are expected and additional iterations would not improve the network conditions significantly. It can be observed from Figure 8 that after 10 iterations the average deviation value flattens out at a value close to zero (0.41) and the improvement in the average deviation value is almost 0 (improvement in the average deviation value = 0.02). Similar observation can also be made in Figure 9 where the average deviation value across each of the 24 travel time matrices is plotted across iterations. As expected, the time varying average deviation value proceeds to a value close to zero with iterations. It is also interesting to note that the deviation reaches a value very close to zero at the start and end of the simulation (4 AM) for the travel day and in between the deviation value is slightly higher. This observation points to the sensitivity of the network model to the demand that is generated. At the start and end of the day when there are fewer trips, network conditions appear to converge faster and the difference in skims is almost zero after 10 iterations whereas in the middle of the day where there are more trips, network conditions are converging but the difference in skims is very close to zero after 10 iterations. This observation of the sensitivity of the network model to demand that is generated highlights the need for a controlled environment such as a bootstrapping procedure to obtain a good estimate of network conditions that can then be utilized to launch a full scale microsimulation-based model where demand keeps varying across iterations. The bootstrapping reduces oscillations in observed behaviors across iterations and ensures faster progression towards stable conditions.

The network conditions that were obtained at the end of the bootstrapping procedure were used to run integrated model using sequential and dynamic approaches. The number of iterations was limited to five based on some earlier test runs of the integrated model system. It can be seen from Figure 8 that both sequential and dynamic reach stability by the end of the fifth iteration. It is interesting to note that the average skim deviation for the first iteration of the integrated model run was smaller for the dynamic approach compared to the sequential approach. However, for subsequent iterations the average deviation and improvement are very comparable. The deviation value seems to flatten out at iteration 5 and the improvement from iteration 4 to 5 was within a 0.10 threshold. Similar observation can be made with the time varying skim deviation measure with the sequential approach having a consistently higher value for the first iteration of the integrated model compared to the dynamic approach but they both end up with almost the same time-varying deviation measures at the end of the fifth iteration. It is also interesting to note that the average deviation value at the end of five iterations is slightly higher than the average deviation value at the end of ten iterations of the bootstrapping procedure. The study of convergence properties beyond five iterations is left for future exercise.

Gap

Another measure that is typically used to monitor convergence on the supply side is the gap value. The gap value is defined as the difference in the experienced and expected travel times. There are variants of the gap measure that one could monitor across iterations to characterize convergence. In this study, the average absolute gap value was used to monitor convergence across iterations. Similar to the average skim deviation, gap measure was also monitored for the bootstrapping procedure and across iterations of the sequential and dynamic model runs as shown in Figure 10.

It can be seen that the gap value plateaus at a value of 2.10 minutes in the bootstrapping run after 10 iterations and the improvement in the gap value is less than a threshold of 0.01. In the sequential run, the gap value seems to flatten out after five iterations and improvement in gap value at the end of fifth iteration is very close to zero, whereas with the dynamic run, the improvement in gap value at the end of fifth iteration is close to 0.02. While there is a slight indication that the sequential run may be approaching convergence faster, the difference is rather minimal. Additionally, some of the differences observed could potentially be just a result of the stochasticity inherent to activity-travel engagement decisions simulated in OpenAMOS. Nonetheless the SimTRAVEL prototype seems to approach stability after about five iterations beyond the bootstrapping process for both sequential and dynamic integration approaches.

It is interesting to note that the gap value plateaus after a few iterations and there is a “residual gap” with a value between 2.10 and 2.20 minutes at the end of the bootstrapping runs and also after five iterations of the sequential and dynamic runs. Ideally one would expect the gap values to progress to a value close to zero with iterations. However, further investigation revealed that the skim generation procedure employed by the network model – MALTA offers a potential explanation of the “residual gap” observed.

In MALTA, a computationally efficient algorithm called the Hierarchical Time Dependent Shortest Path Algorithm (HTDSP, Gao and Chiu 2011) is employed to enumerate paths in the network model and to generate the travel time matrices for use in the travel demand at the end of each iteration as an expectation of the network conditions for use in the subsequent iteration. HTDSP employs a hierarchical search strategy for enumerating paths between given Origin-Destination pairs. First, the path search process identifies paths between Superzones (which are aggregations of smaller geographical units e.g. TAZ) corresponding to the origin and destination. After searching for a shortest path between the corresponding Superzones of an Origin-Destination pair, the algorithm identifies the shortest path within the Superzone to connect the actual origin and destination. While the approach serves well for path enumeration it suffers from some issues in the skim generation process. During the skim generation to gain efficiencies, for a particular Superzone pair (S_o, S_d), all Origin-Destination pairs (o, d) such that o belongs to S_o and d belongs to S_d get the same travel time. The exception being when there is a trip that was executed for the origin destination pair. In that case the travel time for that pair is replaced with experienced travel time. It can be seen that the skim generation process makes a rather strong assumption and the travel times generated are averages of travel times between the Superzones and not the actual finer geographic units (TAZ). As a result there is always a difference between the experienced and expected travel times.

In order to overcome the “residual gap” issue, one can proceed to a finer definition of the Superzones. Alternatively one can make away with the hierarchical search process but that comes at an added cost of significant computational overhead. While the “residual gap” may not pose an issue with the dynamic approach, it may impact the sequential approach as will be described shortly in the subsection on comparing differences in activity-travel engagement decisions simulated using the two integration approaches.

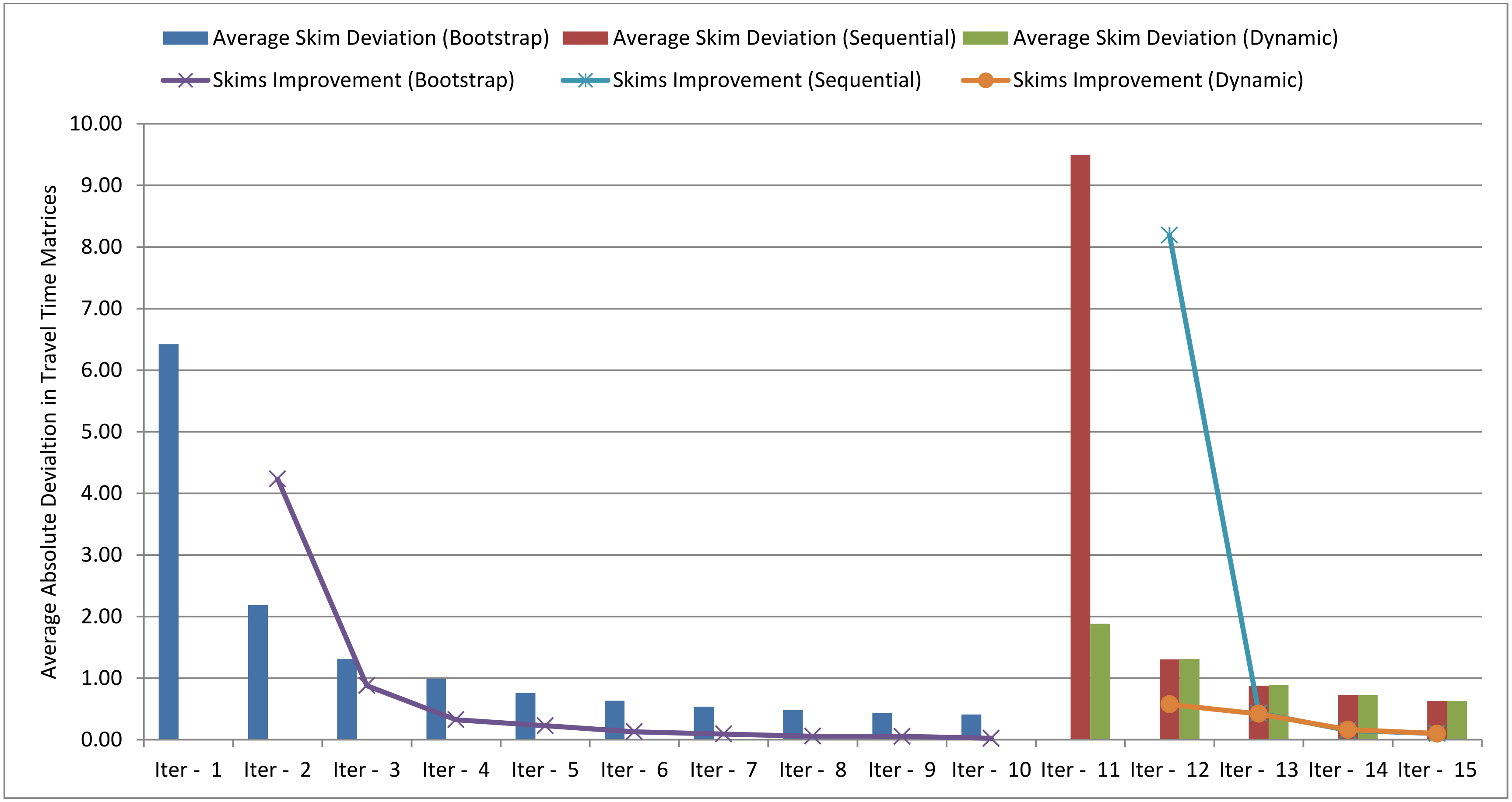

Figure 8: Average Deviation and Improvement in Travel Time Matrices Across Iterations

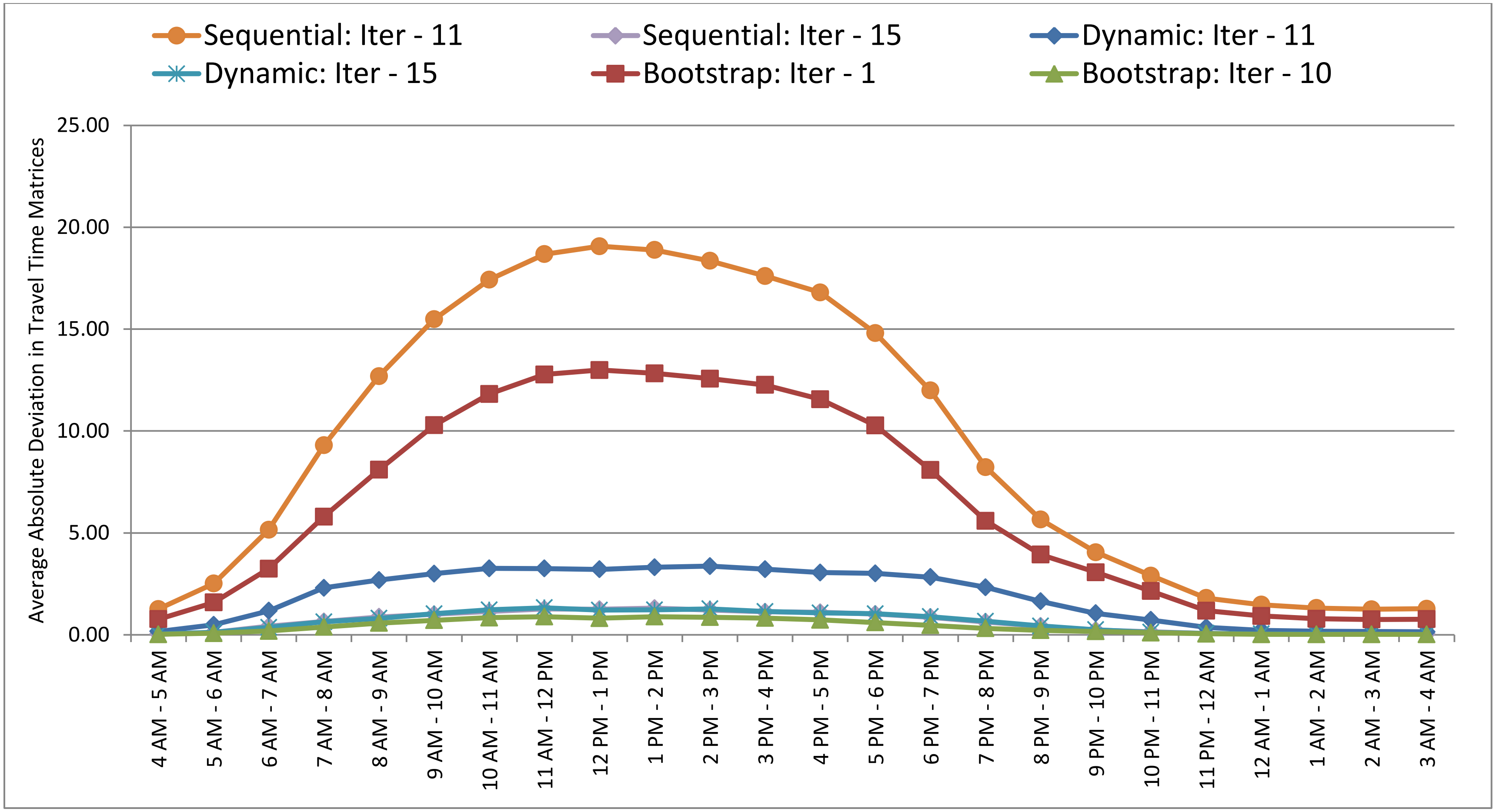

Figure 9: Average Deviation in Travel Time Matrices by Time of Day Across Iterations

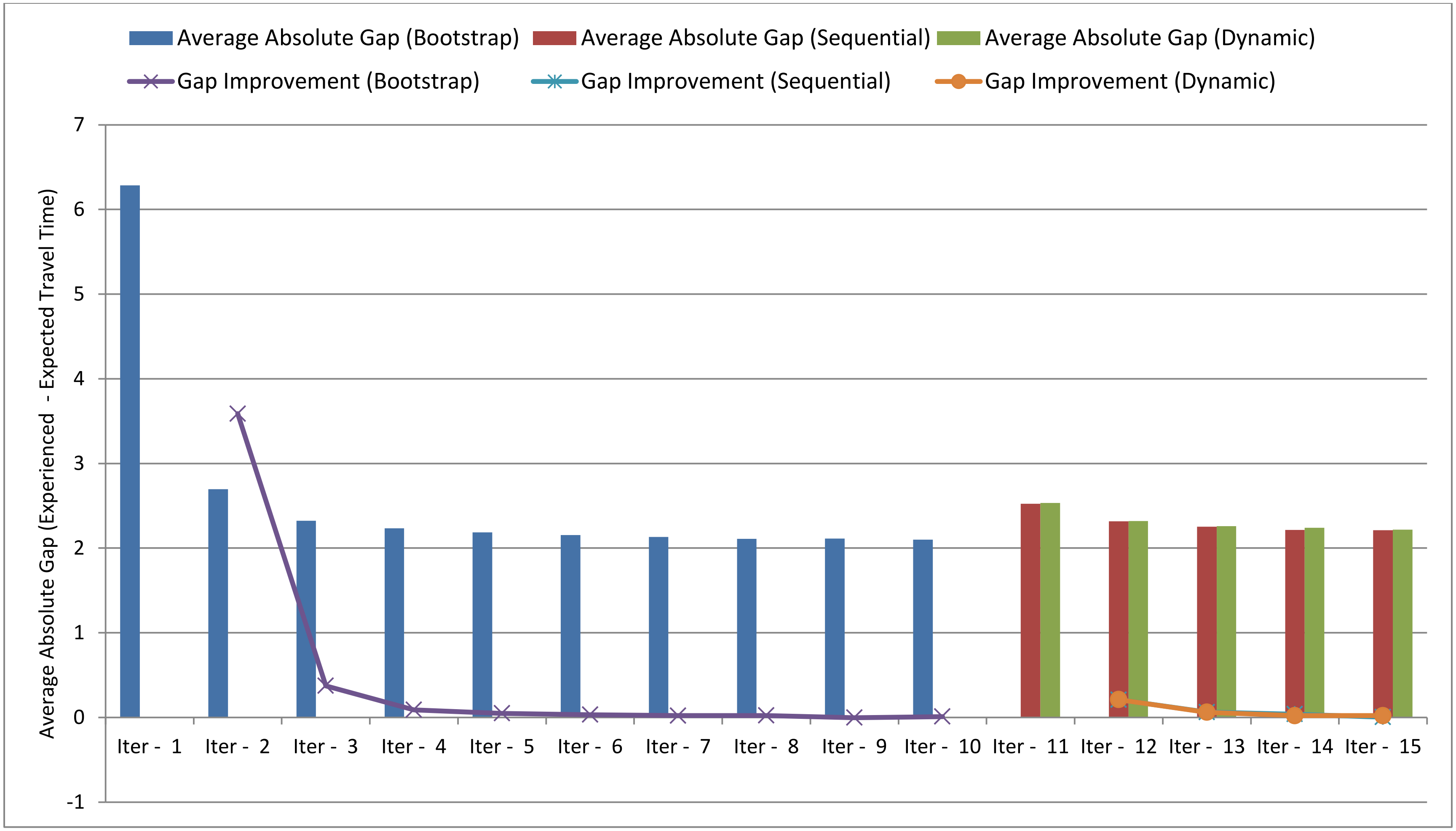

Figure 10: Average Absolute Gap Value and Improvement Across Iterations

Trip Count

As noted earlier, one of the aims of this study was to shed light on the convergence characteristics of the demand model in integrated model implementations. In order to characterize convergence one of the measures used was the total number of trips that are simulated. If the network conditions approach stability then one would expect the trip counts that are generated by the activity-travel microsimulation model to also stabilize. That appears to be the case both with the sequential and dynamic approaches to integration as can be seen from Figure 11 which shows a chart with the trip count (on the secondary Y axis) plotted against the iteration number. While there seems to be a slight hint of oscillation in the vehicle trip count of the dynamic approach with iteration 4 generating more trips than iteration 3 and iteration 5, the sequential approach seems to flatten out at a trip count of close to 14323890. The slight hint of oscillation may be attributed to the stochasticity in the demand modeling process. Also, it must be noted that the values on the axes are indexed (and do not start at zero) in order to exaggerate the differences and in the grand scheme of things the oscillation observed may be rather minimal for all practical purposes.

Aggregate OD Demand Matrix

In addition to trip count, difference in aggregate Origin-Destination demand matrices across iterations was used as a more disaggregate measure compared to aggregate trip count. Figure 12 shows the progression of differences in OD matrices across iterations. As can be seen the differences seem to plateau after 3 iterations with a slight oscillation from iteration 4 to iteration 5 for the sequential approach. The dynamic approach seems to show a downward trend with no oscillation. While the chart indicates progression towards stability, the differences in the OD demand matrices across iterations is rather high. For a population of little over half a million the difference translates to almost two trips. The high difference in OD demand matrices can be attributed to two main reasons. First, across iterations, there are multiple locations that satisfy a given time-space prism constraint and individuals seem to be choosing comparable (in terms of impedances and attractiveness measures) but different destinations. Second, the use of HTDSP approach for generating skims may be causing the impedances to be more uniform than they ought to be. In the HTDSP approach, multiple destinations share the same travel time from a given location if they all fall within the same Superzone. In an effort to further explore and confirm convergence properties of the demand model, a more objective disaggregate measure – trip length distribution is monitored across iterations.

Trip Length Distribution

In addition to showing the progress in the trip counts, Figure 12 also displays the improvement in average trip length for all trips. It can be seen that the average trip length for the dynamic approach decreases continuously up to iteration 4 and shows a slight oscillation with an increase in average trip length for oscillation 5. In the sequential approach, the trip length decreases up to iteration 3 then oscillates with a slight increase in iteration 4 and then decreases in iteration 5. It is interesting to see that both the sequential and dynamic approach seem to be oscillating between average trip lengths of 7.160 and 7.165. For all practical purposes the integrated model can be assumed to have reached a stable state given the small range over which the average trip length seems to be oscillating. The same two reasons that contribute to the high difference in OD cell values across iterations may also be contributing to the slight oscillation in trip lengths past the initial iterations.

All the above measures including both the supply side and demand side measures seem to indicate that both the bootstrapping procedure and the integrated model are reaching stability. Also, the demand side measures are not monitored for the bootstrapping procedure because the demand remains constant across the ten iterations. Therefore convergence properties of the demand side measures need not be characterized for the bootstrapping procedure. While the supply side measures do not show any oscillation, the demand side measures seem to show slight oscillation especially after initial iterations. The oscillations may partially be explained by a key assumption in the network model which is the use of HTDSP to generate paths and skims to achieve computational efficiency.

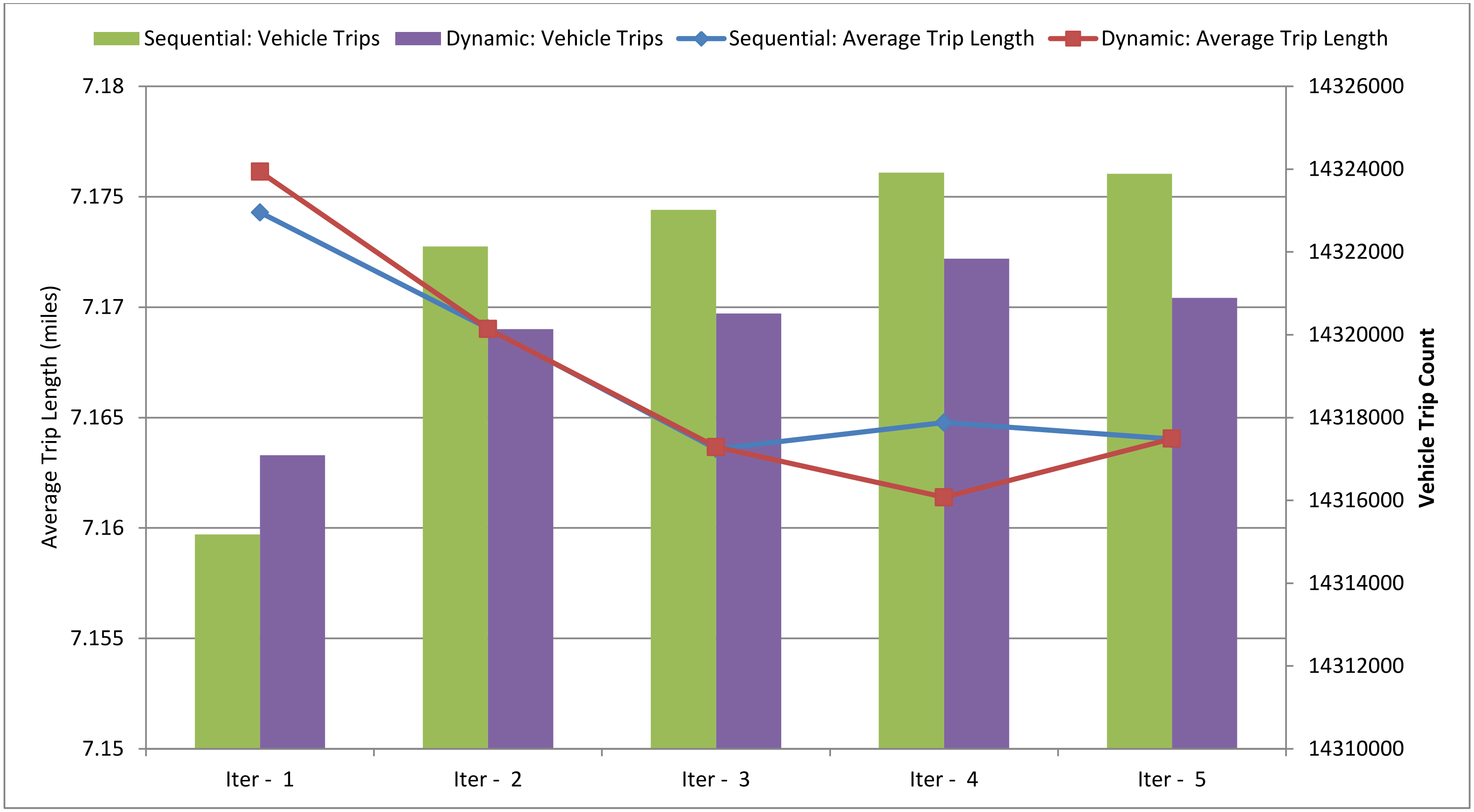

Figure 11: Vehicle Trip Count and Average Trip Length Across Iterations

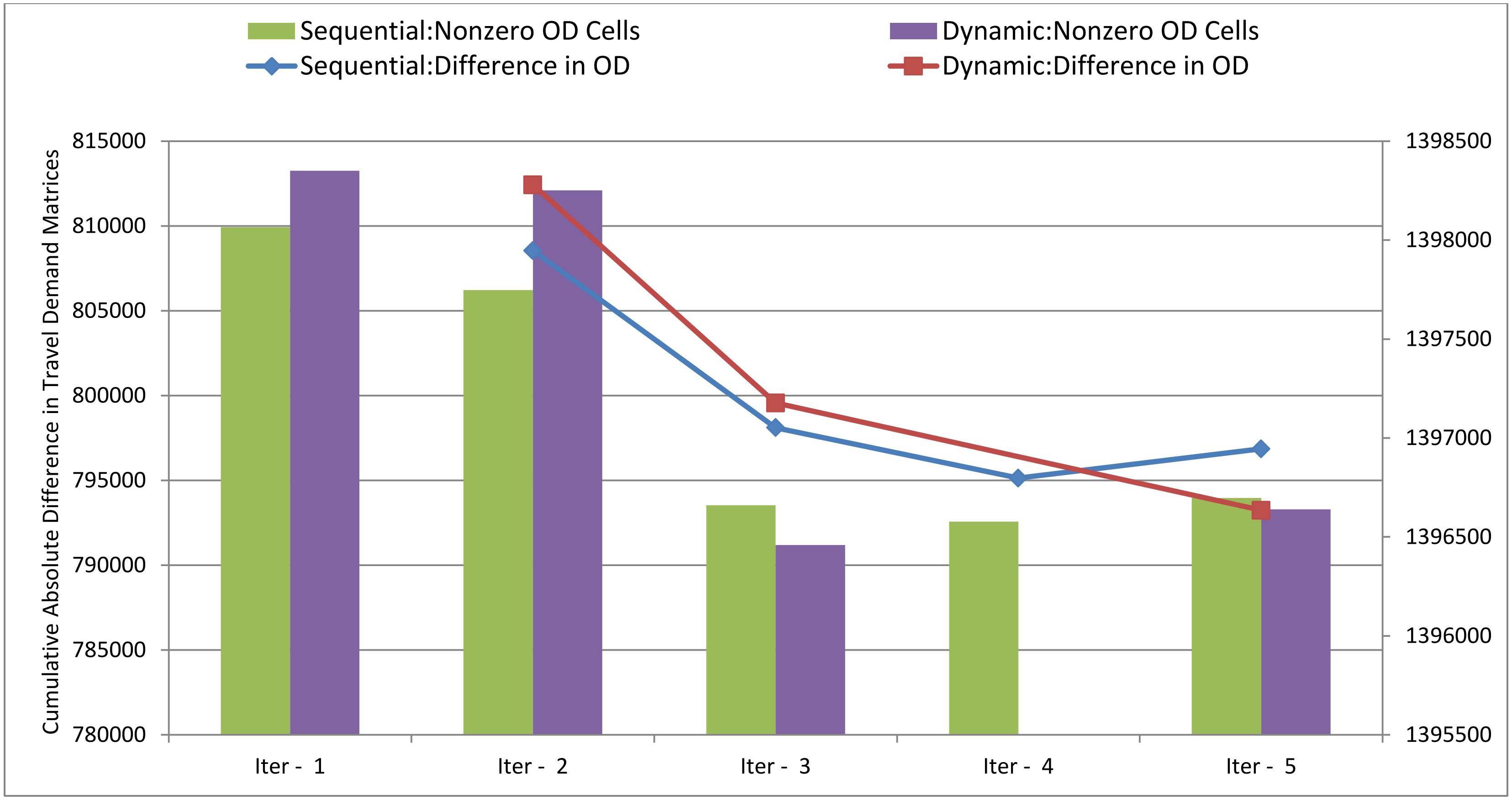

Figure 12: Cumulative Difference in Origin Destination Matrices Across Iterations

Activity-travel Behavior

In this subsection, the activity-travel engagement patterns generated by the two approaches to integration are compared to highlight differences if any between the two approaches to modeling the urban system. The results from the two approaches are also compared against weighted observations from the latest wave of the National Household Travel Survey (NHTS 2008) to demonstrate the applicability of the prototype for replicating observed behaviors. While the SimTRAVEL prototype can model the activity-travel engagement decisions of every individual and household in the region, results for the adult population are only presented. Results of the children demographic are excluded due to the lack of confidence in the observed NHTS data for children between 5 and 17 and also unavailability of data for children younger than 5 years in the latest wave of NHTS.

Trip Start Time Distribution

One of the major design objectives of any microsimulation-based model of the urban system is to ensure that the time of day distributions of the activity-travel engagement decisions are accurately replicated. Figure 13 and Figure 14 show the trip start time distribution for workers and non-workers respectively. It can be seen that the SimTRAVEL prototype replicates the weighted time of day distribution for the demographics reasonably closely. For workers, one can see the typical peaks in the morning and evening with a smaller peak in the noon period, presumably during the lunch hour. However, the midday peak seems to be slightly off with its onset a couple of hours earlier than observed from the NHTS. Also, there is a slight under-prediction of trips between 3 PM and 6 PM and a slight over-prediction of trips between 7:00 PM and 9 PM. For non-workers, the distributions also match extremely well, although it appears that SimTRAVEL is yielding a slight under-prediction of trips between 7:00 AM and 11 AM and a slight over-prediction of trips between 4 PM and 7 PM. Nonetheless the prototype yields time of day distributions that closely match the observed weighted NHTS distributions for both the worker and non-worker demographic. It is interesting to note that SimTRAVEL yields similar time of day distributions with both approaches. If the origin-destination travel time matrices are accurate representations of travel times one would actually experience on the network, then it is unlikely that the dynamic model design and the sequential model design would yield differing results. This appears to be the case as seen in Figure 8 and Figure 9 wherein the network measures seem to plateau out at similar values after five iterations.

To further analyze differences in time of day distributions that are simulated in SimTRAVEL from those observed in the National Household Travel Survey, time of day distributions for workers by activity types were compared. It can be seen from Figure 16, Figure 18, Figure 20 that the start time distributions for work, discretionary, and dropoff activities match distributions from the NHTS almost perfectly. However, trips for home, maintenance, and pickup activities (as shown in Figure 15, Figure 17, Figure 19) are slightly off with under-prediction of trips in the later part of the day (2:00 PM – 6:00 PM) and some over-prediction in the earlier parts of the day (9:00 AM – 12: 00 PM); this observation of mismatch in start time distributions when disaggregated by activity type could potentially explain the slight mismatch in the start time distribution when all trips were considered for workers. The mismatch can partly be traced back to the dependent children, their activity-travel patterns and subsequent allocation to adults in the household. Due to the lack of data from the latest wave of the NHTS, child activity-travel generation and allocation models were estimated using data from the 2001 NHTS. While some calibration was performed for adult models, calibration of children models was rather difficult due to data that is few and far between. Nonetheless, the simulated distributions are very closely matching and follow observed time of day trends.

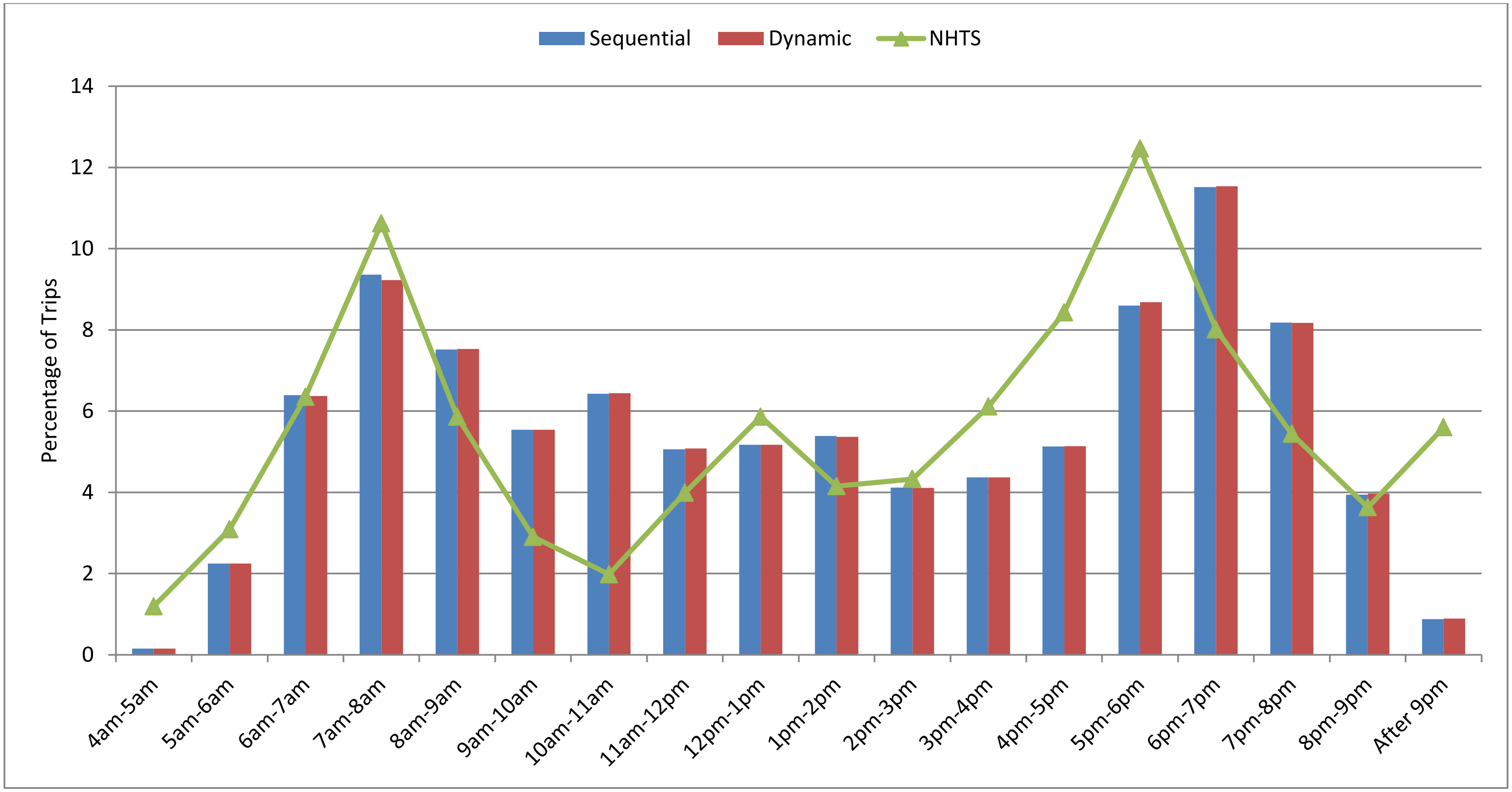

Figure 13: Trip Start Time Distribution for Workers

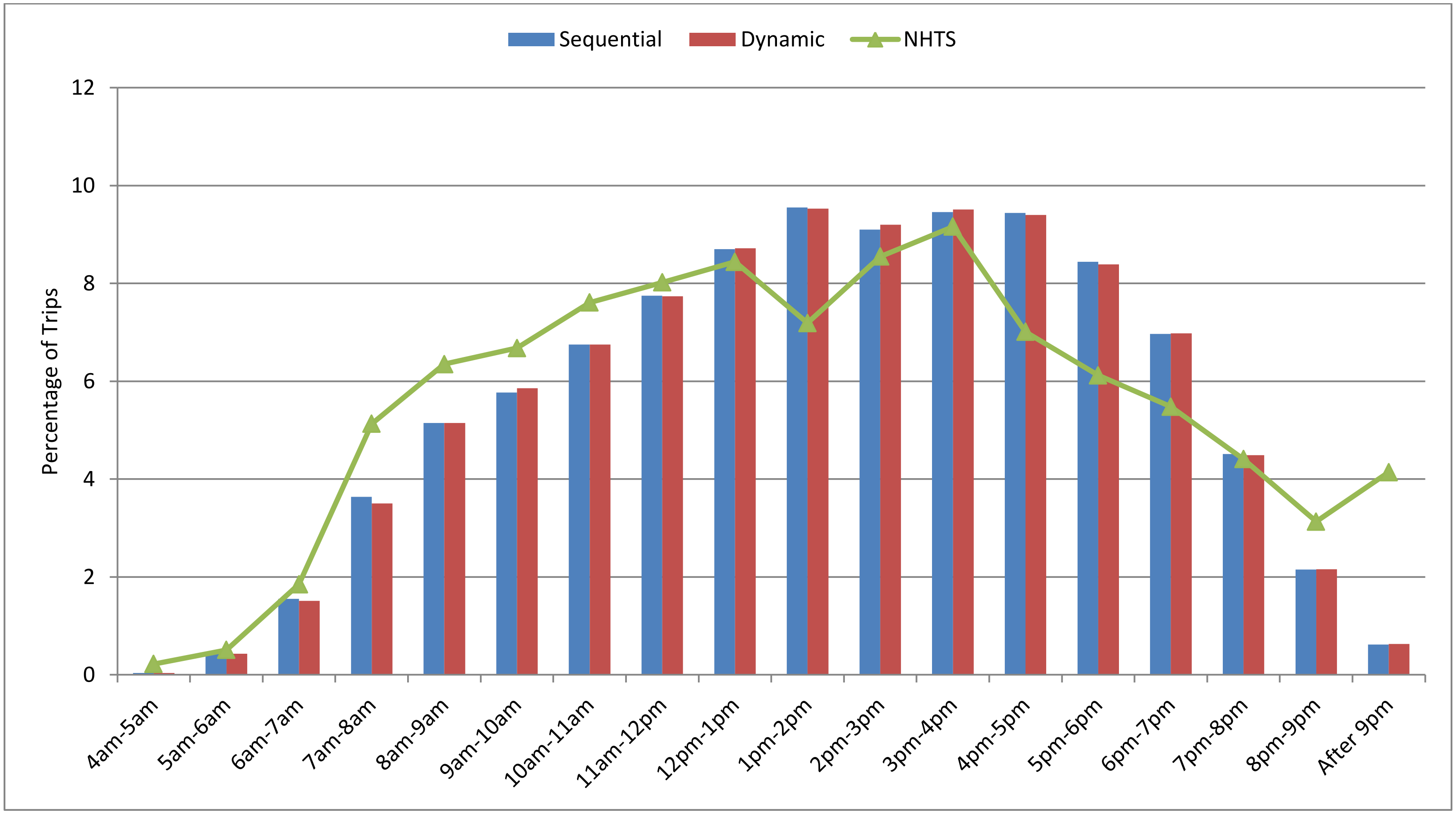

Figure 14: Trip Start Time Distribution for Non-workers

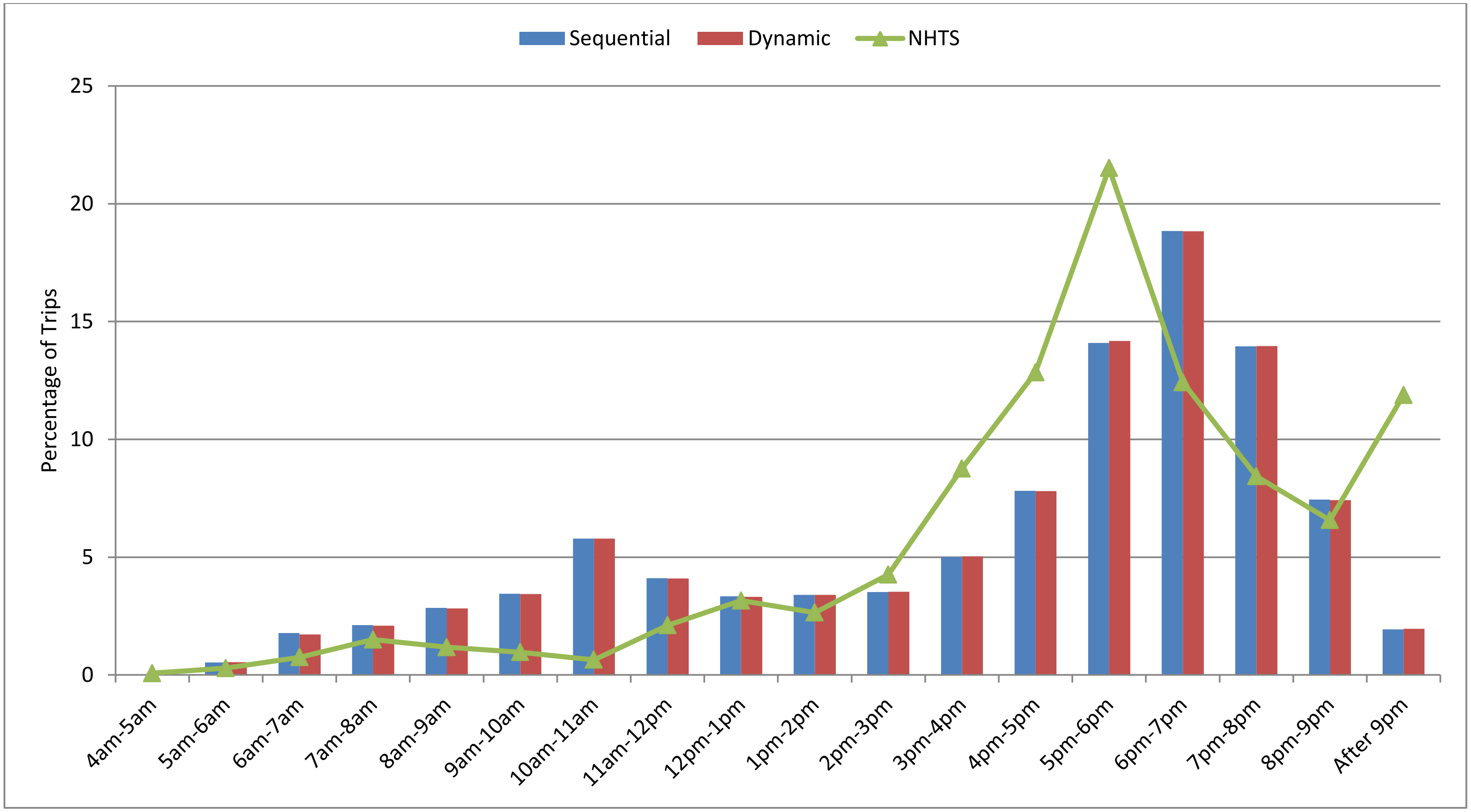

Figure 15: Trip Start Time Distribution of Home Trips for Workers

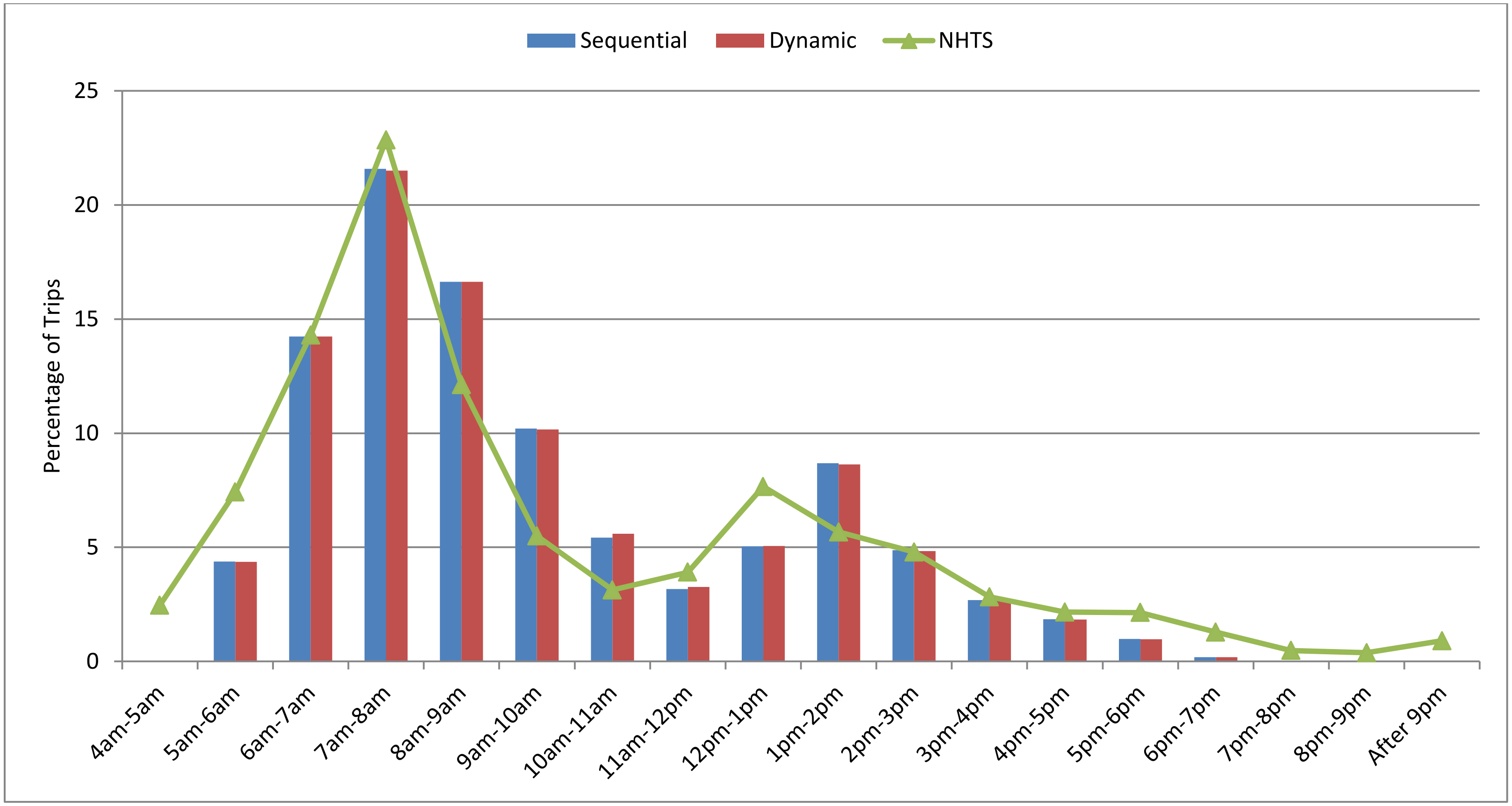

Figure 16: Trip Start Time Distribution of Work Trips for Workers

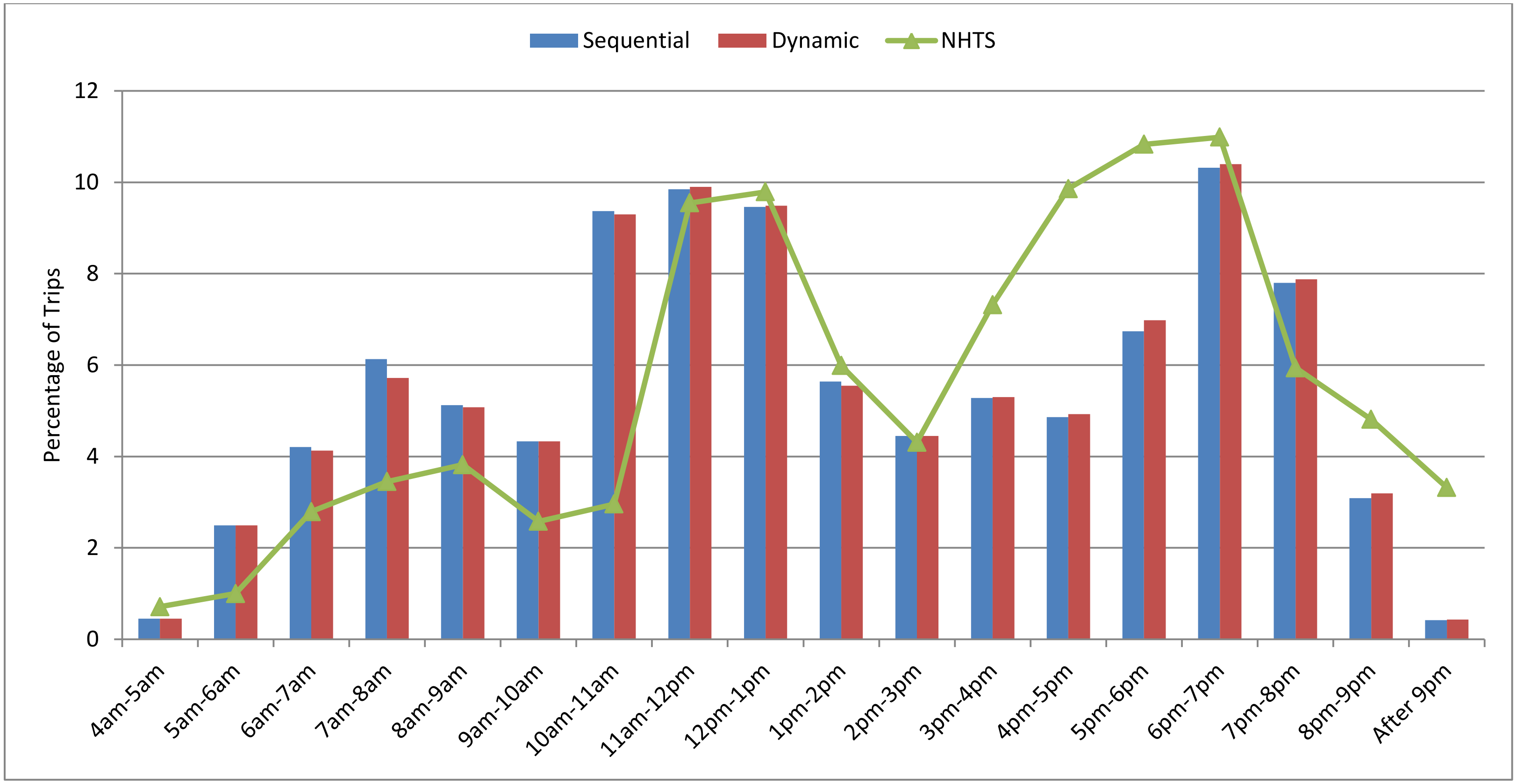

Figure 17: Trip Start Time Distribution of Maintenance Trips for Workers

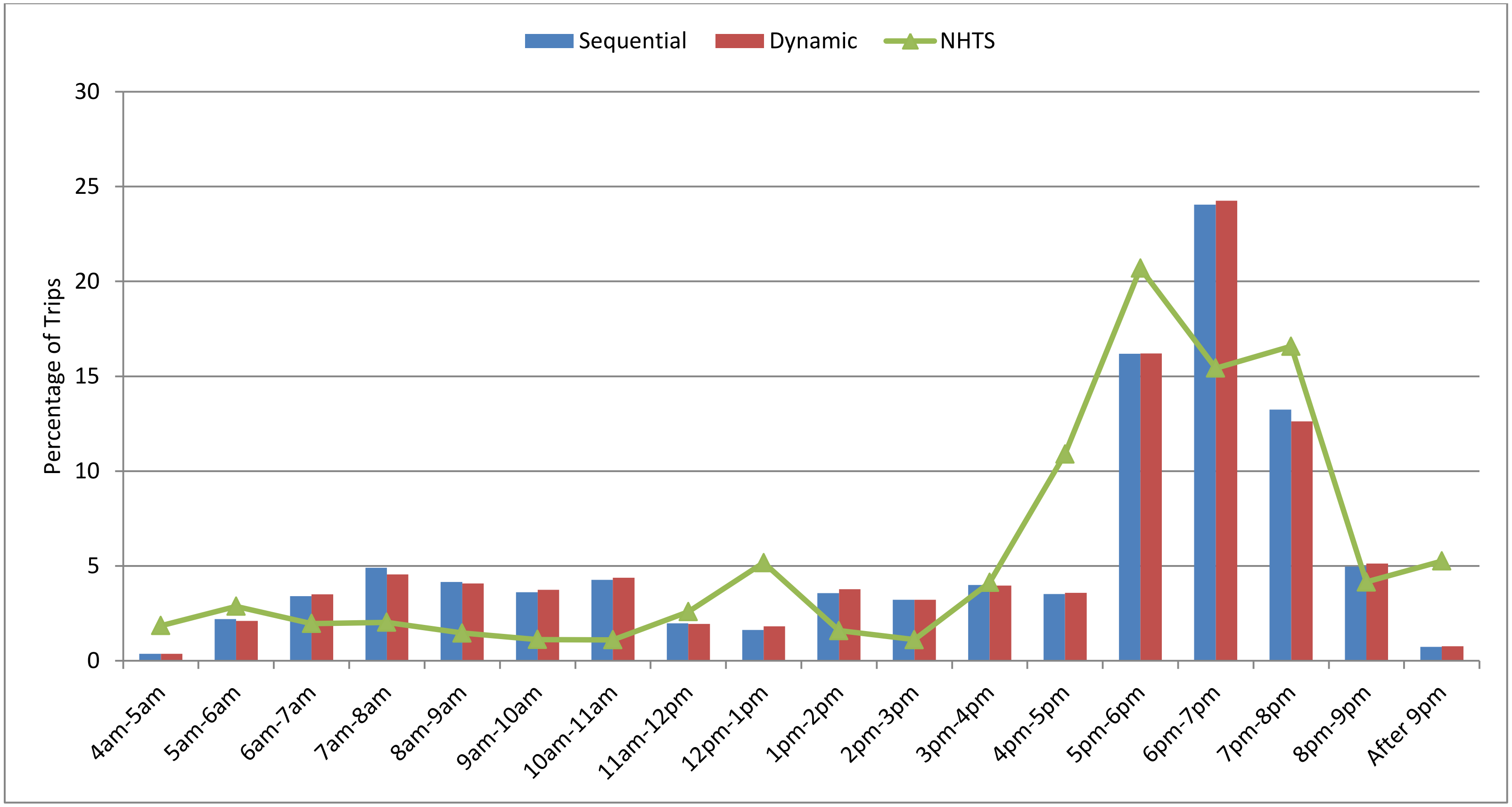

Figure 18: Trip Start Time Distribution of Discretionary Trips for Workers

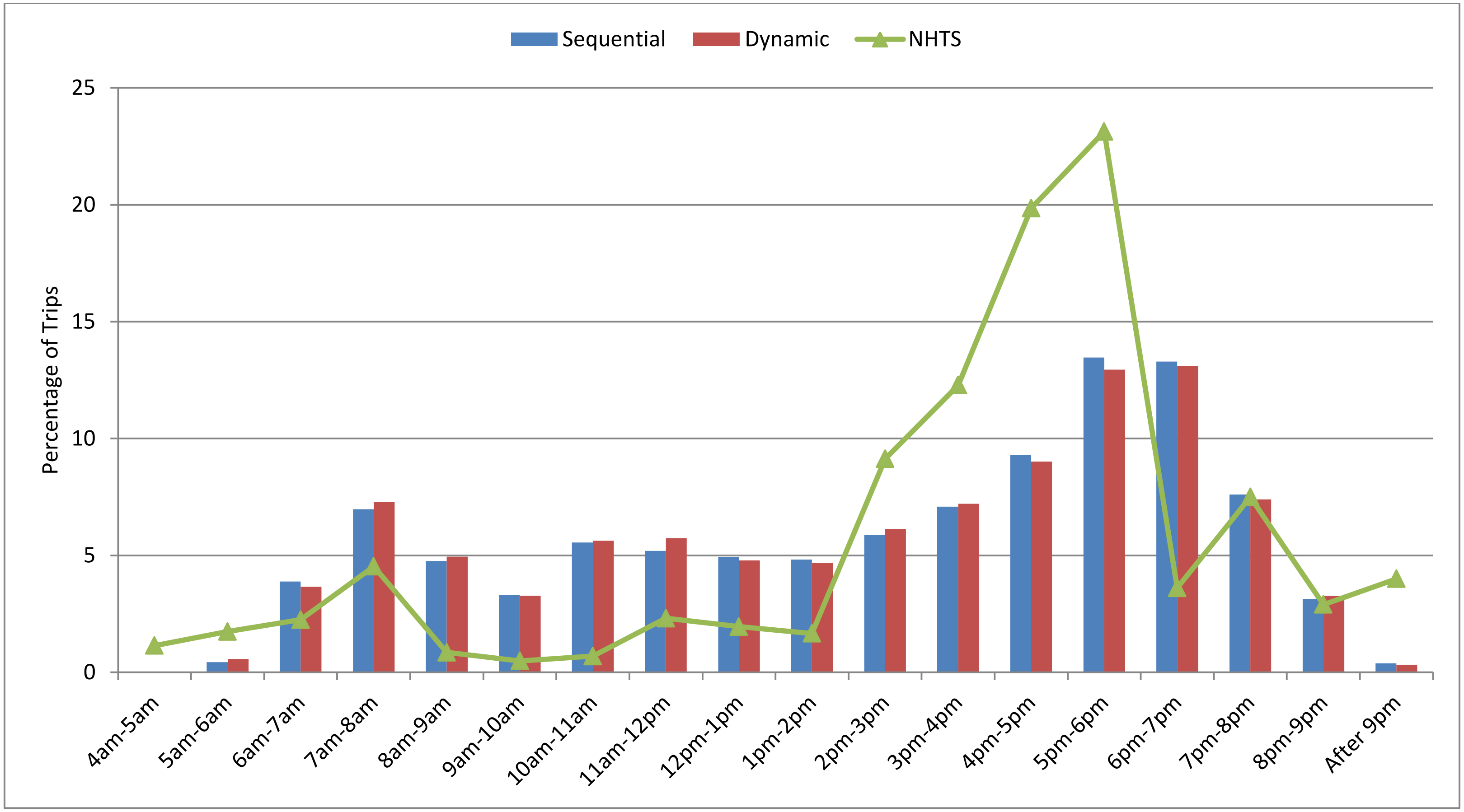

Figure 19: Trip Start Time Distribution of Pickup Trips for Workers

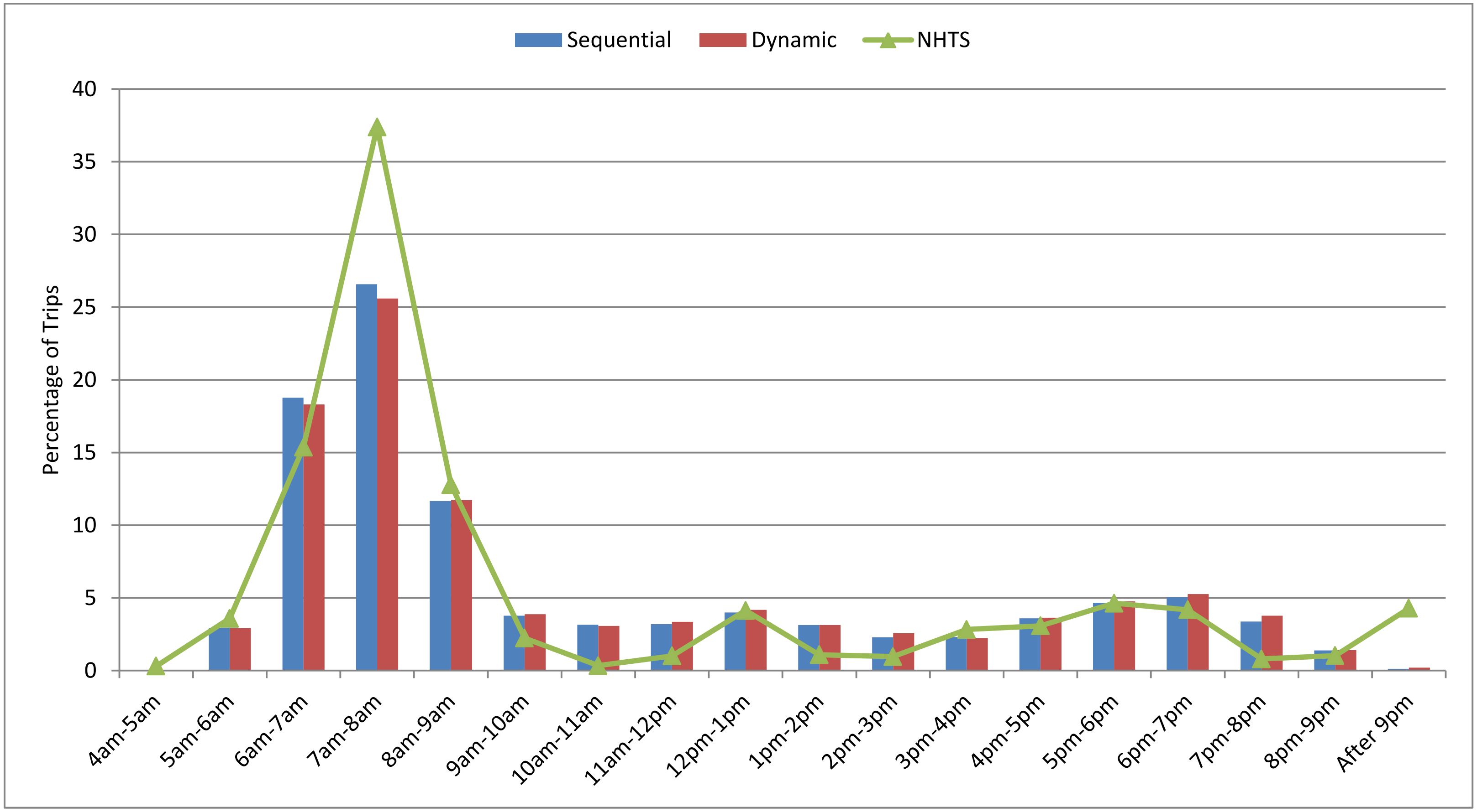

Figure 20: Trip Start Time Distribution of Dropoff Trips for Workers

Trip Duration

Another key dimension that is important in the context of microsimulation-based models of urban systems is the trip length distributions. Matching trip length distributions ensures that trips generated are accurately distributed in space. Trip duration which represents the time taken to travel from one location to another is a good proxy for trip length and matching trip durations serves the same purpose as trip lengths. The trip duration distributions for workers and non-workers are presented in Figure 21 and Figure 22 respectively. As expected the average trip duration values for workers is lower than non-workers. This is reasonable given the higher level of spatio-temporal constraints experienced by workers because of their fixed activity commitments compared to non-workers who are subject to fewer spatio-temporal constraints and have the flexibility to access and travel to locations that are further away without violating any time-space constraints. Similar to the trip start times, the sequential and dynamic approaches generate similar trip duration distributions for both workers and non-workers.

It is interesting to note that while the trip duration distribution of workers closely matches the distribution observed from the NHTS, the duration distribution for non-workers is skewed with a higher percentage of longer trips (trip durations of 20 minutes and higher) and a lower percentage of shorter trips (trip durations of less than 20 minutes). To explore the observation further, the trip duration distributions were disaggregated by trip purpose to identify any trends between trip purpose categories and distribution skews.

Figure 24 shows the trip duration distribution for work trips. As can be seen the distribution for fixed activity matches distribution from the NHTS closely with a slight under-prediction in the work trips that are 10 – 20 minutes in length and a small over-prediction of work trips that are 50 – 70 minutes. Figure 25 and Figure 26 show the duration distribution for non-fixed activities namely, maintenance and discretionary trips respectively. Figure 27 and Figure 28 show the duration distributions for pickup and dropoff activities respectively. In trips associated with activities where a child is involved (maintenance, pickup, and dropoff), the durations are skewed with over-prediction of longer duration trips and under-prediction of shorter duration trips. However with discretionary activities, adults engage in the activity alone. As noted in the discussion on trip start times, there is a need to calibrate models of child activity-travel engagement and ensure that their trips are representative so that the resulting dependency allocations are also accurate. Similar observations are observed for non-worker activity-travel engagement decisions with a skew in favor of trips with longer distribution when children may be involved in activities (Figure 30, Figure 32, and Figure 33). As with workers the trip duration distribution for discretionary activities matches more closely with observed distribution from the NHTS. However, the match is slightly better for workers.

In order to further explore the difference in match for discretionary activities of workers, the paradigm for activity-travel generation was investigated. In OpenAMOS, activity-travel dimensions are simulated within any open time-space prims by respecting the spatio-temporal constraints. While it may be technically possible for an individual in one extreme locale of the region to travel to a location on the completely opposite side of the region to engage in a non-fixed activity without violating any spatial and temporal constraints, it may not be reasonable. It appears like with workers there are additional constraints that are acting as proxies for “threshold” to travel distance or in other words there is an implied search space criterion because of their fixed activity episodes. However, this may not be the case with people without fixed activities such as children and non-workers who have very large time-space prisms at the start of the day. It appears like the “threshold” to travel distance is a key dimension that is not being accounted for in the prism constrained activity-travel simulation process and could potentially explain the skew in the trip duration distributions for children and non-workers. Though the time-space prism paradigm comprises a spatio-temporal constraint on the opportunity space, it doesn’t account for the “threshold” that individuals may incorporate in their activity-travel decision making behavior.

The “threshold” behavior to travel distance offers one potential explanation of the skew in distributions of non-workers and children activity-travel engagement patterns. Additionally, it is very well possible that the suburban nature of the subarea may be contributing to the skew. People may be traveling further to engage in non-fixed activities because of lack of attractive opportunities in the area. The skew may be reasonable now because we are comparing the suburban activity-travel engagement patterns with those from the entire region (i.e. NHTS distributions). Further exploration on all fronts noted above can improve the fit. Nonetheless the distributions are reasonable and follow observed trends closely. These observations in particular the mismatch for activities where children are involved point to the importance of intra-household interactions and their role in the formation of activity-travel engagement patterns of household members.

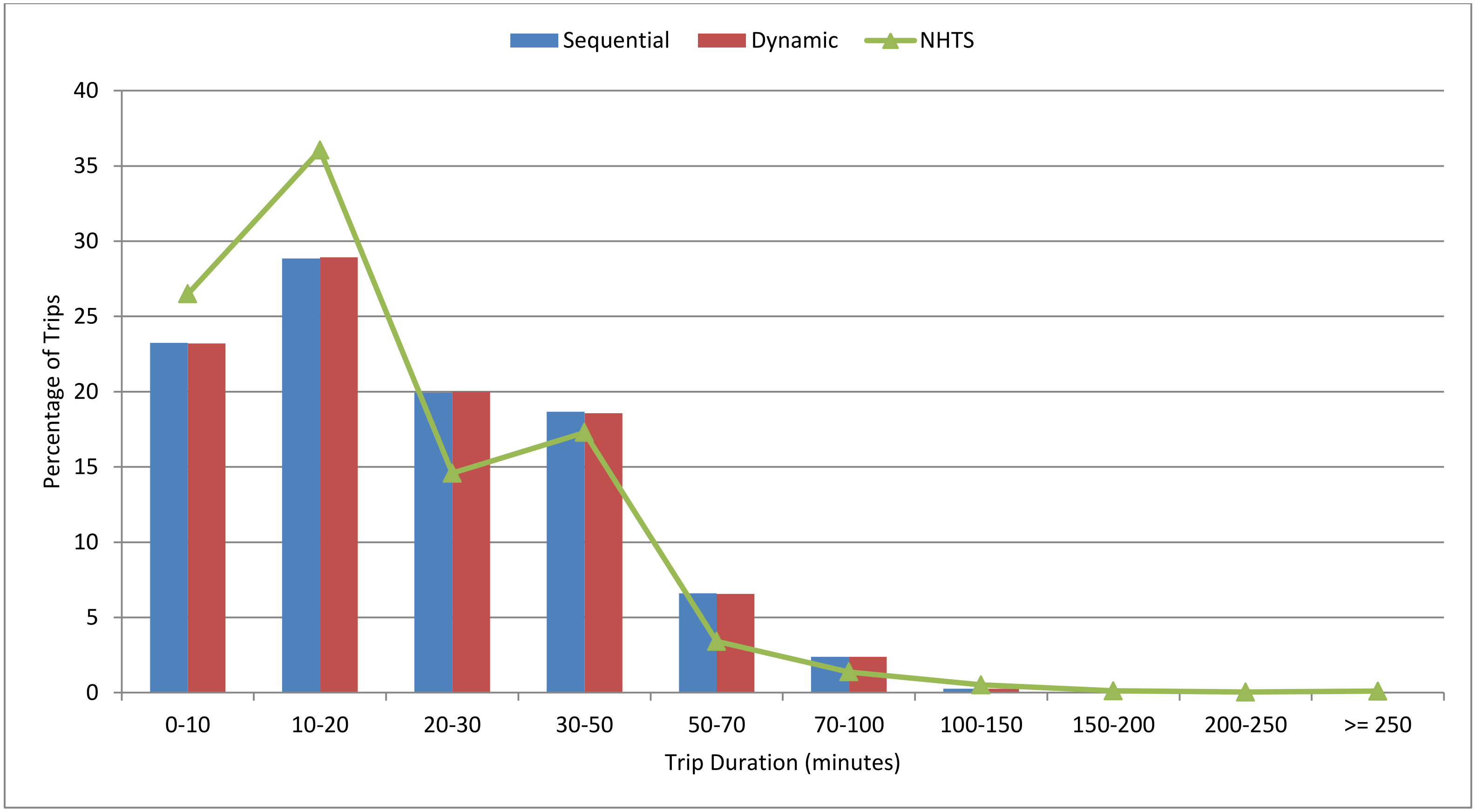

Figure 21: Trip Duration Distribution for Workers

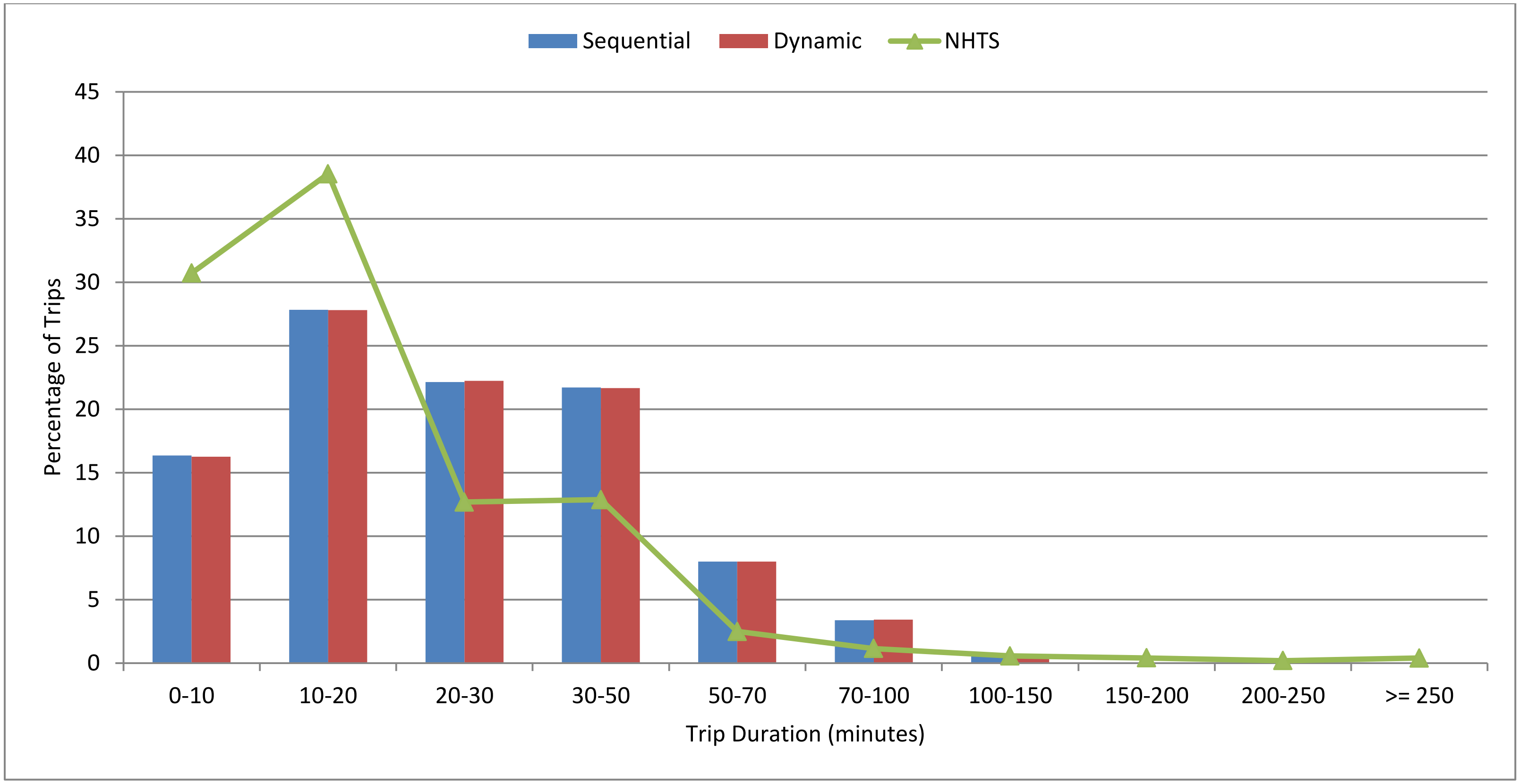

Figure 22: Trip Duration Distribution for Non-workers

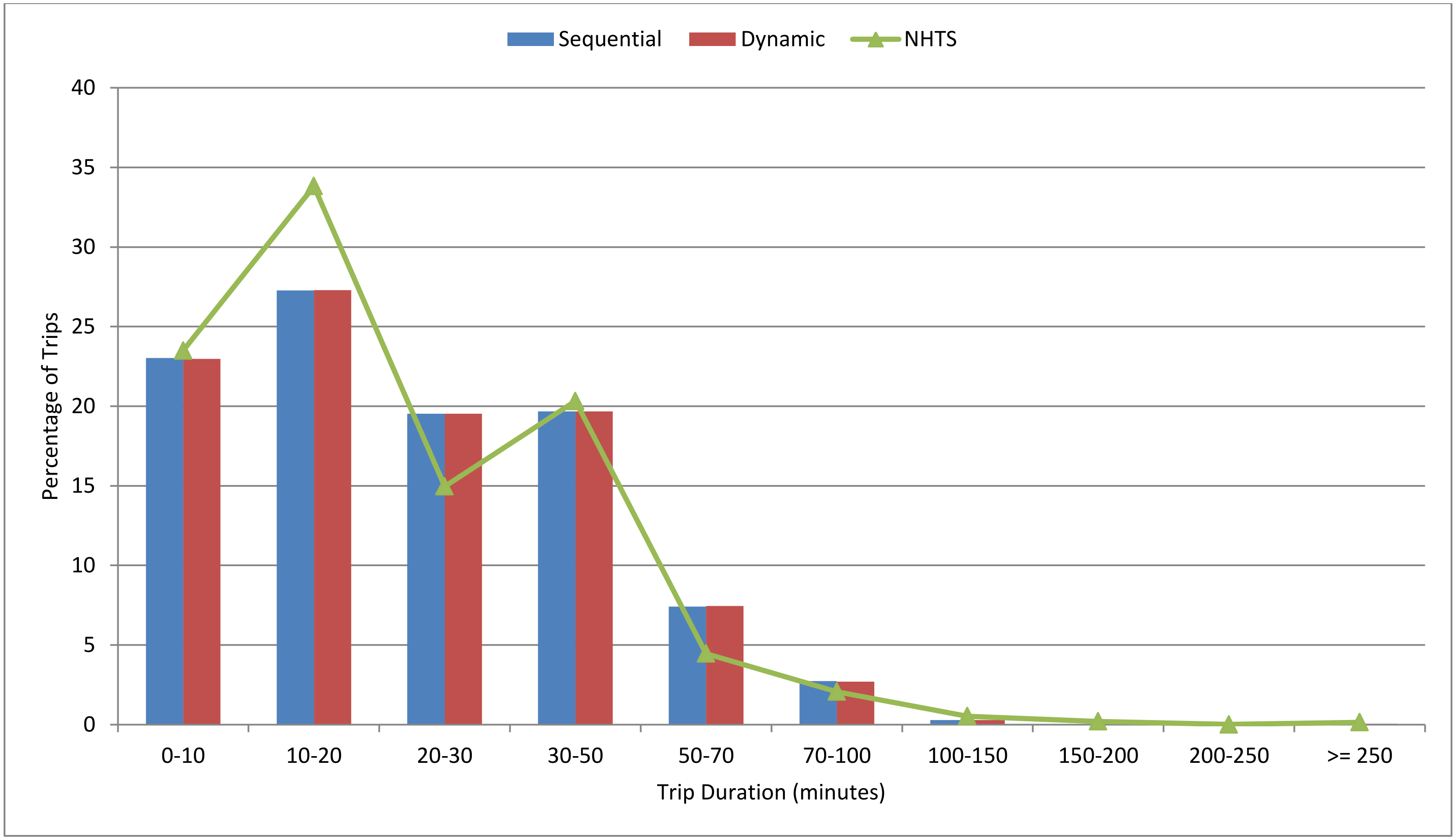

Figure 23: Trip Duration Distribution of Home Trips for Workers

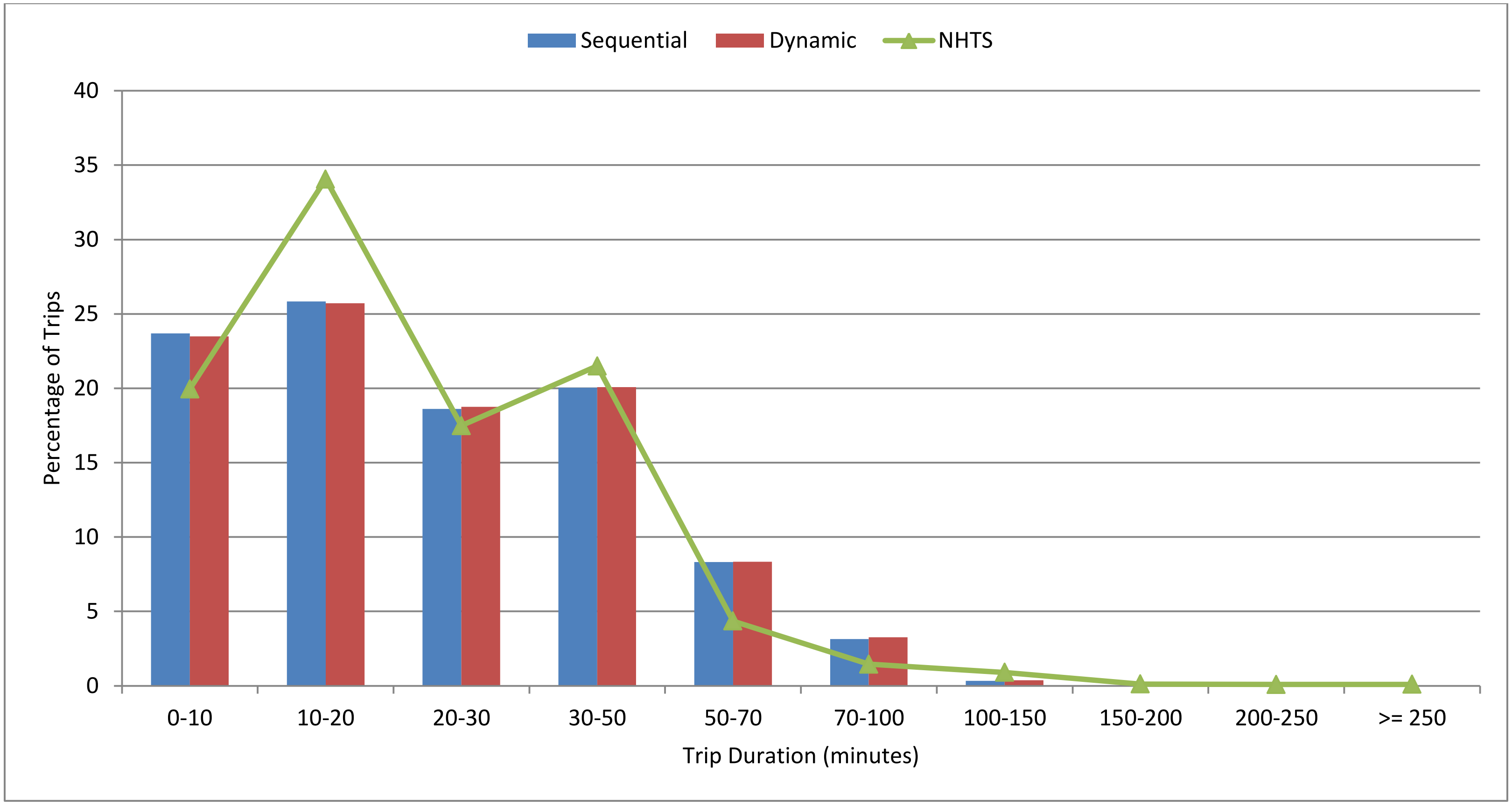

Figure 24: Trip Duration Distribution of Work Trips for Workers

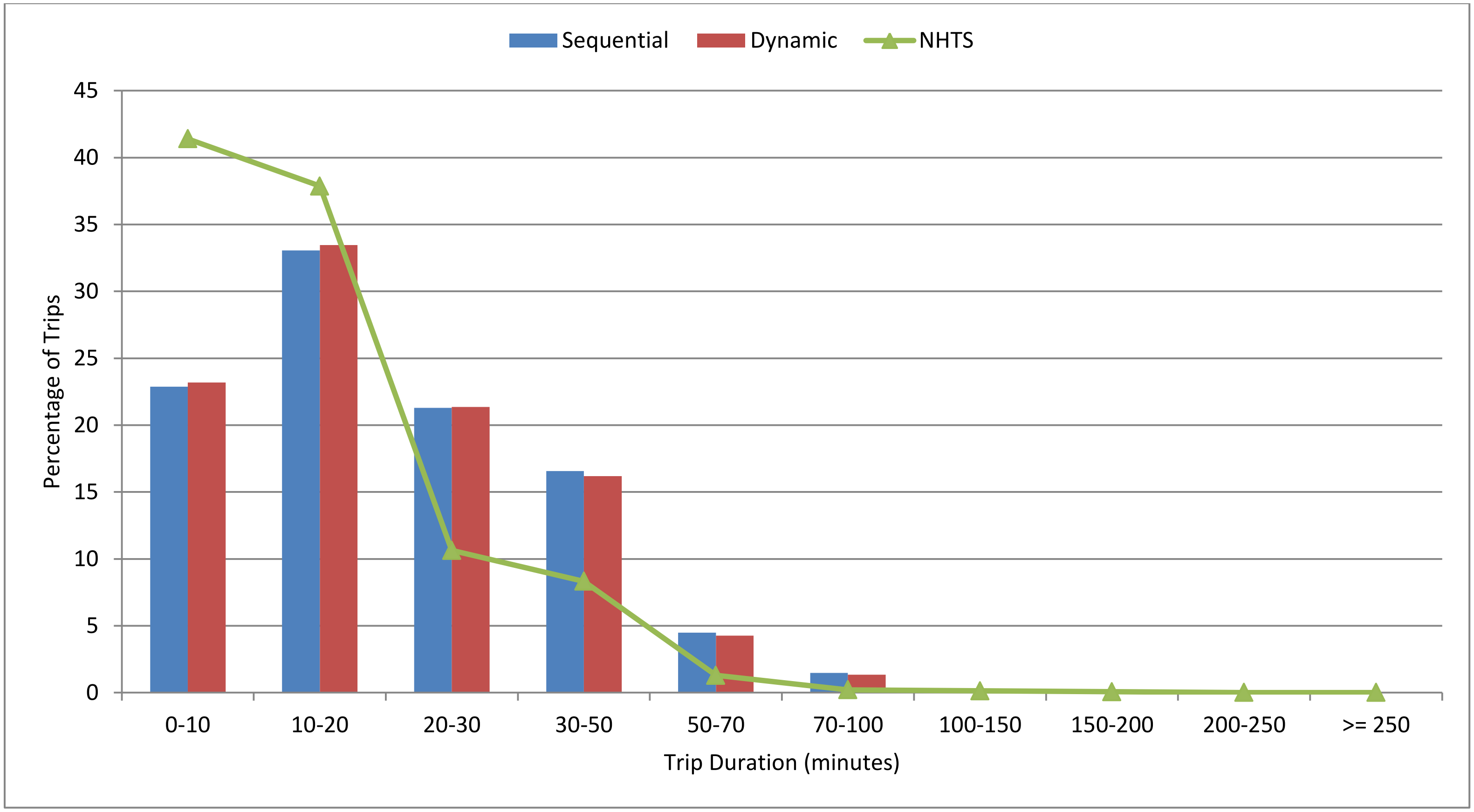

Figure 25: Trip Duration Distribution of Maintenance Trips for Workers

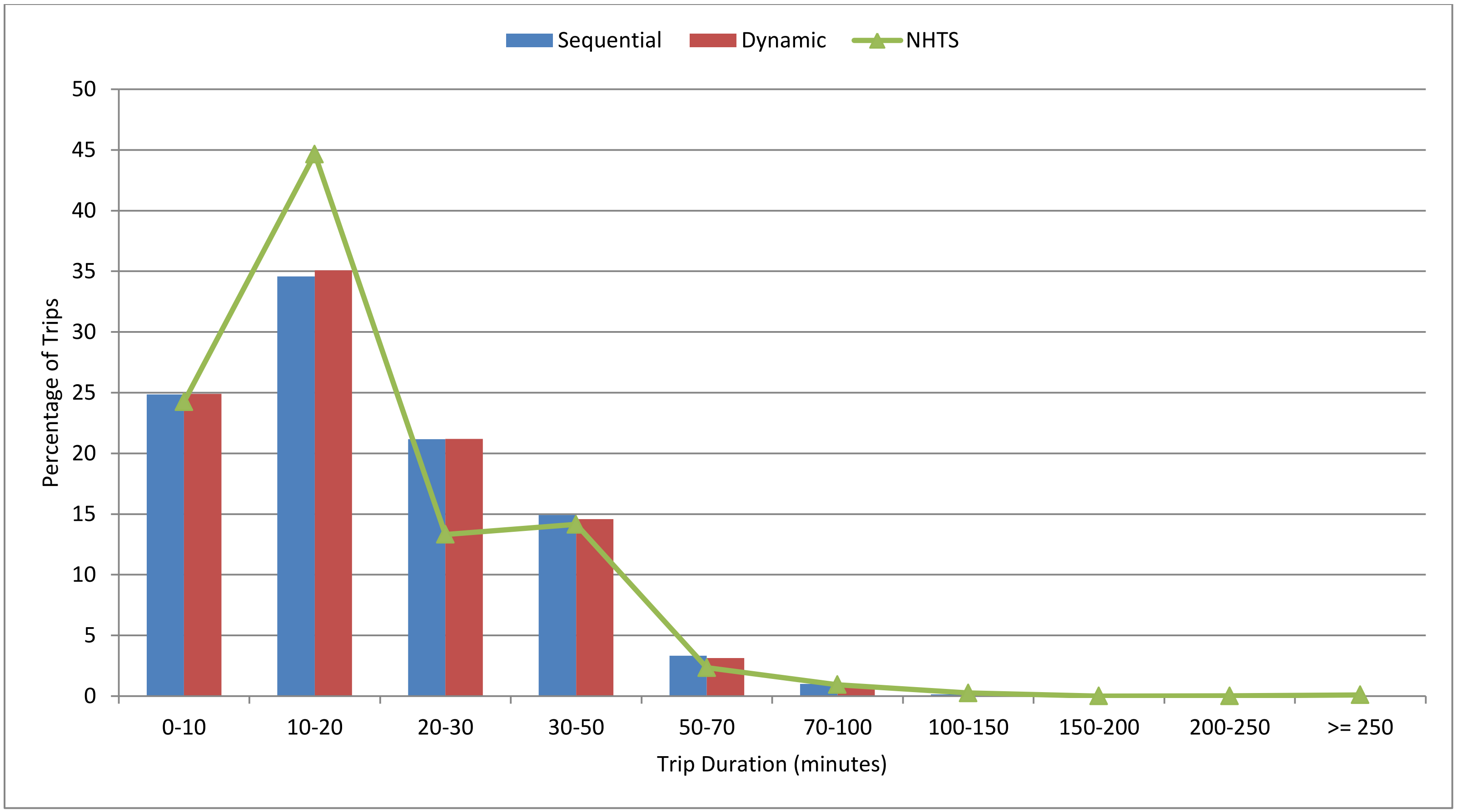

Figure 26: Trip Duration Distribution of Discretionary Trips for Workers

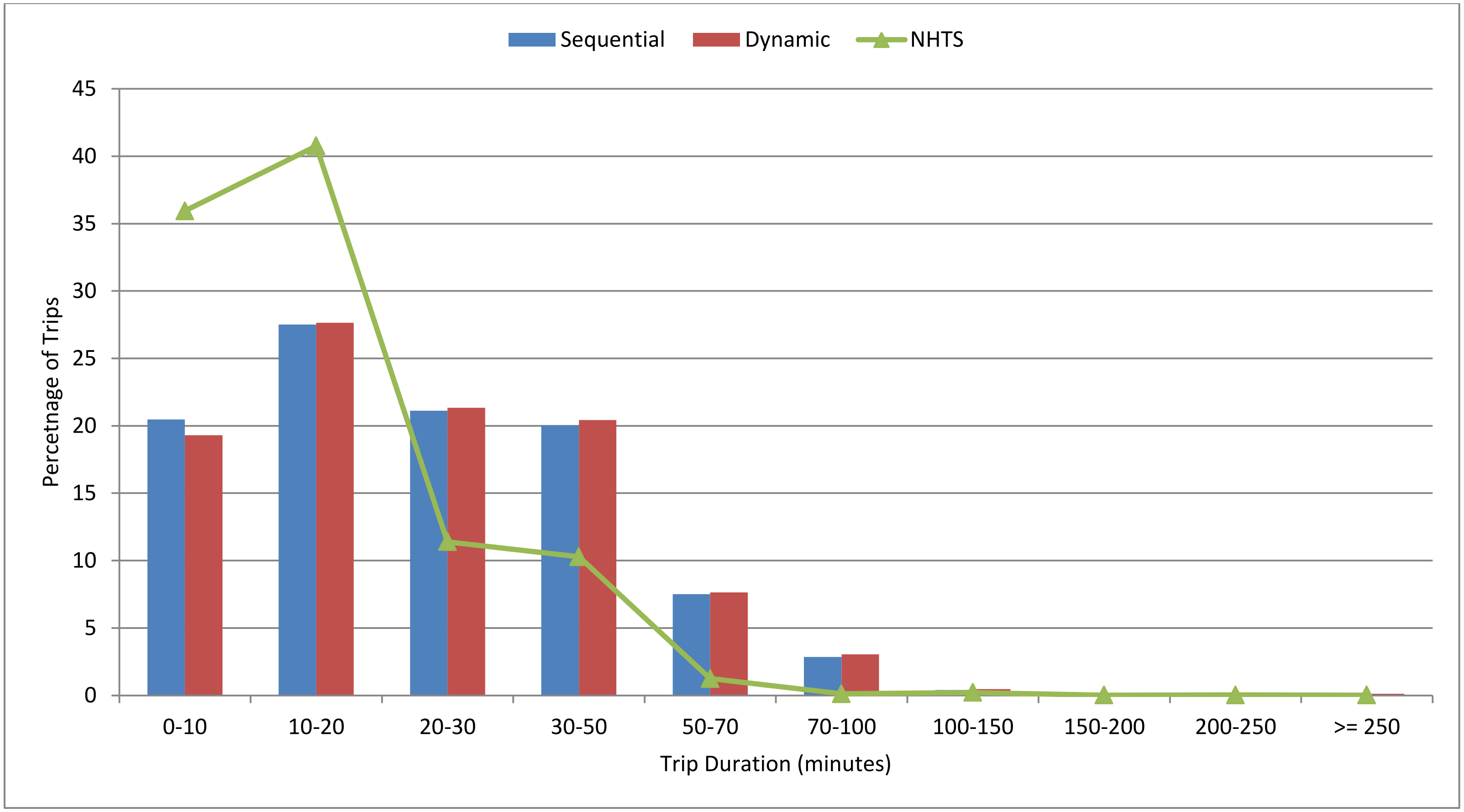

Figure 27: Trip Duration Distribution of Pickup Trips for Workers

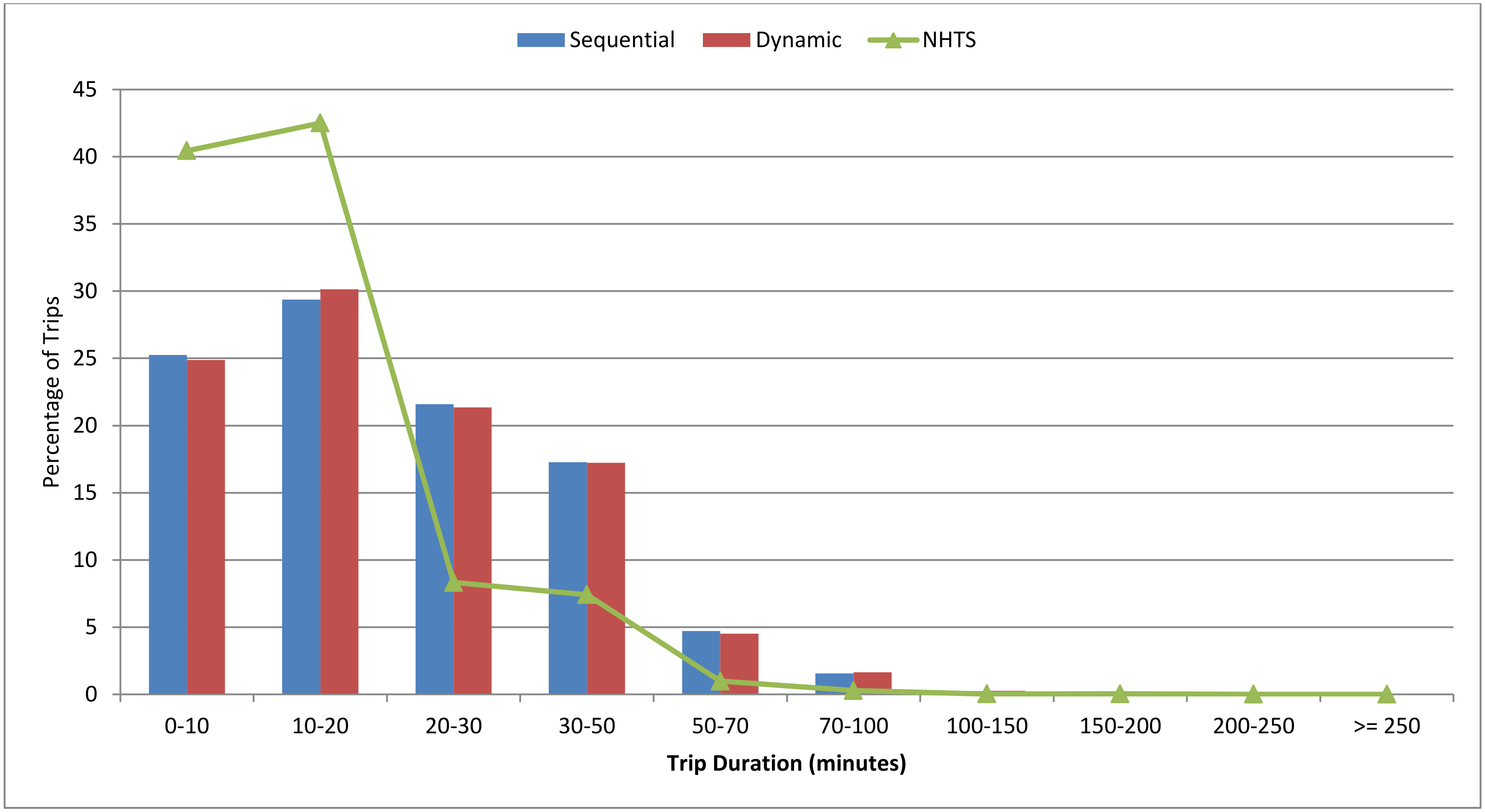

Figure 28: Trip Duration Distribution of Dropoff Trips for Workers

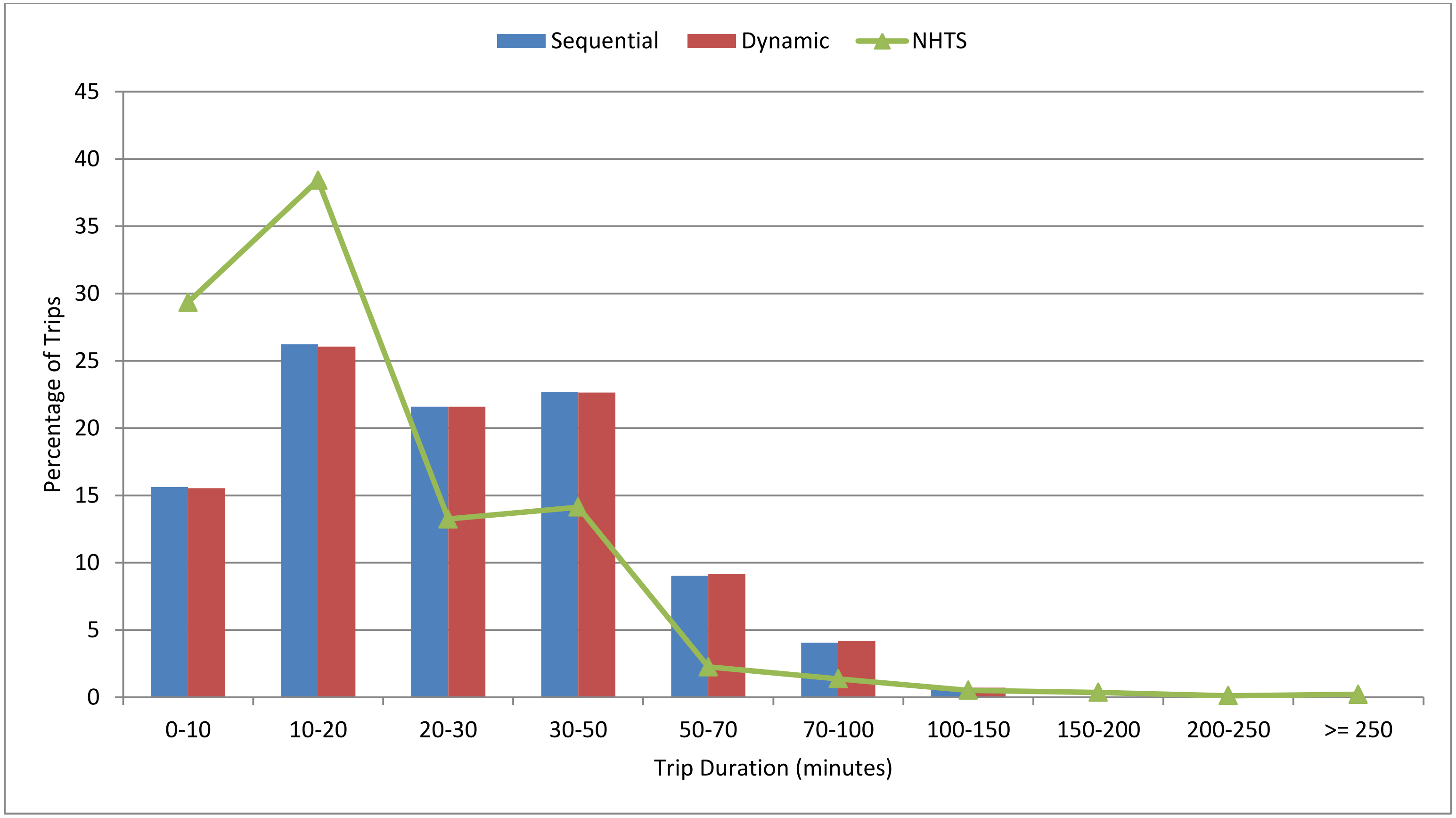

Figure 29: Trip Duration Distribution of Home Trips for Non-workers

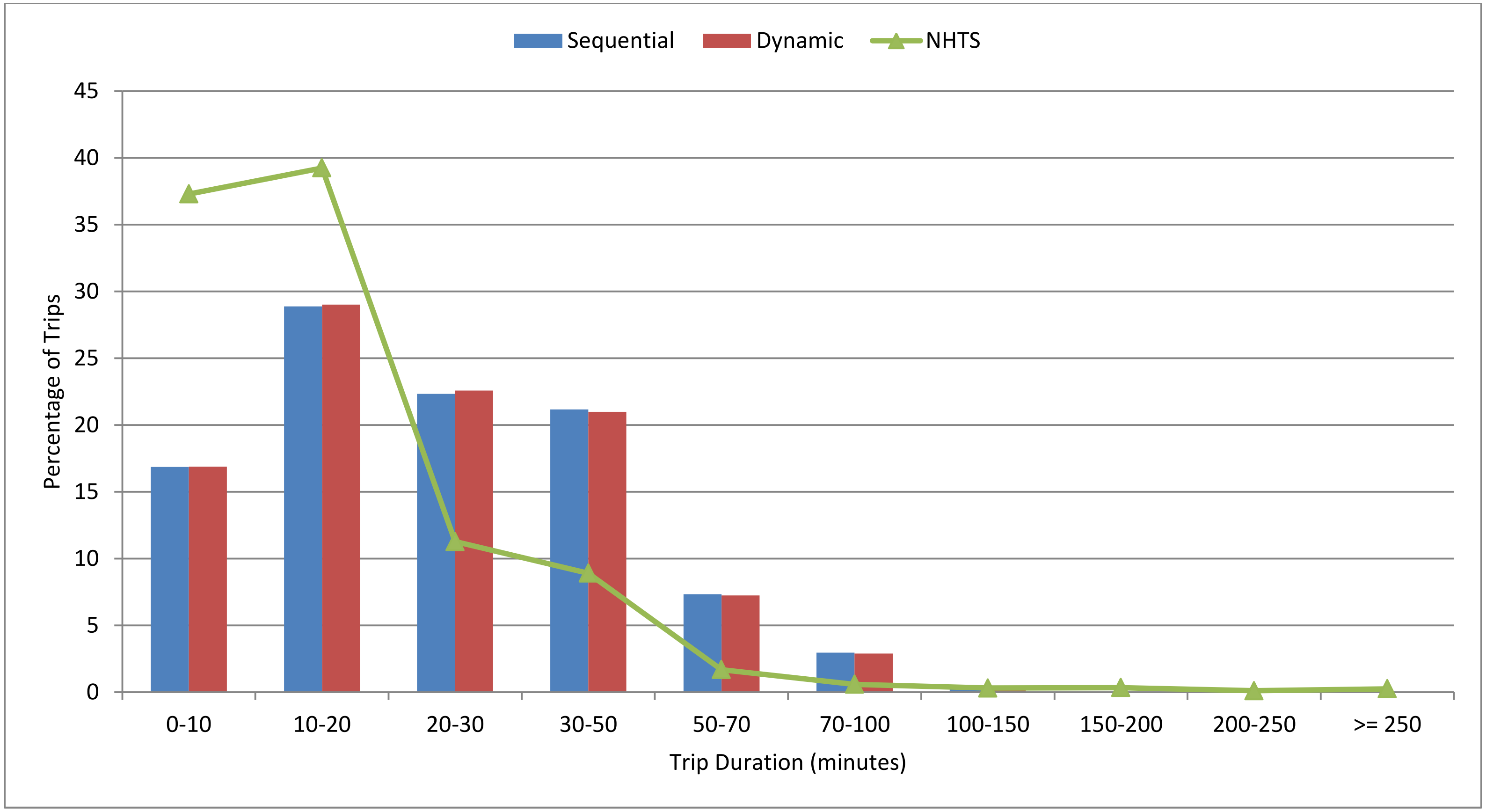

Figure 30: Trip Duration Distribution of Maintenance Trips for Non-workers

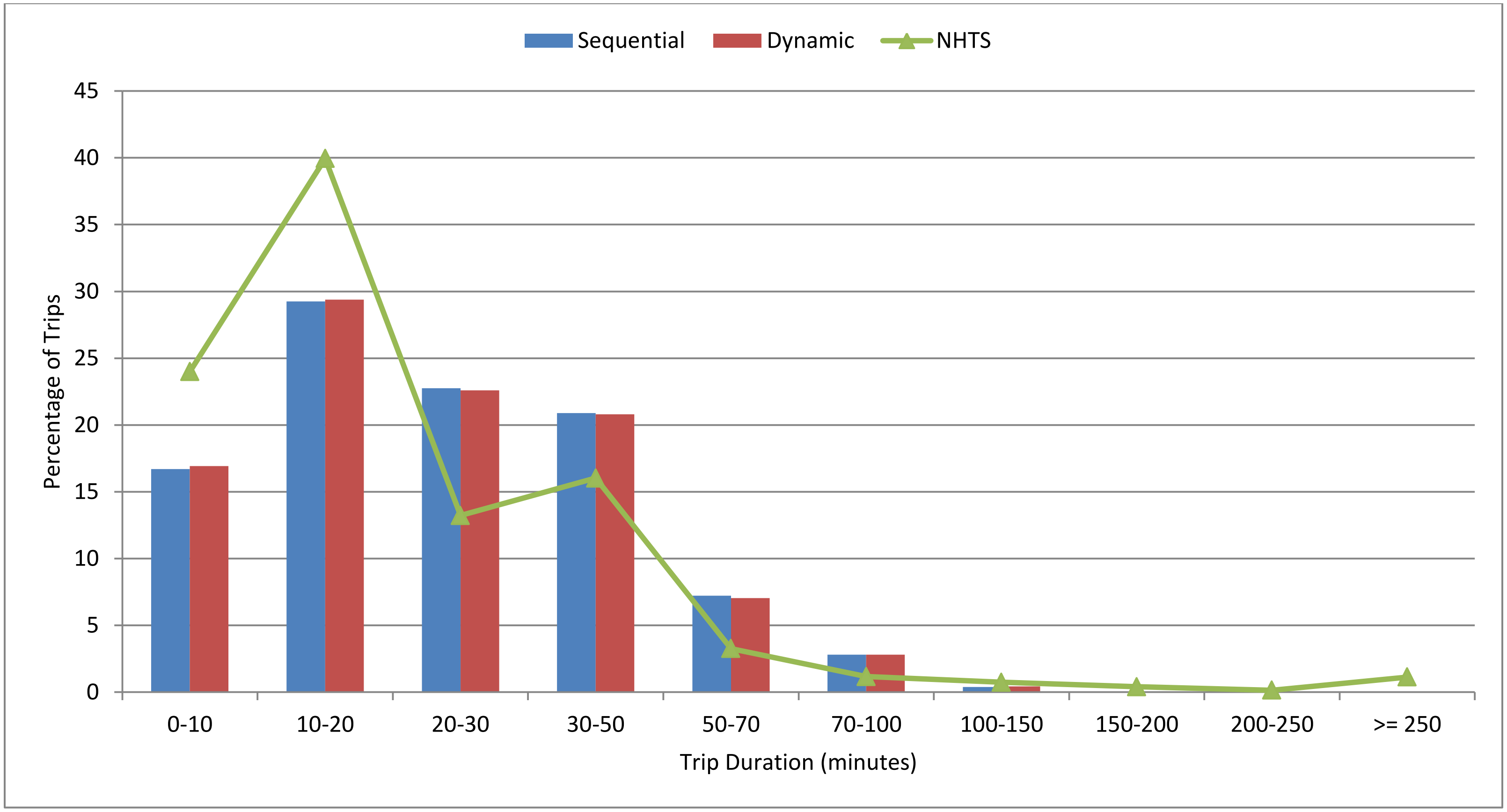

Figure 31: Trip Duration Distribution of Discretionary Trips for Non-workers

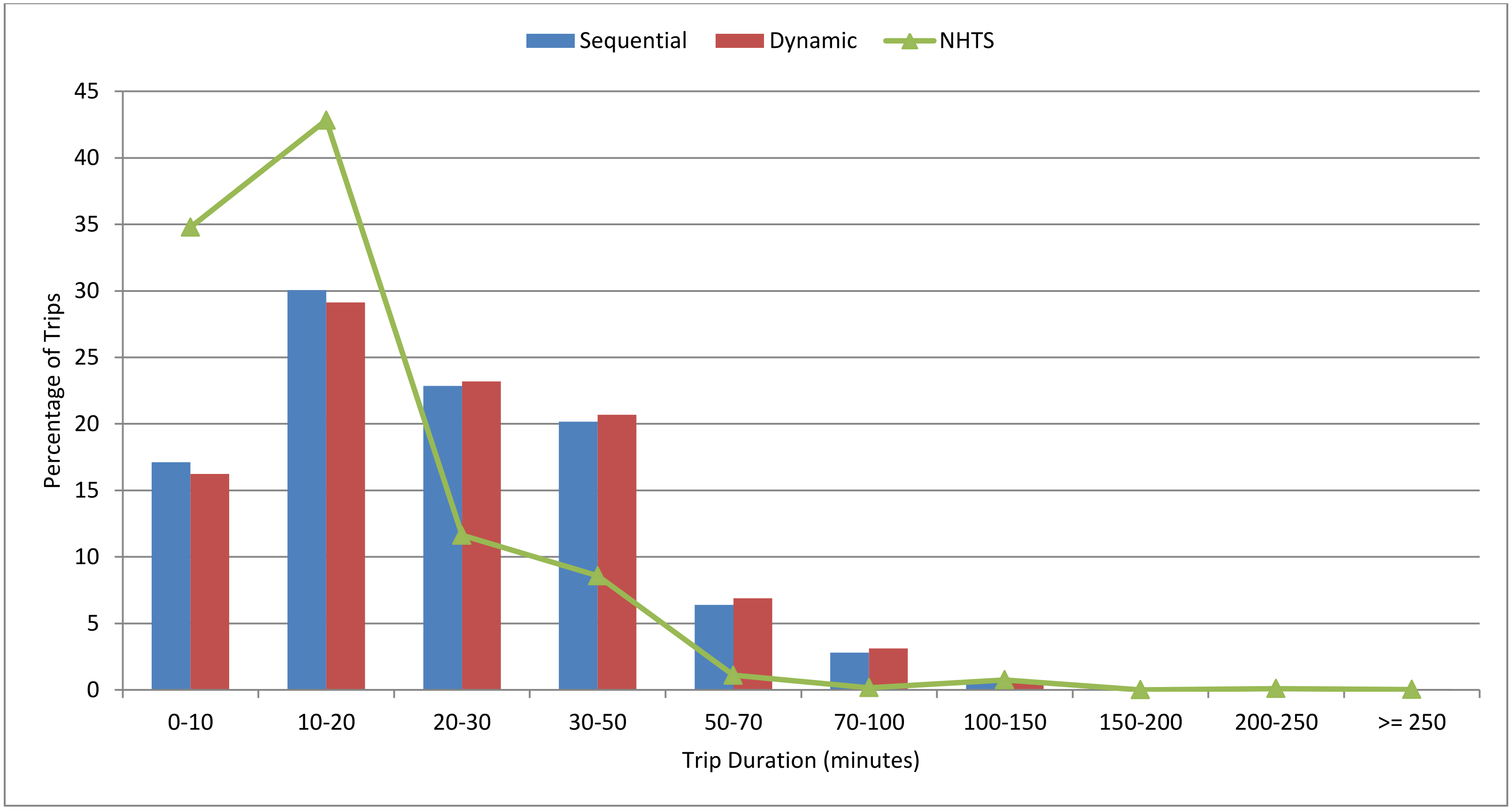

Figure 32: Trip Duration Distribution of Pickup Trips for Non-workers

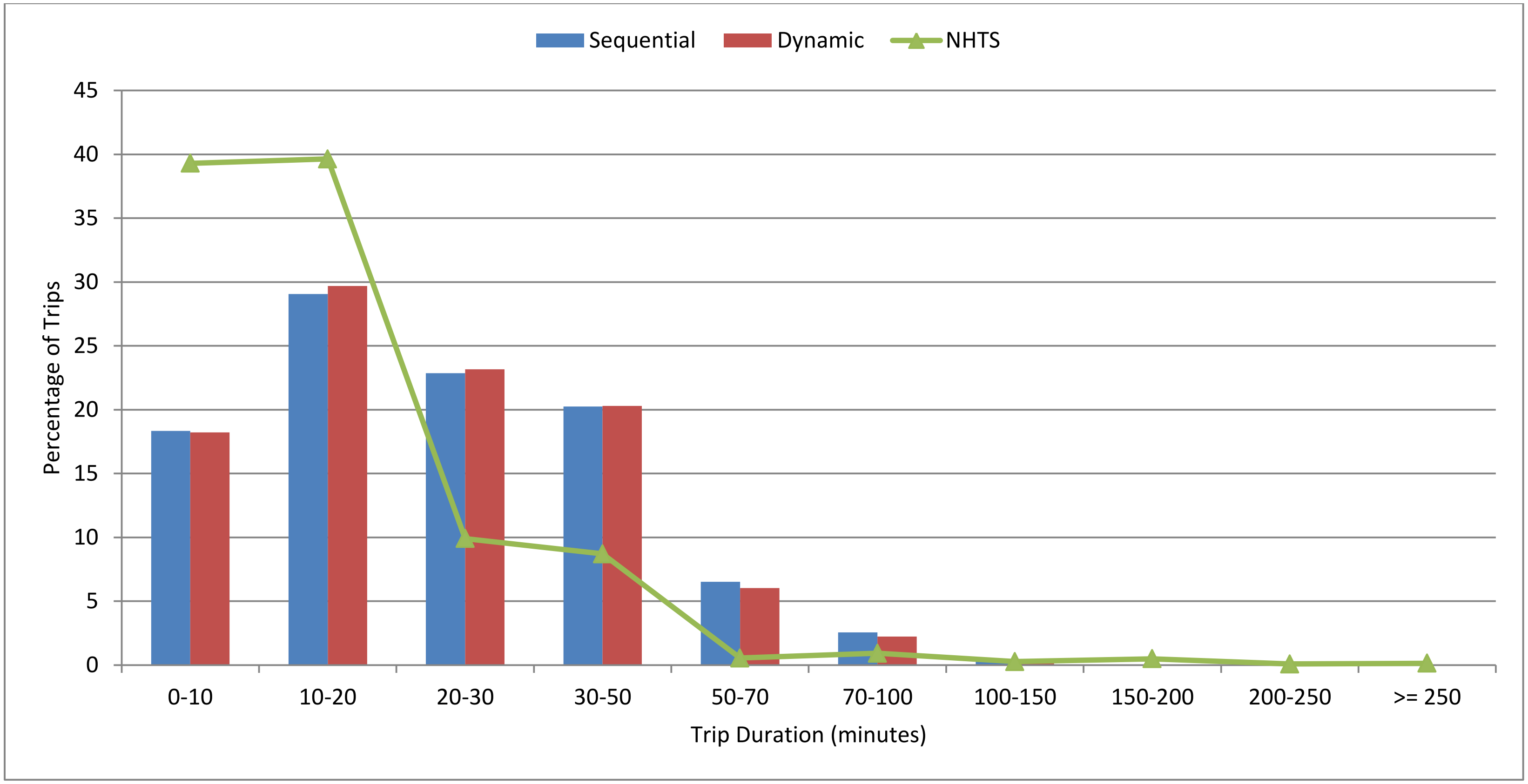

Figure 33: Trip Duration Distribution of Dropoff Trips for Non-workers

Trip Purpose Distribution

Figure 34 and Figure 35 show the trip purpose distributions of workers and non-worker demographics. It can be seen that the distributions match very closely with those from the NHTS. Also, as noted with other measures of activity-travel engagement behavior, SimTRAVEL simulates very similar results with both the sequential and dynamic approaches. There is a slight under-prediction of work trips and a slight over-prediction of home trips and maintenance trips for both demographics.

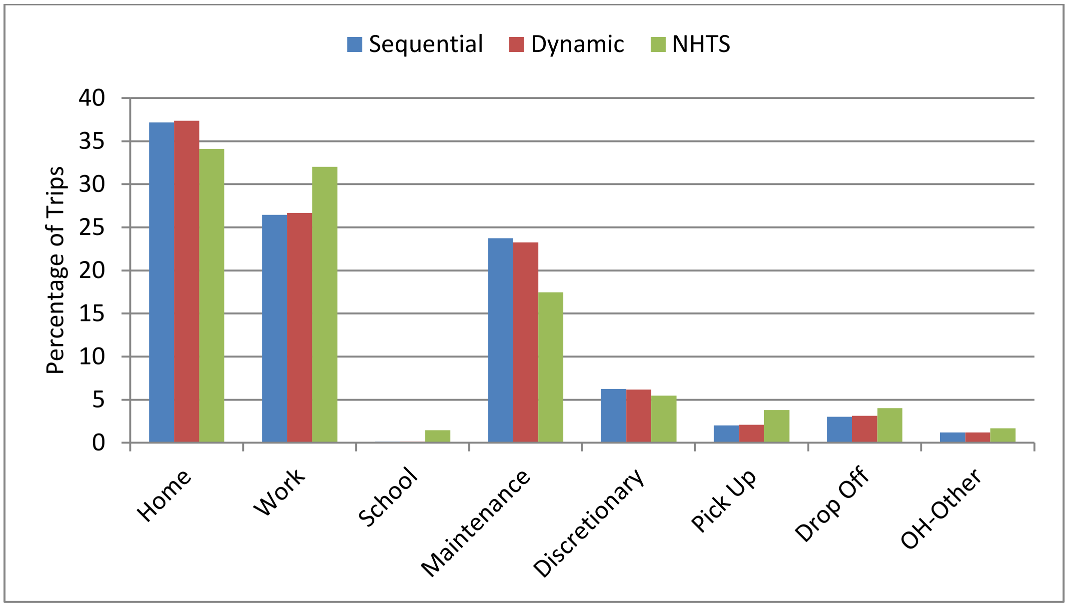

Figure 34: Trip Purpose Distribution for Workers

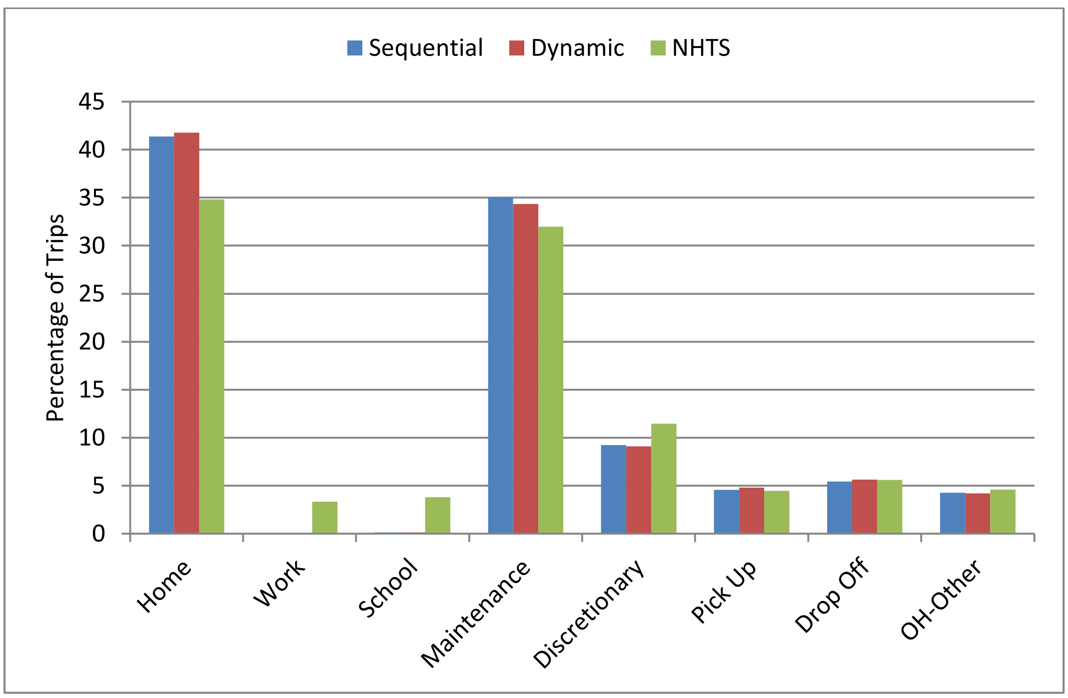

Figure 35: Trip Purpose Distribution for Non-workers

Activity Episode Duration

In addition to matching travel duration distributions that account for how much time individuals spend traveling there is also a need to match distributions of activity episodes that people pursue. Figure 36 and Figure 37 display distributions of activity episode duration for workers and non-workers respectively. It must be noted that OpenAMOS comprises one of the few microsimulation-based demand modeling systems that accounts for in-home activity engagement explicitly in addition to out-of-home activity engagement. In other demand model implementations, in-home activity engagement is implied by constructing a skeleton of out-of-home activity engagement decisions and generating the in-home activity patterns around out-of-home activity engagement. This approach however may fail to capture some of the trade-offs and interdependencies between in-home and out-of-home activity engagement. Also, in OpenAMOS paradigm, time of day is implied unlike other model implementations where time of day needs to be simulated and often generated using coarse aggregations of time. However, time is continuous and aggregations could lead to potential loss in information and behavioral fidelity.

Again the sequential and dynamic approaches simulate activity duration choices that are very similar. The activity episode durations seem to compare well with the weighted observations from NHTS and seem to closely match the trends in the observed distribution. There are slight deviations in the activity episode durations for very large episodes (greater than equals 250 minutes) and for episodes with durations between 50 and 150 minutes). In the demand model (OpenAMOS), a single model is used to simulate the durations of episodes for all activity types. While there are activity type dummies and time of day dummies included in the model specification, the single model does not seem to account for all trends in the data. This can be observed in the figures that show the episode duration distributions for home episodes (Figure 38), work episodes (Figure 39), maintenance activities (Figure 40), discretionary activities (Figure 41), pickup activities (Figure 42) and dropoff activities (Figure 43) for workers. As can be seen, it would be rather difficult for a single duration model to capture all these different trends with a single model specified using activity type and time of day dummies. The specification of separate models for different activity types is left for a future exercise.

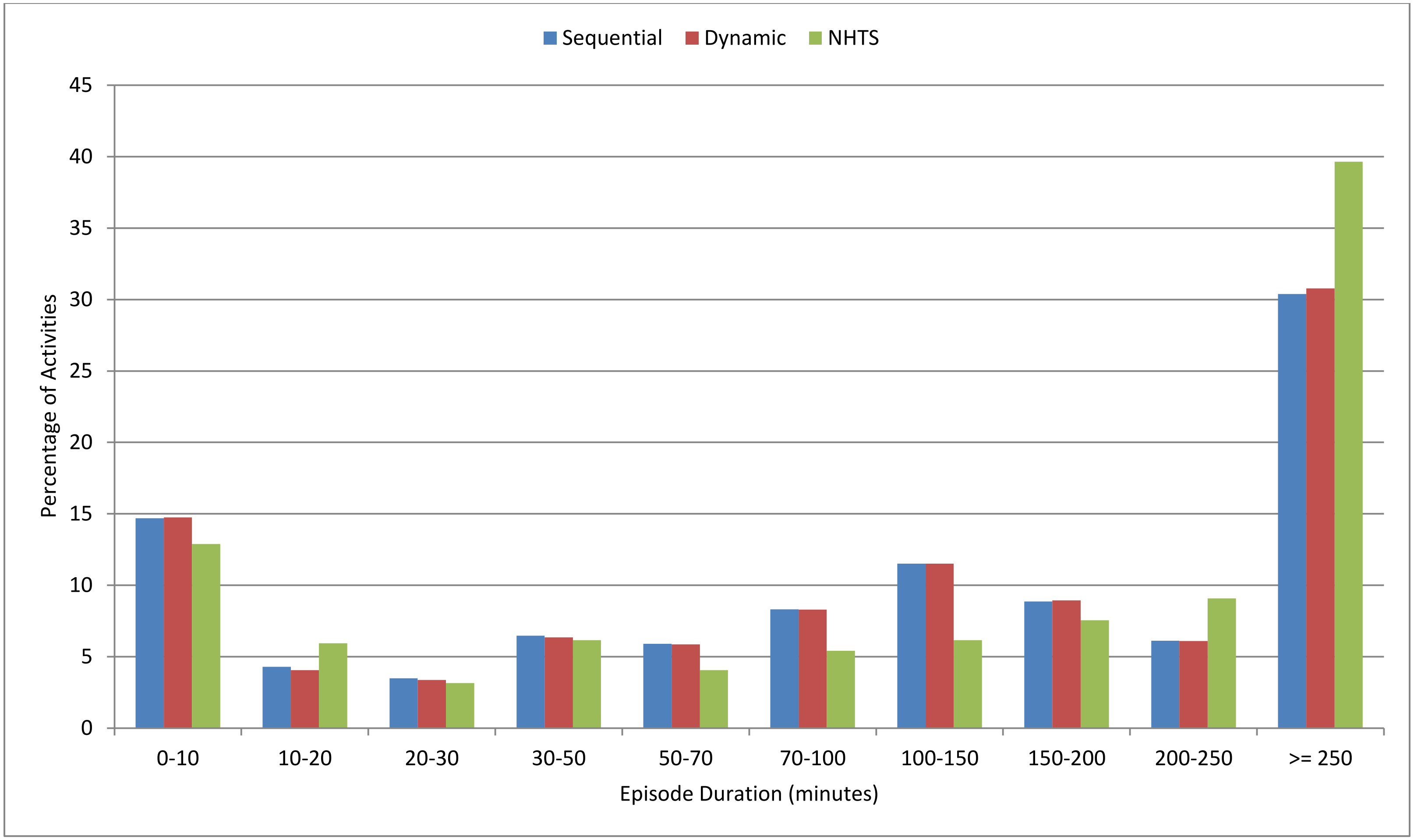

Figure 36: Activity Episode Duration Distribution for Workers

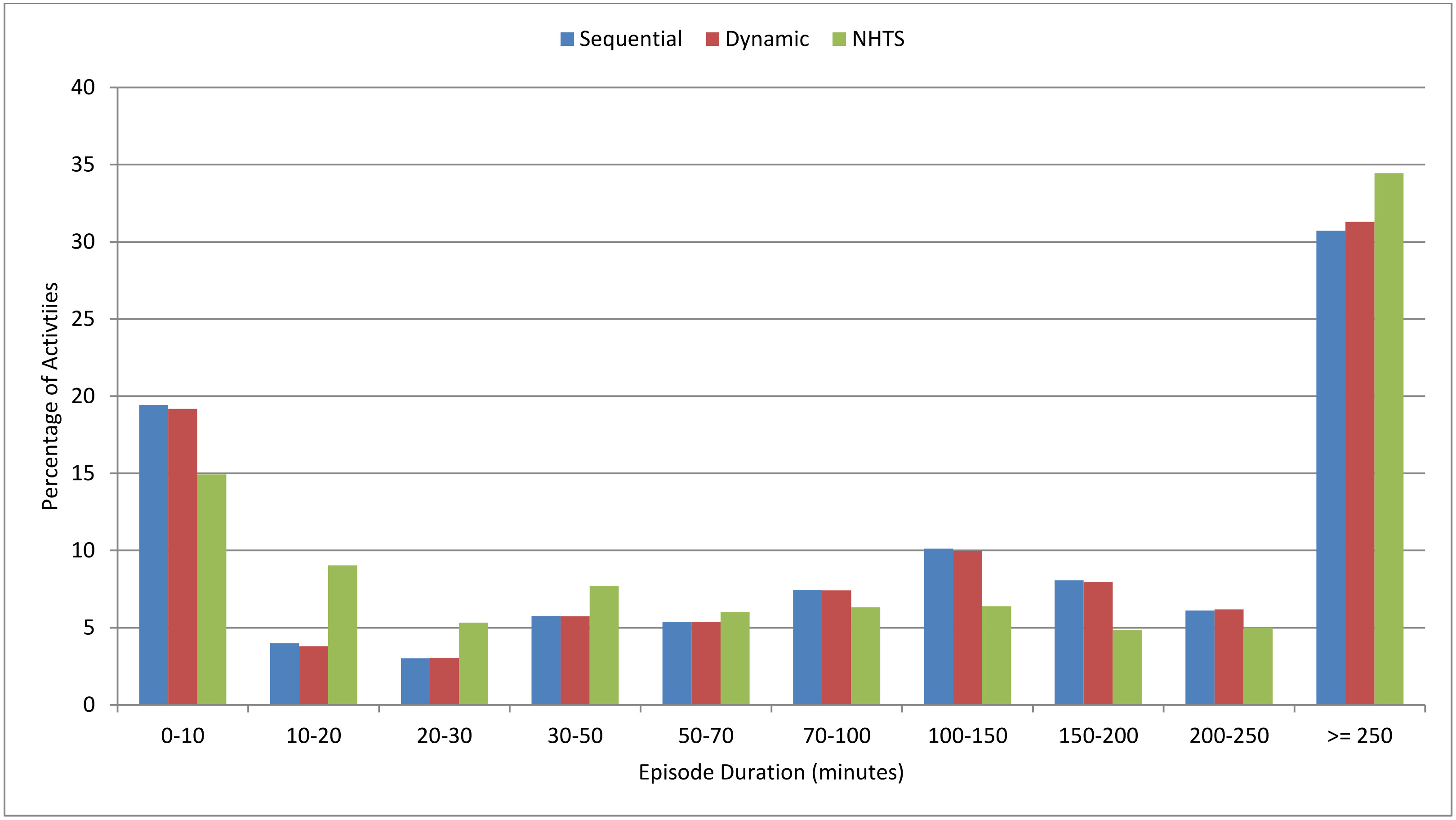

Figure 37: Activity Episode Duration Distribution for Non-workers

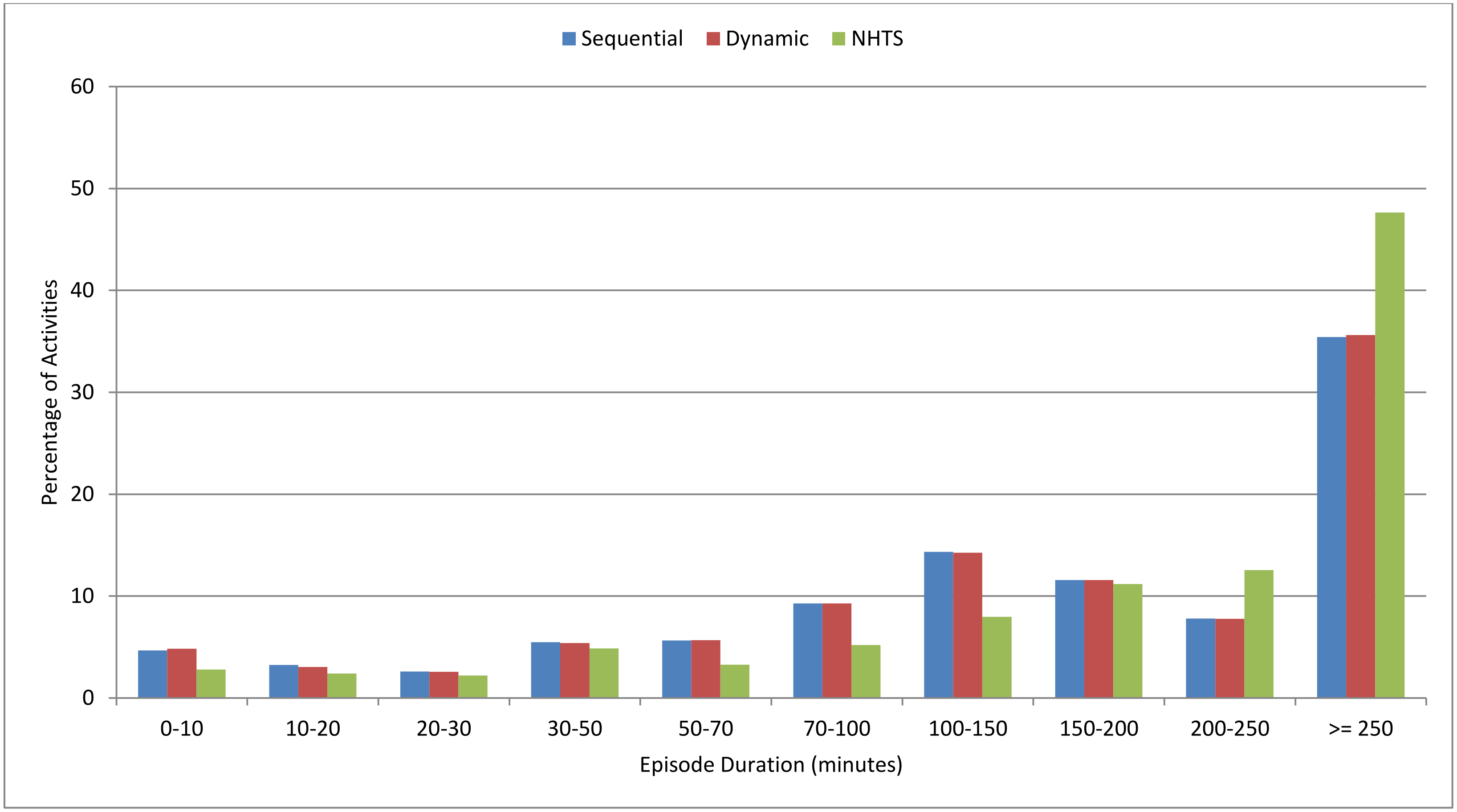

Figure 38: Activity Duration Distribution of Home Episodes for Workers

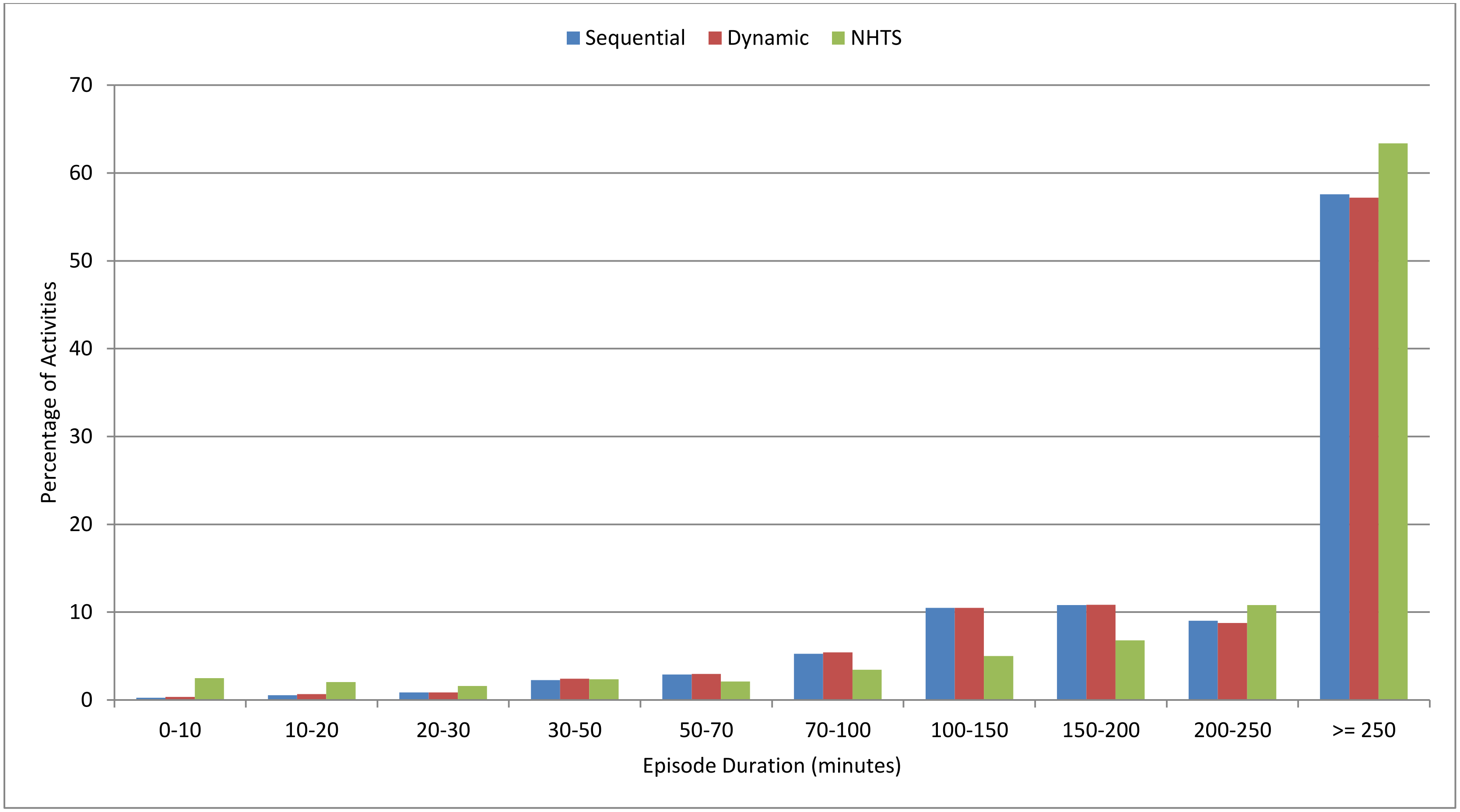

Figure 39: Activity Duration Distribution of Work Episodes for Workers

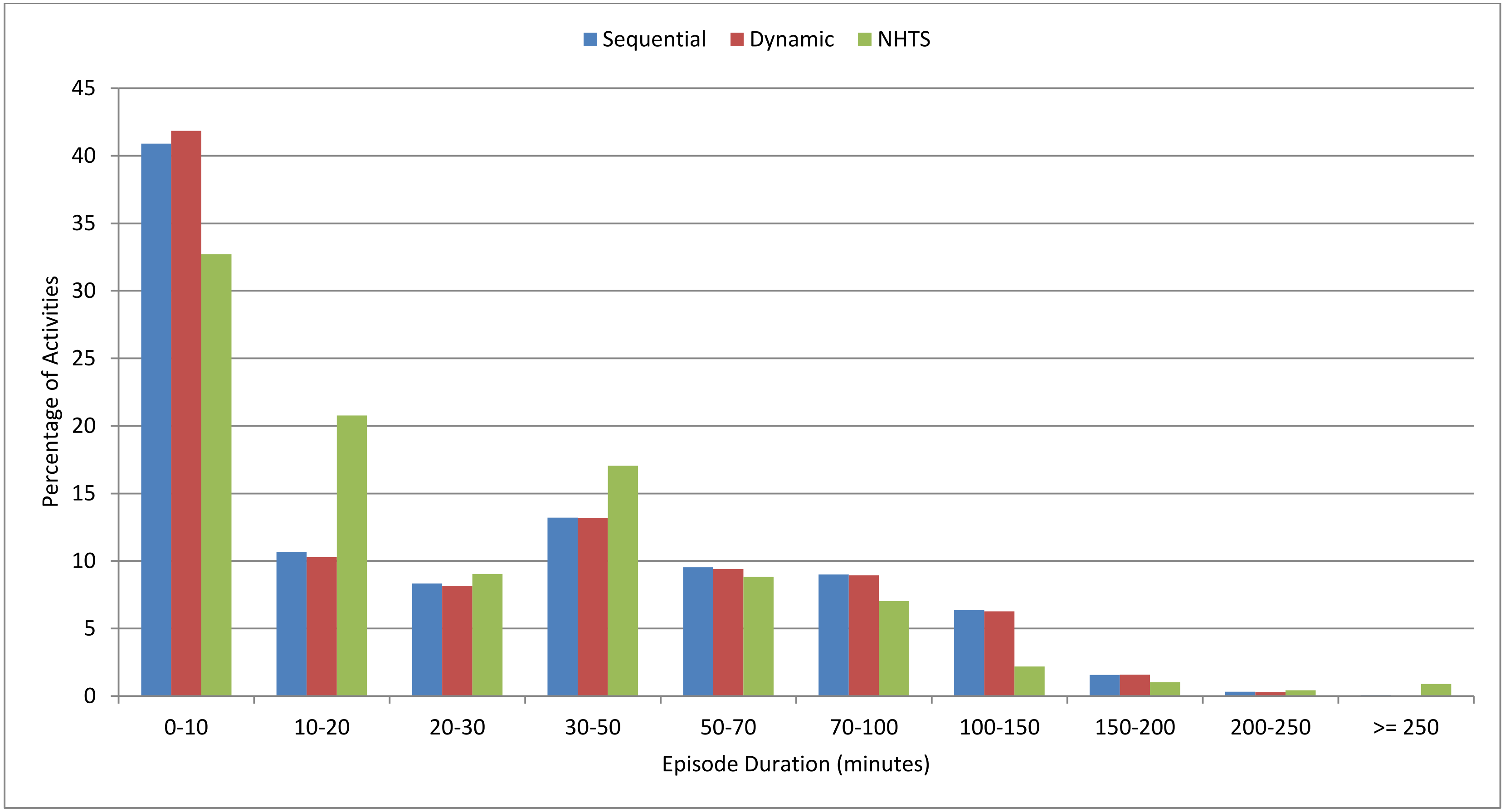

Figure 40: Activity Duration Distribution of Maintenance Episodes for Workers

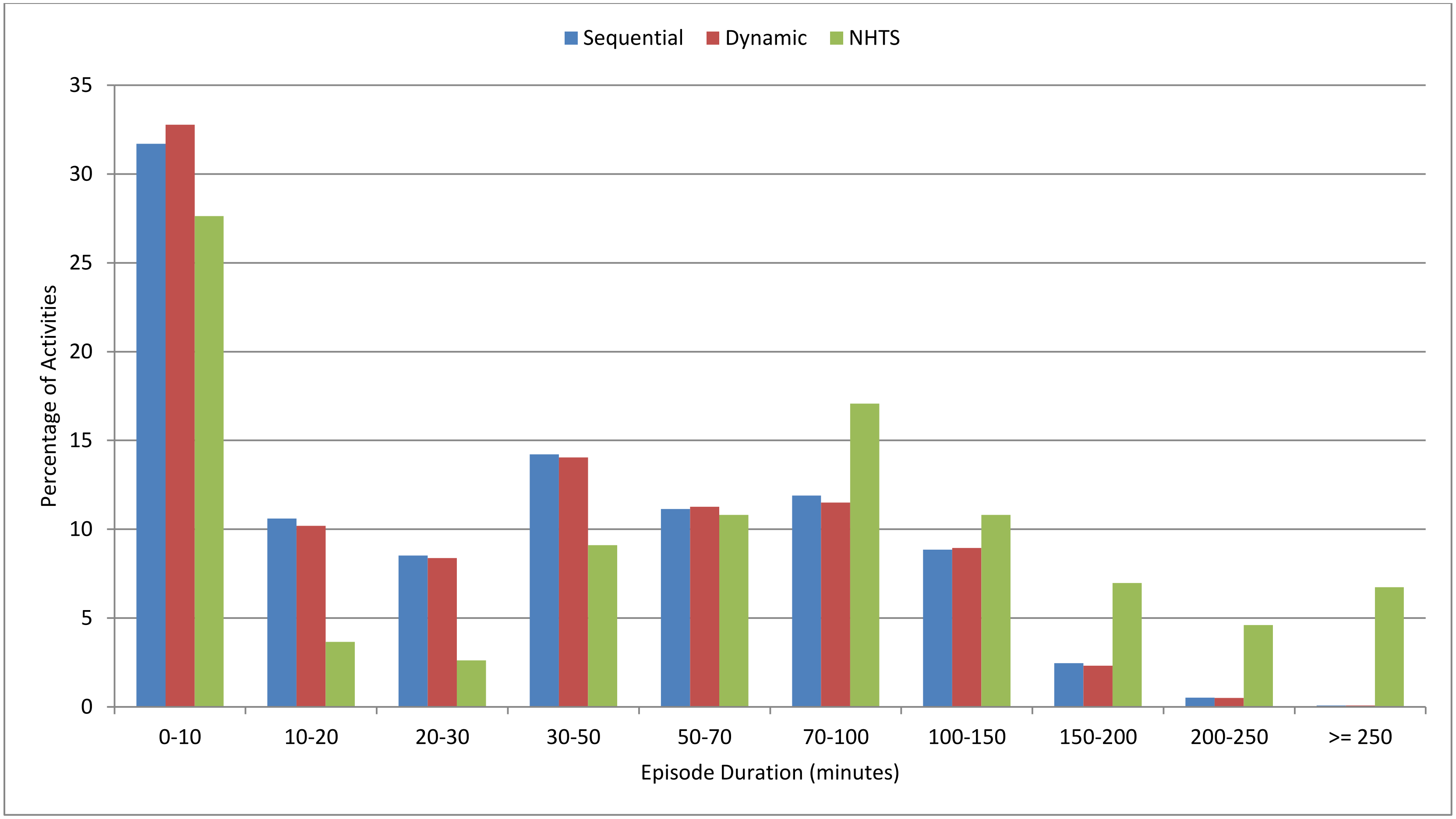

Figure 41: Activity Duration Distribution of Discretionary Episodes for Workers

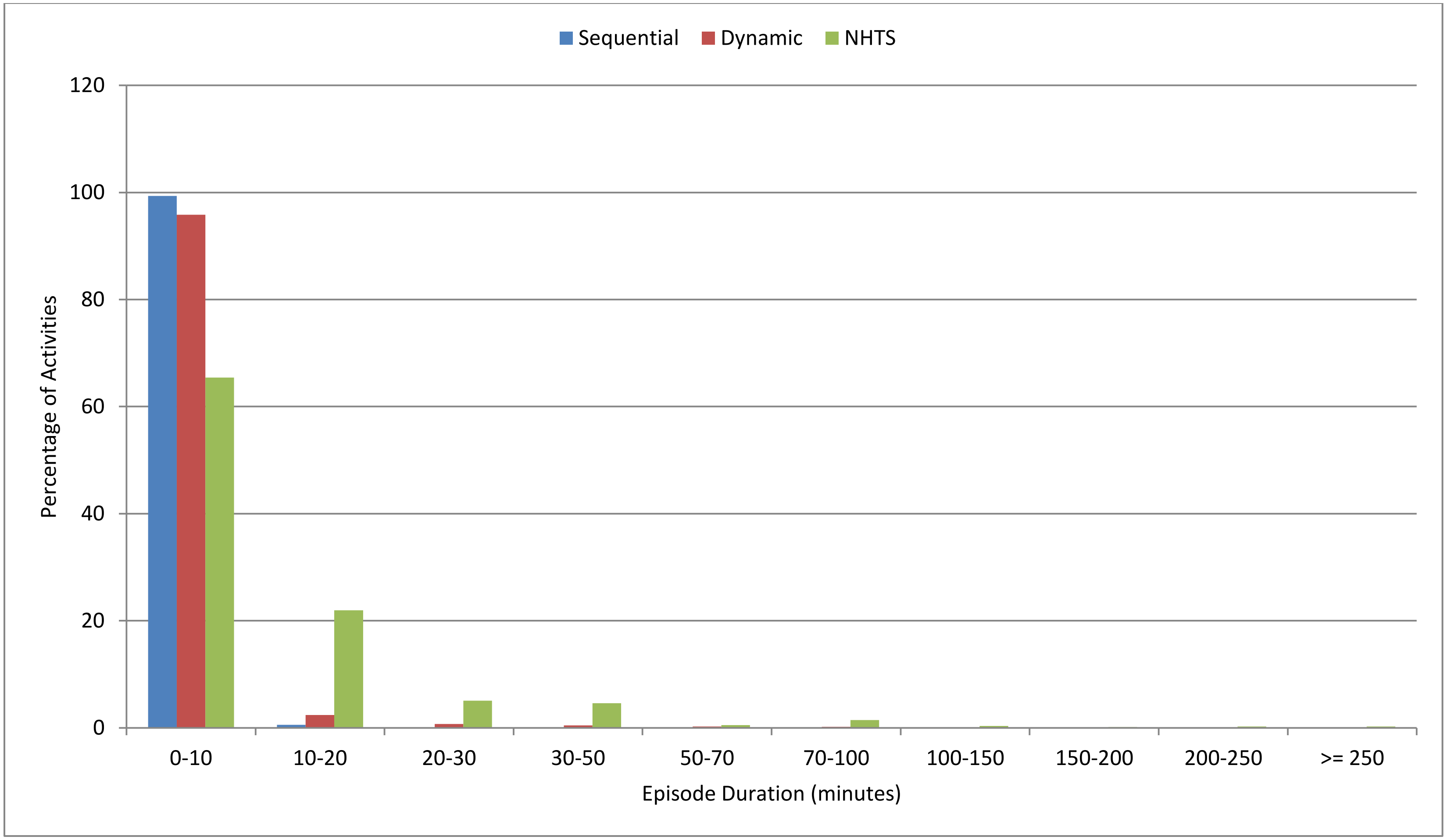

Figure 42: Activity Duration Distribution of Pickup Episodes for Workers

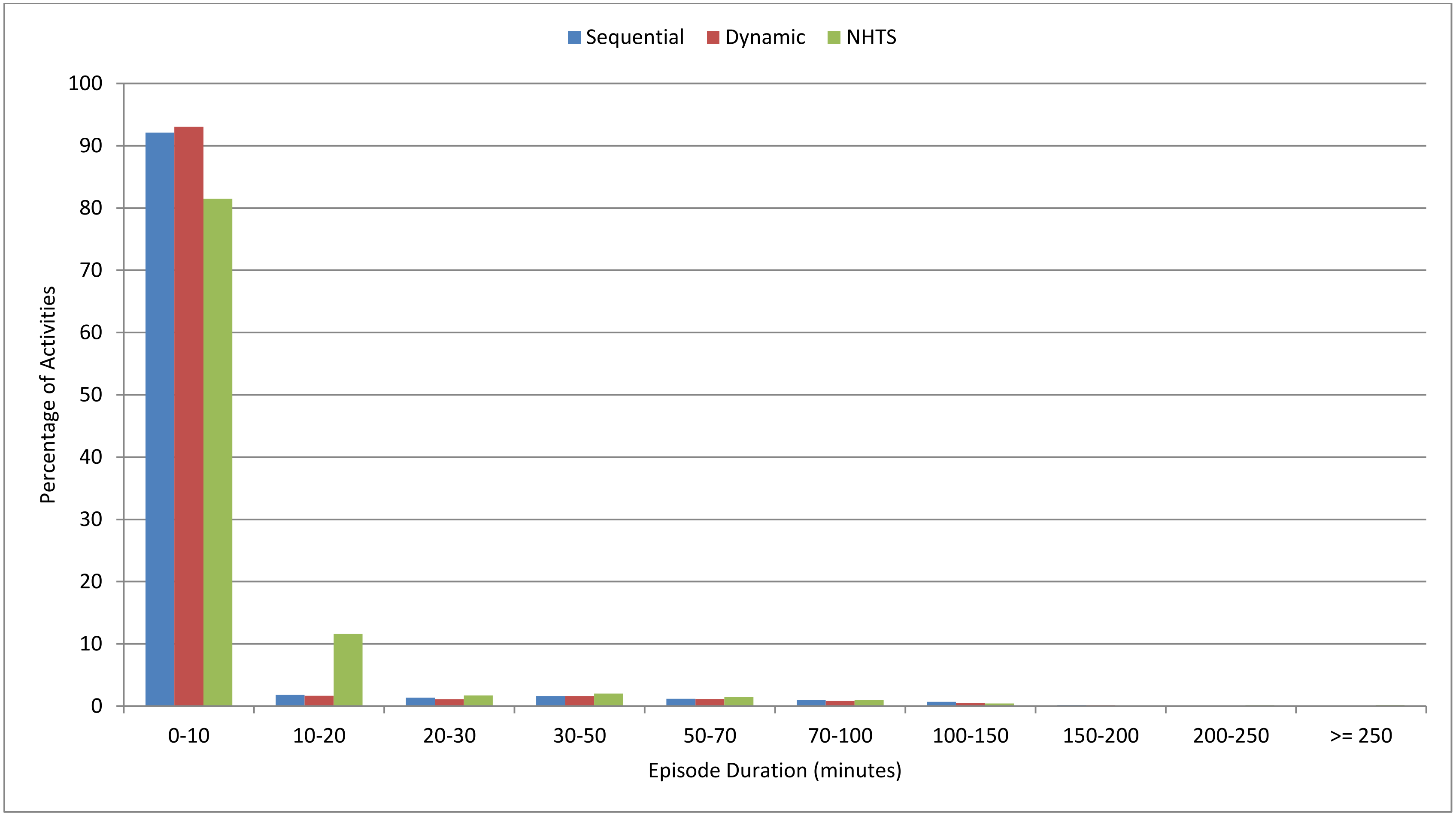

Figure 43: Activity Duration Distribution of Dropoff Episodes for Workers

Trip Rate

Another key dimension of measuring and assessing activity-travel engagement results is to compare individual trip rates. While matching trip duration distribution helps ensure that trips are distributed in space, matching trip rates ensure that the correct number of trips is generated. Table 19 show the trip rate by purpose for both workers and non-workers. It can be seen that the overall trip rates are slightly higher than those observed from the NHTS by about 0.3 across all adults. As noticed in the trip purpose distribution, SimTRAVEL seems to over-predict home and maintenance type activities and slightly under-predicts work trip rates. A potential explanation for the latter observation is the restriction imposed on workers and their fixed activity participation in OpenAMOS; workers are assumed to only participate in a maximum of two episodes.

Figure 44 and Figure 45 show the trip frequency distribution for workers and non-workers respectively. For workers, the trip frequency distribution very closely matches the distribution from NHTS with the deviations for all frequency categories within 5 percent. For non-workers the simulated trip frequency matches closely except for trip frequency zero. SimTRAVEL predicts fewer people to be performing zero trips (11.65 percent versus 20.88 percent). Otherwise the differences in other trip frequency categories are reasonable and within deviations of less than 5 percent. Similar to other activity-travel engagement dimensions, SimTRAVEL produces very similar distributions with both the sequential and dynamic approach to integration.

Table 19: Average Trip Rate by Purpose

	Worker			Nonworker		
	Sequential	Dynamic	NHTS	Sequential	Dynamic	NHTS
Home	1.73	1.74	1.49	1.70	1.71	1.32
Work	1.23	1.24	1.40	0.00	0.00	0.13
School	0.01	0.01	0.06	0.01	0.00	0.14
Maintenance	1.11	1.08	0.77	1.44	1.41	1.22
Discretionary	0.29	0.29	0.24	0.38	0.37	0.44
Pick Up	0.09	0.10	0.17	0.19	0.20	0.17
Drop Off	0.14	0.15	0.18	0.22	0.23	0.21
OH-Other	0.06	0.06	0.07	0.18	0.17	0.17
Total	4.66	4.66	4.38	4.11	4.10	3.80

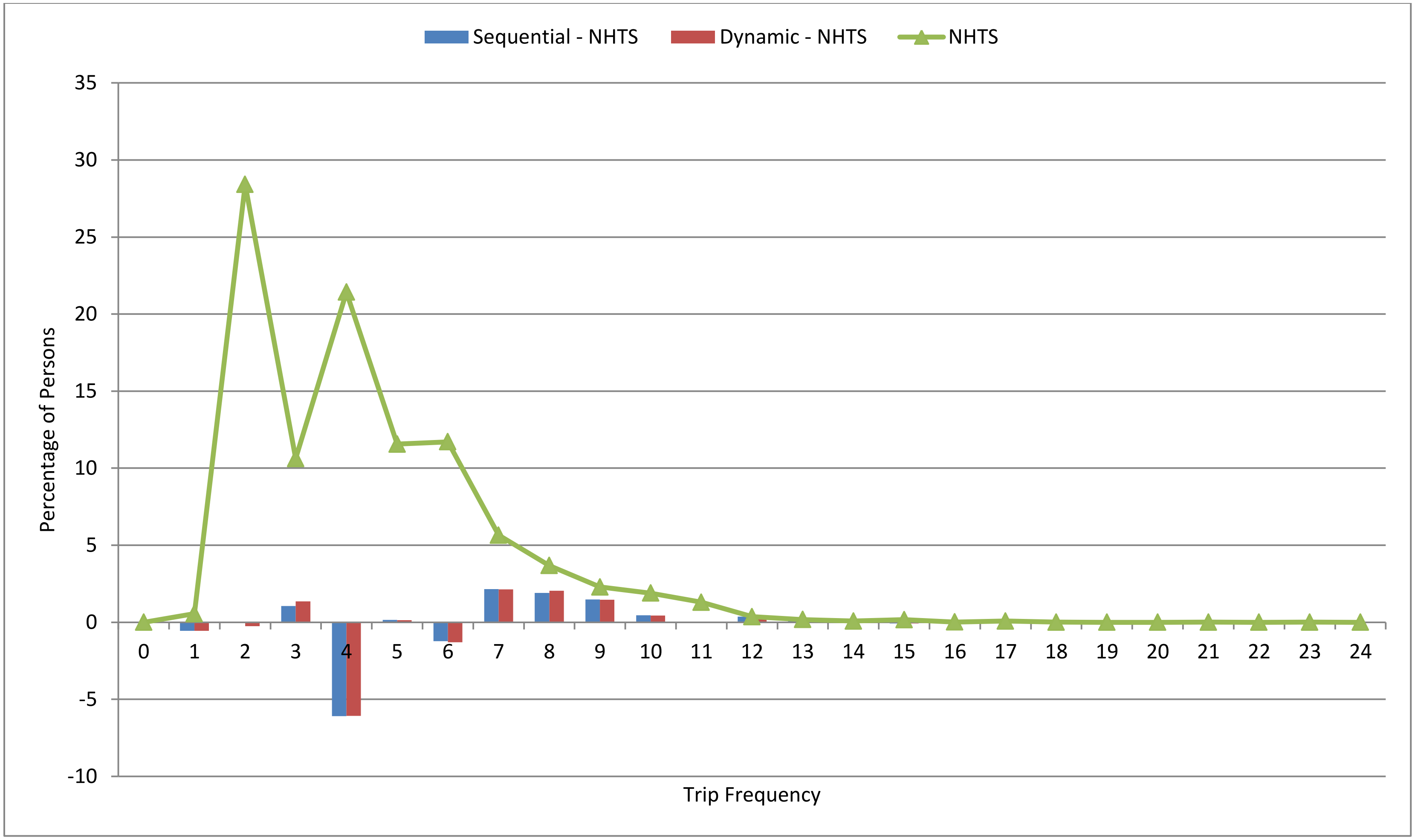

Figure 44: Trip Rate Distribution for Workers

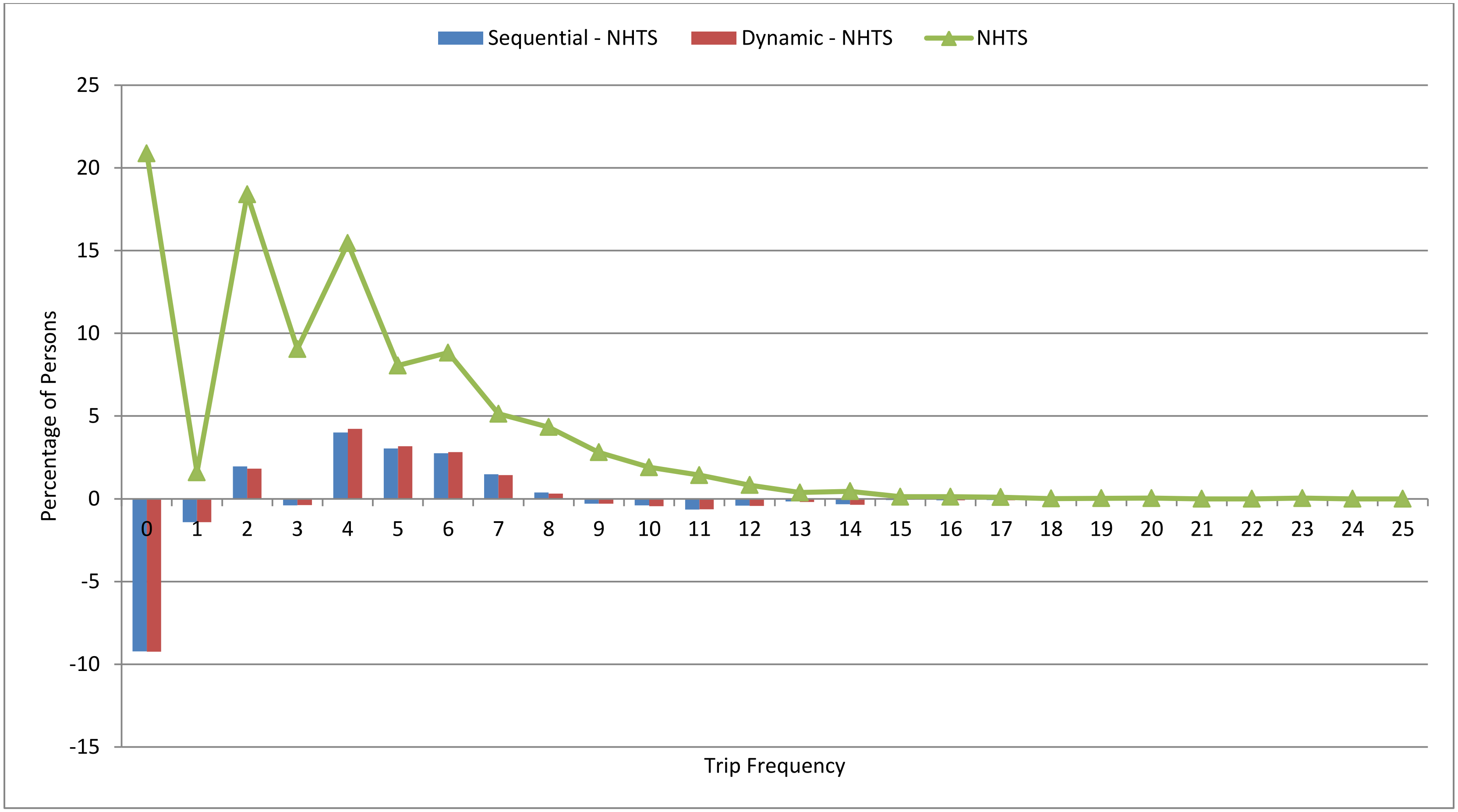

Figure 45: Trip Rate Distribution for Non-workers

Daily Time Allocation to Activities and Travel Episodes

Time is a limited resource and individuals engage in travel and activities subject to a certain daily budget (1440 minutes in a day). Therefore, any microsimulation-based model of the urban system should accurately account for the full day of activities and travel. There are a number of activity-travel engagement decisions that are dependent on earlier activity-travel choices and an inaccurate accounting of the day and its allocation to activities and travel will result in an erroneous representation of agent behaviors and subsequently affect policy and planning analyses.

It can be noted that the activity-travel engagement measures employed so far exhibit similar properties for the sequential and dynamic approach to integration. A key difference between the two approaches will be highlighted by the measure used in this discussion. As noted earlier, in the dynamic approach, individuals schedule/re-schedule activities in response to arrival information whereas in the sequential approach, individuals are oblivious to the arrival information and proceed with activity-travel engagement for the rest of the day. The later approach has the potential for creating "gaps" and "overlaps" in the activity-travel schedule generated and as a result the allocation will not account for full 1440 minutes in a day. For example, in most applications of the integrated model, the models are run iteratively for a set number of iterations when the improvement across iterations is very small. In other words the models are run iteratively to stability and not convergence. More often than not the network conditions obtained at the end of the iterative process are very close approximations of converged network conditions and there are always differences between expected (used in subsequent iteration) and experienced (generated at the end of the iteration). For example, a person may arrive later than expected and in such a case, an “overlap” of the trip episode with the activity episode occurs in the sequential approach. Whereas in the dynamic approach the subsequent activity is adjusted in response to the arrival information and no “overlap” between trip and activity episode occurs. Alternatively, a person may arrive earlier than expected and in such a case, a “gap” is created between the trip episode and activity episode in the sequential approach and there is no accounting of the person during that period. However, in the dynamic approach the subsequent activity is adjusted and the downstream time-space prisms are updated in response to the early arrival. The dynamic approach comprises a very rich and intuitive scheduling and re-scheduling behavior exhibited by individuals in the real world.

While the full daily accounting may not be very important when the network measures that are used at the start of the integrated model run are close approximations to network conditions simulated at the end of the run after loading and simulating trips, it becomes significantly important especially in the cases where there are deviations in the expected and experienced network conditions. Nonetheless it is important to have a model system in place that comprises an accurate representation of underlying behaviors even when the inputs (network measures) are close approximations. As noted earlier, in most situations, the integrated model runs are not run through to convergence instead they are stopped after a certain fixed number of iterations and in those situations the full accounting becomes important. Table 20 highlights the difference between sequential and dynamic approaches to integrated modeling by comparing the daily time allocation to various types of activities and trips. It must be noted that while there is a full accounting of the 1440 minutes in a day in dynamic approach, a few minutes are generally "lost" due to discretization errors associated with how time is treated in SimTRAVEL. While time is treated as a continuous entity it is not represented as a decimal; instead it is treated as a positive number and this leads to some discretization and approximation errors. As a result, the sum of time allocated to activities and trips account is always a few minutes less in SimTRAVEL. This can also be seen in Table 20 where the total time allocation is 1435 minutes and 1434 minutes for workers and non-workers respectively using the dynamic approach (i.e. 5 minutes and 6 minutes are lost due to discretization). However, the daily time allocation for workers and non-workers with the sequential approach adds up to 1447 and 1446 minutes respectively; an obvious inconsistency. This is due to the "overlap" effect described earlier wherein late arrival causes the trip episode and activity episode to overlap and hence the extra accounting of total minutes. In other words, sequential approach may generate activity-travel patterns that are comparable to dynamic approach when the network conditions are stable. However, when the network conditions are close approximations, the sequential approach suffers from inconsistencies in the individual activity-travel agendas such as “gap” and “overlap”. On the other hand the dynamic approach does not suffer from any such inconsistencies and comprises a full daily accounting of individuals in time and space.

Table 20: Daily Time Allocation to Activities and Trips

	Worker			Non-worker		
	Sequential	Dynamic	NHTS	Sequential	Dynamic	NHTS
Time Spent on Activities						
Home	832	829	766	1215	1211	1186
Work	448	443	506	0	0	21
School	1	1	10	0	0	30
Maintenance	39	36	25	74	69	53
Discretionary	13	12	22	29	28	58
Pick Up	0	0	2	0	1	3
Drop Off	1	1	1	3	3	7
OH-Other	5	5	20	14	13	44
Total activity duration	*1338*	*1326*	*1351*	*1336*	*1324*	*1402*
Time Spent on Trips						
Home	42	42	33	48	48	25
Work	31	31	32	0	0	4
School	0	0	1	0	0	3
Maintenance	24	23	10	37	36	19
Discretionary	6	6	4	10	9	10
Pick Up	2	3	2	5	5	2
Drop Off	3	3	2	5	6	3
OH-Other	1	1	2	5	5	6
Total trip duration	*109*	*109*	*86*	*110*	*109*	*74*
Total accounting of time in a day	***1447***	***1435***	***1438***	***1446***	***1434***	***1476***

Computational Overhead

An issue that merits further exploration is that of computational tractability. Run times are naturally dependent on the hardware configuration. On a standard quad-core personal computer workstation, run times for a simulation of about 14.3 million trips are in the order of about 24 hours per complete iteration, with the dynamic model design taking on the order of about 3-4 hours longer than a sequential model design run. It is envisioned that these run times will come down as computing power improves and parallel computing capabilities are harnessed to the extent possible. In both sequential and dynamic approaches, the memory requirement is comparable and is anywhere from 4GB – 8 GB depending on the period of day being simulated.

E. Discussion and Conclusions

In this study, the dynamic and sequential approaches are compared to understand differences/similarities in convergence properties, the activity-travel engagement patterns that are generated at the end of the run, and computational overhead. The results indicate that the sequential and dynamic approaches seem to generate similar results on all metrics at the aggregate level except for the daily time allocation to activities and travel which is a disaggregate measure for assessing the consistency and validity of the of the activity-travel engagement patterns that are generated. The similarity in the results that are generated using the two approaches are consistent with expectations because the network conditions that serve as inputs for producing the activity travel engagement patterns are very similar (as shown in Figure 8 and Figure 9). In other words, the expected and experienced network conditions are almost similar with an average deviation of 0.63 between the expected travel time (skim matrices produced at the end of iteration 4) and the experienced travel time (skim matrices produced at the end of iteration 5). This small difference between the expected and experienced is causing “gaps” and “overlaps” in the sequential approach but nothing that affects the activity-travel patterns significantly compared to the dynamic approach. However, the “gaps” and “overlaps” are manifested in the daily time allocation metric. There is an obvious inconsistency in the daily time allocation to travel and activities in the sequential approach compared to the dynamic approach by about 12 minutes. Additionally, in the sequential approach, the total of time allocated to activities and travel is greater than the allowable time budget in a day of 1440 minutes.

The difference in the daily time allocation observed in this study may not be significant enough to influence typical policy and planning analyses but it does highlight the potential issues with the sequential approach. In situations where “overlaps” occur, people are actually engaging in both trip episodes and activity episodes at the same time and when “gaps” occur, people are unaccounted for during the period between the arrival and the onset of the activity episode. These potential issues will manifest in situations where the network conditions for a certain area in the model region are unreliable and in particular when the expected travel times are always conservative estimates and lesser than experienced. In such a situation the sequential approach will end up generating more trips compared to the dynamic approach. Because in the sequential approach, “overlaps” are caused due to the conservative estimate of network conditions generating more trips than ought to be whereas the dynamic approach adjusts the persons schedule in response to arrival time and ensure that consistency and continuity in the representation of individuals, and their activity-travel patterns.

In some sequential model applications, attempts are made to overcome “overlap” issue by magically moving people from the current location on the network to their next activity/trip engagement. However, one can see the obvious inconsistency such an assumption can cause. Even in applications where the “overlap” issue is accounted for there is no treatment for the “gap” issue. That is how are people changing their activity-travel engagement patterns when there are travel time savings.

Additionally, as discussed, the differences between the sequential and dynamic approaches for a base year simulation are only marginal. It is entirely possible to argue that even a sequential model design can replicate patterns without much difficulty as long as expected travel times (in the skim matrices) are accurately reflecting true travel times in the network. However, it should be noted, that the true merits of the proposed design can only be assessed when the model system is applied to a scenario in which the network is subjected to a perturbation. A simpler naïve sequential model design cannot replicate behaviors and network conditions when a shock or policy is introduced in the system in the middle of a day (simulation). For example, how are people going to alter their activity-travel patterns in the base year if lane restrictions are introduced for a certain time period during the day? Alternatively, how are people going to spend the extra time gained due to improved travel conditions? These types of scenarios cannot be analyzed without making compromising assumptions about behaviors in a sequential approach whereas in the dynamic approach the scheduling behaviors are captured in the dynamic time-dependent activity-travel generation paradigm. Therefore from a pure conceptual standpoint, the dynamic integrated model design would have the ability to simulate adjustments in schedules and behaviors that would follow such an event. It would be virtually impossible for a sequential design to mimic such behavioral adjustment processes.

CHAPTER 8

SIMULATING THE IMPACT OF NETWORK DISRUPTIONS ON ACTIVITY-TRAVEL ENGAGEMENT PATTERNS

A. Introduction

Network disruptions refer to a class of events that alter the regular flow of traffic on one or more roadway facilities. Network disruptions lead to a drop in capacity on the roadway element where the event occurs and cause delays, build up queues and lead to spillbacks on to surrounding links on the network. Network disruptions may include planned events such as full roadway or lane closures to accommodate work zones along a freeway segment or bridge section, or unplanned events such as traffic crashes or roadway/bridge failures. The modeling of the impacts of network disruptions on travel demand and traffic flow has important implications. First, in the context of unplanned network disruptions, understanding the impact of such events and associated delays allows for the planning of emergency response services. Emergency response services can be optimized so that crisis teams can respond to incidents as quickly as possible and alleviate the impact of disruptions. Second, modeling the impact of network disruptions allows for estimating the changes in activity-travel demand along both the space and time dimensions that may result due to such events. Such an understanding would allow professionals to devise traveler information systems and routing strategies that would minimize adverse impacts on people's activity-travel schedules.

The effects of network disruptions may be simulated using a variety of traffic models. However, there are some key considerations which determine the accuracy in representation of the disruption and its associated impacts. First, the model should be sensitive to information provision and reflect the influence of information provided on routing decisions for people entering the network after the onset of the disruption. For example, there are a number of outlets that provide information about network disruptions including radio traffic reports, Google maps about current traffic conditions, and advanced traveler information systems (such as 511 systems) about roadway closures among others. The traffic model should be able to represent the alternate routing decisions that individuals employ in response to this information and resultant network conditions. Second, any model of the network disruption should account for the short-term re-routing decisions that people already on the network employ in order to minimize the impact of disruption. For example, when a crash occurs on a freeway, drivers upstream of the crash may get off at the next exit (if possible) and choose to take alternate routes to get to their destination instead of staying on the freeway waiting for the accident to clear. Third, the network disruption model should be able to capture the impact of disruptions on activity-travel engagement patterns and the demand that is generated. An extra hour spent on the network due to travel delays is an hour that is no longer available for subsequent activity-travel engagement. This may lead to individuals adjusting, or modifying their activity-travel engagement patterns. The last consideration is of particular relevance in the context of planned network disruptions which may affect a sub-population in a region for extended periods of time (e.g. “Carmageddon”, Reuters 2011) and thus influence their quality of life.

There is a rich body of literature on the modeling of unplanned network disruptions (Chang and Nojima 2001, Kamga et al. 2011) and planned network disruptions (Clegg 2007). However, the literature on modeling network disruptions and understanding its impact on activity-travel engagement patterns is limited. Zhu et al. (2010) present a study looking at the impact of the I-35W bridge collapse over the Mississippi River in Minneapolis on traffic flows in the surrounding region and on the travel behavior patterns from observed data. However, the research does not consider the impact on full daily activity-travel engagement patterns. Sundaram (2002) presents a framework for modeling network disruptions and captures its impact on activity-travel behavior. However, the model implementation employs a hybrid model of travel demand and not a full-scale microsimulation model that allows for a more accurate representation of underlying behaviors and the various interactions and constraints that individuals experience.

In this research effort framework for modeling network disruptions which allows for an accurate representation of activity-travel engagement, network dynamics, and the interplay between these two components is presented. The framework combines a travel demand model system (generating the activity-travel engagement decisions) with a traffic simulation model which simulates the routing decisions and movement of vehicles on the network. A prototype system has been developed using microsimulation-based model of travel demand (OpenAMOS – an open-source activity-based travel demand model system) and network microsimulation model (MALTA - Multi-Resolution Assignment and Loading of Traffic Activities) to accurately capture the interactions and constraints that people experience as they pursue their activity-travel agendas. The prototype is used to model an unplanned network disruption on a major freeway corridor. A comprehensive analysis is conducted to assess the impact of the network disruption, and characterize the impact of network congestion on activity-travel engagement patterns under a variety of traveler information provision scenarios. In the next section, the framework is presented followed by a description of the study area and scenarios that will be evaluated in Section C. In section D, results from the application of the framework to model the different scenarios are presented. The final section includes a discussion of the results and concluding thoughts.

B. Dynamic Time-Dependent Activity-Travel Simulation Framework for Modeling Network Disruptions

As noted earlier, one of the key components that need to be included in the context of network disruption models is the activity-travel scheduling and rescheduling behavior exhibited by individuals in response to network delays caused by the network disruption. This calls for an integration of an activity-based travel demand model with a dynamic traffic assignment model. The integration approach should also be able to accommodate constant communication between the travel demand model and the traffic simulation model along the continuous time axis to account for the interaction between the two systems and accurately capture the impact of network delays on subsequent activity-travel engagement decisions.

An approach typically proposed to integrate the activity-travel demand model and the network supply model is to run the models sequentially. Each of the model systems is run independently and coupled together through input-output data flows and feedback loops. However, such an approach cannot be used to model the impacts of network perturbations because the sequential framework does not support constant communication between the model systems along the time axis. The constant communication is an important feature that should be supported by the integration framework to mimic the formation of activity-travel patterns over the course of the day in response to arrival times and network conditions. The modeling of network disruptions calls for an event-based approach to integrating the two model systems which can support a continuous communication between the model systems. Such an event-based framework is presented in Chapter 3. Within each minute of the day, the demand model simulates activity-travel engagement decisions of all individuals. Trip information, including, origin, destination, mode, and vehicle information, is then passed to the dynamic traffic assignment model for routing trips on the network. The traffic assignment model in turn routes the trips and simulates vehicular movements on the network. Once the trips arrive at their destination, the traffic assignment model passes back the arrival information to the demand model to simulate activity-travel engagement decisions in subsequent time steps. The activity-travel demand model simulates adjustments to activity schedules based on actual arrival times experienced by travelers.

The event-based framework presented in Figure 4 lends itself to modeling network disruptions and understanding impacts on activity-travel engagement decisions. In the context of modeling network disruptions, there are two key considerations. First, the actual arrival times need to be fed back to the travel demand model to simulate activity-travel engagement decisions in the subsequent time interval. Second, network conditions after the onset of an incident also need to be passed back to the travel demand model so that the simulated activity-travel engagement patterns are a reflection of the network conditions that prevail at the time. The prevailing network conditions should be used in routing decisions. The framework presented in Figure 4 can accurately capture the first consideration, i.e., adjusting activity-travel scheduling behavior in response to arrival information. However, the framework cannot simulate information provision, i.e., the framework does not accommodate passing the prevailing network conditions for simulating activity-travel choices and routing decisions in the subsequent time period(s) of the day.

Figure 46 presents a revised event-based framework for integrating demand and supply model. The model systems proceeds in a manner similar to the framework presented in Chapter 3, where converged base year link travel times (L_{base}) are used from start of day until the onset of the disruption ($t = a$) and again from the time that the disruption is cleared ($t = b$) until the end of day. However, for the time period between onset and clearing of the disruption ($a \leq t \leq b$), the linkage between the travel demand model and the traffic simulation model is modified as follows:

- At the end of every simulation interval (t), the dynamic traffic assignment model replaces the expected link travel times (L_{base}) with the existing travel times (L_t) for all subsequent intervals because that is the best estimate of prevailing and future network conditions after the onset of an incident.
- The new link travel times (L_t) by time of day are used to generate origin-destination travel time matrices (OD_t) for use in the travel demand model.
- The traffic simulation model passes the travel time matrix (OD_t) reflecting prevailing conditions, along with all trips that have arrived at their destination, to the demand model so that activity-travel engagement decisions for the subsequent time interval may be simulated.
- The travel demand model in turn passes back trips that need to be loaded on the network based on the prevailing network conditions (OD_t). In response to the prevailing (delayed) conditions, people may choose alternate destinations, or may just choose to proceed early to their next fixed activity (e.g., work) because they know it will take longer to get to the fixed activity.

- Once the trips are received by the dynamic traffic network simulation model, routes are identified using prevailing conditions (L_t) as the expectation of the network for all subsequent time intervals. The traffic simulation model then loads and routes/simulates the trips.
- The simulation time step is incremented ($t = t+1$) and the process (Steps 1 - 5) is repeated until the incident is cleared.
- Once the incident has cleared, the base year converged network conditions by time of day are used once again to simulate activity-travel engagement and routing decisions.

The flowchart presented in Figure 46 offers a robust framework for modeling incidents. The framework presented is operationalized in this study and implemented to model scenarios of network disruption with varying levels of information provision.

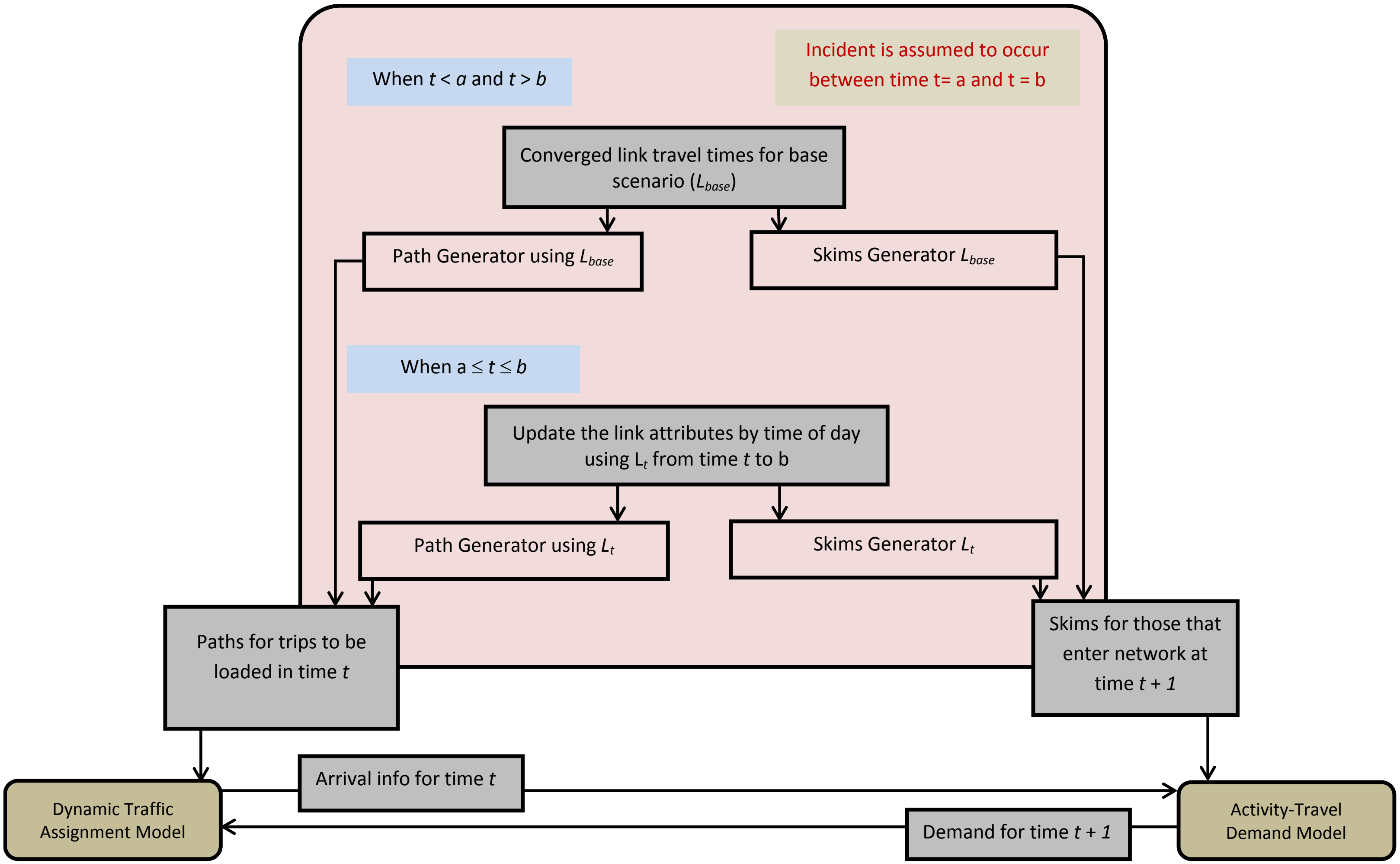

Figure 46: Dynamic Time-Dependent Activity-Travel Simulation Framework for Modeling Network Disruptions

C. Case Study

The framework presented in the previous section for modeling network disruptions is implemented using SimTRAVEL – Simulator of Travel, Routes, Activities, Vehicles, Emissions, and Land. SimTRAVEL (Chapter 4). The prototype has been enhanced to incorporate additional feedback between the model systems as necessitated by the framework presented in Figure 46 to model network disruptions. The study area consists of three cities (Chandler, Gilbert, and Queen Creek) in the southeast region of Maricopa County, Arizona. There are about half a million people residing in about 150,000 households in the three city area. The entire Maricopa region was not considered in the study due to data limitations. The demand for the three city region is generated using a full-scale microsimulation-model in SimTRAVEL and in order to simulate congestion on the network, origin-destination tables from traditional four-step model are used to capture the background traffic. The origin-destination demand table is converted into trip lists disaggregated by time of day using trip start time distribution from the latest wave of the National Household Travel Survey.

As noted earlier, one of the main goals of this study was to extend the integrated model prototype (SimTRAVEL) to allow modeling of network perturbation. Another key goal of this effort was to implement the prototype to study network disruption and understand the impact of various levels of information provision on the activity-travel patterns that are generated. A network disruption is introduced by dropping the lane capacity of a section of the freeway that runs through the middle of the three city region. The idea was to model an incident type situation wherein only one lane in each direction of the freeway segment is operational and other lanes are closed to clear the incident. Three different runs were conducted as described below to conduct the network disruption analysis. The incident was assumed to start at 7:00 AM and end at 10:00 AM. The time period was chosen to capture the peak demand generated by individuals residing in the three city region.

- No disruption: In this scenario, incident does not occur and base line conditions prevail. The scenario was run to establish a benchmark against which other network disruption/ information provision scenarios can be compared and analyzed.
- No information provision: In this scenario, it was assumed that people are oblivious to the onset of the incident and thus corresponds to a no information provision scenario. Individuals are assumed to make activity-travel engagement decisions in OpenAMOS based on their expectation of network conditions. Additionally in the microsimulation it was assumed that individuals are making route choices based on earlier experiences. The assumption of no information provision may be unreasonable because individuals that are on the network are aware of the prevalent conditions. Additionally those that are about to embark on a trip probably know about network conditions through some form of traveler information system such as local radio and 511 systems.

- Full information provision: In this scenario, travelers that are already on the network follow their planned routes even after the onset of the network disruption. Only individuals that are about to embark on a trip are assumed to be aware of the incident and the prevailing network conditions. The activity-travel engagement and routing decisions of these individuals are based on the prevailing network conditions and not based on expected conditions of the network that they generally experience. It must be noted that even this scenario comprises a rather extreme case of information provision. First, it may be unreasonable to assume that every individual that is embarking on a trip is aware of prevailing network conditions. Second, no en-route switching is allowed once people have embarked on a trip.

The two scenarios described above comprise a network perturbation under two extreme levels of information provision namely, no information provision and full information provision. In reality, information provision is probably between the two extremes modeled in this study. Nonetheless it was considered an interesting exercise to model and analyze the two extremes in this study to get a range for the variation in activity-travel engagement behavior in response to network conditions. The simulation runs mimic different levels of information provision to travelers after the onset of a network perturbation, and should provide important insights. First, the study highlights the applicability of an event-based integrated demand-supply model system to study the impacts of network disruptions on activity-travel engagement. Second, the study throws light on the impact of information provision during network disruption on traditional measures of network conditions (total trips, and delays) and also on activity-travel engagement behavior (trip lengths, trip durations, trip rates, and daily time allocation).

D. Results

Before running the three scenarios, SimTRAVEL prototype was employed iteratively to obtain stable base year conditions. The stable network conditions from the base year simulation run were then used to launch the three scenarios. In the no disruption scenario, regular SimTRAVEL prototype is employed and activity-travel engagement decisions are made using expected travel time matrices and route choices are based off expected link travel times. There is no disruption hence no drop in lane capacities. In the no information provision scenario, a disruption occurs and the lane capacity for a section of the network drops to one lane between 7:00 AM and 10:00 AM. However, activity-travel engagement decisions are still made using expected travel times and route choices are still based off expected travel times as individuals are oblivious to the incident and make decisions off of earlier experience. In the full information provision scenario, a disruption occurs and lane capacity drops to 1 lane on the affected section of the network between 7:00 AM and 10:00 AM. However, at the end of every minute, travel time matrices are generated based off of prevailing conditions and passed to OpenAMOS for making activity-travel engagement decisions and prevailing link conditions are used to generate paths reflecting every individual's full knowledge of the incident and its impact on existing network conditions. In order to understand the impact of network conditions on the different levels of information provision, a variety of aggregate measures of network conditions and activity-travel engagement were used.

From this point forward the scenario with no disruption is referred to as base scenario, the disruption scenario with no information provision is referred to as no information scenario and finally the disruption scenario with full information provision is referred to as the full information scenario. Overall the demand model seems to perform as expected. The number of trips generated in the no disruption case is 14,320,888 trips whereas in the full information scenario it is 14,321,746 and lastly in the no information scenario a total of 14,317,790 trips are produced. The number of trips generated in the no information scenario is least and is reasonable with expectations. Because in the no information scenario, people are presumably planning trips and selecting routes oblivious to the occurrence of the incident. As a result they experience higher delays and spend more time on the network which will in turn affect their subsequent activity-travel engagement decisions in the form of smaller time-space prisms to pursue other non-fixed activities. It is however interesting to note that the number of trips generated in the full information scenario is higher than the no disruption scenario by about 858 trips. The total Vehicle Miles Traveled (VMT) on the other hand is 10125 miles. This observation is consistent with expectation because people are probably selecting alternative routes using surface streets to avoid the section of the freeway affected by the incident as they have full information about the network conditions and in effect choosing the fastest routes to get to their activity locations.

In order to study the impact of the incident on trip generation, trip start time distributions were plotted and compared. Figure 47 and Figure 48 show time-varying differences in the counts of trips that were generated in the two disruption scenarios versus the trips that were generated without the disruption for workers and non-workers respectively. It can be seen that there are clear trends in the distribution of trips for workers and non-workers. First, the impact of the disruption on the workers is higher than the impact of the disruption on non-workers. Presumably workers are skipping non-fixed activities but are still pursuing their fixed activity assignments whereas with non-workers they are skipping non-fixed activities completely. As a result the drop in the number of trips for non-workers (2577 in no information provision scenario) is higher than for workers (386 in no information provision scenario). During the period of the incident (7:00 AM - 10:00 AM), both workers and non-workers are making fewer trips in the no information provision scenario compared to the no disruption case. Whereas in the full information provision scenario, workers are making slightly higher number of trips compared to no disruption and non-workers are making fewer trips compared to no disruption. It is also interesting to note that there is a sudden spike in the number of trips generated right after the incident ends. It is plausible that the people affected by the incident are traversing the section of the affected roadway under free flow conditions after the end of the incident and once they have reached their destination, they make schedule adjustments and embark on trips to their next fixed activity locations to pursue activities whose start times may have passed or whose start times will be violated due to the incident delay. It can also be seen that there is a cascading impact of the incident on subsequent activity-travel engagement patterns in the rest of the day.

Figure 49 and Figure 50 show the percent difference in distribution of trip durations for workers and non-workers respectively for the two disruption scenarios compared against the no disruption scenario. As can be seen there is a clear trend in the duration distribution for workers and non-workers for both disruption scenarios. Both workers and non-workers seem to be engaging in a lower percentage of short duration trips and a higher percentage long duration trips. It is also interesting to note that the trend is similar for both disruption scenarios; however, for the scenario with no information provision, the magnitude of differences is higher than the scenario with full information provision. This is reasonable with expectation because in the full information provision individuals are using alternate routes which include surface streets and hence a smaller increase in the durations compared to no information provision where the individuals are using the section of the roadway facilities affected by the incident.

The final metric that was employed to study the difference in activity-travel engagement patterns was the daily time allocation to trips and activities. Time is a limited resource and individuals allocate time to activities and travel episodes subject to daily budget (1440 minutes in a day). As expected individuals are spending slightly higher time on trips at the cost of activity time engagement in both disruption scenarios. In the disruption scenario with no information, workers on an average spend 2 more minutes on trips and 2 less minutes on activities compared to the no disruption scenario. In the disruption scenario with full information, 1 less minute on activities and 1 more minute on trips. For non-workers the trends are very similar with more time spent on trips and less time spent on activities as can be seen in Table 21. It can be seen that the differences in time allocation between the disruption scenarios and no disruption scenario is rather small. In an effort to further explore the observation, the difference in person days between the disruption scenarios and the no disruption case were computed by taking the difference in time allocation between disruption and no disruption and multiplying the difference by the number of individuals belonging to the demographic. Table 22 presents the person day difference in time allocation across all persons belonging to a particular demographic. As can be seen workers and non-workers both are spending more time in trips and less time engaging in activities compared to the disruption scenario. It is also interesting to note that the differences are much smaller in full information scenario compared to the no information scenario. Also interesting is the difference in magnitude for the worker and non-worker demographics. The difference in magnitude points to the differing roles of the two demographics and the role played by their fixed activity spatio-temporal constraints in forming their activity-travel agendas.

It can be seen from the results presented thus far that the network disruption has an effect on the activity-travel engagement patterns. Additionally the decision making behavior is impacted by level of information provision. Given the small magnitude of changes noted in the metrics, one could argue that the changes are just an artifact of the stochasticity associated with the microsimulation-based demand model. While the stochasticity in the demand model does bring about some changes due to random number seed, there should not be any trends in the results obtained. As noted in the results, while some of the changes observed can be attributed to stochasticity, majority of the changes are caused because of the altered inputs (in the disruption scenarios the level of information provision about the network conditions). Also, if the changes were purely due to stochasticity, one would not observe trends in the results. Also, all observations between the disruption scenarios and the base no disruption case are supported by plausible explanations.

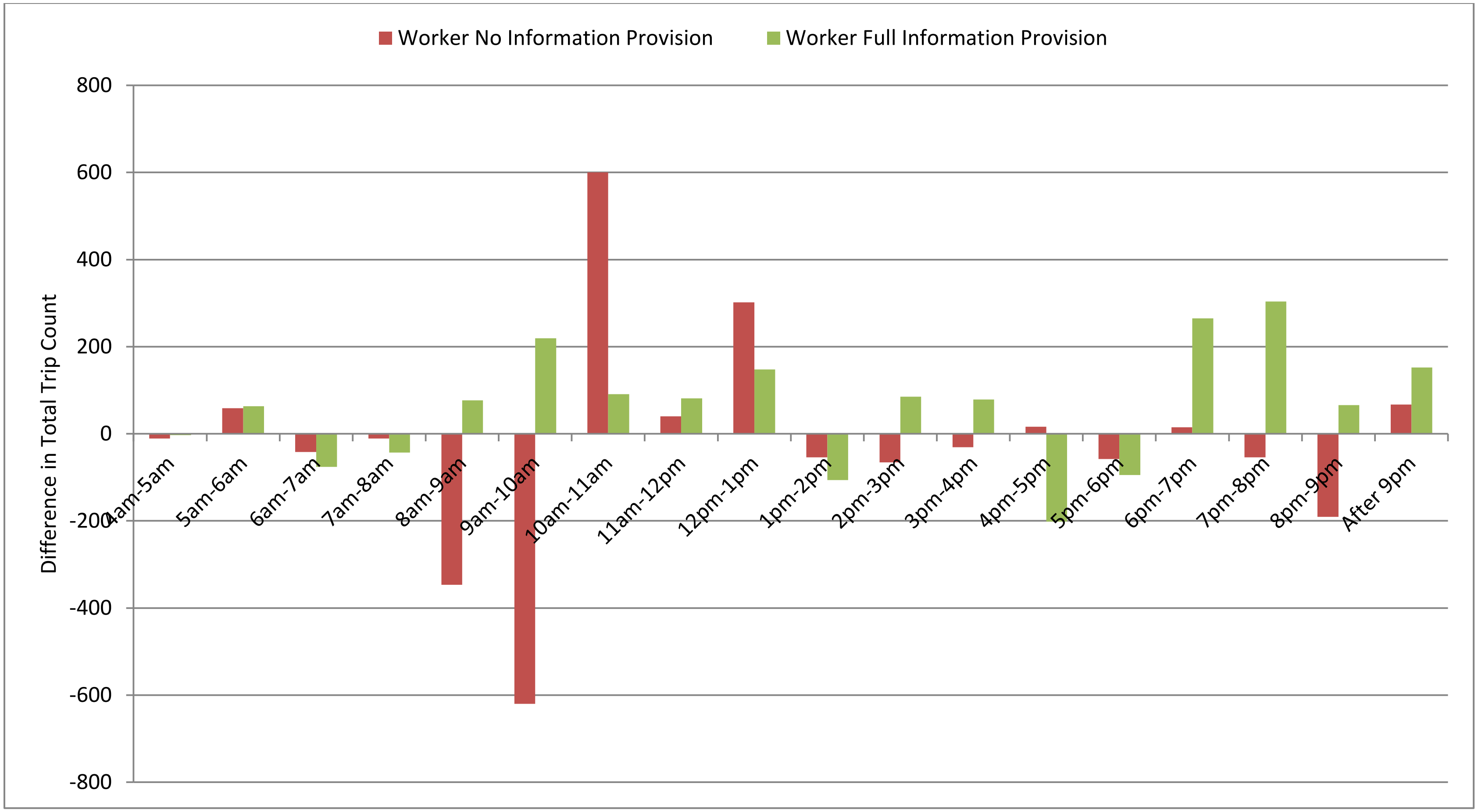

Figure 47: Difference in the Count of Trips by Time of Day for Workers

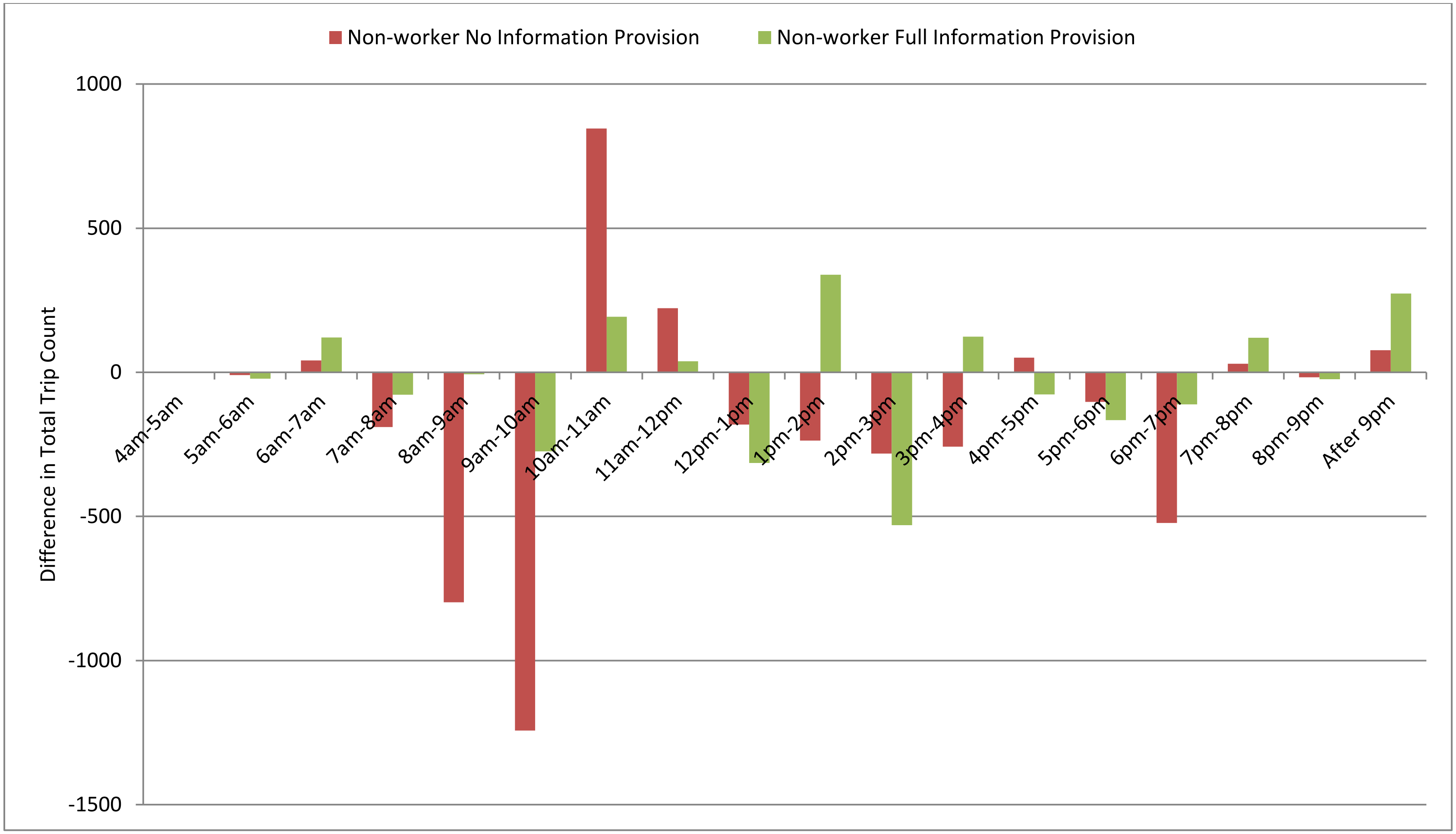

Figure 48: Difference in the Count of Trips by Time of Day for Non-workers

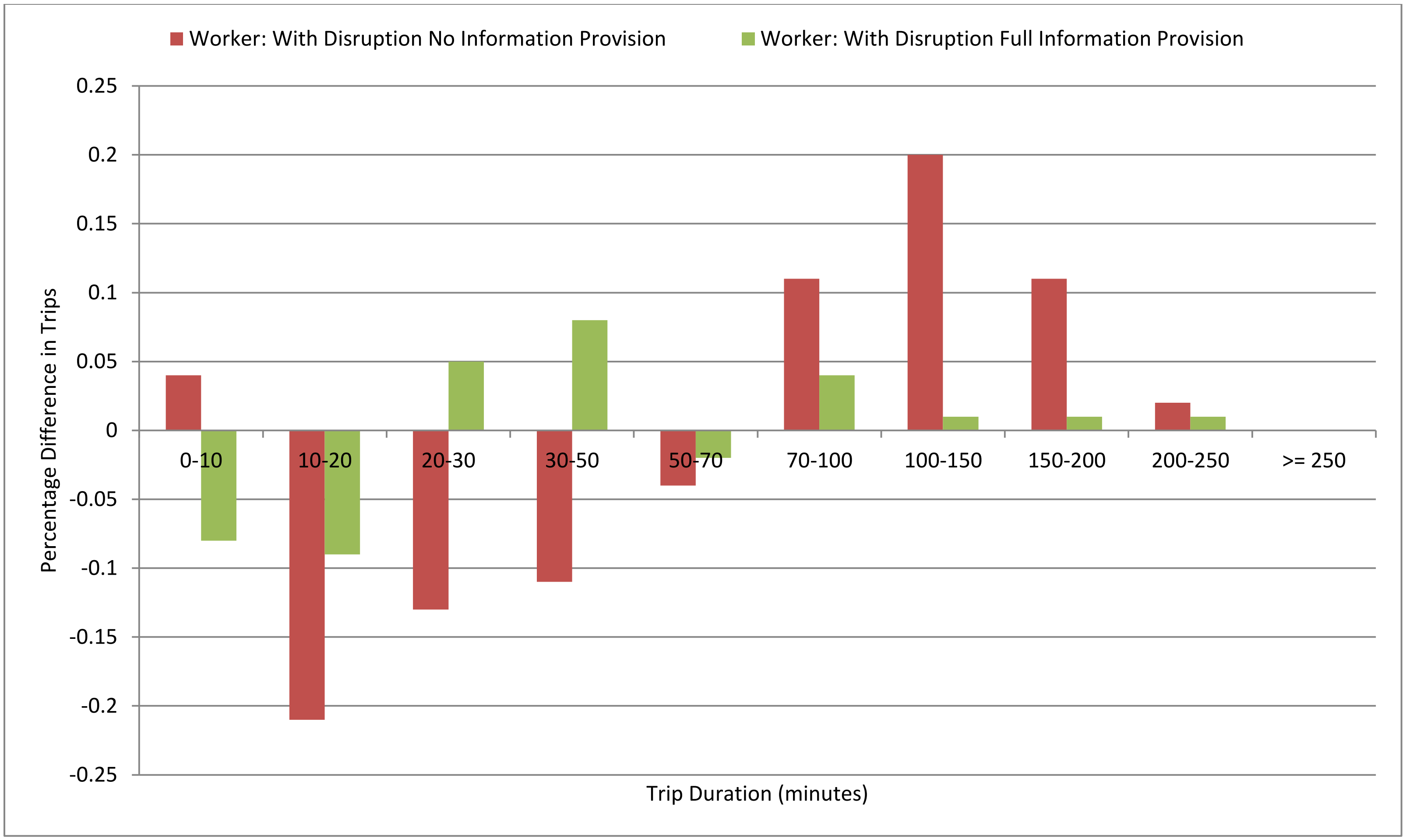

Figure 49: Percent Difference in Trip Durations for Workers

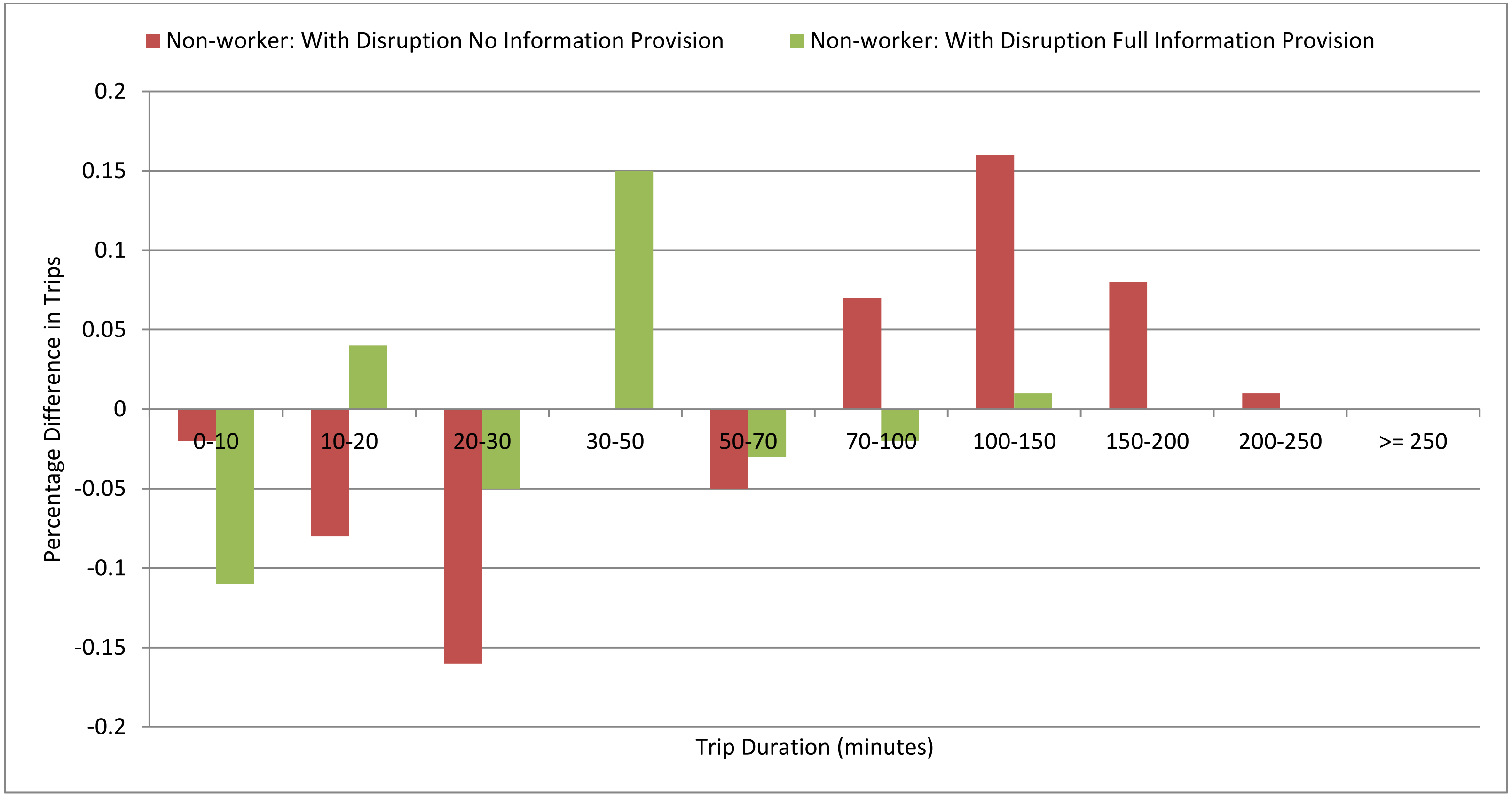

Figure 50: Percent Difference in Trip Durations for Non-workers

Table 21: Daily Time Allocation to Trips and Activities Per-capita for Workers and Non-workers

	Worker			Non-worker		
	No Disruption	No Information Provision	Full Information Provision	No Disruption	No Information Provision	Full Information Provision
Time Spent on Activities						
Home	829	829	829	1211	1210	1211
Work	443	442	443	0	0	0
School	1	1	1	0	0	0
Maintenance	36	35	35	69	68	69
Discretionary	12	12	12	28	28	28
Pick Up	0	0	0	1	1	1
Drop Off	1	1	1	3	3	3
OH-Other	5	5	5	13	13	13
Total activity duration	*1326*	*1324*	*1325*	*1324*	*1323*	*1324*
Time Spent on Trips						
Home	42	43	43	48	49	48
Work	31	32	31	0	0	0
School	0	0	0	0	0	0
Maintenance	23	23	23	36	36	36
Discretionary	6	6	6	9	10	10
Pick Up	3	3	3	5	5	5
Drop Off	3	3	3	6	6	6
OH-Other	1	1	1	5	5	5
Total trip duration	*109*	*111*	*110*	*109*	*110*	*110*
Total daily accounting	***1435***	***1435***	***1435***	***1434***	***1434***	***1434***

Table 22: Daily Time Allocation to Trips and Activities Across All Workers and Non-workers

	Worker		Non-worker	
	No Information Provision	Full Information Provision	No Information Provision	Full Information Provision
Number of people	150435	150435	187757	187757
Time Spent on Activities				
Home	-72	8	-71	-31
Work	-111	-28	0	0
School	4	4	-1	1
Maintenance	-21	-50	-62	-7
Discretionary	-15	-4	-8	13
Pick Up	1	1	2	2
Drop Off	1	1	8	2
OH-Other	-3	-3	9	5
Total activity duration	*-217*	*-71*	*-123*	*-15*
Time Spent on Trips				
Home	46	31	33	9
Work	110	23	0	0
School	2	0	2	0
Maintenance	21	7	22	-9
Discretionary	8	4	12	10
Pick Up	6	0	15	1
Drop Off	24	3	34	7
OH-Other	4	0	7	-3
Total trip duration	*221*	*69*	*124*	*16*

E. Discussion and Conclusions

This research effort comprises one of the very few operational implementations of a microsimulation-based integrated model for simulating network disruptions. This effort constitutes a unique application of a tightly integrated model that involves constant feedback between the activity-travel demand model and the dynamic traffic simulation model so that activity-travel patterns evolve in response to actual network conditions experienced by travelers. The scenario analysis completed in this project provides some important insights into the impacts of network disruptions on time use and travel behavior under different levels of information provision. First, disruptions affect individuals by affecting their activity-travel engagement patterns and network conditions in turn are affected by how individuals react in response to network perturbation information and how they process it to engage in subsequent activities and trips. The observations in this study points to the need for not just considering the trips in isolation when modeling perturbations but to holistically consider the entire transport system in which the trips are generated including the agents and their activity-travel engagement behaviors. This calls for an integrated model system with a high fidelity travel demand model system generating activity-travel patterns combined with a network microsimulation model that routes and simulates the trips. Second, traditional integrated models cannot be used to model network perturbations without making comprises about the decision making units and their underlying behaviors. A dynamic integrated model system where activities and trips are generated in response to network conditions is required to model network disruptions. Third, there are differences in how information about network disruptions affects individual activity-travel engagement patterns and route choice decision making behavior. Therefore, the model system should be able to support the simulation of different levels of information provision.

The scenario analysis and the observations presented in this study open new questions for research in the use of integrated models of travel demand and network models for modeling network disruptions. First, characterize stochasticity of the integrated model system by keeping the inputs constant and altering the random number seed. The range of results obtained can then provide additional guidance to comparative analysis and help isolate stochasticity effects. Second, in the no disruption case hourly skim matrices are applied whereas in the disruption case with full information provision network conditions are provided to OpenAMOS on a minute-by-minute basis. As a result in the no disruption case there is an aggregation error that may potentially affect the results generated while in the full information scenario no such aggregation error occurs at least in the period when the incident occurs and minute-by-minute communication of network conditions occurs. Third, the representation of scheduling and re-scheduling and route choice behaviors can be enriched. In the current implementation the scheduling behaviors that are reflected are due to the shrinking of open time-space prisms due to prevailing network conditions and on the network side routes are altered at the pre-trip stage in response to information provision. While these may be reasonable, they do comprise a simplification of individual scheduling and route choice behavior during network perturbations. People exhibit additional behaviors in response to network perturbations including, en-route rerouting, altering destinations and skipping activities when facing delays along the way among others that should be explored and incorporated.

Nonetheless, the results presented in the study are promising and the framework presented can be used to model network disruptions and understand their impact on activity-travel engagement patterns under varying levels of information provision. The prototype and framework presented are robust and can be extended to include additional behaviors. The prototype and the analysis have important implications for planning and policy analyses. They can be used for evaluating, planning and implementing various types of traveler systems including advanced traveler information systems, and incident response services. The modeling framework allows the characterization of the impact of network perturbations on activity-travel engagement patterns, an angle that is less understood.

CHAPTER 9

SUMMARY

Although there have been considerable developments over the past decade in the integrated transport model formulation arena, the implementation of a tightly integrated model system has remained a major challenge to the profession. In this research effort, an integrated model framework of the urban system is presented that goes beyond a loose coupling of the component model systems. The framework comprises an integration of the component systems under a single unifying framework ensuring consistency in the representation of individual agents and their behaviors. The integrated land use – transport model system design incorporates a tight dynamic coupling between an activity-based microsimulation model system of travel demand and a dynamic network assignment and simulation model of network supply and has a behaviorally intuitive appeal. The integrated model design is a continuous time model system capable of simulating activities and travel patterns in response to actual network conditions experienced by travelers as they execute their daily activities and travel in time and space. The model operates at the level of resolution of one minute. In each minute of the day, the activity-travel demand model provides the network supply model the list of trips that need to be routed to their destination, while the network supply model returns the list of trips that have arrived at their destination locations. This results in dynamic interaction between the demand and supply models on a minute by minute basis.

The model system has been implemented as an open source software package and a prototype dubbed SimTRAVEL (stands for Simulator of Travel, Routes, Activities, Vehicles, Emissions, and Land) was developed. The feasibility of the prototype to model the urban system was demonstrated by applying the integrated model for a three city jurisdiction of the southeast region of the Greater Phoenix metropolitan area. The model system is found to perform quite well in replicating observed activity-travel patterns as reported in the latest wave of the National Household Travel Survey (NHTS 2008) data. The results are promising and the model design appears to provide a conceptually appealing framework for tying together microsimulation model systems of activity-travel demand, network supply, and land use. The integrated model design presented (dynamic approach) was also compared against traditional approach (sequential approach) to integration where component systems are applied sequentially to achieve integration; to highlight differences and similarities between the two approaches. The two approaches seem to produce similar results when metrics of convergence and aggregate measures of activity-travel engagement patterns generated are compared. However, when disaggregate measures of activity-travel agendas are compared, the sequential approach suffered from obvious spatiotemporal inconsistencies whereas the dynamic approach with its arrival-based activity-travel scheduling and rescheduling behavior provided behaviorally consistent and complete schedules.

A key shortcoming of the traditional approach is the inability to model application scenarios that involve modeling of network dynamics and subsequent impact on activity-travel engagement behavior. There are many emerging policy questions that call for an integrated transport demand – supply model system capable of responding to changing network conditions through the course of a day. In the event of unexpected congestion (say, due to an incident), travelers may arrive at their destination location later than expected. This late arrival would have cascading effects on the subsequent activities, destinations, and durations. Through a tightly integrated model design, it is possible to reflect the effects of such network dynamics on emergent activity-travel behavior. Similarly, in the event that intelligent transportation systems or dynamic pricing strategies are deployed, travelers may arrive more quickly at their destinations than originally anticipated. The additional time that becomes available to the traveler may lead to induced travel or activity engagement. The dynamic integration approach presented in this research with its event-based paradigm for activity-travel generation is better suited for modeling network dynamics. The dynamic approach to integration was extended further to model traveler information provision scenarios. Results from application of the dynamic approach to model a planned network disruption under a variety of traveler information scenarios were behaviorally plausible and illustrate the applicability of dynamic integration approach for application scenarios involving network dynamics.

The research effort also adds to the body of literature on activity-based travel demand models by examining two key choice activity-travel engagement behaviors, namely, activity engagement behavior at an episode level and vehicle transaction behavior at tour-level. The studies were conducted in an effort to advance understanding simultaneity in choice dimensions and to explore decision hierarchies among the choice dimensions underlying activity-travel engagement. In the first study, a probit-based joint discrete-continuous model formulation was employed to jointly model the activity-type choice and duration of the activity episode. In another study, the probit-based formulation was extended to study the choice of vehicle type in households with multiple vehicles and the distance traveled at the tour-level. Both studies point to the presence of simultaneity in choice dimensions and the need for employing joint modeling frameworks in microsimulation model systems. Additionally, the two studies also point to the importance of proper accounting of decision hierarchies among choice dimensions to conduct accurate policy analyses. Efforts are currently underway to enhance the choice dimensions and decision hierarchies in the SimTRAVEL prototype based on the observations from the two studies.

This research effort makes contributions to furthering the state of research and practice in the arena of integrated models and activity-based travel demand models. There are tremendous opportunities for further research and inquiry in the arena of integrated modeling of urban systems and activity-based travel behavior analysis. Issues of data availability, disaggregate and aggregate validation, convergence, sensitivity to alternative policies and built environment changes, and computational tractability still exist and need to be tackled before model systems of the nature described in this research effort can be implemented in the real-world.

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