AN INTEGRATED LAND USE – TRANSPORT MODEL SYSTEM WITH DYNAMIC TIME-DEPENDENT ACTIVITY-TRAVEL MICROSIMULATION

Ram M. Pendyala
Arizona State University, School of Sustainable Engineering and the Built Environment
Room ECG252, Tempe, AZ 85287-5306. Tel: (480) 727-9164; Fax: (480) 965-0557
Email: ram.pendyala@asu.edu

Karthik C. Konduri
Arizona State University, School of Sustainable Engineering and the Built Environment
Room ECG252, Tempe, AZ 85287-5306. Tel: (480) 965-3589; Fax: (480) 965-0557
Email: karthik.konduri@asu.edu

Yi-Chang Chiu
The University of Arizona, Department of Civil Engineering and Engineering Mechanics
Room 206A, 1209 E. Second St., Tucson, AZ 85721. Tel: (520) 626-8462; Fax: (520) 621-2550
Email: chiu@email.arizona.edu

Mark Hickman
The University of Arizona, Department of Civil Engineering and Engineering Mechanics
Room 206A, 1209 E. Second St., Tucson, AZ 85721. Tel: (520) 626-9420; Fax: (520) 621-2550
Email: mhickman@email.arizona.edu

Hyunsoo Noh
The University of Arizona, Department of Civil Engineering and Engineering Mechanics
Room 206A, 1209 E. Second St., Tucson, AZ 85721. Tel: (520) 626-9420; Fax: (520) 621-2550
Email: hsnoh@email.arizona.edu

Paul Waddell
University of California at Berkeley, College of Environmental Design
228 Wurster Hall, 1850, Berkeley, CA 94720-1820. Tel: (510) 642-3257; Fax: (510) 642-7560
Email: waddell@berkeley.edu

Liming Wang
University of California at Berkeley, College of Environmental Design
228 Wurster Hall, 1850, Berkeley, CA 94720-1820. Tel: (510) 642-3257; Fax: (510) 642-7560
Email: lmwang@berkeley.edu

Daehyun You
Arizona State University, School of Sustainable Engineering and the Built Environment
Room ECG252, Tempe, AZ 85287-5306. Tel: (480) 965-3589; Fax: (480) 965-0557
Email: dae.you@asu.edu

Brian Gardner
U.S. Department of Transportation, Federal Highway Administration
Office of Metropolitan Planning and Programs, 1200 New Jersey Avenue, SE, HEPP-30
Washington, District of Columbia 20590. Tel: (202) 366-4061; Fax: (202) 493-2198
Email: brian.gardner@dot.gov

ABSTRACT
The development of integrated land use – transport model systems has long been of much interest to the profession due to the complex inter-relationships among land use, transport demand, and network supply. This paper describes the design and prototype implementation of an integrated model system which involves the microsimulation of location choices within the land use domain, of activity-travel choices within the travel demand domain, and of individual vehicles on networks within the network supply modeling domain. While many erstwhile applications of integrated transport demand – supply models have relied on a sequential coupling of the models, the system presented in this paper involves a dynamic integration of the activity-travel demand model and the dynamic traffic assignment and simulation model, with appropriate feedback to the land use model system. The system has been fully implemented and initial results of model system runs in a case study test application suggest that the proposed model design provides a robust behavioral framework for simulating human activity-travel behavior in space, time, and networks. The paper provides a detailed description of the design together with results from initial test runs.

Keywords: integrated models, dynamic transport models, microsimulation models, activity-based models, prototype demonstration

Submitted for Presentation and Publication
Committee ADB40: Transportation Demand Forecasting

91st Annual Meeting of the Transportation Research Board, January 22-26, 2012

Word count: 6900 (text) + 5 (tables/figures) x 250 = 8150 equivalent words

August 1, 2011

INTRODUCTION

Microsimulation approaches to land use and transport modeling allow one to realistically represent choice making behavior of individuals while recognizing the interactions, constraints, and underlying decision making mechanisms at play (Kitamura et al 2000). The implementation of microsimulation approaches has been facilitated by advances along three fronts, namely, the availability of rich data on individual decision making behavior in the form of activity-travel surveys and diaries, advances in econometric and statistical modeling methods which allow one to model the complex behaviors of individual agents without making simplifying assumptions, and advances in computational technologies, both in the software and hardware domains, which have allowed for the efficient estimation of complex models and the simulation of millions of agents within reasonable computational time (Goulias and Kitamura 1992).

Advances in microsimulation approaches to modeling urban environments have happened rather independently in three different streams of research, namely, land use, travel demand, and network supply. In the area of land use modeling, mcirosimulation approaches are applied to model the urban form in a region including, land use choices of individuals, businesses, governments and developers. Households within a region make choices about their residential location, while individuals within a household make choices about their fixed activity locations including work place location, school location, and college location (while accounting for intra-household interactions and constraints). Businesses make choices about locating their offices, and other related facilities. Developers make decisions regarding development (on empty parcels of land) or redevelopment (on parcels of land with existing facilities). These land use choices, along with the socio-demographic and economic evolutionary processes, government regulations, and zoning policies comprise the urban form in a region (Martinez 1992, Waddell 2002, Hunt and Abraham 2005, Salvini and Miller 2005).

In the travel demand arena, the field has experienced an increasing use of activity-based microsimulation approaches to travel demand modeling and forecasting. 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 individuals within a household along a continuous time axis (Kitamura and Fujii 1998). The model system comprises of various sub-models that closely interact with each other 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 (Arentze and Timmermans 2004). There is a rich body of literature on various implementations of activity-based model systems (Henson and Goulias 2006). These model systems differ from each other on the underlying behavioral paradigms to represent activity-travel decision making behavior and by the varying degrees to which choice processes are represented (Pendyala et al. 2008).

Network assignment is typically the last step in any transport model. Conventional assignment methods do not recognize that transportation networks evolve continuously through the day, and the underlying assumption of static network conditions in many assignment models in practice lead to results that are unlikely to be representative of actual network conditions. With microsimulation models of travel demand now capable of generating demand at a fine temporal resolution (e.g., one minute), there is increasing interest in the deployment of dynamic traffic assignment models which explicitly account for network dynamics along a continuous time axis allowing for an accurate representation of people’s path choices and resulting network conditions (Peeta and Ziliaskopoulos 2001, Friedrich et al. 2000). Dynamic traffic assignment models provide the same outputs as static assignment models, but with an added time dimension, i.e., they generate time varying transport accessibility measures of the network. This makes dynamic traffic assignment models ideally suited to simulate the impacts of dynamic pricing strategies, emerging real-time information technologies, and intelligent transportation systems deployments.

Although research in these three fields has proceeded somewhat in parallel, it is widely recognized that there are important inter-relationships and dependencies among these modeling domains and there is a need to account for linkages across the model systems in an integrated framework to accurately model urban environments (Timmermans 2003, Miller 2006). Land use choices are affected by network travel accessibility measures. In turn, land use choices affect travel demand; one of the major factors affecting the activity-travel choices of individuals is their location choices including home location, work location, and school location, among others. Travel demand is affected by network accessibility measures, i.e., the temporal and spatial coordinates of the destination opportunity space is limited by conditions on the network (e.g., speed, delays). Finally, network conditions are affected by travel demand that is generated; where people travel and the routes they take affect conditions on the network.

There has been considerable progress made in the conceptualization and operationalization of integrated modeling approaches which seek to model the different components of the urban environments, namely, land use, activity-travel demand, and network supply in a single unifying framework. While some frameworks have emphasized the linkages between land use and travel demand (Waddell et al 2008, Salvini and Miller 2005, Wagner and Wegener 2007), other frameworks have focused on the travel demand and network supply interrelationships (Lin et al 2008, Cetin 2002, Kitamura et al 2008, Rossi 2011, Castiglione et al 2011). However, in most of these integration approaches, linkages across model systems are established rather loosely through sequential feedback processes and data exchange mechanisms. There have been very limited attempts to integrate the three model systems in a single unifying framework largely due to the complexity associated with individual model systems, the analytical challenges associated with linking these systems which operate at different temporal and spatial resolutions, and computational challenges associated with microsimulating all three components of an urban environment.

In this research effort, an integrated modeling system dubbed SimTRAVEL- Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land - is presented with a view to more tightly tie together component model systems in a behaviorally consistent fashion. A prototype has been developed and tested on a three city subarea in the southeast region of the Phoenix metropolitan area. The next section provides an overview of the integrated model design. The third section describes the operational implementation of the integrated model system along with a description of the individual model systems and the software that support it. In the fourth section, a brief overview of the study area is presented; this is followed by a presentation of results in the fifth section and concluding thoughts in the final section.

INTEGRATED MODEL SYSTEM DESIGN

The proposed design comprises a generalized framework for integrating land use, travel demand and traffic assignment models and is not limited to any particular implementation of the individual model systems. Figure 1 presents a high-level overview of the proposed integrated model design. The process starts with a bootstrapping step. A key input to the integrated model system is origin-destination (O-D) travel times. One can obtain an initial set of travel times from a calibrated four-step travel demand model. However, these travel times are based on coarse aggregations of time (the day is divided into four or five time periods) and the origin-destination matrices used are obtained from trip-based modeling approaches. As a result, the travel times may not reflect actual network conditions and are likely to be inconsistent with the paradigms adopted in activity-based travel demand and network dynamics models. A bootstrapping procedure allows one to generate time varying O-D matrices consistent with the notion of networks which evolve over the course of a day.

In a bootstrapping procedure, the peak and off-peak O-D travel time matrices from a four-step model serve as inputs to a land use model to generate the location choices of all agents within an urban environment. The location choices along with the four-step O-D travel time matrices are then used to generate activity-travel patterns for the entire population in a region. The demand that is generated is then routed and simulated using a dynamic traffic assignment model to obtain time varying travel times consistent with the paradigm of time varying network conditions. In subsequent iterations of the bootstrapping step, the time varying travel time matrices are fed back to the activity-based travel demand model and the process is repeated until convergence in the travel time matrices is achieved. The converged travel time matrices are then used to kick off a simulation run of the integrated model for the base year.

In the base year simulation of the integrated model, 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 network accessibility measures by time of day in generating choices. Trips generated are then routed and simulated through the network in the dynamic traffic assignment model along a continuous time axis. 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 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 it to various individual, household lifecycle socio-economic and demographic events to create a 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 is achieved. This process is repeated for each horizon year.

As can be seen from Figure 1, there is no instantaneous (“real-time”) feedback from the traffic assignment model to the land use microsimulation model. This can be explained by the horizon of the choices that each of these model systems aim to simulate. 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 shorter term activity-travel choices which are closely linked together. 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 for that year.

The proposed approach is quite generic and can be operationalized using any land use, travel demand, and traffic assignment models so long as consistency in the treatment of behaviors, and consistency in the representation of behavioral units, space, and time are maintained across model systems. While it may appear that the integrated modeling framework presented in this section resembles sequential integrated modeling approaches that have been proposed in the literature and implemented in practice, an important distinction can be drawn in the processes used to establish the linkages and inter-dependencies between the travel demand and the traffic assignment components of the integrated model system. This linkage is described in the next section.

Dynamic Activity-Travel Simulation

An approach often proposed to integrate the demand model and the network supply model is to run the models sequentially with feedback of the network conditions to the demand model until convergence is achieved. In this naïve sequential approach to integration, the individual model systems are run independently and loosely coupled together with input-output data flows (Kitamura et al 2005). In sequential implementations of integrated model systems, the activity-based travel demand model is run first to simulate the activity-travel patterns for the entire population for a full 24 hour period. The activity-travel patterns are then converted to trip lists (Castiglione 2011) or trip tables (Lin et al 2008) to feed into a dynamic traffic assignment model. It can be seen that, in this approach, there is a potential loss of information as well as the possibility to introduce spatial and temporal inconsistencies into the activity-travel schedules of individuals. If one considers the approach in which trip tables are created from individual activity-travel schedules, trips can no longer be traced back to the individual that engages in the activity/trip and hence there is a loss of information. Even in approaches where trip lists are passed with individual information attached to each trip, the sequential approach fails to capture the "emergent" nature of activity-travel scheduling behavior in response to "actual" arrival time (network conditions). For example, if a person arrives at his or her destination earlier than expected, the sequential approach would not allow the person to alter or modify his or her activity agenda and will be made to wait until the next activity-travel decision point. However, it is very likely that the person may start pursuing the activity early and also potentially finish the activity early, leaving a larger time-space prism window for engaging in other activities or rescheduling subsequent activities. Thus, sensitivity and response to actual arrival information is very important in simulating activity-travel engagement and scheduling decisions for fixed, and more importantly, for non-fixed (discretionary and maintenance) activities.

Figure 2 presents a framework to accomplish a dynamic integration between an activity-based travel demand model and a dynamic traffic assignment model. This framework overcomes the above mentioned limitations of sequential integration approaches by maintaining consistency in the representation of behavioral units, spatial relationships, and temporal scales. The model design can be traced to the attempts to integrate an activity-based travel demand model system called PCATS - Prism Constrained Activity-Travel Simulator – with a micro-meso scale dynamic traffic assignment model system called DEBNetS - Dynamic Event-Based Network Simulator. Early efforts to integrate the two model systems adopted the sequential approach with simple input-output flows enabling the integration (Kitamura et al 2005). A tighter integration paradigm was proposed to overcome the various challenges associated with sequential approaches (Kitamura et al 2008), wherein the travel demand model and the dynamic traffic assignment model constantly communicate with each other along a continuous time axis. 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.

After obtaining network conditions by time of day from a bootstrapping procedure, the framework as shown in Figure 2 can be employed to simulate activity-travel decisions. The typical time resolution of an activity-travel demand model is one minute. Thus the day can be broken down into 1440 intervals in which activity-travel choices need to be simulated for the entire population. Within each minute, the demand model simulates the activity-travel engagement decisions of all individuals.

For those individuals that make a decision to pursue an activity away from the current location, trip information including, origin, destination, mode, and vehicle is extracted and passed to the dynamic traffic assignment model for loading the trip on the network. The dynamic traffic assignment model 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 pair such that the travel time across all paths between the O-D pair are equal). A dynamic traffic assignment model is usually capable of simulating vehicular movements and positions at a finer temporal resolution (less than one minute). Assume that the dynamic traffic assignment model is capable of simulating vehicle movements at a temporal resolution of six seconds. In order to avoid lumpy loading of the vehicles onto the network within a one minute simulation, the dynamic traffic assignment model uniformly distributes the trips across the one 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, and delays, among others). It is theoretically possible for the traffic assignment model system to store network level of service measures at a resolution of six 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. In addition, it is difficult 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 one minute resolution or higher). The vehicular movements are executed on the network until the trips arrive at their intended destinations. Once the trips have arrived at their destinations, the dynamic traffic assignment model passes back the arrival information to the demand model so that the latter can simulate subsequent activity-travel engagement decisions. After receiving the arrival information, the demand model makes appropriate adjustments to the activity-travel schedule of an individual in response to his or her arrival time and the individual pursues the activity at the destination before reaching the next activity-travel engagement decision point. Since the dynamic traffic assignment model operates at a resolution of six seconds, all of 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 are generated for use in the dynamic traffic assignment model in the subsequent iteration. The updated network conditions are fed into both the demand model and traffic assignment model for the next iteration. The process is repeated until convergence is achieved in both the travel demand and network conditions. It must be noted that 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 simulate activity-travel engagement decisions in any given iteration. However, the arrival time information, based on which activity-travel schedule adjustments and activity engagement decisions are made, is generated in "real-time" as trips are simulated along the day.

The proposed approach to dynamic linkage between the activity-travel demand system and the dynamic traffic assignment model has some very behaviorally appealing features. First, 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. This process maintains continuity and consistency in temporal and spatial representation of activity-travel engagement decisions, which is often a point of contention in the more naïve sequential approach to integration. Second, the feedback of network conditions from one iteration to the next mimics a day-to-day learning process wherein individuals make activity-travel engagement decisions and adjust schedules in response to their travel experience from the previous iteration. This learning behavior is captured by the outer feedback loop shown in Figure 2. Finally, the framework lends itself to evaluating policies and scenarios that involve network dynamics, and understanding the impact of such dynamics on activity-travel engagement behavior. For example, one can evaluate the impact of traveler information systems, or model the dissipation of network shocks (incidents) and their effects on individual time use and activity engagement decisions. It can be seen that scenarios can easily be setup and evaluated in the proposed integrated model design because of the dynamic minute-by-minute handshaking which allows one to capture the scheduling and re-scheduling decisions, and alternative routing decisions that people would pursue, in response to network dynamics. The evaluation of such real-time scenarios in a sequential design would inevitably entail the use of ad-hoc procedures to modify activity-travel patterns. The proposed design offers a behaviorally intuitive framework for modeling dynamics associated with the demand for and supply of transportation systems.

OPERATIONAL IMPLEMENTATION OF INTEGRATED MODEL DESIGN

The framework presented in the previous section has been used to build an integrated model system dubbed SimTRAVEL – Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land. In order to start the microsimulation of the urban continuum, a synthetic population for the entire region is necessary. In this context, it is important to ensure that the synthetic population not only matches known 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 the region, which in turn affect the land use, activity-travel engagement, and route choice decisions. PopGen (Version 1.1) is the synthetic population generator used in SimTRAVEL (Ye et al. 2009). PopGen is a stand-alone open-source package developed using Python and is available to the public under the GNU General Public License (GPL) agreement. The land use microsimulation model that was employed in the development of the SimTRAVEL prototype is UrbanSim (Waddell et al 2008). 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.

The travel demand microsimulation model system incorporated in SimTRAVEL is OpenAMOS. OpenAMOS is an open-source activity-based travel demand model system which generates the daily activity-travel patterns of individuals. OpenAMOS builds on a long legacy of activity-based model development (Pendyala et al 2005, Kitamura et al 2005). Some fundamental behavioral paradigms, such as the explicit modeling and recognition of time-space prism vertices, have been preserved in OpenAMOS from the legacy implementation. However, OpenAMOS enhances the earlier model framework to account for child dependency and allocation processes, intra-household activity-travel engagement interactions, and multi-modal travel simulation. OpenAMOS is implemented in Python and is available to the public under the GNU GPL agreement.

Finally, the dynamic traffic assignment (DTA) microsimulation model system that was deployed in the integrated model prototype is MALTA (Multi-Resolution Assignment and Loading of Traffic Activities) (Chiu and Villalabos 2008). The traffic assignment process is handled by a new Hierarchical Time Dependent Shortest Path (HTDSP) algorithm for the highway modes, and a new microsimulation model for the transit modes. The MALTA model system is primarily written in C++. The model system is also open-source, similar to other packages that are used in the development of the prototype, and is available to the public under the GNU GPL agreement.

Convergence Criterion

The demand and supply model systems are run iteratively with feedback loops, and hence convergence criteria need to be established to stop the iterative process. While the concept of convergence and stopping criteria are well established in the field of traffic assignment, the concept is relatively less established in the travel demand modeling arena. On the demand side, every simulation run represents one stochastic realization of the underlying activity-travel behavior, and convergence is neither monitored nor characterized across loops of a feedback procedure. Traditionally in traffic assignment models, convergence is monitored by comparing origin-destination travel time matrices (Boyce and Bar-Gera 2003) or by comparing a gap measure (Rose et al 1988) across iterations, and the iterative process is stopped once the difference in the convergence measure across iterations is small.

In addition to monitoring convergence on the traffic assignment side, it is also important to monitor convergence on the travel demand side as well. This is because, in the proposed design, the number of iterations required to achieve convergence in the traffic assignment model will be directly dependent on the extent to which activity-travel patterns vary across iterations. In the system prototype, convergence on the travel demand end is monitored by comparing aggregate O-D matrices across iterations. In the future, it is envisioned that more disaggregate measures of convergence may be monitored.

In any iterative process, there is always a concern of feedback measures oscillating across iterations and leading to unstable and inefficient characterization of convergence. Boyce and Bar-Gera (2003, 2006) suggest the use of averaging techniques in feedback processes to avoid oscillations and to proceed towards convergence more efficiently. In the proposed design, the time-varying link attributes are averaged across iterations. The link attributes were selected because they are used to generate O-D travel time matrices for use in the travel demand model and update time-dependent shortest paths for use in the dynamic traffic assignment model for the next iteration.

Case Study Test Site

Initial tests of the prototype are being conducted for a three city subarea in the southeast region of the Phoenix Metropolitan region. The subarea covers the 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. Although activity-travel engagement decisions are being generated only for the three city region in OpenAMOS, the dynamic traffic assignment model (MALTA) is utilizing the entire network of the Phoenix Metropolitan region for routing and simulation. Therefore, in an effort to reflect the presence of congestion on the network, the background traffic that is generated by the population outside the study area was also loaded. Background traffic was incorporated by disaggregating peak- and off-peak O-D matrices obtained from the four-step travel model for the region into trip lists by employing temporal distributions from the latest National Household Travel Survey. In each time step, the disaggregated trip lists were then added as background traffic to supplement the demand generated by OpenAMOS for the subarea and thus capture real world network conditions.

RESULTS

Within the scope of this paper, it is impossible to provide comprehensive results of the case study application of SimTRAVEL. Such a comprehensive case study description will be the primary focus of a future paper. Within the context of this paper, and relevant to the description of the design, two key measures are examined and discussed here.

One of the major design objectives of the tightly integrated model design was to ensure that time of day distributions of activity-travel engagement were accurately replicated by the model system. In the dynamic integrated model design, activity start times get adjusted in response to actual arrival times at destinations simulated by the dynamic network model. In other words, one of the key aspects of the design is the ability to accurately replicate time of day distributions of travel. Now, if the origin-destination travel time matrices are very accurate representations of travel times one would actually experience in the network, then it is unlikely that the dynamic model design and the sequential model design would yield differing results. This is the because the travel time matrices that dictate time of day distributions in the sequential model design would be very similar to actual travel times experienced by travelers in the network as simulated by the dynamic integrated model design. However, the question remains whether the dynamic integrated model design, with all of its schedule adjustments in response to network arrival times, would be able to accurately replicate true time of day distributions of travel in the region. Figures 3 and 4 show time of day distributions of trip start times for adult workers and adult non-workers respectively. It can be seen that the time of day distributions for these two demographic groups compare remarkably well against values derived from the latest edition of the National Household Travel Survey. For workers, one can see the typical peaks in the morning and evening with a smaller peak in the noon period, presumably due to the lunch hour. For non-workers, the distributions also match extremely well, although it appears that SimTRAVEL is yielding a slight over-prediction of trips between 11:00 AM and 5PM and a slight under-prediction of trips beyond 8 PM. These extremely good matches in time of day distributions show that the dynamic design, with its adjustments in activity schedules in response to arrival times actually experienced by travelers, is able to replicate real-world time of day distributions accurately. In other words, individuals in the real world also adjust their schedules in response to network conditions, and the model is able to replicate that behavioral process effectively.

Another key dimension of the integrated model design is investigated through the information in Figure 5. This figure compares the overall trip rates for maintenance and discretionary activities for worker and non-worker segments. The comparison is made between trip rates provided by the sequential model design and the dynamic integrated model design described in this paper. In virtually all cases, it is found that the sequential model design is yielding a higher trip rate than the dynamic integrated model design. In fact, the dynamic integrated model design generated a total of 1.456 million trips for the subarea that constitutes the test area, while the sequential model design generated a total of 1.506 million trips. It appears that the sequential model design may not accurately capture the adjustments in activity engagement that people make as a result of experienced travel times being different from expected travel times. When an actual arrival time is later than an expected arrival time, then the remaining time in the open time-space prism is less than what would be otherwise available. As a result of this shrinkage of the time space prism, an individual might forego undertaking an additional activity, and instead, postpone the activity to the next day. This type of activity generation adjustment is not reflected in the sequential model design. As a result, the average trip rates for non-mandatory activities are higher in the sequential model design than in the dynamic integrated model design. Indeed, one should note that, if the expected travel times closely replicate actual travel times that would be experienced on the network, then these differences would be negligible. However, the dynamic integrated model design ensures that effects of network congestion, that would inevitably impact arrival times, are accurately captured in simulating activity engagement behavior of individuals.

Now, 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. The issue, however, is not whether a sequential model design accurately replicates network conditions and travel demand under normal conditions. The question is whether a simpler naïve sequential model design can replicate behaviors and network conditions when a shock or policy is introduced in the system in the middle of a day (simulation). The dynamic integrated model design presented in this paper is able to accurately and effectively simulate adjustments in schedules and behaviors that would follow such an event. It is simply not possible for a sequential design to mimic such behavioral adjustment processes. The comparisons presented in this paper demonstrate that the integrated model design presented in this paper is able to accurately replicate such adjustment processes, and in doing so, actually reproduces observed activity-travel patterns in the real world.

CONCLUSIONS

This paper presents an integrated land use – transport model system design that 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. 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. 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 be able to 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. An integrated model system that can account for such induced and suppressed demand effects would be of considerable value to the profession which is constantly grappling with the complex inter-relationship between land use development and network accessibility.

The integrated model design described in this paper 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. Thus, there is a dynamic interaction between the demand and supply models on a minute by minute basis. The model system includes algorithms to facilitate convergence, and the final accessibility measures from any single simulation year inform the land use choices of a subsequent simulation year. Thus, the model design accommodates the time lags that are inevitably involved in land use changes in response to changes in network conditions. The integrated land use – transport model system explicitly recognizes that different choice processes operate on different temporal and spatial scales.

The model system has been implemented as an open source software package and a prototype has been tested in 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 national travel survey data. Comparisons between results provided by the dynamic integrated model implementation and the naïve sequential model implementation suggest that the proposed dynamic integrated model design is better able to replicate adjustments in activity-travel schedules that take place through the course of a day in response to network conditions. The results are quite promising and the model design appears to provide a robust framework for tying together any microsimulation model systems of activity-travel demand, network supply, and land use.

ACKNOWLEDGEMENTS

Financial support provided by the Federal Highway Administration of the US Department of Transportation under Contract DTFH61-08-C-00010 of the Exploratory Advanced Research Program is gratefully acknowledged.

REFERENCES

Arentze, T.A. and H.J.P. Timmermans (2004) A Learning-Based Transportation Oriented Simulation System. *Transportation Research Part B*, 38 (7), pp. 613-633.

Beckmann, M., C., McGuire and C. Winsten (1956) Studies in the Economics of Transportation. Yale University Press, CT.

Boyce, D. and H. Bar-Gera (2003) Validation of Multiclass Urban Travel Forecasting Models Combining Origin-Destination, Mode, and Route Choices. *Journal of Regional Science*, 43, pp. 517 - 540.

Boyce, D. and H. Bar-Gera (2006) Solving the Sequential Travel Forecasting Procedure with Feedback. 16th PTV Vision User Group Meeting.

Castiglione, J., S. Lawe, J. Bowman, M. Bradley, and D. Roden (2011) Sensitivity Testing of an Integrated Regional Travel Demand and Traffic Microsimulation Model. Presented at the 13th TRB National Transportation Planning Applications Conference, May 8-12, 2011, Reno, Nevada.

Cetin, N., K. Nagel, B. Raney and A. Voellmy (2002) Large-Scale Multi-Agent Transportation Simulations. *Computer Physics Communications*, 147(1-2), pp. 559 - 564.Kitamura et al 2005

Chiu, Y.-C. and J.A. Villallobos (2008) The Anisotropic Mesoscopic Simulation Model on the Interrupted Highway Facilities. Presented at the Symposium on the Fundamental Diagram: 75 Years (Greenshields 75 Symposium), Woods Hole, MA.

Friedrich M., I. Hofsab, K. Nokel and P. Vortisch (2000) A Dynamic Traffic Assignment Method for Planning and Telematic Applications. Proceedings of Seminar K, European Transport Conference, Cambridge, pp. 29 - 40.

Goulias, K.G. and R. Kitamura (1992) Travel Demand Forecasting with Dynamic Micro¬simulation. In *Transportation Research Record*, No. 1357, Transportation Research Board of the National Academies, Washington, D.C., pp. 8 - 17.

Henson, K.M. and K.G. Goulias (2006) A Preliminary Assessment of Activity Analysis and Modeling for Homeland Security Applications. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1942. Transportation Research Board of the National Academies, Washington, D.C., pp. 13–20.

Hunt, J.D., and J.E. Abraham (2005) Design and Implementation of PECAS: A Generalised System for Allocating Economic Production, Exchange and Consumption Quantities. In M. Lee-Gosselin, and S. Doherty (eds.) *Integrated Land-Use and Transportation Models: Behavioural Foundations*, Elsevier, Amsterdam, pp. 253 - 273.

Kitamura, R. and S. Fujii (1998) Two Computational Process Models of Activity-travel Behavior. In T. Gärling, T. Laitila and K. Westin (eds.) *Theoretical Foundations of Travel Choice Modeling*, Pergamon Press, Oxford, pp. 251-279.

Kitamura, R., C. Chen, R.M. Pendyala and R. Narayanan (2000) Micro-simulation of Daily Activity-Travel Patterns for Travel Demand Forecasting. *Transportation*, 27(1), pp. 25 - 51.

Lin, D-Y., N. Eluru, S.T. Waller and C.R. Bhat (2008) Integration of Activity-Based Modeling and Dynamic Traffic Assignment. In *Transportation Research Record, Journal of the Transportation Research Board*, No. 2076, pp. 52 - 61.

Martinez, F.J. (1992) The Bid-Choice Land Use Model: An Integrated Economic Framework. *Environment and Planning A,* 24(6), pp. 871 - 885.

Peeta S. and A. Ziliaskopoulos (2001) Foundations of Dynamic Traffic Assignment: The Past, the Present and the Future. *Networks and Spatial Economics*, 1(3/4), pp. 233 - 266.

Pendyala, R.M., Y-C. Chiu, and P. Waddell (2008) Modeling the Urban Continuum in an Integrated Framework: Location Choice, Activity-Travel Behavior, and Dynamic Traffic Patterns. Interim Report, Exploratory Advanced Research Program, Federal Highway Administration, US Department of Transportation, Washington, D.C.

Pendyala, R.M., R. Kitamura, A. Kikuchi, T. Yamamoto and S. Fujii (2005) FAMOS: The Florida Activity Mobility Simulator. In *Transportation Research Record, Journal of the Transportation Research Board*, No. 1921, pp. 123 – 130.

Rose, G., M.S. Daskin, and F.S.Koppelman (1988) An Examination of Convergence Error in Equilibrium Traffic Assignment Models. *Transportation Research Part B*, 22(4), pp. 261 – 274.

Rossi, T. (2011) Integration of an Activity Based Model, Traffic and Transit Simulation Model, and MOVES. Presented at the 13th TRB National Transportation Planning Applications Conference, May 8-12, 2011, Reno, Nevada.

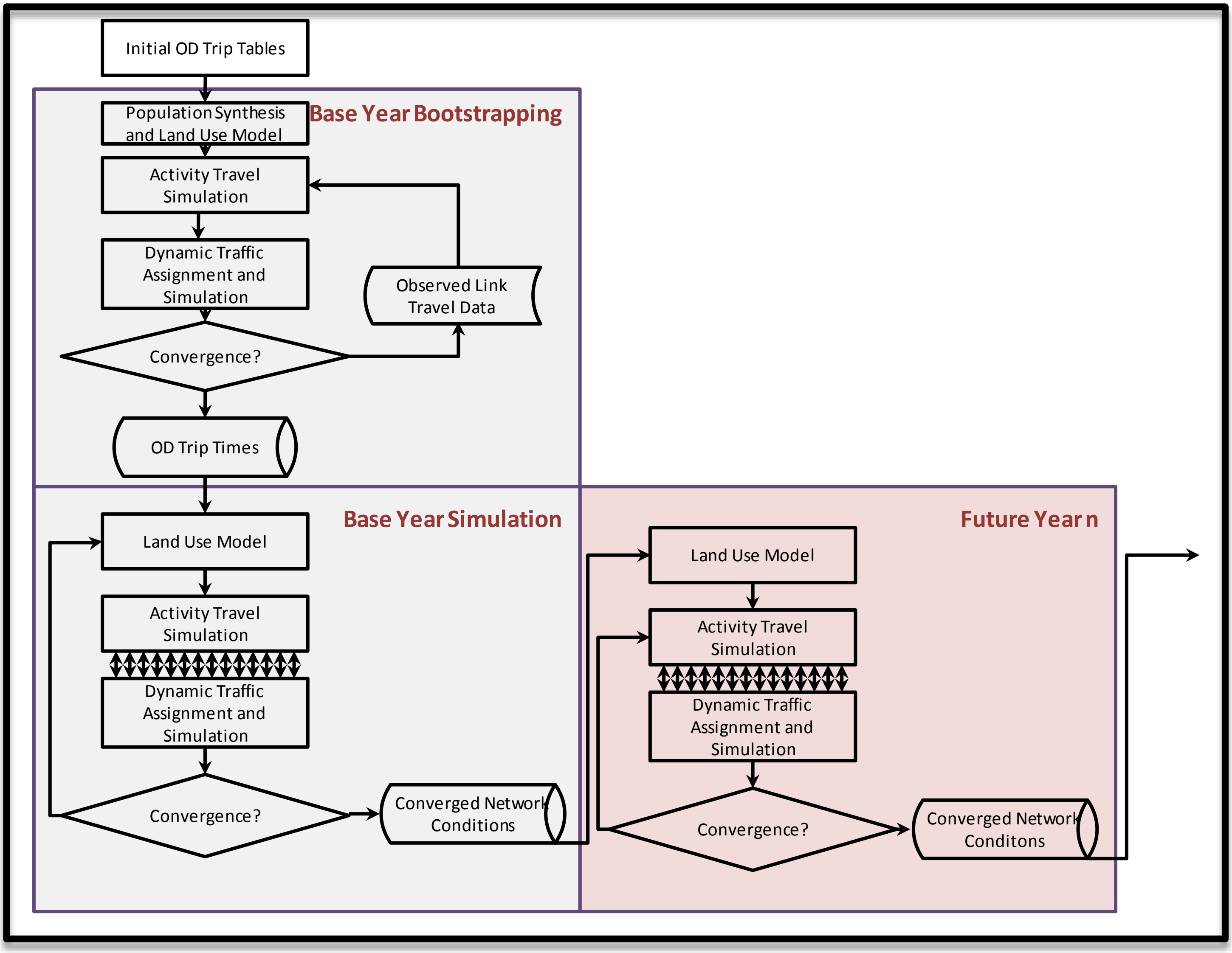
Salvini, P. and E.J. Miller (2005) ILUTE: An Operational Prototype of a Comprehensive Microsimulation Model of Urban Systems. *Networks and Spatial Economics*, 5, pp. 217-234.

Waddell, P. (2002) UrbanSim: Modeling Urban Development for Land Use, Transportation and Environmental Planning. *Journal of the American Planning Association*, 68(3), pp. 297 - 314.

Waddell, P.A., X. Liu and L. Wang (2008) UrbanSim: An Evolving Planning Support System for Evolving Communities. In R.K. Brail (ed.) *Planning Support Systems for Cities and Regions*, Lincoln Institute of Land Policy, Cambridge, MA, Chapter 6, pp. 103 - 138.

Wagner, P. and M. Wegener (2007) Urban Land Use, Transport, and Environment Models. NSL Network City and Landscape: DISP-Online, pp. 45-56.

Ye, X., K. Konduri, R.M. Pendyala, B. Sana and P. Waddell (2009) A Methodology to Match Distributions of Both Household and Person Attributes in the Generation of Synthetic Populations. DVD-ROM of the 88th Annual meeting of the Transportation Research Board, Washington, DC.



1 **Figure 1. Overview of the Framework for Integrating Travel Demand and Supply Models**

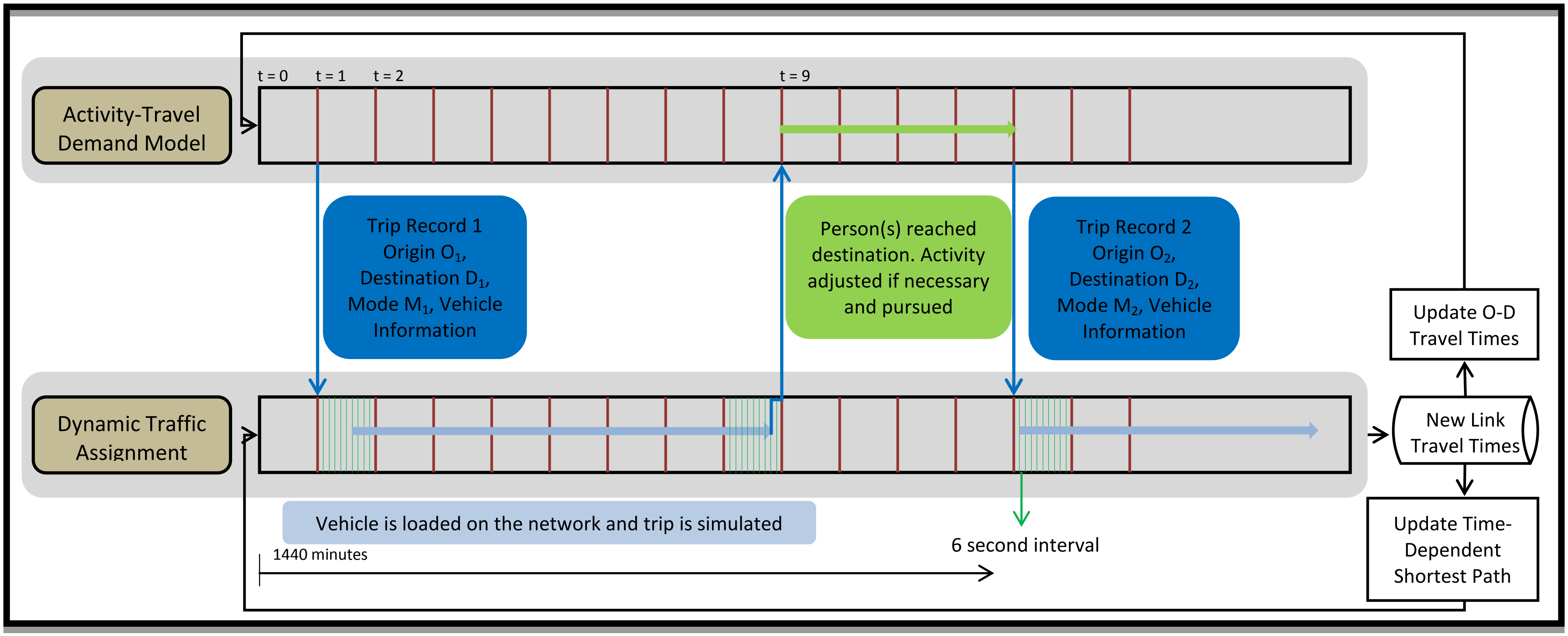


Figure 2. Conceptual Overview of the Framework for Integrating Travel Demand and Supply Models

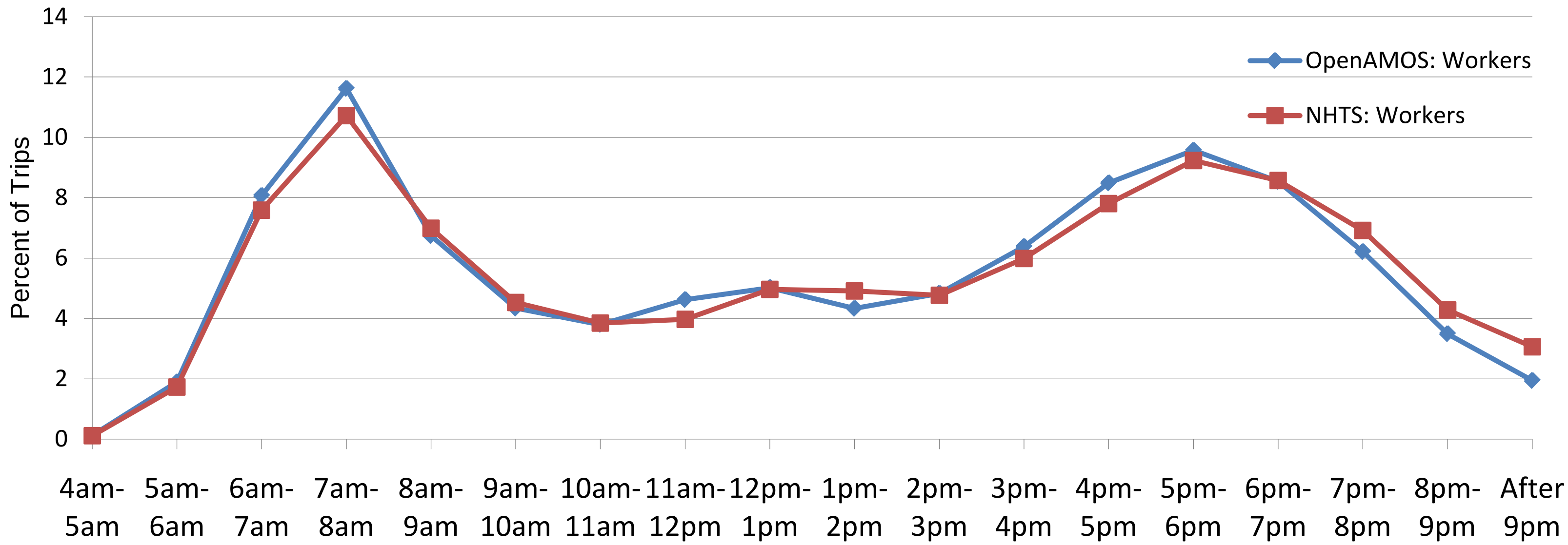


Figure 3: Time of Day Distribution of Trip Start Time for Workers

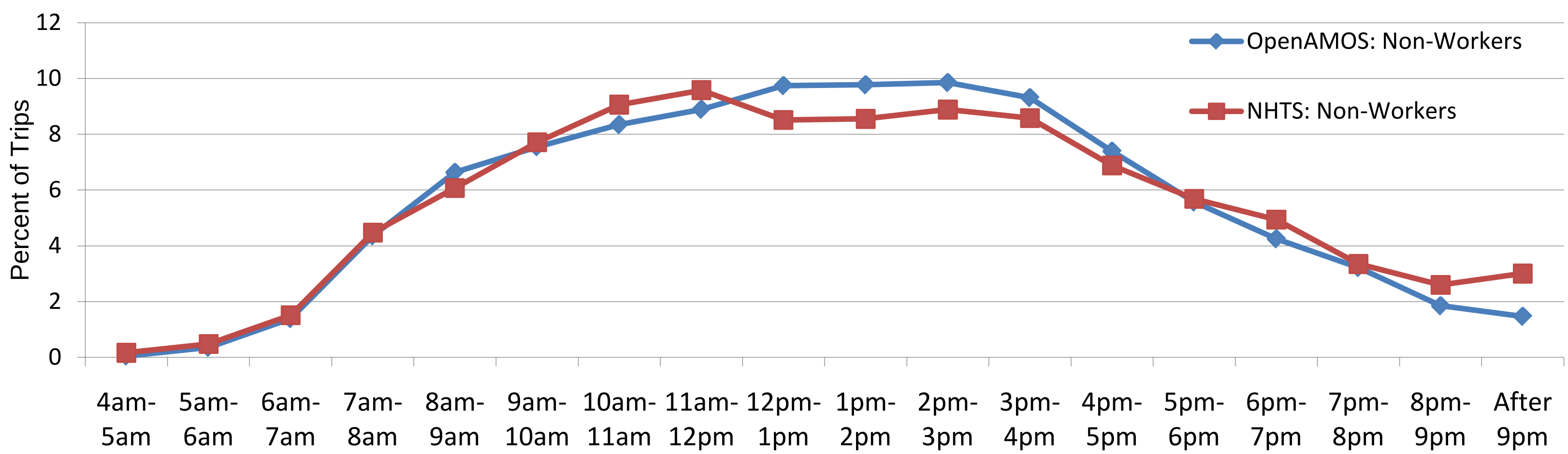


Figure 4: Time of Day Distribution of Trip Start Time for Non-workers

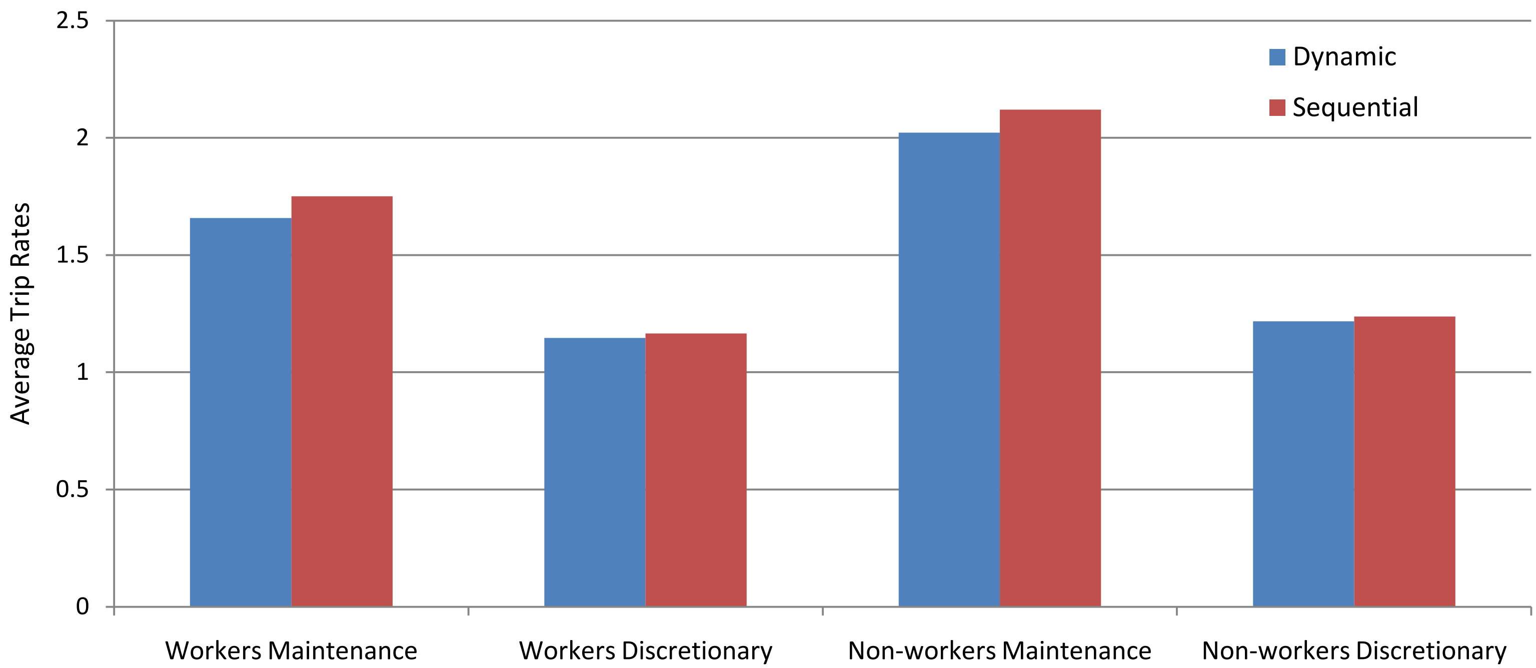


Figure 5. Difference in Average Trip Rates Between Sequential and Dynamic Integrated Model Runs