A Network-Sensitive Integrated Travel Model

for Simulating Impacts of Real-Time Traveler Information

by

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ABSTRACT

Real-time information systems are being used widely around the world to mitigate the adverse impacts of congestion and events that contribute to network delay. It is important that transportation modeling tools be able to accurately model the impacts of real-time information provision. Such planning tools allow the simulation of the impacts of various real-time information systems, and the design of traveler information systems that can minimize impacts of congestion and network disruptions. Such modeling tools would also be helpful in planning emergency response services as well as evacuation scenarios in the event of a natural disaster. Transportation modeling tools currently in use are quite limited in their ability to model the impacts of real-time information provision on travel demand and route choices. This dissertation research focuses on enhancing a previously developed integrated transportation modeling system dubbed SimTRAVEL (Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land) to incorporate capabilities that allow the simulation of the impacts of real-time traveler information systems on activity-travel demand.  The first enhancement made to the SimTRAVEL framework involves the ability to reflect the effects of providing information on prevailing (as opposed to historical) network conditions on activity-travel behavior choices.  In addition, the model system is enhanced to accommodate multiple user information classes (pre-trip and enroute) simultaneously. The second major contribution involves advancing the methodological framework to model enroute decision making processes where a traveler may alter his or her travel choices (such as destination choice) while enroute to an intended destination. Travelers who are provided up-to-date network information may choose to alter their destination in response to

congested conditions, or completely abandon and reschedule an activity that offers some degree of flexibility. In this dissertation research, the model framework is developed and an illustrative demonstration of the capabilities of the enhanced model system is provided using a subregion of the Greater Phoenix metropolitan area in Arizona. The results show that the model is able to simulate adjustments in travel choices that may result from the introduction of real-time traveler information. The efficacy of the integrated travel model system is also demonstrated through the application of the enhanced model system to evaluate transportation policy scenarios.

DEDICATION

To my mother, father and my wife who have supported me through all the ups and downs.

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CHAPTER 1

**Introduction**

Ever increasing energy consumption and greenhouse gas emission (GHG) have been an issue of major concern on a global scale for the past few decades. In the Unites States transportation sector accounts for 28% of GHG emissions in 2012 (EPA, 2013) and 70% of all petroleum consumption in the 2012 (EIA, 2013). One line of effort taken up by the researchers in the field is to develop tools and techniques to efficiently handle network disruptions so that emissions from idling of vehicles can be reduced. This also saves a precious commodity that everyone has but is still scarce – 'time'. Network disruptions can be defined as a class of events that change usual flow conditions of traffic on roadway networks (Konduri et al., 2013). Network disruptions may be classified into two types: planned events and unplanned events. Full or partial roadway closures to accommodate work zones along a freeway segment or bridge section are some examples of planned events. Traffic crashes or roadway/bridge failures are examples of unplanned events. Network disruptions reduce the capacity of roadways, increasing queues which in turn increase the emissions due to idling of vehicles. Another adverse impact of network disruptions is the loss of traveler's productive time due to delays caused by congestion.

Various traveler information systems have been introduced by jurisdictions and Metropolitan planning organizations (MPOs) to mitigate the negative impacts of network disruptions. Advanced Travelers Information System (ATIS) such as Intelligent Vehicle/Highway Systems (IVHS), Variable Message Signs (VMS), and Highway Advisory Radio (HAR) (Adler and McNally, 1994; Adler and Blue, 1998) are a few examples of traveler information systems. The goal of these technologies is to create a

communication link between drivers and traffic control centers. In addition, in-vehicle navigation, real-time traffic conditions (Google Maps) and Global Positioning System (GPS) are capable of providing information not only for shortest path from origin to destination but also alternate route suggestions to the activity destination in light of traffic congestion. All of the technologies mentioned above are being used widely in the current day. These technologies are significantly impacting activity-travel behavior, network performance, and travel safety by improving drivers' perception of current network conditions and assisting drivers with pre-trip and en-route travel decisions (Mouskos and GreenFeld, 1999; Zhang et al., 2008; Yang and Luk, 2008).

**Benefits from Modeling Impacts of Real-Time Traveler Information Provision**

Impacts of real-time traveler information provision should be understood and modeled for a number of reasons (Konduri et al., 2013). First, understanding the impacts of user information provision in the event of planned or unplanned network disruptions (e.g. the collapse of the I-35W bridge in Minneapolis) will help plan for emergency response services (Zhu et al., 2010). Crisis teams may can be informed of delays in real-time which can prevent loss of life. Second, if a transportation modeling tool is capable of accurately simulating the impacts caused by real-time information provision on activity-travel patterns along the time and space dimensions, it would provide transportation professionals with a powerful tool to devise/test better real-time information systems and reduce the adverse effects of network disruptions. Third, transportation planners or policy makers will be able to carry out an array of policy analyses (before their actual implantation) in that require real-time information provision without having to spend a lot of time and money.

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**Considerations for Modeling Effects of Real-Time Information Provision**

Recent research efforts have developed transportation modeling tools (comprising of travel demand and traffic assignment models) capable of simulating the impacts of user information provision in the context of network disruptions (see Konduri et al., 2013 for a detailed explanation of one such tool). However, most of the modeling tools in research as well as practice are not fully competent to allow for modeling the wide array of uses of real-time information provision. The following key considerations are partially or fully ignored by the current model systems in this context.

- The transportation modeling tools should be able to reflect the impacts of user information provision (Konduri et al., 2013). Real-time network conditions are available for travelers through various technologies such as Google maps, radio traffic reports, in-vehicle GPS, and variable message signs. These technologies would impact activity-travel engagement decisions and route choice decisions. In addition, the model system should be capable of accurately modeling the spatial and temporal variance of information provision based on the individual's current location, departure time, and what type of real-time information system they seek to use. For example, if a traveler is driving on an arterial corridor, the traveler might not obtain network condition information through variable message signs that are only placed at select locations on freeways. Google Maps provide real-time network conditions for major freeways and arterial corridors. Travelers who drive on local roads might not able to use Google Maps. Hence, transport model systems should be able to accurately capture different spatio-temporal scales of user information systems while simulating activity-travel engagement patterns.

- The same level of information access should not be applied to all travelers while modeling impacts of real-time information provision (Konduri et al., 2013). Level of access to current network conditions can be classified into three levels namely: no information, pre-trip, and en-route information. Travelers will make different activity-travel engagement and route decisions depending the level of information available to them. For example, if a traveler checks current network conditions before embarking on a trip, he or she may alter activity, destination, and/or mode based on prevailing network conditions. Travelers who have access to en-route traveler information might not change the mode (as they are already on the network) but alter their route, destination, or skip an activity on their agenda in light of current network conditions. The transportation model system should be able to model different user information classes accurately.

- Modeling tools should also consider the cascading effects among trips while modeling the impacts of network disruptions under user information provision (Konduri et al., 2013). A network condition may lead an individual to alter destination, mode, or activity for the subsequent trip or cancel the next activity on his/her agenda and stay at home in light of the delay encumbered on the current trip. For example, if an individual arrives late at a destination due to a network delay, he or she would adjust the duration of the activity, or keep the planned duration of the activity, but alter the plan for the subsequent activity and travel. In another context, individuals might delay departure time for an activity to avoid traffic congestion provided they have information regarding prevailing network condition. The model system should be able to account for different types of

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individuals, their travel behavior and interactions among trips in the daily activity agenda etc.

- In order to model the impacts of real-time traveler information provision, experienced and prevailing network conditions should be used simultaneously to simulate activity-travel engagement patterns. As individuals make decisions to engage in activities, they might have some historical knowledge (from a previous journey) of network conditions. Alternately, an individual might utilize technologies to realize prevailing network conditions, provided he or she has access to the technology. The transportation modeling tool should therefore use both experienced and prevailing network conditions simultaneously while simulating activity-travel patterns and route choices.

**Integrated Model System for Modeling the Impacts of Network Disruptions**

To model real-time traveler information provision, an integrated model system that comprises of land-use, activity-travel engagement, and dynamic traffic assignment sub-models named SimTRAVEL (Pendyala et al., 2012) is used in this research. The development and implementation of integrated models of urban continuum has been a topic of significant interest in the profession for a couple of decades. Number of studies combined activity-based travel micro-simulation models and dynamic traffic assignment models (e.g., Pendyala et al., 2012; Lin et al., 2008; Kitamura et al., 2005) in the recent past. The objective of such model integration is to capture behavioral dynamics in time-dependent networks at the level of the individual traveler, which is not possible using a traditional four step models. With advances in the development and implementation of integrated modeling systems, several studies in the recent past have undertaken the task

of forecasting the impacts of pricing strategies and their impacts on activity-travel schedules in time-dependent networks (e.g., Zhang et al., 2011; Konduri et al., 2013). However, most of integrated modeling systems available today are not capable to fully address policy analyses that require real-time communication between travel demand and network supply models. In spite of several technological and computational advancements, the communication between the demand and supply in integrated modeling frameworks is mostly sequential in nature. This shortcoming makes it difficult to capture behavioral dynamics impacted by real-time information systems in time-sensitive networks at the level of the individual traveler. Pendyala et al. (2012) developed an integrated model system (called SimTRAVEL: Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land) that is capable of handling real-time communication between the two key components (activity-travel demand model and network supply model). Konduri et al. (2013) presented an upgraded version of SimTRAVEL and analyzed the impacts of network disruptions under user information provision. However, the framework of SimTRAVEL still falls short of fully accounting for all design components that should be considered to accurately model impacts of real-time traveler information provision on activity-travel engagement behaviors.

**Objectives of the Research**

This dissertation aims at enhancing an established integrated modeling framework of travel demand and supply to reflect the effects of real-time information provision in a time-space prism constrained behavioral paradigm. In this research, the SimTRAVEL (Pandyala et al., 2012) is updated on the following grounds:

- A new dynamic network model flexible enough to reflect real-time information systems is integrated into the framework of SimTRAVEL. One of the main goals of this research is to enhance SimTRAVEL to accurately model the impacts of real-time traveler information provision. The previous traffic assignment model employed in SimTRAVEL is not flexible to capture pre-trip and en-route decisions in traffic flow simulation. So, this project employs a new dynamic network assignment model (called DTALite) capable of simulating traffic flows taking into account pre-trip and en-route information.

- This research aims to enhance SimTRAVEL to utilize both previous network conditions (experienced network conditions) and prevailing network conditions in determining activity-travel engagement decisions and route choice decisions. In order to accurately capture activity-travel behavior of individuals who use ATIS to make activity, destination, or/and mode choice decisions before embarking on a trip, prevailing network conditions should be available to both travel demand and dynamic network models.

- This research intends enhance SimTRAVEL to handle different levels of access to information provision in synthetic population in the activity-travel demand model. The activity-travel demand model sends information regarding level of access to real-time network conditions of the traveler to the dynamic traffic assignment model in addition to general travel information (e.g. origin, destination, departure time, vehicle type, etc.). This ensures that different levels of traveler information provision in spatio-temporal dimensions is accurately depicted in simulation of

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activity-travel engagement and route choice decisions in response to network delay events.

- Travel behavior choices in response to real-time information provision are added to the framework of the activity-travel demand model in order to reflect decision making process of travelers in light if network delay events. Once the activity-travel demand model receives trips that are in the congested state network from dynamic network model, the model is made capable of responding to the traffic delay event by altering activity, destination, or mode of the individual. In summary, this research upgrades the modeling framework of SimTRAVEL to make it capable of simulating activity-travel patterns in response to network delay events under real-time user information provision.

The enhanced framework of SimTRAVEL is tested on a sub region (City of Chandler, Town of Gilbert and Town of Queen Creek) in the Phoenix Metropolitan Area to analyze the impacts of network disruptions under real time information provision. An unplanned network disruption event is simulated on a major freeway corridor (Loop 202) in the sub region. This study conducts a comprehensive analysis to estimate the effect of real-time information provision on activity-travel engagement behaviors using various traveler information provision scenarios. Another case study analyzes the impacts of a Low Emission Zone (LEZ) policy on energy and emission reductions in a selected geographical area.

The remainder of this paper is organized as follows. The next chapter presents existing literature on activity-based travel demand models, dynamic traffic assignment models, integrated modeling frameworks followed by research regarding network

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disruption with ATISs. Chapter 3 describes the previous version of the integrated model of the urban continuum called SimTRAVEL developed by Pendyala et al. (2012). Fourth chapter describes in detail, the enhancements made to the integrated model system for modeling impacts of real-time traveler information provision. The fifth chapter presents a case study conducted on a Low Emission Zone (LEZ) policy using the enhanced SimTRAVEL. The sixth and seventh chapters provide the results of case studies for pre-trip and en-route decision making processes respectively in response to a network delay event. The final chapter summarizes and lists the contributions of this research work to empirical knowledge in the area of integrated travel demand model systems.

CHAPTER 2

## Literature Review

There has been a significant amount of progress made in micro-simulation approaches of travel demand in the recent past. Several researchers recognized the need of integrating various components (e.g. land-use, travel demand, and traffic assignment) to supplement shortcomings of traditional four step approach. In the last two decades, tremendous progress has been also made in the area of integrated modeling of urban systems. The rich body of literature in integrated model systems is a testament to the progress that had been made. In addition, many researchers have actively researched advanced traveler information systems (ATIS) and real-time communication systems to alleviate the impacts of network disruptions. This chapter provides a review of the literature on the impacts of network disruptions and advanced traveler information systems, activity-travel demand, and traffic assignment. In the next section, a detailed review of literature on integrated modeling of urban systems is described.

### Network Disruptions and Traveler Information Provision

Network disruption may occur anywhere and anytime on traffic networks (accidentally or on purpose). Disruptions can be separated into two types: planned and unplanned (Konduri et al., 2013). A network disruption is an incident that occurs in a specific area, which might impact traffic condition (congestion) on the roads in and around the area from several hours to a few of months (sometimes, even a year). Vehicle crash (unplanned) is a short term example of network disruption. Longer term examples of network disruptions are work zones on roads, rebuilding a collapsed bridge, and reconstruction projects (Yun et al., 2011; Zhu et al., 2010) which are usually planned.

Traffic congestion arising from network disruption has significant implications on energy consumption (wasted fuel), greenhouse gas emissions and traveler's (wasted) time (Adler and Blue, 1998; Kim et al., 2009). There are two main directions in the transportation literature focusing on alleviating the impacts of network delay events. First, there is the analysis of measuring activity-travel behavior changes in response to network perturbation and user information provision. Zhu et al. (2010) investigated commuter travel pattern after the collapse of I-35W bridge on August 1, 2007 by collecting traffic data from loop-detectors and bus ridership and conducting a survey. Yun et al. (2011) explored non-worker traveler behavior changes in response to a planned network disruption (a reconstruction project of Interstate 5 for 9 weeks in Sacramento, California). They conducted two contemporaneous internet surveys to measure changes in travel behavior caused from the planned network disruption events. The results show that respondents are more likely to change non-mandatory (non-work) travel in response to the worsened network conditions. Clegg (2007) presented the behavioral changes down to the individual vehicle level in response to a planned reduction of road capacity. Chang and Nojima (2001), and Kamga et al. (2011) focus on the impacts of unplanned network disruptions to understand traveler behavior changes. Although these studies are helpful to understand the impacts of network disruptions on traveler behavior, their scope is still limited in examining specific dimensions of activity-travel engagement pattern, or exploring specific demographic segments.

Utilizing the lessons learnt from study of network disruptions, various techniques for traveler information provision have been developed to provide accurate information of prevailing network conditions to travelers and thereby offer them a chance to avoid

congestion. In the late 1960s and early 1970s, metropolitan areas such as Los Angeles, Detroit, and Chicago started to research, develop and test for traffic surveillance and real-time information dissemination. The research work focused on using visual displays to inform travelers with prevailing traffic condition and diversion information (Weinberg et al., 1966). In the 1970s, the Federal Highway Administration sponsored a project that developed ERGS (Electronic Route Guidance System). ERGS system focused on providing travelers with in-vehicle route guidance based on their origin-destination information (Rosen et al., 1970). In addition to this, in-vehicle route guidance systems (IVRGS) were developed and tested in Japan (Shibano et al., 1989), Europe (Jeffery et al., 1987) and the United States (Rillings and Krage, 1992) in the 1980s. Variable message signs (VMS) and highway advisory radios (HAR) were designed to mitigate traffic congestion in areas impacted by network disruptions (planned or unplanned) such as special events or incidents (Alder, 1994; 1998). In the late 1990s and early 2000s, geographical information system (GIS) and global positioning system (GPS) were applied into the advanced or real-time traveler information system to calculate the shortest path and provide drivers with prevailing network conditions (Mouskos and Greenfeld, 1999; Zhang et al., 2008). Real-time traffic data are available through various applications such as Google Maps and SmartTrek (Swedlund, 2013) and smart phones (Konduri et al., 2013).

To mitigate traffic congestion caused by a network disruption, various technologies that provide real-time traveler information are employed. Several studies attempted to understand the impact of traveler information provision on traveler behaviors under network disruptions. Levinson (2003) uses a simulation approach,

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which considers "informed" and "uninformed" drivers under recurring and non-recurring congestion scenarios, to explore the benefits from traveler information provision in travel time. The results of the simulation suggest that in-vehicle real-time traveler information systems provide travel time benefits to users and reduce the variance in the travel time. Kraan et al. (2000) investigate the impacts of advanced traveler information system on shopping activity-travel engagement by conducting an interactive stated preference survey. Pre-trip and en-route traffic information were considered for trips to shopping in the survey of the study. From the results of the survey it was found that 25% of the respondents would change their route or shopping mall as they obtain delay information caused by network disruptions. Liu and Mahmassani (1998) estimate a multinomial probit model to understand traveler responses to real-time traffic information. From the results of the model, travelers would make departure time adjustments and route switching at various decision nodes along the trip based on the reliability of real-time information and supplied schedule delay (relative to the commuters' preferred arrival time).

Another steam of research focused on modeling the impacts of traveler information systems on network performance under various network disruption scenarios. Al-Deek et al. (1998) develop a framework that combines a route diversion model and a queuing model for evaluating the effect of advanced traveler information systems. The framework focuses on three different types of travelers because different people may respond differently to traveler information systems along with the level of access to information. The three types of travelers are follows: no traveler information, delayed traveler information, and real-time traveler information. That is, their study

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disaggregates the level of technologies of ATIS and analyzes the traveler and system benefits that come from various technology penetrations. Yang and Luk (2008) developed a dynamic model to evaluate the impacts of ATIS on network performance. The dynamic model consists of traffic information provider, route choice module, traffic simulation module, and evaluation module. The traffic information system provides different level of traffic information access to drivers. This can lead to different route choice behaviors among different types of drivers in the route choice module. The traffic simulation module then simulates dynamic network conditions in response to traffic information. The last step evaluates network performance such as network delay, link specific delay, and flow rate. Their study aimed to study the impacts of ATIS on traveler's route decision and analyze the benefit of reducing total network delay with different levels of access to traffic information. Paz and Peeta (2009) propose a paradigm for generating traffic routing strategies by explicitly accounting for traveler's likely behavior in response to recommended routes informed by a user traveler information system. The objective of their approach is to evaluate the impact of technology on network route selections and performance.

**Activity-Travel Engagement Pattern Micro-simulator**

Kitamura et al. (2000) presents the development and validation results of a micro-simulator for simulating individual daily activity-travel patterns. A sequential simulation approach was adopted to generate daily activity-travel patterns. In this approach, daily activity-travel pattern is separated into components that correspond to certain aspects of observed activity-travel behavior. Thus, the approach establishes a link between mathematical models (i.e. discrete choice models) and observational data. Monte Carlo

simulation was used to generate daily activity-travel patterns. The model system of the micro-simulator consists of activity type choice, activity duration choice, activity location choice, and travel mode choice. In addition, the components include work/school location models, initial departure timing models, and initial location models.

Bowman and Akiva (2000) present a disaggregate discrete choice activity schedule model system for forecasting urban passenger travel demand. A tour-based concept was incorporated into this activity-based model system to explicitly model an individual's choice of an entire day's schedule. The authors estimated models using 24 hour household travel diary survey data collected from the Boston metropolitan area in 1991 along with zonal and time-of-day-specific transportation system attributes from the same time period. In the activity scheduling model system proposed by the authors, household interaction was not considered for forecasting activity decision in an individual's entire day's schedule. Therefore, though the predicted activity-travel patterns may be consistent at the individual level, daily activity schedules of household members may not match which seems counter intuitive knowing the fact that household members depend on each other to make travel decisions.

Jonnalagadda et al. (2001) introduced a framework for implementation of the micro-simulation activity-based model for San Francisco. The model system was applied in the nine-county San Francisco Bay Area, which is represented by the Metropolitan Transportation Commission regional travel demand forecasting model. The activity-based model in this framework consists of destination choice and mode choice models. Two different destination choice models were estimated at tour-level and trip-level. Tour-level destination choice model is to determine the primary destination while the

trip-level model captures the choice of intermediate stops on a tour. A separate model was estimated for each tour purpose such as work, school, other, and work-based. Mode choice models were also separated into tour- and trip-levels. A mode choice model at tour-level is to determine the mode for the tour, whereas the model at trip-level determines the mode for each individual trip on that tour on the basis of the mode chosen by the mode choice model at the tour-level.

Kato et al. (2002) developed an activity-based travel demand model system designed as a series of hierarchical submodels for commuters' work-tour mode and their discretionary activities and travels before and after work by using neural networks. The model system at the highest level is constrained by primary travel pattern of employees, affecting their behavior of whether/not and how to make discretionary tours. The lower level of the system is the choice of discretionary travel generation before and after work and then followed by the choice of their destination, mode and activity duration. The study used the person-trip survey data for the metropolitan area of Nagaoka, Niigata collected by the national government of Japan in November 1999. Their micro-simulation was able to simulate an individual discretionary travel pattern based on a number of conditions that assume the introduction of Travel Demand Management (TDM) measures such as flexible work times or staggered work hours.

A micro-simulation demand-modeling system was developed by Vovsha et al. (2002) for the New York Metropolitan Transportation Council to apply the New York–New Jersey–Connecticut metropolitan models. The objective of developing a micro-simulation model system is to overcome drawbacks of conventional demand models such as a) inefficient computation and storage of large multidimensional probability arrays, b)

lesser behavioral intuition, and c) no variability of travel demand. A Monte Carlo approach is used to simulate discrete choices at the individual level. Model system in the micro-simulation consists of journey-frequency choice, destination choice, and model choice models. In order to improve behavioral realism of travel demand models, it allows for the exploration of a chained or hierarchical structure of travel decisions and the consideration of objective time-space constraints on an individual's daily travel-activity pattern. Modeling the variability of transportation flows is possible in micro-simulation approaches to make a decision on the capacity of a planned transportation facility based on the probability of achieving critical maximum volumes. Micro-simulation also allows constraints into the modeling framework at the destination choice stage so that it has the potential to handle the competition over work attractions and other travel activities in a meaningful fashion.

Vovsha et al. (2007) developed a micro-simulation technique which is capable of simulating daily activity-travel behavior by using activity-based models at the full-disaggregate level of persons and households. This technique was developed in JAVA programming language as a package which can be imported and used in any model development project. An activity-based platform and a tour-based structure are base for the development of this technique. In an activity-based platform, modeled travels are generated within a general framework of the daily activities undertaken by persons and households. The concept of the activity-based modeling structure adopted in this research is proposed by Bowman and Ben-Akiva (1999; 2000). Since this structure does not consider intra-household interactions, the authors transformed it with a cascade of conditional choices, with alternating decision making units (household or person),

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following a set of preference rules. However, activity-travel pattern in this activity-based model system may not be consistent between children and adults in a households because activities undertaken by children who depend on an adult can affect activity-travel pattern of the adult who needs to take care of the children.

Yagi and Mohammadian (2008) developed an activity-based micro-simulation modeling system to estimate travel demand to be used for evaluation of different transportation policy scenarios such as area pricing, parking pricing, and license plate restriction. This modeling system consists of three types of models: daily activity pattern choices, time of day, and mode and destination in the hierarchy. All models in this modeling system were developed using the available activity diary survey and household travel data conducted in 2002 for the Jakarta metropolitan area. The micro-simulation process in their study incorporates activity scheduling decision rules to modify generated activities by controlling for activity rescheduling, joint activity-tour generation, and household maintenance tour restriction. The model system simulates daily activity-travel patterns undertaken by persons or households at tour level for preserving consistency in destination, mode, and time of day across trips. This study assumes that a tour is a home-based tour in which one starts travel from home and ends the travel at home.

**Dynamic Traffic Assignment Simulators**

Dynamic traffic assignment consists of two main steps: i) route selection and ii) traffic movement simulation. In an integrated model system, travel demand model sends trip information to the dynamic traffic assignment with origin and destination information. Using information of vehicle trips, traffic assignment model assigns routes to all vehicle trips based on an optimization criterion of network link impedances before simulating

vehicle movement from origin to destination through the network. There are several methods used for route selection. Wardrop (1952) presented the classic user equilibrium technique in which individual chooses a route that minimizes travel time from a particular origin-destination pair. The user equilibrium method does not allow user to improve travel time by shifting alternative paths. The system equilibrium model aims to minimize travel times across all vehicle trips based on system optimum principles. This technique may not be able to give minimum travel time to all vehicle trips because system optimum may be reached only by minimizing travel time for all individuals together. Similar techniques that are commonly are all-or-nothing assignment, incremental-load assignment, incremental-reload assignment, and Frank-Wolfe assignment (Oppenheim, 1995).

Instead of using user and system equilibrium techniques, simulation-based dynamic traffic assignment models employ discrete choice analysis for route selection (Ben-Akiva et al., 2014). Discrete choice analysis asks disaggregate data to be used to estimate variables that cause the behavior of route selection for a particular origin and destination pair. The disaggregate data can be collected from survey by mail, telephone, and the internet (Ben-Akiva et al., 1984; Prato et al., 2004) or GPS trajectories (Frejinger, 2008; Hou, 2010). Discrete choice models for route selection predict the decision of travelers regarding which route they choose to reach their destination using the choice set and the attributes pertaining alternative routes. The Multinomial Logit model that computes the probability of selecting a route in the given choice set is one of the most popular methods to estimate parameters because its assumption is simplified with identical and independently distributed error terms (Ben-Akiva et al., 2014). Wen et al.

(2006) developed a route choice model using the Multinomial Logit model. However, the Multinomial Logit model is deemed inappropriate to be used in networks with commonly overlapping paths (Ben-Akiva et al., 2014). To overcome limitations of the Multinomial Logit, C-Logit model (Cascetta et al., 1996), Path Size Logit model (Ben-Akiva and Bierlaire, 1999), Multinomial Probit model (Yai et al., 1997) have been developed for route selection in simulation-based dynamic traffic assignment models.

In the subsequent step after route selection, dynamic traffic assignment models simulate vehicle movements for the particular origin destination pair on the simulation region on a continuous time axis. Its model system generates the link volumes and link impedances at the end of simulation run to provide input data to another model system such as land use model, travel demand model, and routing selection model. The traffic movement models can be separated into three groups: macroscopic, microscopic, and mesoscopic models. The macroscopic traffic simulation adopts theories in physics to simulate vehicular traffic and generate transport accessibility measures. In macroscopic approach, traffic flow had been explained by the models developed by Lighthill and Witham (1955), and Richards (1956). The macroscopic models were continuously developed by researchers in a quest to better explain the observed non-equilibrium phase transitions, various non-linear dynamic phenomena (traffic jams), and stop-and-go traffic (Kerner and Rehborn, 1997; Helbing and Huberman, 1998; Kühne, 1984). Helbing et al. (2001) presented the non-local, gas-kinetic-based traffic model to predict consistent traffic flow in the macroscopic approach. The macroscopic approach is not flexible enough to permit the analysis of different dynamic traffic reactions such as gap acceptance, car following, and lane changing behavior. To overcome the shortcomings

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of macroscopic models, microscopic approach for traffic simulation is proposed by several transportation researchers. Microscopic traffic models simulate movement at the level of individual vehicle on the network. Microscopic models provide the much needed flexibility to analyze dynamic traffic behaviors such as gap acceptance, car following, lane changing, shockwaves, and weaving (Mahut et al., 2008; Chandler et al., 1958; Gazis et al., 1959; Kometani and Sasaki, 1961; Gipps, 1981; Van Aerde et al., 1996). With the advancements in computer software, hardware and mathematical techniques (Liu and Ma, 2009), some transportation researchers made efforts to simulate individual traffic movements (including dynamic traffic behaviors) on microscopically real world networks. For example, Nagel et al. (1999) used the Transportation Analysis and SIMulation System (TRANSIMS) for the Dallas/Fort Worth case study. AIMSUN was adopted with a heuristic approach (Barcelo et al., 1999) and a stochastic heuristic dynamic assignment (Barcelo and Casas, 2006) to dynamic traffic assignment. Mirchandani et al. (2003) proposed CORSIM simulation model that is based on an iterated route. VISSIM (Beaulieu et al., 2007) and INTEGRATION (Van Aerde et al., 1996) were also developed as microscopic traffic simulation models. However, it is still difficult to apply microscopic traffic simulation to large scale networks. So, these models are used on rather small networks because of the heavy computational burden involved (Liu et al., 2005; Konduri, 2012).

There is another class of traffic simulation models which are termed mesoscopic models. The objectives of the mesoscopic traffic approach is to reduce high computational burden and memory usage, which is a common problem in microscopic models enabling their application to large scale network for simulating individual vehicle

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movement. Therefore, the mesoscopic approach would selectively omit certain car-following behavior and decrease a simulation temporal resolution for balancing computational burden and keeping realism of macroscopic simulation properties (Tian and Chiu, 2011). The earlier mesoscopic traffic approach in literature includes the headway distribution model (Buckley, 1968; Branston, 1976), the cluster model (Botma, 1981) and gas-kinetic continuum model (Nelson and Sopasakis, 1998). Another model group in the mesoscopic approach is the simulation-oriented models that simulate individual vehicle movements following link, segment, or cell structure in a simulation area at every second by commonly employing the Queue model (Gawron, 1998; Cetin et al., 2002). The simulation-oriented models estimate traffic flow characteristics on the network and then use it as input to simulate vehicular movements at the individual level (Cetin et al., 2002; Balakrishna et al., 2008). Chiu et al. (2010) presented the anisotropic mesoscopic simulation (AMS) model that determines each vehicle's prevailing speed at current simulation time by taking an average density in the front of the following vehicle. CONTRAM (Taylor, 2003), DYNASMART-P (Mahmassani et al., 2001), DynaMIT (Ben-Akiva et al., 1998), and DTALite (Zhou and Taylor, 2011) are some other dynamic traffic assignment models that have been developed based on the properties of mesoscopic traffic simulation approach.

**Integrated Model System of the Urban Continuum**

Kitamura et al. (1996) proposed an integrated urban model system called as the Sequenced Activity-Mobility Simulator (SAMS) to overcome shortcomings of traditional four-step models that have not been able to serve as an effective planning and policy tools. The framework of SAMS comprises of an urban system, a socio-

economic/demographic, vehicle transactions, an activity-mobility, a dynamic network, and air quality emissions simulators. The urban system simulator is a dynamic, market-based micro-simulator of the urban evolution. It simulates household residence and job location choice, firms' location decisions, and developers' development decisions at microscopic levels. The socio-economic/demographic simulator is a stochastic micro-simulator of the socio-economic/demographic evolution of households and firms that generates synthetic population. Location decisions are generated with feedback between the urban system and the socio-economic/demographic simulators. The outputs of both simulators are fed into the vehicle transaction simulator as endogenous variables. The vehicle transactions simulator is a dynamic stochastic micro-simulator that models acquisition, disposal and replacement of vehicles in a household. SAMS includes an activity-based model (called as AMOS – the activity-mobility simulator) of travel decisions. AMOS simulates activity engagement, scheduling and travel behavior along a continuous time axis at the level of an individual using endogenous variables from other simulators in the system (urban system, socio-economic/demographic, and vehicle transactions simulators). The trips generated from AMOS are then fed into the dynamic network simulator which simulates network assignment and reports network conditions on a continuous time-of-day basis. An air quality emissions module takes the output of dynamic network simulator and evaluates emission footprint from personal travel.

Ben-Akiva et al. (1996) proposed a framework of an integrated model system of the urban continuum. The framework is based on a tour-based approach for modeling the activity-travel engagement patterns and houses an urban development, mobility and lifestyle decisions, activity-travel pattern choices, and transportation system performance

modules. The model of activity-travel pattern choices focuses on individual or household decisions. First, the urban development module simulates industrial development, firm location decisions, and residential development decisions. Mobility and life style module then simulates employment, housing, activity program, auto ownership, and information technology options. The results of mobility and life style module are fed into a model of activity-travel pattern choices which generates activity-travel patterns with activity schedule, activity type, destination, departure time, travel model and route at the tour level. These activities can be rescheduled for an individual in light of transport network conditions. The modeling process evaluates transportation system performance using the rescheduled activity-travel patterns. The transportation system performance is used in the urban development module as a feedback because there are interactions between the decisions of individual's activity-travel patterns and the transportation system characteristics. The integrated urban model system iteratively runs the simulation until convergence.

Strauch et al. (2003) presented ILUMASS (Integrated Land-Use Modelling and Transportation System Simulation), an integrated model of urban system. The objective of ILUMASS is to simulate the interaction between urban land-use development, activity-travel demand, traffic flow and environment. In the framework of ILUMASS, changes in land use patterns impact activity behavior and hence transportation demand. The impacts of activity-travel engagement patterns and land-use also effect the environment. The results of transportation demand, traffic flow, and environment are fed into land-use model to simulate location choice such as residences, workplaces, shops, or

leisure facilities. ILUMASS iteratively runs micro-simulation from land-use model to environmental impact model until convergence is achieved.

Salvini and Miller (2005) present the development of an operational prototype for a comprehensive micro-simulation model of urban systems called as the Integrated Land-use, Transportation, and Environment (ILUTE). The objective of ILUTE is to analyze transportation, housing and other urban policies by simulating the evolution of an integrated urban system over an extended period of time. The ILUTE model system consists of four inter-related components: land-use, location choice, auto ownership, and activity-travel. An integrated full-feedback model is employed 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, flows, times, and external impacts are used as input data to simulate market interaction (purchase of a home or automobile, selection of a spouse, decision to choose a job, etc.) and activity scheduling at the level of person, household, and families. Miller et al. (2011) presents an update on ILUTE by integrating the agent-based Travel and Activity Scheduler for Household Agents (TASHA) with a network assignment model (MATSim). Synthetic population, labor market, housing market, and auto ownership are fed into TASHA to simulate activity and travel patterns for each person. MATSim assigns trips that come from TASHA on the networks. ILUTE also includes a model of transportation emissions and dispersed pollution concentrations (called as CALPUFF) to compute pollutant concentrations over time and space. However, ILUTE still adopts sequential integration

between TASHA and MATSim through feedback processes and data exchange mechanisms.

Lin et al. (2008) discuss efforts at designing and developing a comprehensive econometric micro-simulator for urban systems (CEMUS) which is a model system to predict socioeconomic characteristics and activity-travel environment. CEMUS comprises of a synthetic population generator (SPG), a land-use simulator called as CEMSELTS (socioeconomics, land-use and transportation system characteristics simulator), an activity-travel simulator (CEMDAP), and a dynamic traffic micro-assignment (DTA) module. CEMUS employs a sequential framework. Before starting process of CEMUS, SPG prepares a subset of socioeconomic characteristics (Guo and Bhat, 2007). First, CEMSELTS produces socioeconomic characteristics and activity-travel environment. Eluru et al. (2008) developed a population evolution method within the CEMSELTS module of the CEMUS. It consists of the migration model system and the socioeconomic evolution model system. CEMDAP takes this as input and then produces individual-level activity-travel patterns. DTA uses the travel patterns from CEMDAP, assigns the traffic on networks and calculates level of service in the study region. The results from DTA are fed back into CEMSELTS as input data. The sequential process in this framework continues until consistency and equilibrium are achieved. Lin et al. (2009) applied an integrated urban model system to evacuation planning. The integrated model system consists of activity-based model (CEMDAP) and dynamic traffic assignment (Visual Interactive System for Transport Algorithms: VISTA) model. VISTA is a comprehensive dynamic traffic assignment system that is comprised of traffic simulation, time-dependent routing algorithms, and path assignment (Waller and

Ziliaskopoulos, 1998). The integrated model system offers the required spatial, temporal and human behavior information capable of modeling evacuation planning.

Another notable effort at developing an integrated urban model system is Transportation Analysis Simulation Systems (TRANSIMS) (Barrett et al., 1999). TRANSIMS is comprises of a population synthesizer, activity generator, route planner, and traffic micro-simulator. First, the population synthesizer generates a synthetic population of households and individuals using census data and population demographic projections. TRANSIMS also simulates activity location (households, work locations, schools, stores, and shops) along the transportation network. The activity generator builds an activity list for each individual. Each activity list includes activity type, start time, end time, travel mode, and travel duration to the activity. Using shortest (travel time, travel distance, or minimal cost) path algorithms, the route planner assigns each activity on the network during a simulation day. The traffic micro-simulator simulates each travel movement on the transportation network using information of the activity list on at the resolution of a second. TRANSIMS is capable of simulating various travel modes such as walk, car, and transit. After completing the traffic simulation, the emission estimator calculates vehicle emissions using results from the micro-simulation to predict tailpipe emissions for light and heavy-duty vehicles.

Rieser et al. (2007) proposed to use activity chain in addition to time-dependent origin-destination (O-D) matrices to pass more detailed travel information of each individual from activity-based demand generation (ABDG) to dynamic traffic assignment (DTA). Using activity chain that includes activity locations, activity types, and number of activities in a tour, it is possible to simulate cascading impacts between prior activity

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and next activity for each individual. If the current activity for an individual is delayed, there is a cascading impact on participation in the next activity. Rieser et al. (2007) employed the Kutter model that is a disaggregated activity and behavior-oriented traffic demand generation model and modified it to generate activity chain. MATSim was employed to simulate agent movements on the network after converting activity chain data to one hierarchical (XML) file and reading it as input data. MATSim is able to simulate only individual car traffic and hence, simulation of their integrated model concerns only individual car trips. Berlin urban area in Germany, with a population of about 6 million inhabitants was chosen to test their integrated urban model system and then compare the results with real-world traffic counts. Hao et al. (2010) developed an integrated model system between agent-based travel demand model called TASHA and MATSim. TASHA, which comprises of the scheduling and mode choice models, was developed to improve traditional four-stage models for forecasting travel demand. In addition to the integration, an emission model is also added to be sensitive to the effect of congestion. Bekhor et al. (2011) also used MATSim with Tel Aviv activity-based model to develop an integrated model system. Their model system eliminates the use of aggregated origin-destination (O-D) matrices. Instead, Tel Aviv activity-based model passes each individual's daily travel that includes the types and number of daily tours, the number of intermediate stops, the destination for each activity, and the mode used in the tour to MATSim agent-based traffic assignment model. Using activity-travel schedule for each individual, MATSim runs the mobility simulation in an iterative fashion until convergence in agents schedule score (plan evaluation) is achieved.

In the first part of literature review, efforts from many researchers aimed at alleviating the impacts of network disruptions by developing technologies of advanced (real-time) traveler information systems (ATIS) are discussed. The technologies such as 511 systems, radio, and real-time traffic data like Google Maps are able to send information regarding real-time network conditions to travelers although availability or accessibility of real-time traveler information is different according to where the traveler is, what time he or she is driving, and which ATIS technology the user has access to. Literature shows that these technologies are able to effect on traveler's activity-travel behavior and route choice decisions to reduce network congestion and enhance traffic flow. Modeling the impacts of network disruptions under user information provision is also important in the context of planning emergency response services and various policy analyses regarding the impacts of network delay events (Konduri et al., 2013).

Model systems of travel demand and network flow have been developed individually to generate trips and simulate traffic flows, respectively. These model systems may simulate the effects of network disruptions incorporating simplified assumptions. Independent model system may not be able to simulate realistic activity-travel decisions and traffic flows as travel demand is affected by network conditions and network condition in turn is impacted by travel demand. Especially, modeling the effects of network delay under user information system calls for communication between demand and supply models to accurately simulate activity-travel engagement patterns and traffic movements. For this reason, integrated model systems are a better choice for accurately modeling the impacts of network disruptions under user information provision. Most of the extant integrated models employ loose coupling of travel demand and traffic

assignment models through data exchange protocols and feedback processes. In order to capture activity-travel patterns with network disruptions under various user information systems, the integrated model systems in which the two model components are sequentially connected are not adequate as the model systems are not able to accurately represent the interaction between trips in a traveler's schedule and prevailing network conditions. It is essential to have a tight coupling between travel demand and network model systems to realistically simulate activity-travel engagement decision under network disruption and user information provision using.

An integrated model system called Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land (SimTRAVEL) developed by Pendyala et al. (2012) adopts a framework that ensures tight coupling between the two model components. This research work proposes to enhance SimTRAVEL with an intent to capture the impacts of network disruptions under different levels of user information provision. In order to reflect real-time communication between travel demand and network flow, prevailing network conditions should be available for both model systems. The previous version of SimTRAVEL does not consider exchange of prevailing network condition information between two model components. This study proposes to upgrade SimTRAVEL by enhancing the communication schematic that includes information of prevailing network conditions. The activity-travel demand model (called as openAMOS) in SimTRAVEL should be enhanced to properly capture the impacts of network delay events with due consideration for user information provision on activity-travel behavior. The next chapter will describe in detail, the framework used in the previous version of the SimTRAVEL.

CHAPTER 3

**Integrated Urban Model System with a Tight Coupling: SimTRAVEL**

The objective of this research effort is to enhance the integrated urban model system (SimTRAVEL) developed by Pendyala et al. (2012) to allow for modeling the impacts of real-time traveler information provision on activity-travel engagement decisions and route choices. This study learns and builds on the existing version of SimTRAVEL with an intent to provide the flexibility to conduct various policy analysis exercises. This chapter describes functionalities of previous version of SimTRAVEL.

In many previous research efforts concerning integrated urban model systems, a sequential paradigm had been used to tie activity-based travel demand models with dynamic traffic assignment micro-simulation models (e.g., Lin et al., 2008; Kitamura et al., 2005). In a sequential integration framework, an activity-travel demand model and dynamic traffic assignment model are run independently and outputs from each model feed into the other iteratively. This looping mechanism between travel demand and network supply models continues iteratively until convergence is achieved.

Though the sequential integration of travel demand and network supply models is more convenient, two major limitations hold down such an implementation from realistic representation of travel behavior. First, the activity-travel demand model will not be able to accurately depict the current network conditions in simulating activity choice, destination choice, activity start time, and activity duration. For example, if an individual arrives at the desired destination later than his or her expected arrival time, this delay could potentially affect the next activity-travel engagement decision for the individual. That is, the individual may choose a different location (within a shorter distance) to

pursue the next activity, reduce the duration of engagement in the current activity, or cancel a subsequent activity to recover the delay. Activity-travel demand models in the context of sequential integration paradigm are not capable of reflecting a number of time-space and household constraints that travelers encounter in real world.

Second, the sequentially integrated model systems cannot accurately simulate activity-travel patterns, network assignment, and movement of each trip in the occurrence of network delay events. There are two types of network disruptions: planned (auto crashes) and unplanned (road works). Various type of information such as highway advisory radio, real-time traveler information, and signs on highways are utilized to evenly distribute trips around area of network disruptions in order to minimize delays. Within a sequential integration framework where the activity-based model and network, assignment model are run in isolation, it is impossible to depict such real-time information provision. To overcome these limitations, activity-based demand models have to be integrated closely with dynamic traffic assignment models accommodating for constant communication between the two models and thus allowing for exchange of prevailing network condition information at each time step of the simulation.

Kitamura et al. (2008) proposed a dynamic event-based integrated modeling framework to solve the limitations of sequential integrated modeling systems. Pendyala et al. (2012) operationalized this method by developing a model framework dubbed SimTRAVEL. This chapter describes the modeling framework and operational details of previous version of SimTRAVEL. The first section describes overall framework of SimTRAVEL that allows for a tight coupling between the synthetic population generator, land-use, activity-based demand, and network supply models. In the second section,

issues encountered in the design and development of SimTRAVEL along with approaches address those issues are discussed. The third section presents details regarding different model components in SimTRAVEL. The fourth section presents the framework of the dynamic time-dependent activity-travel simulation adopted in SimTRAVEL to allow micro-simulation in a tight coupling schematic. The last section describes the framework of modeling effects of network disruptions under user information provision employed in the previous version of SimTRAVEL.

**Overall Framework of SimTRAVEL**

Figure 1 presents the overall design of the integrated urban model system, SimTRAVEL (Pendyala et al., 2012). Micro-simulation run of the integrated model starts with base-year bootstrapping procedure to set up real world network conditions before launching the integrated model system simulation for the base year. Initial origin-destination trip tables from a traditional four step model are used as input data in base-year bootstrapping procedure. The activity-travel demand model generates trips and passes this information to a traffic assignment model. The network model simulates each trip's movement between origin and destination and then generates O-D travel times that are fed back to the activity-travel model. The bootstrapping procedure iteratively continues between the two model components until convergence is achieved.

For the base year simulation, first, a synthetic population generator generates synthetic population in the region based on sample and marginal data from American Community Survey (U.S. Census Bureau, 2014). The O-D travel times from the bootstrapping procedure are fed into a land use model which simulates the longer-term location choices of households, persons, firms, retail, and real estate developers based on

the current network conditions by time of day. Using results from land use model and network model (O-D travel times), an activity travel model micro simulates the activity-travel engagement decisions at the level of each individual in the synthetic population (activity type choice, activity duration, and activity destination models are run). The generated activity-travel information (travel start time, activity duration, activity type, mode type used to pursue the activity, and destination of the activity) from the activity-travel demand model at the individual level is fed into a dynamic traffic assignment model. The network model routes travelers and simulates the trip movement every six seconds until the traveler reaches his/her destination. The dynamic traffic assignment model passes arrival information back to activity-travel demand model. This process continues from start of the day (minute '0') to end of the day (minute '1440'), where the information exchange between the model systems occurs at a temporal resolution defined by the user (say every minute). One run from 0-1440 minutes constitutes a complete iteration of the integrated model system. This iterative process continues until convergences is achieved both on the demand and supply sides of the model system. The activity-travel demand model is integrated with the dynamic traffic assignment model using a tight coupling framework. This framework is discussed in detail in the following sections.

For a future year, the synthetic population generator provides the future year synthetic population to simulate activity-travel patterns and traffic flows in the region. The land use model uses the converged base-year network conditions (O-D travel times) from the previous iteration to simulate the location choices of households, persons, land use development patterns, and other real-estate market processes (rents, prices) for the

future year. The converged base-year network conditions are fed into the activity-travel demand model to simulate activity-travel engagement process (for the first iteration). The iterative process between activity-travel demand and the dynamic traffic assignment models is run in a similar fashion as described above.
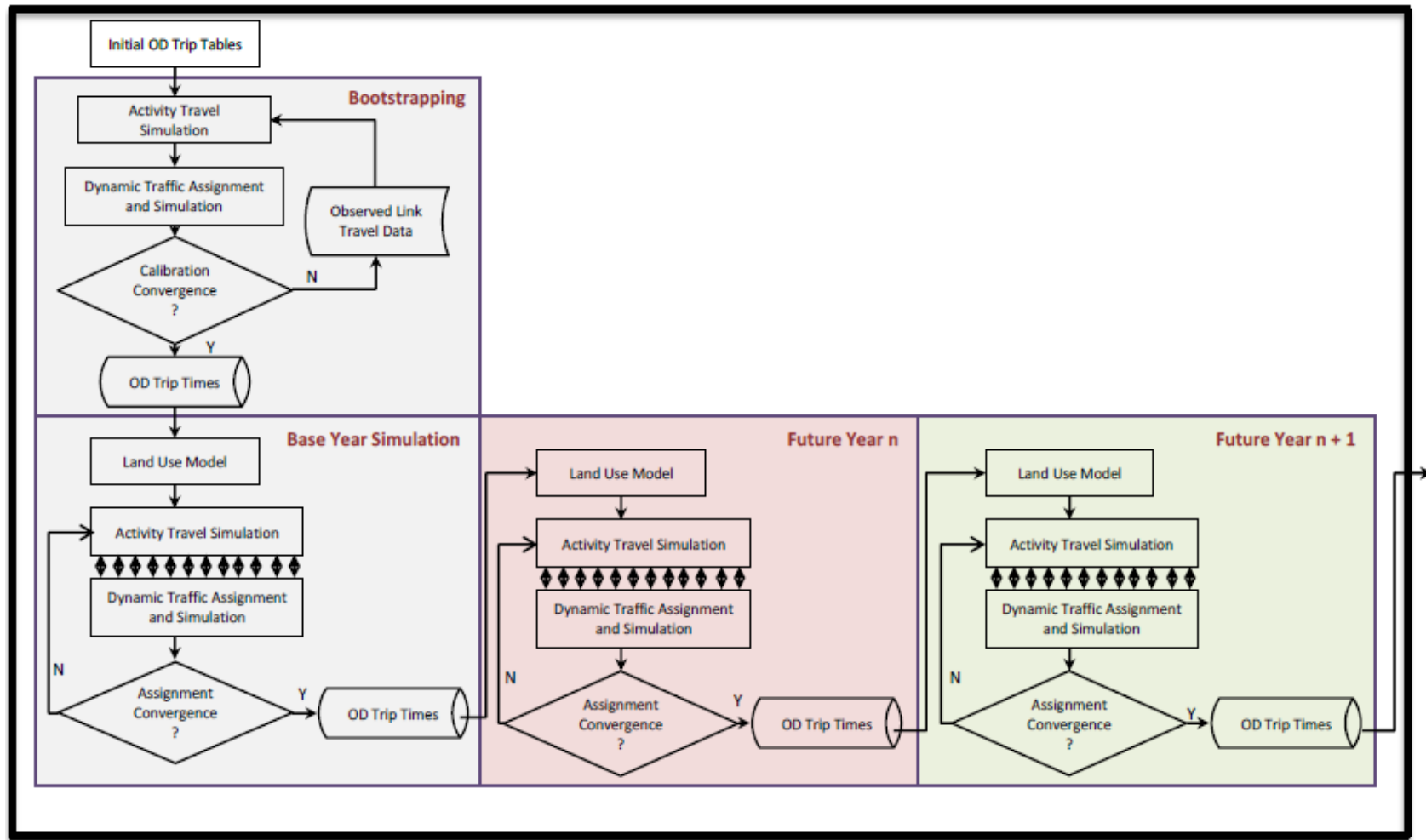
*Figure 1.* Framework of the integrated model of the urban system developed by Pendyala et al. (2012).

**Design Considerations in SimTRAVEL**

In the development and implementation of the integrated model system (SimTRAVEL), some important issues were identified. Some of these issues were addressed by previous research efforts in the area and some others were handled during development of SimTRAVEL. The SimTRAVEL framework addresses some of these issues by either simplifying assumptions or ignoring some instances. Table 1 presents the specific model design issues with the corresponding treatments implemented in SimTRAVEL (Konduri, 2012).

Table 1. *The Model Design Issues and the Treatments Employed in SimTRAVEL (Konduri, 2012)*

| Challenges | Treatment |
| --- | --- |
| Choice of Behavioral Unit | The basic units of analysis is at the level of individuals; the study simulates the activity-travel patterns of individuals while considering the various interactions (child dependency and allocation, joint activity engagement) |
| Identification of Choice Dimensions and Representation of Decision Hierarchies | The previous openAMOS identifies choice dimensions for various attributes of activity-travel engagement and establishes decision hierarchies. Konduri in 2012 describes the travel demand model system and enhancements over the implementation of AMOS that was developed by Kitamura et al. (2000) |
| Representation of Space | Traffic Analysis Zone (TAZ) is employed as the basic unit of space |
| Representation of Time | The temporal scales have been identified across choice dimensions. Feedback processes are used to accurately reflect the dependencies through all choice dimensions. The temporal resolution of 1 minute and 6 seconds are used to generate activity-travel patterns and to simulate traffic movements, respectively |
| Representation of Time-Dependent Networks | Network level-of-service (origin-destination pair travel times) conditions by time of day are used as skim matrices for 24 hourly periods in a day |

Table1. *The Model Design Issues and the Treatments Employed in SimTRAVEL (Konduri, 2012) (continued)*

| Challenges | Treatment |
|---|---|
| Representation of Stochasticity | Random utility based frameworks account for stochasticity and appropriate modeling methodologies are used to model various choice dimensions |
| Representation of Activity Types | SimTRAVEL considers for even in-home activity engagement patterns as well as a series of out-of-home activity types (including work, school, personal business, shopping, eat meal, social, sports and recreation, other, pickup, drop-off) to simulate the full range of activities that people engage through a day |
| Feedback Processes: Behavioral and Computational | Feedback processes are used to consider for behavioral and computational household interaction across components of the urban system |
| Model Calibration, Validation and Sensitivity Analysis | 5% synthetic population sample was used to perform model calibration by taking to replicate weighted survey distributions (NHTS in 2009). Validation was checked by how much the results obtained from full population runs replicate observed activity-travel characteristics from the survey sample. Replication was executed by comparing a series of activity-travel engagement attributes obtained from full population runs with observed weighted survey distributions, although it was limited to travel demand characteristics. |
| Software Architecture | Python for openAMOS and UrbanSim, and C/C++ programming language for MALTA are employed in component model system implementations |
| Data Structures | OpenAMOS uses PostgreSQL that is Relational Database Management System (RDBMS) for data storage, UrbanSim utilizes a native data format and MALTA employs flat file formats to manage data |
| Computational Issues | The activity-travel demand model in SimTRAVEL uses a hybrid approach in which a matrix concept is employed wherein each individual row corresponds to an agent and the computations proceed by using matrix capabilities. The hybrid approach do not involve rules/heuristics for choice dimensions but generating the choice for one agent at a time |

**Model Components Used in SimTRAVEL**

This section describes the implementation of component model systems that are employed in SimTRAVEL. It is composed of synthetic population generator, land-use micro-simulator, activity-based demand model, and dynamic traffic assignment simulator.

Synthetic population generator dubbed PopGen (Population Generator) was employed to generate synthetic population for the target region which goes in as input to SimTRAVEL (Ye et al., 2009). SimTRAVEL adopts a land use micro-simulator named UrbanSim (Wadell, 2002) to simulate the location choices of households, persons, businesses and real-estate agents. Activity-travel demand model (openAMOS) simulates activity-travel patterns and generates trip information. PopGen is described at a greater detail in the next chapter. The next section presents a detailed description of the land use micro-simulator used in SimTRAVEL.

**Land use model.** Residential, work, business, and/or employment location significantly impact activity-travel decisions (Waddell et al., 2003). The integrated model system includes a land-use model to accurately predict activity-travel patterns for each individual. Land use choices are provided by running the land use micro-simulation model (UrbanSim) which simulates the long term location choices of households, persons, firms and real estate developers (Waddell, 2002; Waddell et al., 2003). The land use micro-simulation model employed in SimTRAVEL uses network level of service and accessibility measures to predict the location choice decision of individuals, businesses and developers. Since the general assumption in land use model systems is that current network level of service and accessibility measures affect next year's location choice decisions, this model system uses the information of the previous year's network

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conditions to simulate the long term location choice decisions. These location choices then effect the activity-travel pattern decisions and route choices on network in the same year. Converged network level of service and accessibility measures from integrated activity-travel demand and supply model system are used again for subsequent year's land use simulation. This routine continues until the system reaches a preset horizon year.

In the integrated model system, there are no feedbacks from the traffic assignment model system to the land use micro-simulation model system because activity-travel and traffic assignment decisions are regarded as shorter term decisions but land use choices considered as longer term choices. Land use model simulation for a base year employs network level of service and accessibility measures provided by a traditional four-step model.

**Dynamic traffic assignment simulator.** Multi-Resolution Assignment and Loading of Traffic Activities (MALTA) was used in SimTRAVEL as a dynamic traffic assignment (DTA) model to assign trips generated from activity-travel demand model on networks and simulate movement of each trip through assigned links until the trip reaches its destination. MALTA, comprises of Anisotropic Mesoscopic Simulation (AMS), partitioning scheme and auto load balance, time-dependent hierarchical shortest path, and relative-gap based assignment algorithm (Chiu and Hickman, 2010). The two key concepts underlying the AMS framework are: (1) a vehicle's prevailing speed is affected only by the vehicles before it at any time and (2) the influence of traffic downstream on a vehicle decreases with increased distance (Tian and Chiu, 2011). MALTA employs a new Hierarchical Time Dependent Shortest Path (HTDSP) algorithm for the traffic assignment process (Gao and Chiu, 2011). The relative-gap based assignment algorithm

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is used to assign paths to the vehicles for each iteration. Figure 2 shows the framework implemented in MALTA. C++ is primarily used to develop MALTA. PostgreSQL database is used to store project and network information. The Model system is open-source and is available to everyone under the GNU GPL license agreement.
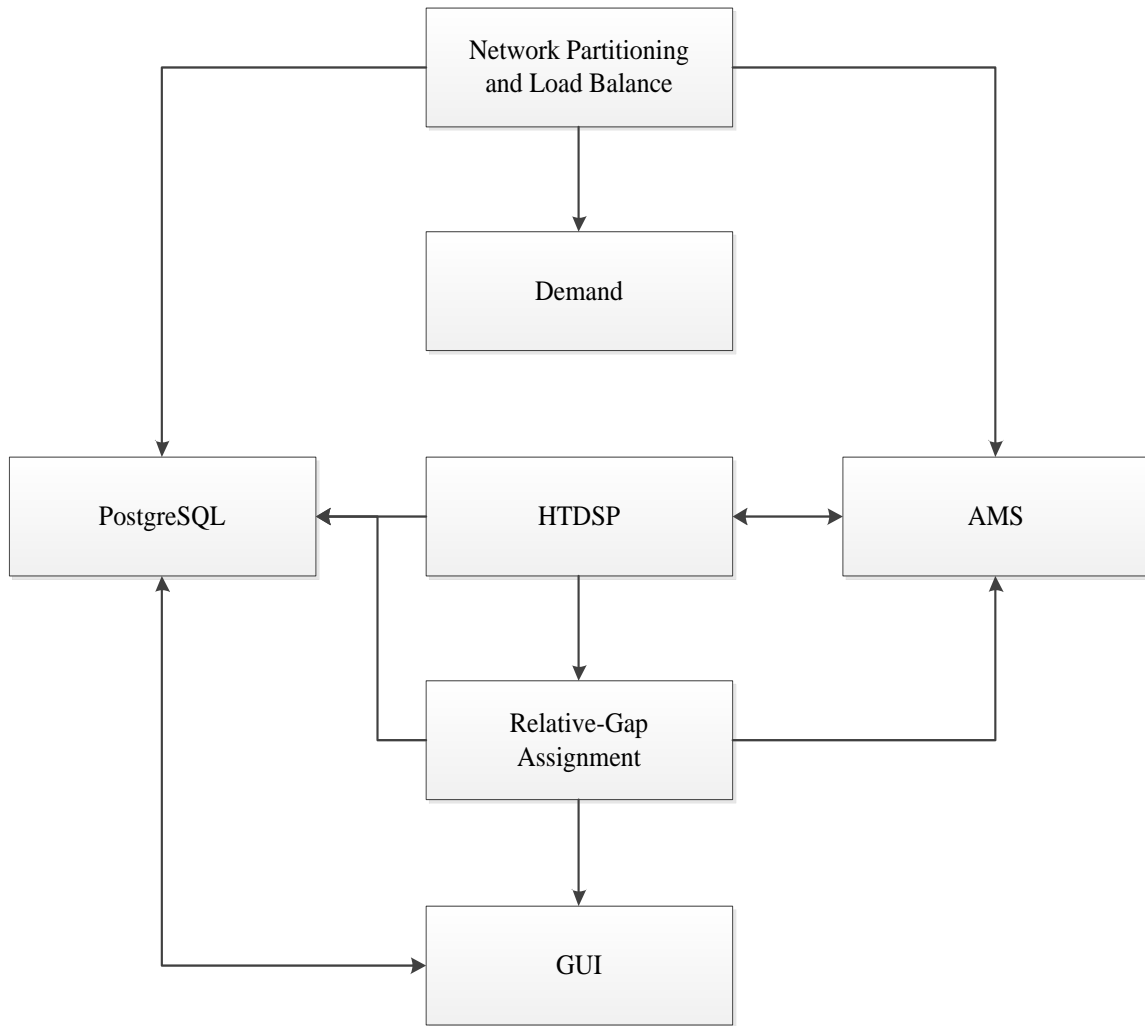


*Figure 2*. Framework of the multi-resolution assignment and loading of traffic activities (MALTA).

**Open activity mobility simulator (openAMOS).** This section presents an activity-based travel demand model system called as Open Activity Mobility Simulator (openAMOS). Kitamura et al. (2000) pioneered the development of an activity-based

travel demand model system called Activity Mobility Simulator (AMOS). Pendyala et al. (2005) enhanced AMOS to simulate activity-travel patterns for each individual along the time-of-day axis. openAMOS was further upgraded by Pendyala et al. (2012) following legacy implementation of AMOS with several functionalities capable of handling a variety of activity-travel engagement behaviors and constraints. As openAMOS is a key component in the current study, the following two sub-sections describe AMOS and openAMOS in detail. In the first sub-section describes the implementation of AMOS. The second sub-section illustrates the functionalities added in the open-source travel demand model system (openAMOS) over and above AMOS.

*Activity Mobility Simulator: AMOS.* There are two primary components in AMOS: Household Attributes Generation System (HAGS) and Prism-Constrained Activity Travel Simulator (PCATS). Figure 3 shows the entire framework of AMOS. HAGS is tasked with generating synthetic population and constructing fixed activity skeletons. At the beginning of simulation, AMOS generates synthetic population with household and person level attributes by using a regional travel survey to match known distributions for variables of interest. In the next step, morning and evening sojourns at home, work episodes for workers and school episodes for students are generated using synthetic population, zonal socio-economic data, and network level-of-service data for all individuals (as fixed activity skeletons). The HAGS includes work and school location models that identify the spatial locations of the mandatory activities simulated for all workers and students. In the final step, non-mandatory activities such as maintenance and discretionary activities will be identified in open time-space prisms (periods when individuals are not pursuing any fixed activities). The Prism-Constrained Activity-Travel

Simulator (PCATS) is employed to simulate the activity-travel engagement decisions within any open time-space prism. Figure 4 describes an overview of the PCATS that simulates non-mandatory activity engagement decisions for the synthetic population using information regarding zonal socio-economic data and network level-of-service data. PCATS contains activity type choice model, a joint destination-mode choice model and activity duration model to simulate the activity-travel engagement patterns. Before generating any activity-travel decision, a check is made to see if there is enough time in the individual's open time-space prism to pursue a non-mandatory activity. If an individual has enough time in the open prism, a series of models in PCATS simulate the activity-travel engagement decisions that include trip mode assignment and activity duration. PCATS then returns to a check to see whether there is enough time to pursue a second flexible activity or not. These two sub steps continue until there is no more time to engage in any more activities in the open prism. If there is no time in time-space prism, the individual is assigned into the next fixed activity location with a choice of trip mode. After completing simulation of activity-travel demand choices for the synthetic population, the output processor generates origin-destination (OD) matrices by mode, trip purpose, and time of day by aggregating the activity-travel records from PCATS. These matrices are presented in two ways: output reports and GIS visualization (Figure 3). However, PCATS might violate time-space prism constraints as it does not house a comprehensive reconciliation module to make adjustments either to the flexible activity or the fixed activity skeleton.

While PCATS provides a behaviorally intuitive framework to determine activity-travel engagement decisions, it is not able to reflect household interaction and constraints

to which individuals are subjected while they are making these decisions. For example, if a dependent child is present in a household and the child has to attend after-school activities, the child needs an adult to chauffer him (pick-up and drop-off). Intra-household interactions should be considered while making such activity-travel engagement decisions. In addition, individuals may be subjected to vehicular constraints. For example, a household may have a vehicle that should be shared across multiple household members. If a member in the household that has multiple drivers but only one vehicle makes activity-travel demand decisions, the individual is subjected to a constraint as to whether the household vehicle is available or not before making the mode choice. Therefore, interactions and constraints must be considered during the process of simulating activity-travel engagement decisions in order to lead to provide accurate inferences in response to policy measures.
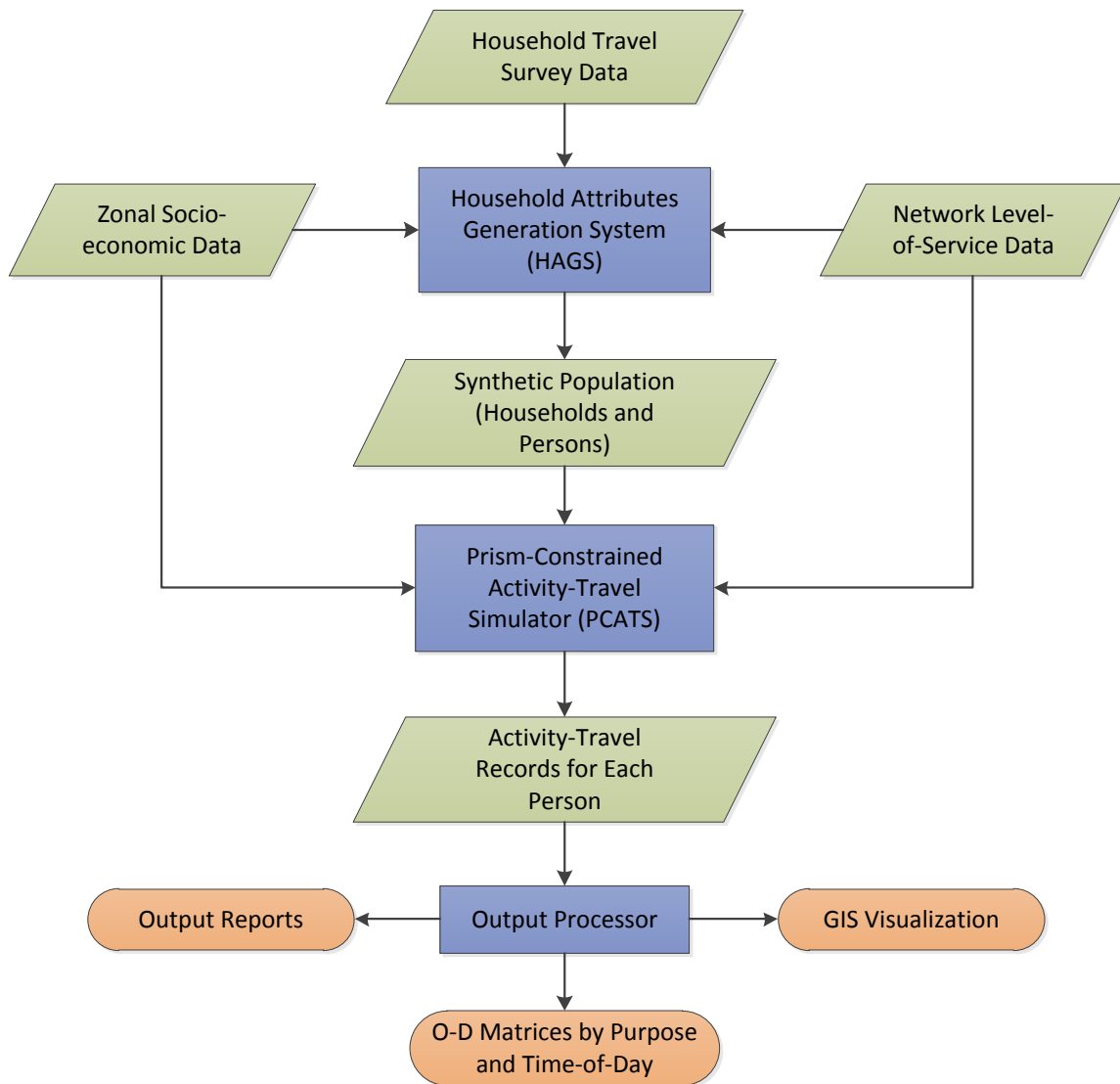
*Figure 3*. Framework of activity mobility simulator (Pendyala et al., 2005).
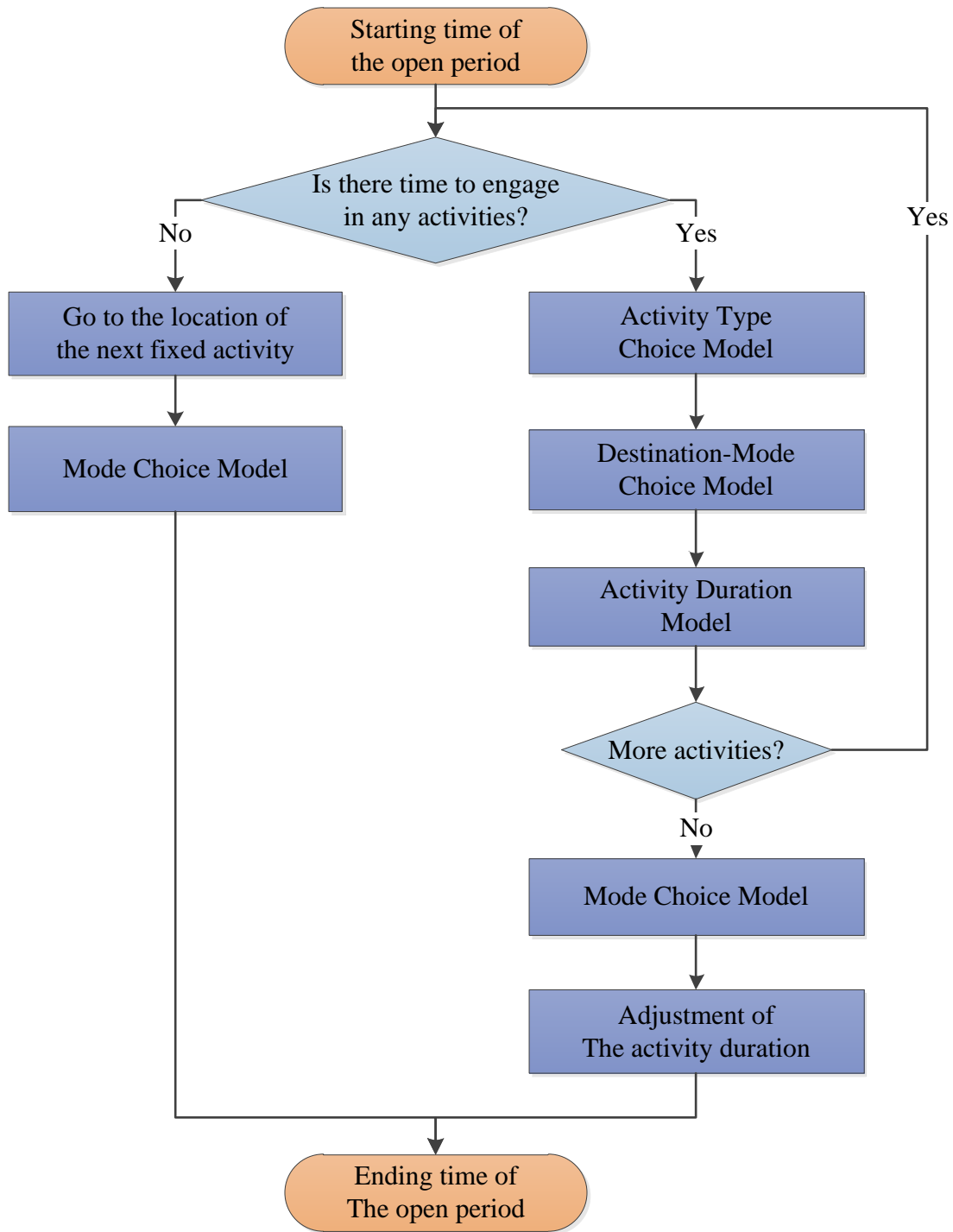
*Figure 4*. Framework of prism-constrained activity-travel simulator (Pendyala et al., 2005).

***Previous Version of the Open-Source Activity Mobility Simulator.*** The structure of openAMOS is similar to the framework of AMOS. This section describes the framework incorporated in openAMOS to simulate activity-travel engagement patterns and enhancements made over AMOS. First, synthetic population is generated for the desired simulation region using PopGen (Ye et al., 2009). The synthetic population is given as an input to openAMOS to first generate fixed activities (work and school activities) for all individuals. In the next step, non-mandatory activities (such as discretionary and maintenance activities) are assigned in open time-space prisms around fixed activity episodes. Two major enhancements are made in openAMOS over AMOS: (1) travel demand model system and (2) software infrastructure. The following subsections describe these improvements over the legacy version of AMOS.

The first enhancement in openAMOS is consideration of intra-household interactions in generating activity-travel patterns. The fact that activity-travel engagement decisions simulated by AMOS might potentially violate the time-space prism constraints is one of the primary motivations to develop an open-source activity mobility simulator (openAMOS) (Pendyala et al., 2012; Konduri, 2012). In order to model consistent activity-travel behavior on spatial and temporal scales, an activity-travel demand model should account for interactions among household members. Literature in the recent past had described the importance of intra-household interactions in shaping activity-travel engagement patterns (Zhang and Fujiwara, 2006; Bhat and Pendyala, 2005). openAMOS includes child dependency and allocation models to simulate child related intra-household interactions.

Child dependency and allocation models simulate the status of child dependency for activity-travel engagement decisions and allocate activities to both the child and the adult assigned to take care of the child. The models can be applied to mandatory activities like going-to-school as well as non-mandatory activities such as after-school activities. Children can independently engage in activities by taking school bus, public transportation, bike, or walk to go to activity destination. On the other hand, children may involve in activities with an assigned adult's care. In this case, child dependency and allocation models simulate either the assignment of an adult to a child and child's activity based on spatio-temporal availability of adults, or allocation of a child to the assigned adult's activities. openAMOS first simulates the child dependency process before proceeding to the dynamic activity-travel generation process. That is, joint activities are treated similar to fixed activities such as work or school episodes. If a dependent child could not to be assigned to any adult in the household, openAMOS assumes that a non-household member supervises the child.

The constraints created by child dependency are translated and accurately depicted in adult's activity-travel patterns. Children are separated in two types: pre-school students (age less than or equal to 4-years-old) and students (age between 5 and 17). Pre-school students must be assigned to an adult whereas students can make either independent or dependent activity-travel decisions. Figure 5 presents the framework of activity-travel engagement decisions for pre-school students implemented in openAMOS. Figure 6 describes the procedure of generating activity-travel patterns using a series of models for children whose age is between 5 and 17. More detailed explanation of child

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dependency and allocation models employed in openAMOS is available in Konduri et al.

(2012).
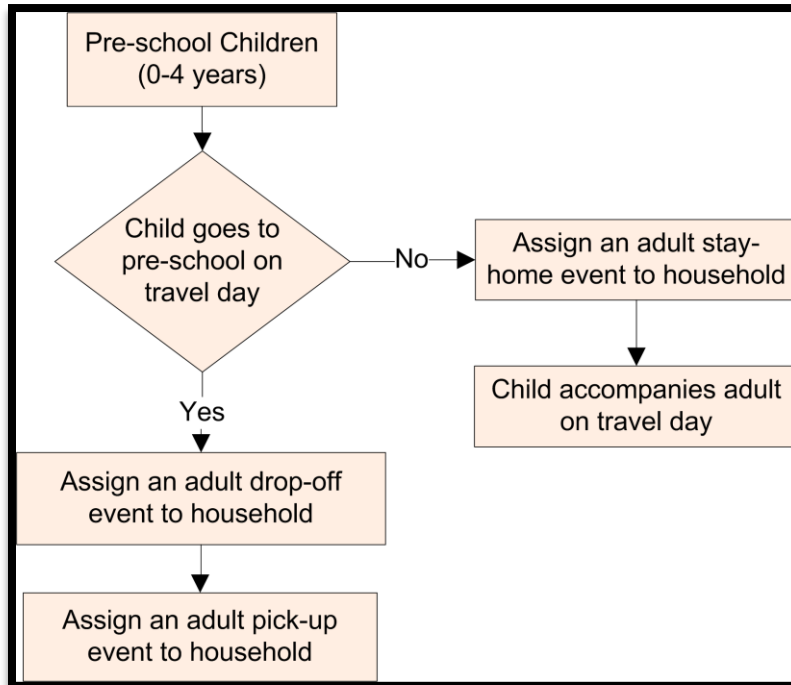


*Figure 5*. Framework for generating activity-travel patterns of children who are younger than 5 years old (Sana, 2010).
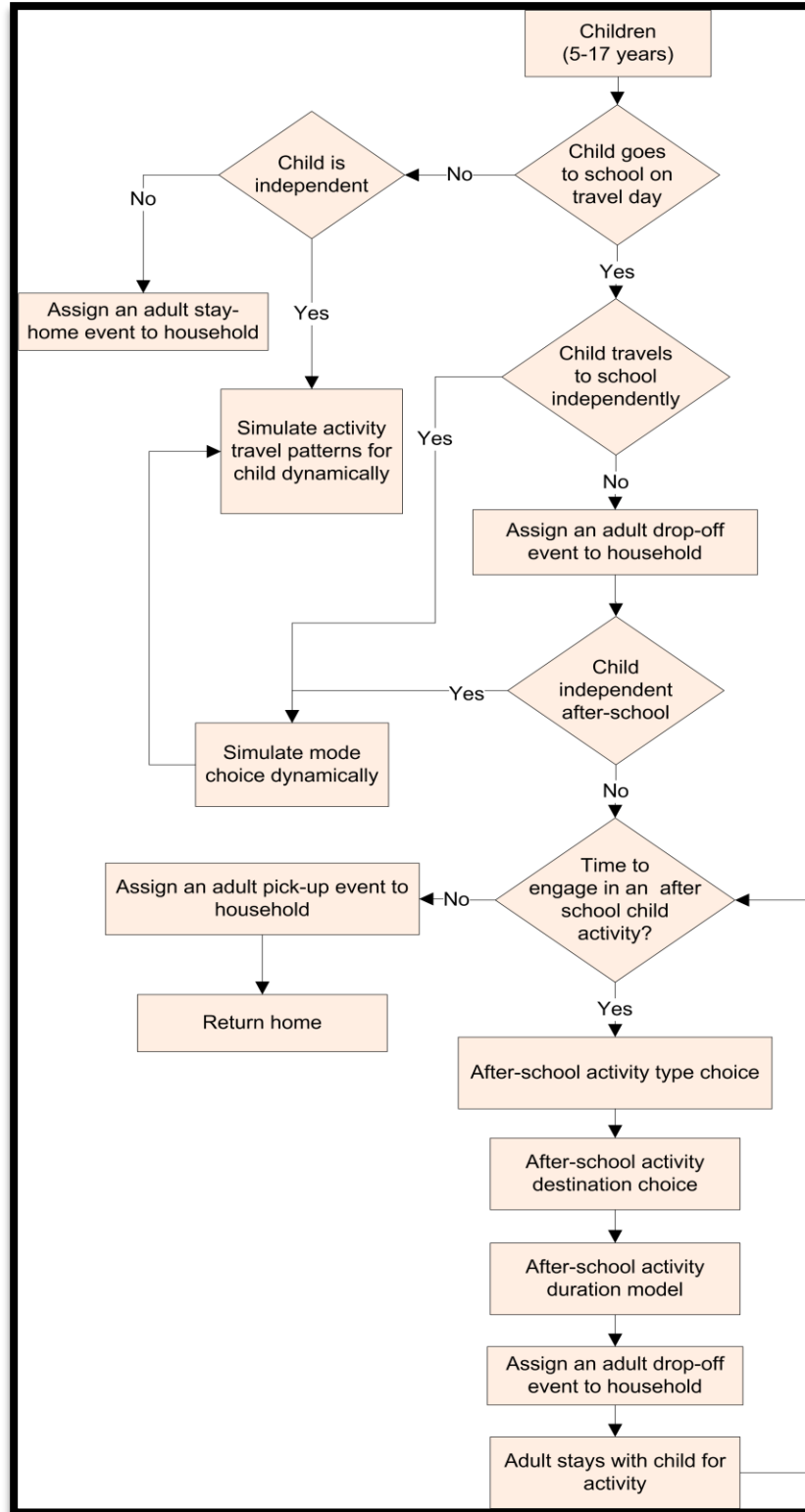
*Figure 6.* Framework for generating activity-travel patterns of children who are between 5 and 17 years old (Sana, 2010).

The second enhancement in openAMOS is on the side of software infrastructure to make the model system robust and flexible. openAMOS, developed using Python programming language, a database system, and XML (Extensible Markup Language) scripts. A number of Python libraries (e.g. Numpy, Scipy, PyTables, ArgParse, etc.) are used in building openAMOS. openAMOS is available online to general public under open-source licensing. Python language and additional libraries are also available to the public free of cost. A Relational Database Management System (RDBMS) called PostgreSQL is used to store and retrieve socio-economic and demographic data regarding household's and person's activity-travel records. In openAMOS, an XML based schematic is adopted for including the submodels (e.g. destination choice, mode choice, activity duration, etc.) that describe choice dimensions and for specifying the decision hierarchies. The model simulation engine parses the XML document to store the choice dimensions, decision hierarchies, specifications, and formulations in memory. This information is used to generate activity-travel demand by simulating the various choice dimensions. openAMOS users can easily modify the model specifications and decision hierarchies in the XML configuration files per their requirements.

However, previous version of openAMOS (Pendyala et al., 2012) is not flexible enough to consider multiple origin-destination travel times to simulate activity-travel engagement decisions. It only allows for using experienced network conditions (O-D travel time matrices by time-of-day) provided by a traffic assignment model from a previous iteration. In the real world, all travelers do not necessarily use experienced network conditions (travel times from their most recent travel to same place) as they make a destination choice and route choice to pursue their activities. For example, a

traveler, who checks network conditions using radio or internet before leaving from the current place to next place, uses prevailing network conditions to make a choice regarding destination, activity, or route rather than his experienced network condition from a previous journey to the same place.  Similarly, HOV lane travelers may also use different network conditions because travelers who drive through HOV lane tend to reach their destinations faster than the travelers who drive on regular lanes during peak hours. openAMOS cannot accurately simulate activity-travel engagement decisions without considering multiple network travel times (applicable to different types of travelers).

**Framework of Dynamic Time-Dependent Activity-Travel Simulation**

This section describes in detail, linkage between the activity-travel demand and dynamic traffic assignment models in SimTRAVEL.  Figure 7 describes the framework of dynamic time-dependent simulation between two key components in SimTRAVEL. Experienced network conditions (Origin-destination travel times) by time of day from previous iteration or bootstrapping run are fed into the activity-travel demand model. Activity-travel engagement decisions including activity type choice, destination choice, mode choice, and activity duration is simulated by the activity-travel demand model for all individuals using the experienced network conditions in the simulation region.  Trip information (origin, destination, activity to pursue, and trip mode) is exchanged at the temporal resolution of a minute between activity-based model and network assignment model. Each minute, information regarding all individuals who made the choice to pursue an activity in that minute (and start their journey at that specific minute), is passed to the dynamic traffic assignment model. The dynamic traffic assignment model in return sends back the trip information of all individuals who reached their destination in that minute.

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This process continues from 0 to 1,440 minutes (A day is 1,440 minutes). The temporal resolution of the integrated model system is set as one minute in SimTRAVEL to simulate travel demand and network supply. This can be changed in a straightforward manner (to every 5 or 10 minutes) by the user. The activity-based demand model runs simulation at the person level. As trips from the activity-based demand model are loaded, the dynamic traffic assignment model assigns vehicles on routes from origin to destination using a time-dependent shortest path algorithm and then simulates vehicle movements every 6 seconds until each vehicle arrives at its designated destination. Each individual vehicle is simulated using trip information from the demand model. Once vehicles are arrived at their destinations in a simulation minute, trip arrival times are fed back to the activity-based demand model. If a trip is arrives at the planned destination a few seconds before the minute, the trip information is saved until that exact minute and then trip arrival times are sent to the travel demand model.

After arriving at the planned destination, the individual stays at that place for a set duration (performing the activity) as determined by the activity-duration model. After completing the activity, individuals who have open time-space prism, plan for the next activity. The trips starting in the next minute are again sent to the DTA model. This iterative information exchange process continues between two components every minute until the end of the simulation day (1,440 minutes). After completing the micro-simulation run for a day, the dynamic traffic assignment model provides O-D travel time matrices by time of day and updates time-dependent shortest paths between origin-destination pairs. The O-D travel time matrices are then fed back to the activity-travel demand model to use as experienced network conditions for the next iteration. The

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updated time-dependent shortest paths are used in the traffic assignment model in the next iteration, as well.

Figure 7 shows the framework of the integrated urban model system with a tight coupling paradigm wherein two models communicate with each other by exchanging input-output data every minute. The following steps describe implementation of the integrated model system presented in Figure 7:

1. An individual, who is at origin O1, decides to go to destination D1 to engage in activity A1 using transportation mode M1 at time t=1 (minute).

2. Activity-travel demand model sends trip information of all trips starting at t=1. The trip information (origin, destination, mode, and vehicle attributes) is fed into dynamic traffic assignment model to assign routes and simulate vehicle movements until the trips reach their respective destinations.

3. Once trip information for all trips starting at time t=1 is received by the dynamic traffic assignment model, it searches time-dependent shortest path for the given O-D pairs based on link travel times from the previous iteration. In the current example, dynamic traffic assignment model assigns a route from O1 to D1 based on time-dependent shortest path and simulates individual's vehicle until the trip reaches its destination D1.

4. For the trips which start from the same origin at the same minute, the trip start times are evenly distributed across interval (between 1 and 2 minutes) to prevent lumpy loading. The individual in the example starts moving on the network at t=1 minute and 36 seconds although the trip information for the person is received at time t =1 minute (see Figure 7).

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5. The dynamic traffic assignment model simulates movement of the trip on the network.

6. The simulation of the trip is finished at time t=8 minutes 48 seconds and the individual arrived at the destination D1. However, the arrival information will not be sent to the travel demand model until t=9 minutes (trips are accumulated by the DTA model at one minute resolution). Arrival information for all trips reaching their destination between t=8 and t=9 minutes are sent to the travel demand model (at t=9).

7. The travel demand model receives arrival information. Travelers stay at the given destination for the simulated activity duration. In the current example, the individual stays for 4 minutes at the destination D1 performing activity A1.

8. Steps (1-7) are repeated to simulate activity-travel engagement decisions and vehicle movements on the network until the end of simulation day (1,440 minutes).

The approach described for integrating the activity-travel demand model with the dynamic traffic assignment model includes three behaviorally appealing features. First, the process of activity-travel engagement along a continuous time axis is more realistic than that of the integrated model system in a sequential paradigm. The subsequent activity is determined only after the previous trip and corresponding activity are completed. In SimTRAVEL, real-time conditions on the network are able to impact the individual's decision for scheduling the next activity. Second, using network conditions from a previous iteration in the activity-travel demand system mimics a day-to-day learning behavior exhibited by travelers in the real world. After completing the

simulation run, the dynamic traffic assignment provides average network conditions by time of day that are fed back into the activity-based model to be used for the next iteration (see Figure 7). Third, the dynamic traffic assignment system computes travel times based on time-dependent shortest paths. It considers the notion of dynamic traffic assignment and changing network conditions for obtaining more realistic travel times for all vehicle trips. That is, the traffic assignment model is able to estimate more realistic travel times for each link with due consideration given to time of day (peak and off-peak hours), and current network conditions (road works or traffic crashes).
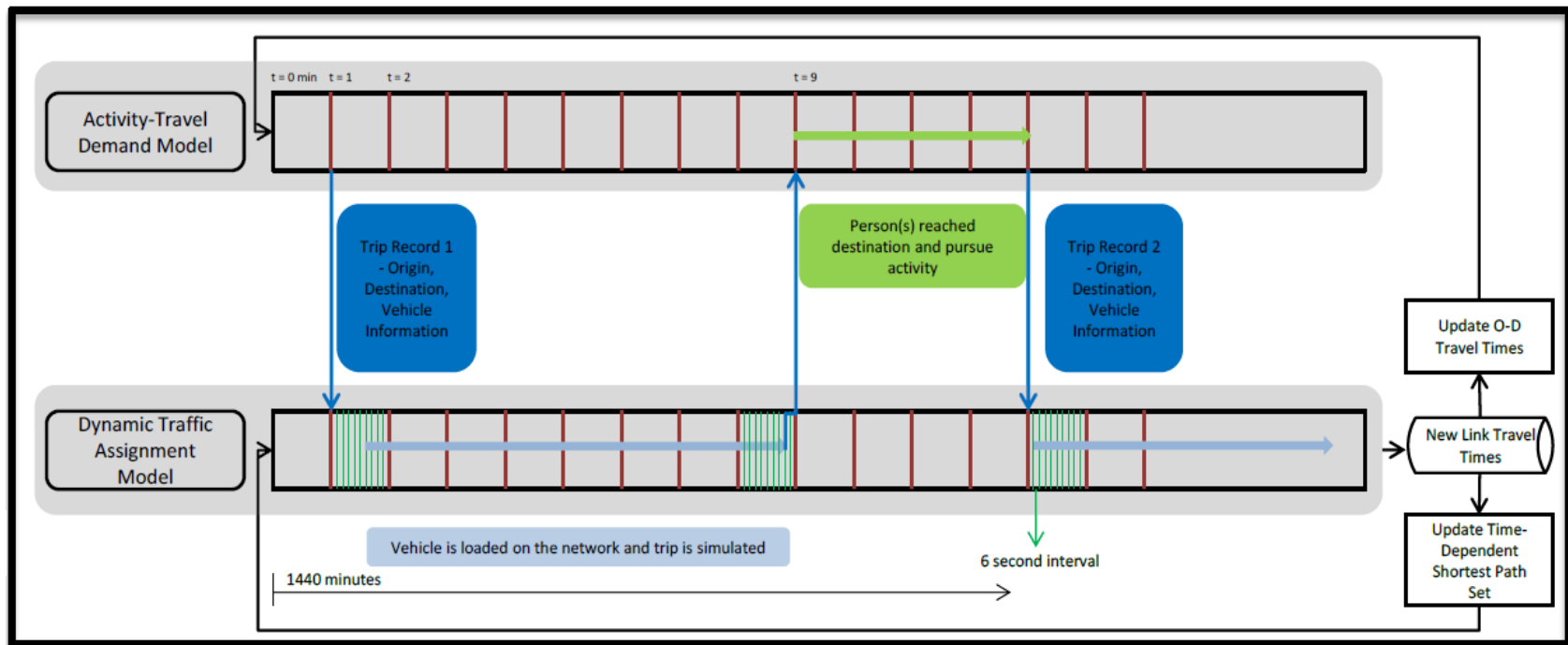
*Figure 7.* Framework for integrating activity-travel demand and dynamic traffic assignment models with dynamic time-dependent activity travel simulation (Konduri, 2012).

**Modeling Impacts of Traveler Information Provision in SimTRAVEL**

The integrated model system comprising the activity-based travel demand model and dynamic traffic assignment model (SimTRAVEL) has been revised by Konduri et al. (2013) to support the modeling of user information provision in the event of a network disruption. Integrated urban model systems developed in a sequential paradigm are not capable of modeling impacts of network disruptions considering user information provision as they lack least two key features to support such an effort. First, the actual arrival information should be fed into the activity-based demand system to simulate activity-travel engagement decisions along a continuous time axis. For example, if an individual arrives late at the destination as a result of an unplanned network delay event, this delay may impact the individual's subsequent activity-travel patterns. Without knowing actual arrival time, the activity-based model system cannot accurately capture interactions between subsequent activities and the corresponding travel for each individual. Second, the integrated model system should be able to use not only experience network conditions from the previous iteration but also prevailing network conditions (real-time network conditions). The integrated model system presented by Pendyala et al. (2012) lacks this key feature thereby limiting its capability to model the impacts of user information provision during network disruptions.

Konduri et al. (2013) present a revised integrated urban model system to this effect. The dynamic traffic assignment simulator (MALTA) is capable of providing prevailing network conditions to the activity-based demand system from the onset of network disruptions till the end of the disruption (in addition to experienced network conditions from the previous iteration). The traffic assignment model should use both

prevailing and experienced network conditions to simulate trip movements on the network based on the time-dependent shortest path algorithm. The traffic assignment model should use prevailing network conditions for the travelers who have access to user information systems and could potentially avoid the congestion area, in light of current network conditions. The experienced network conditions (from a previous iteration) should be used for the travelers who do not have access to information regarding current network conditions. The activity-based travel demand model is also modified to accommodate the capability of utilizing prevailing network conditions to model the activity-travel engagement decisions for the individuals who have access to user information systems such as 511 systems, radio, or real-time traffic data such as Google Maps. O-D travel times from the previous iteration are used by the activity-based demand model before the onset of network disruptions and after the network disruption is cleared. On the other hand, prevailing network conditions are utilized to simulate activity-travel engagement patterns during a network disruption event. That is, the activity-based demand is made capable of reflecting the impact of user information provision in light of a network disruption event. The process followed by the revised integrated urban model system for modeling user information provision in the event of network disruptions is described below:

1. Before the onset of an incident (unplanned network delay) at the simulation interval (t), the activity-based demand model uses the expected origin-destination travel times, which are converged for base year, for making activity-travel engagement decisions.

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2. As the simulation time (t) reaches the incident time ($a \leq t \leq b$), the dynamic traffic assignment model employs the existing travel times ($L_t$) on the network for the current and subsequent time interval instead of the expected link travel times ($L_{base}$). The existing travel times are estimated using link travel times simulated in the current iteration so that they are the best estimate for being used as prevailing network conditions after the onset of an incident.

3. The dynamic traffic assignment model generates the current network conditions as O-D matrices ($OD_t$) using the current travel times ($L_t$).

4. The O-D travel time matrices ($OD_t$) reflecting prevailing network conditions are passed to the activity-based demand model. The activity-based model uses prevailing travel times to simulate activity-travel engagement decisions for the subsequent time interval.

5. The activity-based demand model passes trips to the dynamic traffic assignment model. The trips are generated reflecting the current network conditions so that travelers may choose alternative destination to avoid the network delay or may leave early to their mandatory activity (e.g., work or school) as they expect longer travel times to arrive at their destinations.

6. The dynamic traffic assignment model uses prevailing network conditions ($L_t$) as the condition of the network for all subsequent time intervals to identify routes for the trips and then simulates vehicular movements through the network until they reach their destination.

7. The simulation time step is increased by 1 (t = t+1) and the process goes to step 2 if the simulation time is still before the incident is cleared (t <= b). Otherwise, it goes to step 8.

8. Once the incident is cleared (t > b), the dynamic traffic assignment model turns back to using the expected link travel times ($L_{base}$) to identify routes in the network and the activity-based demand model adopts corresponding O-D travel times ($OD_{base}$) from the previous iteration for simulating activity-travel engagement decisions.

The modified SimTRAVEL framework is shown in Figure 8 to allow modeling the impacts of user information provision in the event of network disruptions. In normal network conditions, the framework described in Figure 7 is applied to simulate activity-travel engagement patterns and route assignments. During network disruption conditions, the framework in Figure 8 is used to capture the effects of network delay under user information provision on activity-travel decision behaviors.

The modified SimTRAVEL framework with a tight coupling between two major components (activity-travel demand and dynamic traffic assignment models) is only capable of modeling the impacts of user information provision during network disruptions. User information provision may be classified into two types: pre-trip information and en-route choice. Pre-trip information may be defined as the (prevailing) network information received by travelers before embarking on a trip. This is akin to travelers checking the prevailing travel times on Google Maps before starting a trip in order to decide the (best) destination, transportation mode, or activity type to avoid potential delays before they leave to pursue their desired activities. In addition to pre-trip

information, individuals who use real-time traveler information systems (e.g., radio, in-vehicle navigation, or Google Maps for real-time traffic data using a smart phone) as they are making trip (en-route), can alter their destination/activity/route choice in response to prevailing network conditions. Transportation models should be able to capture the impacts from both pre-trip and en-route information provision particularly in case of network delay events as the available information can significantly alter activity-travel engagement patterns and route choices. The previous version of SimTRAVEL updated by Konduri et al. (2013) is not quite capable of handling both experienced and prevailing network conditions (and for different user information classes simultaneously). The integrated model system is not capable of exchanging real-time traveler information between two major components (openAMOS and MALTA). The current research enhances the integrated urban model system and imparts the flexibility to handle multiple network conditions (previous iteration and prevailing network conditions) as well as different user information classes (no information, pre-trip, en-route etc.). The next chapter discusses the enhancements made and the challenges encountered in attaining this research objective.
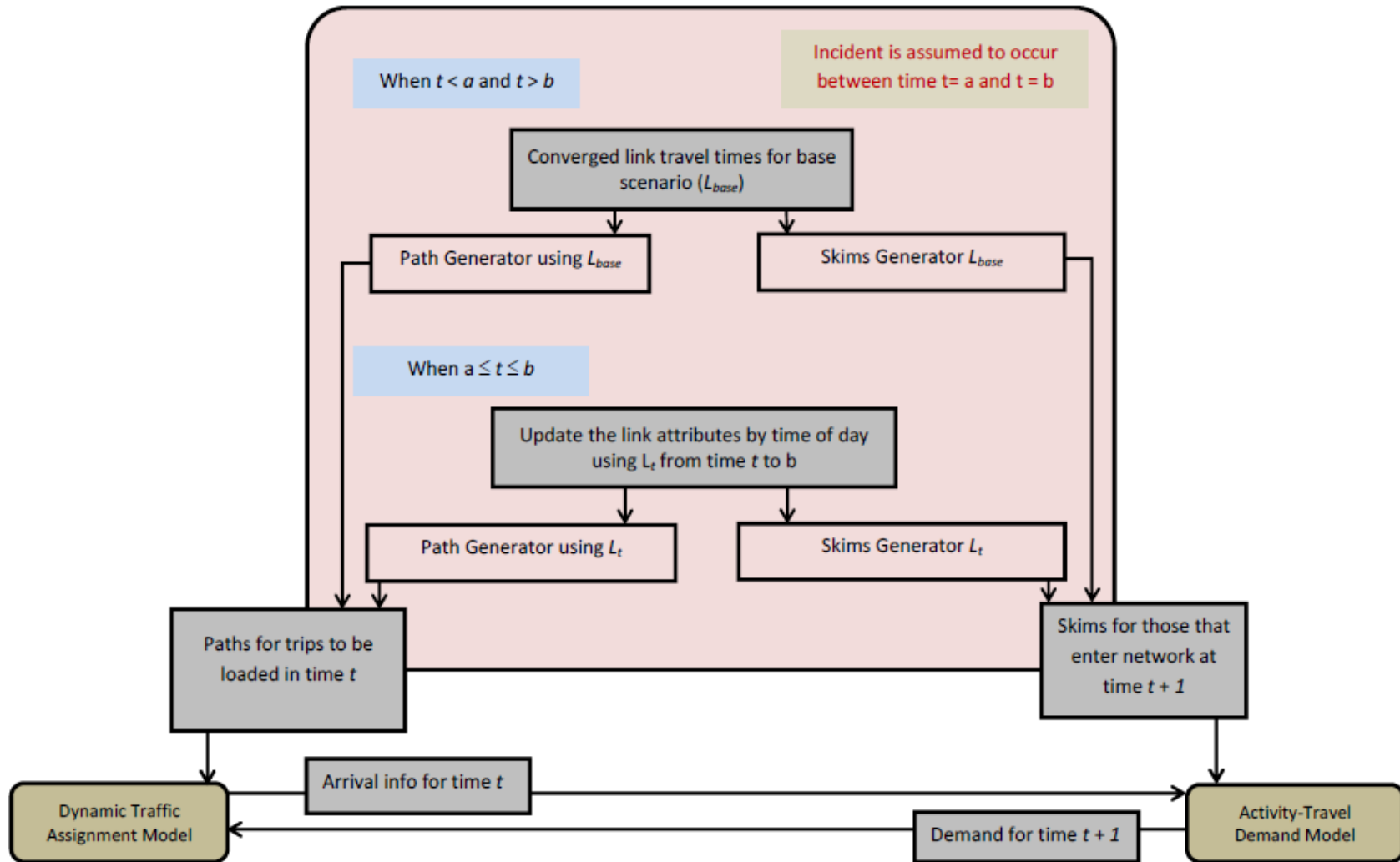
*Figure 8.* Modified framework in SimTRAVEL for modeling impacts of network disruptions under user information provision (Konduri, 2012).

CHAPTER 4

**Enhancements in the Tightly Integrated Model System**

In order to model the impacts of real-time traveler information provision, a tightly coupled integrated urban model system such as SimTRAVEL is relevant. This is because activity-travel demand models should be able to reflect prevailing network conditions while simulating activity-travel engagement patterns. In addition, a prototype of an integrated model system should be enhanced to fluently communicate between the travel demand model and the dynamic traffic assignment model to allow analysis about network delay events that concern advanced or real-time traveler information systems. For this reason, this research is motivated to enhance the existed SimTRAVEL to allow modeling of the impacts of real-time information provisions on activity-travel patterns and traffic flows on network.

This chapter describes how to enhance the integrated model system called SimTRAVEL. The first section provides an overview of the framework and enhancements of SimTRAVEL which are updated in this study. In the second section, components (synthetic population generator, activity-travel demand model, and dynamic traffic assignment model) of the enhanced integrated model system are described. This section is followed by an explanation of the linkage between activity-travel demand and dynamic traffic assignment models. The fourth section presents three incremental steps for integration between two key components in the enhanced SimTRAVEL for modeling real-time traveler information provision. The last section describes the bootstrapping procedure employed in this study to provide converged level of service on the network for main simulation runs.

**Overview of Framework and Enhancements in SimTRAVEL**

Figure 9 presents an overview of the integrated models of the urban system proposed by this study. Since this research is to upgrade the model system in SimTRAVEL developed by Pendyala et al. (2012) and Konduri et al. (2013), the framework of the integrated model system is very similar to that of the previous work. The framework of this integrated model system is separated into three terms: long, medium, and short. In long term simulation, a synthetic population, land-use, and household level vehicle ownership are provided. In the base year simulation, the first step is to generate a synthetic population for the simulation region using a synthetic population generator (PopGen 1.1). The location choice model (UrbanSim) then simulates the long term location choices of households, persons, firms and real estate developers. Using information from PopGen and UrbanSim, the activity-travel demand model simulation provides predicted vehicle ownership at the level of household. The demand model (openAMOS) also includes a model (probability distribution) of status of user information provisions for the entire synthetic population in the long term simulation. That is, each individual is assigned a traveler information status along with traveler information access levels.

In the medium term simulation, openAMOS constructs the skeletons of fixed activities along a continuous time axis for a simulation day. Fixed activities are work episodes for workers and school episodes for students. The module of child daily status and allocation in openAMOS identifies all children who are not able to independently pursue any activity episodes and allocates them to household/non-household members

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based on spatial and temporal availability. All child-related activities are generated and constructed in the skeletons of fixed activities.

In the short term simulation, activity-travel demand and dynamic traffic assignment models communicate at every minute. At each minute, openAMOS generates trips for each individual if he or she arrived at his or her destination and completed an activity and there is enough time for a new activity in the open time-space prism. DTALite sends arrival information to openAMOS at every minute. In addition to trip and arrival information, DTALite sends prevailing network conditions (origin-destination travel time matrices) at every $n$ minute. Then, openAMOS adopts prevailing traffic conditions (O-D pair travel time matrix) to simulate activity-travel engagement decisions with respect to the impacts of network disruptions under user information provisions. The activity-travel demand model should inform the level of traveler information access to the dynamic traffic model in addition to trip information. Therefore, the DTA is able to simulate en-route choices for the traveler who uses a real-time traveler information system to avoid network disruptions. The activity-travel demand model produces activity-travel schedules for each individual at the end of the simulation.

Enhancements in this research are summarized below:

- User information status: A series of models in openAMOS includes a model that predicts status of user information provision in three levels: no traveler information, pre-trip traveler information, and real-time traveler information

- Prevailing network conditions: The activity-travel demand model is able to use multiple types of skim data (Origin-Destination travel times) such as experienced, prevailing, and HOV network conditions.

- Communication between openAMOS and DTALite: Trip information that is sent to DTA includes traveler information status in addition to origin, destination, transportation mode, and activity type. DTALite sends arrival time information with current network conditions to openAMOS.

- Generalized travel time measure by zone: The activity-travel demand model (openAMOS) is enhanced to measure generalized travel time by link and zone.

Before the base year simulation, the process of the integrated urban model system begins with a base year bootstrapping procedure. Synthetic population generated by PopGen and land-use choice simulated by UrbanSim feed into the bootstrapping procedure as input data (Figure 1). A base year bootstrapping procedure generates the link travel times which vary by time of day and are used as input data for starting a simulation run of the integrated model system for the base year. Since it would require realistic network conditions in a main simulation run, the bootstrapping procedure is essential to set closed real world network conditions for the network before running an integrated model for the base year.
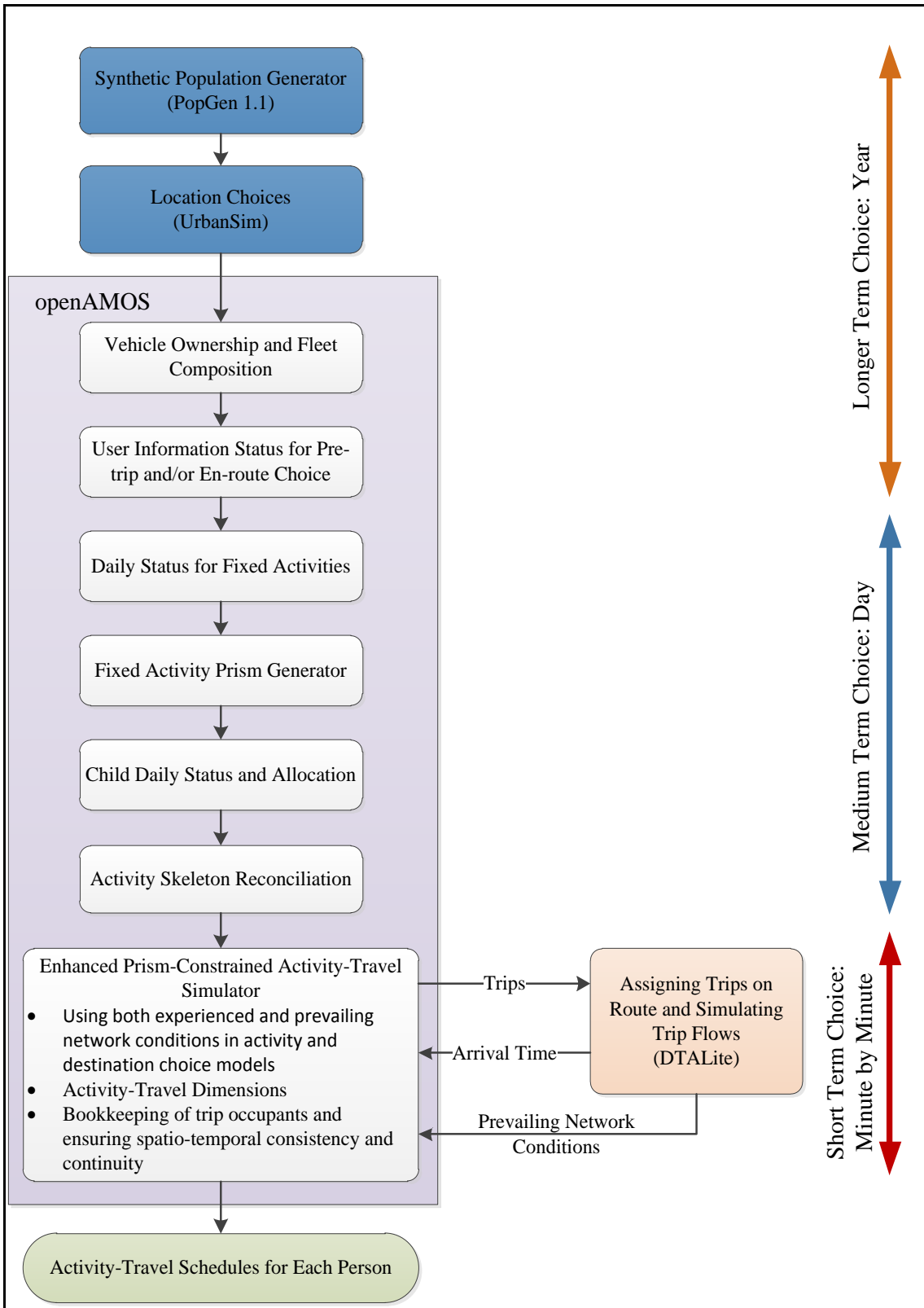
*Figure 9.* Flowchart that shows overview of SimTRAVEL enhanced in this research.

**Components of the Enhanced SimTRAVEL**

The integrated model system in this study consists of a synthetic population generator, land-use choice model, activity-based demand model, and traffic assignment model (see Figure 9). This section describes the synthetic population generator, activity-travel demand model, and traffic assignment model. The land-use model (UrbanSim) is adopted from the previous version of SimTRAVEL without change so that this section omits the description of UrbanSim.

**Synthetic population generator.** As micro-simulation model systems operate at the level of the individual travelers, synthetic population must be prepared for forecasting travel demand in a target region. Significant attributes of household and person characteristics are usually not available for entire population to calibrate, validate, and apply urban system modeling for an entire region. For this reason, a synthetic population instead of an actual population can be used to forecast travel demand at the level of the individuals. In the current research effort, Population Generator (PopGen) developed by the Transportation System Engineering group at Arizona State University is adopted to generate a synthetic population. PopGen uses disaggregate household and person information for a random sample of households, which are available from U.S. Census Bureau (e.g. Census 2000, or Public Use Microdata Sample), to create a synthetic population for an entire target region. Beckman et al. (1996) generated synthetic populations using the Iterative Proportional Fitting (IPF) from the PUMS. Arentze et al. (2007) introduced an improved method that uses relation matrices to convert distributions of persons to distributions of households to match both household-level and person-level distributions for all attributes of interest. However, neither of these methods can solve

the problem about mismatching person-level distribution when one creates a synthetic population. PopGen is capable of creating a synthetic population matching both household-level and person-level distributions of attributes of interest by using a heuristic iterative approach (Ye et al., 2009). Therefore, PopGen is adopted to generate a synthetic population with critical attributes at both the household level and person level for this research.

**Activity-based demand model: openAMOS.** The activity-based demand model simulates activity-travel patterns including activity choice, destination choice, and activity duration for all individuals for a whole day (1,440 minutes). The study adopts openAMOS (an open-source activity-based travel demand model system), which is developed by Pendyala et al. (2012), to generate activity-travel patterns. The openAMOS system is developed on the basis of AMOS (Activity-Mobility Simulator), which is developed by Kitamura et al. (2000) and implemented for the state of Florida (called FAMOS – Florida Activity-Mobility Simulator). However, AMOS may not reflect household interactions into activity-travel patterns and capture some activity-travel engagement constraints (Chapter 3 describes the shortcoming of AMOS). Pendyala et al. (2012) presented openAMOS to improve the various activity-travel engagement behaviors and constraints through the addition of a series of models: child dependency and allocation, intra-household activity-travel engagement interactions, and multi-modal trip generation. The activity-based demand model system is developed using Python and is available to the public online (Google Code) with the GNU GPL agreement.

Still, openAMOS has limitations for modeling the effects of both unplanned and planned network delay events under user information provision. First, a model for

predicting status of user information provision for all synthetic persons is omitted in openAMOS. Second, openAMOS is not able to handle multiple different types of skim data. Only experience from the previous iteration or prevailing network conditions from the current iteration could be used in openAMOS. Third, only one type of generalized travel time measure is available in the activity-based model. This research is motivated to address the limitations by improving openAMOS. It should be improved in both software (Python codes) and choice model systems (XML configuration documents) to simulate user information provisions under network disruptions on activity-travel engagement patterns. The following three sub-sections describe how to enhance openAMOS to allow various policy analyses.

*Status of user information provision.* The process of activity-travel engagement decisions may be different among travelers according to what information they are accustomed to use, what technology they use to obtain network condition information, where travelers are, and what traveler information they are able to obtain as happening network disruptions happen. Transportation modeling systems should be able to capture different processes of activity-travel engagement decisions within the synthetic population for realistically modeling the impacts of network disruptions under user information provisions. In this research, a model that predicts the status of user information provision for each individual is added into the activity-based model (openAMOS) to capture different processes of activity-travel engagement decisions according to level of access to network condition information. This study assumes there are three different levels of access to traveler information. First, there are individuals who only use their network condition experiences to make activity-travel engagement

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decisions. In this case, individuals would determine their activity, destination, activity duration, and transportation mode based on their experience about network conditions. Second, individuals may use current network conditions to make decisions of travel before they embark on a trip (pre-trip). That is, the current network conditions before travelers leave the origin location are used for decisions of activity-travel behaviors. Third, individuals, who are able to reach to real-time traveler information through radio, in-vehicle navigation, or Google Maps via smart phone may change their route, destination, or skip the activity altogether. For this reason, openAMOS separates synthetic populations into three groups: no traveler information, pre-trip traveler information, and en-route traveler information provisions (see Table 2).

There is a configuration document (Extensible Markup Language) used in openAMOS to simulate activity-travel patterns. The configuration document that represents choice dimensions and specifies the decision hierarchies is updated by adding a choice model of traveler information provision status. User information status for the entire synthetic population is determined at the level of household using a probability distribution analysis. The same status of user information provision is assigned to all individuals in a household. After all, the enhanced openAMOS shines a light on the potential to capture the different decision process for activity-travel patterns while reflecting the impacts of real-time traveler information as network delay events because it is capable of specifying levels of access to user information provision for each individual.

Table 2. *Type of User Information Provision Used in openAMOS*

| Types of Traveler Information Provision | Description |
|---|---|
| No traveler information provision | Travelers are assumed to only use their historical experience about network conditions to make activity-travel engagement decisions |
| Pre-trip traveler information provision | Travelers are assumed to check prevailing network conditions before leaving their current place to pursue their next activity at different place |
| En-route traveler information provision | Travelers are able to check prevailing network conditions in their vehicle during driving and switch to an alternative route to escape network congestions |

*Various skim data in openAMOS.* In the previous framework of SimTRAVEL for integrating models with dynamic time-dependent activity travel simulation, origin-destination travel times (experience of network conditions) from the traffic assignment model were fed into the travel demand model from iteration to iteration (see Figure 7). As individuals make activity-travel engagement decisions and adjustments based on their travel experience, the travel demand model captures the learning behavior using network conditions from the O-D travel times of the previous iteration. However, in the real transportation world, individuals may recognize different experienced network conditions. For example, highway systems in metropolitan areas includes High Occupancy Vehicle (HOV) lanes during at least peak hours. During peak hours, the travelers with passenger(s) may drive their vehicle through HOV lanes faster than the travelers who are with no passengers in general purpose lanes. The experienced network conditions of travelers with HOV will therefore be different from that of drivers who use general

purpose lanes. For this reason, integrated model system may need to support various network conditions to realistically simulate activity-travel engagement decisions along with various travelers' characteristics. However, the previous openAMOS is able to feed only one type of O-D travel times (network conditions) as the learning behavior to simulate activity-travel patterns.

In this research, openAMOS is improved to use various network conditions for realistic simulation of activity-travel engagement decisions by including more than a single type of network conditions in addition to experienced network conditions from the previous iteration. First, the updated openAMOS is capable of using HOV network conditions. The dynamic traffic assignment model (called DTALite) employed in this integrated model system is capable of producing results of network conditions by HOV and SOV lanes at the end of each iteration. The two types of O-D travel times are fed into openAMOS. It then uses HOV lane network conditions for trips with passenger(s) and network conditions of SOV for trips with no passengers for simulating activity-travel engagement patterns. Second, prevailing network conditions are used to simulate activity-travel engagement decision for the individuals who are able to reach pre-trip information through communication technologies (e.g., 511 systems, radio, and real-time traffic data like Google Maps). Many individuals are able to reach prevailing network conditions using real-time communication technologies. In order to model more realistic simulation activity-travel patterns, openAMOS was enhanced to reflect prevailing network conditions on activity-travel engagement decisions in this study. Figure 10 describes the flow of different types of O-D travel times from a dynamic traffic assignment model to travel demand model (openAMOS) adopted in the enhanced

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activity-based model. A dynamic traffic assignment model (DTALite) sends information of real-time network conditions to the travel demand model (openAMOS) at every 15 minute time interval until the end of the simulation day (1,440 minutes). Thus, the enhanced openAMOS is able to use prevailing network conditions for individuals who are able to check travel information prior to embarking on a trip as well as to learn network conditions from the previous iteration for individuals who use past experience only (see Figure 10). Therefore, policy analysis for advanced or real-time traveler information is possible through the improved openAMOS in this study by running the integrated model with DTALite.
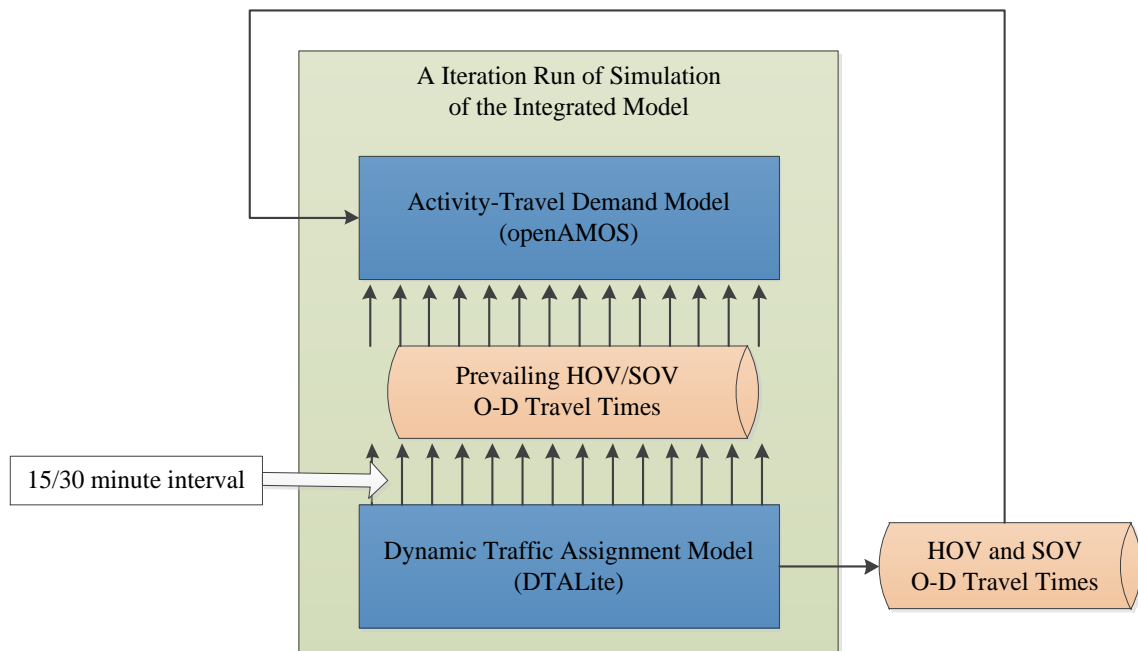


*Figure 10.* Feedback of various types of O-D travel times from a dynamic traffic assignment.

*Enhancement for generalized travel time measure in openAMOS.* With rising concerns about traffic congestion, energy sustainability, and greenhouse gas emissions, the implementation of pricing policies and strategies is employed in many different places around world to manage travel demand and better distribute traffic over time and space, thus mitigating congestion on the network (Konduri et al., 2013). Pricing policies are also adopted with a view toward revenue generation mechanisms that generally raise financial resources to invest in the transport infrastructure (Hensher and Puckett, 2007; Kockelman and Kalmanje, 2005). The rising interest in implementation of pricing policies and strategies leads researchers to focus on modeling the impact of pricing policies on travel demand and network dynamics in a behaviorally realistic way. For example, Zhang et al. (2011) develop frameworks and operational model systems to forecast the impacts of pricing strategies. Vovsha and Bradley (2006) also developed a tour-based travel demand model that is capable of reflecting the impacts of pricing policies through the use of logsum terms.

The activity-based model (openAMOS) uses a concept of generalized travel time to reflect the impacts of pricing policy on activity-travel pattern choices. Both actual and generalized travel time can be used in openAMOS to simulate activity-travel engagement patterns. As no pricing policy is considered, the actual travel time measure is used to simulate the feasible destination choice set if there is enough time to pursue an additional activity in open time-space prism (between fixed activities). In a pricing policy analysis, the generalized travel time that includes the time equivalent of cost (based on value of time) is used to simulate the actual destination choice set for an activity. Under the influence of the generalized travel time to activity-travel choice, individuals may choose

different activity-travel behaviors although they are given the same activity with the same open prism. This is because individuals may have different values of time. On the network side, the actual arrival time to the destination is determined by not generalized travel time but actual network travel time that accurately reflects vehicular movements on the network.

To obtain the generalized travel time measure, the first step is to derive values of time that are based on household income (household wage rate, $\omega_h$, in dollars per minute) in openAMOS. Because household income exists not at the person level but at the household level, openAMOS assumes that persons in the household share the same values of time. The household wage rate, $\omega_h$, for household $h$ is:

$$\omega_h (\$/min) = Annual\ Income_h\ (\$) \times \frac{1}{250(days)} \times \frac{1}{6(hr/day)} \times \frac{1}{60(min/hr)} \quad (1)$$

The value of time is calculated in two ways: zero workers in the household and greater than zero workers in the household. In the case of greater than zero workers in the household, the value of time, $\tau_i^h$, for an individual $i$ in a household $h$ with number of workers ($n_w^h > 0$) is:

$$\tau_i^h (\$/min) = \frac{1}{3} \times \omega_h \times \frac{1}{n_w^h} \quad (2)$$

In the case of zero workers in the household, the value of time, $\tau_i^h$, for an individual $i$ in a household $h$ with number of adults ($n_a^h > 0$) is:

$$\tau_i^h (\$/min) = \frac{1}{2} \times \omega_h \times \frac{1}{n_a^h} \quad (3)$$

The second step is to compute the time equivalent of cost, $v_i^h$, for an individual $i$ in a household $h$ with a pricing policy equivalent to a fee ($q$ dollars per mile of travel) as following:

$$v_i^h(min/mile) = \frac{1}{\tau_i^h(\$/min)} \times q(\$/mile) \tag{4}$$

Finally, the generalized travel time measure, $\gamma_i^h$, for an individual $i$ in a household h with a distance ($\delta$) between origin and destination is calculated as following:

$$\gamma_i^h(min) = t(min) + v_i^h(min/mile) \times \delta(mile) \tag{5}$$

The previous version of openAMOS is capable of reflecting pricing effects only based on travel distance of activity-travel choice decisions. However, travelers may consider pricing effects by particular regions as they choose a destination to pursue an activity. For example, drivers should generally pay for parking in downtown areas if they are pursuing an activity in the region where drivers are forced to pay. In this case, a parking penalty should be calculated not by travel distance but by region in which drivers engage in activities, because parking prices are equally applied to all drivers who park their vehicle in parking payment areas. Thus, openAMOS additionally employs pricing effects by zones in the calculation of a generalized travel time measure. As an individual $i$ in a household $h$ chooses a destination ($q$ dollars to travel to the destination) to pursue their desired activity, this time equivalent of cost may be derived as:

$$v_i^h(min) = \frac{1}{\tau_i^h(\$/min)} \times q(\$) \tag{6}$$

The value of time, $\tau_i^h$, in the equation (6) is computed by either the equation (2) or (3) based on the number of workers in the household. The generalized travel time for an individual $i$ in a household $h$ at the zonal level is:

$$\gamma_i^h(min) = t(min) + v_i^h(min) \tag{7}$$

After all, a generalized travel time can be computed using equation (6) and (7) at the zonal level, as well. If an individual $i$ in a household $h$ chooses a destination where there is no penalty to travel, the generalized travel time is equal to actual network travel time to the destination because $v_i^h(min)$ from the equation (7) is zero for the individual. In this research, openAMOS is enhanced to be capable of conducting various pricing policy analyses, both travel distance base and zone base.

**Dynamic traffic assignment model: DTALite.** To assign trips from the activity-based demand model and simulate trip movement from origin to destination, a traffic assignment model is essential in an integrated model system. The updated SimTRAVEL in this study adopts Light-weight Dynamic Traffic Assignment Engine (DTALite) developed by Zhou et al. (2010). DTALite uses time-dependent origin-destination demand matrices to assign vehicles to different paths on the basis of dynamic link travel time. The time-dependent shortest path model in DTALite uses link travel times for path selection through a certain route choice. The previous version of the integrated model system called SimTRAVEL employed MALTA (Multi-Resolution Assignment and Loading of Traffic Activities) as a dynamic traffic assignment model. However, MALTA is limited in its ability to accurately simulate trip assignments on networks and vehicle movements through links before arriving under conditions of different types of traveler information strategies (i.e. historical information, pre-trip, and en-route choice).

The current version of DTALite is already capable of analysis affecting agents' route choices or activity-travel decision making behaviors with different types of traveler information strategies. Therefore, DTALite is used in the enhanced SimTRAVEL as a key component. DTALite is developed by Visual C++ and is open-source to be available to the public under the GNU GPL agreement.

**Linkage between openAMOS and DTALite**

This integrated model system is made up of two key components: a travel demand model (openAMOS) and a dynamic traffic assignment model (DTALite). The previous SimTRAVEL adopted an additional C++ library to call Python code as an object in the dynamic traffic assignment simulator (MALTA). Thus, MALTA calls Python objects of openAMOS to run an activity-travel demand simulation after finishing simulation of traffic assignments and movements at every simulation interval (SimTRAVEL uses a 1-minute time interval as temporal resolution of micro-simulation). However, two simulators should be independently treated to maintain or update software. There are at least three reasons. First, developers may find it difficult to check codes of computer languages that are developed by other developers because the developers of the traffic assignment model are different from the developers of travel demand model. Second, communication between developers is needed more often and it is difficult for the developers to understand one another's needs for the integration of the two simulators. In the development of the previous SimTRAVEL, the developers of the dynamic traffic assignment simulator needed to understand the activity-based model to enter Python code as objects into C++ project. That is, developers should explain every detail about their own codes to other programmers. Their communications continue until both sides

understand thoroughly. Third, it needs an additional library so that codes become larger and are more complicated. For these reasons, the activity-travel demand model is separately processed from the dynamic traffic assignment model in simulation runs.

In order to independently run simulations of the travel demand model and traffic assignment model, a data hub concept is employed in this research. Two key model components in the new integrated model system are only able to exchange information through a data hub. Therefore, if the activity-travel demand model needs arrival information from a dynamic network model, it should check the data hub because the network model exports outputs into the data hub. At every $n$ minute (a 1-minute is time resolution in this study), openAMOS should check the data hub to obtain arrival information. DTALite also needs to continuously check trip information in data hub at every simulation time interval. The data hub includes a control file (comma delimited file: CSV). This control file stores input and output information from both openAMOS and DTALite. Figure 11 shows an example control file that is placed on the data hub. This control file should include at least four columns: time interval, output file name from openAMOS, output file name from DTALite, and filename of prevailing O-D travel times from DTALite. The two components load the information from the control file before running the micro-simulation so that each component knows what file name should be used to generate output and what input data should be checked at each simulation time interval. The activity-based model generates trip data using information (output file names) from the control file and then saves trip data on this data hub. After creating an output file at a time interval, openAMOS waits for input data that contains

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arrival information at this time interval from DTALite. Once input data is found from the data hub, it reads arrival information from the input data.

The same process is applied for DTALite. After loading information settings from the CSV file on the data hub, DTALite waits for trip data based on the given data file name at every time interval. Once receiving trip data from openAMOS at a particular time interval, DTALite loads trips on the network and simulates trip movements through assigned routes. DTALite then generates arrival information if there are some trips that reach the desired destination at the next time interval. In the enhanced integrated model system, this wait-and-simulation process is repeated on both openAMOS and DTALite at every time interval until the time interval reaches 1,440 minutes. For example, according to Figure 11, which shows an example format in the control file, openAMOS generates a trip data called trip_infor_450.csv at the time interval ($t = 450$ minutes) and waits for a file that is arrival_infor_450.csv by checking on the data hub. On the other hand, DTALite waits for trip_infor_450.csv to load new trips generated at 450 minutes. It also creates arrival_infor_450.csv to inform trips that arrived at this time interval at the simulated destinations.

There is another link between openAMOS and DTALite: information of prevailing network conditions (O-D pair travel time matrices by time of day) are sent from DTALite to openAMOS at every $N$ minute ($N >= 15$ minutes) during simulation of the integrated model system on a minute-by-minute basis (In the analysis of this study, $N$ is 30 minutes for efficient simulation run time). Information of prevailing network conditions is essential for openAMOS in order to simulate activity-travel engagement patterns while reflecting the impacts of network disruptions under real-time user

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information provisions. The control file also stores information (matrix file name) of prevailing O-D pair travel times that are generated by DTALite. Thus, as the activity-travel demand model (openAMOS) loads information from this control file, it knows the file names of both the O-D travel time matrix and a time interval when the matrix is generated by DTALite. For example, at time interval 450 minutes, DTALite generates od_current_tt_450.csv on the data hub (see Figure 11). The activity-based model loads prevailing travel times (stored in od_current_tt_450.csv) into its memory and then simulates activity-travel engagement patterns for individuals who are able to reach pre-trip information. Simply, the activity-travel demand simulator (openAMOS) was updated to use both historical and prevailing O-D travel times to simulate activity-travel engagement decisions along with each individual's user information provision status.

| Time Interval | openAMOS | DTALite | Prevailing Network Conditions |
|---|---|---|---|
| ⋮ | ⋮ | ⋮ | ⋮ |
| 449 | trip_infor_449.csv | arrival_infor_449.csv | None |
| 450 | trip_infor_450.csv | arrival_infor_450.csv | od_current_tt_450.csv |
| 451 | trip_infor_451.csv | arrival_infor_451.csv | None |
| ⋮ | ⋮ | ⋮ | ⋮ |

*Figure 11*. Example of the control file employed in the enhanced SimTRAVEL.

**Integration for Modeling Real-Time Traveler Information**

The integration between an activity-based model and a dynamic traffic model in this study was processed in three incremental steps. First, pre-trip information provision is considered in the integration to allow analysis of impacts on activity-travel engagement patterns. Second, route change is modeled in this step of the integration to allow

simulation of route switching to avoid network disruptions in response to real-time information. In the third step, change of activity and/or destination in addition to route change is modeled to simulate activity-travel engagement behaviors under real-time information provision. The integration between an ABM and a DTA is described in the following three sub-sections.

**Level 1 – Pre-trip information provision.** Figure 12 shows a flowchart that represents the framework of modeling pre-trip information provision by employing the integrated model system (SimTRAVEL) between an activity-based model (ABM) and a dynamic traffic assignment (DTA) model. An ABM generates trips at time t=0 minute. Trip information (activity duration, activity type, activity destination, trip mode, and indicator of pre-trip information for each individual) are sent to a DTA. The DTA loads trips on the network and simulates each individual vehicle movement from origin to destination at every 6 seconds. The DTA sends trips that arrive at the activity destination at time t=0 with arrival information. Feedback of trip and arrival information between the ABM and DTA repeats until t=1,440 minutes. From the start of an integrated model system run, the dynamic traffic model (DTALite) continuously generates prevailing network conditions at the end of every $N^{th}$ minute (It can be changed by the user as long as it is greater than 15 minutes). It should be noted that a prevailing network condition (O-D travel time matrix) at t = 0 is generated based on free-flow speed. Otherwise, each O-D travel time matrix includes average travel times for all O-D pairs for previous $N$ minutes. Thus, a DTA repeats sending prevailing network conditions to an ABM at every $N$th minute until t=1,440 minutes. In this study, $N$ is set at 30 minutes to use

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prevailing O-D travel time matrices that are fed into the side of the ABM for pre-trip information provision.

Figure 13 describes an example of a particular individual to present the framework of modeling pre-trip information in the integrated model system as the flowchart shows in Figure 12. The steps of this framework are summarized below:

1. Start simulation run at time t=0 (0 minute represents 4 am in the integrated modeling system). First, DTA generates an O-D travel time matrix based on free-flow speed as prevailing network conditions and sends it to an ABM

2. At t = 30 minutes, a DTA calculates average O-D travel times (an O-D travel time matrix) between t=0 and t=30 minutes and then sends the prevailing travel time matrix to the ABM. In the example, the prevailing network conditions reflect the network disruptions that occurred at t=28 minutes (see Figure 13)

3. At t=31 minutes, an individual (I1), who is accustomed to using pre-trip information and is currently at home, makes the decision to engage in activity A1 at destination D1 for 12 minutes. Since prevailing network conditions that arrived at t=30 minutes from the DTA were used to determine an activity-travel engagement pattern for the individual I1, D1 may not be on the affected area by the network delay event at t=28 minutes

4. ABM sends all trips generated at t=31 minutes to DTA. Trip information that is sent to DTA would include activity type, activity duration, departure place, activity destination, and indicator for whether the individual would use pre-trip information or not

5. DTA loads trips on the network and assigns routes based on the indicator of pre-trip information. That is, routes for the trips with pre-trip information provision are determined using prevailing link travel times. Otherwise, link travel times from the previous iteration are used to assign routes. After choosing a route for each trip, DTA simulates traffic flow for each vehicle at every 6 seconds

6. DTA finishes simulation of traffic flow for the trip of the individual (I1). The trip arrives at the destination (D1) to pursue activity (A1) at time t = 39 minutes, 42 seconds. DTA waits until t = 40 minutes to send trip information with arrival time because the integrated model system adopts time resolution as 1 minute.

7. At t = 40 minutes, DTA sends all trips, which arrive to each desired destination at that time, with arrival time to ABM. ABM considers all individuals who arrive their destination at this minute (t = 42 minutes) and engages their activities for the simulated activity duration. That is, the individual (I1) engages in the activity (A1) for 12 minutes at the destination (D1)

8. At t = 52 minutes, ABM simulates the activity-travel engagement decision for the individual (I1) because the activity A1 is done at this time. ABM uses the prevailing network conditions that arrive at time t = 30 minutes from DTA to simulate activity-travel engagement patterns for the individual (I1)

9. Repeat steps 2 through 8 until t = 1,440 minutes
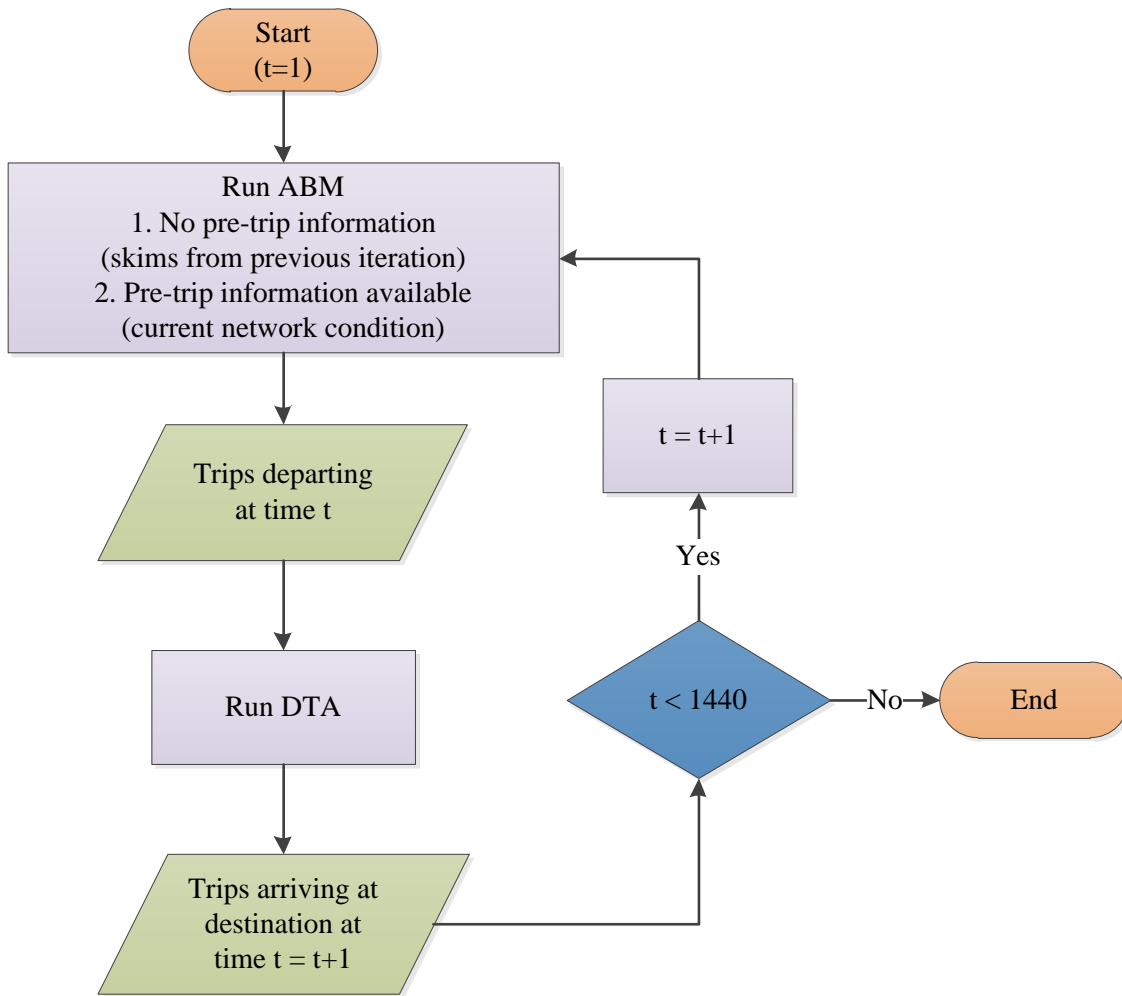
*Figure 12.* Flowchart of the integrated model system between ABM and DTA for reflecting pre-trip information into activity-travel engagement patterns.
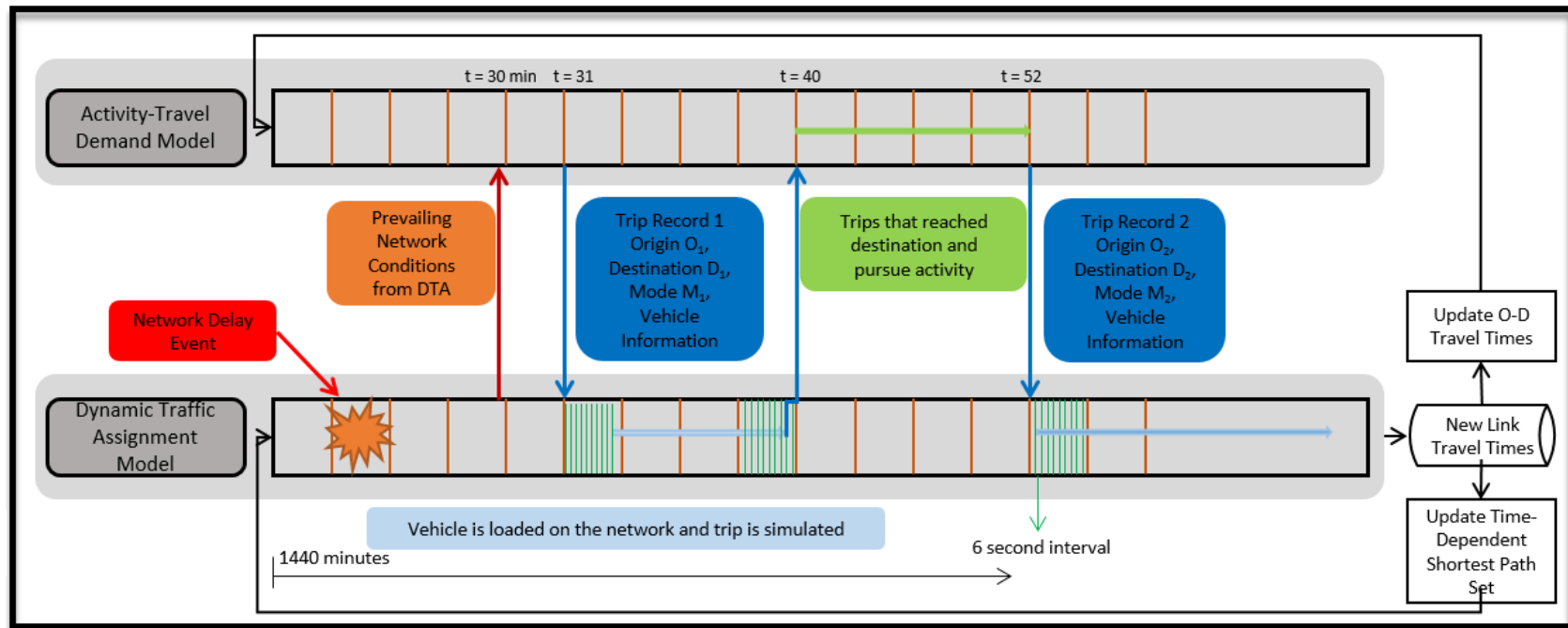
*Figure 13*. Framework for integrating ABM and DTA with dynamic time-dependent activity travel simulation in terms of pre-trip information provision.

**Level 2 – Route change affected by real-time information provision.** Figure 14 represents the overview of the algorithm of the integrated model system for modeling impacts of real-time traveler information on route change as a network disruption event is happening on a minute by minute basis. The algorithm in Figure 14 is similar to the framework introduced in the previous section except for part of the dynamic traffic assignment model (see Figure 12). On the DTA side, it checks the status of trips every $N$th minute whether trips are under network delay events or normal network conditions. If trips are placed under a network delay event and travelers are able to obtain real-time network conditions, DTA assigns new routes through which travelers are able to avoid the network congestion and arrive early to the activity destination. In this prototype of the integrated model system, ABM should send an attribute that indicates whether a trip can access real-time traveler information or not. Sending trip information and receiving arrival information on the ABM side, and loading trips and sending arrival information on the DTA side are repeated until the end of the simulation – that is 1,440 minutes. However, a DTA simulates traffic movements on networks with respect to real-time information provision under current network conditions.
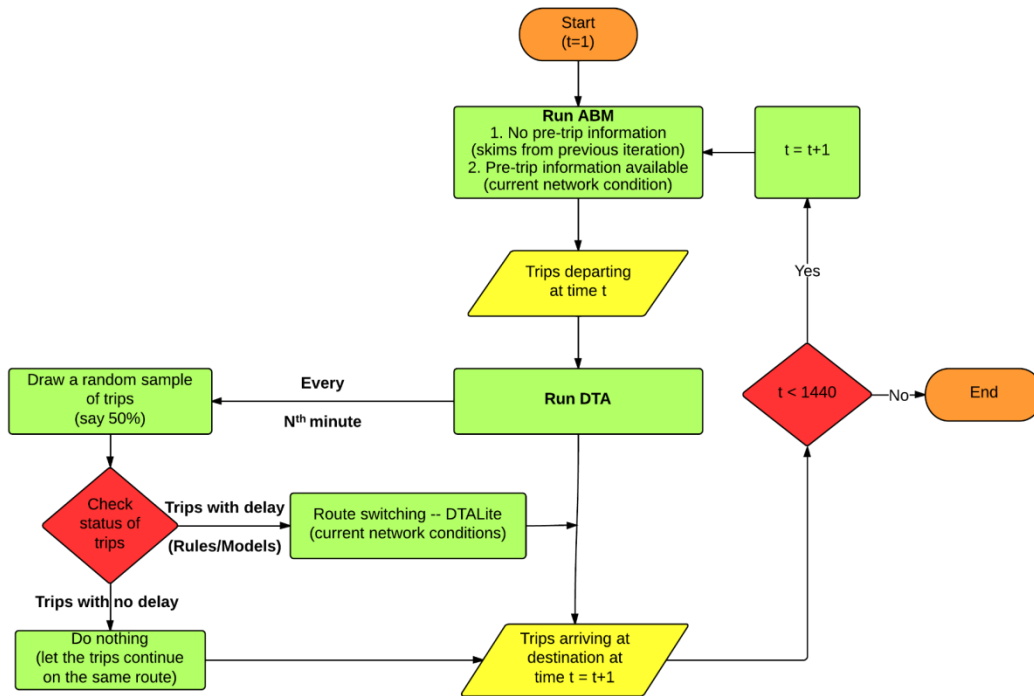
*Figure 14*. Flowchart of the integrated model system for reflecting route change by impacts of real-time information provisions.

The framework of the integrated model system, which reflects the impacts of real-time traveler information as travelers are en-route to activity destinations, is described using an example trip on a continuous time axis in Figure 15. The steps of this framework are summarized as follows:

1. Start simulation run at time t=0 (0 minute means 4 am in the integrated modeling system). First, a DTA generates an O-D travel time matrix based on free-flow speed as the prevailing network conditions and sends it to ABM

2. At t=2 minutes, an individual (I1), who is able to reach real-time information about current network conditions and currently located at home, makes the

decision to engage activity A1 at destination D1 for 4 minutes. (Note that prevailing network conditions are not used to simulate activity-travel engagement decisions for the individual)

3.  ABM sends all trips generated at t=2 minutes to DTA.  Trip information includes activity type, activity duration, departure place, activity destination, and an attribute for information type.  Information type of the individual (I1) would indicate whether the individual uses a real-time information system or not

4.  DTA loads trips on the network and assigns routes based on the attribute of information type.  That is, routes for travelers that use pre-trip information or en-route choice are assigned on the basis of prevailing link travel times.  Otherwise, link travel times from the previous iteration are used to assign routes for trips without real-time information.  After choosing a route for each trip, DTA simulates traffic flow for each vehicle at every 6 seconds

5.  At t=6 minutes 30 seconds, DTA recognizes there is an unplanned network delay event happening (see Figure 15).  DTA assigns new routes for all trips that are with real-time traveler information system and in the region affected by the delay. It simulates traffic flow for the trips from their current location to the activity destination through the re-assigned routes.  Thus, the individual (I1) is also assigned to a new route to avoid the region of the network delay event

6.  DTA finishes simulation of traffic flow for the trip of the individual (I1).  The traveler arrives at the destination (D1) to pursue activity (A1) at time t = 10 minutes 48 seconds.  DTA waits until t=11 minutes to send trip information with

arrival time because the integrated model system adopts a 1-minute simulation time resolution.

7. At t=11 minutes, DTA sends all trips, which arrive to their activity destination at this time, with arrival time to ABM. ABM regards all individuals who arrive at their destination at this minute (t=11minutes) as engaging in their activity for the estimated duration. That is, the individual (I1) engages the activity (A1) for 4 minutes at the destination (D1)

8. At t=15 minutes, ABM simulates activity-travel engagement decisions for the individual (I1). ABM sends trip information about trips that are generated at t=15 minutes to the DTA with the trip's attributes for individual (I1)

9. Repeat step 2 through 8 until t = 1,440 minutes
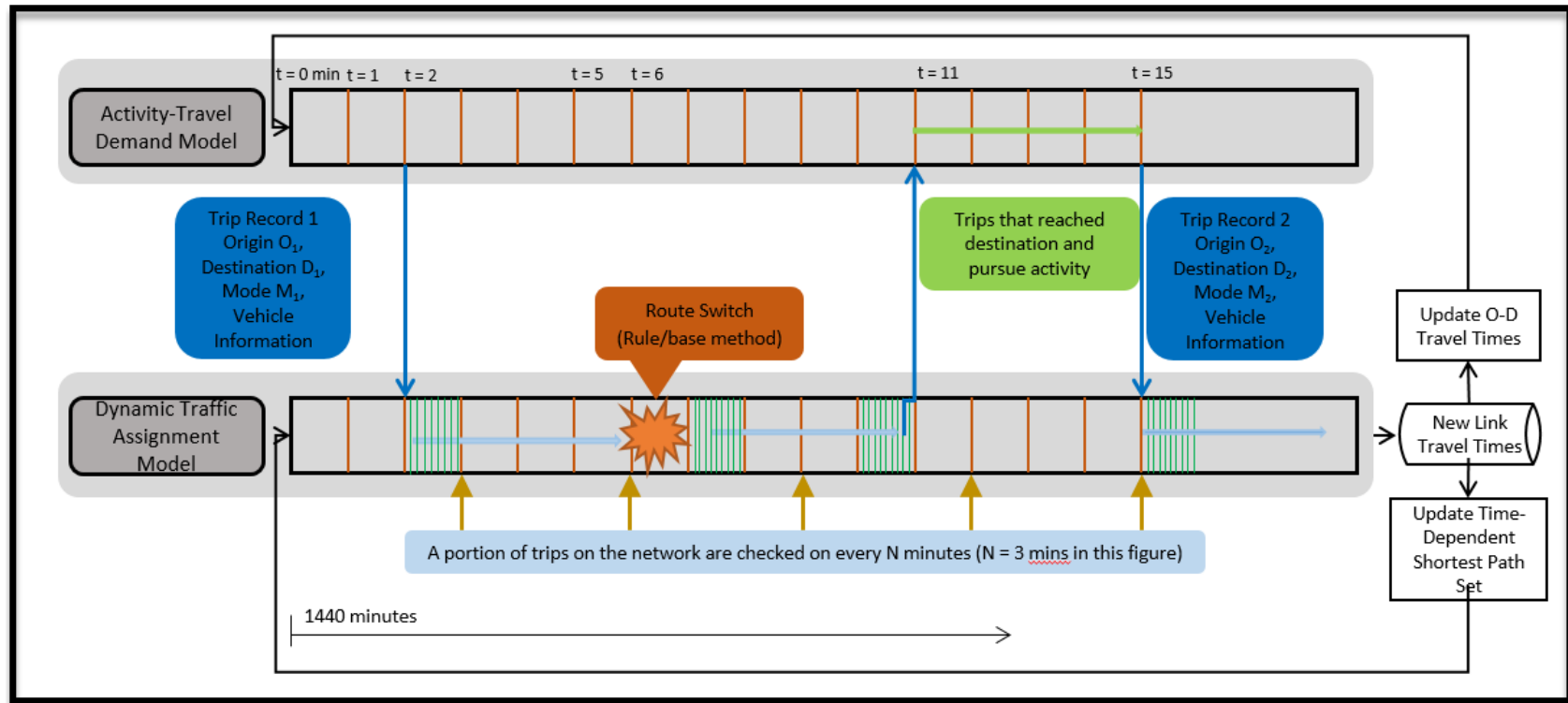
*Figure 15*. Framework for integrating travel demand and traffic assignment models with dynamic time-dependent activity travel simulation in terms of switching route on real-time information provision.

**Level 3 – Change in activity-travel patterns caused by real-time information provision.** The enhancement of the integrated model system to allow modeling of the impacts of real-time traveler information into activity-travel demand patterns means that travelers are able to alter not only routes but also activity-travel behaviors. For example, if an individual, who is able to use a real-time information system to check current network condition en-route, is traveling to go to a grocery market to buy goods, the individual may alter the destination to some other grocery market if there is severe network delay caused by an auto crash near the original grocery. Or, the individual may make a decision to abandon the current trip for the grocery shopping altogether because a real-time traveler information system shows there is a long delay time from the auto crash. The individual may then choose a new activity at a different location where there is no traffic distress. This section describes how to implement this case of the impacts of real-time information provision on change of activity-travel engagement patterns.

In order to capture the travel behaviors, the integrated model system should be enhanced in both a dynamic traffic system and activity-based demand model. The activity-travel demand model should be enhanced to allow processes of activity-travel choices in response to real-time information provision by altering activity, mode, and/or destination. In the first enhancement, the ABM should be able to send the DTA a maximum delay time (minutes) that each individual may be willing to accept from the network delay event. From now on, this maximum affordable delay time is referred to as the 'threshold minute'. For example, an individual may alter the activity currently being pursued as there is no better alternative route and traffic is delay too long to be patient. That is, an individual may allow a 5 minute delay caused by a network disruption. On

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the other hand, the individual may not wait through a 30 minute delay. Therefore, the AMB sends an attribute of threshold minute for all trips to a DTA in addition to trip information. The threshold minute should not be applied as one fixed minute to all synthetic persons in the population because individuals have different perceptions about delay time. For this reason, the activity-travel demand model (openAMOS) uses an approach of probability distribution. This approach is able to give various threshold minutes among individuals. DTA uses this time to decide to send trip information back to ABM whether trips are in a network delay event or not.

In the second enhancement, once trip information without arrival times arrives from the traffic assignment model with a flag of "Trips in Distress" (see Figure 16), the travel demand model considers three choices in response to network disruptions. First, travelers may alter destinations or change activities altogether. In this case, the activity-based model should simulate activity, destination, or activity duration to reflect impacts of real-time information systems on change of activity-travel patterns. Second, travelers may choose to stay the current route to pursue the activity on the unchanged destination. Otherwise, the trip is canceled and then proceeds to the next fixed activity such as school or work activity episode. For the first two choices, it should be asked whether there is enough time to pursue an activity in the open time-space prism before sending new trip information to a DTA. If there is not enough time to pursue the activity in the open time-space prism, the trip will be canceled and then will proceed to the next fixed activity. Figure 16 describes the framework of modeling real-time information provisions that allows changes of activity-travel patterns caused by network disruptions.

A dynamic traffic assignment model should be able to pass information for trips that are in network disruptions (delay) to an activity-travel demand model whenever there are trips in the regions affected by network delay events. Because activity choice, mode choice, and destination choice models are part of the activity-travel demand model, traffic supply models are not capable of modeling activity-travel engagement patterns. For this reason, a traffic assignment model should send trip information for those trips which are experiencing delay because of network congestions to the activity-travel demand model (openAMOS) to re-simulate activity, activity duration, and/or destination choice. DTAs should first find an alternative route and then compare a threshold minute to actual delay time through the alternative route. If travel time through the alternative route is greater than the threshold minute, the trip information should be sent back to AMB for re-simulating activity-travel patterns for the trip. Otherwise, DTA switches to a better route and then simulates traffic flow for the trip until arriving at the activity destination.

The flowchart shown in Figure 17 provides an overview of the algorithm of the integrated model system for modeling the impacts of real-time traveler information on a traveler's overturning decision of activity-travel patterns in addition to en-route choice. This framework is very similar to the algorithm in the previous section (see Figure 12 and Figure 14). ABM and DTA communicate every minute by switching trip and arrival information until 1,440 minutes (one simulation day). That is, a loop in this algorithm continues from 0 to 1439 minutes. In order to simulate the impacts of real-time traveler information provision, two main keys are enhanced in this research efforts. First, at every $N^{\text{th}}$ minute, the dynamic traffic assignment model checks the status of all trips on the network. If trips are in distress (network disruptions) and expected delay time is

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greater than a threshold minute for a trip, DTA sends that trip information back to the travel demand model. Second, the activity-travel demand model re-simulates activity-travel engagement patterns for the trips in distress. It then returns re-generated trip information to DTA for simulating traffic flow to obtain trip arrival information.

Using an example trip on a continuous time axis, Figure 18 describes the framework of the integrated modeling system that is to capture travel behaviors of altering activity-travel engagement decisions based on impacts of network disruptions under real-time information provision. The steps of this framework are summarized below:

1. Start a simulation run at time t=0 (0 minute means 4 am in the integrated modeling system). First, a DTA generates an O-D travel time matrix based on free-flow speed as prevailing network conditions and sends it to an ABM

2. At t=1 minute, an individual (I1), who is able to reach real-time information to obtain current network conditions and is currently at home, makes the decision to engage in activity A1 at destination D1 for 12 minutes.

3. ABM send all trips generated at t=1 minute to DTA. Trip information sent from ABM to DTA includes activity type, activity duration, origin, destination, and variables of information type. Information type of the individual (I1) is the indicator for real-time traveler information. In addition, ABM sends a threshold minute to DTA. For example, ABM sends a threshold minute of 20 minutes for the individual (I1)

4. DTA loads trips on the network and assigns routes based on the variable of information type. That is, routes for trips that are with real-time information

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systems are determined using prevailing link travel times.  Otherwise, link travel times from the previous iteration are used to assign routes.  After choosing a route for each trip, DTA simulates traffic flow for each vehicle at every 6 seconds

5. At t=4 minutes 30 seconds, there is an auto accident.  DTA recognizes there is an unplanned network delay event happening at t=6 minutes (see Figure 18).  DTA finds an alternative route for each trip that is using real-time traveler information systems in the region affected by the delay.  It compares a threshold minute from ABM with travel times through the alternative route from the current location to the activity destination.  If the travel time is smaller than the threshold minute for the trip, DTA simulates traffic flow for the trips from their current location to the destination through the re-assigned route.  Otherwise, DTA sends the trip flagged with "Trips in Distress" back to ABM.  For example, the trip for the individual (I1) is sent back to ABM because travel time of 30 minutes is greater than the maximum affordable delay time of 20 minutes

6. ABM receives trip information which is flagged as "Trips in Distress" at t=6 minutes and then re-simulates activity-travel engagement decisions in response to real-time information systems under the network disruption.  It then sends re-generated trip information to DTA with new trip information.  In the example, the individual (I1) makes the decision to switch to activity A2 at destination D2 with 4 minutes as activity duration

7. At t=7 minutes, DTA loads the re-generated trip on the network, assigns a route from the current location to the re-simulated destination, and simulates traffic

flow every 6 seconds. The individual (I1) starts to move from the current location C1at t=7 minutes

8. At t = 60 minutes, DTA sends prevailing network conditions (an O-D travel time matrix) to ABM

9. DTA finishes simulation of traffic flow for the trip of the individual (I1). The trip arrives at the destination (D2) to pursue activity (A2) at time t = 10 minutes 48 seconds. DTA waits until t = 11 minutes to send arrival information because the integrated model system adopts 1 minute as the simulation time resolution

10. At t = 11 minutes, DTA sends all trips which arrive to activity at their destinations, with arrival time, to ABM. ABM regards as all individuals who arrive at their destinations at this minute (t=11 minutes) as starting to engage in their respective activities. That is, the individual (I1) engages the activity (A2) for 4 minutes at the destination (D2)

11. At t=15 minutes, ABM simulates the activity-travel engagement decision for the individual (I1) because the activity A2 is done at this time

Repeat step 2 through 11 until t=1,440 minutes
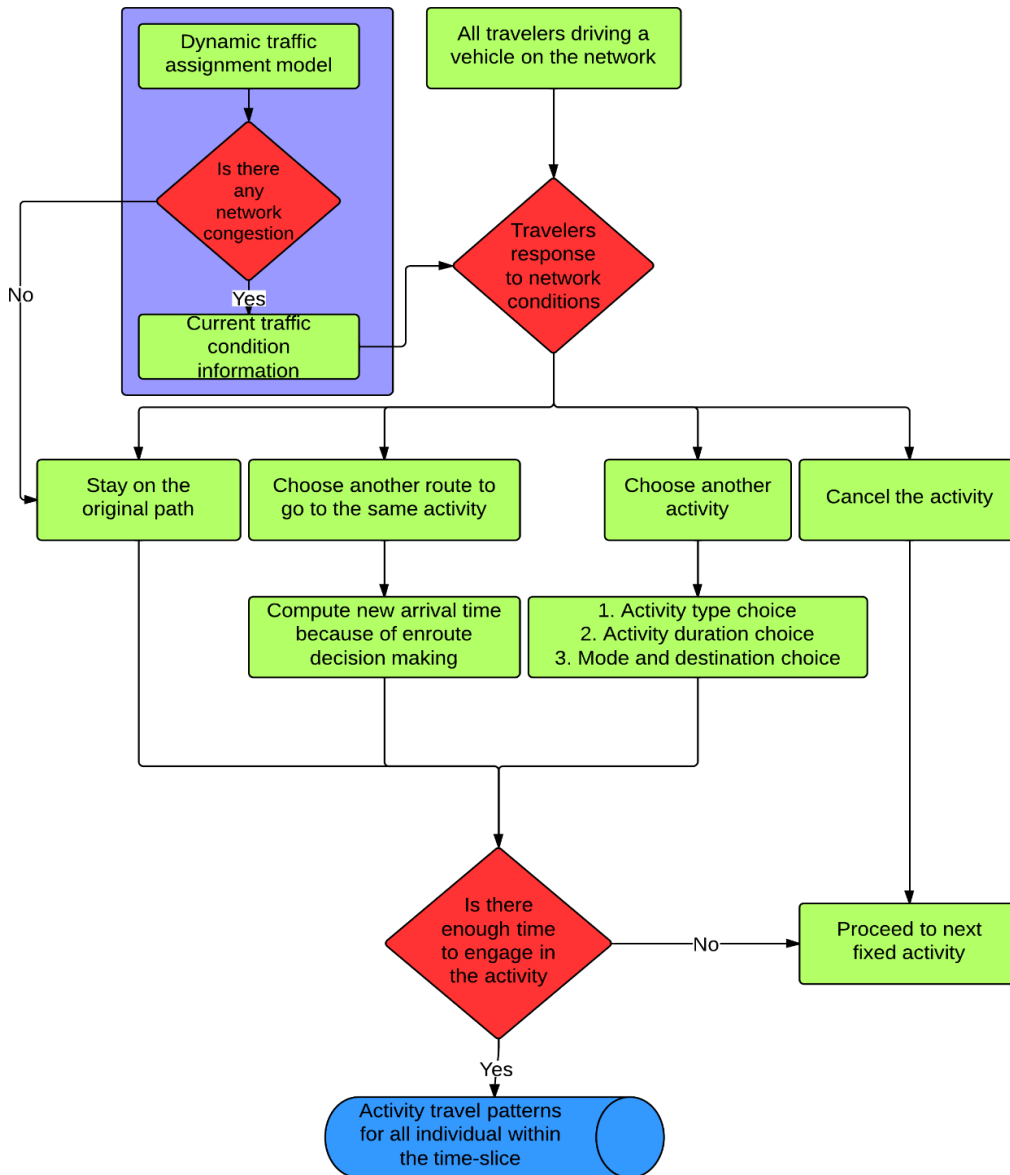
*Figure 16.* Flowchart to show an activity-travel decision flow against network delay events under real-time traveler information provision.
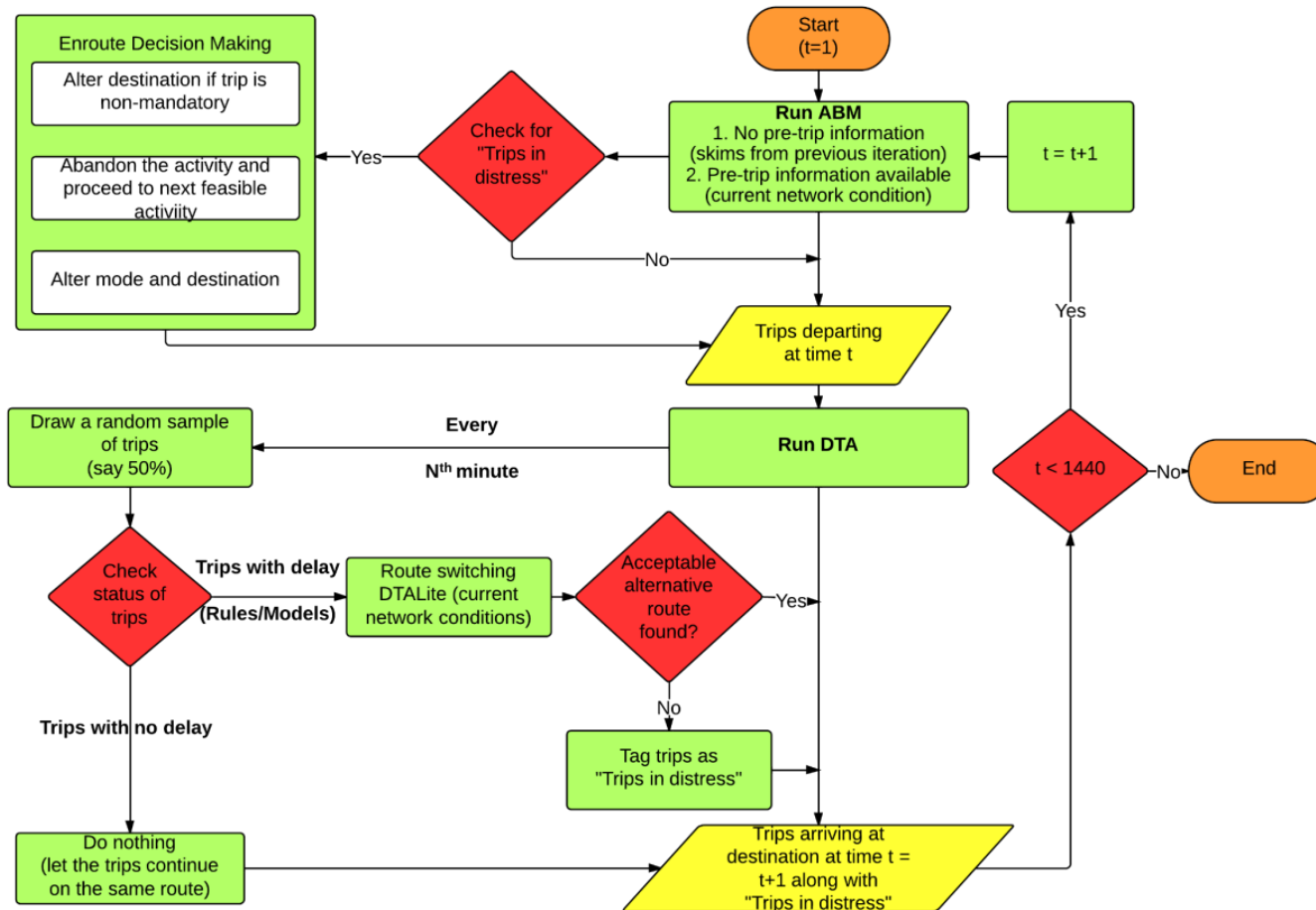
*Figure 17*. Flowchart of the integrated model system to capture activity-travel pattern changes in respond to network delay events under real-time information provision.
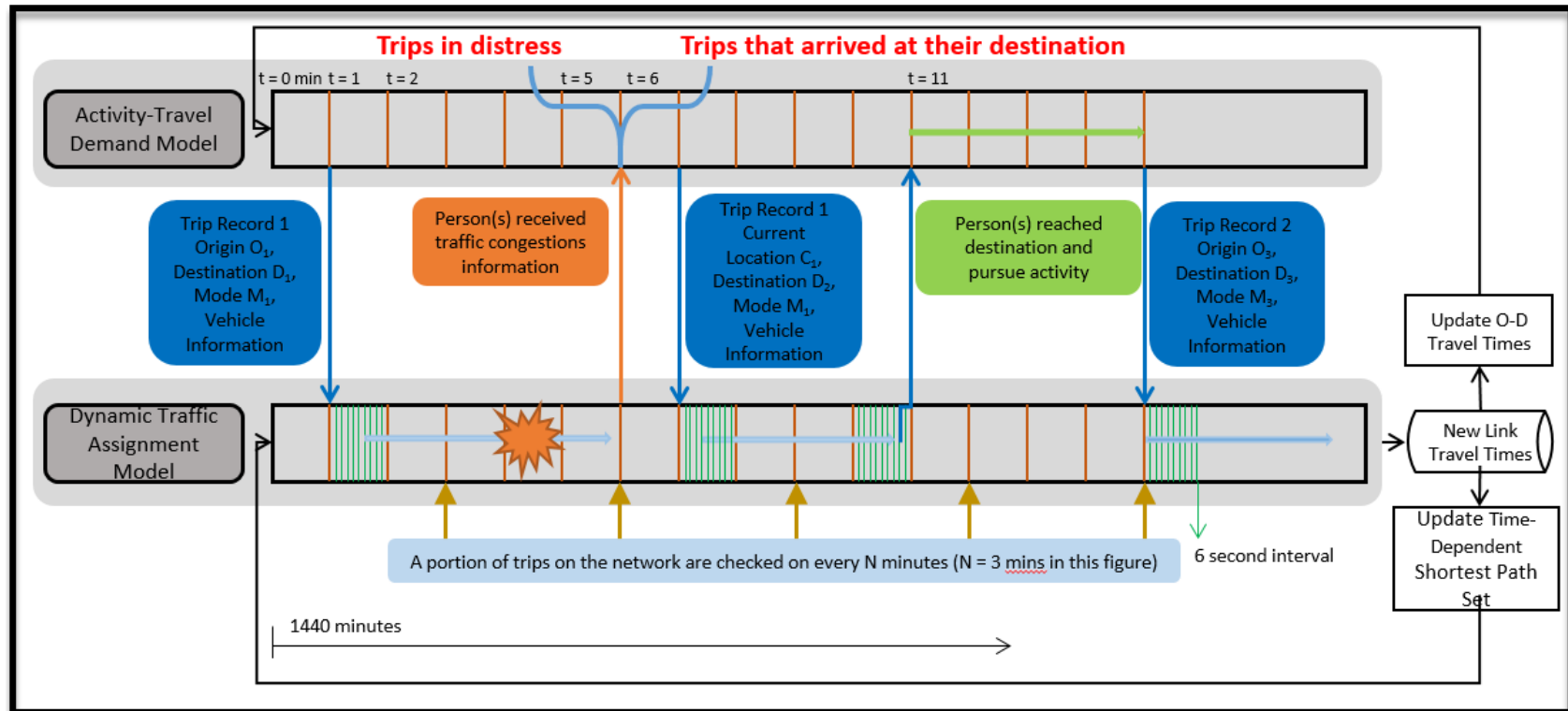
*Figure 18.* Framework of the integrated model system with dynamic time-dependent activity travel simulation in terms of altering activity-travel patterns on real-time information provision.

**Bootstrapping Procedure**

This section describes the bootstrapping procedures that are used to obtain values of link travel times (network level of service conditions) by time of day prior to running a simulation of an integrated model system. A calibrated four-step travel demand model could be used to get origin-destination and link travel times. However, the traditional approach may not be a good way to obtain consistent travel times for two reasons as follows (Konduri, 2012). First, the traditional approach calculates travel times based on coarse aggregations of time because the whole day is divided by four or five time periods. Second, trip-based modeling approaches are used to obtain the origin-destination matrices. The result of the origin-destination travel times may not be consistent to be employed in the context of activity-based travel demand and dynamic traffic assignment models. For these reasons, this study does not use traditional four-step procedures to obtain origin-destination travel time matrices by time of day to start simulation runs of the integrated model system called SimTRAVEL.

There are several methods for processing a bootstrapping procedure. This section describes three different bootstrapping procedures. First, an integrated model system could be applied iteratively between the activity-based demand model and the dynamic traffic assignment model in sequence. The two models are run sequentially with feedback loops until some convergence is achieved on the network conditions to obtain the consistent O-D travel times. The second bootstrapping procedure option is to generate the travel demand only one time from a four step model and the dynamic traffic assignment model is only run repeatedly with the same travel demand until some convergence is achieved. Third, another bootstrapping procedure is a tightly coupled

integrated simulation run between travel demand model and traffic assignment model (see Figure 1 and Figure 7). In this procedure, the travel demand model generates trip information based on free flow network conditions at the start of a bootstrapping process. Both simulators continue to switch trip and arrival information every time (every one minute in SimTRAVEL because time resolution is a minute) until the end of an iteration (1,440 minutes in SimTRAVEL). The outputs of network conditions are then fed into the next iteration of the bootstrapping run. Thus, the two simulators (travel demand and traffic assignment simulators) use the outputs of network conditions from the previous iteration. Tightly coupled integrated simulation runs will be repeated until some convergence is achieved on the network.

The bootstrapping procedure used in this study is very similar to the implementation of the integrated model system in sequence with a feedback loop that is suggested by earlier researchers. The travel demand model (openAMOS) is run sequentially with the dynamic traffic assignment model (DTALite) until some convergences in the network conditions are achieved. As oscillation in network convergence measures across iterations is less than a predefined threshold, we assume that convergence (stability) in network conditions is achieved. At the start of a bootstrapping run, the network conditions are assumed free flow on all links for a whole simulation day. The travel demand model uses O-D travel times obtained based on free flow conditions to simulate activity-travel engagement decisions. The dynamic traffic assignment model routes trips based on time-dependent shortest path in free flow network conditions.

Figure *19* presents the bootstrapping procedure used in this study. The steps involved in the bootstrapping procedure are also described below:

1. First, the bootstrapping procedure requires initial (free flow) O-D travel time matrices by time of day for the travel demand model

2. The travel demand model generates trips for a whole simulation day based on O-D travel time matrices (in the first iteration, free flow O-D travel time matrices are used. Otherwise, the O-D travel time matrices generated by the traffic assignment model in the previous iteration are used)

3. Travel information (origin, destination, transportation mode, and activity duration) is fed into the traffic assignment model. It assigns routes to trips and simulates travel movements until each trip arrives at its destination

4. The traffic assignment model produces time-varying travel time matrices for use in the travel demand model and time-dependent link travel times for its own use

5. Steps (2-4) are repeated until some convergences in the network conditions are achieved

6. The converged O-D travel time matrices are used in the main run of the integrated model system
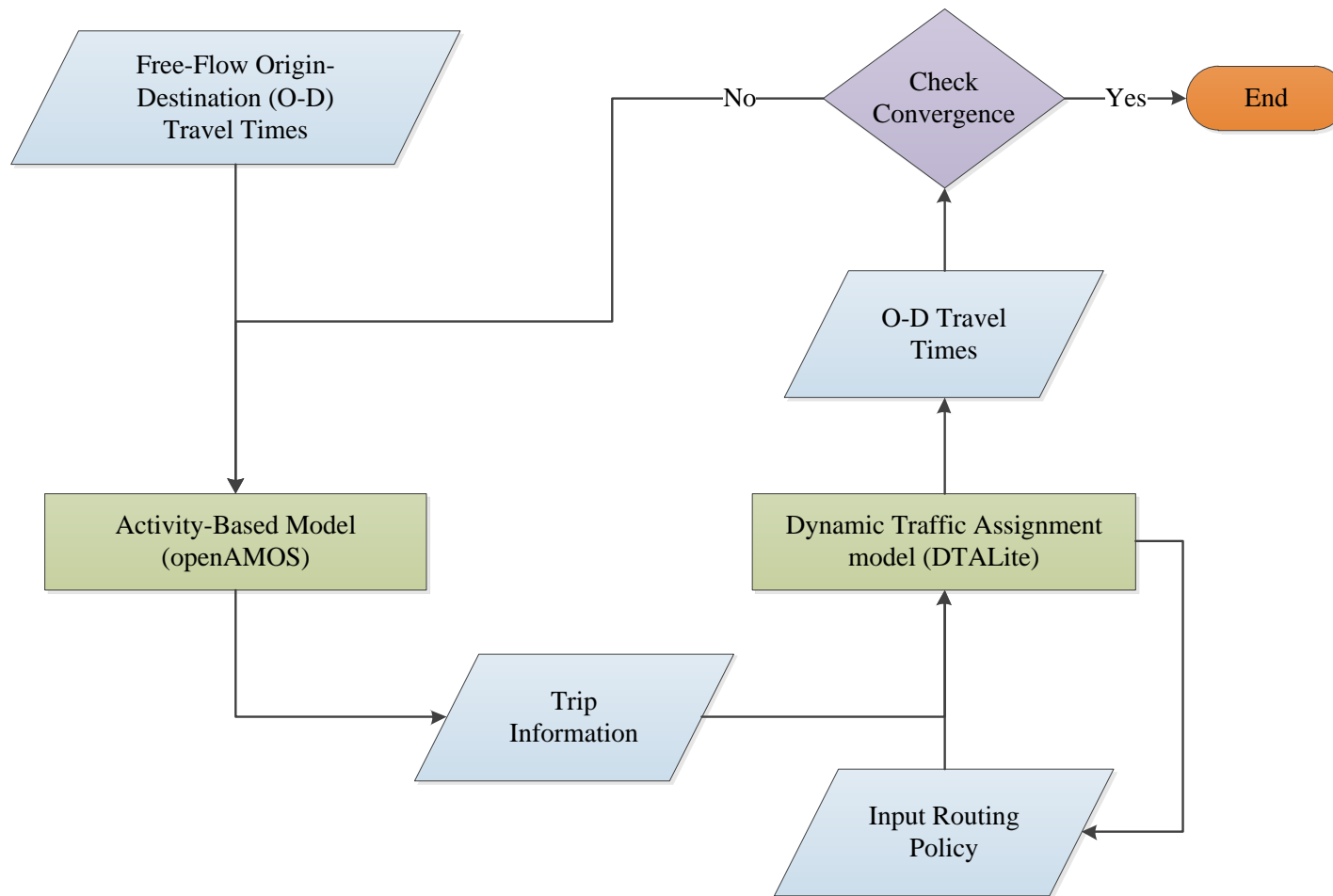
*Figure 19*. Bootstrapping procedure employed in this research.

**Results of bootstrapping procedure.** A bootstrapping procedure is essential to obtain the stable time-varying network conditions that are relevant to be fed into simulation of the integrated model system on a base year. The bootstrapping procedure introduced in the previous section is used to obtain stable origin-destination time-dependent travel time matrices for travel demand model (openAMOS) and time-dependent link travel times for traffic assignment model (DTALite). The bootstrapping procedure consists of 5 outer iterations with 5 inner iterations. An outer iteration requires sequential simulation runs from travel demand simulator to traffic assignment model. The travel demand model (openAMOS) sends trip information to traffic assignment model (DTALite). DTALite loads the vehicle trips to simulate trip assignment and movement and then prepares outputs of O-D pair travel time matrices and link travel times for the next outer iteration at the end of an outer iteration. An outer iteration is composed of 5 inner iterations. The dynamic traffic assignment model (DTALite) offers one additional function to choose multiple inner simulation runs. Once DTALite loads trip information from the travel demand model, it simulates trip assignments and movements for the entirety of the loaded vehicle trips. This simulation run is iteratively continued until the number of iterations (users should set the number of inner simulations) is reached. DTALite in a subsequent inner iteration randomly chooses 50 percent of loaded trips and then reassign the chosen trips on better routes based on time-dependent shortest path algorithm. In the bootstrapping procedure, DTALite is set with 5 inner simulation runs to find consistent user equilibrium network conditions that are used in the next outer iteration. This study provides four different types of results to check whether

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convergence on network conditions is achieved: average user equilibrium gap, relative user equilibrium gap, average travel times in time of day, and skim deviation.

*Relative user equilibrium gap*.  The dynamic traffic assignment model (DTALite) computes values of relative user equilibrium (UE) gap.   To check the level of convergence on network conditions, relative UE gap is one approach.  If relative UE gap (percent %) does not fluctuate from iteration to iteration and the percent of gap is small enough to accept, traffic flows (network conditions) would be regarded as stable for the purpose of comparison of several scenarios.   DTALite uses two sequential inner iterations to compute relative UE gap percent.  Since this study sets 5 inner iterations for an outer iteration in traffic assignment simulation run, four different relative UE gaps are generated at the end of an outer iteration in the dynamic traffic assignment model (DTALite).  Figure 20 presents changes of relative UE gap from iteration to iteration. Figure 20 sequentially shows all relative UE gaps from iteration 1 to iteration 5 including results of inner iterations.  The first two relative UE gaps in outer iteration 1 are of 15.8% and 10%, respectively.  It means that network conditions are not converged, yet.  From outer iteration 3, the relative UE gap has not fluctuated and does not gradually decrease and increase from iteration to iteration.  Every first relative UE gap in outer iterations is gradually decreased until the fourth outer iteration.  After the third outer iteration, the first relative UE gap is below 5%.  It explains that the previous network conditions are used in the subsequent outer iteration to simulate traffic flows in DTALite.   Trip information from the travel demand model is different from iteration to iteration because of a stochasticity effect.  For this reason, the dynamic traffic assignment model may be not able to perfectly reflect previous network conditions to simulate trip assignments and

vehicle movements on the network. The last relative UE gaps from outer iteration 2 are very small and lower than 1.4%. This small percentage of relative UE gap is acceptable to assume stable network conditions.

*Average user equilibrium gap.* In addition to relative UE gap percent, the dynamic traffic assignment model calculates average user equilibrium gap (minutes) capable of checking convergence and stability of network conditions. Figure 21 presents the results of average UE gap of all outer and inner iterations. In outer iteration 1, the average UE gap is 49.86 minutes. Gap minutes decline steeply down to below 9 minutes from outer iteration 2. Average UE gap gradually decreases across outer iterations. After outer iteration 3, the change in average UE gap is very stable around 2.9 minutes. Average UE gaps for the fifth inner iterations from outer iteration 2 barely fluctuate between 0.2 and 0.4 minutes. The trend of average UE gap is very similar to that of relative UE gaps (see Figure 20).

*Average speed and travel time.* Figure 22 represents the results of average speed and average travel time of the fifth inner iterations for all outer iterations. Both average speed (MPH) and travel time (minutes) become stable after the third outer iteration. Average speed and average travel time barely fluctuate around 36 MPH and 8.3 minutes, respectively.

*Vehicle Trip Count.* This study employed sequential runs between travel demand and traffic assignment models by feeding input each other to obtain converged network conditions. Figure 23 shows the results of vehicle trip count by outer iterations. The first iteration generated the highest vehicle trip count because free-flow network conditions were applied to generate trips in the demand model. In the second iteration, vehicle trip

count is steeply down to 1,602,000 from 1,605,000. The reason trip count is decreased is that average travel times by time of day were increased because the traffic assignment model estimated travel times using the highest trip count that is generated by free-flow network conditions. The change of vehicle trip count becomes stable after iteration 2. The fluctuation is almost negligible between iterations 4 and 5.

*Average travel time by time of day.* A convergence check is carried out by reviewing average travel time by time of day. Figure 24 presents average travel time in every hour for 5 outer iterations. In Figure 24, the line that represents the average travel time of iteration 1 is not overlaid on the other lines throughout the entire day except for in the first two hours from 4 am to 6 am. The gap between iteration 1 and the other four iterations is always huge in all hours after 6 am. However, the gap between iteration 2 and iteration 5 is decreased. The line of iteration 4 is almost overlaid on the line of iteration 5. It means that average travel time in time of day is successfully converged after iteration 4.

*Skim deviation.* At the end of each iteration, the dynamic traffic assignment simulator (DTALite) generates O-D pair travel time matrices (skim data). The smallest time resolution to generate skim data is 15 minutes in DTALite. If DTALite is set to generate skim data every 15 minutes, there are 96 O-D travel time matrices generated for a simulation day. The skim data are imported to a travel demand model for destination, mode, and activity choice. In order to check convergence on network conditions using skim data, this study adopted scatter plots to compare O-D pair travel times between iteration 4 and iteration 5. In this paper, results of skim data between iteration 4 and 5 for only two hours are shown.

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Figure 25 and Figure 26 includes four different scatter plots because DTALite generates O-D pair travel time matrix every 15 minutes. In each scatter plot in the figures, the X-axis and Y-axis in the plots represent each O-D pair travel time from iteration 5 and iteration 4, respectively. Each dot represents the same origin and destination pair in both iteration 4 and 5. Skim data are compared in two different time ranges: morning peak hour (7 am – 8 am), and evening peak hour (4 pm – 5 pm).

Figure 25 and Figure 26 show 7 am through 8 am and 4 pm through 5 pm, respectively. In the context of convergence on link flows and network conditions, a narrow line with a 45 degree angle should be expected in all scatter plots, because travel times for O-D pairs should be very consistent from iteration to iteration.

Figure 25 presents the comparison of two iterations in morning-peak time ranges. The figure shows almost a 45 degree line. It means every O-D pair travel time is almost the same between iteration 4 and iteration 5. Figure 26 shows comparison of iteration 4 with iteration 5 in evening peak ranges. The scatter plots in Figure 26 show that dots are very narrowly scattered on the 45 degree line, as well. Therefore, convergence on the network conditions is achieved for employing the O-D pair travel times to simulate different scenarios for analysis of impacts of user information provision using the integrated model system (SimTRAVEL).
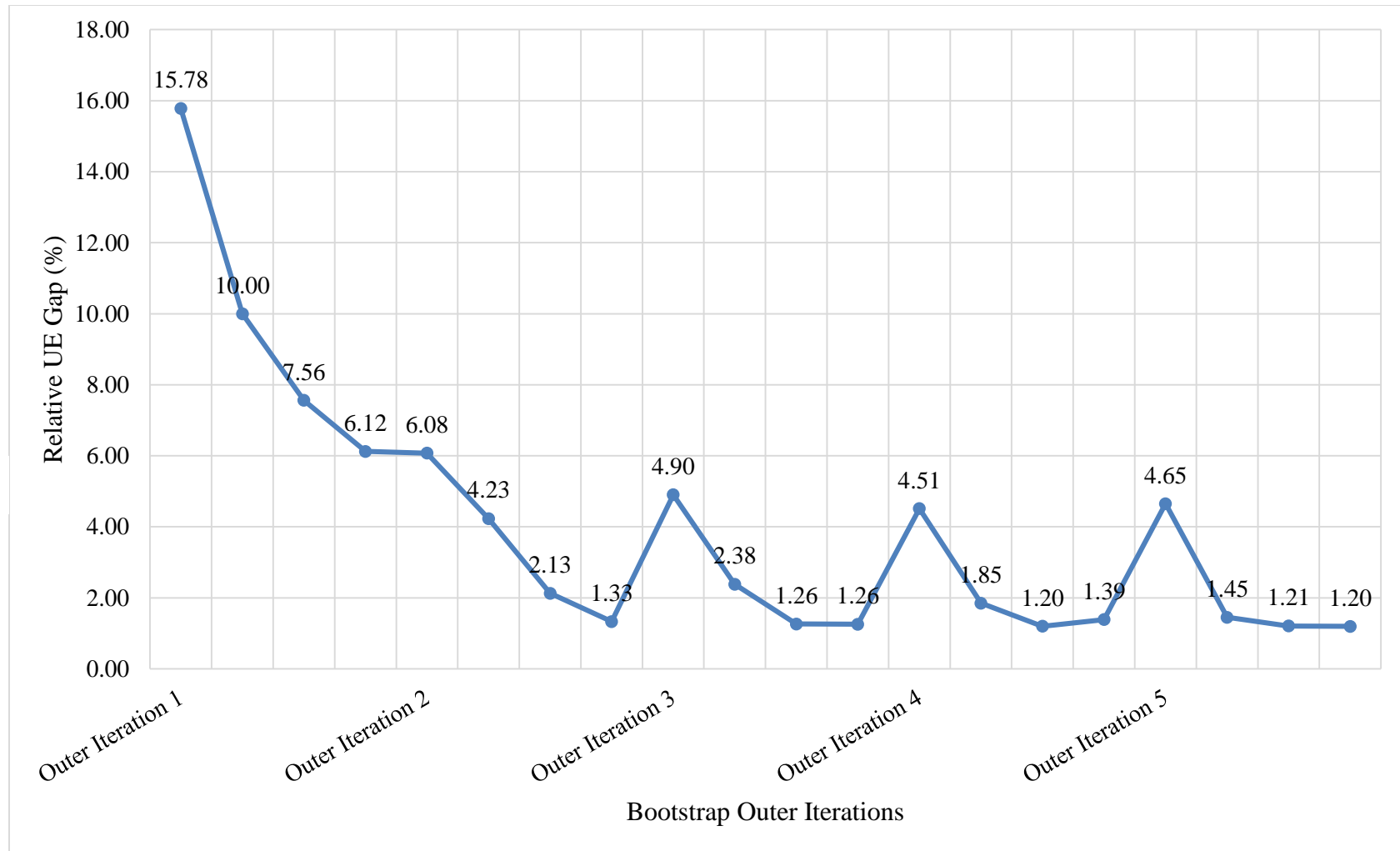
*Figure 20*. Change of relative user equilibrium gap values across bootstrapping iterations.
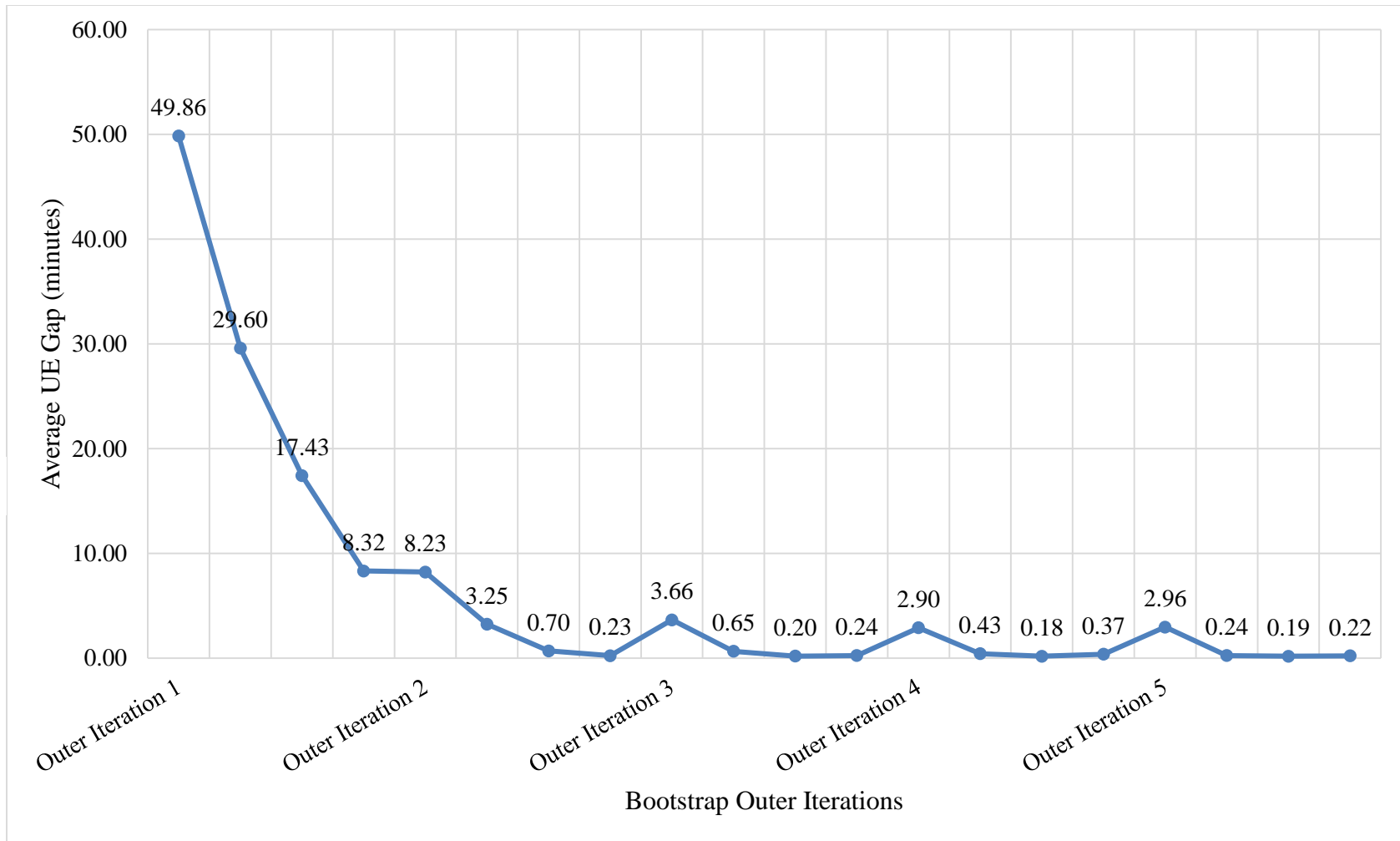
*Figure 21*. Change of average user equilibrium gap across bootstrapping iterations.
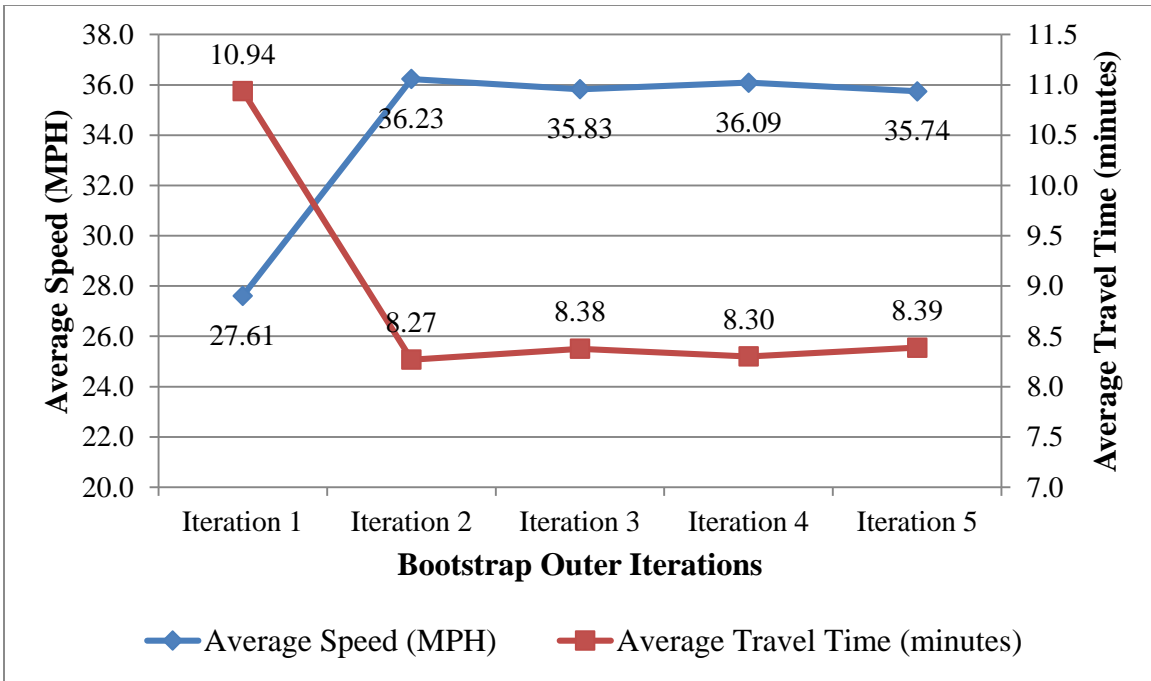
*Figure 22*. Change of average speed and average travel time across bootstrapping iterations.
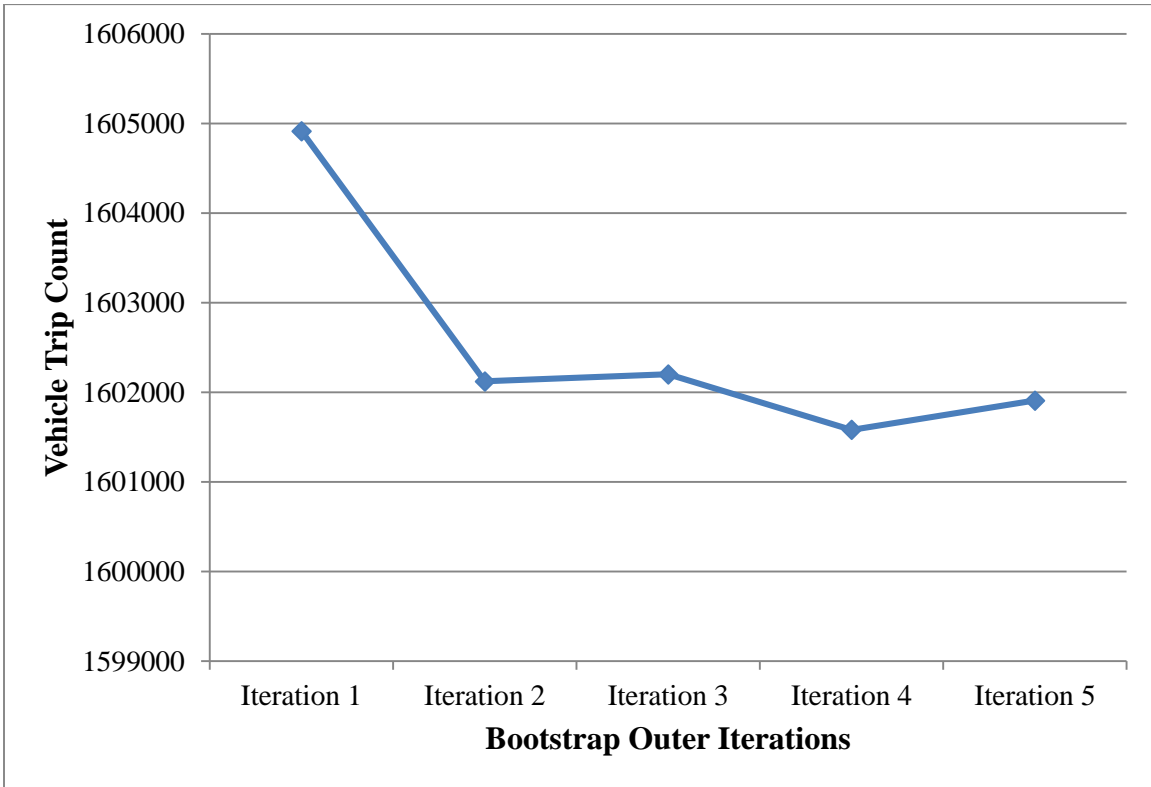


*Figure 23*. Change of vehicle trip count across bootstrapping iterations.
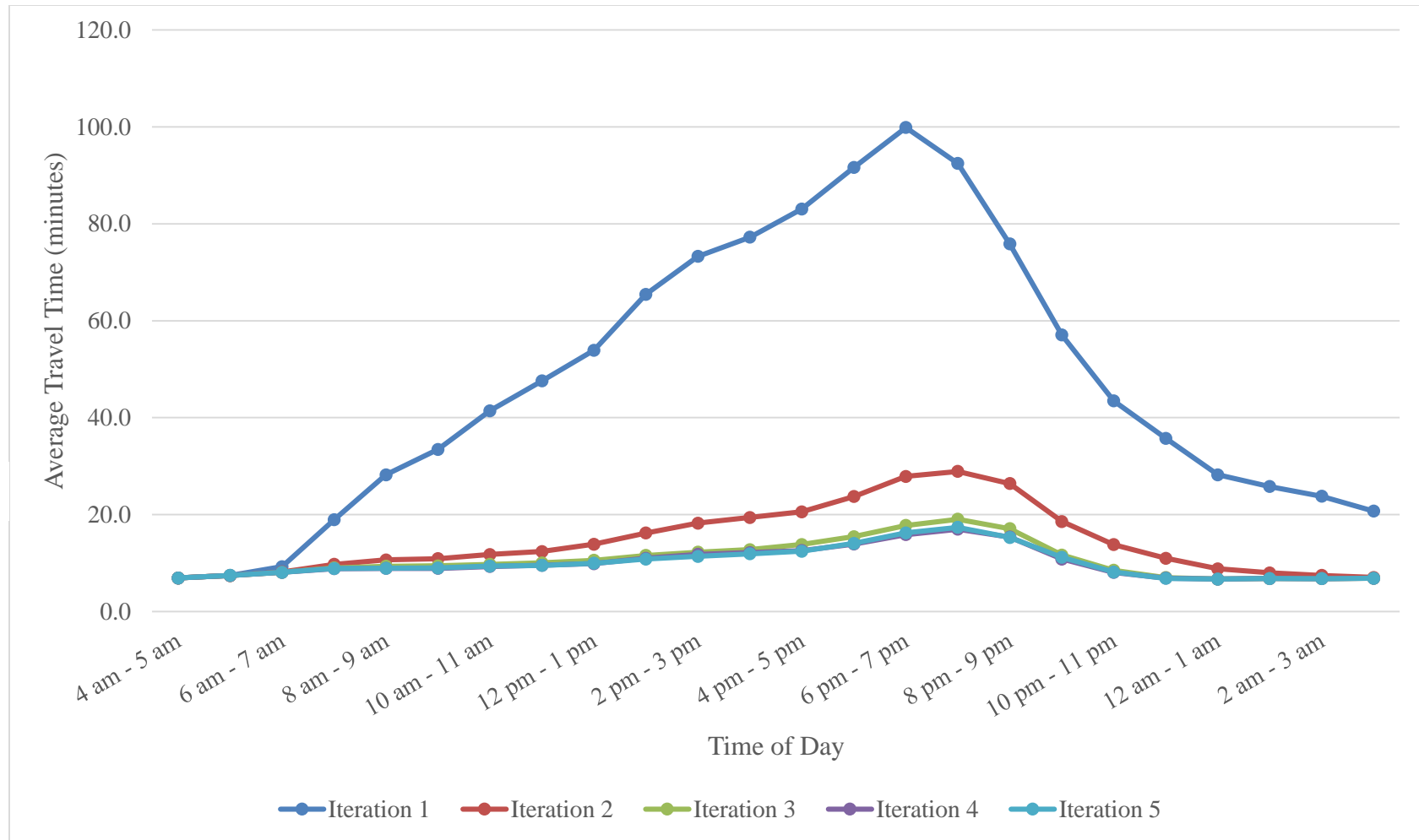
*Figure 24*. Average travel time profile in time of day across bootstrapping outer iterations.
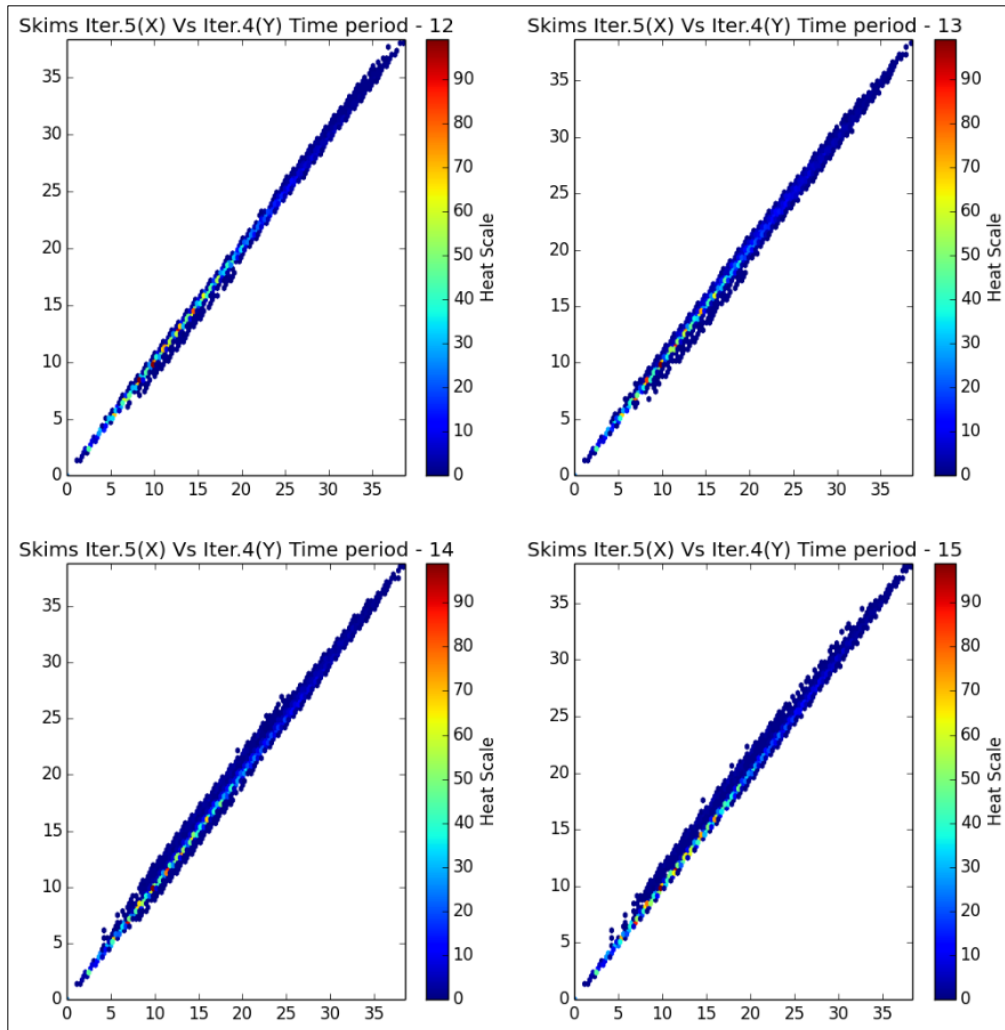
*Figure 25*. Scatter plot for average travel time comparison between iteration 4 and 5 during peak hour (7 am – 8 am).
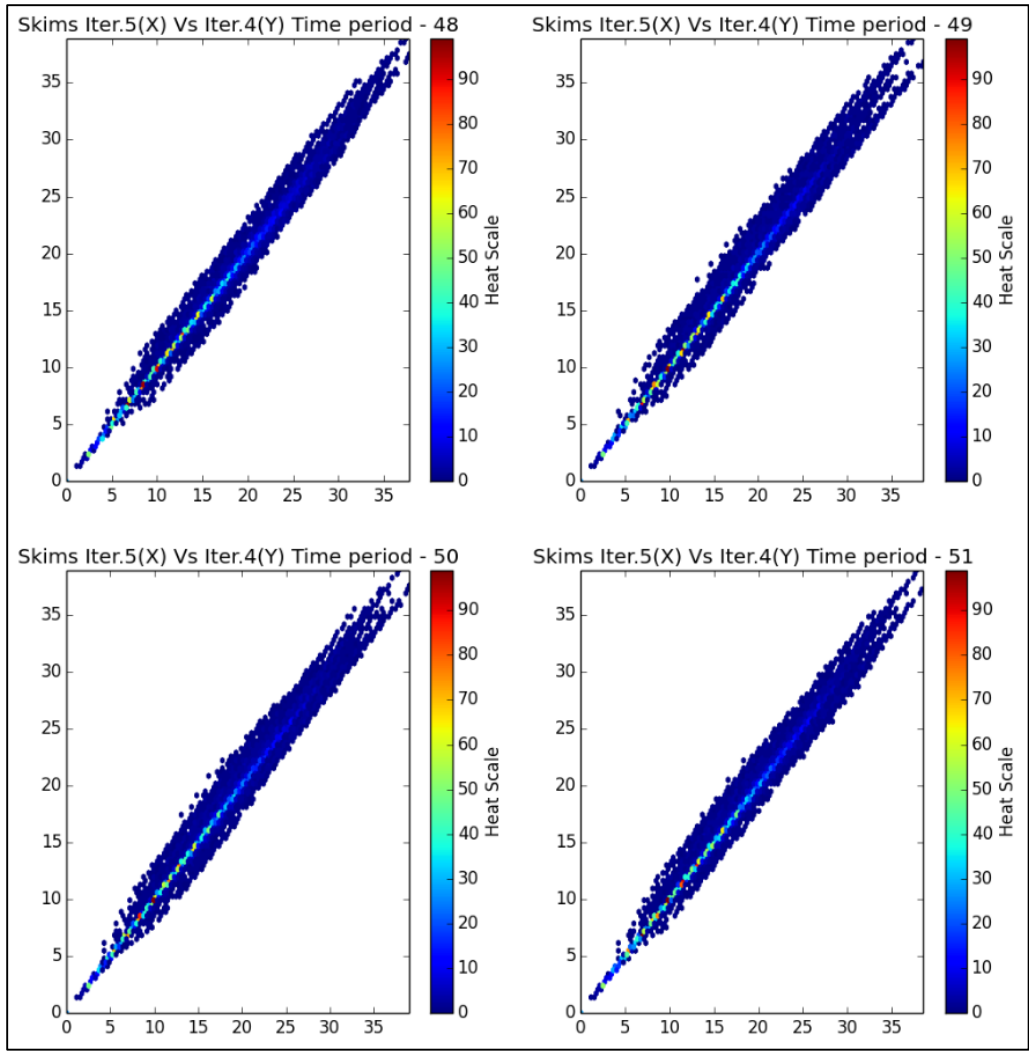
*Figure 26*. Scatter plot for average travel time comparison between iteration 4 and 5 during peak hour (4 PM – 5 PM).

# CHAPTER 5

## Modeling Low Emission Zone

**Introduction**

Greenhouse gas emissions and increasing fuel consumption have been issues of major concern in the United States (U.S) owing to the fact that gasoline and diesel vehicles are the major means of transportation. Transportation accounts for 28% of greenhouse gas emissions in the United States (EPA, 2013) and 70% of the U.S. petroleum in 2012 was consumed in the transportation sector (EIA, 2013). Several research efforts in the transportation arena are motivated by this fact and aim to reduce the adverse effect of increasing travel through better modeling techniques. Parallel efforts to reduce emissions on the industry front propelled the development of hybrid/electric vehicles (eco-vehicle) by several auto manufacturing companies and are slowly penetrating the auto-market. While these technologies undoubtedly help in reducing the emission footprint, they also come with a steep price tag. The government offers rebates and tax incentives intended to encourage the households to purchase and use eco/clean vehicles. In addition to this, several policies aimed at improving mode share of public transit are being introduced. Mixed use development (zones in which residences, schools, stores, and businesses are developed together) is an effort aimed to reduce travel and thus the emissions associated with it.

To change household vehicle composition to eco/clean vehicles or reduce greenhouse gas emissions in most congested areas, Transport for London started implementing the Low Emission Zone (LEZ) policy in London, United Kingdom in the year 2008. LEZs are geographically defined areas that seek to incentivize "green

transportation choices" or prevent high-polluting vehicles from entering the zone to improve air quality within the geographic area (Schneeberger et al., 2013). The LEZ policy implemented in London uses a penalty-based scheme to restrict heavily polluting vehicles from entering the busiest parts of London. In order to enter the LEZs, drivers should either use vehicles that comply with the LEZ emissions standards or pay a (hefty) daily charge.

The objective of this study is to model the effects of various LEZ policies on activity-travel patterns and traffic flows using the updated integrated model system (SimTRAVEL) framework. The framework is updated to be flexible enough to devise and test various policies (such as the LEZ policy) that could potentially provide solutions to critical issues in the transportation industry (e.g. greenhouse gas emissions and energy consumptions). This provides policy makers with a powerful tool to test a wide range of policy scenarios before they are actually implemented and this in turn saves a lot of time and money. In London, the penalty-based LEZ policy has been employed to restrict regular vehicles that do not meet the LEZ emission standards. However, penalizing a specific segment of vehicles might bring about an anti-sentiment toward such policies and there is a potential possibility that such policies might do more harm than good. An alternate way to pitch an eco-friendly idea (such as the LEZ policy) to the public is using an incentive-based policy where cleaner (eco) vehicles are rewarded. Enhancing public transit services to LEZs might also bring about a positive shift toward the lesser polluting transit option. A lot of infrastructure and effort are required to test all possible combinations of LEZ policies in the real world. Instead, advanced transportation modeling tools can be utilized to understand the effects of various LEZ policies on

activity-travel patterns, household vehicle fleet composition, and link flows etc. before their actual implementation.

This scenario analysis developed in this case study adopts the updated integrated model system (SimTRAVEL) for modeling the impacts of various LEZ policies on energy consumption and emissions. For modeling the impacts of LEZ policies on activity-travel/emission patterns, previous version of SimTRAVEL (Konduri et al., 2013) was updated to allow analysis of different pricing scenarios. There are two approaches being tested as a part of LEZ policy in this study: i) incentives to eco travelers and ii) enhanced transit service to LEZs. The incentive-based LEZ policy is to offer incentives (monetary/non-monetary) to eco travelers who drive eco/clean vehicles to LEZs. The travelers using non-eco vehicles are not penalized in any way. For the purpose of this study an eco-vehicle is defined as a hybrid (such as Prius), plugin-hybrid (such as Chevrolet Volt) or an electric (such as a Tesla) vehicle. Enhanced transit service to LEZs means offering improved transit services both in terms of frequency (increasing frequency of transit service can decrease waiting time at station) and discounted fare for transit services to LEZs. The enhanced transit services are provided to eco and non-eco travelers alike. To estimate the effects of these two different approaches, this study uses five different scenarios using the updated SimTRAVEL framework on the three city (City of Chandler, Town of Gilbert, and Town of Queen Creek) sub-region in the southeast part of the Great Phoenix Metropolitan Region.

**Methodology for Modeling Impacts of Low Emission Zones**

Modeling the impacts of low emission zones requires transportation modeling tools to be capable of simulating activity-travel patterns including mode choice (auto vs.

transit) using a generalized travel time measure. The following two sub-sections describe how generalized travel time measure and mode choice model are handled in the updated integrated model system.

**Generalized travel time at the zone based.** In the previous version of SimTRAVEL, the activity-travel demand model (openAMOS) uses a travel time measure to determine a feasible destination set for all synthetic population. That is, if sufficient time is available in the open time-space prism to engage in an additional activity (prior to the onset of the next fixed activity), openAMOS simulates destination choice for each individual for engagement of an activity using a feasible destination choice set. Konduri et al., (2013) enhanced openAMOS to use a generalized travel time measure that includes the time equivalent of cost. The generalized travel time measure is used to simulate a destination choice so that any general pricing policy can be converted to an equivalent generalized cost on the demand side. The traffic assignment model however, uses actual travel times to simulate vehicular movements on the network from origin to destination. Thus, actual arrival time at destination is used to determine the time-space prism constraints. Since activity generation and destination choice will change based on generalized travel time, it is imperative that activity-travel/traffic patterns on the network also change in a scenario where an incentive is provided (in comparison to the network conditions from the baseline scenario where no incentive is provided).

The integrated model system should be able to reflect the monetary benefit for eco travelers (who drive eco/clean vehicles such as hybrid or electric vehicle) or an equivalent toll for non-eco travelers (who drive regular vehicle) respectively in the context of travel to/from LEZs. The monetary incentive to LEZs is converted to

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generalized travel time (in minutes) using a personalized value of time based on household income. The activity-travel demand model obtains the generalized travel time using the procedure described in Chapter 4. Generalized travel time is the sum of actual travel time between an origin-destination pair and time equivalent of any other costs associated with the travel. The value of time in the equation (6) is computed by either using equation (2) or (3) based on the number of workers in the household (all the equations mentioned are from Chapter 4). Incentive/penalty is reflected in the generalized travel time computation as travelers choose an LEZ to pursue a activity so that time equivalent of cost need not be divided by travel miles. The time equivalent of cost can be applied to the generalized travel time either negatively or positively (depending on whether the person is getting an incentive or a penalty). For example, if an eco-traveler chooses to pursue an activity in a LEZ, an incentive would be given to the traveler. In this case, the generalized travel time is computed as actual travel time minus the incentive (converted to equivalent travel time). On the other hand, if a non-eco traveler decides to engage an activity in LEZs, a penalty is applied to the traveler to get into the zone. In this case, the generalized travel time is computed as the sum of actual travel time plus penalty (converted to equivalent travel time). This study uses an incentive-based LEZ policy to study the impacts of such a policy on activity-travel engagement patterns and travel flows on the network.

**Mode choice model.** The second component to LEZ policy considered in this study is offering enhanced transit services to LEZs. The transit enhancement is done on two grounds: i) increasing the transit service frequency to LEZs and ii) reducing the fares on transit services to LEZs. To reflect the impact of transit enhancements on travel to

LEZs, the integrated model system (SimTRAVEL) should include a mode choice model in the series of activity-travel demand choice models to account for traveler's mode choice behavior. This study considers two transportation modes (auto and transit) for modeling the impacts of LEZ on emissions and energy consumptions. A simple binary logit model is employed to model the choice dimension (auto vs. transit). Utility function of the binary logit model includes a variable (generalized travel time) and an asserted alternative specific constant. The asserted coefficients for auto and transit are obtained after calibrating the constants to match observed mode shares in the survey data. American Community Survey (ACS) data shows that population of 4% in the Great Phoenix area use transit service and the same is reflected by the model after minor calibration effort.

## Study Area

The study area used for this modeling effort is the southeast region of Greater Phoenix Metropolitan Area (Maricopa County). The sub-region comprises of three cities: City of Chandler, Town of Gilbert, and Town of Queen Creek. The sub-region is separated from the Maricopa region for testing/implementation of the updated version of SIMTRAVEL. There are about half a million people from 150,000 households residing in the study area. The population used for this analysis is generated using a synthetic population generator (PopGen). In order to gain efficiencies in model implementation, 50% of population i.e., about 250,000 people from 85,000 households are considered to conduct LEZ analysis. The spatial resolution of analysis for used for the current study is a Traffic Analysis Zone (TAZ). The three city sub-region consists of 175 TAZs.

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In this case study, two zone-clusters are selected to test an LEZ policy using the integrated model system. Figure 27 shows the three city sub-region from the Greater Phoenix Metropolitan Region (LEZs are identified with a highlighted boundary). One of the LEZ areas (designated with number 1 in the figure) comprises of 5 TAZs and the other (designated with number 2 in the figure) has a total of 7 TZAs. In total 12 (~7%) out of 175 TAZs are selected as LEZs. The factors considered in selecting LEZs are: i) heavy retail employment and ii) high residential population. Since both these characteristics attract a lot of traffic to the TAZ, it was felt prudent to select zone that had high 'activity' w.r.t both these dimensions. One of the LEZs has a big shopping mall called the Chandler Fashion Center which is a major attraction for discretionary travel. The other LEZ houses more of a mixed development with a fair share of retail employment as well as residential population.
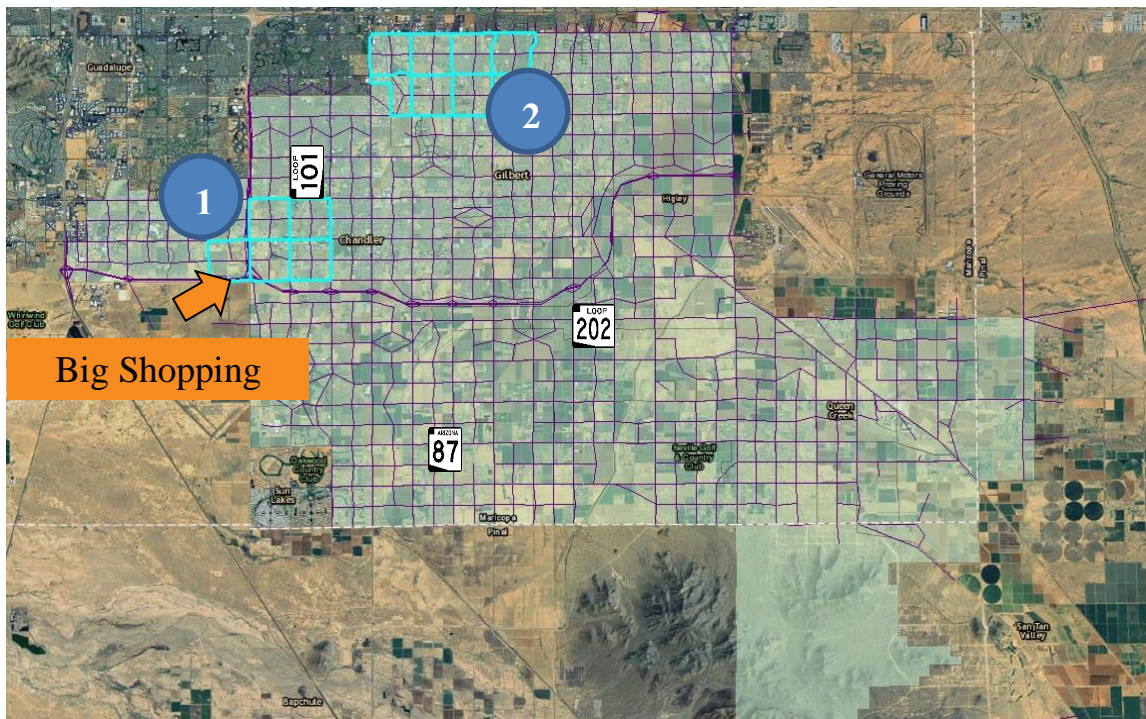


*Figure 27.* Map of study area and LEZs that are shown in highlighted boundary.

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One of the main goals of analysis of Low Emission Zones (LEZ) is to encourage mode shift toward eco/clean vehicles such as hybrid, plug-in hybrid or electric vehicles and thereby reduce air pollution in areas with heavy traffic. The second goal of this study is to encourage non-eco travelers to shift to transit in the context of travel to LEZs. The updated integrated model system (SimTRAVEL) framework is flexible enough to test a wide array of policy measures, LEZ policy being one of them. The two levels in LEZ policy implementation are described below.

- Incentive only LEZ policy: Travelers who drive an eco-vehicle are given a monetary (cash) or non-monetary (free parking/priority parking, eco-credit, restaurant coupons, retailer discounts, grocery market coupon, etc.) incentive to travel to LEZs. The intent of an incentive only LEZ policy is to encourage acquisition and use eco-vehicles.

- Enhanced transit services to LEZs: Transit service to LEZs is made twice as frequent with respect to the baseline scenario. With enhanced transit frequency, people could potentially access LEZs faster as the wait time at transit station is decreased in light of increased frequency. Transit fare is reduced to half of current fare to induce a mode shift.

The activity-travel demand model (openAMOS) converts the incentive and discounted transit fare to generalized travel time which is the sum of actual travel time (auto/transit) and time equivalent of incentive (or transit fare). The generalized travel time would impact the activity-travel/mode choices of individuals in the context of their travel to/from LEZs.

Design considerations observed in the LEZ modeling effort for LEZ policy analysis, are as follows: i) Eco-travelers (who drive an eco-vehicle) would receive a monetary incentive if they choose to travel to LEZs; ii) It is assumed that transit service to LEZs is enhanced in such a fashion that there is 30% reduction in travel times. In addition to this transit fares to LEZs are reduce to half from the baseline scenario and iii) Different levels of market penetrations of eco-vehicles are applied to each simulation run according to level of LEZ incentive. Five different scenarios are designed conduct an incremental analysis of LEZ policies. Each of the scenarios is described below

- Baseline: In this scenario, no incentive is given to eco-travelers. Transit services operate at regular frequencies and normal fares. This scenario is intended to serve as a benchmark against all the other scenarios. Two percent eco-vehicle penetration is observed in baseline. The baseline market penetration of eco-vehicles was determined after a careful analysis if the National Household Travel Survey from the year 2008-2009 for the Phoenix Metropolitan Region. From the survey results, it was found that 2% of households residing in the Great Phoenix Metropolitan Region own eco-vehicles (hybrid, hybrid-electric, or electric vehicle).

- $0.5 incentive with regular transit service ($0.5, RT): In this scenario a $0.5 incentive is given to eco-travelers for each trip they make to a LEZ. However, enhanced transit service is not introduced to LEZs. This scenario assumes a 3% eco-vehicle penetration in the synthetic population.

- $1.5 incentive with regular transit service ($1.5, RT): In this scenario, a $1.50 incentive is given to eco-travelers for each trip they make to a LEZ. Enhanced

transit service is not introduced to LEZs. Five percent eco-vehicle penetration is assumed in this scenario.

- $0.5 incentive with enhanced transit service ($0.5, ET): In this scenario a $0.5 incentive is given to eco-travelers for each trip they make to a LEZ. Enhanced transit service is introduced to LEZs as described in the previous section. The enhanced transit services are intended to bring about a modal change in non-eco travelers by providing a transit alternative that competes with an auto mode. This scenario assumes 3% eco-vehicle penetration in synthetic population.

- $1.5 incentive with enhanced transit service ($1.5, ET): In this scenario a $1.5 incentive is given to eco-travelers for each trip they make to a LEZ. Enhanced transit service is introduced to LEZs. 5% eco-vehicle penetration is assumed in this scenario.

Impacts of the LEZ policies described above are expected to manifest themselves in different ways. An incentive only LEZ policy might increase travel to LEZs as eco-travelers are encouraged (incentivized) to travel to LEZs. However, non-eco travelers might not be impacted in anyway as they are neither getting incentivized nor getting penalized. The activity-travel patterns of non-eco travelers are therefore not expected to change. Eco-travelers may travel farther distances to travel to LEZs in order to realize the incentives provided. Enhanced transit service to LEZs may might encourage a mode shift for non-eco travelers more than eco-travelers (who already receive an incentive to travel to LEZs).

**Results**

This section presents results of five scenario runs in the context of analyzing the impacts of a Low Emission Zones (LEZ) policy on activity-travel patterns, emissions and energy consumptions. The section divided in to the following three subsections for ease of presentation

(1) Changes in activity-travel patterns

(2) Changes in mode choice patterns

(3) Change in energy consumption and emissions

Results pertaining to each of these subsections is discussed below.

**Change in activity-travel engagement patterns.** Table 3 represents results of aggregate travel characteristics from the five different scenario runs using the enhanced SimTRAVEL framework for 50% of synthetic population in the three city sub-region. From the table, it can be observed that total number of trips is slightly lower in the two scenarios that observe enhanced transit services (30% lesser travel time and 50% fare reduction) to LEZs. Average trip rate of the enhanced transit service scenarios is also slightly lower than that of the other scenarios. This is understandable as taking the transit might limit the flexibility in activity engagement patterns for individuals. The results of aggregate travel characteristics for synthetic population of 50% in the sub-region show that the updated integrated model system is able to accurately capture the impacts of enhanced transit services to LEZs. The activity-travel demand model is also able to depict the cascading effects among trips along continuous time axis. For example, if a trip is delayed on network, subsequent trips for that individual might be impacted causing them to reduce activity duration or skip the next activity. Transit travel times are usually

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longer than auto travel times. Travelers who use transit modes to access LEZs should adjust their activity-travel behaviors in light of their mode shift. Average trip length observed across all scenarios is about 7 miles which is acceptable given the small size of the sub-region network used for this case study. Average travel speed across all scenarios is also observed to be fairly stable. Consistent network conditions across different scenarios facilitate the comparison of activity-travel engagement patterns between them.

Table 4 presents the results of aggregate travel characteristics from the five scenario runs for eco-travelers. From the table it can be observed that total trips made by eco-travelers gradually increases as incentives to LEZs are increase. This is a direct manifestation of increasing eco-vehicle penetration with increasing incentive levels. The fluctuation of total transit trips for eco-travelers across the five scenarios runs is not much. This is also expected behavior as eco-travelers who are already receiving an incentive to use their eco-vehicle to travel to LEZ would be reluctant to shift to transit even when there is an enhanced transit service. Enhanced transit service are offered to all travelers who travel to LEZs but is expected to have a greater impact on non-eco-travelers than eco travelers. The results in Table 4 show that average trip length for eco-travelers gradually increases with increasing incentive levels. This is expected, as eco-travelers might be travelling from farther distances to LEZs in order to realize the incentives. In other words, there is 'higher but cleaner' vehicle miles traveled in response to the incentive only policy.

The result of aggregated travel characteristics for non-eco travelers is shown in Table 5. Average trip rate for this segment is very stable across three scenarios that do

not have enhanced transit service to LEZs.  On the other hand, average trip rate is slightly decreased in the two scenarios that do offer enhanced transit service to LEZs.  While the generalized cost structure might make transit a competing alternative on par with the generalized cost of auto, actual transit travel times are longer in comparison to auto trips (between the same O-D pair).  Hence, transit travelers might be slightly impacted by the longer travel times and subsequent activity-travel engagement after their trip to the LEZs prompting them to reduce their activity participation duration or skip the activity altogether.  Thus, average trip rate for non-eco travelers sees a downturn as transit rideshare increases.

In Table 6 and Table 7, change of auto and transit trips to LEZs across the scenarios is presented.  These two tables also show information regarding trips to all other (regular) zones to which LEZ policy does not apply.  From Table 6, it can be observed that there is a slight increase in auto trips to LEZs in the 'incentive only' scenarios.  This increase is expected as eco-travelers might be accessing LEZs more to realize the benefits of the incentive provided.  On the other hand, for scenarios in which enhanced transit is introduced to LEZs, a 30% reduction is observed in auto-share (coupled with a corresponding increase in transit-share).  This phenomenon is mainly propelled by the decision of non-eco travelers to switch transit in the context of their travel to LEZs.  Both Table 6 and Table 7 show no fluctuation in auto and transit trips to all regular zones.  This is an intuitive finding as regular zones are not impacted by the LEZ policy and the model is able to aptly depict the distinction in activity-engagement patterns between LEZs and regular zones.

Figure 28 depicts the change in vehicle mix and mode shares in LEZs across the five scenarios. Mode shares for eco vehicles, non-eco vehicles and transit are show to explain the impacts of the LEZ policies considered in this study. It can be seen that eco-vehicle share for trips to LEZs gradually increases as the level of incentive increases, which is consistent with expectation. While the non-eco vehicle share in trip to LEZs is a little over 90% in baseline, this share decreases to as low as 65% in the scenario with maximum incentives coupled with enhanced transit services to LEZs. The major contributor for the change observed in vehicle mix is enhanced transit service to LEZs targeted at the major mode segment (non-eco vehicles). Energy and emission benefits might be expected as a direct manifestation of mode shift away from non-eco vehicles.

Figure 29 presents thematic geographical maps showing the total number of trips made by eco-travelers to LEZs for the baseline and two incentive only scenarios. The maps are color coded where a dark blue color indicates lesser number of eco-trips and dark red color signifies a high eco-trip count to LEZs (note that dark red color in maps does not mean traffic congestion). The comparison bin ranges are kept constant across the maps to show an accurate depiction of changes in trip making patterns. Low emission zones are identified with a highlighted boundary in the map. The color (depicting number of trips) in the LEZs is gradually changes from blue to red as incentives given to eco-travelers to LEZs are increased from $0 (baseline) to $1.5. This shows that the incentive policy introduced in LEZs is impacting activity-travel patterns (destination choice) of eco-travelers and the integrated model system is able to model this phenomenon in an intuitive way. An 'incentive only' policy might attract eco-travelers to

LEZs neglecting the consequence of greater travel distances. So, it was felt prudent to couple incentive only policy with enhances transit service to LEZs.

Count of transit-trips to LEZs across the five scenarios is presented using thematic geographical maps shown in Figure 30. It can be observed from the figure that as transit services are enhanced to LEZs transit (bus) trips to LEZs show a commensurate increase. This means that the transit policy is attracting more transit trips to LEZs (thereby reducing emissions) and also impacting the activity-travel engagement behaviors (transportation mode and destination). The model is able to depict these finer nuances in travel behavior quite well. Upon further analysis, it was observed that the mode shift is observed mostly in the non-eco traveler segment. This is understood as eco-travelers might be disinclined to shift to transit in light of an incentive for using their eco-vehicle.

Figure 31 and Figure 32 show daily activity itinerary for a female worker generated from the results of the activity-based model (openAMOS). The synthetic female worker uses a regular vehicle in the base scenario whereas the same individual supposedly acquired an eco-vehicle in light of the incentive ($1.5) provided. Figure 31 shows the person's daily activity itinerary before changing to eco vehicle. Figure 32 shows her itinerary after changing to eco vehicle. Before changing to eco vehicle, the individual engaged in three out-of-home activities (personal business, work, and shopping), none of them ending up in LEZs. She pursued a personal business activity and came back home on her first tour. She then went to work, stopped for a shopping activity on her evening commute and came back home in her second tour. In both the tours, destination zones for all activities that she engaged in were not in LEZs identified for this analysis. After changing to eco vehicle (Figure 32), the individual's activity-

travel engagement pattern was changed.  Although she engaged in the same activities (personal business, work, and shopping) in her daily activity itinerary, she pursued the non-mandatory activities (shopping and personal business) in LEZs in order to realize the incentive given to eco-travelers.  This is a phenomenal finding as to how such a policy might have direct impacts on the activity/destination choices at the level of each synthetic individual.  Having the capability to predict and depict such subtle changes in activity travel patterns provides a huge advantage to planners/modelers to test the sensitivity of various policies before actually implementing them in the real world.

Table 3. *Aggregated Travel Characteristics for Both Eco and Non-eco Travelers*

| Indicator | Baseline | $0.50, RT | $1.50, RT | $0.50, ET | $1.50, ET |
|---|---|---|---|---|---|
| Population | 252,999 | 252,999 | 252,999 | 252,999 | 252,999 |
| Total Trips | 1,135,899 | 1,136,401 | 1,135,487 | 1,126,034 | 1,129,877 |
| Total Auto Trips | 1,086,515 | 1,086,702 | 1,086,544 | 1,050,424 | 1,055,352 |
| Total Transit Trips | 49,384 (4.3%) | 49,699 (4.4%) | 48,943 (4.3%) | 75,610 (6.7%) | 74,525 (6.6%) |
| Total Travel Distance (mile) | 7,781,422 | 7,792,089 | 7,790,525 | 7,756,704 | 7,800,878 |
| Average Trip Rate | 4.49 | 4.49 | 4.49 | 4.45 | 4.47 |
| Average Trip Length (mile) | 6.85 | 6.86 | 6.86 | 6.89 | 6.90 |
| Average Travel Speed (mph) | 29.40 | 29.31 | 29.25 | 29.74 | 29.59 |

Table 4. *Aggregated Travel Characteristics for Eco-travelers*

| Indicator | Baseline | $0.50, RT | $1.50, RT | $0.50, ET | $1.50, ET |
|---|---|---|---|---|---|
| Population | 5,137 | 7,681 | 12,735 | 7,681 | 12,735 |
| Total Trips | 23,327 | 34,873 | 57,772 | 34,651 | 57,790 |
| Total Auto Trips | 22,293 | 33,502 | 55,565 | 32,868 | 55,327 |
| Total Transit Trips | 1,034 (4.43%) | 1,371 (3.93%) | 2,207 (3.82%) | 1,783 (5.15%) | 2,463 (4.26%) |
| Total Travel Distance (mile) | 160,315 | 567,634 | 405,594 | 580,791 | 404,618 |
| Average Trip Rate | 4.54 | 4.54 | 4.54 | 4.51 | 4.54 |
| Average Trip Length (mile) | 6.87 | 6.88 | 7.02 | 6.90 | 7.00 |

Table 5. *Aggregated Travel Characteristics for Non-eco Travelers*

| Indicator | Baseline | $0.50, RT | $1.50, RT | $0.50, ET | $1.50, ET |
|---|---|---|---|---|---|
| Population | 247,862 | 245,318 | 240,264 | 245,318 | 240,264 |
| Total Trips | 1,112,572 | 1,101,528 | 1,077,715 | 1,091,383 | 1,072,087 |
| Total Auto Trips | 1,064,222 | 1,053,200 | 1,030,979 | 1,017,556 | 1,000,025 |
| Total Transit Trips | 48,350 (4.35%) | 48,328 (4.39%) | 46,736 (4.34%) | 73,827 (6.76%) | 72,062 (6.72%) |
| Total Travel Distance (mile) | 7,621,107 | 7,552,072 | 7,384,930 | 7,517,444 | 7,396,260 |
| Average Trip Rate | 4.49 | 4.49 | 4.49 | 4.45 | 4.46 |
| Average Trip Length (mile) | 6.85 | 6.86 | 6.85 | 6.89 | 6.90 |
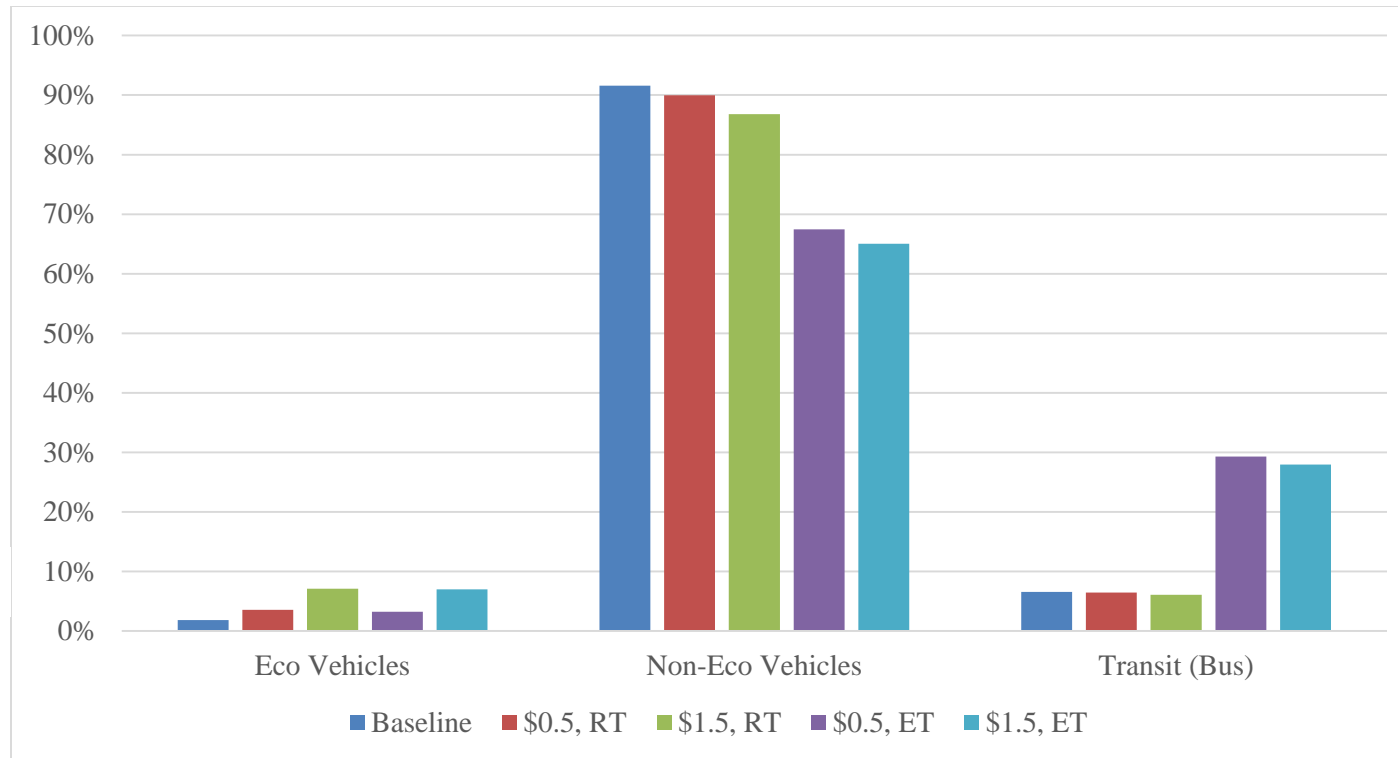
*Figure 28*. Vehicle mix for low emissions zone trips.
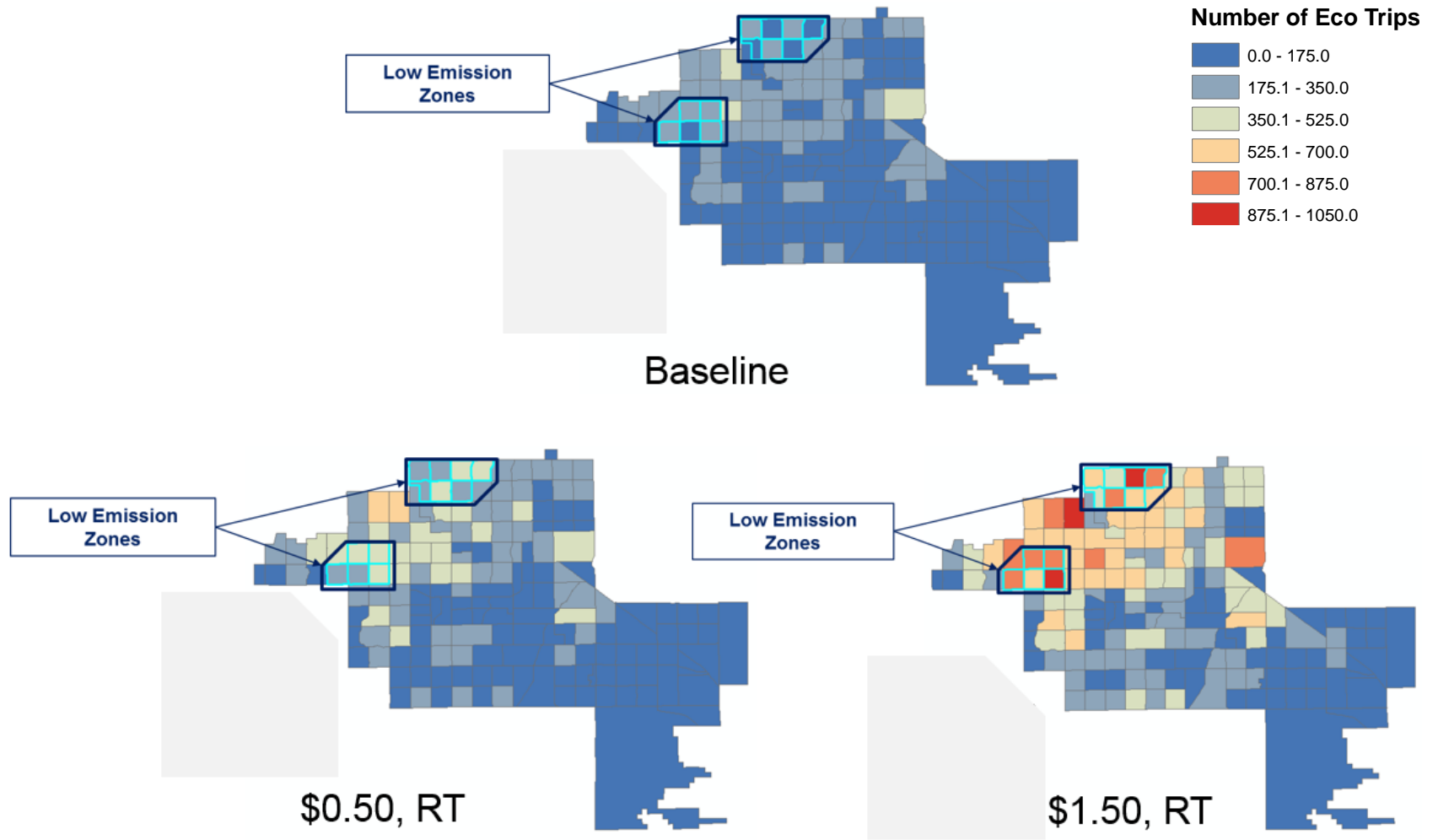
*Figure 29*. Change of eco-traveler's trip count by TAZs across two LEZ incentive-based scenarios from baseline.
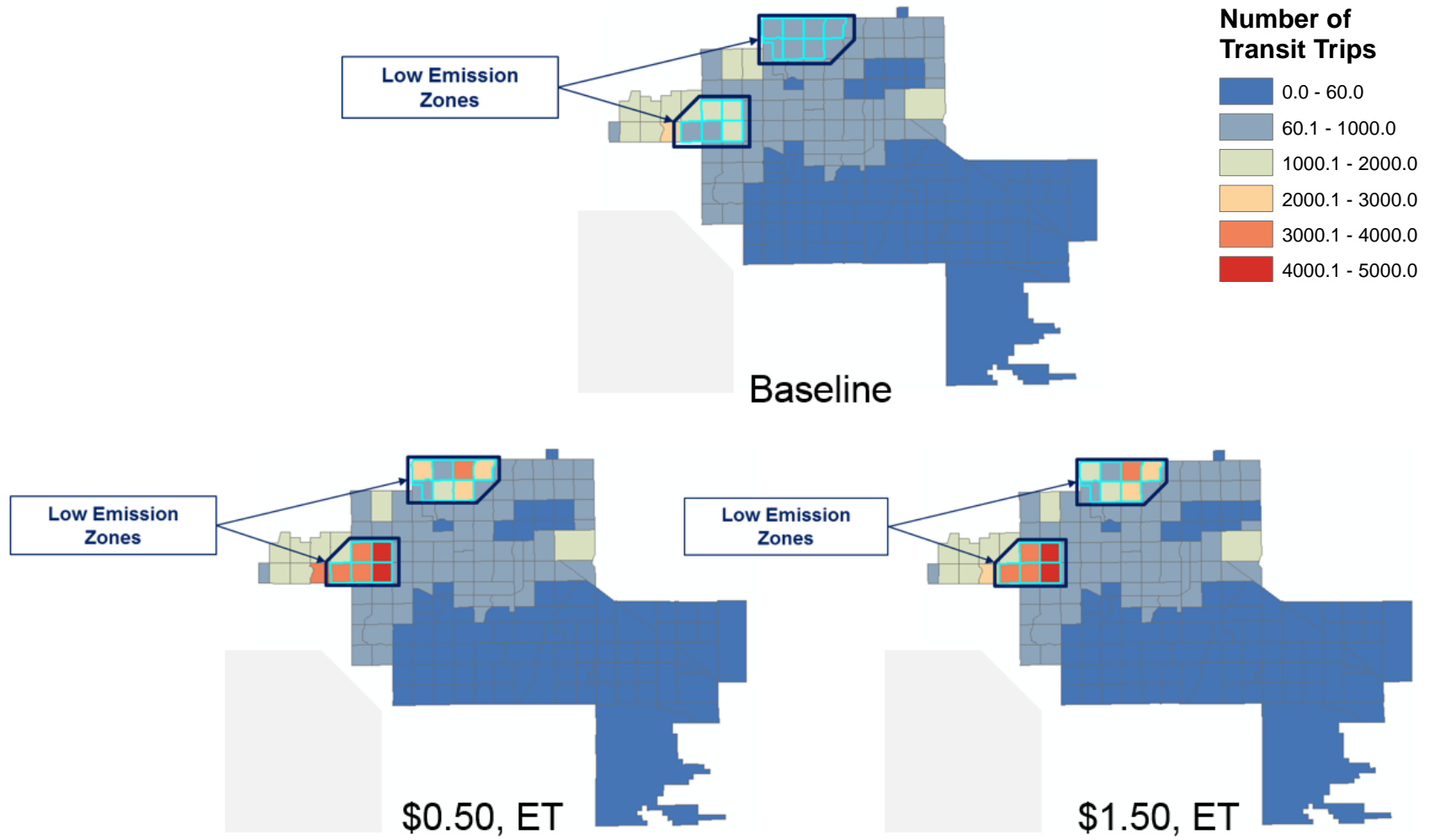
*Figure 30.* Change of transit trip count across two scenarios about enhanced transit service from baseline.

Table 6. *Count of Auto Trips – LEZs vs Regular Zones*

|  | **All LEZs** | **All RZs** | **All Zones** |
| --- | --- | --- | --- |
| Baseline | 109,712 (93.43%) | 976,803 (95.91%) | 1,086,515 (95.65%) |
| $0.50, RT | 110,838 (93.53%) | 975,864 (95.87%) | 1,086,702 (95.63%) |
| $1.50, RT | 112,508 (93.92%) | 974,036 (95.90%) | 1,086,544 (95.69%) |
| $0.50, ET | 82,064 (70.69%) | 968,360 (95.88%) | 1,050,424 (93.29%) |
| $1.50, ET | 85,119 (72.05%) | 970,233 (95.90%) | 1,055,352 (93.40%) |

Table 7. *Count of Transit Trips – LEZs vs Regular Zones*

|  | **All LEZs** | **All RZs** | **All Zones** |
| --- | --- | --- | --- |
| Baseline | 7,718 (6.57%) | 41,666 (4.09%) | 49,384 (4.35%) |
| $0.50, RT | 7,664 (6.47%) | 42,035 (4.13%) | 49,699 (4.37%) |
| $1.50, RT | 7,282 (6.08%) | 41,661 (4.10%) | 48,943 (4.31%) |
| $0.50, ET | 34,018 (29.31%) | 41,592 (4.12%) | 75,610 (6.71%) |
| $1.50, ET | 33,025 (27.95%) | 41,500 (4.10%) | 74,525 (6.60%) |
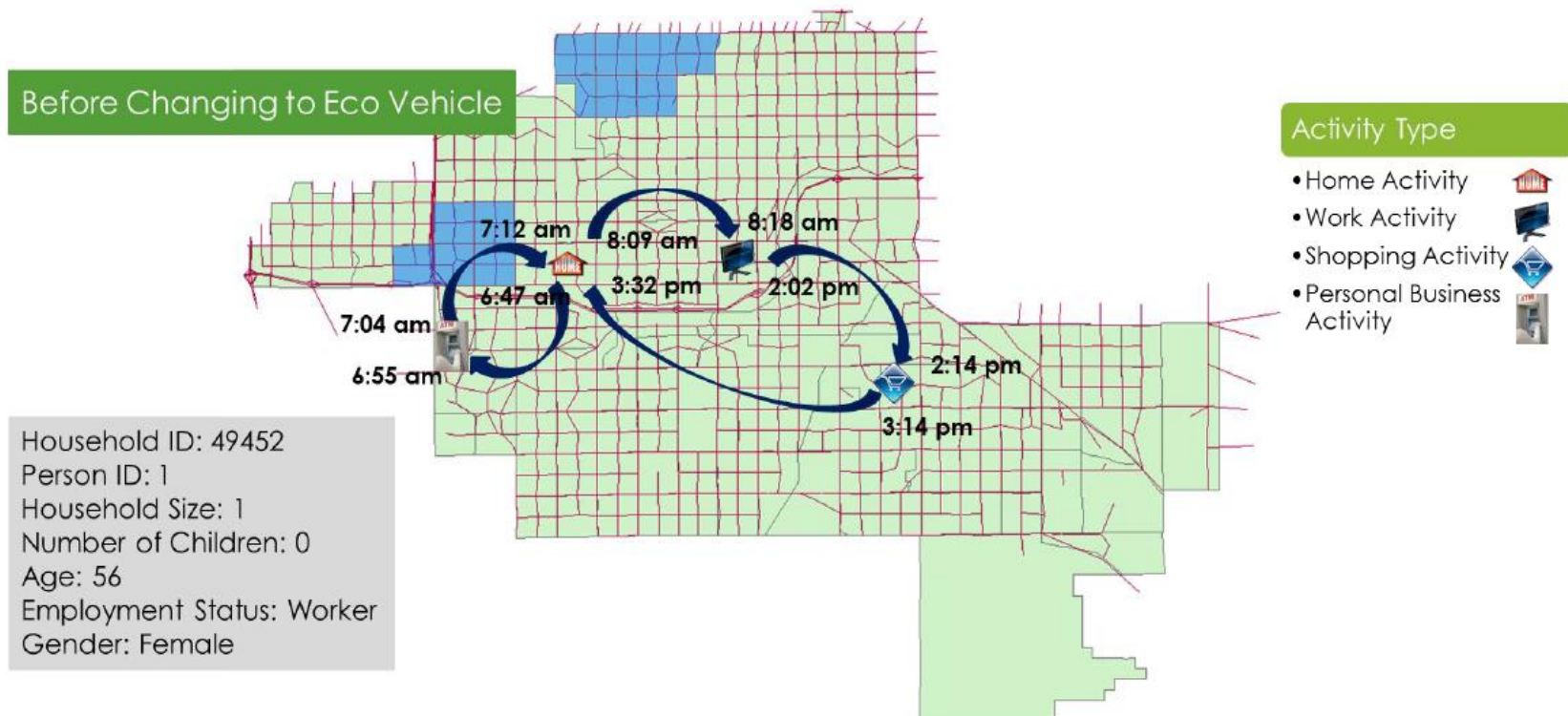
*Figure 31*. Daily activity itinerary for an individual before changing to eco-vehicle.
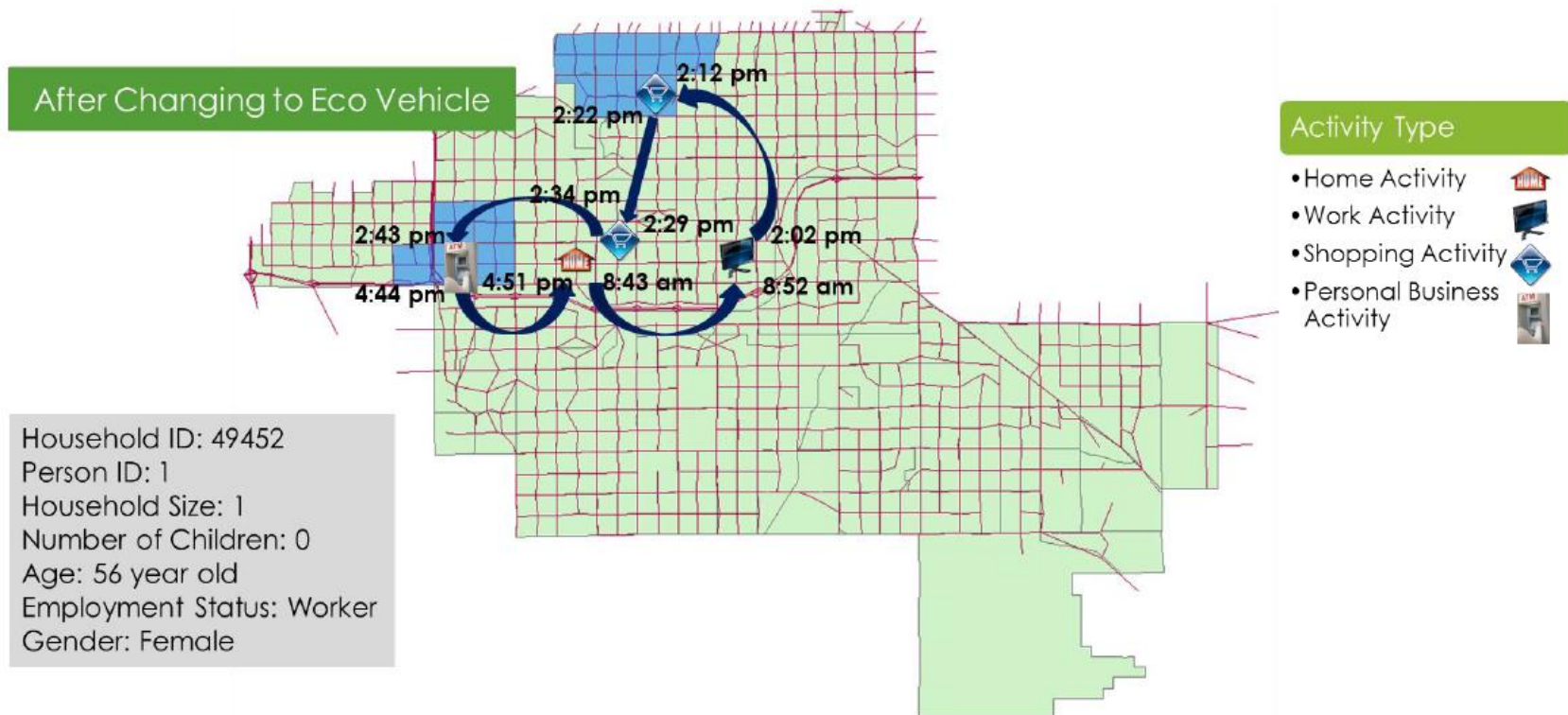
*Figure 32*. Daily activity itinerary for an individual after changing to eco-vehicle.

**Change in energy consumptions and emissions.** In the two scenarios that offer only incentives ($0.5 or $1.5) to eco travelers to travel to LEZs, a slight increase is observed in total vehicle miles traveled (VMT) from 7.233 to 7.250 million miles from baseline scenario (see Figure 33). This finding is consistent with expectation as eco-travelers would drive their eco-vehicles to LEZs (to get the incentives) even if it means that the trip is a little farther than usual. VMT is decreased in the other two scenarios that offer enhanced transit service in addition to incentives. Mode switch to transit is directly driving this reduction in VMT (see Figure 33). Although total VMT is slightly higher in 'incentive only' scenarios, emission and energy consumptions patterns see a downward trend owing to the fact that these are 'higher but cleaner VMT' (see Figure 34 and Figure 35). The incentive policies encourage households to acquire and use eco-vehicles. The change in fleet mix is expected (and observed) to subdue the dis-benefits of increased travel bring greater savings in energy and emission footprint of the region.

Enhanced transit service to LEZs has a major impact in reduction of VMT, energy consumptions, and emissions (Figure 34 and Figure 35). This is another intuitive finding exhibited by the model output as transit in general is purported to be the 'cleaner way to travel'. The results indicate that a 4% of reduction of energy consumption can be expected from baseline to the scenario in which the LEZ policies are implemented at full scale ($1.5 incentive and enhanced transit service) (see Figure 34). Figure 35 shows the percent reduction in $CO_2$, NOX, CO and HC emissions from the baseline scenario. The scenarios that introduce enhanced transit services to LEZs experience greater reduction in energy and emissions. The results of this policy analysis corroborate the belief that reduction in greenhouse gas emissions and petroleum energy consumptions can be

realized with a combination of policies that encourage eco-vehicle acquisition as well as transit ridership.  LEZ policy introduction is an ideal way reduce the emission footprint within selected geographical boundaries as well as the entire region.
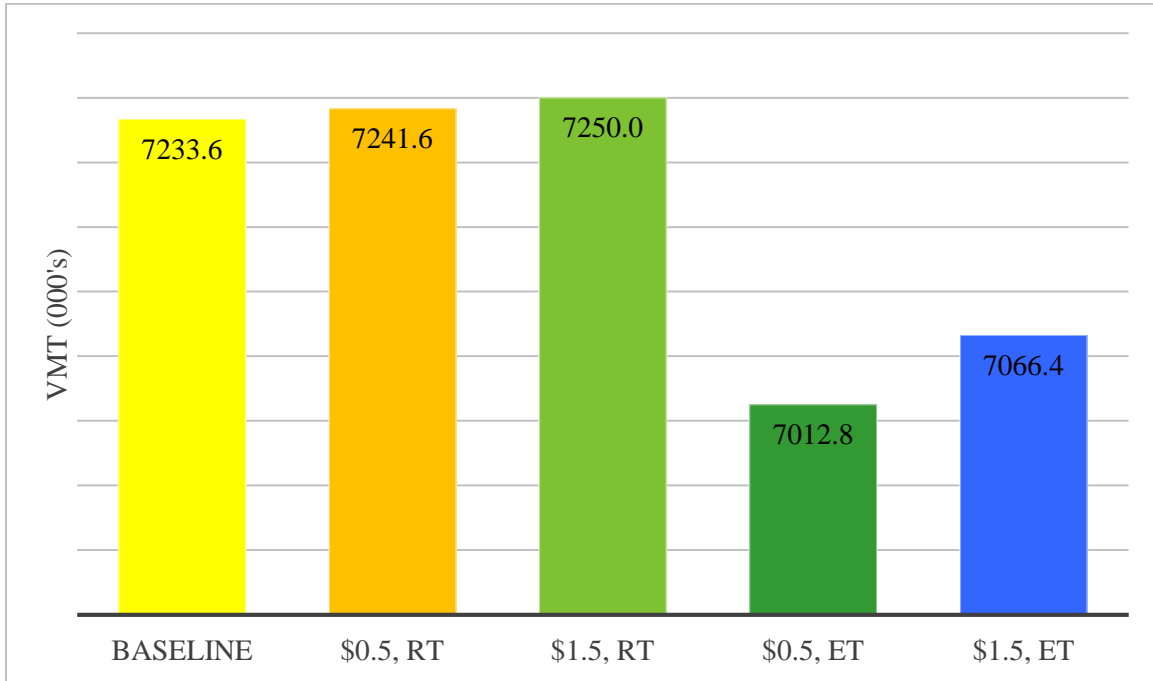


*Figure 33*. Change of vehicle miles traveled (VMT) across the five scenarios.
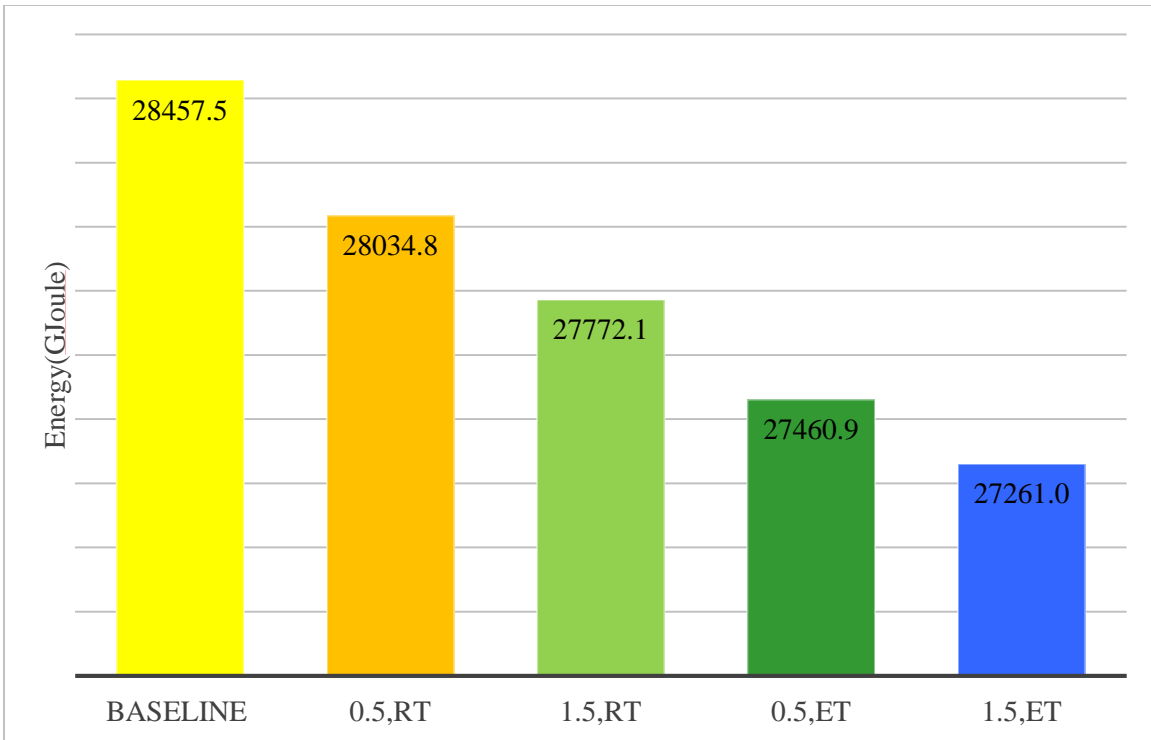
*Figure 34*. Reduction in total energy consumption.
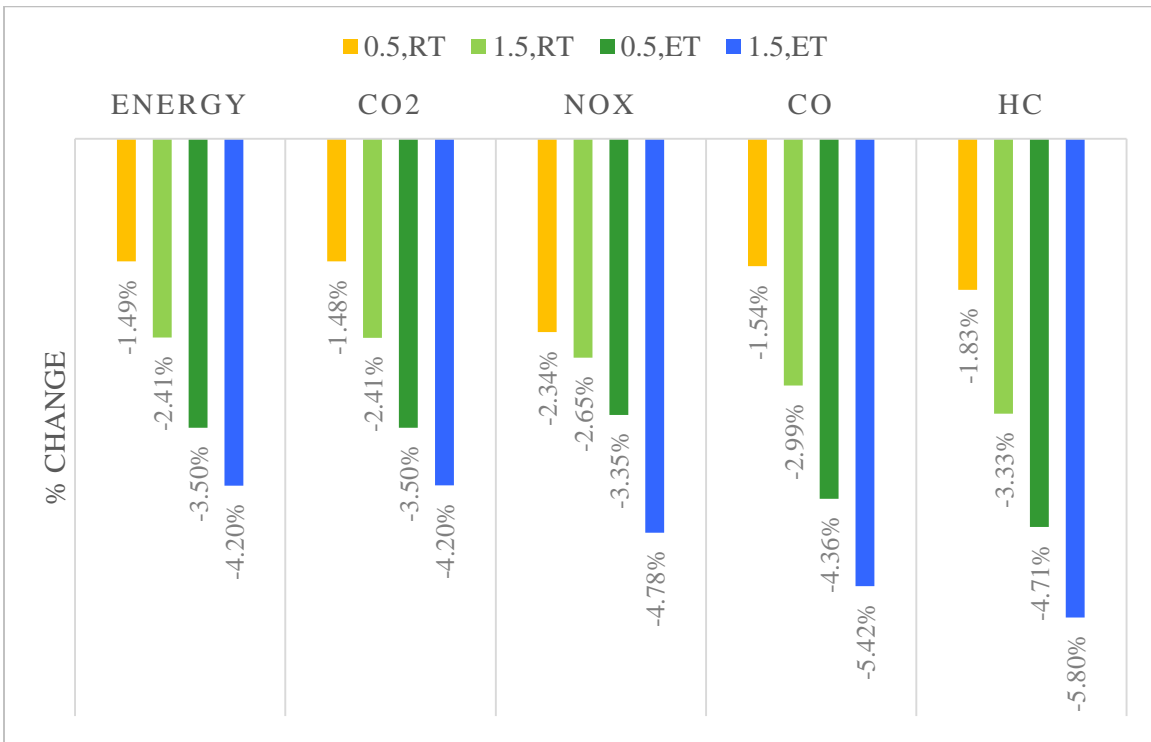


*Figure 35*. Reduction in energy and emissions from baseline.

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## Conclusions and Discussion

The goal of this case study is to model effects of Low Emission Zones (LEZ) on activity-travel engagement patterns, energy consumption and emissions using the integrated model system (SimTRAVEL) that was enhanced as a part of this research effort. Ever increasing energy (gasoline) consumptions and alarming greenhouse gas emission levels from personal travel are a topic of major concern in the field of transportation. To solve this issue, many auto manufacturers are beginning to show interest in developing/producing hybrid as well as electric vehicles to save energy and reduce emissions. However, the 'cleaner vehicle (eco-vehicle)' market is still in its incipient stages and as a result, eco-vehicles are usually costlier thereby making them out of reach for general public. The government is beginning to intervene and encourage the purchase and use of 'greener vehicles' by introducing rebates, tax incentives etc. To help device such policies transportation engineers and policy makers need to explore a wide array of options and their repercussions before finalizing a specific policy (or set of policies). One such approach that is beginning to pique the interest of policy makers and researchers alike is the LEZ policy. At its heart, and LEZ policy is intended to reduce the emission footprint of a specific geographical region (city, two, county or a state). One such policy that has seen great success is the penalty-based LEZ policy implemented in London, United Kingdom. According to the London LEZ policy eco-vehicles (vehicle complying with the emission standards set by authorities) are only allowed to enter specified areas called low emission zones. Vehicles that do not meet the set emission criteria should pay a (heavy) penalty to enter LEZs.

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Another LEZ policy that is gaining much interest on the United States is that of an incentive-based scheme where people are incentivized to acquire and use eco-vehicles to travel to LEZs. This policy is a win-win proposal as the public is receiving an incentive to purchase state of the art technology and this also reduces pollution. Enhanced transit services are introduced to LEZs to increase the transit ridership to LEZs (targeting the market segment that do not acquire eco-vehicles). This study conducts an analysis to study the impacts of LEZ policies on the change in vehicle fleet mix and corresponding emissions.

The framework in SimTRAVEL is enhanced to allow for testing of LEZ (and many other) policies. A total of five scenarios are considered and the results show promise in terms of change in fleet mix and usage patterns as well as emission reductions. An incremental approach was adopted where an incentive only policy is tested first and a transit enhancement to LEZs is introduced in the subsequent scenarios. In the incentive only policy eco-travelers are given an incentive for each trip they make to a LEZ in their eco-vehicle. An un-intended consequence of this policy that was identified from the modeling effort was increase in VMT as eco-travelers drove to LEZ from farther distances (than usual) to realize the benefits of the incentive. The increased VMT however should not be viewed in isolation as these are 'higher but cleaner' VMT. The broader goal of this policy is to reduce emission in specific geographical regions by encouraging the purchase and use of eco-vehicles.

Enhanced transit service to LEZs was found to be a key contributor in reducing energy consumption and bringing emission reductions by encouraging travelers to switch to transit. The transit mode share of trips to LEZs increased from 6% (in the baseline

scenario) to over 27% (see Table 7) in the enhanced transit service scenario bringing significant emission reduction benefits. The result also show notable decreases in energy consumption from the baseline scenario (1,000 ton reduction in the scenario that offers $0.5 incentive + enhanced transit service and 1,200 ton decrease in the scenario that offers $1.5 incentive + enhanced transit service). The results suggest a 4.2% decrease in $CO_2$ emissions (from the baseline) in the full scale scenario ($1.5 incentive and enhanced transit service) (see Figure 35).

The modeling framework used (enhanced SimTRAVEL) is sensitive to activity-travel pattern changes. The model system is capable of handling different types of users simultaneously (eco or non-eco travelers) and accurately depict each classes' activity-travel engagement decisions. Eco-travelers are shown to be impacted by incentive-based LEZ policies on a generalized travel time measure, while non-eco travelers remain inert to the policy as they are neither incentivized nor penalized. On the other hand non-eco travelers are impacted by the enhanced transit service policy as it influences all the population alike. The model system is able to accurately reflect the effect of different level of incentives ($0, $0.5, or $1.5) on activity-travel patterns of individuals. The enhanced modeling framework is capable of simulating mode choice decision for each individual. This is reflected by the changes in transit mode shares in response to enhanced transit services.

Future efforts in the context of LEZ modeling using the integrated model system should focus on enhancing the mode choice model to include more variables and incorporate more modes. The current mode choice model uses only two significant variables to determine mode choice: travel time by mode and cost (transit fare, vehicle

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operating cost, parking penalty, or incentive). These two factors are converted to a generalized travel time measure and each individual choses a mode that maximizes his/her utility based on the computed generalized travel time. Therefore, the mode choice model uses only generalized travel time to simulate mode choice decisions. However, mode choice could potentially be impacted by other factors such as activity type, employment status, gender, household income, number of children in the household or individual age. For example, a woman who is assigned to take care of her children might not want to take transit (even if it has a better generalized travel time) to pick up or drop off her children at school. In this case, gender and number of children in the household are major factors that decide mode choice. The mode choice model in SimTRAVEL should be enhanced to include various household, person and trip characteristics to be able to accurately simulate mode choice decisions at the individual level.

This case study is conducted on the three city sub-region to gain computational efficiencies. The comparative analysis carried out on such a small sub-region might not be able to provide policy makers with an accurate depiction of the effects of such a policy if it were to be implemented for a larger region. Future efforts should focus on expanding the geographical resolution of this study to entire Greater Phoenix Metropolitan Region so that magnitude of results can provide an accurate picture of benefit to cost ratio for different incentive scenarios. A busy zonal-cluster such as the Phoenix downtown should be tagged as a LEZ for such an effort. This study does not consider the financial ramifications of implementing a LEZ policy, i.e., the cost of providing incentives/infrastructure for enhanced transit services. Future efforts should include this as an integral component of the LEZ modeling effort. One way to finance

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the implementation of LEZ policy is adopting the penalty based LEZ implementation followed in London. A toll only LEZ policy might not garner the support of the public. So, a combination and incentive and toll (penalty for most polluting vehicles to enter LEZs) schematic should be tested in future efforts to make this policy a revenue neutral one.

# CHAPTER 6

## Case Study 1– Pre-Trip Information

**Introduction**

This chapter demonstrates the capability of the enhanced SimTRAVEL framework discussed in the previous chapter in the context of a network disruption scenario with pre-trip information provision. If current network condition information is made available to individuals prior to embarking on a trip, they may alter their destination or mode, or completely forego participating in an activity in light of current network conditions. On the other hand, individuals who do not have such information before embarking on a trip, may keep their original plans and in turn be impacted by the network disruption. A key consideration in modeling the effects of pre-trip information provision is that the integrated model system should be able to capture the activity-travel scheduling and rescheduling behavior based on current network conditions and availability of pre-trip traveler information. For evaluating the applicability of the framework and prototype of the enhanced integrated model system, this case study models four different scenarios with varying penetration of pre-trip traveler information in synthetic population. The first scenario is baseline conditions in which no information is available for entire synthetic population and no disruption is assumed. This scenario is run to provide a datum against which rest of the scenarios can be compared and contrasted. In Scenario 1, a network disruption is simulated but the synthetic population does not have access to pre-trip information. Scenarios 2 and 3 assume that 25% and 50% of synthetic population have access to pre-trip information, respectively.

The next section describes how to adopt the framework used in the enhanced SimTRAVEL for modeling pre-trip information provision. In the third section, a brief description of the study area used for this analysis is presented. The fourth section presents results of scenario runs with different levels of penetration of pre-trip information. The last section presents the conclusion and scope for future research.

**Implementing the Model of Pre-Trip Information Provision**

Framework discussed in the previous Chapter 4 was adopted to implement this case study that conducts an analysis of impacts of pre-trip information provision on activity-travel engagement patterns (see Figure 12), in the event of a network disruption. Pre-trip information is defined as information regarding current network conditions provided to individuals before they embark on a journey. Prevailing network conditions could greatly influence individual's activity-travel engagement decision such as activity type, duration, destination, and/or travel mode (if the individuals have access to pre-trip information). For example, checking the current network conditions on Google Maps before embarking on a trip is synonymous to pre-trip information.

To implement the framework for modeling pre-trip information provision, both activity-based model and dynamic traffic model need some functions. On the side of activity-based model, two essential inputs are required. First, openAMOS should include an attribute that indicates whether individuals have access to pre-trip information or they use their past experience of the network conditions to make activity-travel engagement decisions. This study assumes the attribute of pre-trip information flag as a household level variable so that persons in a household have the same characteristics regarding access to information. However, individuals in a household may exhibit different

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behaviors in the context of using the information available. For example, the husband might always check traffic conditions before leaving to work to avoid peak hour congestion. Whereas, the wife may depend on her own experience regarding network conditions to go shopping because traffic is usually not much between morning and evening peak hours. Therefore, she might be more inclined to decide her departure time and destination without using pre-trip information. As a simplifying assumption, this research models the information provision as a household level characteristics. Modeling user information provision at the person level is complicated as interaction of household member's activity-travel engagement patterns need to be taken into consideration. For example, if two household members made a trip together and the two individuals have different levels of user information provision, which individuals characteristics should be attributed to the trip under consideration? The activity-travel demand simulator should compare the characteristics of all individuals engaging in a joint activity to determine appropriate network conditions (prevailing or experienced network conditions). In order to avoid the complication, this research treats characteristics of user information provision at the level of households so this issue does arise not in joint travel. Future efforts in this area should focus on accurately representing household interactions in the context of joint-travel, thereby facilitating modeling of user information provision at the person level.

Second, the activity-travel demand model should be able to handle both experienced and prevailing network conditions while simulating the activity-travel engagement patterns for all individuals. Experienced network conditions (which are available from the previous iteration as origin-destination travel time matrices) are used

for individuals who do not have access to pre-trip information. Prevailing network conditions are used for individuals who are able to access pre-trip information before making an activity-travel engagement decision. The enhanced SimTRAVEL framework developed in this dissertation is capable of handling multiple skim data simultaneously, which greatly facilitates the analysis of impacts of pre-trip information provision.

On the side of the dynamic traffic assignment model, prevailing network (link) conditions should be used to assign trips (on the network), which are generated for individuals who use pre-trip traveler information. The dynamic traffic assignment model has to provide not only expected travel times but also current network conditions. Therefore, the activity-based model is able to utilize both historic and current network conditions to model activity-travel engagement decisions such as activity type, duration and destination choices. Expected travel times are provided by bootstrapping run using only the dynamic traffic assignment model. The dynamic traffic assignment model needs to provide prevailing network conditions as O-D travel time matrices at every $N^{th}$ minute from the beginning to the end (1,440 minutes) of simulation. In the current exercise, the DTA model sends current network conditions at the end of every 30 minutes to the ABM.

**Study Area and Scenarios**

In this study, the enhanced SimTRAVEL is used to capture the impacts of user information provision on travel in three cities (City of Chandler, Town of Gilbert and Town of Queen Creek) of the Maricopa (Greater Phoenix) region in the United States (see Figure 36). This research separates the three cities from the Greater Phoenix Region for the implementation of the integrated model system and to conduct subsequent comparative analysis. The three cities are regarded as an island in this study so that trips

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are only generated inside these cities. That is, trip origin and destinations for all individuals are inside the sub-region. In the sub-region, the total number of households is 167,738 and the total population is 505,350. However, this study uses a quarter sample of the synthetic population (125,861 persons) residing in 41,675 households. Traffic Analysis Zone (TAZ) is chosen as the spatial resolution of analysis for the implementation of this case study.

In the subarea, there are two major highway systems (Loop 101 and 202). Loop 202 passes through the middle of the sub-region from one end to the other (east to west). Loop 101 is crosses the sub-region in the direction of north and south. A big shopping center (Chandler Fashion Center) is located near the intersection of Loop 101 and 202 on the west of the sub-region. Large retail areas are present in the north of city of Chandler. A large scale industry (Intel) is located south of Chandler. Residential communities are built around Intel premises to cater to the company's employees. These factors contribute to a sizeable amount of work, school and discretionary travel in the sub-region.

Dynamic traffic assignment model is not used in this study to model the impacts of pre-trip information provision as the study focuses primarily on the on change in activity-travel 'demand' patterns in light of information provision. However, this study needs arrival information and prevailing network conditions to model the impacts of pre-trip information provision. For arrival information, this study assumes that all O-D travel times under normal network conditions without network disruption are same as the O-D travel times provided by the bootstrapping procedure detailed in Chapter 4. The arrival information under normal network conditions is used to simulate activity-travel patterns for the individuals with no pre-trip information provision.

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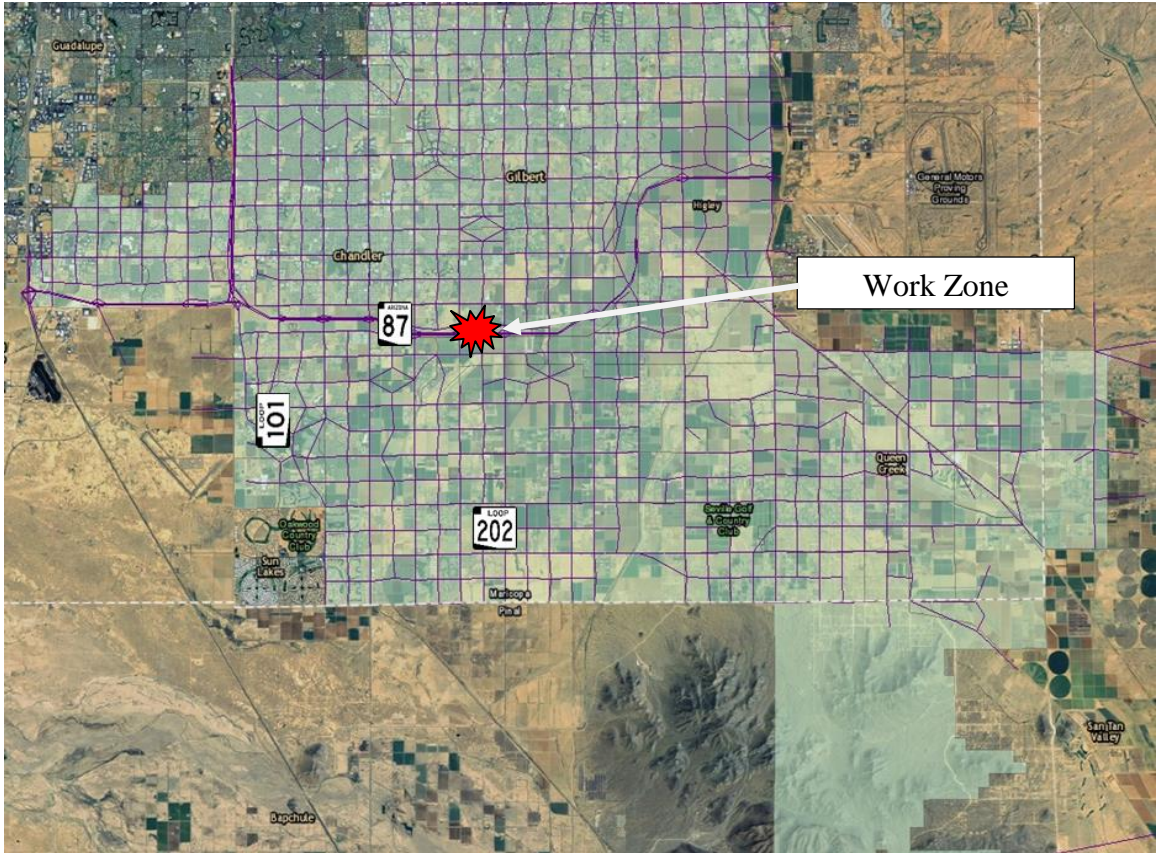
*Figure 36*. Map of study area located on southeast of the Great Phoenix region.

In addition, prevailing network conditions should be provided to the activity-based model to be used for individuals with pre-trip traveler information. Since a planned network disruption is assumed in this study, prevailing network conditions should reflect traffic congestion so that the traffic delays can emulate an impact on individual activity-travel schedules. This study simulates a planned network disruption (work zone) in the middle of 202 Loop freeway for 4 hours from 8 am to 12 pm (see Figure 36 and Figure 37). Because this study uses only an activity-based model, prevailing network conditions are not readily available for the activity-based model to simulate activity-travel patterns for individuals who have access to pre-trip information.

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To overcome this issue, prevailing network conditions are artificially generated using the following steps:

1.  In ArcGIS, highway link feature data is overlaid on zone (polygon) feature system that represents the study area

2.  Segments from the highway link feature data (that represents Loop 202) on which work zone is set are selected

3.  1.0 mile and 2.5 miles (radius) buffers are drawn from the selected segments (see Figure 37)

4.  All zones falling within 1.0 mile, > 1.0 and ≤ 2.5 miles buffers are segregated into sets

5.  To generate prevailing network conditions that reflect the planned network disruption, penalty factors (Table 8) are applied to the O-D travel times obtained from the bootstrapping procedure. Between 8 am and 12 pm, different penalty factors are utilized to obtain prevailing O-D travel time matrices for different buffer segments. For example, if origin zone is in the 1 mile buffer and destination zone is on outside 2.5 miles buffer, penalty factor of 2.3 is multiplied to the travel time from the previous iteration for the O-D pair to get prevailing travel time. Before 8 am and after 12 pm, the O-D travel times for prevailing network conditions are assumed to be same as the expected O-D travel times from the previous iteration.

The prevailing network conditions are generated for every 30 minutes for a simulation day (48 O-D pair matrices in total). All O-D travel time matrices are same as the O-D travel time matrices from the bootstrapping procedure before 8 am and after 12 pm

(noon). Between 8 am and 12 pm, the O-D travel times from the previous iteration are multiplied by the factors shown in Table 8 if either origin or destination, or both origin and destination are within the selected buffer areas. The activity-based model uses expected O-D travel time matrices from the previous iteration for simulating activity-travel engagement patterns of the individuals without pre-trip information. The artificially generated prevailing network conditions are used to simulate activity-travel engagement patterns for individuals who have access to pre-trip information.

Table 8. *Penalty Factors Used to Obtain Prevailing Travel Time Matrices in Time of Day*

| Place of Origin and Destination for Each Trip | Penalty Factor |
|---|---|
| 1. Both origin and destination are inside 1 mile | 3.0 |
| 2. One zone is inside 1 mile buffer and the other zone between 1 mile and 2.5 miles | 2.7 |
| 3. One zone is inside 1 mile and the other zone outside 2.5 miles | 2.3 |
| 4. Both origin and destination are between 1 mile and 2.5 miles | 2.5 |
| 5. One zone is between 1 and 2.5 miles and the other zone outside 2.5 miles buffer | 2.0 |
| 6. Both origin and destination are outside 2.5 miles buffer | 1.0 |
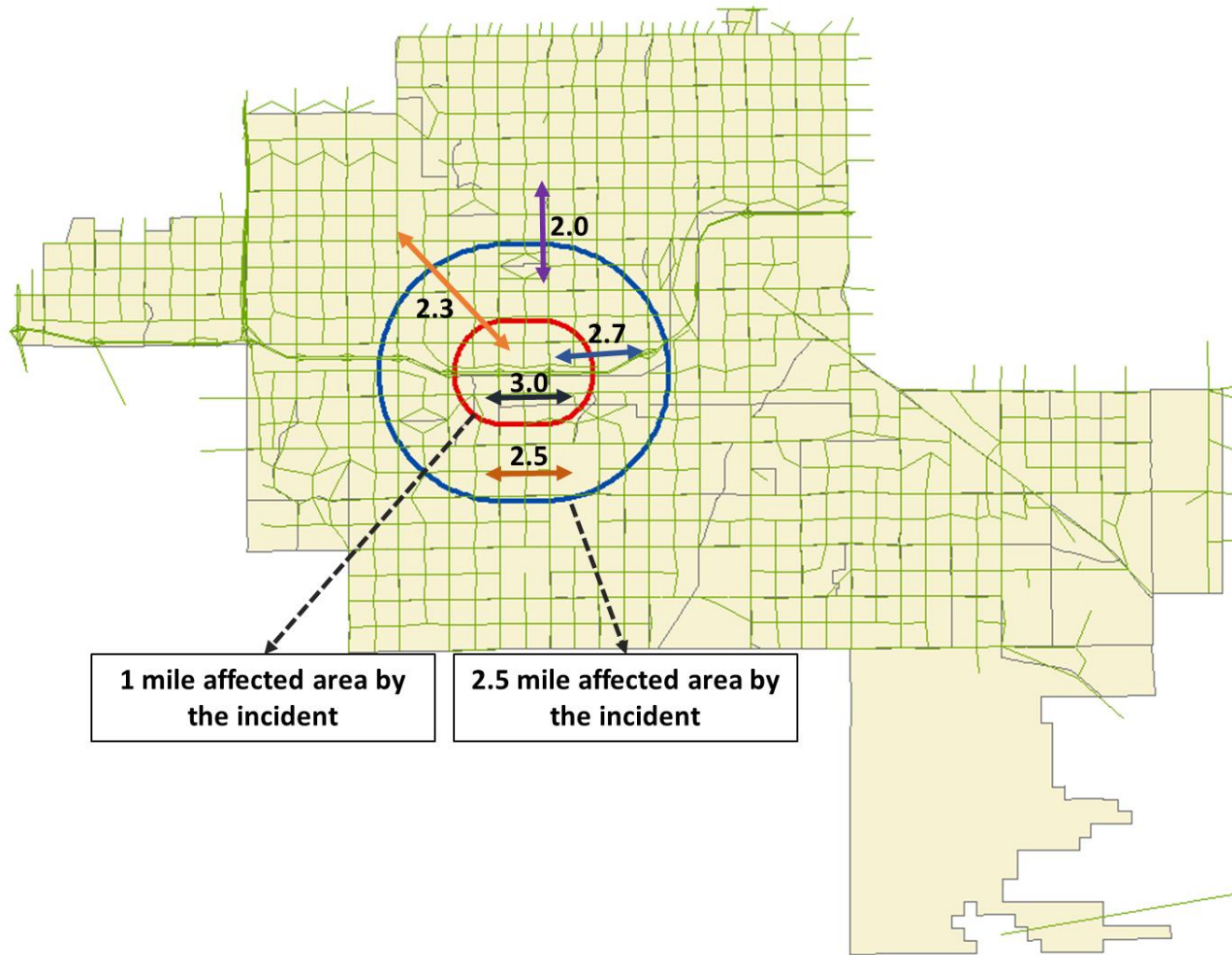
*Figure 37*. Penalty factors by buffer size to generate prevailing O-D travel time matrices.

To evaluate the capability of the prototype of enhanced SimTRAVEL to model impacts of pre-trip information provision, four different scenarios are run in this case study. The scenarios consider two types of travelers: with and without pre-trip information provision. The four scenarios simulated in this study are summarized as follows:

- Baseline (No network delay event): In this scenario, network conditions are assumed to be normal. It means that neither planned nor unplanned network disruptions occur on the network. This scenario serves as the 'datum' to compare other scenarios.

- No pre-trip information: A planned network disruption is assumed on 202 Loop freeway in the study area (see Figure 37). None of the travelers have access to pre-trip information.

- 25% pre-trip information: A quarter of population has access to pre-trip information. A network disruption is assumed on 202 Loop freeway in the study area.

- 50% pre-trip information: 50% of population used in this case study is assumed to have access to pre-trip information. The same network disruption is assumed on 202 Loop freeway in the study area.

**Results**

This section presents the results from all four scenario runs using the enhanced SimTRAVEL for level 1 integration (Chapter 4). From this point forward, the scenario with no disruption is referred to as the base scenario, the scenario with 0% population with information provision under network disruption is referred to as 0% information, the

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scenario with 25% population with information provision under the disruption is referred to as 25% information, and the scenario with 50% population with information provision under the disruption is referred to as 50% information. Table 9 presents the aggregate travel characteristics for the four scenarios under consideration. Total trips and average trip rate are seen to decrease in the scenarios in which work zone disruption is assumed to occur on the 202 freeway (see Figure 36) compared to the base scenario. As persons with pre-trip information provision increases, trip count and trip rate are observed to increase. Trip rate changed from 4.46 to 4.50 and trip count increased by 5,500 trips from 0% information provision to 50% information scenario. On the other hand, total trip duration and average trip duration decrease as the percent of population with pre-trip information provision increases. The network incident is found to impact participation in subsequent activities and associated travel for individuals who have no information. Therefore, travelers may not have enough time to engage in as many activities because they spent longer time stuck in the traffic due to the network disruption. As the percentage of individuals who have access to pre-trip information increases, adverse impacts of network disruption are seen to decrease. From Table 9 it can be observed that the total adult work trips are very stable across all scenarios. Workers may not have the flexibility to cancel work episodes because of a network delay event. The travel demand model system built in SimTRAVEL is able to reflect the fact that work trips would not be impacted by network disruptions.

Trip counts by destination during hours of the network disruption were measured to study how pre-trip information provision impacts the activity-travel engagement patterns, specifically destination choice. Destinations were aggregated into three

segments dictated by buffer sizes: 1 mile buffer zones (within 1 mile from the work zone), 2.5 miles buffer zones (between 1 and 2.5 miles from the work zone), and outside the affected areas (outside 2.5 miles buffer zones from the work zone). Total trips were counted in all the scenarios in each of these segments. Figure 38 shows percent difference in trip counts for three scenarios in which a network disruption is assumed from the no disruption (baseline) scenario. From the figure, a clear trend can be observed in the destination choice where choosing zones in 1 mile and 2.5 miles buffer zones for engaging activities was gradually decreasing with increasing penetration of pre-tri information provision. Zones outside the affected areas were chosen more as level of information provision increased from 0% to 50% population. This trend is consistent with expectation as persons who have access to pre-trip information would prefer choosing un-affected locations to avoid the disruption in the context of non-mandatory activity engagement (e.g. discretionary or maintenance activities).

Figure 39 presents the percent difference in trip duration distributions for the three disruption scenarios from baseline (that assumes no network disruption). The trends observed from the comparison are intuitive and consistent with expectation. Shorter trips that are less than 15 minutes decreased for all disruption scenarios compared to baseline scenario. On the other hand, longer trips (≥15 minutes) increased for all disruption scenarios compared to baseline scenario. Therefore, the planned network disruption (work zone) between 8 am and 12 pm impacted the travel in the region in a manner that is consistent with expectation. As persons who use pre-trip information increase, the magnitude of decrease in shorter trips (< 15 minutes) from baseline scenario is lower than the scenario with zero percent population for information provision. In the two scenarios

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with 25% and 50% pre-trip information provision, longer trips (≥ 15 minutes) decreased from the scenario where 0% population have pre-trip information under a network disruption.

Matrices of daily time allocation to travel and activities are used to analyze the results of all scenario runs. Table 10 shows the output produced by the activity-travel demand model. Individuals should allocate their time budget in a day (24 hours ~ 1,440 minutes) to travel and activity episodes. Table 11 houses a different column for each scenario and each type of information provision. Results are presented in this table as difference from the baseline scenario after normalizing time spent for activities and travel to 1,440 minutes. As expected, Table 10 and Table 11 show that individuals spent slightly higher time on travel than on activities in all of the network disruption scenarios. Although total activity time decreased by 3.4 minutes for the first disruption scenario with no information provision against baseline scenario, the lost time is seen to recover with increasing information provision. Complementing this finding, total travel time shows a spike in the no information provision scenario and slowly comes down as the penetration of pre-trip information increases. This result is consistent with the trip duration distributions shown in Figure 39. The bottom line from this analysis is that people make better activity-travel decisions with pre-trip information than without.

The activity time drops of 2.3 and 2.4 minutes (and the corresponding travel time increases) for travelers with pre-trip information between 25% and 50% scenarios are almost similar. This is a rather interesting observation that might warrant further investigation. One would expect that as more travelers have pre-trip information, the average travel time should follow a downward trend than plateau out. A possible reason

for this phenomenon might be the optimal penetration of pre-trip information provision. If everyone individual has pre-trip information and is altering his/her activity-travel engagement patterns, this might not lead to a system optimal solution. More disaggregate levels of penetration pre-trip information provision should be studied to identify the information provision threshold, in case one exists.

From all of the results presented, we can clearly observe that the network disruption indeed impacts activity-travel engagement patterns and pre-trip information provision is an effective counter-measure to alleviate the adverse impacts of network disruptions. Though the network conditions under the disruption assumption are not estimated by a dynamic traffic assignment model, the trends presented in the results are consistent with expectation. Also, the trends in this study are very consistent to the results of a similar study (Konduri, 2012) that presents results of two cases: i) no information provision or ii) full information provision. Therefore, the integrated model system enhanced in this research is able to model the impacts of network disruptions under different levels of pre-trip information provision in a behaviorally realistic fashion.

Table 9. *Aggregated Travel Characteristics for the Impacts of Pre-Trip Information Provision*

| | No Disruption | No Information Provision | 25% Information Provision | 50% Information Provision |
|---|---|---|---|---|
| Population | 125,861 | 125,861 | 125,861 | 125,861 |
| Total persons with information provision | 0 | 0 | 31,947 (25%) | 63,095 (50%) |
| Total trips | 574,795 | 561,055 | 562,857 | 566,565 |
| Total trips with information provision | 0 | 0 | 145,146 | 287,529 |
| Total adult work trips | 46,546 | 46,548 | 46,532 | 46,544 |
| Total travel time (minutes) | 5,512,943 | 5,798,556 | 5,759,397 | 5,746,306 |
| Average trip rate | 4.57 | 4.46 | 4.47 | 4.50 |
| Average travel time (minutes) | 9.59 | 10.34 | 10.23 | 10.14 |
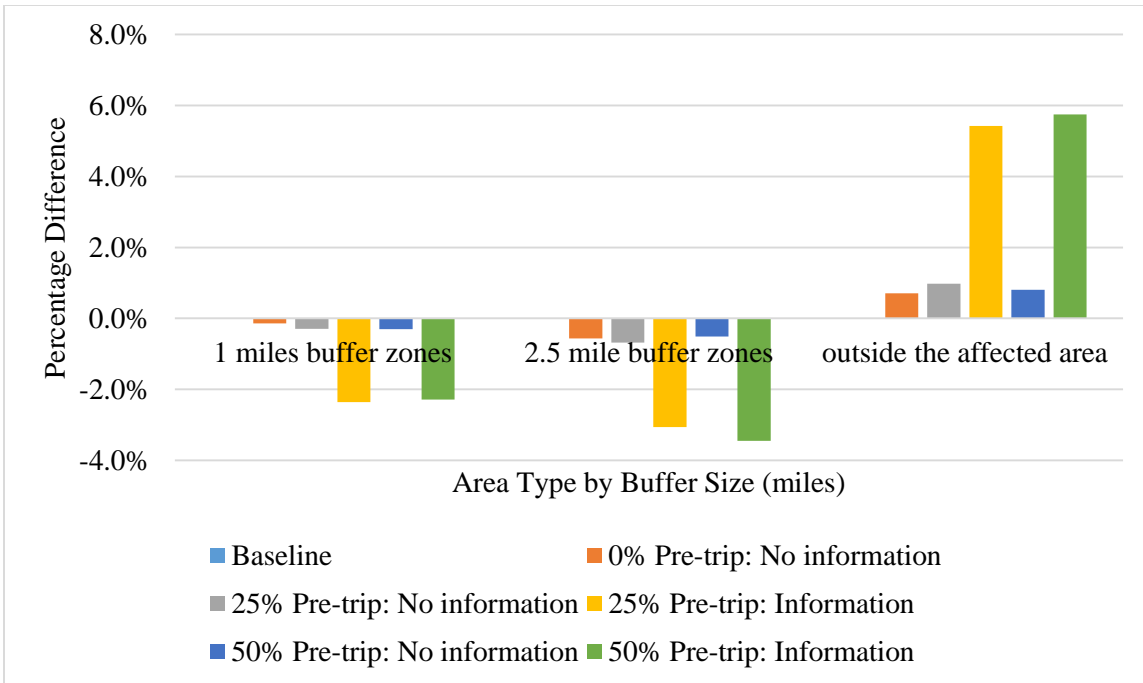
*Figure 38*. Percentage difference in trip count from baseline from 8 AM to noon for pre-trip information provision.
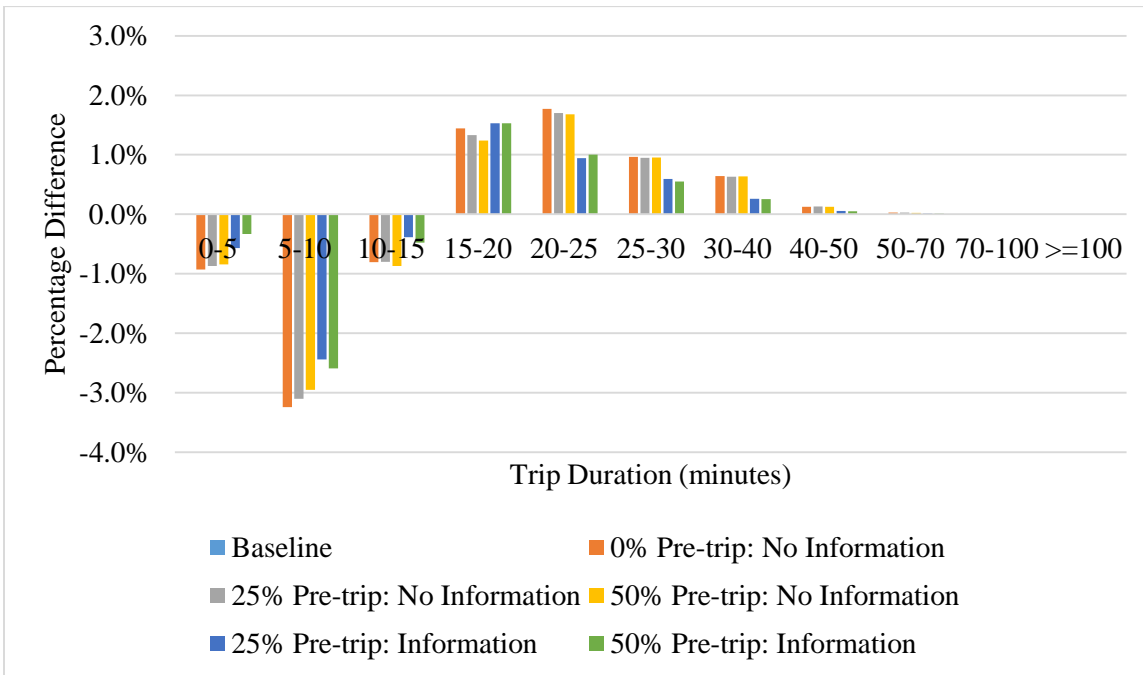


*Figure 39*. Percentage difference in the distribution of trip duration from baseline for pre-trip information provision.

Table 10. *Daily Time Allocation to Travels and Activities Per-capita in Pre-trip Information Provision*

| | Baseline | No Pre-trip | 25% Pre-trip | | 50% Pre-trip | |
|---|---|---|---|---|---|---|
| | **No Disruption** | **No Information** | **No Information** | **Information** | **No Information** | **Information** |
| *Time Spent on Activities* | | | | | | |
| Home | 1072.8 | 1069.5 | 1070.0 | 1072.9 | 1070.1 | 1071.1 |
| Work | 196.6 | 196.0 | 196.0 | 196.4 | 195.6 | 197.0 |
| School | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 | 0.5 |
| Maintenance | 73.8 | 71.9 | 71.4 | 73.0 | 72.2 | 73.3 |
| Discretionary | 29.1 | 28.2 | 28.4 | 28.2 | 28.2 | 28.5 |
| Pick Up | 0.4 | 2.3 | 2.3 | 0.6 | 2.4 | 0.4 |
| Drop Off | 2.2 | 2.1 | 2.1 | 2.3 | 2.1 | 2.2 |
| OH-Other | 12.0 | 11.8 | 11.9 | 11.4 | 11.7 | 12.1 |
| *Total Activity Duration* | *1387.6* | *1382.3* | *1382.8* | *1385.3* | *1383.0* | *1385.1* |
| *Time Spent on Travels* | | | | | | |
| Home | 19.7 | 20.7 | 20.6 | 20.6 | 20.6 | 20.6 |
| Work | 6.5 | 7.2 | 7.2 | 6.9 | 7.2 | 6.9 |
| School | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Maintenance | 13.8 | 14.8 | 14.7 | 14.3 | 14.7 | 14.4 |
| Discretionary | 3.9 | 4.1 | 4.1 | 4.0 | 4.0 | 4.0 |
| Pick Up | 1.9 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| Drop Off | 1.9 | 1.9 | 1.9 | 2.0 | 1.9 | 1.9 |
| OH-Other | 1.4 | 1.6 | 1.6 | 1.5 | 1.6 | 1.5 |
| *Total Travel Duration* | *49.1* | *52.4* | *52.2* | *51.4* | *52.0* | *51.5* |
| *Total Daily Accounting* | *1436.7* | *1434.7* | *1435.0* | *1436.8* | *1434.9* | *1436.6* |

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Table 11. *Difference of Daily Time Allocation to Travels and Activities from Baseline in Pre-trip Information Provision*

| | Baseline | No Pre-trip | 25% Pre-trip | | 50% Pre-trip | |
|---|---|---|---|---|---|---|
| | No Disruption | No Information | No Information | Information | No Information | Information |
| *Time Spent on Activities* | | | | | | |
| Home | 0.0 | -1.9 | -1.5 | 0.0 | -1.4 | -1.7 |
| Work | 0.0 | -0.4 | -0.4 | -0.3 | -0.8 | 0.3 |
| School | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.1 |
| Maintenance | 0.0 | -1.8 | -2.3 | -0.8 | -1.5 | -0.5 |
| Discretionary | 0.0 | -0.9 | -0.6 | -0.9 | -0.9 | -0.5 |
| Pick Up | 0.0 | 1.9 | 1.9 | 0.2 | 2.0 | 0.0 |
| Drop Off | 0.0 | -0.1 | -0.1 | 0.1 | -0.1 | 0.0 |
| OH-Other | 0.0 | -0.3 | -0.1 | -0.6 | -0.3 | 0.0 |
| *Total Activity Duration* | 0.0 | *-3.4* | -3.1 | -2.3 | -3.0 | -2.4 |
| *Time Spent on Travels* | | | | | | |
| Home | 0.0 | 1.0 | 0.9 | 0.9 | 0.9 | 0.9 |
| Work | 0.0 | 0.8 | 0.8 | 0.4 | 0.7 | 0.5 |
| School | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Maintenance | 0.0 | 1.0 | 0.9 | 0.6 | 0.9 | 0.6 |
| Discretionary | 0.0 | 0.2 | 0.2 | 0.1 | 0.1 | 0.1 |
| Pick Up | 0.0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Drop Off | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 |
| OH-Other | 0.0 | 0.2 | 0.2 | 0.1 | 0.2 | 0.1 |
| *Total Travel Duration* | 0.0 | *3.4* | 3.1 | 2.3 | 3.0 | 2.4 |

**Conclusions and Discussion**

The enhanced SimTRAVEL framework was employed for modeling impacts of pre-trip information provision under a planned network disruption event. The microsimulation-based integrated model system used in this research observes a tight coupling with constant feedback between an activity-based demand model and dynamic traffic simulation model. Konduri (2012) illustrates why a tightly integrated model system should be used to conduct analysis of network disruptions under different levels of information provision. Network delay events effect individual's activity-travel engagement patterns and the affected activity-travel engagement behaviors in turn impact the network conditions. Using traditional integrated model systems that employ a sequential connection between a travel demand model and traffic simulation model, it is difficult to accurately capture interactions between activity-travel engagement patterns and network conditions in a behaviorally realistic way. The previous version of SimTRAVEL developed by Konduri (2012) identifies and addresses this issue, but it is not capable of modeling network disruptions under various levels of information provision.

The framework of the integrated model system enhanced in this study is able to capture interactions among activities that form activity-travel agenda for each individual in the event of network disruptions under varying levels of information provision. If individuals spent longer time on trips because of a network disruption, they may reduce activity duration or skip subsequent activities. The results obtained from the runs of four different scenarios clearly show that the model system is able to simulate activity-travel patterns with due consideration to interactions among activities and trips for each

individual. First, total number of trips in the three disruption scenarios is observed to decrease from the base scenario. This means that a portion of individuals who engaged in activities in or near the areas affected by the network disruption had to skip their subsequent activities in light of the network delay. Hence, the result presents a decrease of trip count in all the three scenarios where a network disruption is assumed. Second, the comparison of daily time allocation to travel and activities per-capita show that individuals spent a little more time on travel and a little less time on activities under three network disruption scenarios. The integrated model system employed in this study is capable of capturing impacts of network disruption on activity-travel engagement process in a behaviorally consistent way.

In addition, the integrated model system accurately depicted the varying magnitudes of network disruptions under different levels of information provision. The percent of population with access to pre-trip information provision can be changed in accordance with transportation policies to be tested. In the three disruption scenarios, various levels (0%, 25%, and 50%) of information provision penetration were introduced to analyze the impacts of pre-trip information provision on activity-travel engagement processes. The results across the three disruption scenarios show that the framework used in the enhanced model system is capable of modeling varying levels of information provision in the event of a network disruption. The enhanced SimTRAVEL model system is robust and can be extended to conduct policy analyses for evaluating, planning, and implementing various types of traveler information technologies.

The results from different scenario runs show intuitive trends and corroborate the capability of enhanced SimTRAVEL in capturing the impacts of pre-trip information

provision on activity-travel engagement patterns. First, travelers with access to pre-trip information would most likely avoid choosing an activity destination in the areas affected by a network disruption (see Figure 38). Second, the percentage of longer trips (over 20 minutes) was observed to decrease for travelers with pre-trip information, which is a direct manifestation of the decision making process in light of availability of current network conditions (see Figure 39).

However, it is to be noted that only activity-travel demand model was used in this case study to simulate the impact of network disruptions under varying levels of pre-trip information. Current (prevailing) network conditions were obtained by multiplying asserted delay factors to the expected O-D travel times from the bootstrapping procedure as this case study primarily concerns with analysis of activity-travel engagement patterns (demand side decisions) in light of a network disruption with information provision. However, real-time network conditions are needed to conduct a more accurate analysis of activity-travel behavior and future efforts should focus on testing the framework in the context of an integrated model system where an activity-based model and a dynamic traffic assignment model are in continuous communication with each other.

# CHAPTER 7

## CASE STUDY 2 – En-route Decision Process

**Introduction**

This chapter demonstrates the applicability of the enhanced SimTRAVEL framework in accurately capturing en-route decision making processes. This effort is detailed as level 3 enhancement in Chapter 4. En-route decision paradigms that characterize how individuals' process information while they are en-route (on the way) to a destination are different from decision processes made with pre-trip information (before starting a journey). With respect to decision process in the context of pre-trip information, individuals make decisions regarding activity-travel engagement prior to embarking on a trip based on network conditions. On the other hand, individuals who have real-time information may alter their route, destination, or skip the activity altogether in response to network delays. The integrated model system (SimTRAVEL) is enhanced to model not only pre-trip but also en-route decisions in response to network delay events.

This chapter comprises of four sections detailing the case study for modeling en-route activity-travel engagement decisions. The next section presents the case study implementation details. The third section describes study area and scenarios. In the fourth section, results of micro-simulation runs for different scenarios, with different levels of en-route traveler information penetration (0% or 50% of synthetic population) are presented. The last section presents concluding thoughts and discusses avenues for future research in this domain.

**Implementing En-route Decision Process in the Enhanced SimTRAVEL**

The enhanced SimTRAVEL framework (level 3) described in Chapter 4 was used to perform a case study to estimate impacts of real-time information provision on activity-travel engagement behaviors in the event of a network disruption. Similar to the previous case study that estimated impacts of pre-trip information provision, only the activity-based model system (openAMOS) was used to implement this case study for conducting simulation runs for different scenarios with real-time traveler information provision under a network disruption. In the model framework, some information is delivered by a simplified dynamic traffic assignment model to an activity-based model system to mimic real-time information provision. To establish behavioral realism in the framework, a few key pieces of information need to be exchanged between the demand and supply model systems. First, information regarding trips that are in distress is sent to an activity-based model to identify which trips are experiencing heavy delays (determined by a user set threshold value). Second, information regarding the time at a trip should be checked for distress status is exchanged. Third, current location for all trips in distress should be known to the activity-based model. Therefore, a simplified network model was created to provide the essential input data required by the activity-based model system. The following paragraph describes the process involved in generating this input data.

As soon as a trip is realized to be in distress, a dynamic traffic assignment model sends the trip back to the activity-based model. Activity-travel engagement patterns are simulated in response to the network congestion. A critical judgment to be made here is when should the trips that are in distress be sent back to the demand model? When should

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a trip be checked for determining whether it is in distress or not? The current study chooses this time as 1 minute after trips depart from their origin. It assumes all travelers with real-time information access current network conditions as soon as they get in their vehicle. That is, after a traveler embarks on a trip, the trip is sent back to the demand model in 1 minute, if the trip is tagged to be in 'distress'. For example, if a traveler departed at 3:30 pm, the trip is checked for its status at 3:31 pm and if the trip is determined to be in distress, it is sent back to the activity demand model for further action.

All travelers may not change their route, activity, destination, or trip mode as they receive real-time information regarding a network disruption. Some travelers would incur minor delays and stick to their current route. Hence, all trips that are in traffic distress are not required to change activity-travel pattern. To model this concept of travel behavior, this study employs a 'threshold value' schema. If the delay caused by network disruption is greater than the threshold determined (threshold is a user set parameter) for a traveler using real-time information system, the enhanced model system regards this trip as a 'trip in distress' and is considered for change of activity-travel engagement to avoid the distress. Different individuals may perceive delay at different degrees. So, a fixed value is not ideal for defining a threshold for all of the synthetic population. Instead, this study employs a varying threshold minutes between 5 and 15 minutes, randomly determined for each individual. For example, if an individual who is assigned a threshold value of 10 minutes, experiences a 20 minute network delay on a specific trip, the activity-based model regards that the trip under consideration is in 'distress' and hence the individual would change his/her activity-travel decision in order to reduce adverse impacts of the network delay.

The current location for each traveler who is en-route to an activity destination should be known to the activity-based model to accurately simulate the change in activity-travel engagement. The current location of each individual is critical in simulating the activity-travel choices as destination preferences for travelers are heavily influenced by their current location. Usually, a dynamic traffic assignment model sends information regarding the current location of trips that are on network, but the implementation for this case study does not use a dynamic traffic assignment model. In order to overcome this issue, a novel approach is employed to identify each individual's current location. Figure 40 shows an example that describes how to determine the current location while travelers are en-route to their destination. The approach is summarized below:

1. Use an O-D travel time matrix from the previous iteration to determine the distance between origin and destination. As the travel demand model knows origin as well as destination (from a destination choice model) location information for each trip , it is easy to get the O-D distance from the matrix

2. Draw radial buffers around origin and destination using the O-D distance as radius. There will be two circles drawn for each O-D pair, one for origin and one for destination (see Figure 40).

3. Select all zones (Traffic Analysis Zones) that fall inside the circles. Since there are two circles drawn, there will be two lists. One list stores all TAZs within the radial buffer for the origin and the other list stores all TAZs within the radial buffer for destination.

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4. Determine the intersection of these two lists. That is, select the zones that exist in both lists

5. Randomly select a zone from the intersection list, which will be regarded as the current location for the trip
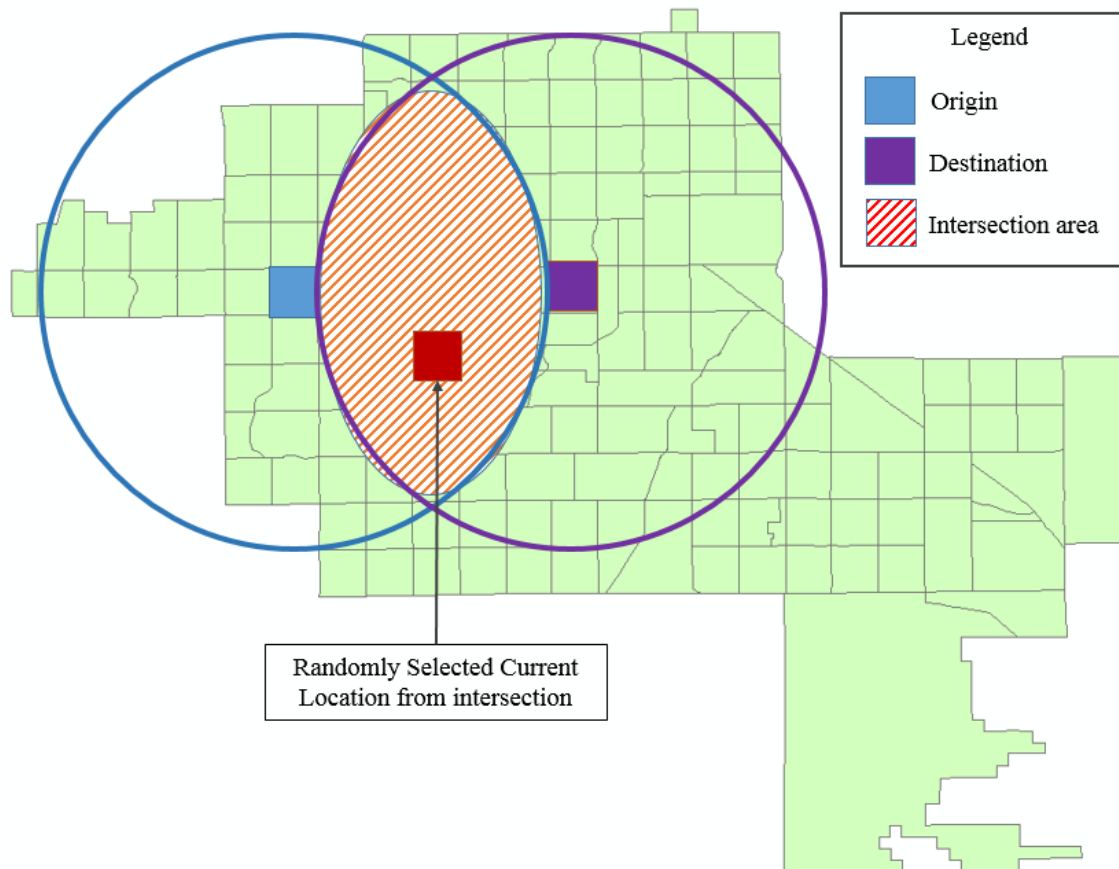


*Figure 40*. Example of selecting a current location for en-route decision process.

**Study Area and Scenarios**

The same study area used in the previous case study is employed for modeling the impacts of real-time information provision on change of activity-travel patterns en-route. This study uses the same synthetic population that comprises of 125,861 people residing in 41,675 households in three cities (Chandler, Gilbert, and Queen Creek) in the southeast

of Great Phoenix region. This study regards the three cities as an island so that there are no out-going trips and in-coming trips to the study area. Enhanced SimTRAVEL is used to generate the travel demand for the three city region. In this case study, prevailing network conditions be available to the activity-based model (similar to the previous case study) to model changes in activity-travel patterns in response to real-time information. The same prevailing O-D pair travel matrices described in Chapter 6 are used in this study to model en-route decision making process in light of a planned network delay event in the middle of Loop 202 freeway from 8 AM to 12 PM (see Figure 37). Prevailing network conditions are used to simulate activity-travel engagement patterns of individuals who have access to real-time information en-route to their destination. Before embarking on a trip, experienced network conditions (from the previous iteration) are used for determining activity type, destination, duration and mode although travelers have access to real-time information system. Real-time information is used only for en-route decision making process. For travelers without access to real-time information, experienced network conditions are always used to simulate activity-travel engagement patterns.

To evaluate the applicability of the prototype of the enhanced SimTRAVEL to modeling impacts of en-route decision processes, three different scenarios are tested in this case study. The scenarios accommodate two classes of travelers: i) travelers with no en-route information and ii) travelers with en-route information. The three scenarios evaluated in this study are summarized as follows:

- Baseline (No network delay events): In this scenario, network conditions are assumed to be normal. It means that neither planned nor unplanned network

disruptions occur on the network. This scenario provides a datum for comparing other scenarios.

- No real-time information: In this scenario, none of the travelers have access to real-time information in the event of a network disruption.

- 50% real-time information: 50% of the synthetic population are assumed to have real-time information en-route to their destination.

**Results**

In order to estimate impacts of real-time traveler information system on change in activity-travel patterns, full-scale simulation runs are carried out using the enhanced SimTRAVEL. This section presents the results from the different scenario runs. Figure 41 shows percent difference in trip count from baseline scenario from 8 am to 12pm (noon) across three different type zones defined by buffer size. Percent differences for no information travelers in all disruption scenarios are less than 1% on the three zonal segments. This means that the destination choice patterns for travelers with no real-time information do not change across different scenarios as they make activity-travel decisions based on experienced travel times (from previous iteration) oblivious of the network disruption in the current iteration. However, travelers with real-time information provision will try to avoid travelling to the zones affected by the network disruption. Trip count for the travelers with real-time information is decreased by 1.9% and 2.1% in 1 and 2.5 mile buffer zones, respectively. Trip counts increased by a commensurate amount (4.1%) outside the area affected by the network disruption. Therefore, if the travelers have information regarding current network conditions en-route and their

activities are flexible, they are more likely to alter their destinations to avoid the network disruption.
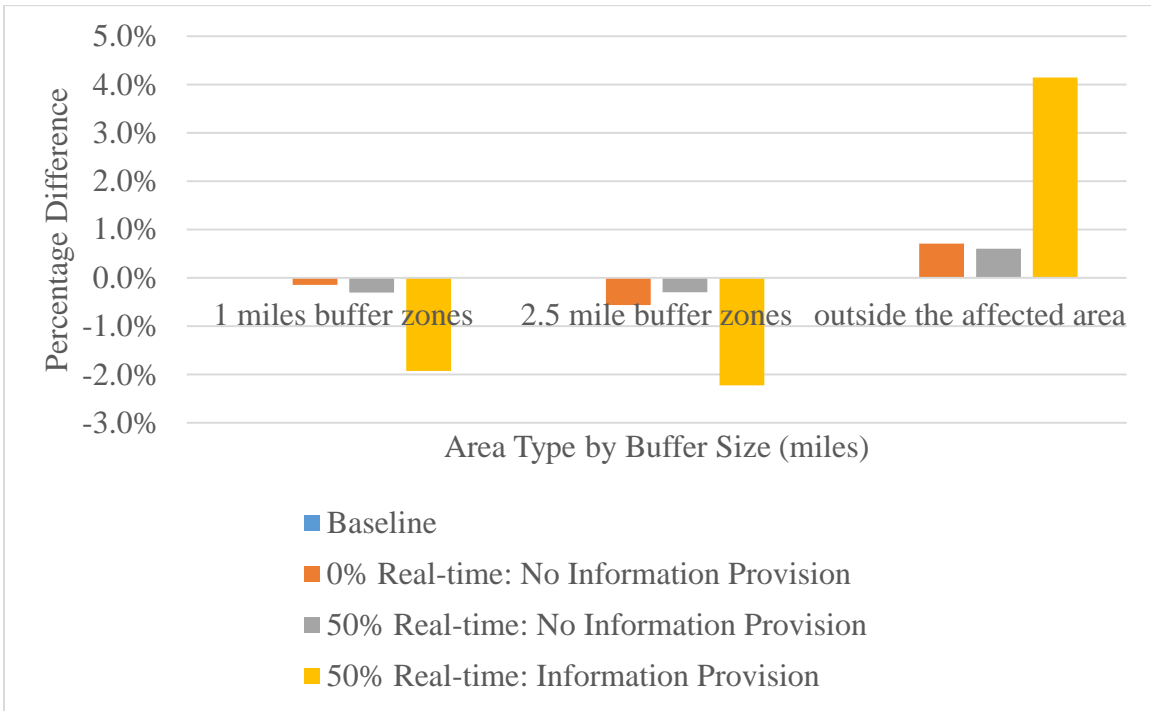


*Figure 41.* Percentage difference in trip count from baseline from 8 am to noon for real-time information provision.

Figure 42 presents percentage difference in trip duration distribution for all disruption scenarios from the baseline. The trend observed from the results of this case study is similar to the results of pre-trip information case study from Chapter 6. Number of trips that are shorter than 15 minutes are observed to decrease in light of network disruption. On the other hand, longer duration trips ($\geq$ 15 minutes) increased due to the network disruption. The percent difference for travelers who have access to real-time information in the 50% information scenario is less than that of travelers with no information.
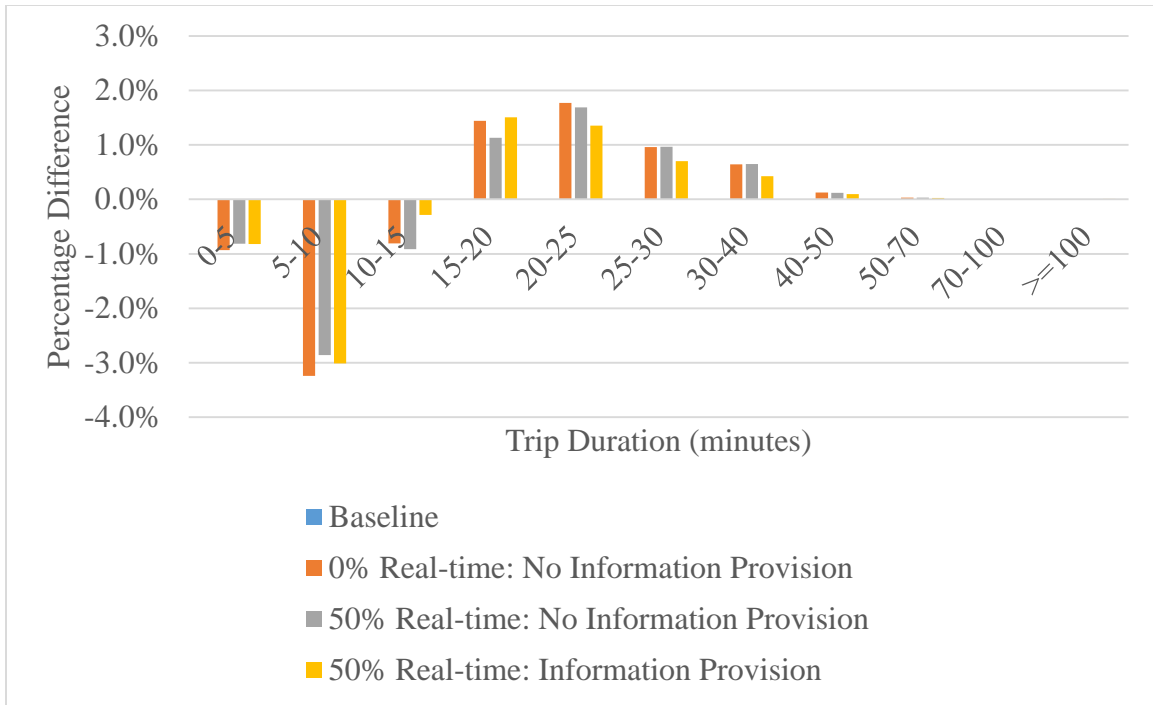
*Figure 42*. Percentage difference in trip length from baseline for real-time information provision.

Table 12 shows time allocation to activities and travel per-capita for adults (≥ 18 years old) across all scenarios in this case study. Since this chart pertains only to adults, time allocated on school episodes is negligible. Decrease of total activity duration in the two disruption scenarios can be observed from Table 12. On the other hand, total travel duration increased commensurately from baseline in the two disruption scenarios. This trend is similar to the results of the previous case study that estimated impacts of pre-trip information provision on activity-travel decision patterns. The sum of time spent on activities and travel is very close to 1,440 minutes in all scenarios employed in this case study.

Table 13 presents difference of time allocation to activities and travel per-capita from the baseline scenario. Before computing the difference of time allocation on

activities and travel, the result shown in Table 12 was normalized to 1,440 minutes for each column of the table. It can be observed form the table that activity time for in-home episodes and maintenance activity is decreased from the baseline scenario. The decrease of total activity duration from the baseline is -3.4 in the scenario with no information provision, -2.9, and -2.5 minutes for individuals without and with information in the final scenario. From the result, it can be seen that each traveler with real-time traveler information can potentially save up to 1 minute of travel in the event of network disruption. Bottom half of Table 13 shows difference of time spent on travel per-capita from the baseline scenario. Time spent for travel is increased in all activity types under network disruption scenarios. The smallest increase (2.5 minutes) of travel duration is observed for travelers with real-time information in the scenario that assumes 50% population with real-time information provision. The reason for this is that as travelers with real-time information are able to access current network conditions, they could potentially change their destination to avoid congested areas (if activities that they pursue are not mandatory).

Table 12. *Daily Time Allocation to Travels and Activities Per-capita in Real-Time Information Provision*

| | Baseline | No Real-time Information | 50% Real-time Information | |
|---|---|---|---|---|
| | No Information | No Information | No Information | Information |
| ***Time Spent on Activities*** | | | | |
| Home | 1072.82 | 1069.50 | 1070.55 | 1069.64 |
| Work | 196.65 | 195.99 | 195.67 | 196.26 |
| School | 0.61 | 0.57 | 0.54 | 0.50 |
| Maintenance | 73.80 | 71.94 | 71.84 | 71.73 |
| Discretionary | 29.05 | 28.16 | 28.05 | 28.88 |
| Pick Up | 0.41 | 2.28 | 2.44 | 2.10 |
| Drop Off | 2.20 | 2.10 | 2.00 | 2.15 |
| OH-Other | 12.04 | 11.76 | 12.08 | 11.94 |
| *Total Activity Duration* | *1387.58* | *1382.29* | *1383.17* | *1383.21* |
| ***Time Spent on Travels*** | | | | |
| Home | 19.74 | 20.73 | 20.55 | 20.42 |
| Work | 6.47 | 7.22 | 7.20 | 7.17 |
| School | 0.08 | 0.08 | 0.08 | 0.07 |
| Maintenance | 13.76 | 14.76 | 14.63 | 14.32 |
| Discretionary | 3.90 | 4.12 | 4.08 | 4.04 |
| Pick Up | 1.91 | 2.04 | 2.01 | 2.04 |
| Drop Off | 1.87 | 1.90 | 1.86 | 1.95 |
| OH-Other | 1.40 | 1.59 | 1.58 | 1.54 |
| *Total Travel Duration* | *49.11* | *52.44* | *51.98* | *51.54* |
| *Total Daily Accounting* | *1436.69* | *1434.72* | *1435.16* | *1434.74* |

Table 13. *Difference of Daily Time Allocation to Travels and Activities from Baseline in Real-time Information Provision*

| | Baseline | No Real-time Information | 50% Real-time Information | |
|---|---|---|---|---|
| | No Information | No Information | No Information | Information |
| *Time Spent on Activities* | | | | |
| Home | 0.0 | -1.9 | -1.1 | -1.7 |
| Work | 0.0 | -0.4 | -0.8 | -0.1 |
| School | 0.0 | 0.0 | -0.1 | -0.1 |
| Maintenance | 0.0 | -1.8 | -1.9 | -2.0 |
| Discretionary | 0.0 | -0.9 | -1.0 | -0.1 |
| Pick Up | 0.0 | 1.9 | 2.0 | 1.7 |
| Drop Off | 0.0 | -0.1 | -0.2 | -0.1 |
| OH-Other | 0.0 | -0.3 | 0.1 | -0.1 |
| *Total Activity Duration* | *0.0* | *-3.4* | *-2.9* | *-2.5* |
| *Time Spent on Travels* | | | | |
| Home | 0.0 | 1.0 | 0.8 | 0.7 |
| Work | 0.0 | 0.8 | 0.7 | 0.7 |
| School | 0.0 | 0.0 | 0.0 | 0.0 |
| Maintenance | 0.0 | 1.0 | 0.9 | 0.6 |
| Discretionary | 0.0 | 0.2 | 0.2 | 0.1 |
| Pick Up | 0.0 | 0.1 | 0.1 | 0.1 |
| Drop Off | 0.0 | 0.0 | 0.0 | 0.1 |
| OH-Other | 0.0 | 0.2 | 0.2 | 0.1 |
| *Total Travel Duration* | *0.0* | *3.4* | *2.9* | *2.5* |

**Conclusions and Discussion**

In conclusion, the enhanced framework of the integrated model system is capable of evaluating the impacts of real-time information provision on activity-travel behavior in a behaviorally realistic way. The SimTRAVEL model system was enhanced in this research effort to allow modeling of travel demand decision en-route to activity destination. The framework assumes continuous exchange of information between two key components, the activity-based model and dynamic traffic assignment model system. Hence, the activity-based model has information whether travelers are in distress or in normal network condition. The activity-based model (openAMOS) is able to use the current travel status to adjust activity-travel engagement patterns in response to real-time traveler information in the event of a network disruption. The adjusted trips with new travel information are sent back to the dynamic traffic assignment model to be re-routed on the network.

This case study offers intuitive results that demonstrate the capability of the enhanced SimTRAVEL to evaluate impacts of real-time traveler information provision on activity-travel engagement patterns in the event of a network disruption. This study employed three different scenarios (Baseline, No real-time information, and 50% real-time information) and conducted comparative analysis among the results from the three micro-simulation runs to test the impact of real-time traveler information on activity-travel patterns. A couple of interesting trends are observed from the results. First, travelers who have access to current network conditions en-route to their destinations would choose destinations in such a fashion that they avoid congested areas on the network. Second, total travel duration for the travelers with real-time information

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decreased from the scenario that assumes no information provision. This finding is consistent with expectation as travelers with real-time information were found to choose destinations outside the areas affected by a network delay event, they are able to reduce time spent on travel. The results corroborate the fidelity of the enhanced integrated model system in simulating the impacts of real-time traveler information provision under varying levels of user information provision.

Future research should focus on enhancing the integrated model system along the following lines of inquiry. First, the activity-based demand model (openAMOS) should be made capable of accurately predicting the array of changes in activity-travel engagement patterns impacted by real-time information provision under network disruption events. Travelers who have access to real-time information and are en-route to an activity destination could alter their route, destination, or skip the activity altogether. The enhanced model system only models altering route and destination for travelers who are en-route and impacted my network congestion. A series of models in SimTRAVEL should be enhanced to make the model system capable of predicting change of activity or skipping the activity altogether in the case the traveler is en-route and experiences severe congestion. Second, the activity-based model should use accurate current location information for each traveler, who is en-route to the destination. In this study, the current locations of trips in distress were not provided by a dynamic traffic assignment model but are simulated using an approximation method. This approximation can be overcome in a straightforward way if a dynamic traffic assignment model is employed in the integrated model system. Third, the integrated model system should be made capable of modeling travel behavior of individuals with pre-trip and en-route information simultaneously. In

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the real world, some travelers decide activity-travel engagements using pre-trip information before embarking on a trip and some others use real-time information en-route to their destination. The integrated model system (SimTRAVEL) should be enhanced to handle these different types of travelers simultaneously.

CHAPTER 8

## Summary and Contributions

The impetus for this research stems from the necessity to develop an integrated urban model system that is flexible enough for testing an array of policy scenarios based on real-time information provision. With ever increasing air pollution and greenhouse gas emissions from the transportation sector, such a model is needed now more than ever to devise/test policies of the new age that make use of the technology available at hand. To simulate the activity-travel patterns/ traffic flows in response to real-time information provision, transportation modeling tools should be enhanced with state-of-the art capabilities that 'mimic' the real-world decision making process of individuals. In a sequentially operated travel demand model system, the travel demand of a region is generated for an entire day (or for a few time periods such as peak, off-peak etc.) and then the traffic assignment model routes these trips on the network to identify critical bottlenecks. While such a framework is sufficient to test the infrastructural necessities of a city for a given travel demand, it is not much useful to simulate network disruption events such as an accident or the closing of a highway lane etc. To be able to accurately reflect travel behavior in real-time, there needs to a tight coupling between the travel demand model system and the traffic assignment model. Many research efforts in the recent past have developed integrated urban model systems that combine an activity-based micro-simulation model with a dynamic traffic assignment model. One such model is SimTRAVEL proposed by Pendyala et al. (2012). The authors not only propose a methodological framework but also demonstrate the capabilities of an operational prototype of model system. However, the previous version of SimTRAVEL (Simulator

of Travel, Routes, Activities, Vehicles, Emissions, and Land use) is not fully capable of handling scenarios that involve modeling the impact of real-time information dynamics on activity-travel engagement behavior. Although a case study was presented in the context of pre-trip information provision using the SimTRAVEL (Konduri et al., 2013), the scenarios presented used only extreme cases where either none (0%) or all (100%) of the population have access to pre-trip information. This assumption is made for operational convenience owing to the limitations of the model system in handling multiple network conditions and user classes simultaneously. In the current research effort, SimTRAVEL is enhanced in three incremental steps to allow more realistic micro-simulation of activity-travel engagement patterns particularly in light of availability of real-time information. In the first step, the model system was enhanced by incorporating the ability to handle multiple network conditions i.e., in addition to experienced network conditions, the model system is also made capable of handling prevailing network conditions so that different network skims (origin-destination travel time matrices) can be used for people with different levels of access to information in the activity-travel demand model. Prevailing network conditions are very helpful to conduct analysis regarding the impacts of pre-trip information provision on activity-travel patterns. This enhancement enables the integrated model system to conduct policy analyses that require simultaneous use of multiple network conditions. One such policy called the Low Emission Zone (LEZ) policy is tested using a case study in the Phoenix region. LEZs are geographically defined areas that seek to incentivize "green transportation choices" or prevent high-polluting vehicles from entering the zone to improve air quality within the geographic area (Schneeberger et al., 2013). In the case study, an LEZ policy that

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incentivizes green transportation modes and also provides enhanced transit services to LEZs is studied to understand the impacts of LEZs on activity-travel engagement patterns, energy consumption and emissions. Network conditions for different modes (auto vs. transit) and different types of travelers (eco vs. non-eco) are simultaneously used in the enhanced model system to conduct this case study.

The second enhancement made to the model is incorporating the capability to allow for a route change in light of real-time information. This enhancement is made entirely on the side of dynamic traffic model (for switching route). Case study to demonstrate the second enhancement was not presented as this research mainly focuses on the demand choices. Third, a series of choice models were incorporated into the activity-based model (openAMOS) in SimTRAVEL framework for modeling the change in activity-travel engagement patterns in light of a network disruption event and availability of real-time traveler information. In the enhanced prototype of the integrated model system, the dynamic traffic assignment model identifies trips that experiencing severe congestion (and have access to real-time traveler information), and sends those trips back to the activity-based model. The demand model evaluates and re-simulates activity-travel engagement patterns for trips that are in distress and sends back the changed activity-travel information (destination) to the dynamic traffic assignment model. The two key components in the tightly integrated model system are enhanced to allow modeling the change of activity-travel engagement patterns en-route in light of real-time information.

This research makes important contributions to empirical literature on activity-based travel demand models, develops state-of-the art knowledge for use in research and

practice in the area of integrated model systems. The capabilities incorporated in the integrated model system provide transportation policy makers with an abundance of options to test policies that hinge on provision of real-time information (dynamic tolls, time-of-day based lane closures etc.). The contributions made by this research effort are summarized below:

1. The enhanced integrated model system (SimTRAVEL) is capable of modeling the impacts of real-time information provision while accurately representing the effects of different levels of access to information for different travelers. The level of access to information greatly influences the activity-travel engagement patterns of individuals. For example, in the event of a network disruption a person who does not have access to information regarding prevailing network conditions might start a journey and get stuck in traffic inordinately. In the same situation, if the individual has access to current network conditions, he/she might alter the destination/departure time or cancel activity altogether if need be so. The enhanced integrated model system is able to accurately capture different decision paradigms across cohorts with varying levels of information.

2. Transportation policy makers can use the enhanced integrated model system, to conduct a wide range of policy analyses. For example, this paper presents the results of a case study in the context of introducing Low Emission Zones (LEZ) in a three city sub region of the Greater Phoenix Metropolitan Area. In this case study, LEZ policies are tested by incentivizing 'greener' transportation modes and also enhancing the transit service to LEZs. The case study provided intuitive results and proved that the enhanced model system is flexible enough to be

applied to a tailor made policy. In addition, the enhanced model system was also tested on an eco-lane (Eco-lane could be defined as a dedicated lane, similar to a HOV lane on which only eco-vehicles are allowed to travel) policy analysis. Results of the eco-lane analysis are not provided in the interest of brevity.

3. The research contributes to technical advancement in operational implementation of integrated models of urban continuum. This research builds on a state-of-the art integrated model system SimTRAVEL and enhances the system with several operational capabilities. This research enhances linkages between the activity-based travel demand model and the dynamic traffic assignment model and provides a behaviorally consistent approach to simulate activity-travel patterns in light of availability of real-time network information.

4. This research contributes to the empirical literature in transportation planning arena. The integrated model of the urban continuum used in this study observes a tight coupling between the activity-travel model and the dynamic traffic assignment model. The key components are linked in an efficient fashion with an intent to overcome the shortcomings of the previous implementations that employ input-output protocols and feedback processes sequentially.

5. This research integrates a dynamic traffic assignment model to the activity-based travel demand model using the concept of classes in object-oriented programming. This concept in SimTRAVEL can open possibilities for researchers to switch to any dynamic traffic assignment model of their choice by adding a class to integrate it to openAMOS. This feature is built into the model software so that the model can be seamlessly transferred to cutting edge dynamic traffic

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assignment models as and when they become available. Users will always be able to resort to the older versions of SimTRAVEL by using the built-in classes. For example, the previous version of SimTRAVEL employed the framework of UrbanSim-openAMOS-MALTA. In this iteration of the model, MALTA is replaced with another dynamic traffic assignment model called DTALite. If a user wants to switch back to MALTA in light of future advancements, SimTRAVEL is capable of easily invoking the built-in class to integrate MALTA to openAMOS.

For future works, the updated model system in this study should be enhanced in a couple of points to accurately model activity-travel engagement patterns and traffic flows under real-time traveler information provision. First, the integration between an activity-based demand model and dynamic traffic system at the second level presented in Chapter 4 should be tested using the integrated model system (SimTRAVEL). Since this study focus on analyses of activity-travel engagement decision processes under real-time traveler information provision, the test for the integration at the second level is skipped. In real world, travelers who have access to real-time traveler information systems are able to switch their route to avoid network delay events and quickly arrive their activity destinations. Transport model tools should be able to capture impacts of route switching using real-time information provision to accurately predict traffic flows and activity-travel decision patterns. Second, the activity-based model (openAMOS) should be able to accurately simulate en-route choice processes under various levels of real-time information provision in the latest version of SimTRAVEL that was enhanced in this study. In addition to choice of a destination change during travelers are en-route, they

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may abandon their current pursuing activities and skip the activity altogether. Although the integrated model system in this study is able to capture a destination change, it should be enhanced to reflect various activity-travel decision behaviors in en-route decision processes under real-time information provision in future researches. While an integrated model system is enhanced in order to capture various en-route decisions, the activity-based demand model should consider for reconciliation among activities and travels for each individual's daily activity-travel agenda. For example, if a traveler would skip the current pursuing activity and alter activity and destination altogether, the new activity should not conflict to the subsequent activities and travels in the traveler's activity-travel schedules. That is, an activity-based demand model should include a process to reconcile among activities and travels to be consistent across an entire schedule for a simulation day for all synthetic persons.

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BIOGRAPHICAL SKETCH

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