

**Framework for Multi-Resolution Analyses of  
Advanced Traffic Management Strategies  
FDOT Project BDV29-977-19**

**Final Report**

**Prepared for**

**Florida Department of Transportation**



**By**

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Florida International University**



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## **DISCLAIMER**

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation.

# METRIC CONVERSION CHART

## APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
<b>LENGTH</b>				
<b>in</b>	inches	25.4	millimeters	mm
<b>ft</b>	feet	0.305	meters	m
<b>yd</b>	yards	0.914	meters	m
<b>mi</b>	miles	1.61	kilometers	km
<b>AREA</b>				
<b>in<sup>2</sup></b>	square inches	645.2	square millimeters	mm <sup>2</sup>
<b>ft<sup>2</sup></b>	square feet	0.093	square meters	m <sup>2</sup>
<b>yd<sup>2</sup></b>	square yard	0.836	square meters	m <sup>2</sup>
<b>ac</b>	acres	0.405	hectares	ha
<b>mi<sup>2</sup></b>	square miles	2.59	square kilometers	km <sup>2</sup>
<b>VOLUME</b>				
<b>fl oz</b>	fluid ounces	29.57	milliliters	mL
<b>gal</b>	gallons	3.785	liters	L
<b>ft<sup>3</sup></b>	cubic feet	0.028	cubic meters	m <sup>3</sup>
<b>yd<sup>3</sup></b>	cubic yards	0.765	cubic meters	m <sup>3</sup>
NOTE: volumes greater than 1000 L shall be shown in m <sup>3</sup>				
<b>MASS</b>				
<b>oz</b>	ounces	28.35	grams	g
<b>lb</b>	pounds	0.454	kilograms	kg
<b>T</b>	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
<b>TEMPERATURE (exact degrees)</b>				
<b>°F</b>	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
<b>ILLUMINATION</b>				
<b>fc</b>	foot-candles	10.76	lux	lx
<b>fl</b>	foot-Lamberts	3.426	candela/m <sup>2</sup>	cd/m <sup>2</sup>
<b>FORCE and PRESSURE or STRESS</b>				
<b>lbf</b>	poundforce	4.45	newtons	N
<b>lbf/in<sup>2</sup></b>	poundforce per square inch	6.89	kilopascals	kPa

\*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.

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## **EXECUTIVE SUMMARY**

Demand forecasting models and simulation models have been developed, calibrated, and used in isolation of each other. However, the advancement of transportation system technologies and strategies, the increase in the availability of data, and the uncertainty of traveler behavioral responses to new strategies have increased consideration of integrating different modeling tools. The goal of this project is to investigate the ability of combinations of tools to assess congestion impacts and advanced strategies that address such impacts and also recommend a multi-resolution modeling framework for use in support of agency analyses and modeling of congestion impacts and advanced strategies. To achieve this goal, a number of activities were conducted, which are summarized below.

### ***Development of a Multi-Resolution Modeling Framework***

A multi-resolution modeling framework was proposed in this project. It consists of three components: (1) Data sources and tools that allow the utilization of data from multiple sources to support modeling tasks; (2) Supporting environment that assists modelers in developing, calibrating, and processing the results of the selected modeling tools; and (3) Modeling tools of different types and resolution levels that allow the estimation of various performance measures. An important module of the support environment, a list of tool assessment criteria, was proposed in this study, and the capabilities of a number of modeling tools were presented in relation to these criteria.

### ***Managed Lane Modeling***

As an example, the multi-resolution modeling framework proposed in this project was applied to model managed lanes. The assessment of a number of managed lane modeling tools based on the proposed criteria shows that different managed lane modeling tools have different strengths. The Cube Avenue model for I-95 managed lanes developed in the previous study (FDOT project BDK80-977-30) was converted into other tools including ELToD, DTALite, and VISUM utilizing the NeXTA interface. The impacts of traffic flow modeling and origin-destination (O-D) matrix estimation on managed lane modeling results from different tools were also studied and compared based on real-world data. The supply calibration results show that the use of the calibrated capacity and jam density in the traffic flow model improves the simulation results, and reduces the deviations from the real-world speeds. The demand calibration results indicate that the dynamic O-D matrix estimation (ODME) can produce better estimates of the O-D matrix than static-based ODME. The quality of the O-D estimation in all tools is found to be greatly dependent on the quality of the initial O-D matrix. The ODME process in DTALite can produce better link volume results than those obtained using Cube Avenue and VISUM although the quality of the VISUM ODME results is close to that of DTALite.

The core of managed lane modeling is to accurately model travelers' preference to use managed lanes. This preference greatly relies on input parameters, including the value of time (VOT), value of reliability (VOR), and dynamic toll pricing. A sensitivity analysis was conducted in this study to examine the impacts of VOT. The results showed that a VOT of \$40 produced the best results in terms of predicting the utilization of managed lanes. This value is much higher than the VOT commonly used in current assignment modeling. For example, the VOT value used in the SERPM model is \$13.30. The results from this research also confirmed that utilizing a statistical distribution of VOT, instead of a fixed value, produces better predictions of real-world utilization of managed lanes. The analysis results also highlighted the importance of utilizing the VOR in the generalized cost functions. The above discussion indicates the importance of selecting a tool that allows the inclusion of VOR in the assignment and the consideration of VOT variations between users.

When the managed lanes are congested, the toll rates can be increased to divert vehicles out of managed lanes in order to relieve the congestion on these lanes, as was done with the Florida Department of Transportation (FDOT) District 6 system I-95 Express Lane. The ability of modeling tools to assess the impacts of such changes in toll policy was also investigated in this study. The shifts in managed lane usage resulting from changing pricing policy as estimated by the DTA-based tools were comparable to those observed based on real-world data. Static traffic assignment models were less successful in estimating the link volumes, but they also produced reasonable results in terms of the amount of vehicles shifted to managed lanes. This clearly indicates that DTA-based models are preferred, compared to STA-based models like ELToD and FITSEVAL.

This study also proposed a method to model the impacts of adaptive cruise control (ACC) and Cooperative Adaptive Cruise Control (CACC) combined with a toll policy that gives incentives to the vehicles equipped with CACC to encourage them to use the managed lanes by providing toll pricing discounts to these vehicles. This method was implemented in both static and dynamic assignment models based on capacity estimates from microscopic simulation models. For a given demand, the maximum managed lane throughput is expected to increase as the percentage of CACC vehicles traveling along a lane increases due to smaller gaps between vehicles.

### ***Origin-Destination Matrix Estimation Using Data from Different Sources***

Time-dependent demand matrix is an important input for dynamic-traffic-assignment-based modeling tools. Traditionally, these matrices have been estimated based on temporary traffic counts. Recently, there has been an increasing interest in using data from Automatic Vehicle Identification (AVI) technologies or third party vendors to estimate O-D matrices. In this study,

an investigation of the utilization of data from multiple sources as part of the ODME process was conducted. The results showed that the inclusion of the partial trips retrieved from Bluetooth AVI technology and third party vendors can significantly improve the ODME performance. The incorporation of turning movement counts can also produce better matches to the real-world counts, which is especially important for evaluating arterial-related traffic management strategies. Whenever such partial trip data or turning movement counts are available, it is recommended to include them in the ODME process.

The production of good turning movement counts is particularly difficult from dynamic traffic assignment models. Inputting the turning movement counts and coding the signal control was found to help in producing better turning movement counts. It should be noted that among the examined off-the-shelf ODME tools, only the one that is based on Cube Avenue allows utilizing the turning movement counts and partial trips based on AVI and/or third party vendors, as part of the ODME optimization process. Nevertheless, the turning movement counts can be used in other commercially available tools, if each turning movement is coded as a link. Another approach is to sum the turning movements leaving a link and those entering a link to produce additional “virtual detectors” on all approaches that are leaving or entering the intersection. This should allow better consideration of the turning movements in the ODME process.

### ***Construction Modeling***

The existence of construction zones can result in negative impacts to road users. The estimation of mobility impacts based on multi-level traffic analysis tools were first compared using a construction zone in a simple network. The comparison indicates that only FREEVAL-WZ and VISSIM utilize a true “horizontal queue.” The other tools use vertical queues. Q-DAT, QuickZone, DTALite, and deterministic queuing theory analysis produce similar estimates of travel delay at the work zone, while FREEVAL-WZ and VISSIM produce higher delay.

In addition, a case study was conducted using a subarea network around the Port of Everglades in Broward County, FL. The network was imported into the NeXTA environment, the graphic user interface of DTALite. Three types of traffic diversion models for work zones were examined in this study: (1) diversion during short-term construction utilizing a logit model developed in a previous study; (2) diversion during long-term construction where the network reaches user equilibrium (modeled using dynamic user equilibrium in DTALite); (3) diversion through a day-to-day learning assignment in DTA modeling that accounts for the number of days that the construction zone is active (modeled using day-to-day learning assignment in DTALite). Compared to the other two diversion models, the day-to-day learning method is able to better explain the process of drivers’ route choice with shorter-term work zones. Furthermore, the traffic demand after diversions obtained from the above diversion models was input to a

microscopic simulation model, VISSIM, and the resulting delay, queue length, and other performance measures were compared.

### ***Arterial Traffic Management (ATM) Strategies***

There is a strong trend to invest in ATM strategies on urban streets with signalized intersections. Methods are needed to assess the impacts of these ATM strategies. This study demonstrated the utilization of combinations of data analytics, DTA modeling, and advanced simulation to assess the impacts of ATM strategies on urban streets traffic through a case study. Instead of modeling an average day, representative days with different demand levels were selected in this study for modeling. ODME processes were conducted to calibrate the demands for these days based on turning movement counts in addition to the previously commonly used midblock traffic counts. Mesoscopic and microscopic models were used in combination with a signal timing optimization tool to demonstrate the application of multi-resolution modeling to assess ATM strategies.

### ***Assessment of Link Level Variation of Connected Vehicle Market Penetration***

Estimation of the market penetration of connected vehicles (CV) and automated vehicle (AV) is important for identification of the impacts of these technologies. Past efforts have assumed the growth in the CV market penetration without considering the variations in the socio-economical characteristics between regions and zones within a region. This study proposed a methodology to determine the variations of CV market penetration between regions, zones within a certain region, links within the region, and time-of-day. The methodology was implemented with various CV implementation scenario assumptions and considered the variations in the socioeconomic characteristics of travelers of a region.

Applying the methodology of this study to a case study indicates that the distribution of the link-specific CV market penetration follows a lognormal distribution. The percentage variation in the market penetration was shown to be the highest in the first year of CV implementation and decreases exponentially with the number of years passing since the implementation. The market penetration variations between links are the highest on collectors, followed by arterials, followed by freeways. The study also showed that the average percentage increase in the CV market penetration grows in the first several years then remained almost constant before dropping sharply.

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## 1. INTRODUCTION

Modeling of transportation systems is becoming an essential component of transportation system planning and operations. Transportation modeling tools are generally categorized as macroscopic, mesoscopic, and microscopic tools, based on the resolution at which vehicle flows are simulated.

Regional demand forecasting models generally utilize simple macroscopic traffic flow relationships such as the Bureau of Public Road (BPR) and Akcelik equations that relate the travel time or speed on a segment to the segment demand-to-capacity ratio. These equations generally do not consider queuing and spillback effects. More advanced macroscopic simulation models used in dynamic traffic assignment and traffic operations analysis utilize various forms of the relationships between traffic flow, speed, and density parameters of the traffic stream combined with queuing and/or shockwave analysis. In general, macroscopic models simulate the impact of the traffic as a whole, on a section-by-section basis rather than by tracking individual vehicles. Macroscopic models are less complicated and have considerably lower computer requirements than microscopic models. They do not, however, have the ability to analyze transportation improvements in as much detail as microscopic models, although some of these models are able to model queuing, shockwaves, and spillbacks, as stated above. Examples of macroscopic models that consider spillbacks are those implemented in the freeway facility procedure of the Highway Capacity Manual (HCM) and the one used in combination with dynamic traffic assignment (DTA) module of the VISUM modeling tool.

Microscopic simulation tools analyze the network at much more detailed levels than macroscopic models. In general, microscopic simulation tools simulate the movement of individual vehicles based on microscopic traffic flow models such as car-following, lane-changing, and gap acceptance. Vehicles are tracked through the network over small time intervals, as low as one tenth of a second. The modeling effort and computer requirements for microscopic models are significantly more than macroscopic models, usually limiting the network size and the number of simulation runs that can be completed. In particular, extensive effort is required for the calibration and validation efforts of large networks modeled using microscopic simulation. Examples of microscopic simulation models are TransModeler, VISSIM, PARAMICS, CORSIM, and AIMSUN.

Mesoscopic models have more detailed traffic representation than macroscopic models, but less detailed representation than microscopic models, allowing the modeling of larger sub-networks and possibly small to midsize regional networks. Mesoscopic simulation models generate and track individual vehicles or packets of vehicles. The movements of these vehicles or packets, however, follow the macroscopic approach of traffic flow described above. As with advanced macroscopic models, mesoscopic models utilize the relationships between speed, density, and

flow and consider queuing and spillback due to the subject link capacity and downstream link queuing capacity. Mesoscopic models provide less fidelity than microscopic simulation models. However, they provide better computational and modeling efficiency, which is important for simulation-based dynamic traffic assignment (DTA). Examples of mesoscopic simulation tools are Dynasmart-P, DynusT, Direct, DTALite, Cube Avenue, and Dynameq (the first four tools are based on the original development of Dynasmart). A recent release of VISSIM includes a mesoscopic modeling option. Although significant amount of data is still required to develop, calibrate, and validate mesoscopic traffic simulation models, the required calibration and validation effort is significantly lower than microscopic simulation tools.

As can be seen from the above discussion, the existing transportation tools vary widely in their implementations requirements. Depending on the project under consideration, each type of tools can play a role in the modeling process utilized in the project. Multi-Resolution Modeling (MRM) has been proposed as an integrated approach that combines different modeling levels to produce a powerful modeling environment of advanced strategies that are considered as alternative to address transportation system congestion problems. However, there is a need for methods and tools for the integration of different tools and a need for assessing and documenting the benefits of combining these tools.

An important component of MRM is DTA. DTA provides a more realistic modeling of traffic flow and driver responses compared to the static models used in traditional demand forecasting models. DTA tools combine the modeling of traffic operations with advanced time-dependent, shortest path identification, and associated assignment algorithms to model route choice impacts as a result of changes in network performance. These tools model route choices at fine-grained time intervals (15-30 minutes is usually used). The traffic modeling associated with DTA can be at the macroscopic, mesoscopic, and microscopic levels. One of the main advantages of using DTA to model traffic networks is that the outputs of the model describe the time-dependent network states. Outputs from the model include time-dependent system level, route level, and link level performance statistics. From these statistics, a set of metrics can be derived for studying system performance and for providing inputs to other higher resolution modeling, if necessary. More details about DTA can be found in Hadi et al. (2012), Hadi et al. (2013), DTA primer (Chiu et al., 2011), and FHWA DTA guidelines (FHWA, 2012a).

Combinations of advanced modeling tools and methods are particularly needed for analyzing recurrent and non-recurrent congested conditions and advanced strategy applications such as managed lanes (ML), dynamic pricing, active traffic management, smart work zones, incident management, freight corridors, integrated corridor management, automated/connected vehicle implementations, and other intelligent transportation systems (ITS) and transportation system management and operations (TSM&O) strategies . Depending on the level of the analyses and the specific problem under consideration, a number of tools have been used to assess these

strategies including tools that can be classified as sketch planning, dynamic traffic assignment, macroscopic simulation models, mesoscopic simulation models, microscopic simulation models, and combinations of these tools.

The FHWA traffic analysis toolbox documents have provided guidance regarding the use of traffic analysis tools including simulation and DTA tools. These documents are valuable to transportation system modeling and can be found in the FHWA website (<http://ops.fhwa.dot.gov/trafficanalysistools>). However, there is a clear need to build on the existing state of practice and research and development efforts to establish a comprehensive framework for multi-resolution analyses to support the modeling processes. Additional tools and methods will have to be built and developed to support MRM, in order to fully realize the benefits of this approach.

This project aims at investigating the ability of combinations of tools to assess congestion impacts and advanced strategies that address such impacts, and also recommending a MRM framework for use in support of agency analysis and modeling of congestion impacts and advanced strategies. The organization of this document is as follows. Section 2 summarizes the review of literature regarding on the existing simulation tools and past experience with multi-resolution modeling and advanced strategy modeling. Section 3 provides a detailed description of the recommended MRM framework, while Sections 4 to 8 demonstrate how this MRM framework can be used for modeling managed lanes, origin-destination estimation, analyzing construction zone, evaluating active traffic management strategies for urban streets, and connected vehicle market penetration.

## 2. LITERATURE REVIEW

### 2.1. Existing Simulation Tools

Existing simulation and DTA tools will be important components of the MRM framework developed in this study. As stated earlier, the traffic modeling associated with DTA can be at the macroscopic, mesoscopic, and microscopic levels. This section presents an overview of some of the available DTA tools with different levels of associated traffic models.

- ***VISUM***

VISUM is a tool that allows modeling transportation systems and includes a DTA model that has been added to this software for the advanced modeling of the interaction between traffic path performance and route selection. The DTA model assigns dynamic Origin-Destination (O-D) matrices onto the network based on Dynamic User Equilibrium (DUE). The model converges to the equilibrium state in which no travelers can have less experienced travel time by unilaterally changing their paths (PTV Vision, 2013a).

To represent a spillback in VISUM, it is assumed that each link is characterized by two time-varying bottlenecks: one located at the beginning, and another located at the end of the link, called “entry capacity” and “exit capacity”, respectively. VISUM applies Traffic Flow Fuzzy (TFlowFuzzy) model to allow Origin-Destination Matrix Estimation (ODME) using observed count data and simulated volumes. The matrix estimation data is done using an iterative method to adjust the initial O-D matrix cells to achieve better matching of observed and simulated volumes (PTV Vision, 2013a).

- ***DYNASMART***

Dynamic Network Assignment-Simulation Model for Advanced Telematics (DYNASMART) is one of the first DTA tools developed to implement a simulation-DTA modeling of transportation networks by Mahmassani et al. (2009). DYNASMART provides a mesoscopic level of traffic representation, which combines a microscopic level of representation of individual travelers with a macroscopic description of traffic flow. The movements of vehicles are governed by a modified version of the Greenshields’ macroscopic speed-density relationship, but vehicular movements are tracked at the level of individual vehicles or groups of vehicles. Delay is computed using node transfer logic based on the time that takes for vehicles to transfer considering link capacity and downstream link queue spillback. The model requires that the O-D demands or individual vehicle trajectories are provided. This tool is not currently commercially available. However, it continues to be used in researching advanced applications of DTA. In

addition, open source tools that are based on Dynasmart including DTALite and DynusT, which are described below) have been used in real world applications.

- *DynusT*

DYNAMIC Urban Systems for Transportation (DynusT) was developed at the University of Arizona based on DYNASMART. DynusT is an open source program that was developed by Chiu (2012).

The default assignment in DynusT is based on a gap-based assignment which replaces the Method of Successive Average (MSA) assignment in a recent version of DynusT although the MSA assignment can still be requested. The gap-based assignment produces much better convergence and computational efficiency compared to MSA (Chiu and Bustillos, 2009). DynusT is an open-source tool that can be downloaded and used. It is not commercially sold, although the developers can sign agreement to provide technical support. It has been used in a number of projects in recent years.

- *Dynameq*

Dynameq is a DTA software developed by INRO Consultants, Inc. Dynameq is a DUE-based model that iterates between finding time-dependent path flows and determining the corresponding path travel times. Vehicles are assigned to paths using the MSA, which assigns a decreasing fraction of vehicles to the shortest path in subsequent iterations. The fraction is equal to one divided by the current iteration number, so that in the first iteration, all vehicles are assigned to the shortest path. Half of all vehicles are assigned to the shortest path in the second iteration, and so on. The developers have also tested more efficient and better converging methods of assignment (Mahut et al., 2007). Dynameq is different from other mesoscopic model in that it can model individual lane flow with the lane-changing decisions are made upon entering each new link. Modeling individual lanes has the advantage of explicitly modeling scenarios when certain types of vehicles are restricted from specific lanes such as high occupancy vehicle lanes. To improve computational efficiency and allow for regional-level modeling, Dynameq's behavioral rules are simplified relative to microscopic simulators. These simplifications include not allowing vehicles to reconsider their lane choice while traveling on the link. Also, the model is updated each time an event occurs, rather than at pre-defined time intervals. Thus, Dynameq may be considered as higher fidelity mesoscopic model. More information about Dynameq and its application can be found in Mahut et al. (2004) and Florian et al. (2008).

- ***Cube Avenue***

Cube Avenue is a dynamic traffic assignment extension of Cube Voyager (Citilabs, 2013). It models traffic at more details than the Cube Voyager's Highway program which utilizes macroscopic models, and at less detail than microscopic models. With Cube Avenue, routes and flow rates change during the modeling period based on congestion. One of the strength of Cube Avenue for regions that use the Cube modeling environment is to apply the same data format and scripting language as Highway Cube Voyager. Using this scripting language also provides more flexibility in modeling approaches. The assignment in Cube Avenue is based on user equilibrium utilizing the MSA method.

- ***TRANSIMS***

Transportation ANalysis and SIMulation System (TRANSIMS) is an open-source software developed at the Los Alamos National Laboratory to conduct transportation system analysis. It consists of four steps, one of which estimates demand by an activity-based model, which is not available in other assignment tools. TRANSIMS has been implemented for large networks such as Dallas and Portland. However, it requires an extensive amount of input data compared to other DTA models. More information about TRANSIMS can be found in Lee (2014). TRANSIM can be considered as a low-resolution microscopic simulation model

- ***DTALite***

DTALite is an open-source DTA package that has been developed by Zhou and Taylor (2012) and has been supported by FHWA through a number of research projects. DTALite is a mesoscopic simulation-based DTA package that works in conjunction with the Network EXplorer for Traffic Analysis (NeXTA) graphical user interface. The DTALite tool aims to integrate modeling and visualization capabilities. The traffic assignment and simulation modules in DTALite iterate to either capture day-to-day user response or find steady-state equilibrium conditions. Speed, volume and density measures at the network, specific links, and vehicle trajectories can be visualized using the NeXTA user interface (Zhou and Taylor, 2012).

DTALite is a link-based simulation with capacity constraints and it has been used recently in several pilot and research project sponsored by FHWA program (FHWA, 2013a). More information about NeXTA/DTALite can be found at <https://code.google.com/p/NeXTA> (DTALite, 2012).

- ***TransModeler***

TransModeler is a microscopic simulation-based traffic assignment tool offered by Caliper (Caliper Corporation, 2011). One of the interesting features of TransModeler is that it allows the network modeling based on the microscopic, mesoscopic, and/or macroscopic simulation level in the same run.

TransModeler applies different algorithms that are suitable for microscopic simulation-based DTA. TransModeler can handle large-scale networks based on the microscopic simulation-based DTA. Micro-level simulation provides a more accurate representation of traffic and management operations compared to mesoscopic modeling. As these models become more efficient, this increases their attractiveness. However, calibration microscopic simulation still requests significantly more time than mesoscopic models, especially when combined with DTA. More information about TransModeler can be found at <http://www.caliper.com/TransModeler/Simulation.htm> (Caliper Corporation, 2011).

- ***VISSIM***

Verkehr In Stadten Simulation Model, which means “Traffic in Towns Simulation Model” (VISSIM) was developed by PTV Group in Germany (PTV Vision, 2013b). Most existing simulation models operate using link-node configurations. VISSIM is a detailed microscopic simulation tool that models vehicles at the 0.1-second resolution level. VISSIM differs from these models and it utilizes a link-connector structure. This involves coding movement individually at each intersection, allowing for increased precision and flexibility in modeling traffic flow. Although this process has been simplified in more recent versions of the software, it is more complex than coding link-node models. VISSIM can display microscopic simulation results in 3D animations, including a feature that allows viewing from a selected driver’s perspective. VISSIM has also a power programming extension that allows modelers to program advanced managements and pricing strategies that correspond to real-world advanced strategies. VISSIM 8 allows the user to specify the demands based on turning movement volumes, partial routes, or utilizing DTA to determine paths between origins and destinations. In addition, the tool has a managed lane model to estimate the diversion between managed lanes and general purpose lanes. (PTV Vision, 2015).

- ***AIMSUN***

Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (AIMSUN) was developed by TSS-Transportation Simulation Systems in Spain. It is an integrated traffic modeling software that fuses travel demand modeling, static and dynamic traffic assignment mesoscopic and microscopic simulation into one environment. It can be used to model various

applications, such as toll and road pricing, work zone management, evaluation of travel demand management strategies and so on. Hybrid simulation that combines mesoscopic and microscopic simulations can also be conducted using the AIMSUN software, which allows the modeling of a large area while zooming in areas with more details. Stochastic and discrete route choice model and dynamic user equilibrium are available in AIMSUN at both the mesoscopic and microscopic levels. Three types of shortest paths can be selected in dynamic traffic assignment of AIMSUN, that is, user predefined path, calculated shortest path tree based on initial default or user defined costs, and calculated shortest path tree based on statistical data collected in the simulation. AIMSUN also provides the functions of Application Program Interface (API) for modeling ITS applications, the AIMSUN Microscopic Simulator Software Development Kit (microSDK) for overriding default behavioral models, and the AIMSUN Platform Software Development Kit (platformSDK) for developing interfaces. More information about AIMSUN can be found in [http://www.aimsun.com/wp/?page\\_id=21](http://www.aimsun.com/wp/?page_id=21).

- *Summary*

The simulation-based DTA tools described above vary in the level of details from macroscopic to mesoscopic to microscopic. Tools with different level of resolution are suitable for different applications. However, combining these tools in a single application can provide capabilities and functionalities that are not possible with the use of one type of models as described next. The selection of the specific tools or combination of tools should be made based on detailed requirements to determine which tools can best satisfy the needs for the project. All of the above tools can be considered as candidates for use. However, not all the tools can meet specific project requirements. For example, only some of the above models are capable of assigning individual trips from activity-based models to the network. Thus, if other tools are used, these trips will have to be aggregated into O-D matrices, resulting in the loss of some of the resolution in the process.

The above discussion indicates that agencies will have to assess the suitability of a given tool for a certain applications based on detailed requirements. With the goal of assisting agencies in this effort, Hadi et al. (2012) presents a catalog of assessment criteria to allow the comparison and testing of various assignment methods and tools. Additional criteria may have to be added when modeling advanced strategies based on a close examination of these strategies. The use of these criteria will be discussed further in the MRM framework section of this report.

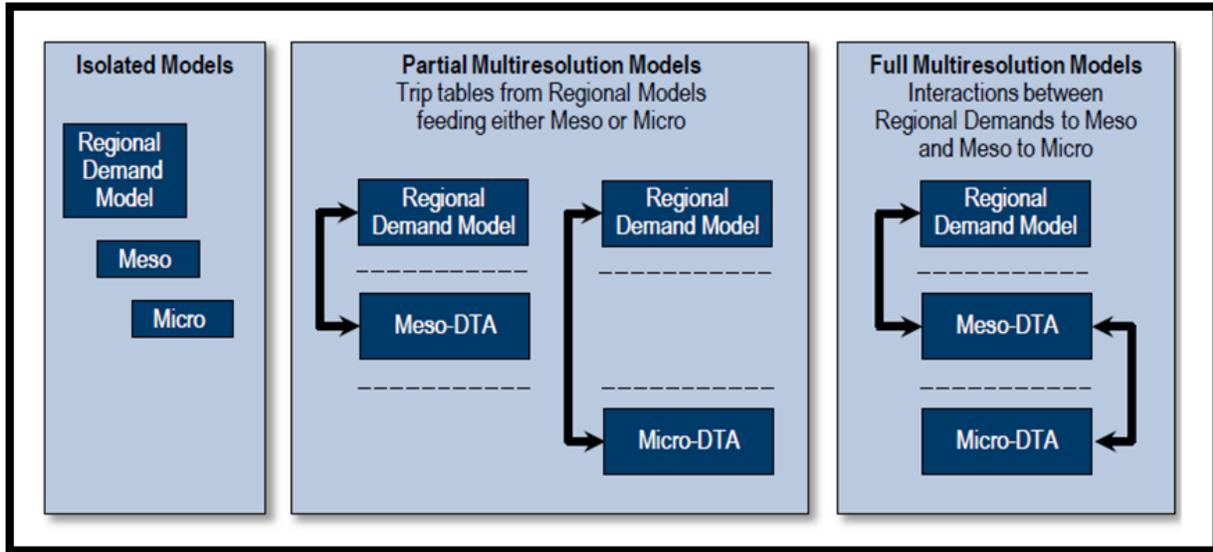
Some of the reviewed tools in this section are open source tools, while other are commercial tools. Some of the issues with the open source software versus propriety software that are supported by vendors are the level of technical support provided to the customers, adequate documentation of software enhancements, and ensuring continuity in the support of the software in future years. These are very important issues that need to be confirmed before the use of open

source software in large-scale projects. If the user of the tool is a “power user” that can use the tools with a minimal need for technical support, then the use of open source tools is possible. Otherwise, the slow technical support associated with open source tools can be a problem. On the other side of the coin, some of the open source tools have been used in FHWA, SHRP2, and NCHRP projects and implemented several advanced modeling techniques that may not be available in commercially available tools.

## **2.2. Experience with Multi-Resolution Modeling**

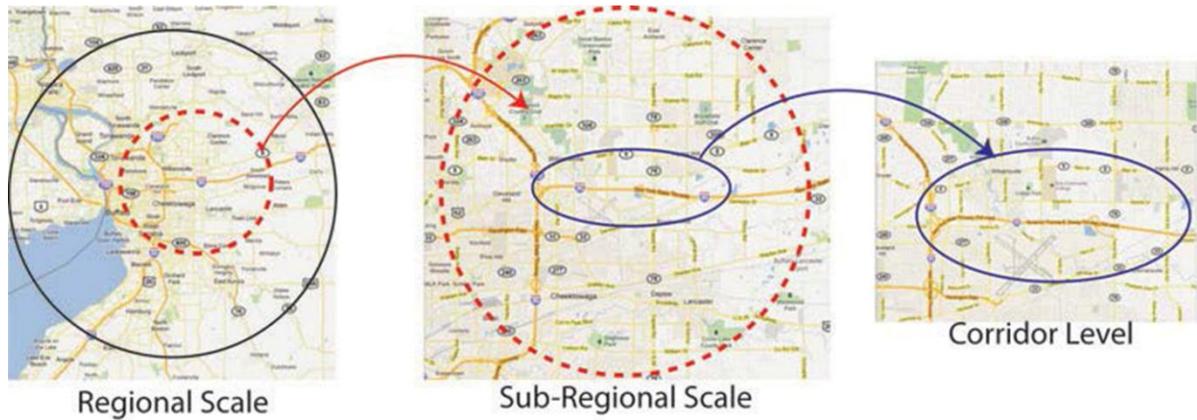
MRM refers to a modeling framework that combines microscopic, mesoscopic, and macroscopic representations of traffic flow in the modeling effort of a single project. It has been argued that such framework can allow a better assessment of traffic operations and advanced strategy. At the start, there is need to differentiate between two types of MRM (Davis and Hilestad, 1998). The first involves building a single model with different levels of simulation resolution for different parts of the network. The second type, and the type that most analyst think of when mentioning multi-resolution modeling, is the use of a combination of two or more models with different modeling resolution levels to analyze a project. These models are generally applied with different transportation network geographic coverage and are used for different purposes to satisfy the overall project objectives.

The Federal Highway Administration (FHWA, 2012a) classified MRM into partial MRM and full MRM, as shown in Figure 1. An example of a simple partial MRM is to use demand forecasting models to provide initial demand estimates to mesoscopic or microscopic modeling tools. This process is currently used by the modeling community in Florida to a certain degree. A full MRM, according to the FHWA document definition, utilizes three modeling levels: demand forecasting models, mesoscopic simulation-based DTA models for a large subarea using trip demands from the demand models, and microscopic models (with or without DTA) to provide detailed analyses of selected sub-areas, corridors, or facilities within the larger subarea already modeled using the mesoscopic simulation-based DTA. It was stated that the full MRM approach addresses issues that are beyond the capabilities of macroscopic models, mesoscopic models, and microscopic models by themselves (FHWA, 2012a).



**Figure 1 Examples of MRM Structure (FHWA, 2012a)**

A typical proposed application of the full MRM approach (see Figure 2) is to determine the initial demands and network configuration based on the approved regional demand forecasting process. The network and demands are then used as inputs to mesoscopic simulation-based DTA to determine diversions and bottleneck impacts on traffic demands. This will allow generating capacity constrained demands with the consideration of diversion due to congestion for use as inputs to detailed analysis of traffic operation using microscopic simulation models.



**Figure 2 Modeling Levels of a Full MRM (FHWA, 2012a)**

As stated earlier, it is becoming evident that to take a full advantage of advances in traffic modeling, analysts will need to use combinations of tools with different functionalities, resolutions, and capabilities. However, a main obstacle to an integrated use of combinations of these tools is the difficulty in interfacing and translating data between various software packages. (Holyoak and Branko, 2009). Thus, there is a need for automated tools to convert the inputs and

outputs from one tool to the other and also to facilitate the use of real-world data as inputs to the modeling process.

In most previous applications of MRM, the interfaces between tools have been in one direction, from the low level of modeling details to the high level of modeling details (e.g., from macroscopic to mesoscopic to microscopic models). However, two-way interfacing is also possible and can be beneficial (e.g., from microscopic back to mesoscopic or macroscopic). For example, if a specific intersection's signal timing is causing a significant bottleneck in the mesoscopic model, the use of the microscopic model will allow a better diagnosis of the problem and outputs from microscopic simulation can be used for better modeling of the intersections at the mesoscopic level (Duthie et al., 2012). This will be further investigated in this study.

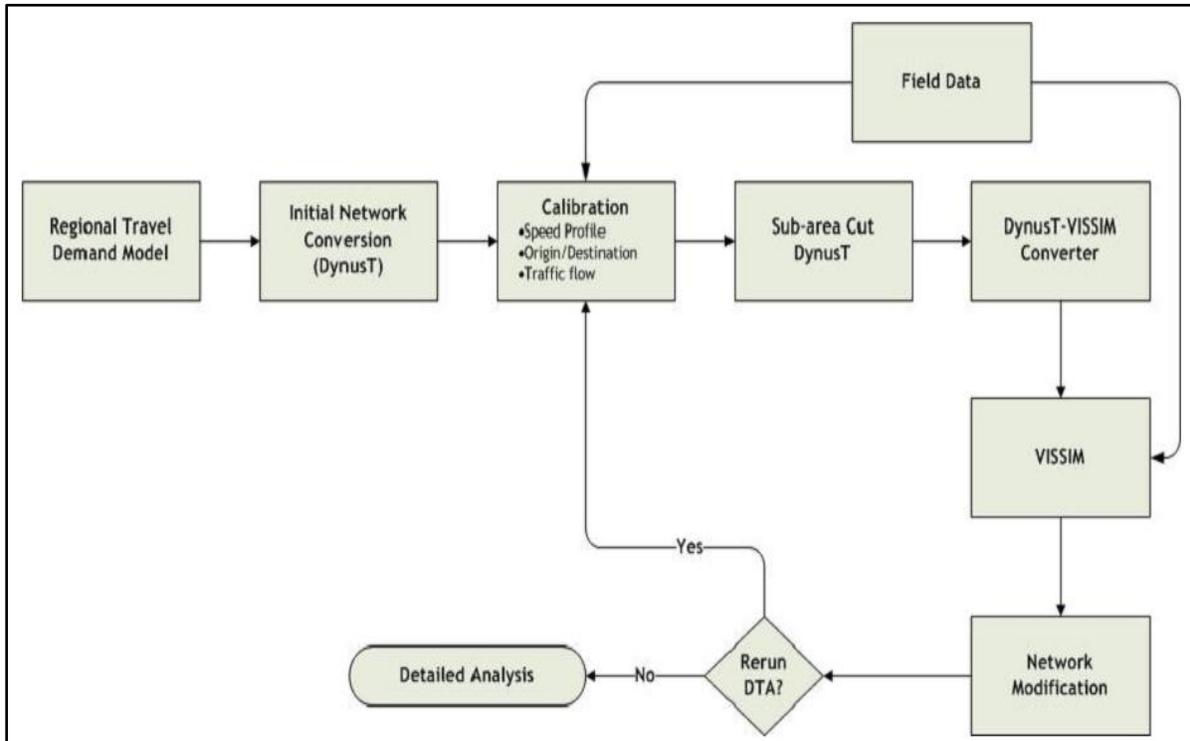
Sbayti and Roden (2010) compared the use of partial MRM (macroscopic model to microscopic model structure) versus full MRM (macroscopic to mesoscopic to microscopic model structure). In the partial MRM, a sub-area from the demand forecasting model is converted to run in a microscopic simulation tool. With this structure, the O-D demands that are departing and entering the boundaries of the sub-area are not capacity constrained. From the macroscopic model's perspective, this results in links with volume-to-capacity ratios exceeding 1.0. However, microscopic models are capacity-constrained and will have difficulty with the utilization of such inputs from the demand model. To compensate, the sub-area network must be manually adjusted and calibrated until the model is close to the actual system dynamics, which has a significant element of judgment and a negative impact on the predictive power of the model for future year cases. When using a full MRM approach, the output from the macroscopic model is fed into a mesoscopic DTA model, which produces time-dependent flows that are capacity constrained for use as inputs to microscopic models. This produced realistic demands and route diversions due to time-varying congestions.

Sbayti and Roden (2010) surveyed agencies and identified the following common challenges to effectively integrate their regional demand models and network simulation tools (mesoscopic or microscopic simulation):

- Estimating demands that can produce acceptable link traffic counts
- Network loading differences in that aggregated transportation analysis zone (TAZ) level data and connectors must be disaggregated to support actual entry points to a network (driveway, parking lot, etc.) within a simulation model
- Adequate processing power and hardware to support the integrated modeling analysis.

In recent years, a few studies have used full MRM in practices. A combination of the DynusT mesoscopic tool and VISSIM microscopic tool was used by Shelton and Chiu (2009). In their study, a subarea was defined and cut from a calibrated large regional DynusT network. To

facilitate this process, a tool was developed to convert DynusT inputs and outputs to VISSIM inputs. Without the development of this tool, outputs from DynusT in the form of time-dependent shortest paths and flows would have to be manually fed into VISSIM, as model input parameters. In addition, the roadway network would have to be created manually in VISSIM. A conversion tool was developed to read files from DynusT inputs and outputs and generate the corresponding network and demands in the format required by VISSIM. Figure 3 illustrates the modeling framework that was used by Shelton and Chiu (2009).



**Figure 3 Modeling Framework for Mesoscopic-Microscopic Integration (Shelton and Chiu, 2009)**

Duthie et al. (2012) used a combination TransCAD (macroscopic-flow based demand forecasting model), VISTA (mesoscopic simulation-based DTA model), and VISSIM (microscopic simulation-based DTA model). The study used a MRM approach that allowed for each individual model to be strengthened by using beneficial outputs from the other models.

Martin et al. (2011) developed a partial MRM structures that involved travel demand forecasting (macroscopic) and microsimulation models. The travel demand forecasting model was implemented in VISUM. A subarea was cut from the VISUM model and was fed to the VISSIM microscopic simulation tool. The sub-network generator in VISUM allowed cutting the sub-area of interest for detailed analysis without the loss of the reference to the original region model. This included the time-varying boundary path flows and the path flows within the sub-network. Additional network details were added to the model in the subarea in the macroscopic model

before the conversion of the data to microscopic model inputs. This included adding minor roads, previously not included in the macroscopic model and additional connectors. Both of these modifications are expected to improve the modeling of traffic flow in the network.

In summary, it can be concluded that MRM has been considered and referenced recently as an approach to improve the assessment of the impacts of time-varying traffic demands that are capacity constrained and the associated vehicle routings that can be used as inputs to microscopic simulation model.

### **2.3. Managed Lane Modeling**

Managed lane (ML) strategies involve operating lanes adjacent to the General Purpose Lanes (GPL) of a freeway facility, providing congestion-free trips to eligible users, such as transit, high-occupancy-vehicles (HOV), or toll-payers. Combinations of access control, pricing, and vehicle eligibility define different types of ML. High occupancy toll lanes (HOT lanes) and high occupancy vehicle lanes (HOV lanes) are the most commonly deployed types of ML across the country. HOV was the preliminary form of ML that was first implemented in Virginia in the late 1960s. During rush hour, HOV lanes can only be used by transit or eligible high occupancy vehicles (a minimum of two or three passengers). In many congested urban areas, however, HOV lanes no longer function as intended. Either they become as congested as GPL lanes, or there is an unused capacity available when GPL suffer from severe traffic jams. HOT lanes take advantage of the excess capacity on ML by allowing non-eligible vehicles, such as Single Occupancy Vehicles (SOVs), to use it by paying a toll. In addition to HOV and HOT lanes, other forms of managed lanes include express lanes, truck-only-lanes, bus-only-lanes, reversible lanes, and ramp metering, coupled with priority access.

ML policies greatly vary in different regions and by time-of-day/day-of-week, and should be tailored to local traffic conditions. In basic applications, the toll values are fixed. In most applications, however, the toll varies by time of day and is adjusted dynamically based on the congestion levels in time intervals as short as three minutes. Different toll values may be applied to different user groups based on different criteria.

The criteria to select the operation parameters of ML can include one or more of the following: preserving a certain level of service in the ML, maximizing revenue, supporting environmentally-friendly vehicles, improving trip reliability, improving safety, and encouraging the use of public transit (FHWA, 2008b). Although the objective of the strategies utilized in existing managed lane applications is mainly to maintain an acceptable level of service of the priced lanes, studies show that travelers in general purpose lanes also benefit from managed lane deployments (Safirova et al., 2013; Janson and Levinson, 2013).

Effective planning and implementation of ML strategies require the utilization of advanced modeling methods to allow better assessment of the impacts of changes in traffic flow conditions and the impact of operation strategies. Various models have been reported to assess managed lane operations, including nested Logit models (DeCorla-Souza, 2003), traffic simulation models (He et al., 2000), optimization models (Li and Govind, 2003), or combination of these models (Murray et al., 2001). In the remainder of this section, various approaches to ML modeling are reviewed.

### ***2.3.1. ML Modeling Input Parameters***

Regardless of the type and level of the tool used in modeling managed lanes, there are a number of modeling parameters that need to be identified or estimated for the modeling effort. An essential parameter for modeling traveler choice of managed lanes is the Value of Time (VOT). Recently, the Value of Reliability (VOR) has been proposed as another parameter that can be used in conjunction with the VOT, when assessing the value that the travelers put on the improved conditions on the ML. VOT and VOR are measures of a driver's willingness-to-pay for travel time and travel improvements. These measures are important inputs to static and dynamic assignment procedures. However, the VOR and VOT are expected to be both different for different traveler categories and also vary randomly within each categories. If these two measure are coded as variables by vehicle class and/or are allowed to vary stochastically, they can be used to capture dissimilarities between the behaviors of different classes of drivers that reflect their willingness to pay for improvements. It should be mentioned that there are factors that can affect the VOT and VOR values and thus traveler's decision to choose the ML. These can include travel distance, income, car occupancy, trip purpose, and time constraints on the trip time on the day of travel. Some of these factors can be captured by coding different values for different categories. Others may be accounted for to some degree by generating the values randomly from a statistical distribution.

A VOT of \$11.75/hour and a VOT of \$2.99 for VOR were recommended for use in the SERPM framework (Resource Systems Group, 2012). This value is based on stated and revealed preference surveys from Fall 2011. The VOR in this estimation seems to be low.

State and revealed preference surveys conducted as part of the tolling modeling for the Florida Turnpike up to 2003 revealed a VOT ranging from \$3/hour to \$13.50/hour, based on the trip purpose and income level (Dehghani et al., 2003). A customer satisfactory survey conducted by the Florida Turnpike Enterprise (FTE) in 2005 showed that 91% of the responders perceived the benefit of paying the toll in terms of service, safety, and convenience (FTE, 2005). Nava et al. (2013) identified a VOT of \$15.50/hour for SOV and HOV users and a VOT of \$46.50/hour for commercial trucks. The value of time estimated by the study of Hadi et al. (2014) is \$42 based on the analysis of real-world detector data of ML utilization.

Recent findings recommended including travel time reliability as a decision factor in the assignment process, and subsequently, VOR was introduced in the generalized cost/utility function. Two general approaches were introduced in measuring travel time reliability. The first approach relates reliability to variability, meaning the higher variability in travel time (measured as trip travel time variance or similar concepts) is equivalent to a less reliable trip. The second approach measures reliability as a portion of success or failure against pre-established thresholds, such as proportion of trips with a delay less than a predefined threshold (Cambridge Systematics, Inc., 2012).

The Strategic Highway Research Program (SHRP) 2 CO4 project (2013) found that drivers place a value on travel time across a wide range from \$5 to over \$50 per hour and approaching \$100 per hour when trip pressure is high. Therefore, toll levels have to be significant to influence congestion on ML. Travelers' responses to congestion and pricing are also dependent on the options available to the travelers to choose from for their trips. The CO4 research team also evaluated the reliability ratio (VOT/VOR for an average trip distance). They found ratios in the range of 0.7 to 1.5 for various model specifications based on stated preference (SP) survey.

Another important input parameter in ML modeling is link capacity for ML. The Highway Capacity Manual (HCM) is the primary source for estimating highway capacity for planning and operation applications. The HCM capacity values are expressed in passenger car per lane per hour and should be converted to vehicle per lane per hour by considering heavy vehicle percentage measurements. In addition to the development of the speed-flow curve, the capacity of the ML facility can be estimated based on field data. Estimating capacity based on field data rather than the HCM procedure is recommended when data is available, particularly when there are evidences that the capacity at the site is different from the average conditions recommended by the HCM.

Researchers have proposed a number of approaches to real-world capacity measurements. Dervisoglu et al. (2009) estimated capacity as the maximum observed 5-minute flow rate over several days. Chao et al. (2005) estimated the capacity as the maximum hourly flow observed during a 30-day period. Jia et al. (2010) estimated capacity as the average of the top one percentile of a 15-minute flow rate over several days, which turned out to be close to values estimated by the HCM. Arem and Van Der Vlist (1991) estimated capacity by determining the maximum occupancy in the uncongested part of the fundamental traffic flow diagram and the associated volume. Bassan and Polus (2010) approximated the capacity by fitting data into parabolic speed-flow and flow-occupancy models. Similarly, Wang and Rajamani (2012) used the apex of a flow-density curve as capacity. Rakha and Mazen (2010) performed an automated fitting procedure of a quadratic speed-flow function to loop detector data.

The ML capacities were found to vary for different types of ML separation. The NCHRP 3-96 project (Wang and Rajamani, 2012) classified ML implementations into five types based on combinations of the GPL and ML separation type and the number of lanes along the ML. The five types are plastic pole separated (Pylon), buffer separated ML with one or two lanes (Buffer 1 and Buffer 2), and barrier separated managed lanes with one or two lanes (Barrier 1 and Barrier 2). The NCHRP 3-96 project determined the impacts of the ML separation types on the capacity of the managed lanes. The ML capacity was calculated using the average of the top one percentile of the 15-minute flow rates over a three day period. The capacity value for the Buffer 2 type according to the study was 1750 pc/h/ln. For the Barrier 2 type separation, the study identified a maximum flow of 1800 pc/h/ln. However, this flow did not cause traffic breakdown. Thus, the actual capacity of the Buffer 2 type could not be identified by the NCHRP study but it is definitely higher than 1,800 pc/h/ln, according to the observation of a study conducted by Khazraeian et al. (2014).

### ***2.3.2. Sketch Planning and Demand Model-Based Tools***

The FHWA developed an open source sketch planning tool (POET-ML) to perform a quick evaluation of ML functionality and pricing policies. The inputs required to use this spreadsheet includes eligibility policies such as occupancy restrictions; physical characteristics such as the lengths and numbers of the lanes, median types, and buffer types, and demand information such as the peak hour volumes on ML and GPL facilities. The outputs from the tool include the potential impacts on travel demands, revenues, mobility, and the environment (Smith et al., 2008).

Another spreadsheet-based application, developed by the University of Texas at Austin is the Project Evaluation Toolkit (PET) that allows the evaluation of networks' improvements and modifications. PET includes a travel demand estimation module implemented as a set of external C++ programs for time of day modeling and route choices behavior, across multiple user classes. PET developers have extended the original version designed initially for evaluating strategic network expansions, allowing it to evaluate various operational network improvements, including hard shoulder use, speed harmonization, dynamic message signs, ramp metering, signalization changes, managed lane applications, incident management/incident response time changes, and advance traveler information systems. ML may be directly implemented in PET by adjusting tolling rates by vehicle class and time of day, as well as varying capacity by time of day. PET can accommodate most of these functions, with variable pricing by time of day and mode. Variable capacity settings can be changed by time of day to model reversible lanes. Vehicles classes can be excluded from using the HOV and ML lanes by setting the tolls extremely high. The users must also allow for an on- or off-link between the main lanes and the HOV or ML lanes. HOV and ML settings can also vary over times of day (Kockelman et al., 2012).

FITSEVAL is another sketch planning tool developed for the Florida Department of Transportation (FDOT) by Florida International University in Miami, Florida by Hadi et al. (2008) to evaluate and assess ITS alternatives within the Florida Standard Urban Transportation Model Structure (FSUTMS) framework. This tool evaluates the effects of different ITS applications including ML, on network performance measures such as Vehicle Mile Traveled (VMT) and Vehicle Hour Traveled (VHT), crash statistics, emissions, average speed, and fuel consumption. The ML module in FITSEVAL utilizes the static assignment of the Cube software.

The FHWA developed an interactive spreadsheet sketch planning tool referred to as Tool for Rush-Hour User Charge Evaluation (TRUCE) to quantify the impacts of congestion pricing on urban highways. In its current form, the model considers scenarios for congestion pricing on the network of limited-access highways or freeways. The charges in a congestion pricing scheme are set partially based on how much driver's value travel time savings. The overall value of travel time is derived in TRUCE as traffic weighted average of values calculated for cars and trucks. For trucks, the calculation allows for the differences in wages between drivers of light and heavy trucks, as well as the value of time for freight cargo. Values of time can differ between urbanized areas because of differences in income and wage levels. To estimate the values for a particular urban area, the users of TRUCE must enter the median household income reported for that area in the American Community Survey. Wage and employment data for truck drivers and general wage data for all occupations are also required. The wage and employment data, hourly wage and number of employees for both heavy and light truck drivers, were obtained from Bureau of Labor Statistics (<http://www.bls.gov/bls/blswage.htm>) (FHWA, 2008a).

FDOT (2013) developed a standard approach for managed lane demand forecasting applications in the Florida Standard Urban Transportation Model Structure (FSUTMS) as a project with different phases. Each phase produced a toolbox for managed lane applications that varies in the level of resolution and sophistication between the different phases, as described below. Phase I focused on the use of static assignment in developing route choice in managed lane modeling and analysis. The input demand for the entire peak period was obtained from sub-area extractions from regional demand forecasting models. The model developed in this phase did not change the split between different user groups, including SOV, HOV, and transit users, as estimated by the regional demand forecasting models. The developed model was used to determine the proportion of drivers willing to use ML, given the charged tolls and the difference in performance between ML and GPL lanes, based on a static assignment procedure combined with a willingness-to-pay curve (Ruegg et al., 2013). In Phase II (Parsons Brinckerhoff, 2013), the choice between GPL and ML was formulated by a logit model in the mode choice step of the traditional four-step demand forecasting procedure. The Phase II model was able to estimate the impacts of managed lane on mode choice, (split between SOV, HOV, and transit), in addition to the proportion of travelers using ML.

The Florida Turnpike Enterprise (2012) has developed a tool that can evaluate a tolled corridor with a competitive non-tolled alternative at a sketch planning level. The tool is referred to as the Express Lanes Time of Day (ELToD). ELToD utilizes a dynamic pricing policy, VOT, and VOR in the evaluation. Some recent work on this tool has included a validation based on ML traffic data from I-95 in southeast Florida. Recent enhancements has included allowing smaller analysis time intervals (e.g. 15 minute), allowing VOT updates based on the study area supported by stated preference surveys and a corridor diversion option. The ELToD procedure used four primary sets of inputs:

- Traffic demand estimates for the corridor
- Distribution of total traffic within the corridor (by direction)
- Network configuration and parameters of the facility including section length, free flow speed, lane capacity, passenger car equivalent factor (PCE), and the numbers of general use and express lanes
- Maximum/minimum toll rates (\$/mile)

ELToD holds the daily traffic and hourly distribution constant and estimates the split that will occur between the general purpose lanes and express lanes given these volumes. It does this by solving the supply/demand equilibrium problem considering both the toll level and travel times for each analysis time interval. An important input to ELToD is the O-D matrices which are output from the travel demand models.

### ***2.3.3. DTA Modeling of Managed Lanes***

The impacts of advanced strategies such as ML are particularly significant when the facility is operating near its capacity. Applying these strategies is time-dependent and highly sensitive to dynamic changes in traffic flow performances. Therefore, these applications require a more advanced modeling, compared to the approaches used in traditional demand forecasting. The use of simulation-based DTA has been proposed to provide more realistic and detailed analyses of ML. DTA can model the impacts of time variant demands, time variant operational strategies (such as those applied in ML), associated travelers' responses, dynamic variations in network performance, and dynamic events such as lane blockage incidents. DTA models the demands over short-time intervals and, for each O-D pair, vehicles that depart at different time intervals (e.g., 15-30 minute) can use different paths and may experience different travel times. These three main components of DTA that are based on the Dynamic User Equilibrium (DUE) principals are:

- Shortest path identification: This includes the identification of a set of attractive paths between each O-D pair. In DTA, this component is time-dependent and includes

updating the set of attractive paths given the generalized costs of the paths during the previous assignment process.

- Assignment of the trip demands to the identified attractive paths: This component results in the estimation of link flows by assigning the demands to the competing attractive paths. In DTA, the proportions of demands assigned to each path are calculated for each assignment time period. In general, a time period of 15-30 minutes is most widely used.
- Network loading: This component refers to the representation of the movement of vehicles on the network as they travel from origins to destinations. Network loading allows the estimation of performance measures for use in the assignment, such as route travel time between origins and destinations. In DTA models, network loading procedures can be classified as analytical procedures or simulation procedures. Due to the complexity of traffic operations, particularly with the presence of congestion and traffic control, simulation-based procedures are the most widely used types of procedures at the present time. Simulation-based DTA tools utilize macroscopic, mesoscopic, or microscopic simulation to assess traffic performance after each iteration assignment.

Convergence of DTA models is also an important issue that needs to be considered by modelers. In static user equilibrium, the convergence of the solution of some of the used algorithms is theoretically provable, which is not the case with the algorithms used for DTA. Therefore, arbitrary performance measures are introduced as convergence criteria, with no agreed-on acceptance levels (Hadi et al., 2012).

The I-95 managed lane facility in Miami, Florida was evaluated in a study conducted by Shabaniyan (2014) using two different approaches: 1) managed lane costs in the objective function, which is an approach traditionally applied in toll modeling and that has been utilized with dynamic traffic assignment (DTA) modeling of toll facilities and managed lanes, and 2) utilizing a willingness-to-pay curve in conjunction with the DTA, which was the approach recommended in the FDOT Phase 1 managed lane modeling process based on static traffic assignment (FDOT, 2013). The ML modeling in the above mentioned study contains a toll diversion process, as well as a congestion-based (dynamic) tolling selection process, so that it estimates the toll trips and the toll costs for each time segment in the managed lanes.

The application of a simulation-based DTA methodology to the analysis and evaluation of network performance under various schemes for the design and operation of ML lanes was also investigated by Abdelghany et al. (2000) using the Dynasmart tool. Two classes of vehicles were considered in the analysis: single occupancy vehicles (SOV) and high occupancy vehicles (HOV). Dynasmart was capable of assessing the impacts of several operating characteristics of the ML. These characteristics included: (a) lane utilization in terms of adding a new lane to the facility or reusing an existing lane as a ML; (b) physical separation of the ML in terms of access point frequency; (c) access restriction on the basis of vehicle occupancy; (d) ML pricing

structure, which can be either fixed or congestion dependent; and (e) different demand levels of SOV and HOV ratios.

Kerns and Paterson (2011) developed a dynamic toll algorithm for making adjustments to the toll prices at regular intervals based on measured traffic density. They used the microsimulation based DTA in the TransModeler tool to enhance the development and implementation of a dynamic toll algorithm for the Capital Beltway HOT lanes in Northern Virginia. The utilized algorithm itself is developed in an environment separate from that of TransModeler to emulate the algorithm's logic and required inputs. TransModeler's functionality was also extended to add better support for zone-based toll algorithms. In this extension, the total trip cost was the sum of the rates of the zones a user passes between the origin and destination, subject to minimum and maximum rates.

#### **2.4. Modeling of Other Active Traffic and Demand Management**

With the increasing deployment of Active Transportation and Demand Management (ATDM) strategies, there has been an increasing interest in modeling the impacts of these strategies on system mobility and reliability. ATDM implements dynamic approaches to manage, control, and influence travel demand and traffic flow performance. ML strategies, addressed in detail in the previous section, are examples of ATDM strategies. However, there are many other strategies that are increasingly being deployed. These strategies are meant to address congestion during normal conditions, incidents, bad weather, and construction events. Table 1 presents a list of ATDM strategies. MRM is ideal for modeling the impacts of many of these strategies. The level of the tool used for analysis typically depends on the scope of the analysis and the existing models and tools that the agency currently uses. The FHWA has been conducting efforts for identifying the best approaches for the analysis, modeling, and simulation (AMS) of these strategies and has funded testbeds in a number of locations to pilot test such analysis (FHWA, 2013a). An important concept of modeling ATDM strategies is to model days with different traffic patterns rather than an average day. This is because the benefits of ATDM strategies are mainly to accommodate the variations in recurrent and non-recurrent traffic conditions. In addition, different ATDM strategies are beneficial under different traffic condition scenarios. Table 2 presents examples of the applicability of different ATDM strategies to different scenarios. Thus, an important component of MRM of ATDM strategies is to identify representative traffic patterns to determine modeling analysis scenarios. Data categorization and clustering algorithms based on detailed data collected using monitoring systems for a long period of time have been used for this purpose.

This section presents an overview of existing approaches to assess ATDM strategies. These approaches range from spreadsheets to HCM procedures to simulation modeling. Please note again that managed lanes with dynamic pricing, reviewed in the previous section, are considered

as active demand management strategies as listed in Table 1. Thus, the discussion in this section is also applicable to ML with dynamic pricing.

**Table 1 ATDM Strategies Classified by Category**

Active Demand Management Strategies	Active Traffic Management Strategies	Active Parking Management Strategies
1. Dynamic Ridesharing	10. Dynamic Shoulder Lanes	19. Dynamically Priced Parking
2. Dynamic Transit Capacity Assignment	11. Dynamic Lane Use Control	20. Dynamic Parking Reservation
3. On-Demand Transit	12. Dynamic Speed Limits	21. Dynamic Wayfinding
4. Predictive Traveler	13. Queue Warning	22. Dynamic Parking Capacity
5. Dynamic Pricing	14. Adaptive Ramp Metering	
6. Dynamic Fare Reduction	15. Dynamic Junction Control	
7. Transfer Connection	16. Adaptive Traffic Signal	
8. Dynamic HOV Conversion	17. Transit Signal Priority	
9. Dynamic Routing	18. Dynamic Lane Reversal or Contraflow Lane Reversal	

**Table 2 Operational Scenario and ATDM Strategies Applicable to Each Analysis Package**

ATDM Strategies	Analysis Scenarios			
	1: Normal Operations— No Incident	2: Incident— On Freeway During AM Peak	3: Planned Event—Baseball Game During PM Peak	4: Planned Event— Blizzard During AM Peak
Dynamic ridesharing			X	
On-demand transit			X	
Predictive Traveler Information	X	X		X
Dynamic pricing (roadway and transit)	X			
Dynamic shoulder lanes	X			X
Dynamic speed limits		X		X
Queue warning		X		
Adaptive traffic signal control	X		X	X
Adaptive ramp metering		X		
Dynamically priced Parking			X	
Dynamic wayfinding			X	

### ***2.4.1. Florida ITS Evaluation Tool (FITSEVAL)***

The Florida ITS Evaluation tool (FITSEVAL) (Hadi et al., 2008) is a sketch planning-level ITS evaluation tool that was developed for the Florida Department of Transportation (FDOT) by FIU researchers. The tool works within the Florida Standard Urban Transportation Modeling Structure (FSUTMS)/Cube environment. It can be used to estimate the benefits and costs of various types of ITS deployment as listed below.

- Ramp Metering
- Incident Management Systems
- Highway Advisory Radio (HAR) and Dynamic Message Signs (DMS)
- Advanced Travel Information Systems (ATIS)
- Managed Lane
- Signal Control
- Emergency Vehicle Signal Preemption
- Smart Work Zone
- Road Weather Information Systems
- Transit Vehicle Signal Preemption
- Transit Security Systems
- Transit Information Systems
- Transit Electronic Payment Systems

The first nine of the above strategies can be considered as ATDM strategies. The evaluation methodology implemented in FITSEVAL varies with the type of ITS deployments. The output of the FITSEVAL tool includes the impacts of ITS on performance measures including mobility, safety, fuel consumption, emission and other measures. FITSEVAL also outputs the benefits and costs in dollar values of ITS applications and the resulting benefit/cost ratios. These outputs can be used to assess the ITS deployment, prioritize alternatives, and support long range plan. In a recent assessment by the University of Virginia, twelve different existing tools were evaluated and FITSEVAL was recommended for use in Virginia (Ma and Demetsky, 2013).

### ***2.4.2. TOPS-BC***

TOPS-BC (Sallman et al., 2013) is an Excel-based tool that is designed to support practitioners to conduct benefit and cost analyses. It has four main capabilities: 1) Investigate the impacts associated with prior deployments and Transportation System Management and Operations (TSM&O) strategies; 2) Include methods and tools at different analysis levels for benefit/cost analysis; 3) Estimate life-cycle costs, replacement costs, and annualized costs based on default cost data. The life-cycle costs include capital costs as well as the soft costs required for design, installation, operations and maintenance of the equipment. The replacement costs are the

periodic cost of replacing/redeploying system equipment and the annualized costs represents the average annual expenditure that would be expected in order to deploy, operate, and, maintain the TSM&O strategies; 4) Estimate benefits for particular TSM&O strategies. Default impact values and parameters are recommended in this tool. The TSM&O strategies that can be evaluated in TOPS-BC are listed below.

- Traveler information
  - a. Highway Advisory Radio (HAR)
  - b. Dynamic Message Signs (DMS)
  - c. Pre-Trip Travel Information
- Ramp Metering Systems
  - a. Central Control
  - b. Traffic Actuated
  - c. Preset Timing
- Traveler information
  - a. Highway Advisory Radio (HAR)
  - b. Dynamic Message Signs (DMS)
  - c. Pre-Trip Travel Information
- Ramp Metering Systems
  - a. Central Control
  - b. Traffic Actuated
  - c. Preset Timing
- Incident Management Systems
- Signal Control
- Emergency Vehicle Signal Preemption
- ATDM Speed Harmonization
- Employer Based Traveler Demand Management
- ATDM Hard Shoulder Running
- ATDM High Occupancy Toll Lanes
- Road Weather Management
- Work Zone
- Supporting Strategies
  - a. Traffic Management Center
  - b. Loop Detection
  - c. CCTV

#### ***2.4.3. HCM-Based ATDM Evaluation Approach***

The Highway Capacity Manual (HCM) include simple procedures to evaluate ATDM strategies based on the outputs from the operational analysis methodologies of the HCM (Dowling et al.,

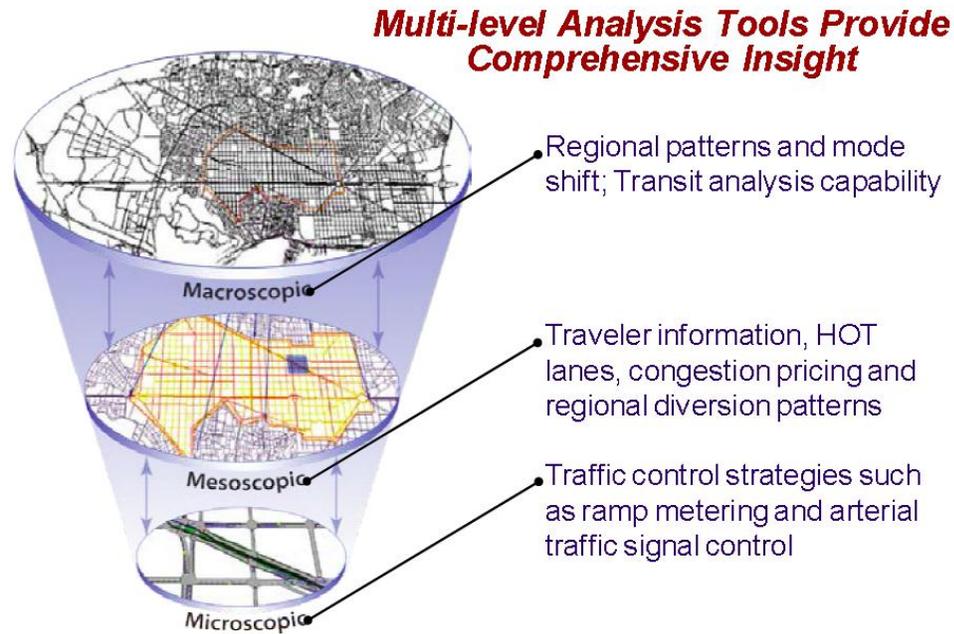
2013). The methodology assess the impacts on the mean travel time, travel time reliability, and facility demand. The conventional HCM data is supplemented with local historic data on incidents, work zones, and weather; allowing the generation of a set of scenarios representative of the range of conditions that may be present on the facility over the course of a year. The effects of weather, work zones and incidents on capacity and speed are computed for each scenario and the adjustments are applied using standard HCM operational analysis methodologies to determine the impacts on the facility performance measures.

As with other HCM procedures, the analysis remains facility based (freeways or arterials separated from each other in the analysis) and thus system level impacts are not reflected. Also, the analysis is done at the 15 minute analysis level, as with other HCM analysis procedures, and thus highly dynamic responses below the 15 minute threshold of the HCM must be modeled, approximately.

#### ***2.4.4. Simulation and Multi-Resolution Analysis***

Simulation modeling has been used for some time to model and assess ATDM strategies. Perhaps the most extensive efforts on modeling advanced strategies in simulation models are the one's sponsored by the FHWA, as part of the Integrated Corridor Management (ICM) initiative and the on-going Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) testbeds, also sponsored by FHWA.

The ICM initiative developed an Analysis, Modeling, and Simulation (AMS) methodology to assist agencies in forecasting and assessing the potential benefits and implications of ICM. An ICM AMS Guide has been incorporated into the Federal Highway Administration (FHWA) Traffic Analysis Toolbox (Volume XIII) (FHWA, 2012c). This AMS Guide recognizes the complexity of this type of analysis and recommend the combined use of multiple classes of available modeling tools (utilizing a MRM approach), as shown in Figure 4. The rule and extent of each tool type depends on the scope, complexity, and questions to be answered in the effort under consideration.



[Source: Cambridge Systematics, Inc., September 2009.]

**Figure 4 The ICM AMS MRM Methodology**

The ICM AMS document stated that the use of the different models allows specific strengths of the individual models to be combined since each tool type (macroscopic, mesoscopic, and microscopic) has different advantages and limitations and is better than other tool types at some analysis capabilities. The guide further stated that “there is no one tool type at this point in time that can successfully address the analysis capabilities required by the ICM program. An integrated approach can support corridor management planning, design, and operations by combining the capabilities of existing tools.” The integration of multiple tools was the analysis approach eventually selected by all three ICM Pioneer Sites funded by the FHWA (Dallas, Minneapolis, and San Diego). However, the guide recognizes that interfacing between different analysis tool types presents challenges that need to be addressed including: a) maintaining consistency across analytical approaches in the different tools, and b) maintaining the consistency of performance measures used in the different tool types.

An important aspect of the ICM AMS methodology is the need to simulate transportation systems under varying operational conditions including those associated with both recurrent and non-recurrent traffic congestion. The Guide stated that the key ICM impacts may be lost if only “normal” travel conditions are considered. Thus, the analysis should take into account both average- and high-travel demands within the corridor, with and without incidents. The frequency of non-recurrent events such as incidents is also important to estimates of the impacts of advanced strategies.

The AMS Guide also highlight the importance of the selection of the appropriate approach and tool type, and the specific tools that meet the needs of the study. This analysis should be done based on clear project analysis requirements. The FHWA Traffic Analysis Toolbox Volume II (Luttrell et al., 2008) includes a spreadsheet-based decision support tool that can be used to weigh various factors. However, this tool will not recommend a specific tool, but the category of tool and the analysis team will still need to evaluate specific vendor products within these categories. Figure 6 provides an overview of the basic factors considered in the FHWA Traffic Analysis Toolbox method.

Another important FHWA initiative is the on-going “Analysis, Modeling, and Simulation (AMS) Testbed Framework for Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Program.” (FHWA, 2013c; FHWA, 2013d; FHWA, 2013e). This effort is investigating a suite of modeling tools and methods that allow the evaluation of the potential benefits of implementing ATDM and AMS strategies for planning, design, and operations purposes. To support the planning and design phases, a “simulated” real-time analysis capability is recommended to quantify the potential. The effort identified AMS needs in a concept of operation (CONOPS) report, then identified the AMS gaps in this report. A number of testbeds have been selected to test the ATDM and DMA AMS concepts. These include the San Mateo (US 101), Pasadena, Dallas, San Diego, Phoenix, and Chicago testbeds. The AMS effort implemented in these testbeds emphasized the importance of multi-resolution analysis. On the supply side, it is important to model changes to network supply or capacity between days; and on the demand side, it is necessary to capture the changes in demand patterns between days and traveler behaviors, as a response to implemented dynamic actions. The ATDM AMS also emphasized that it is essential to capture the dynamic interactions between supply and demand and how the supply changes affect the trip chain. Special considerations listed for modeling ATDM includes the need for the identification of the appropriate performance measures, supporting data, capabilities of modeling advanced strategies, traveler behavior modeling, and model execution speed for real-time operations. Clustering analysis to determine various analysis scenarios is an important component of the MRM approach utilized in the ATDM and DMA modeling.

Analysis Context: Planning, Design, or Operations/Construction						
1	2	3	4	5	6	7
Geographic Scope	Facility Type	Travel Mode	Management Strategy	Traveler Response	Performance Measures	Tool/Cost-Effectiveness
What is your study area?	Which facility types do you want to include?	Which travel modes do you want to include?	Which management strategies should be analyzed?	Which traveler responses should be analyzed?	What performance measures are needed?	What operational characteristics are necessary?
<ul style="list-style-type: none"> <li>• Isolated Location</li> <li>• Segment</li> <li>• Corridor/ Small Network</li> <li>• Region</li> </ul>	<ul style="list-style-type: none"> <li>• Isolated Intersection</li> <li>• Roundabout</li> <li>• Arterial</li> <li>• Highway</li> <li>• Freeway</li> <li>• HOV Lane</li> <li>• HOV Bypass Lane</li> <li>• Ramp</li> <li>• Auxiliary Lane</li> <li>• Reversible Lane</li> <li>• Truck Lane</li> <li>• Bus Lane</li> <li>• Toll Plaza</li> <li>• Light Rail Line</li> </ul>	<ul style="list-style-type: none"> <li>• SOV</li> <li>• HOV (2, 3, 3+)</li> <li>• Bus</li> <li>• Rail</li> <li>• Truck</li> <li>• Motorcycle</li> <li>• Bicycle</li> <li>• Pedestrian</li> </ul>	<ul style="list-style-type: none"> <li>• Freeway Mgmt</li> <li>• Arterial Intersections</li> <li>• Arterial Mgmt</li> <li>• Incident Mgmt</li> <li>• Emergency Mgmt</li> <li>• Work Zone</li> <li>• Spec Event</li> <li>• APTS</li> <li>• ATIS</li> <li>• Electronic Payment</li> <li>• RRX</li> <li>• CVO</li> <li>• AVCSS</li> <li>• Weather Mgmt</li> <li>• TDM</li> </ul>	<ul style="list-style-type: none"> <li>• Route Diversion               <ul style="list-style-type: none"> <li>- Pre-Trip</li> <li>- En-Route</li> </ul> </li> <li>• Mode Shift</li> <li>• Departure Time Choice</li> <li>• Destination Change</li> <li>• Induced/Foregone Demand</li> </ul>	<ul style="list-style-type: none"> <li>• LOS</li> <li>• Speed</li> <li>• Travel Time</li> <li>• Volume</li> <li>• Travel Distance</li> <li>• Ridership</li> <li>• AVO</li> <li>• v/c Ratio</li> <li>• Density</li> <li>• VMT/PMT</li> <li>• VHT/PHT</li> <li>• Delay</li> <li>• Queue Length</li> <li>• # Stops</li> <li>• Crashes/Duration</li> <li>• TT Reliability</li> <li>• Emissions/Fuel Consump</li> <li>• Noise</li> <li>• Mode Split</li> <li>• Benefit/Cost</li> </ul>	<ul style="list-style-type: none"> <li>• Tool Capital Cost</li> <li>• Effort (Cost/Training)</li> <li>• Ease of Use</li> <li>• Popular/Well-Trusted</li> <li>• Hardware Requirements</li> <li>• Data Requirements</li> <li>• Computer Run Time</li> <li>• Post-Processing</li> <li>• Documentation</li> <li>• User Support</li> <li>• Key Parameters User Definable</li> <li>• Default Values</li> <li>• Integration</li> <li>• Animation/Presentation</li> </ul>

Figure 5 Basic Factors Considered in the FHWA Tool Category Selection Method (Jeannotte et al., 2004)

#### ***2.4.5. Data-Based Assessment and Support***

The ITS Data Capture and Performance Management (ITSDCAP) tool developed for the FDOT by FIU has a model to support the benefit analysis of ITS deployment and strategies. Two types of supports are provided in this module. The first is to provide the input required for other ITS evaluation tools such as FITSEVAL and TOPS-BC. The second is to estimate the benefits directly based on data and modeling. For this second type of the benefit evaluation support, only incident management on arterials and freeways can be evaluated using the current version of ITSDCAP.

### **2.5. Modeling of Construction Impacts**

Proper assessment of work zone impacts is required at various stages of construction to support decisions regarding on when, where, and how the work zone construction would be implemented. An important component of the decision making process is to assess the work zone impacts. A report by the Federal Highway Administration (Mallela and Sadasivam, 2011) identified four main components of road user costs associated with the work zone impacts: mobility costs, safety costs, emission costs and other non-monetary costs.

The type of analysis required in assessing the work zone impacts on system performance and the associated user costs depend on the stage of construction decision processes and other factors that determine the required level of analysis details. During the early planning stage, simple analysis tools may be sufficient. In the design and implementation stage, more detailed analysis of work zone impacts is required at the corridor and possibly at the network levels, with more detailed traffic flow analysis and the consideration of travel demand reduction, route diversion and so on. Highway capacity facility based procedures and in some cases simulation modeling, possibly combined with DTA can be utilized at this stage to assess work zone impacts as well as the impacts of alternative construction, implementation, and management strategies. During the construction stage, data from point detectors, automatic vehicle identification (AVI), or other technologies can be collected that can be directly analyzed to determine work zone impacts. A number of tools have been developed to assess the impacts of work zones on mobility. The FHWA Traffic Analysis Toolbox Volumes IX (Hardy and Wunderlich, 2009) classifies these tools; as sketch planning tools, traffic demand models, signal optimization tools, macroscopic simulation, mesoscopic simulation, and microscopic simulation. This FHWA report provides guidance to assist in selecting between these different types of tools based on various factors.

### ***2.5.1. Sketch Planning/Spreadsheet Methods***

There are several sketch planning tools mostly in spreadsheet environments that have been developed by the FHWA and state departments of transportation. Typically, these tools utilize daily or hourly traffic demands and capacity estimates to quantify work zone impacts. The results are less accurate than using more advanced approaches. In this section, three tools of this type are reviewed that vary in their levels of details, as examples of available tools. There are several other similar tools available that require similar data inputs. A complete review can be found in the FHWA reports mentioned earlier (Hardy and Wunderlich, 2009; Mallela and Sadasivam, 2011).

The Q-DAT tool developed by the Texas Transportation Institute is a simple Microsoft Excel spreadsheet-based tool for construction impact analysis. Two types of analysis can be conducted using this tool: “Delay and Queue Estimation” and “Lane Closure Schedule”. For the first type of analysis, with simple inputs consisting of travel demand and lane closure information, the tool can output the value of queue length by comparing traffic demand with reduced work zone capacity and delay due to work zone based on a regression equation. In the Lane Closure Schedule analysis, the queue length and delay for every possible combination of construction hour and number of lanes blocked are calculated and the scenarios with queue length and delay less than certain predefined thresholds are recommended to the user. Q-DAT requires simple inputs and can produce estimates of queues and delays, which is applicable for planning purpose. However, only the mobility impacts due to work zone are assessed, and the outputs are not given as road user costs directly.

RealCost is a Visual Basic for Applications (VBA) macro-enabled Microsoft Excel-based tool for life cycle cost analysis in pavement design, which was developed by the FHWA. In addition to traffic demand and work zone configuration, RealCost also needs as inputs the pavement design alternatives and construction costs. RealCost can calculate the life cycle values for both user costs and agency costs. Agency costs have to be directly input by the users. User costs can be either a user-input or calculated by the RealCost tool based on the procedures recommended by the NCHRP 133 study (Curry and Anderson, 1972). The cost analysis results from RealCost for multiple pavement alternatives can be used to prioritize alternatives. RealCost can provide estimates for user costs and agency costs with simple traffic flow and project information, however, only mobility costs can be estimated using this tool. Safety and emission costs are not included in the analysis.

QuickZone is a more detailed sketch planning tool developed by FHWA for analyzing work zone mobility impacts such as traffic delays, queue, and associated delay costs. It uses a node- and link- based network layout and estimates delay and queues based on a deterministic queuing model. The mobility impacts estimated by QuickZone can be used to compare alternative project

phasing plans. QuickZone is capable of modeling a facility with construction activities and associated alternative routes for work zone mobility impact analysis, and it can also be applied to evaluate traveler behaviors with the presence of work zone such as route changes, peak-spreading, mode shifts, and trip losses. However, QuickZone mainly focuses on the mobility impacts for user costs.

### ***2.5.2. HCM-Based Macroscopic Analysis***

A procedure is provided in the Highway Capacity Manual (HCM 2010) to calculate the reduced freeway capacity due to short term and long term constructions along a basic freeway segment. This procedure can be used in combination with other procedures to estimate work zone impacts. For short term construction, the reduction in roadway capacity can be calculated from the number of available lanes, activity type and density, and the presence of adjacent on-ramps. However, for long term construction, only a table that lists some values of long term construction zone capacity as reported in previous studies is presented in the HCM. In addition, the HCM 2010 provides macroscopic procedures to calculate the performance of freeways and urban streets. The HCM work zone capacity procedure has been updated in a recent National Cooperative Highway Research Program (NCHRP) project 03-107 (NCHRP, 2014). The HCM freeway and urban facility procedures are now being updated based on the results of the above mentioned report with the expected release of the updated HCM in 2015. The corresponding computational engines to the freeway and urban street facilities are FREEVAL and STREETVAL, respectively. Recently, these two tools are further enhanced to model travel time reliability, which are called FREEVAL-RL and STREETVAL-RL. In addition, the updated HCM work zone procedure mentioned above have been incorporated in these models. These models can be considered as macroscopic simulation models and can provide higher levels of analyses than those provided by the sketch planning procedures mentioned earlier.

In FREEVAL or FREEVAL-RL, the freeway facilities are divided into different types of segments, including basic, merge, diverge, and weaving segments. Different analysis approaches are used for undersaturated and oversaturated conditions. For undersaturated conditions, roadway segments are analyzed independently. Depending on segment type, the corresponding HCM procedure is applied to calculate the segment speed, capacity, and in turn density and the level of service. When traffic is under oversaturated conditions, the freeway facility is analyzed as a node-link system and a cell transmission model based algorithm is utilized to track queue accumulation and dissipation over multiple segments and periods.

Urban street facility can be coded in STREETVAL or STREETVAL-RL as segments with boundary points that represent signalized and unsignalized intersections. The performance of a segment for the automobile mode is analyzed by first determining the segment running time, through movement delay, and stop rate based on the free-flow speed and the control types, and

then calculating the segment travel speed, stop rate, and level of service. The level of service of signalized intersections is determined based on control delays. In the HCM procedure, this is a function of adjusted saturation flow rate and percentage of vehicles arriving on green.

A new version of FREEVAL (FREEVAL-2015E) has been developed in JAVA programming language that incorporates this updated work zone procedure. In FREEVAL-2015E, traffic demand and constructions are modeled deterministically while the occurrence of incidents and weather are modeled using a stochastic approach. In addition to the work zone capacity for basic freeway segment; approaches to calculate work zone capacity for merging, diverging, weaving and crossover segment types are also proposed in HCM 2015 and implemented in FREEVAL-2015E. The work zone impacts according to the procedure are functions of work zone configurations (normal and reduced number of lanes), segment type, ramp volumes, acceleration/deceleration lane length, among other factors. The output performance measures from FREEVAL-2015E include average speed, density, and LOS for each segment and each time interval.

The impacts of construction can be modeled using these HCM tools by reducing the number of available lanes and adjusting the speed limit and capacity of the work zone. The output performance measures include travel time, delay, average speed, and so on.

### ***2.5.3. Simulation-Based Dynamic Traffic Assignment***

The Work Zone Impacts and Strategies Estimator (WISE) is a product produced by the SHRP2 R11 Project. It is a decision-support tool for assisting agencies to evaluate the impacts of work zones and work zone-related mitigation strategies along a given corridor or for a network (Peseky et al., 2012). WISE is able to evaluate renewal projects at both the planning and operation levels. When used as a planning tool, the user can evaluate the effectiveness of various travel demand and construction duration strategies for multiple projects by comparing two main measures: construction cost and traveler delay cost. When used at the operational level, time-dependent congestion and diversion caused by congestion can be captured by a simulation-based dynamic traffic assignment (DTA) tool. More accurate estimation of the diversion due to the impacts of capacity reduction resulting from work zones can be obtained using the operation module based on the simulation outcomes. The user can model whether to change the sequence of projects based on the diversion rate results.

## **2.6. Modeling Vehicles Equipped with Advanced Technology**

Advanced automated and connected vehicle technologies are expected to change traffic flow characteristics. At the microscopic level, these technologies are expected to change vehicle interactions, including car-following, lane changing, and gap acceptance characteristics. These

changes are expected to influence highway capacity, stability of traffic flow, and queue discharge during slow and go operations. However, these impacts on traffic parameters have just started to be investigated. The effects of these technologies on traffic flow need to be identified to justify the additional investment in these technologies by public agencies, private sectors, and travelers. The market penetrations of advanced vehicle technologies are expected to increase significantly in the coming years. Two examples of these technologies are Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC). ACC is a radar-based system, which is designed to increase driving comfort and safety by automatically adjusting the speed of the vehicles according to the speed of the preceding vehicle. An ACC-equipped vehicle automatically slows down when it gets close to the preceding vehicle and speeds up to the set level of speed when the preceding vehicle accelerates or is not there anymore. CACC is an extension of ACC that utilizes a control logic that takes advantage of wireless vehicle-vehicle (V2V) communication. With CACC, in addition to maintaining a proper following distance and speed as in the case of ACC, the system also allows cars to “cooperate” by communicating with each other, resulting in a vehicle changing speed in response to the locations and speeds of other equipped vehicles ahead of the vehicle. This can provide higher impacts on safety and, possibly, mobility, compared to the basic ACC systems.

An interesting operational scenario involves operating ML with preferential treatment of vehicles with advanced technologies such as ACC or CACC vehicles. Such operations could be beneficial since the performance of these vehicles is expected to improve the efficiency and safety of ML. There will be also a time when the designation of special lanes for these vehicles may be advisable and advantageous. Precedent for vehicle eligibility for special lanes is well-established through the implementation of HOV and HOT lanes, bus lanes, truck lanes, and so on. It should be recognized, however, that the managed lanes that involve vehicle eligibility restrictions present enforcement challenges. In addition, eligibility restrictions must be implemented at the appropriate time, considering the proportions of the vehicle types in traffic. The proportions of the ACC- and CACC- equipped vehicles will be driven by the purchase rates of new smarter vehicles and the replacement rates of vehicles that are not equipped with advanced technologies (FHWA, 2013b). Another advantage of providing preferential treatments to equipped vehicles on ML is to ensure that a higher percentage of CACC vehicles are using the same lane, increasing the collaboration between vehicles on the lane.

To evaluate the interactions between vehicles with various advanced technologies and manually driven vehicles, it is necessary to use advanced models to capture the traffic flow characteristics of these vehicle types and the interactions between these vehicles. A MRM approach that combines macroscopic, mesoscopic, and microscopic simulation modeling with DTA is proposed in this research to assess the impacts of the advanced vehicle technologies on ML operations.

The review of literature conducted in this study was able to identify studies that focused on predicting the effects of ACC/CACC vehicles on traffic flow using microscopic simulation modeling. Microscopic simulation has been used extensively in these researches to evaluate traffic flow, considering vehicle capabilities (acceleration, deceleration, and speed) as well as driver behavior (car following, lane changing, and time gap setting) (Ngoduy, 2013; Tapani, 2012; Bifulco et al., 2013; Yeo et al., 2010).

Kesting et al. (2007) identified significant improvements in performance measurement with the use of ACC. According to that study, at penetration rates as low as 10 percent, the maximum travel time delay of individual drivers can be reduced by about 30 percent and the total delay by 50 percent. Van Driel and van Arem (2008) focused on the effects of ACC vehicles in congestion condition and they found that the ACC vehicle reduced the maximum queue length significantly. Elefteriadou et al. (2011) also concluded that ACC could significantly increase the speeds for congested conditions, even at a market penetration rate of 20 %.

However, not all evaluations of ACC have yielded positive results. Shladover et al. (2012) applied microscopic simulation modeling to estimate the effect of varying market penetrations of ACC on highway capacity based on car-following behavior. Their results show that conventional ACC is unlikely to produce any significant change in highway capacity because drivers are only comfortable with the ACC system at gap settings similar to the gaps they choose when driving manually. Similarly, Davis (2004) found that bottleneck occurs for penetration rates of 40% or more because of longer selected time gaps. Other studies (Wang and Rajamani, 2010; Arnaout and Bowling, 2014; Calvert et al., 2012) evaluated the importance of headway setting with respect to capacity impacts of ACC vehicles. They pointed out that ACC systems are commonly designed to maintain longer time-gaps between vehicles to increase safety. The results showed that there was no improvement in capacity especially when 100% of vehicles are ACC equipped. Based on these studies, the potential benefits of ACC appear to be more definite at higher market penetration rates of these vehicles.

On the other hand, recent researches based on microscopic simulation confirm that the increase in market penetration of CACC will increase capacity, significantly. In 2010, Nowakowski et al. (2010) performed a study to evaluate drivers' choices of the following distances while operating a vehicle with CACC. The results showed that drivers of the CACC selected vehicle-following gaps that were approximately half of the length of the gaps they selected when driving vehicles equipped with ACC. The gaps selected for ACC vehicles were comparable to manually driven vehicle-following gaps. The drivers' selection of shorter gaps will result in highway lane capacity increases with the increase in CACC proportion in the traffic stream. A similar study (Milanés et al., 2014) also found that the use of CACC results in reduced gap variability indicating the potential for CACC to attenuate disturbances, improve highway capacity, and improve traffic flow stability. The increase in capacity due to CACC will depend on most drivers

being willing to travel at much shorter time gaps than usual. This will also depend on how to address drivers' concerns that shorter time gaps may reduce the time available for corrective actions due to poor judgment (Jones, 2013).

The most current use of tools in modeling and evaluating the impacts of ACC and CACC on traffic flow and operations are based on microscopic traffic simulation models. Most of the work done using microscopic simulation models has been on ACC or CACC and has been focused on analyzing these technologies' impacts on traffic flow without the consideration of using ACC or CACC on exclusive or mixed use ML. However, as advancements of CACC or ACC and managed lane strategy occur, more research should look at the application of these technologies on ML. Regional or subarea impacts in addition to facility based impacts will have to be studied and MRM will be a powerful approach for this purpose.

### 3. MULTI-RESOLUTION MODELING FRAMEWORK

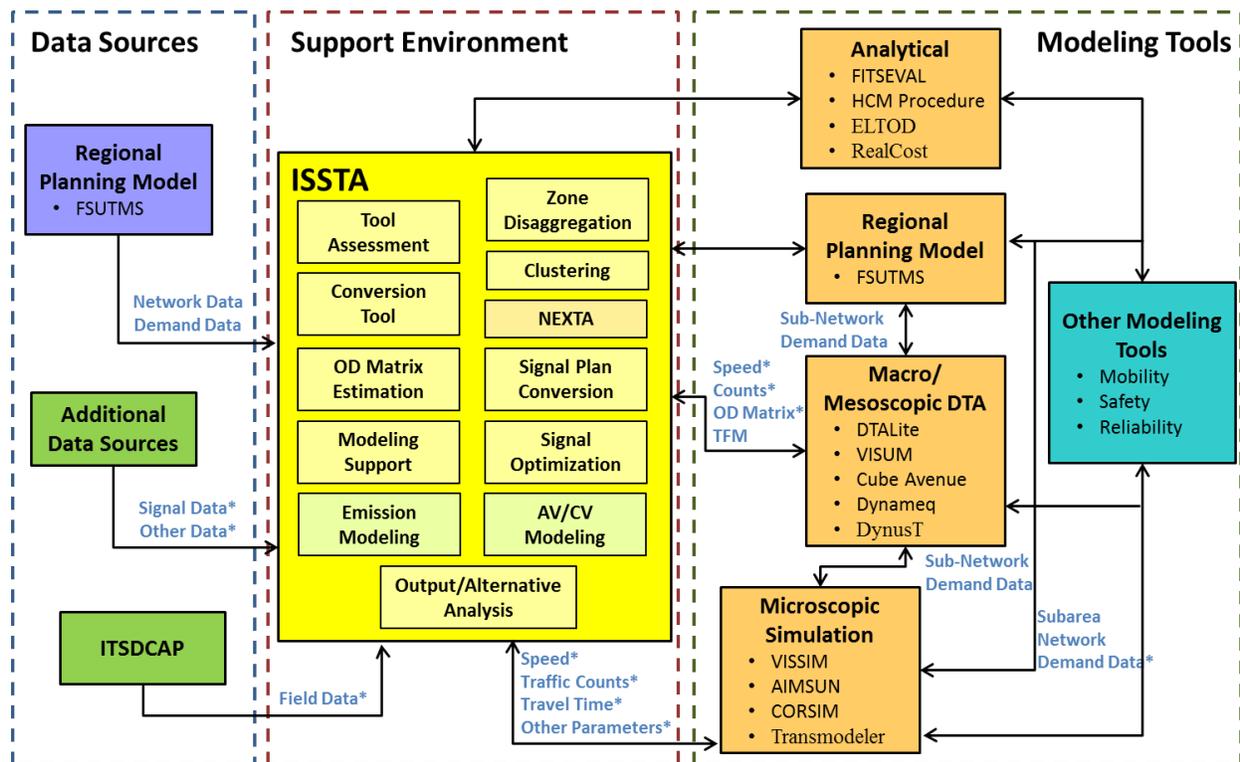
In this section, an overview of the developed MRM framework is first presented followed by more detailed descriptions of the framework’s modeling components.

#### 3.1 Overview of Developed MRM Framework

Figure 6 illustrates the multi-resolution framework recommended in this project. As shown in this figure, the framework consists of three components:

- Data sources and tools that allow the utilization of data from multiple sources to support modeling tasks;
- Supporting environment that assist modelers in developing, calibrating, and processing the results of the selected modeling tools
- Modeling tools of different types and resolution levels that allow the estimation of various performance measures.

The details of these components are discussed in the following section.



\*: The data files are interfaced through the csv format.

Figure 6 Multi-Resolution Modeling Framework

## **3.2. MRM Framework Components**

This section provides a detailed description of the components and supporting tools included in the MRM framework shown in Figure 6.

### ***3.2.1. Data Sources and Tools***

Advanced modeling tools such as dynamic traffic assignment (DTA) and simulation tools require high-quality processed data to ensure that the developed model applications accurately simulate existing and future real-world conditions under different scenarios and strategies. The needed inputs to these simulation models include roadway geometry and physical characteristics (for example, link length, free-flow speed, capacity, etc.), signal timings and control, transit route schedules if needed, travel times under different conditions, and dynamic origin-destination demand matrices or time-dependent vehicle trips. Modeling advanced strategies also require other parameters such as incident, work zone, weather, and special event statistics. Reliability modeling requires these additional parameters, as well.

There are two main data sources that can provide the inputs for multi-resolution analysis. The first are models developed in the previous studies, especially, travel demand forecasting models, which can actually be also considered, as a modeling tool within the developed framework. The second category of data sources are archived real-world data collected using ITS devices, planning statistic office detectors, third party vendors and agencies, conventional data collection methods, surveys, accident/incident reports, weather agencies, signal control agencies, and/or other sources. Soon, data from connected vehicles will be available to supplement the modeling activities of transportation systems. The data from both source categories have to be processed and converted to a format accepted by the selected modeling tools. To reduce the required effort, this conversion task should be supported by an automatic data conversion tool, as part in the support environment tools, as shown in Figure 6. This tool would convert the demand forecasting and model and real-world data to a format that can be read by other modeling tools, to help in developing the input data for the tools. This tool will be discussed further in the next section.

#### **3.2.1.1. Data from Models**

Regional demand forecasting model or other previously developed model provide a good starting point for creating a multi-resolution model. These models provide valuable information such as the socio-economic characteristics of the population in each traffic analysis zone, origin-destination matrices, average trip length, network geometry, and attributes for each link such as length, number of lanes, free-flow speed, capacity, and so on.

### **3.2.1.2. Real-World Data**

The advancement in traffic monitoring and detection technologies makes traffic data much easier to obtain. These data can be used in the development and calibration of simulation tools. Below is a description of real-world data from multiple sources.

- **Conventional Data Collection Methods**

Traditionally, data collected for modeling purposes were for a short period of time using manual data collection techniques such as test cars, tube counts, and turning movement counts. Such data is still useful to supplement automatically collected data from permanent or portable monitoring systems. It has been recognized that such data is not sufficient to determine the performance of the system and the impacts of confounding factors such as the impacts due to variations in demands, capacity, weather, and incidents. In addition, in many cases, small sample sizes do not allow statistically valid inference, particularly that the data collection does not consider the influences of confounding factors and thus normally exhibits large variances increasing the needed sample sizes. There is an increasing realization that data from multiple sources for long periods of time are required to conduct complex evaluation studies. The SHRP 2 L02 and L03 projects confirmed a year worth of data is needed to be able to estimate the reliability and the impacts of the confounding factors. However, manual counting methods are still the preferred methods for collecting some measures such as turning movement counts and intersection movement delays. Turning movement counts are required inputs to several analysis and microscopic simulation tools. In addition, the utilization of turning movement counts as inputs to the Origin-Destination Matrix Estimation (ODME) process was found to improve the O-D estimation results significantly in this study.

- **Point Traffic Data**

The deployment of point detectors has become common on urban freeway facilities. However, due to cost constraints, the point detection coverage is much lower at rural freeways and urban street midblock locations, although point detectors are also used for the stop bar detection required for actuated control of signalized intersections. The use of the data from these stop bar detectors for performance measurements have been limited due to hardware and software limitations. There are several types of point detection technologies, each with its strengths and weaknesses. The most commonly utilized technologies are loop detectors, true presence microwave detectors, and video image detectors. The basic parameters that can be measured by these technologies are speed, volume, and occupancy/presence. Space measurements, including travel time, travel time reliability, queue length/back of queue location, density, and shockwave speed have been estimated for freeway segments based on point measurements of the basic parameters. Various methods with different levels of complexity are proposed for this purpose,

particularly in research literatures. However, in general, most existing traffic management systems utilize simple methods to estimate travel times based on point measurements. Density has also been estimated using simple methods and used as an input to applications such as dynamic managed lane pricing algorithms. The use of the point detector to estimate space measures is not appropriate for urban streets due to the impacts of signals between point detections.

Traffic measurements can be either collected through permanent or temporary traffic detection devices. The FDOT, and more recently counties and cities in Florida, have widely installed point traffic detectors along major freeways and arterials, as part of their advanced traffic management systems (ATMS). These detectors continuously produce lane by lane measurements of speed, volume, and occupancy at a short time interval such as 20-second interval. With respect to the FDOT ATMS, the raw detector data are saved in the FDOT traffic management software, known as SunGuide, in a text file in comma separated file (csv file) format. Since the raw detector data may include erroneous or missing measurements, these raw data have to go through a set of data preprocessing procedures, such as data filtering, temporal and spatial data aggregation, and data imputation, to achieve high data quality. Even though travel time and queue length cannot be directly measured from point traffic detectors, they can be estimated from detector measurements. Currently, the cleaned and aggregated data can be downloaded from the website of the Regional Integrated Transportation Information System (RITIS) (University of Maryland CATTI Lab, 2016).

In addition to point traffic detector data, the FDOT Transportation Statistics Office (TranStats) collects traffic data through various telemetered and portable traffic monitoring sites along all Florida state highways. Telemetered traffic monitoring sites (TTMSs) refer to traffic counters that are permanently placed at specific locations throughout Florida to record the distribution and variation of traffic flow by hour of the day, day of the week, month of the year, and from year-to-year. They provide counts classified by 13 FHWA vehicle categories and average speed per lane and per direction of travel. The data is usually archived at one-hour intervals. Portable traffic monitoring sites (PTMSs) are temporarily placed at critical locations including on-ramps and off-ramps. 15-minute volume counts are usually provided for each PTMS location. Based on the TTMS and PTMS measurements, information including annual average daily traffic (AADT), peak hour factors, directional distribution factors, and truck factors are also reported.

However, it is important to ensure that the used data has acceptable data quality. Even with proven technologies such as point traffic detectors, it is important to ensure that the detectors are well installed, calibrated, and maintained to provide the required data. This is also important when using, new, sometime unproven, data collection technologies. Two important data quality measures are (FHWA, 2004):

- 1) accuracy, which is the degree of agreement between a data value or set of values and a source assumed to be correct, and
- 2) validity, which is the degree to which data values satisfy acceptance requirements of the validation criteria or fall within the respective domain of acceptable values.

As stated earlier, traffic operations centers collect traffic data that is also archived for use for off-line analysis purposes. This data is increasingly being used for evaluation, performance measurement, and modeling. However, the quality of archived data from traffic operations systems need to be examined before utilization for these purposes because of the difficulty in maintaining traffic sensors and communication by some public agencies and the fact that the real-time traffic operations applications have different data quality requirements than historical/analytical applications of archived operations data (Turner, 2006). Problems in detection and communications often result in systematics and random errors. Thus, the user should examine the communication and detector failure and calibration problems in the before and after conditions and any changes in the methods used to account for missing and bad data. Data processing is expected to have a significant impact on data quality and analysis results. The data processing processes include: data staging and segregation, data aggregation, data quality screening, data imputation, and data characterization (Park, 2005). All of these processes have impacts on data quality and need to be checked for effectiveness and for consistency in the before and after conditions. It is important that modelers have a good understanding of the quality of the data collected from point detectors and coordinate with traffic management centers to ensure that the detectors are well calibrated and the data is well processed to allow its use in modeling.

- **Automatic Vehicle Identification (AVI) Data**

Deriving travel times based on point detectors is particularly difficult for urban streets (interrupted facilities). There are a number of challenges when deriving travel times for urban arterials, including lower volumes (thus lower sample sizes), interrupted flow operations that cause variations in travel times in time and space, driveways, and adjacent land uses, and activities that may affect the data collection effort. There has been an increasing interest in the use of automatic vehicle re-identification techniques and third-party vendor data (discussed in the next section) for travel time estimation. In addition, the research conducted in this study indicates that using this data as part of the ODME process can improve the estimation results significantly.

Automatic Vehicle Identification technologies, sometimes referred to as automatic vehicle matching technologies and automatic vehicle re-identification technologies; such as Bluetooth, Wi-Fi, electronic toll collection, license plate readers, magnetometer-based, and so on; automatically detect vehicle identifications (IDs) with enabled devices when passing detection stations. Matching the unique IDs at two detection locations allows the measurements of travel

time as well as the number of trips between two points in the network, allowing the estimation of the numbers of trips between the origins and destinations (O-D) for at least part of trips (partial trips) and possibly the proportions of vehicles on the paths between these origins and destinations. However, it should be noted that the matched vehicle travel times may not represent the actual travel time along the road as some of vehicles may stop during their journey. These outliers are normally filtered out to ensure the accuracy of travel time. The accuracy of AVI data also greatly depends on the market penetration (sample size) of AVI devices. A testing of a Bluetooth reader deployment in Arizona showed that with detectors about 0.5 to 1 mile apart, match rates of about 5 to 10 percent of traffic were achieved; although higher sample sizes were reported when combining Wi-Fi and Bluetooth device ID identifications at the same locations. In general, the Bluetooth and Wi-Fi readers cannot be placed short distance apart due to the inaccuracy of the identification of the position of the vehicles. Thus, they cannot be used to determine travel time on short urban street links between intersections.

- **Third Party Data**

Third party, sometimes referred to as crowd sourcing data, such as INRIX, TomTom, Airsage and HERE data are collected from multiple sources including commercial fleet, delivery and taxi vehicles across the U.S., as well as consumer cellular devices including smartphones and onboard driver assistance systems, sometimes combined with traditional traffic information. The data from the above sources are fused to produce speed and travel time estimates and/or O-D estimates, which can be used for simulation model calibration and validation. The GPS trajectory data, if available, can also be directly used to calibrate driving behaviors in microscopic simulations. As is the case with AVI data, trips between origin-destination pairs can be derived from GPS data and utilized in origin-destination matrix estimation processes. Modelers need to be aware of factors associated with third party data including the sample size/accuracy of measurements, compositions of collected data (trucks vs taxis, vs. passenger cars), data sources (detectors vs. probes), and processing and estimation algorithms.

- **Signal Control Data**

Depending on model resolution, signal control data may or may not be needed when modeling intersections. In case signal control data is needed, signal timing operational plans and their associated activation time can be requested from counties and cities. In general, the modeler should input signal control parameters for micro-simulation analysis and DTA-based modeling. Experience, including those from the current study, shows that requesting the synthesis of signal timing, as part of DTA modeling, which is a feature available in most existing DTA tools, does not produce acceptable turning volume estimates from the DTA models.

- **Event Data**

Event data is needed when identifying normal traffic operations or modeling incident conditions. In Florida, traffic management centers store detailed incident information in the SunGuide Oracle database, including incident timestamps (detection, notification, arrivals, and departures), incident ID, responding agencies, event details, chronicle of the event, and environmental information. The detection timestamp is the time when an incident is reported to the TMC and inputted in the SunGuide system. The notification timestamps are recorded per responding agency and refer to the time when such responding agencies are notified. The arrival and departure timestamps are also recorded per responding agency and refer to the time when responding agencies arrive and depart from the incident site. However, the event data is only available for those facilities that are managed by FDOT traffic management centers (primarily limited access facilities in urban areas at the present time). It should be mentioned that the FDOT traffic management center is currently receiving WAZE event data for traffic operation purposes. However, this data is not currently shared for used for other purposes such as planning and planning for operations.

- **Crash Data**

There are two sources of crash data, one is from the Crash Analysis Reporting (CAR) System, and another one is from the Florida Highway Patrol (FHP) that can be useful particularly at locations where no event data is available such as urban arterial streets and rural highways. The CAR system is maintained by the FDOT. In Florida, all crashes that occur on state roads and result in a fatality, an injury, or a property-damage-only (PDO) higher than \$1,000 are included in the CAR System, and the data in this system is updated yearly. Based on the police report, 38 data elements for crashes are recorded in the CAR System, including crash location, time stamp, property damage dollar value, injury, fatality, pavement conditions, weather and lighting conditions, and crash cause.

The Florida Highway Patrol (FHP) data can be accessed through the Signal Four Analytics, a traffic crash database environment developed for the FHP. Currently, this program gathers information from FHP reports on a daily basis. The information of crash occurrence time and the FHP response timeline are archived in the database.

- **Weather Data**

Severe weather greatly affects available roadway capacity. Weather data is required to filter out such severe weather conditions when modeling normal traffic conditions. Weather data is also needed when examining the impacts of weather on traffic. National Climate Data Center (NCDC) is a major source for obtaining weather data. Detailed temperature and precipitations

information can be downloaded from its website. In addition, weather data can be collected from the Road Weather Information System (RWIS) if such system is available. For example, seven RWIS monitoring sites have been deployed along the I-95 corridor by the FDOT District 4. These sites measure the road surface status, air and surface temperature, relative humidity, precipitation type, intensity and rate, visibility distance, wind speed and direction, and barometric pressure. The reported RWIS data can be downloaded from the FDOT District 4 TMC SCAN Web webpage. Connected vehicle data can be also used for this purpose as discussed later in this section.

- **Construction Data**

The Office of Maintenance in each FDOT district maintains records of construction. As an example, the FDOT District 6 lane closure construction data include the information of construction location, starting and ending date and time, total number of lanes, number of lane closed, description of construction work, and agency that requests the construction. This type of database is currently planned to be developed for all FDOT districts.

- **Pricing/Toll Data**

Dynamic pricing data are required for the modeling of managed lanes. Such information can be retrieved from traffic management centers. The toll rate data usually include timestamp and the corresponding toll pricing. For I-95 Express Lane in Miami, FL, the toll rate data are updated every 15 minutes.

- **Other Advanced Strategy Data**

When modeling advanced strategies such as incident management, ramp metering, and so on, the related parameters (for example, strategy activation and deactivation times) can be obtained from transportation system management and operations agencies.

Additional data such as available survey data (for example, driver willingness-to-pay data and freight GPS data) can also be used to support modeling.

- **Connected Vehicle Data**

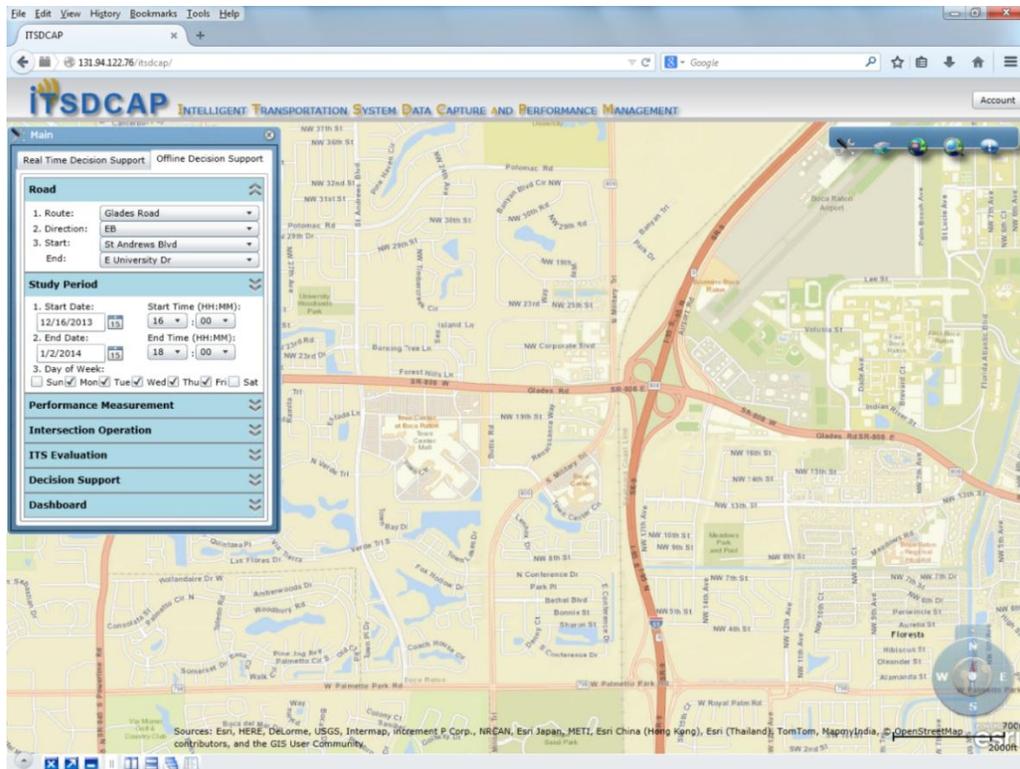
Data generated by the connected vehicles are useful for mobility, safety, and environmental applications. These data can also be used for modeling. Although some of the data elements such as speed and acceleration and deceleration can be obtained without the need to connect to a vehicle's onboard diagnostic port (OBD-II), obtaining many other useful data elements requires connection to the OBD-II. The data will then need to be transmitted using connected vehicle

messages, utilizing dedicated short-range communication (DSRC) or other communication technologies, such as cellular, Wi-Fi, and WiMAX. The connected vehicle (CV) message types and components are specified in the Society of Automotive Engineers (SAE) J2735 standards (SAE International 2009). The basic safety message (BSM) contains vehicle safety-related information broadcasted to surrounding vehicles, but can be also sent and/or captured by the infrastructure. The BSM, as defined in the J2735 standards, consists of two parts. Part 1 is sent in every BSM message broadcasted 10 times per second and will be mandated to be broadcasted by the NHTSA ruling. It contains core data elements, including vehicle position, heading, speed, acceleration, steering wheel angle, and vehicle size. BSM Part 2 consists of a large set of optional elements such as precipitation, air temperature, wiper status, light status, road coefficient of friction, Antilock Brake System (ABS) activation, Traction Control System (TCS) activation, and vehicle type. However, not all of these parameters are currently available from every vehicle and they will not be mandated by the USDOT. Part 2 elements are sent based on criteria that are not specified in the J2735 standards.

The National Highway Traffic Safety Administration (NHTSA) is expected to mandate connected vehicle technologies on all new vehicles. Apart from this mandate, after-market plug-in equipment will be available for installation on older cars, yet this is not expected to be mandated. General Motors announced that the 2017 model of the CTS Cadillac will be equipped with CV equipment and a number of other manufacturers are expected to follow in their 2018 models. Thus, connected vehicle data is expected to be available in the near future and will provide an important input to the multi-resolution modeling framework of this study.

### **3.2.1.3. Data Support Tool**

As discussed above, data validation and data cleaning are extremely important steps before utilizing the data for analysis. Integration of data from different sources may compensate for the limitations of each data type. Data support tool are needed to fulfill such functional requirements. One example of data support tools is the ITSDCAP tool developed by Hadi et al. (2012). This tool has been developed to capture and fuse data from multiple sources, estimate various performance measures, provide decision support to agencies, support simulation development and calibration, and allow the visualization of data and analysis outputs. Figure 7 shows the web-based interface of the ITSDCAP tool.



**Figure 7 ITSDCAP Tool User Interface**

The data sources and tools described in this section are important components of the modeling process. However, there is a need for additional support tools that allow the extraction, fusion, and conversion of these tools to produce the inputs required to the modeling process. These additional tools are described further in the next section. ITSDCAP, or other similar tools, could be extended and further developed to satisfy the needs of the modeling community in Florida to provide the data in the needed format for the analysis.

### **3.2.2. Modeling Support Environment**

As stated earlier, an effective multi-resolution model strongly relies on different tools with different levels of details, complimenting each other to provide the needed functionalities by modelers. Regardless of the specific modeling tools selected for modeling, there is a need for preprocessing and post processing tools that support the connections between data sources and modeling tools, connection between modeling tools, processing of the outputs, and other modeling processes. A number of tools are available to fulfill certain needs, while additional support tools will have to be developed. This section provides a detailed discussion of the modeling support environment, available tools, and recommendations.

As shown in Figure 6, a number of components and modules are needed in this modeling support environment, which are listed below.

- Tool assessment module that specifies criteria to help agencies to select appropriate tool(s) for their analysis.
- Conversion support tools to help convert real-world data to a format useful for modeling and to convert input and output files from one format to another depending on the specific modeling tool used.
- Time-dependent O-D matrix estimation tools based on combinations of demand forecasting model outputs and real-world data.
- Zone aggregation/disaggregation support when converting between different levels of models.
- Clustering traffic into different patterns to allow the modeling of different traffic patterns instead of a single pattern, which is being recommended in the upcoming new revision of Volume 3 of the FHWA Tool Box and is used in the ATDM and DMA AMS testbeds mentioned earlier.
- Modeling support tools to provide statistical analysis support and visualization for the validation, calibration, and assurance of convergence of models.
- Signal timing selection/optimization support.
- Signal timing conversion from county and city database to a format accepted by modeling tools.
- Automated/connected vehicle modeling support
- Alternative analysis support tools that post-process the outputs from different models and produce additional statistical parameters and visualization for use in alternative comparisons.

The Network Explorer for Traffic Analysis (NeXTA) tool developed by Zhou and Taylor (2014) is an example of an open-source support tool. NeXTA includes certain functions that can be used in this support environment such as conversion to Synchro; conversion between Cube, DTALite, and VISSIM files; and visualizations of the outputs. This tool is further discussed later in this section.

A description of the support tools listed above is presented in the remainder of this section.

### **3.2.2.1. Tool Assessment**

With the availability of various modeling tools that have ranges of functionalities and capabilities, transportation agencies usually face the challenge of selecting appropriate tools for their projects. A tool assessment module was developed in this project as a part of the modeling supporting environment for multi-resolution analysis. This module built on the initial work conducted by Hadi et al. (2012), which developed a list of criteria for the assessment of

simulation-based DTA tools. In this research, more detailed criteria were developed for general modeling and specific applications. These criteria can be used to allow general comparison of various modeling tools to ensure that they meet the needs of the specific modeling problem. Agencies can add additional criteria specific to their projects, as needed, when selecting the tool(s). These additions should be shared with the rest of the modeling community by submitting it to the central office to add to the initial criteria developed in this project.

The criteria for tool assessment developed in this project include three main categories for general modeling, that is, general criteria for hardware, software, and interface, shortest path and path choice, and traffic flow model. Additional criteria were also added for specific applications, such as managed lane, construction zone, and advanced traffic management strategies. Table 3 presents a complete list of assessment criteria.

**Table 3 Criteria for Tool Assessment**

<b>Criterion</b>
<ul style="list-style-type: none"> <li>● <b>General Criteria (Hardware, Software, Interface, and etc.)</b> <ul style="list-style-type: none"> <li>● Open source</li> <li>● Utilization of additional hardware computational capabilities</li> <li>● Flexibility in Modifying Procedures</li> <li>● User Interface/Software Interface</li> </ul> </li> <li>● <b>Shortest Path and Path Choice</b> <ul style="list-style-type: none"> <li>● Assignment Type</li> <li>● En-route Dynamic Routing (e.g., in-vehicle dynamic navigation system, DMS)</li> <li>● Specification of Fine-Grained Assignment Interval (e.g., 15-30 minutes)</li> <li>● Allows Fixing Paths for Parts of the Demands</li> <li>● Convergence Criteria</li> <li>● Outputting and Using Interval-based Convergence Gap</li> <li>● Assignment of Individual Vehicles</li> <li>● Assignment of Multiple Demand Types</li> </ul> </li> <li>● <b>Traffic Flow Model (TFM)</b> <ul style="list-style-type: none"> <li>● Traffic Flow Model Type</li> <li>● Queuing and Spillback</li> <li>● Modeling of Signalized Arterials</li> <li>● Modeling of Freeways</li> <li>● Modeling of Alternative Routes to Facilities</li> <li>● Automatic Calculation of Signal Timing in Dynamic Traffic Assignment</li> <li>● Lane-by-Lane Simulation</li> <li>● Merging/Weaving Simulation</li> <li>● Modeling Turn Lane and Bay Length</li> </ul> </li> </ul>

**Table 3 Criteria for Tool Assessment (Cont'd)**

<b>Criterion</b>
<ul style="list-style-type: none"> <li>• <b>ML Modeling</b> <ul style="list-style-type: none"> <li>• Generalized Cost in Assignment</li> <li>• Incorporation of Willingness-To-Pay (WTP) into Assignment</li> <li>• Link Access Restrictions/Prohibitions by Vehicle Type</li> <li>• Modeling Managed Lanes and Reversed Lanes</li> <li>• Fixed and Time-of-Day Pricing by User Types</li> <li>• Dynamic Pricing</li> <li>• Inhomogeneous VOT and VOR</li> </ul> </li> <li>• <b>Work Zone Modeling</b> <ul style="list-style-type: none"> <li>• Capacity in Work Zone</li> <li>• Duration of work zone</li> <li>• Geometry features of work zone, e.g. length, No. of lanes</li> <li>• Queuing Warning System</li> <li>• Day-to-Day Learning</li> <li>• Specification of Traffic Diversion rates</li> </ul> </li> <li>• <b>Advanced Vehicle Technology</b> <ul style="list-style-type: none"> <li>• Capacity as a Function of Proportion of Vehicle Types</li> <li>• Fixed and Time-of-Day Pricing by different percentage of Advanced Vehicle Technology</li> </ul> </li> <li>• <b>Other Advanced Strategies</b> <ul style="list-style-type: none"> <li>• Modeling DMS/HAR</li> <li>• Modeling Ramp Metering</li> <li>• Modeling Variable Speed Limits</li> <li>• Modeling Traveler Information System</li> <li>• Modeling incidents and work zones</li> <li>• Modeling Traffic Response Systems</li> <li>• Modeling Traffic Adaptive Systems</li> <li>• Vehicle trajectory processor</li> <li>• Scenario generator</li> </ul> </li> </ul>

A summary of assessment criteria and the capabilities of a number of modeling tools are also presented in Appendix A. It should be mentioned that the information included in Appendix A is completed based on the feedback from reviews, vendor responses, and/or testing of these tools. The tool selection process should be based on the project under consideration and future plans for further application. It is important for modelers to identify their modeling requirements before selecting the tools. For example, different models vary in their ability to support several features dynamic tool pricing, stochasticity in the value of time, value of reliability, lane-by-lane modeling, signal control details, automated vehicle modeling, etc. If the user starts their modeling without consideration of these abilities, they will be forced to change software or accept less effective modeling of their project. Again, Appendix A should be consulted in this process.

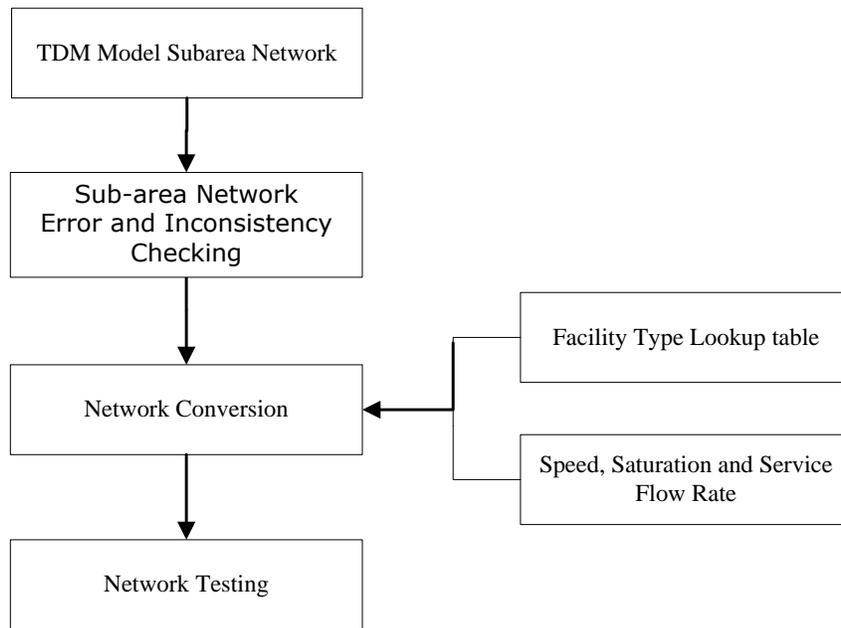
### **3.2.2.2. Conversion Support**

The MRM approach to analyzing advanced strategies requires the use of combinations of modeling tools. Most of analysis tools allow the import of network in GIS shapefile format and demand data in a csv format. They also allow the export of output in csv files. However, the direct import and export capabilities to other models vary between tools. Support tools are needed to automatically convert input/output data and possibly model outputs from the format of one tool to the format of another. Real-world data also need to be processed and converted into a format that can be used by analysis tool. A tool that automates this process will be beneficial. A few supporting tools are available to convert models from one tool to another.

It should be emphasized that even with an automated conversion process, the resulting model after conversion still needs to be edited and built upon to produce the final required model. For example, when converting a model from a less detailed regional demand tool to produce an input to a more detailed mesoscopic or microscopic simulation tool, a thorough network check and editing will have to be conducted, as the original network coded in the demand model can have errors and inconsistencies that may not affect the regional model results but can result in inaccurate results or errors when running more detailed models, for example, ramp locations and lengths, centroid connector locations and capacities. These errors and inconsistencies need to be resolved before using this network as an input to the more detailed model. In addition, more detailed roadways and network attributes, demands, and other parameters will have to be also added when converting a model from a regional demand toll to a mesoscopic to microscopic simulation toll. A fine-tuning of the converted network can be further conducted by running the new model after conversion.

- **ISSTA Conversion Tool**

The Integrated Support System for Traffic Assignment (ISSTA) was developed as a proof of concept modeling support tool that supports model conversion in addition to other functionalities. The original ISSTA tool supports converting the Cube Voyager network and demand matrices to the inputs required by DynusT, a mesoscopic DTA simulation tool. Figure 8 shows the flow chart of this conversion process. It should be mentioned that ISSTA has not been further developed since its original development as part of an FDOT research project conducted by FIU(Hadi et al., 2012).



**Figure 8 Original ISSTA Network Conversion Tool Flow Chart**

As shown in Figure 8, the first step in the conversion process is to conduct an initial check of travel demand model network for potential errors and inconsistency. This check examines:

- Zone connection to network: An isolated zone that is not connected to a network is allowed in the FSUTMS model but is not acceptable in DynusT.
- Zone connection to freeways: Such connection is not allowed in DynusT.
- Destination node: In DynusT, one node cannot be used as the same destination node for more than two zones.
- Minimum link length: DynusT requires the link length to be greater than a certain value to properly model queue propagation.

These issues are addressed automatically through routines in ISSTA.

In the second step, network conversion, network node, link, zone data as well as traffic flow model data and movement data are converted into the format required by DynusT. Table 4 shows the six required data files and information included in each file in order to model traffic network in DynusT.

**Table 4 Required Data to Model Traffic Network in DynusT**

<b>Type</b>	<b>Required Data</b>	<b>Input File</b>
Node data	Node number	network.dat
	Total number of nodes	network.dat
	Node coordinates	xy.dat
	Link coordinates	linkxy.dat
Traffic Flow Model data	Parameters for modified Greenshields model	TrafficFlowModel.dat
Link data	Total number of links	network.dat
	Link horizontal alignment	linkxy.dat
	Saturation flow	network.dat
	Speed limit	network.dat
	Free-flow speed adjustment parameter	network.dat
	Traffic flow model type	network.dat
	Link type	network.dat
	Link name	linkname.dat
	Link grade	network.dat
Movement data	Allowed movements from all links	movement.dat

Once the network conversion step is finished, a further fine-tuning of converted network may be needed to correct errors when running DynusT.

In addition, centroid connectors are used in the FSUTMS models to connect zones to the network, while vehicles are loaded to the network through generation links within each zone in DynusT. Note that, unlike the centroid connectors in the FSUTMS, the generation links in DynusT have limited physical capacity as a function of number of lanes. Also, various O-D trip tables with different trip purposes in the FSUTMS model need to be combined into the maximum of three matrices allowed in DynusT. These matrices can be for passenger car trips or total trips, truck trips, and High Occupancy Vehicle (HOV) trips. Utilities were developed in ISSTA to accomplish this conversion.

- **NEXTA Conversion Tool**

The NEXTA tool provides capabilities to import networks from typical demand models such as Cube, TransCAD, and VISUM through GIS shape files and demand data in csv or matrix format. The data set from DTA tools including TRANSIMS, DTALite, and DynusT, as well as real-world detector data can also be imported to NEXTA. A further refinement of imported network can be conducted through the NEXTA interface. Furthermore, the NEXTA tool allows exporting the data in Synchro and VISSIM file format. As an example, the conversion process from the FSUTMS Cube model to DTALite using the NEXTA import tool is explained below.

The first step is to export the node, link, and zone layer shape files from the Cube model and import them into the NEXTA environment. The importing process is accomplished through a configuration file named “import\_GIS\_Setting.csv” file, which maps the field names in the shape files to those fields used in NEXTA. Note that the link types used in Cube network differ from NEXTA’s link types. Table 5 illustrates such differences. For comparison purpose, the link types used in DynusT are also listed in the same table. In order to use NEXTA conversion tool, the user has to add the link types to the exported shape file from Cube as a link attribute.

**Table 5 Link Type Comparison among FSUTMS, DTALite and DynusT Required Data to Model Traffic Network**

<b>FSUTMS Model Link Types</b>	<b>DTALite Link Types</b>	<b>DynusT Link Types</b>
10-19: Freeway	1: Freeway	1: Freeway
20-29: Divided arterial	2: Highway/Expressway	2: Freeway segment with detector (for ramp metering)
30-39: Undivided arterial	3: Principal arterial	3: On ramp
40-49: Collector	4: Major arterial	4: Off ramp
50-59: Centroid Connector	5: Minor arterial	5: Arterial
60-69: One way facility	6: Collector	6: HOT
70-79: Ramps	7: Local	7: Highway
80-89: Exclusive HOV lanes	8: Frontage road	8: HOV8
90-99: Toll facilities	9: Ramp	9: Freeway HOT
	10: Zonal connector	10: Freeway HOV
	100: Transit link	
	200: Walking link	

With regard to demands, the demand Meta database configuration file in NeXTA needs to include only specific information related to the demand type and demand loading time periods in the files to be converted from Cube to NeXTA.

A common method of building traffic networks for more detailed models such as microscopic simulation is that a portion of mesoscopic simulation network is extracted and then fine-tuned to meet the requirements of microscopic simulation. A new approach has been taken in a recent update and utilization of NeXTA. It was found that the fine-tuning of the mesoscopic model network for microscopic modeling applications require significant effort. To reduce the time it takes to produce the network while ensuring harmonization between the mesoscopic and microscopic models, it was recommended that the network is coded from scratch in microscopic simulation and a special tool was developed to convert the microscopic simulation network to the mesoscopic simulation network compatible format.

- **DTA Anyway Conversion Tool**

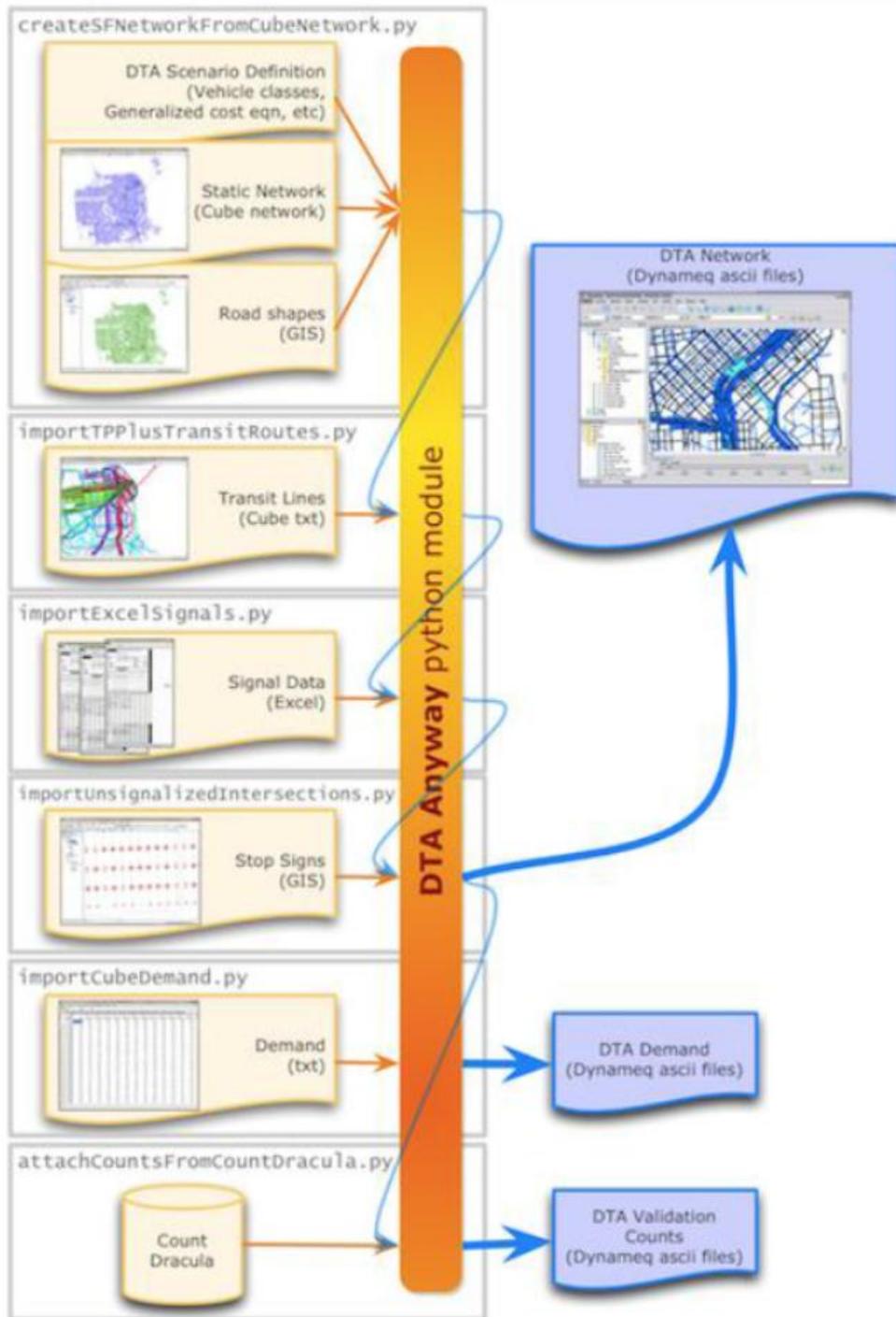
DTA Anyway is a library of Python scripts that was developed by San Francisco Transportation Authority to automatically convert their Cube network to the input required by Dynameq. It has the functions of creating a DTA network from the Cube network and importing transit line data, signal data, unsignalized intersection data, Cube demand data, and real-world traffic counts. Figure 9 presents the flow chart of this conversion tool.

### **3.2.2.3. Demand Estimation Support**

Time-dependent demand estimates are important inputs for dynamic traffic assignment-based modeling tools. All tools can utilize O-D demands as inputs. Some tools also accept individual vehicle trips that can possibly be obtained from activity-based models.

Traditionally, trip (O-D) matrices utilized in traffic analyses have been derived from daily or time-of-day (peak period) demand matrices produced from regional demand models by fine-tuning these matrices to produce acceptable assignment results. For more detailed applications, more accurate and higher temporal resolution O-D matrices (e.g., for 15- or 30-minute intervals) are needed. ODME modules have been developed by the vendors of the static and dynamic traffic assignment tools. Examples include the NeXTA ODME tool, Cube Analyst, and Analyst Drive, the TflowFuzzy module in VISSUM, and so on. The static and/or dynamic ODME procedures implemented in these tools apply an optimization procedure to derive an O-D matrix based on an initial O-D matrix by minimizing the differences between the estimated volume from the assignment results and the measured values. Traffic counts are the commonly used field measurements in the optimization process of these tools. The Cube Analyst Driver also allows the usage of partial trips and turning movements as inputs to the ODME process. It has been recommended that other measures, such as travel time, density, and queue length, should also be used in the optimization process for congested conditions to account for the fact that the same volume measurement can occur in congested and uncongested conditions. Although research has proved the effectiveness of this approach, this has not been generally implemented

as part of the commercially available ODME modules in the past. However, the O-D matrix estimation of the version of NeXTA recently used as part of the Phoenix ATDM and DMA AMS effort include density as the measure in the ODME process.



**Figure 9 Flowchart of DTA Anyway Conversion Tool**  
 (Parsons Brinckerhoff & San Francisco County Transportation Authority, 2012)

It should be mentioned that the ODME modules do not reach a global optimal solution, and generally reach a local optimal solution that depends on the initial O-D matrix. If the quality of the O-D matrix is not good, the optimization does not reach a good correspondence with field measurements. The analysis in this study proved this point, however, it also showed that the degree of the dependency of the quality of the solution on the initial matrix is different with different software.

As stated earlier, there has been an increasing interest in using data from AVI technologies or third party vendors to estimate O-D matrices. In this study, an investigation of the utilization of data from multiple sources as part of the ODME process was conducted, as described later in this report. The results show that the inclusion of the partial trips retrieved from Bluetooth and third party vendors can significantly improve the ODME performance. The incorporation of turning movement counts can also produce better matches to the real-world counts, which is especially important for evaluating arterial-related traffic management strategies. Whenever such partial trip data or turning movement counts are available, it is necessary to include them in the ODME process. The production of good turning movement counts is particularly difficult from dynamic traffic assignment models. Inputting the turning movement counts and coding the signal control was found to help in producing better turning movement counts. It should be noted that among the examined off-the-shelf ODME tools, only the one that is based on Cube Avenue allows utilizing the turning movement counts and partial trips based on AVI and/or third party vendors, as part of the ODME optimization process. Nevertheless, the turning movement counts can be used in other commercially available tools, if each turning movement is coded as a link. Another approach is to sum the turning movements leaving a link and those entering a link to produce additional “virtual detectors” on all approaches that are leaving or entering the intersection. This should allow better consideration of the turning movements in the ODME process and has been done when estimating the O-D matrices as part of the assessment of arterial active traffic management conducted in this study, as described later in this document.

#### **3.2.2.4. Zone and Connector Disaggregation**

Regional demand model usually consists of large traffic analysis zones (TAZs) with less detailed network information. It is recommended to use a more refined zone system to ensure accurate representation of O-D trips and appropriate access to the network when developing a mesoscopic model. There are several approaches that can be used to disaggregate trips from larger regional TAZs to the smaller zones (FHWA, 2012). The simplest approach is to distribute the trips to the smaller zones based on the ratio of the area of the subarea zone to the larger regional zone. This approach does not take into account the locations of the developments within the zone. The FHWA DTA Guide states that “A better approach is to distribute the trips based on the actual land uses within each of the smaller subarea zones. Using parcel data or other land use data that

are defined at the local level, estimates of trip making activity at each of the subarea zones can be made by applying trip rates to the land use from sources such as the Institute of Transportation Engineers (ITE) Trip Generation Manual or by applying the trip rates developed for the regional model. These estimates of trip activity can then be used to redistribute the regional zone-based trips.” The locations of the zone connectors are also important and they should be checked to ensure that they provide reasonable access to the network that is similar to what is expected in the real-life.

The disaggregation of the TAZ into Micro Analysis Zone (MAZ), when developing the activity-based model in the Southeast Florida Regional Planning Model (SERPM) Version 7.0, was a manual process. Each involved Metropolitan Planning Organization (MPO) designated a staff person to draw the MAZs. They were asked to draw them respecting the existing TAZ boundaries and trying to isolate areas of relatively uniform land use patterns (for example, separate industrial and commercial areas from residential areas). They were also asked to plan on approximately 4-6 MAZs per TAZ to achieve the goal of having the number of MAZs around 15,000. And finally they were asked to try as much as possible to consider the census block group boundaries unless doing so resulted in very strange looking MAZs. This was considered important to maintain as much consistency as possible with census products that provide person and household data. A support tool can be developed in a future work to automate the zone and connector disaggregation process.

#### **3.2.2.5. Traffic Pattern Clustering**

Traditionally, a “typical” or “normal” day is modeled in current practices, which is the average of several days. However, such an average day may not exist in the real-world. Furthermore, as described in the review of literature section, most advanced strategies are effective in relieving congestions during non-typical days, possibly of specific patterns. It is necessary to model different traffic patterns when assessing the benefits of advanced strategies. One approach to identify traffic patterns is to sort the days based on either congestion index or vehicle miles traveled. The days that correspond to different percentiles of traffic, such as 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup>, or 95<sup>th</sup> percentiles and so on, can then be determined and modeled in analysis tools. This approach is utilized in this study when examining arterial traffic management strategies; as explained later in this document.

The FHWA is recommending the utilization of clustering analysis to group the days into clusters with similar patterns and use the days that are close to the centroids of the clusters in the analysis. The upcoming version of Volume 3 of the FHWA analysis toolbox will describe this recommendation. A clustering-based traffic pattern identification function has also been implemented in the ISSTA tool mentioned earlier. With such approach, the clustering can be based on different traffic, incident, and weather data. Another approach recommended and used

by the researchers of this study is to first categorize the days based on certain criteria, for example, by season, no-incident versus incident days, clear versus rainy days and so on. A clustering analysis can be used to further group the days into different traffic patterns based on time series of volume counts, speeds, event attributes, and so on. It should be mentioned that this type of categorization and clustering analysis can be implemented as part of a data analytic tool such as the ITSDCAP mentioned earlier,

#### **3.2.2.6. Signal Timing Estimation and Optimization**

Detailed signal operational plan and signal timings are generally required in microsimulation models. However, such information is usually ignored in macroscopic demand forecasting models and often ignored in mesoscopic simulation and other DTA models. The researchers of this study pointed out the increased accuracy of DTA modeling with the realistic modeling of signal timing control as part of DTA analysis. When converting networks from demand forecasting models to more detailed models, signal timing information has to be added. For existing conditions, it is best to obtain existing signal timing plans from signal control agencies. Supporting tools could be helpful in automatically converting the signal timing into formats accepted by the detailed modeling tools. For example, the Python-based signal importing function of DTA Anyway, described earlier, can import signal data and add them to the Dynameq networks. However, when modeling future years and/or improvement alternative scenarios that change the demands or the network, there is a need for the calculation of new signal timing plans. A genetic algorithm-based signal optimization is provided in the Highway Capacity Software (HCS). In NEXTA, the user can apply the Excel spreadsheet-based Quick Estimation Method to produce an initial estimation of signal phasing and timing. NEXTA also supports the optimization of signal timing by allowing user to export the data to Synchro file format. Synchro analysis can be conducted to optimize the signal timing and the resulting signal timings can be feedback to the original model. The VISSIM software from the PTV group also include a signal optimizer for fixed signal timing control and a full optimization can be achieved by using another product from the same developer, Vistro. The TransModeler 4.0 traffic simulation software has also introduced a signal timing optimization feature.

#### **3.2.2.7. Calibration and Convergence Support**

- **Calibration Support**

Calibration is one of time-consuming and complex steps in model development. It requires iterative adjustments of demand, supply, and assignment/simulation input parameters and compare the model results with real-world data. The types of these parameters vary with the level of the model. For the demand side, either O-D matrix or volume counts are needed. The O-D matrix estimation can be conducted as described earlier. The supply calibration of

macroscopic and mesoscopic models involves estimating the segment's capacity, free-flow speed, jam density, and traffic flow model (TFM) parameters. The calibration parameters for microscopic models are related to individual drivers and vehicles such as driver's lane changing, car following, and gap acceptance behaviors and vehicle type and performance. In most current applications of microscopic simulation models, the parameters of microscopic parameters are adjusted to produce macroscopic parameters such as capacity and measures of performance. However, individual vehicle trajectory data has been collected and used to validate microscopic models.

When lacking of real-world data, the segment capacity and free-flow speed can be calculated using the Highway Capacity Manual (HCM) 2010 procedures. However, these parameters are preferred to be estimated based on real-world traffic data when the data is available. Based on the recommendations of HCM 2010, freeway free-flow speeds can be identified using speed data under traffic conditions with a volume less than 1000 pc/hr/ln. No recommendations are made in HCM 2010 for detector data-based estimation of arterial free-flow speed. However, the 85<sup>th</sup> percentile of speed can be used to approximate the free-flow speed as suggested in literature. A number of methods can be applied to estimate capacity, including the maximum 5-minute or 15-minute interval volume observed, maximum hourly volume average, top 1% hourly volume, pre-breakdown volume, queue discharge rate, or volume corresponding to maximum occupancy in fundamental diagram. The parameters of TFM can be calibrated by fitting pre-defined curves to traffic detector data using different methods of regression and optimization. As an example, the ISSA tool developed by this research team provides functions to fit the curves of Bureau of Public Roads (BPR), modified Greenshields, Van Aerde, and Akcelik models. Note that TFM model parameters can be only fully obtained at locations where the fundamental diagram contains data for the whole range of traffic conditions from free flow speed to high congestion, and the recurrent congestion is not due to propagation of congestion from downstream bottlenecks. A data analytic tool, such as the ITSDCAP tool, can be used to support the estimation of the macroscopic modeling parameters based on real-world data,

For those parameters that cannot be directly measured from real world, they can be calibrated by comparing the model results with real-world measurements such as speed, volume counts, travel time, queue length, and so on. The quality of calibration can be evaluated through various performance measures, such as mean error (ME), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE), root-mean-square error (RMSE), R-squared and adjusted R-squared. Equations 1 to 7 show the expressions for these measures.

$$ME = \frac{1}{N} \sum_t (P_t - P_{t,a}) \quad (1)$$

$$MAE = \frac{1}{N} \sum_t |P_t - P_{t,a}| \quad (2)$$

$$MPE = 100 \frac{1}{N} \sum_t \frac{(P_t - P_{t,a})}{P_{t,a}} \quad (3)$$

$$MAPE = 100 \frac{1}{N} \sum_t \frac{|P_t - P_{t,a}|}{P_{t,a}} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_t (P_t - P_{t,a})^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_i (P_t - P_{t,a})^2}{\sum_i (P_{t,a} - \bar{P}_a)^2} \quad (6)$$

$$R_a^2 = 1 - (1 - R^2) \frac{N - 1}{N - m - 1} \quad (7)$$

where,  $P_t$  is the estimated variables such as volume count, speed, travel time, and queue length at time interval  $t$ , and  $P_{t,a}$  is the corresponding real-world data used for comparison.  $N$  is the total number of the time intervals.  $m$  is defined as number of independent variables used in regression analysis and it usually has a value of 1 for calibration assessment. Different measures describe different aspects of calibration results. ME shows the trend of underestimation or overestimation in terms of actual values while MPE reveals the same trend but in a percentage value. MAE, MAPE, and RMSE emphasize the degree of deviations in comparison results without consideration of signs. The differences among them are that MAE is defined in terms of absolute values, while MAPE is based on percentage of absolute values and RMSE gives more weights to large errors. Different from other statistical measures, R-squared and adjusted R-squared are measures that reflect how close the modelled results are to actual real-world data when fitting a regression line between these two sets of values. Compared to R-squared, the adjusted R-squared takes the number of predictors into accounts. Again, a support tool should be developed for the estimation and comparison of these performance measures based on model results and real-world measurements.

It should be mentioned that the FHWA is in the process of publishing a new version of Volume 3 of the FHWA Toolbox, as stated earlier. This volume should be reviewed and used as part of the multi-resolution modeling process in Florida.

- **Convergence**

The assessment of convergence is important to ensure the quality of the traffic assignment results. Convergence of the user equilibrium assignment is necessary to ensure the integrity of the resulting solution and to ensure that the model can be used in assessing alternative designs and operational strategies. A widely used measure for convergence is relative gap, which measures the difference between the current iteration solution and the ideal solution. This concept has been

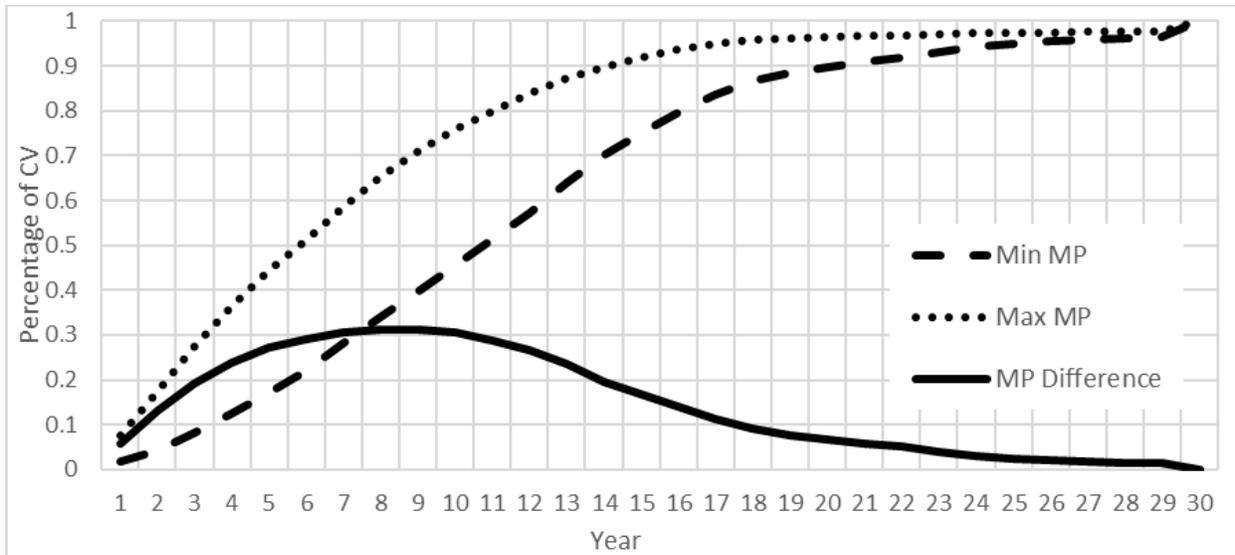
applied with slight difference in formulation in different studies. “Link-based” measures versus “Path-based” measures have been suggested and implemented by tool developers. Path-based or trip-based measures exploit disaggregate and tractable information of trips instead of aggregated link volumes. These measures allow the utilization of heuristics targeting those trips, travelers, households or market segments that are most impeding convergence to achieve better solutions (Resource Systems Group, 2010).

In the case of static assignment, where the user equilibrium (UE) is solved analytically, it is possible to define a desirable level of convergence with very small gap. However, there is still not a certain value of convergence agreed on by researchers for DTA, nor a unique formulation or general agreement of the best measure to evaluate the convergence in simulation-based DTA models. In order to support convergence analysis, the supporting tools should allow the user to visualize the variation of the convergence criteria with respect to the iteration number. Also, the tools should list the top links with the largest deviations in link volumes between two consecutive iterations when link-based criteria are used, or identify the O-D paths with the largest differences in path travel time or generalized costs between two iterations for path-based convergence analysis. Such information can help users to examine model convergence and quickly locate the critical links or O-Ds that affect the convergence of model.

#### **3.2.2.8. Automated and Connected Vehicle Modeling Support**

AV and CV technologies are expected to change individual driving behaviors and in turn travel patterns and transportation system characteristics. At the strategic planning level, the adoption of AV/CV may cause variations in auto ownerships, trip generation, mode and route choices, vehicle-mile traveled, roadway capacity, and so on. At the microscopic simulation level, the parameters of car-following model and lane-change models have to be changed to reflect the operations of AV/CV. Modifications and update to these algorithms may be needed to reflect the AV operations. At the macroscopic and mesoscopic level, there will be a need to identify the capacity at different market penetrations. Thus, there will be a need of research to document these required inputs to MRM. An example of this effort is the relationship between the roadway capacity and the percentages of ACC and CACC market penetrations developed by Shladover et al. (2012), which will be discussed in detail in the next section.

Another important input to CV/AV modeling is the prediction of AV and CV market penetrations for future years. An example of this prediction, derived by the authors of this study, is shown in Figure 10, as will be discussed later in this document.



**Figure 10 Variation of the CV Market Penetration in Different Areas Based on Income**

With the advancement in AV and CV, it is expected that more tools will be developed to support the modeling and assessment of AV/CV. These tools can be incorporated in the multi-resolution modeling framework developed in this project. At the macroscopic and mesoscopic levels, the capacity of the links can be set as a variable that is a function of the percentage of AV/CV on each link. This function can be derived based on simulation and real-world studies. This approach was used in this study, as described later in the document. The function that estimates capacity as a function of the CV/AV percentage was coded using the script language of Cube. At the microscopic level, tools have already been developed to extend the existing simulation tools to allow the modeling of the CV/AV technologies. These include two tools developed by the Federal Highway Administration. The first is the Trajectory Conversion Algorithm (TCA) developed by the Federal Highway Administration (Deurbrouck et al., 2015). Vehicle trajectory data, either generated from a microscopic simulation software or collected from the real world can be used as an input to the TCA. The input trajectory file to the TCA should contain vehicle ID, time, speed, position coordinates, and acceleration data of the vehicles. The second tool is the CACC-VISSIM Algorithm (FHWA, 2016), which is designed to simulate close-spaced CACC vehicle platoons in VISSIM.

### 3.2.2.9. Visualization Support

Visualization provides a straightforward way to understand model input and output. Even though most of analysis tools have their own interface that can display such information, it is useful to have a visualization support tool that can compare results from different models. For example, the users can use the visualization function of the open-source software NEXTA or the Cube environment, as part of the developed framework. NEXTA can act as a data hub that imports

data from multiple sources including results of demand models, meso-/micro-simulation models and real-world data and display them in NeXTA interface in the format of map, charts, and animations (Zhou and Taylor, 2012). It allows the visualization of link-based attributes and performance measures as well as path-based statistics. It also supports the visualization of measures for selected vehicle groups by vehicle types, value of time, traveler information class, and modeling intervals. In addition, modeling results for two alternatives can be displayed side by side for comparison.

### **3.2.2.10. Alternative Analysis Support**

Agencies are usually facing the challenges of selecting between alternatives. Various scenarios can be modeled utilizing modeling tools. However, alternative analysis support tools are needed to compare the output for these scenarios, conduct statistical tests on their differences, and select the best alternatives. Examples of advanced alternative comparison methods are the return on investment techniques; multi-criteria decision analysis methods such as the Analytic Hierarchy Process (AHP) and The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and various forms of sensitivity and risk analyses.

### **3.2.3. Modeling Tools and Methods**

A core component of the multi-resolution framework, modeling tools allow agencies to model various traffic conditions including recurrent congestion, incidents, severe weather, construction and special events, and also allow the assessment of the impacts of advanced traffic management strategies. This section provides a discussion of available analysis tools and methods. Note that there are several open source or commercial tools available for modeling. The discussion in this section is not meant to review these tools.

#### **3.2.3.1. General Modeling Tools and Methods**

As shown in Figure 6, analysis tools can be classified as analytical, macroscopic, mesoscopic, and microscopic simulation tools. These modeling tools can be considered as mobility and associated routing assessment tools. For a framework that includes a full assessment of system performance and impacts, additional tools and methods are required to estimate other performance measures including reliability, safety, and emission.

- **Mobility and Routing Assessment Modeling**

Almost all the tools can be used to model mobility of transportation system. Examples of analytical tools are FITSEVAL, HCM procedure (and computational engines and software), and ELToD. FITSEVAL is a sketch planning level tool developed by this research team that can be used for the assessment of various ITS applications. HCM software such as FREEVAL,

STREETVAL, and HCM-facility procedures apply the HCM freeway and arterial facility procedures, and can be considered as macroscopic deterministic simulation models. ELToD is a logistic model-based managed lane modeling tool developed by Florida Turnpikes. . The static assignment and traffic flow model components of regional planning models can be also considered as analytical models. Macroscopic and mesoscopic simulation-based DTA tools include DTALite developed by Zhou and Taylor (2014), VISUM provided by the PTV Group, Cube Avenue from Citilabs, Inc., Dynameq developed by INRO, DynusT developed by Chiu (2012), and so on. Compared to other level analysis tools, static and dynamic traffic assignment can provide routing information, which can be used to assess diversion under recurrent conditions. Some of these tools have assignment procedures, such as day-to-day learning and en-route assignment that allow the assessment of diversion under incidents and work zones, with and without the provision of information. Examples of used microscopic simulation tools are VISSIM developed by the PTV Group, Transmodeler from Caliper Corporation, AIMSUN developed by TSS-Transport Simulation Systems, and CORSIM developed by FHWA.

- **Reliability Modeling**

Increasingly, travel time reliability is considered as an important component of the performance of transportation systems and of travelers' perceptions of this performance. For example, the National Transportation Operations Coalition initiative selected travel time reliability as one of a few good transportation operation measures to use for internal management, external communications, and comparative assessments (National Transportation Operations Coalition, 2005). MAP-21 identifies travel time reliability as one of the goals of the federal highway programs to be supported by established performance measurement processes in each state.

Travel time reliability is important because uncertainty in travel time requires travelers to build in extra trip time or risk arriving late. Therefore, reliability influences decisions about where, when, and how travel is made. The extra costs of unreliable travel require traffic management agencies to consider reliability in their decision-making processes. In addition, the main impact of many advanced technologies is improving reliability rather than the average travel time.

The SHRP 2 Reliability Program has developed products to support the modeling of reliability and the impacts of reliability. As with the transportation system modeling tools described in the previous section, the reliability estimation models of the SHRP 2 program range in their details from a high level appropriate for sketch planning tools to advanced models that appropriate for integration with mesoscopic and microscopic simulation tools. Below is a description of three SHRP 2 products with different levels of detail that can be considered for implementation as part of the developed framework.

- The SHRP 2 Project C11 procedure “Development of Improved Economic Impact Analysis Tools” can be considered as the simplest sketch planning reliability estimation tool produced by the SHRP 2 program (Economic Development Research Group, Inc., et al., 2014). The procedure is based on estimating the mean recurrent and non-recurrent delays to estimate the mean travel time index, then using a regression equation to estimate the 80<sup>th</sup> and 95<sup>th</sup> Travel Time Index (TTI) as a function of the mean TTI. These equations have been recently calibrated for the Tampa Bay area and incorporated in the travel demand forecasting model of the Tampa Bay Area, referred to as the Tampa Bay Regional Planning Model (TBRPM).
- The SHRP 2 L07 project produced a sketch planning–level spreadsheet that can be considered to be more detailed than the SHRP 2 C11 sketch planning estimation of reliability (Potts et al., 2014). The tool produces a cumulative distribution frequency (CDF) curve of the travel time index (TTI) for each hour. The utilized equations to estimate the TTI distributions are lane hours lost due to incidents and work zones, critical demand-to-capacity ratio, and hours of rainfall exceeding 0.05 inch during the time slice and study period of interest. These equations were calibrated for the I-95 by the research team of this study for I-95 in Miami, as part of their work on the SHRP 2 L38 project.
- The SHRP 2 L04 project suggests a framework on how to assess reliability when using microscopic and mesoscopic simulation model (Mahmassani et al., 2014). The framework distinguishes between sources of nonrecurring congestion external (exogenous) to a simulation model and internal (endogenous) to it. Exogenous factors include incidents, weather, and work zones, while endogenous factors include heterogeneity of driver behavior and vehicle type on the demand side and breakdown of flow, traffic control, and differences in car-following behavior on the supply side. The approach utilized both a pre- and post-processor tools to simulation modeling to estimate travel time reliability on a network or part of it.

The simple sketch planning reliability estimation tool produced in the SHRP 2 C11 project and the spreadsheet-based reliability tool produced in the SHRP 2 L07 project for highway design treatment can be incorporated into traditional travel demand forecasting models to estimate reliability. Instead of using reliability estimation models, another approach to analyze reliability is to generate various scenarios based on real-world occurrence of normal demand, incidents, severe weather events, constructions, and so on. These scenarios can be modeled using the mobility modeling tools as describe above, and their results can be combined to produce the estimates of reliability performance measures. This research developed a new method to assess reliability in macroscopic and mesoscopic simulation based on the equations developed in the SHREP 2 L03 and L07 projects, which is documented later in this document.

- **Emission Modeling**

Environmental impacts have to be considered when modeling advanced traffic management strategies. They can be either simply estimated based on predefined emission rates as a function of speed and/or acceleration, or calculated using the MOVES model released by the Environmental Protection Agency (EPA). The EPA's MOVES model estimates emission at three different scales: National, County, and Project scales. The National and County scales are usually applied to a large area such as a state or a county, but are not appropriate for the analysis of a small or a medium size network. The project scale in MOVES is more appropriate for small to medium networks (U.S. Environmental Protection Agency, 2012). The project level is the finest level of vehicle emission estimation in MOVES. It has three different estimation methods: the average speed approach, the drive schedule approach, and the operating mode distribution approach. The average speed approach is the simplest of the three and is based on the average speed of the vehicles and the vehicle miles travelled by vehicle type. This approach can be easily integrated with modelling tools of various levels by exporting the link-based measures from models and using them as input to MOVES to estimate emission. The drive schedule method uses second-by-second speed profiles of vehicles as an input to estimate emissions. However, only one representative speed profile from traffic models can be input to this method. The operating mode distribution approach is a detailed emission estimation approach that requires the input of the distribution of each operating mode. Note that operating modes are defined based on Vehicle-Specific Power (VSP), vehicle speed, and vehicle acceleration. Such information can be generated from microscopic simulation outputs.

- **Safety Modeling**

Another potential component of the developed framework is component that allows estimating property damage only (PDO), injury, and fatality crashes based on parameters such as traffic demand or volume/capacity (v/c) ratio and the impacts of advanced strategies on these estimates. Two approaches can be applied to model safety impacts. The first approach is to estimate the number of property damage only (PDO), injury, and fatality crashes based on vehicle mile traveled and crash rate. As implemented in FITSEVL tool, the crash rate is a function of facility type (i.e., freeways or arterials), v/c ratio, and vehicle type (i.e., auto or truck). Such crash rate can be modified using crash reduction factors proposed in the Highway Safety Manual (HSM) (AASHTO, 2010) to account for the impacts of advanced technologies. Crash reduction factors (CRF) have also been provided in a number of resources including the FHWA's Desk Reference (Bahar et al., 2008). There are opportunities to include these procedures and parameters in the developed framework. This safety impact estimation approach can be utilized with different levels of modeling.

Instead of directly calculating crash frequency, the second crash impact analysis approach is to estimate safety surrogate measures such as mean time to collision based on vehicle trajectories. This types of analysis can be conducted using microscopic simulation combined with the Surrogate Safety Assessment Model (SSAM) developed by FHWA (Gettman et al., 2008).

### **3.2.3.2. Managed Lane Modeling**

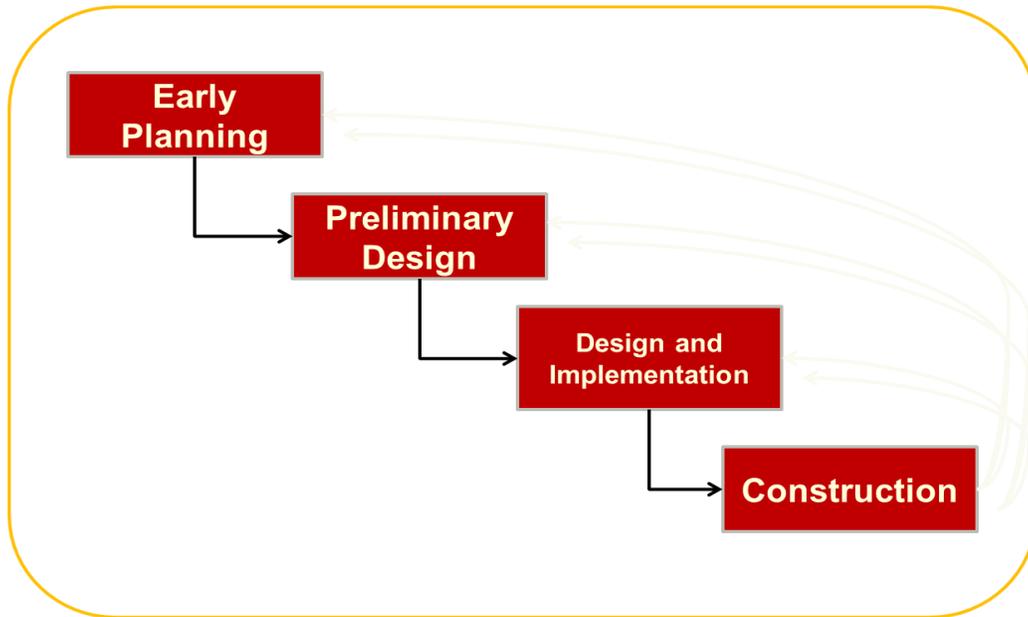
Successful implementation of managed lanes depends on understanding and predicting the trip makers' choice to use these lanes in the presence of various pricing and management strategies and the impacts of these choices on system performance and revenues. Also, agencies want to know what managed lane strategies will provide the maximum congestion relief on the managed facility including managed lanes, general-purpose lanes, and possibly other alternative routes. Answers to these questions can be provided using the multi-resolution modeling approach.

Managed lanes can be modeled using sketch planning tools, regional demand model, mesoscopic simulation-based DTA, and microscopic simulation separately or in combination. FITSEVAL and ELToD are the tools that can estimate the impacts of managed lanes at a sketch planning level. The static assignment-based and DTA-based analysis tools, such as Cube, VISUM, DTALite, VISSIM, and so on, can be utilized to produce the route choices between managed lanes and general-purpose lanes as well as the performance measures along both types of lanes. Two approaches are commonly used to model such route choice for managed lanes, that is, the methods of generalized cost function and willingness to pay. In the generalized cost function approach, the usage of managed lanes relies on the difference in generalized costs between managed lanes and general-purposed lanes. The generalized cost usually includes travel time and toll cost. As travel time reliability is also an important factor that influences traveler's route decisions, it is being considered as a part of generalized cost. In the willingness-to-pay approach, the percentage of travelers using managed lanes is calculated using a logit model based on traveler's willingness to pay for certain time savings. Compared to other levels of modeling tools, microscopic simulations tools can model roadway performance in a more detailed way given the input of demands on managed lanes and general-purposed lanes. An important consideration in managed lanes modeling is the estimation of traffic assignment parameters, such as value of time, associated stochasticity, and the value of reliability are then tested

### **3.2.3.3. Construction Modeling**

Analysis tools of different levels have been developed in the literature to model construction impacts. These tools in their details and can be applied at different levels of analysis according to the user requirements. The type and level appropriate for work zone analysis is different depending on the roadway project's phase in development or construction Figure 11 shows a

diagram of typical stages of required analysis. In addition, the level of analysis depends on the project characteristics and available resources to the analysis.



**Figure 11 Diagram for Multi-Level Work Zone Impact Analysis Framework**

At a high level, the analysis of work zone impacts may be conducted at the sketch-planning level as there is very limited work zone information available. Available sketch-planning tools such as Q-DAT, SHRP 2 C11, and RealCost can be applied to evaluate work zone impacts with simple inputs. A combination of the QuickZone tool and SHRP 2 L07 tool is recommended for use instead for a relatively more detailed analysis. However, if the construction impacts have to be assessed at a high level of details, then the system will have to be modeled utilizing static and dynamic traffic assignment procedures utilizing methods recommended and tested in the SHRP 2 R 11 and SHRP 2 C05 projects.

#### **3.2.3.4. Arterial Traffic Management Strategies Modeling**

Active Transportation and Demand Management (ATDM) dynamically manages and controls travel demand, traffic demand and traffic flow of transportation facilities (Sheehan et al., 2012). The FHWA initiated the ATDM to promote active, integrated and performance-based solutions to improve safety, maximize system productivity, and enhance individual mobility in multi-modal surface transportation systems. Examples of ATDM strategies are shown in Table 6.

**Table 6 Examples of ATDM Strategies**

Active Demand Management	Active Traffic Management Strategies	Active Parking Management Strategies
Dynamic Fare Reduction	Adaptive Ramp Metering	Dynamic Overflow Transit Parking
Dynamic HOV/Managed Lanes	Adaptive Traffic Signal Control	Dynamic Parking Reservation
Dynamic Pricing	Dynamic Junction Control	Dynamic Wayfinding
Dynamic Ridesharing	Dynamic Lane Reversal or Contraflow Lane Reversal	Dynamically Priced Parking
Dynamic Routing	Dynamic Lane Use Control	
Dynamic Transit Capacity Assignment	Dynamic Merge Control	
On-Demand Transit	Dynamic Shoulder Lanes	
Predictive Traveler Information	Dynamic Speed Limits	
Transfer Connection Protection	Queue Warning	
	Transit Signal Priority	

In recent years, there has been an increasing emphasis on the need to assess the benefits of Active Traffic Management (ATM) strategies on urban streets. This is because most regions in Florida have already deployed ITS devices and associated strategies on freeways. As they start moving to deployment on signalized arterials, they are faced with challenges to identify the urban street corridors that benefit the most from the implementation, what strategies are most beneficial, and the magnitude of the benefits under different conditions. A number of tools are available to assess ATM strategies. Examples of sketch-planning level tools are FITSEVAL and TOPS-BC. These tools allow performing benefit and cost analyses for assessing ITS alternatives at high levels. Macroscopic level ATM evaluation tools include HCM computational engine, FREEVAL and STREETVAL, VISUM, etc. The impacts of ATM can be modeled in more details using advanced approaches such as meso- or microscopic simulations combined with DTA.

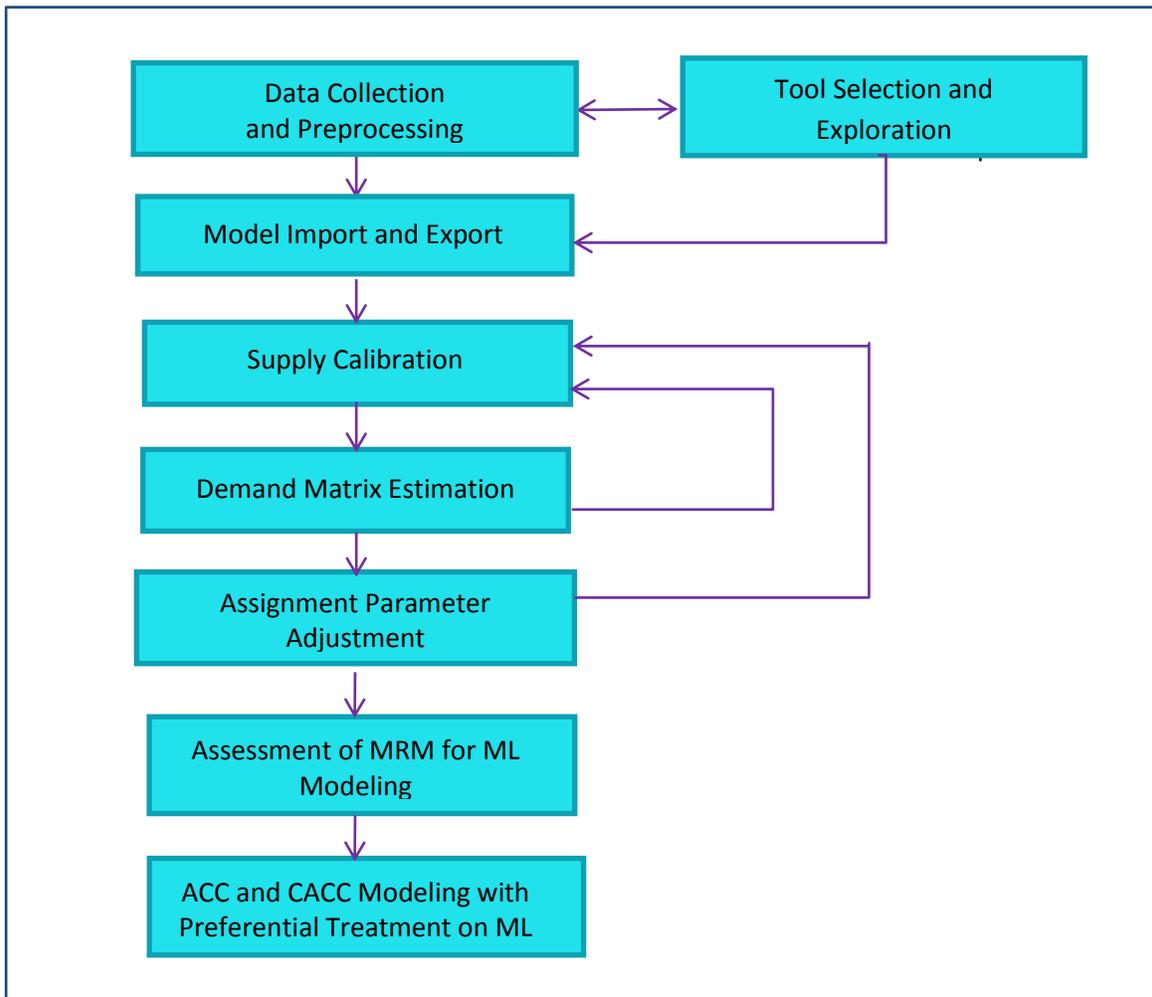
In this study, the effectiveness of the proposed MRM framework is tested for different modeling use cases and scenarios including managed lane, origin-destination matrix estimation, construction zone, and active traffic management for arterial streets. The remaining sections of this report document these efforts.

## **4. MODELING OF MANAGED LANES**

This section focuses on the modeling of managed lane strategies, assessment of various modeling approaches, and investigation of the input parameters to the modeling process.

### **4.1. Overview of the Modeling Process**

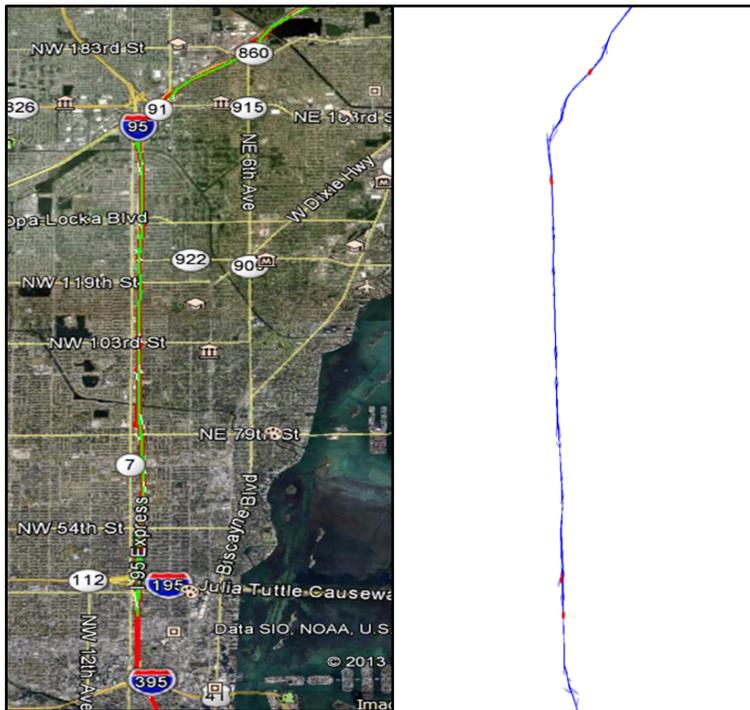
Figure 12 presents an overview of the methodology and tasks implemented in this study. As shown in Figure 12, the first step is data collection and preprocessing. This step makes use of the data that is becoming available from multiple sources with the advancement in data collection technologies and sharing. Next, different combinations of tools are tested for a later use in the analysis of this research. Following that, a method is used to automate the conversion of the input and/or output data between different levels of the selected modeling tools. Then, an iterative calibration process is conducted to calibrate the transportation network supply, demand and traffic assignment parameters that are closely related to travelers' route decisions. In the supply calibration of macroscopic and mesoscopic simulation, roadway capacity and traffic flow models are calibrated based on real-world measures such as speed, volume, and queue length on each link. The demand calibration aims at producing a realistic dynamic origin-destination matrix at short time intervals (e.g., 15 minutes or 30 minutes). The impacts of traffic assignment parameters, such as value of time, associated stochasticity, and the value of reliability are then tested. Once the calibration process is accomplished, an assessment is conducted to by examine the model performance under different managed lane strategies, for example, toll policy changes and implementation of automated and connected vehicle technologies, adaptive cruise control (ACC) and connected adaptive cruise control (CACC), as shown in the last step of the methodology. It should be noted that there was a plan to integrate a microscopic simulation as part of the assessment process. The plan was to utilize a microscopic simulation model for the I-95 facility in Miami-Dade County. The I-95 model was supposed to be available several months before this final report was due. However, this was delayed due to revisions requested by FDOT to the model.



**Figure 12 Flowchart of ML Modeling Methodology**

#### **4.2. Application of Developed Methodology**

The methodology outlined in the previous section was applied to a subarea around I-95 corridor in Miami, FL, as shown in Figure 13. This network has a total number of 288 nodes, 303 links and 57 zones. Two-lane managed lanes are deployed along the I-95 corridor with a soft barrier separation from parallel general-purposed lanes. This relatively small subarea network has been modeled, calibrated, and tested in a mesoscopic simulation-based DTA tool (Cube Avenue) by Hadi et al. (2013). The remaining part of this section describes the related efforts.



**Figure 13 Study Network Used in Managed Lane Modeling**

#### ***4.2.1. Data Processing and Importing to ML Modeling Tools***

A number of modeling tools are used in this study, which includes two macroscopic tools, Express Lanes Time of Day (ELToD) coded in Cube and VISSUM, and two mesoscopic DTA tools, Cube Avenue and DTALite (the VISSIM microscopic simulation was supposed to be used if the calibrated model for the corridor becomes available from the FDOT District 6 study). As mentioned above, the network has been modeled in the Cube and Cube Avenue environment in the previous research project conducted by the research team, which provides a basis for modeling the same network in other two tools, DTALite and VISUM. The discussion below describes the related efforts for data preparation and model conversion.

##### **4.2.1.1. Network and Demand Data Conversion to DTALite**

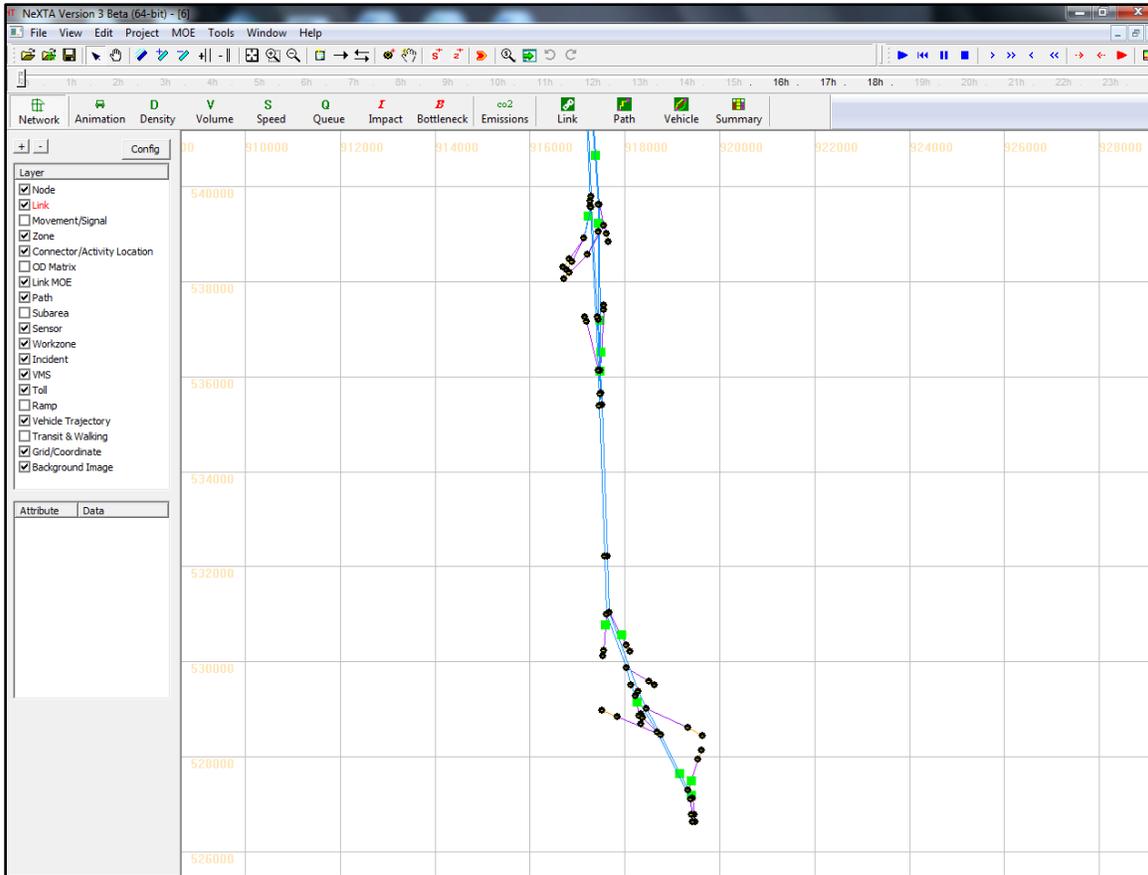
This project utilizes the NeXTA “data hub” tool, an open source tool that has been utilized in a number of USDOT and SHRP 2 projects. It also serves as the graphical user interface for the DTALite DTA tool. The first step was to create a set of shape files describing the network to be imported to NeXTA from Cube Avenue. The network data structure in these files defines the basic node and link structure used in the NeXTA tools, along with the attributes for each link and node. The node and link shape files exported from the Cube model were imported into NEXTA,

through the network importing function. The corresponding link and node attributes, such as the number of lanes, free-flow speed, link capacity, traffic control type, and so on, were configured in the “import\_GIS\_Setting.csv” of NeXTA. In addition, the link types used in the Cube model are different from those used in DTALite. In Cube, there is no limitation in the number of link types, while a total number of 12 link types are allowed in DTALite. The conversion of link types from Cube to DTALite was conducted based on the matches listed in Table 7.

**Table 7 Required Data to Model Traffic Network in DTALite**

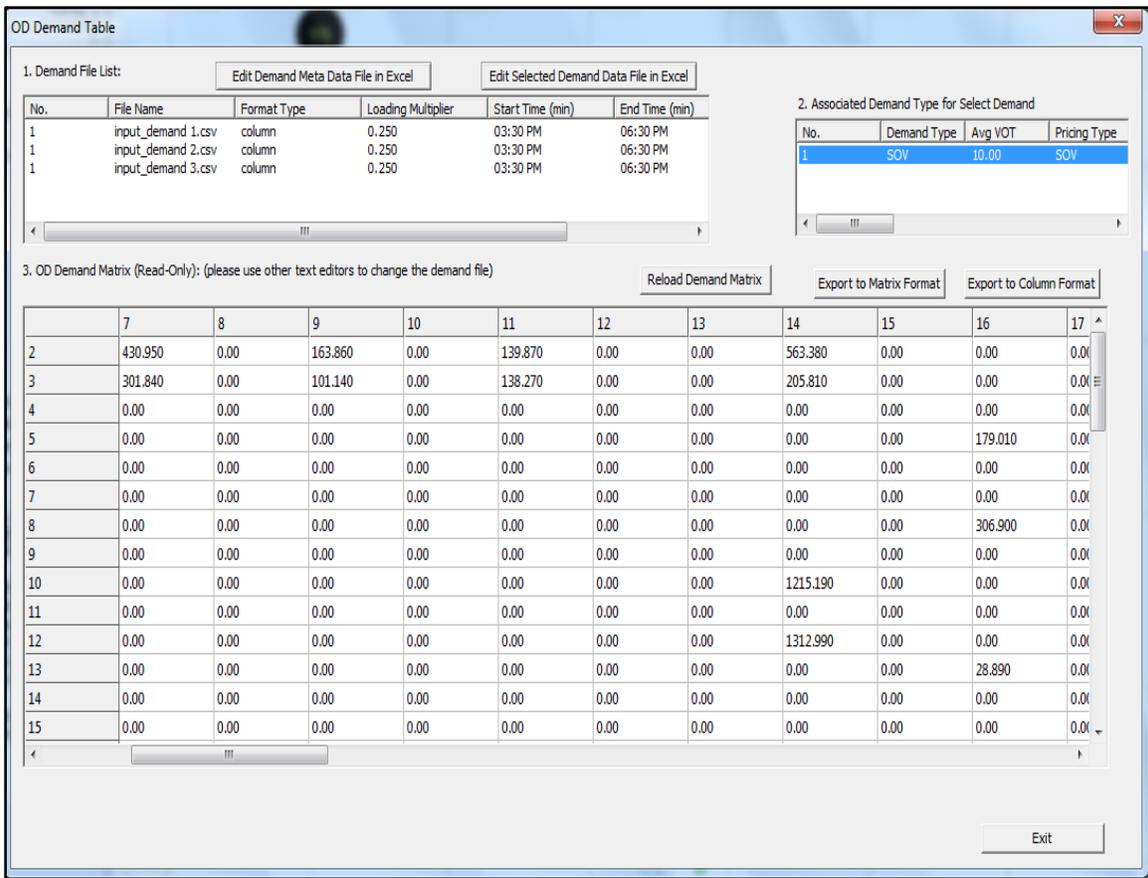
Cube Model	NeXTA/DTALite
10-19: Freeway 20-29: Divided arterial 30-39: Undivided arterial 40-49: Collector 50-59: Centroid Connector 60-69: One-way facility 70-79: Ramps 80-89: Exclusive HOV lanes 90-99: Toll facilities	1: Freeway 2: Highway/Expressway 3: Principal arterial 4: Major arterial 5: Minor arterial 6: Collector 7: Local 8: Frontage road 9: Ramp 10: Zonal connector 100: Transit link 200: Walking link

It should be noted that the zone layer is not required in the Cube model as the zone centroid information is specified through centroid nodes. However, the zone numbers have to be explicitly specified in NeXTA. In this study, the zone number attribute is added to the nodes located at the centroid of the zones. Figure 14 shows the final imported network in NeXTA.



**Figure 14 The Final Imported Network in NeXTA**

In addition to the network data, the demand data should be input to the modeling tools to run the assignment procedure. In this research, the demands matrices from the Cube Avenue model were imported to the other tools and used as a baseline initial matrices in the analysis. It should be mentioned that these demands were derived by Hadi et al. (2013) based on the initial demand matrices extracted from the Southeast Regional Planning model for the peak period and further calibrated using the static Cube Analyst ODME procedure. The Cube demand matrices were converted to the csv file format and imported into NeXTA through the demand META database configuration file in NeXTA as shown in Figure 15. As illustrated in this figure, the user has to specify the vehicle type, demand matrix type, and the corresponding time period covered by the matrix.



**Figure 15 Demand Import Interface in NeXTA**

Before running the DTALite model, the user needs to configure the scenario setting file, which is the “input\_scenario\_settings.csv” file. This file allows the user to change the simulation parameters, such as the traffic flow model, assignment method, number of days to simulate, and so on. The user can also define different simulation scenarios, for example, managed lane, work zone, and incident scenarios to be modeled. In this study, a managed lane scenario was created using this function, as shown in Figure 16.

Link	Scenario No	Start Day No	End Day No	Start Time in Min	End Time in min	Charge for LOV (\$)	Charge for HOV (\$)
[407,405]	1	1	1	990	1050	2.5	2.5
[409,184]	1	1	1	990	1050	2.5	2.5
[170,184]	1	1	1	990	1050	2.5	2.5
[184,185]	1	1	1	990	1050	2.5	2.5
[185,187]	1	1	1	990	1050	2.5	2.5
[187,189]	1	1	1	990	1050	2.5	2.5
[189,191]	1	1	1	990	1050	2.5	2.5
[191,193]	1	1	1	990	1050	2.5	2.5
[193,195]	1	1	1	990	1050	2.5	2.5
[195,197]	1	1	1	990	1050	2.5	2.5
[197,200]	1	1	1	990	1050	2.5	2.5
[200,202]	1	1	1	990	1050	2.5	2.5
[202,204]	1	1	1	990	1050	2.5	2.5
[204,206]	1	1	1	990	1050	2.5	2.5
[206,208]	1	1	1	990	1050	2.5	2.5
[208,210]	1	1	1	990	1050	2.5	2.5
[210,212]	1	1	1	990	1050	2.5	2.5
[212,214]	1	1	1	990	1050	2.5	2.5

**Figure 16 Managed Lane Scenario Configuration**

**4.2.1.2. Network and Demand Data Conversion to VISUM**

VISUM provides an Add-In feature to import network files from other software such as NeXTA or Cube. However, after applying this function, a further check is still needed to ensure the consistency of the network presentation and data inputs, as different models may have different spatial and temporal resolutions. In this study, the input link types and node types were updated first. The corresponding GIS shape files were prepared based on the format required by VISUM and imported into VISUM. The Cube demand matrices were then converted into csv files and imported into VISUM. Figures 17 and 18 show the final imported network and demand matrices in VISUM, respectively.

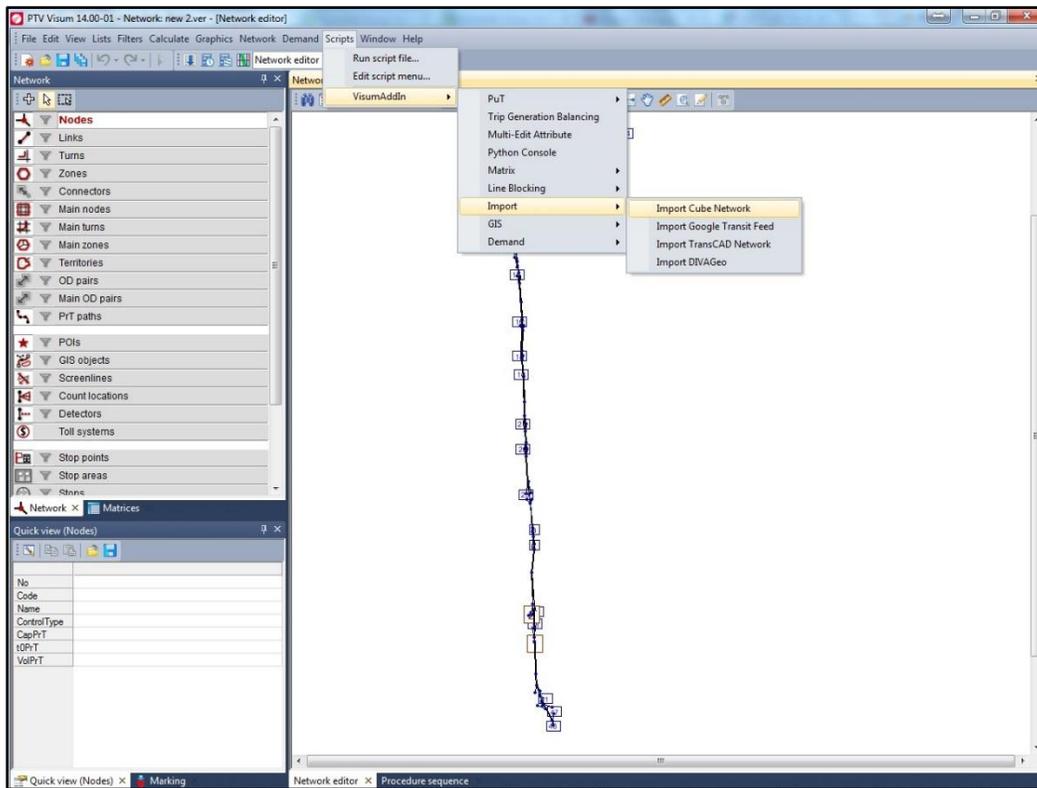


Figure 17 Imported Network in VISUM

The screenshot shows the Matrix editor (Matrix 1 DA) in PTV Visum. The main window displays a table with 16 columns (labeled 2 to 16) and 41 rows (labeled 2 to 41). The table contains numerical values representing demand between nodes. The left sidebar shows a tree view of matrices, including 'All matrices', 'Demand matrices', and 'Data matrices'. The bottom status bar indicates 'Network' and 'Matrices'.

Name	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
2	979.17	0.00	0.00	197.60	0.00	4704.17	7043.69	0.00	1003.97	0.00	4354.71	0.00	0.00	14508.92	0.00	1488.55
3	1302.32	0.00	0.00	0.00	0.00	214.92	0.00	39.40	0.00	226.12	0.00	0.00	254.12	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	512.95	0.00	29.70	0.00	231.32	0.00	0.00	387.14	0.00	0.00	0.00
5	2745.79	0.00	0.00	18.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	250.83
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	4467.16	0.00	0.00	37.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	339.94
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	2922.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2522.45
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	1853.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1768.68
13	986.26	0.00	0.00	7.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	35.70
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	345.90	0.00	0.00	2.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	1510.14	0.00	0.00	20.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	1932.90	0.00	0.00	23.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
19	1093.40	0.00	0.00	10.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21	1616.95	0.00	0.00	25.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	1393.93	0.00	0.00	11.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	2094.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	13153.38	0.00	0.00	29.20	0.00	3930.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	734.97
26	2637.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2535.95
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	1302.23	0.00	0.00	0.00	0.00	0.00	395.14	0.00	1.90	0.00	17.00	0.00	0.00	0.00	0.00	737.37
30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	382.60	0.00	0.00	0.00	0.00	0.00	201.32	0.00	27.60	0.00	166.61	0.00	0.00	0.00	0.00	440.45
32	1487.93	0.00	0.00	0.00	0.00	0.00	392.13	0.00	43.20	0.00	232.22	0.00	0.00	0.00	0.00	642.46
33	1958.37	0.00	0.00	0.00	0.00	0.00	361.53	0.00	82.51	0.00	299.23	0.00	0.00	0.00	0.00	883.08
34	307.08	0.00	0.00	0.00	0.00	0.00	351.63	0.00	5.70	0.00	178.52	0.00	0.00	0.00	0.00	231.42
35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37	8061.71	0.00	0.00	0.00	0.00	0.00	1524.56	0.00	251.32	0.00	1067.41	0.00	0.00	0.00	0.00	1421.94
38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
40	2774.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 18 Imported Demand Matrix in VISUM

#### ***4.2.2. Network Supply Calibration***

The network supply calibration estimates the network parameters such as capacity and traffic flow model (TFM) parameters that define network performance in producing travel time, forming queues, and queue spillback.

Different modeling tools have different traffic flow models. For example, the Bureau of Public Road (BPR) function is usually used in the FSUTMS model within the Cube environment although the Akcelik model has also been used. DTALite allows the use of BPR, vertical queue model, and spatial queue model (Newell's N-Curve model). VISUM also provides multiple forms of traffic flow models, such as Isochronse and Spatial Queue Model. This study examined the impacts of utilizing calibrated and uncalibrated TFM parameters, which are capacity and jam density, on the simulation results using different modeling tools.

The previous study conducted by Hadi et al. (2013) on a segment of I-95 emphasized that only data from congested segments that are not affected by downstream bottlenecks should be used to calibrate the parameters of TFM. In this study, data from the bottleneck locations on the I-95 northbound segment in Miami (NW 79th St. and NW 103rd St. on-ramp merge area) were collected and used in calibrating the different TFM models in the utilized tools. The calibrated capacity and jam density are 1,850 vehicles per hour per lane (vphpl) and 190 vehicle per mile per lane (vpmpl), respectively. However, the default values (uncalibrated) for capacity and jam density are about 2,100 vphpl and 190 vpmpl, respectively. In this study, the impacts of these calibrated parameters on network performance in terms of bottleneck speeds and segment travel time were examined through different analysis tools, ELToD, Cube Avenue, DTALite, and VISUM. The results show that the bottleneck speeds and segment travel time can follow the trend of the real-world measurements better with calibrated parameters.

#### ***4.2.3. Origin-Destination Matrix Estimation (ODME)***

The estimation of time-variant trip matrices is an important step in DTA-based tools. DTA analysis requires dynamic or time-variant trip matrices specified for short time intervals (e.g., 15 minutes or 30 minutes). However, regional demand models were traditionally daily or time-of-day model that can only produce daily trip matrices. More recently they became "time-of-day" models that produce trip matrices that represent the peak periods as a whole. An origin-destination matrix estimation process is needed to fill this gap, that is, to estimate the trip tables for short intervals based on an initial matrix obtained from the regional demand models combined with field data. A simple ODME method is the factorization method that applies factors to convert daily or time-of-day demand matrices to matrices for short time intervals. A more advanced method is estimating the O-D matrices by minimizing the difference between the simulated performance measures and real-world measurements using an optimization procedure.

The resulting time-variant matrices, when loaded onto the calibrated network, should be able to replicate the observed link volumes and congestion patterns.

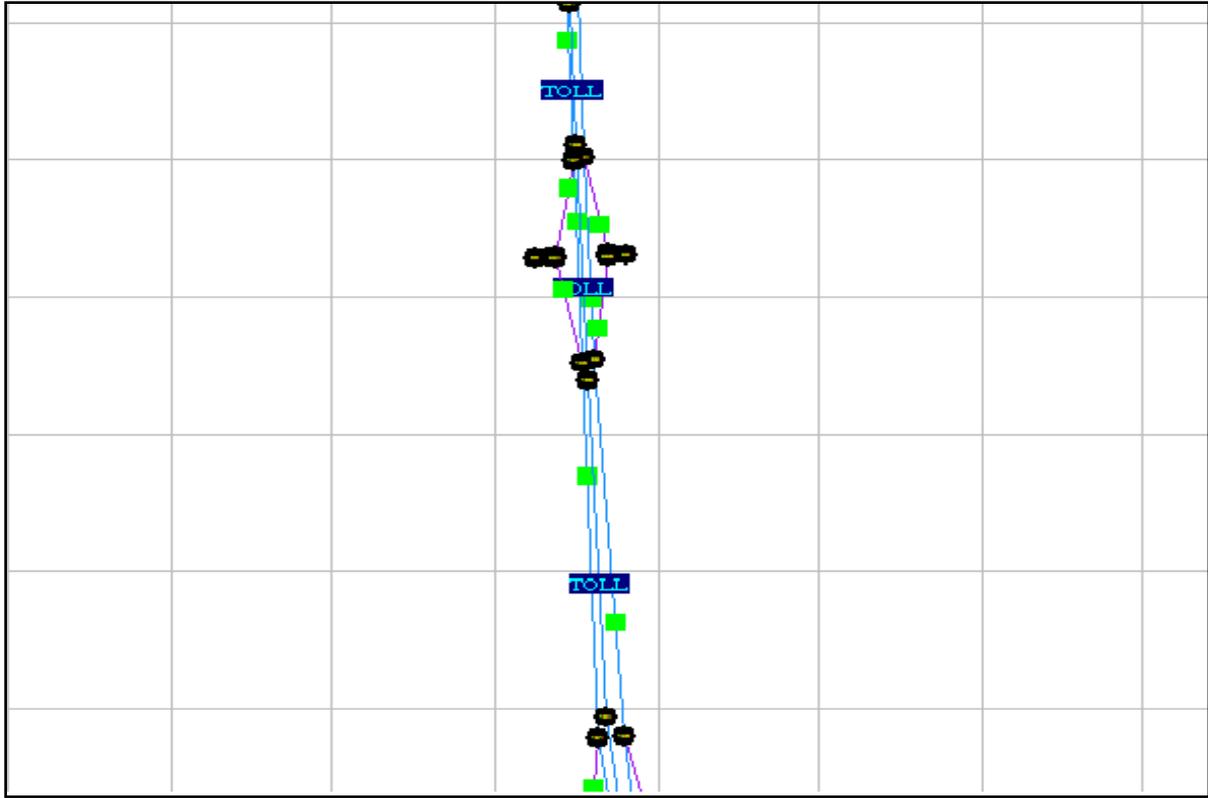
ODME tools are usually provided with currently available static and dynamic traffic assignment software. For example, Cube Analyst and its updated version Analyst Drive are the ODEM modules of the Cube modeling environment. The TflowFuzzy module is the ODME module in VISUM. An ODME tool is also included in the NeXTA interface of DTALite.

As stated earlier, the time-variant trip matrix for the study network has been calibrated by Hadi et al. (2013). The core of that demand calibration in that study was the application of a static assignment-based ODME (Cube Analyst) and further significantly fine-tuning the resulting matrix to improve the results. The additional fine-tuning was needed since existing ODME tools generally do not reach global optimal solution and the rea.

The present study investigates the following aspects of the ODME process:

- What is the impact of the initial matrix on the ODME optimization provided with different ODME tools
- How well are the counts produced by different ODME processes can replicate real-world counts
- How well do the assignment tools work when the O-D matrix is estimated using the ODME optimized using tools that are based on other assignment tools?
- Whether utilizing the ODME procedure of tools can improve on the O-D estimated by an ODME procedure provided with another assignment tool.

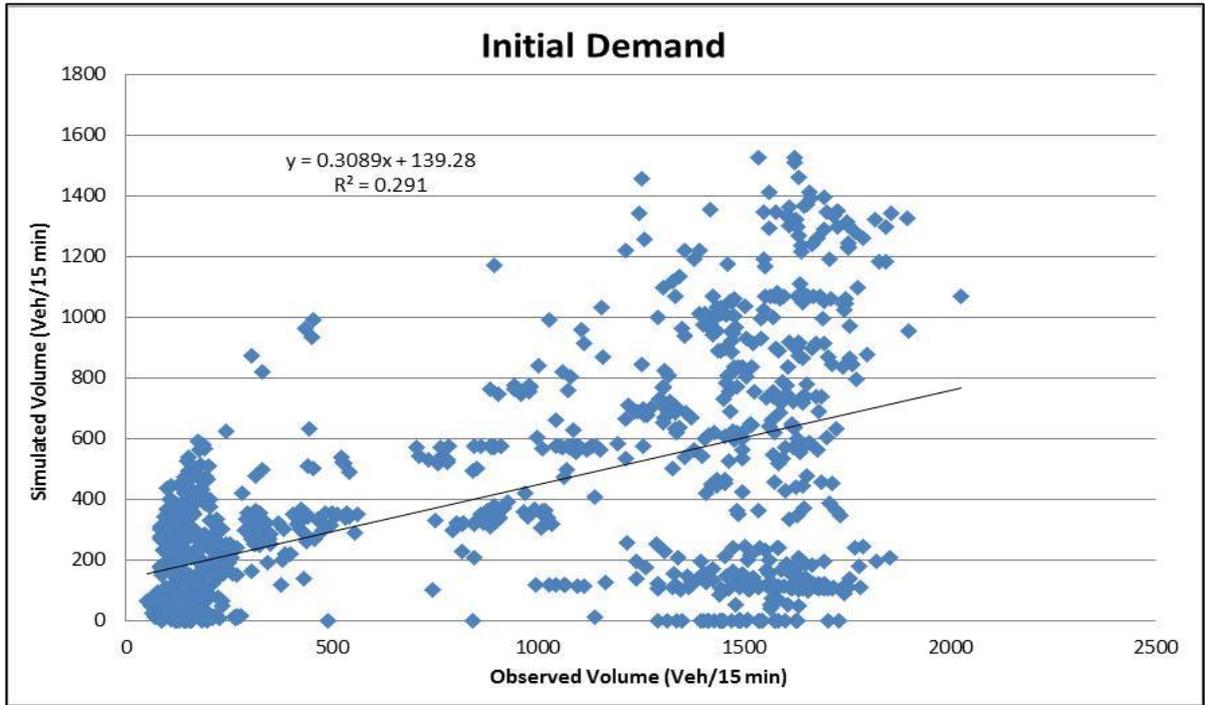
The sensor data for the case study include 15-minute volume counts collected at 87 locations on the GPL, ML, and ramps of the I-95 facility in Miami, FL. This data were input by the ODME module in each tool. The green squares shown in Figure 19 represent some of the detectors as an example.



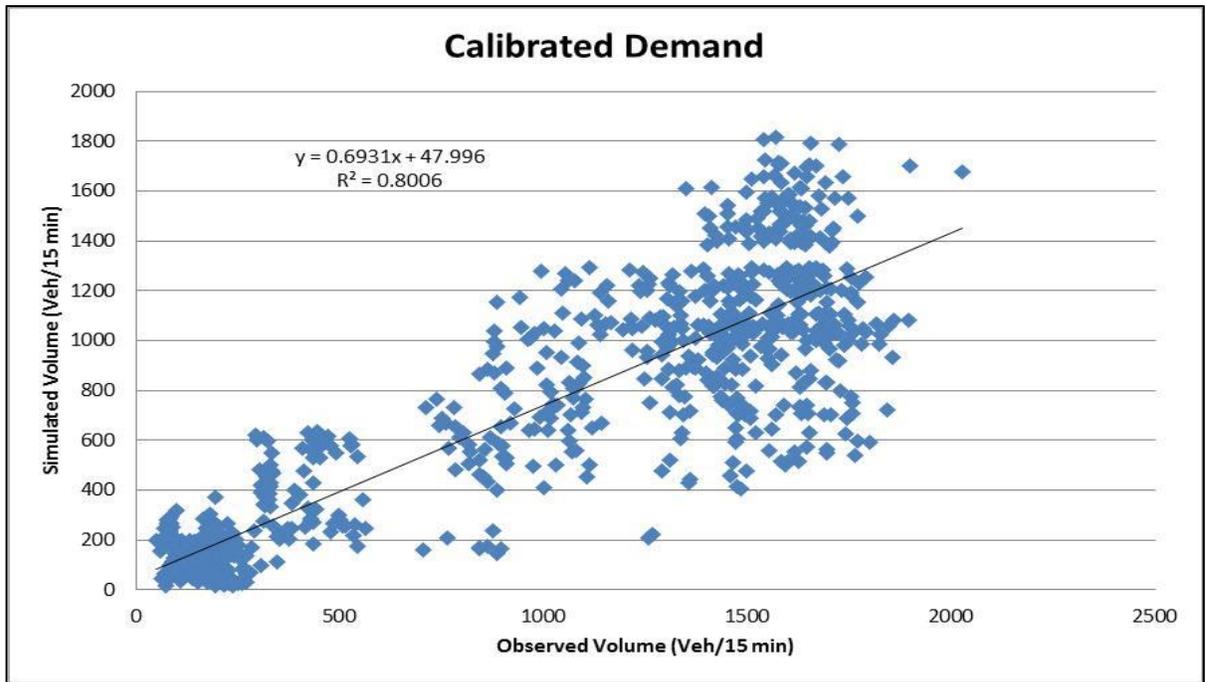
**Figure 19 Schematic of Sensor Locations for the ODME Process**

**4.2.3.1. ODME Process in Cube**

Figure 20 presents a comparison of simulated link volumes with real-world traffic counts for two different sets of matrices using Cube Avenue. The first set was produced by factorizing the demand matrix extracted from regional demand model. The second matrix is the calibrated demand matrix produced by Hadi et al. (2013), which was obtained by using a combination of the Cube Analyst ODME procedure but with additional fine-tuning of the results. Note that these simulated results are obtained from running the Cube Avenue dynamic traffic assignment tool. As shown in this figure, the simulated link volumes cannot replicate the observed link volumes when factorization of the demand matrix was used since the corresponding  $R^2$  is only 0.29. With calibrating the demands, the simulated link volumes get closer to the observed link volumes with a  $R^2$  value of 0.80.



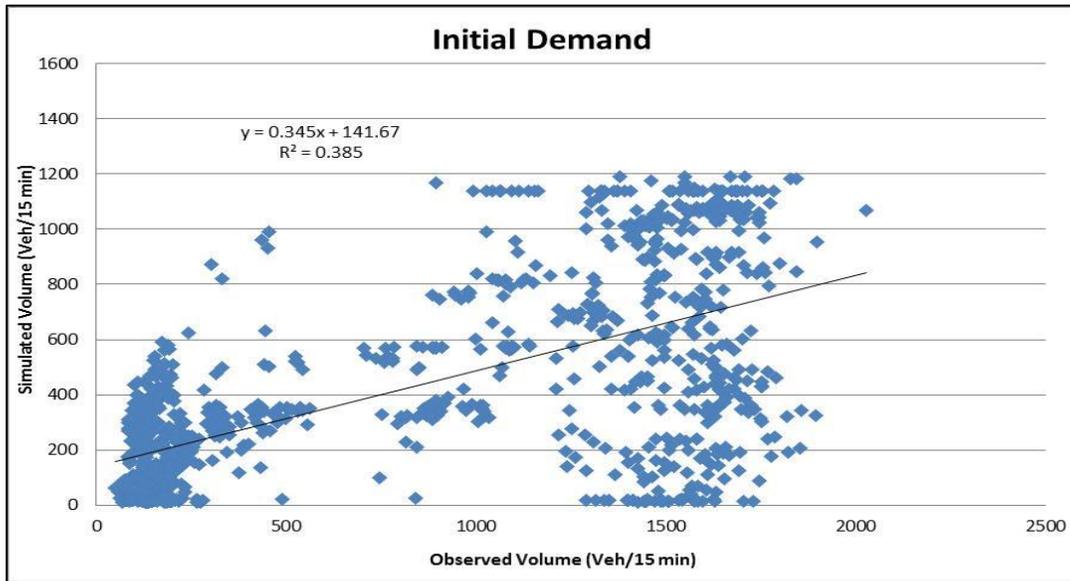
(a) Initial Demand



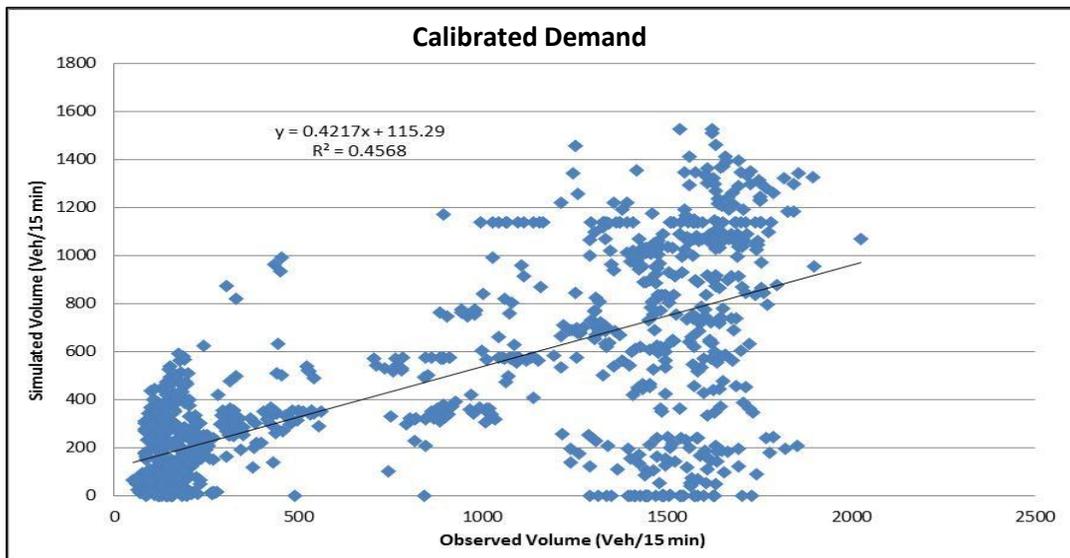
(b) Calibrated Demand

**Figure 20 Comparison of Observed Link Volumes vs. Simulated Link Volumes Produced by Cube Avenue**

Figure 21 presents the comparison results when using the Cube Analyst ODME procedure in Cube was used without fine-tuning the results. When using the initial factorized input demand matrix as an input to the ODME, the  $R^2$  value only improved from 0.29 to 0.39. This indicates that inputting low quality demand matrices to the ODME process does not allow the ODME to produce good results. The calibrated O-D from the previous study was input again for the ODME process to see if it can be improved further. The improvement in the  $R^2$  value is not significant (from 0.80 to 0.81). This is due to the fact that the ODME in Cube has already been used as part of the derivation of the calibrated matrix in the previous study.



(a) Initial Demand

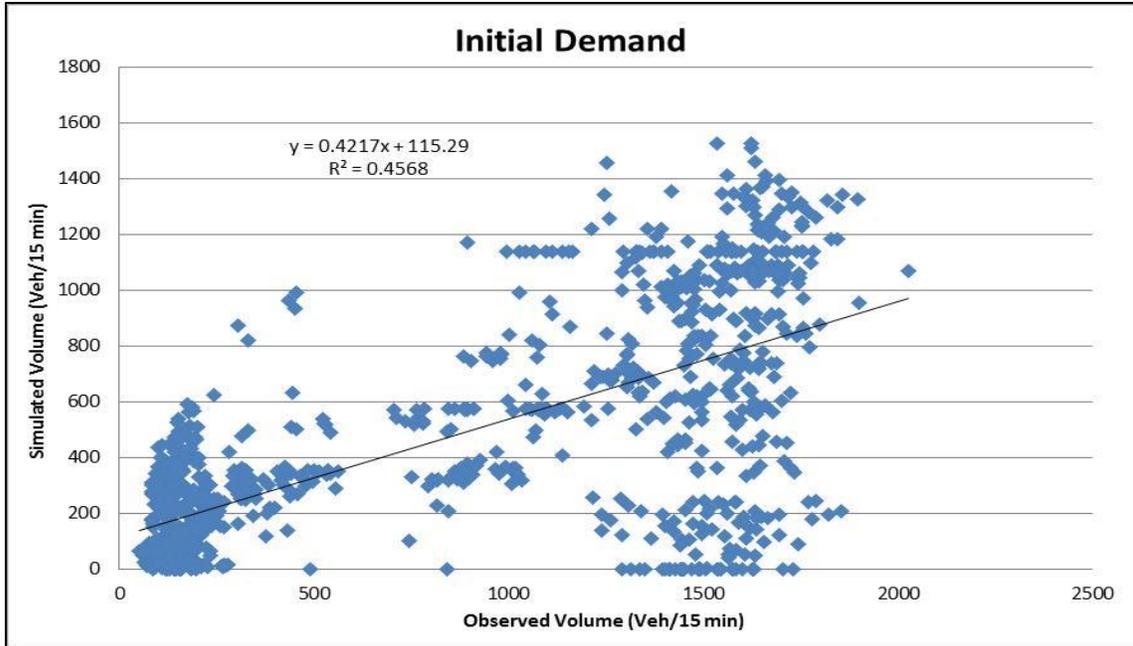


(b) Calibrated Demand

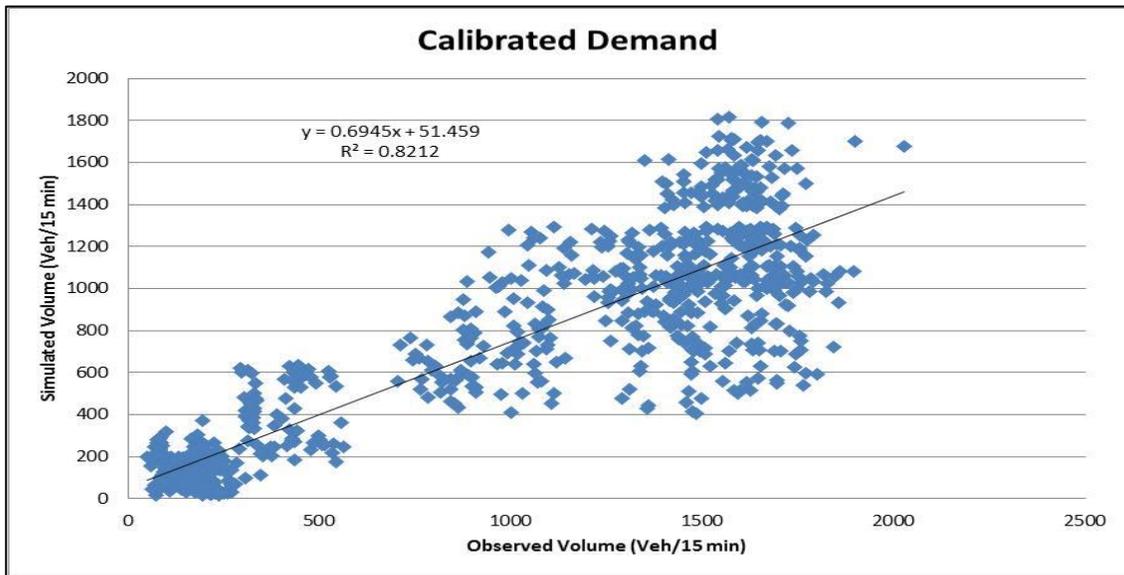
**Figure 21 Comparison of Simulated Link Volumes vs. Observed Link Volumes after Running ODME in Cube**

#### **4.2.3.2. ODME Process in VISUM**

As stated earlier, the matrix estimation function in VISUM is referred to as TFlowFuzzy (TFF) module. As with the ODME modules available in other tools, it iteratively adjusts the demand matrix such that the assigned link volume can be close to reference data such as count data. It is a dynamic process that is able to capture queue spillback in space and time. As mentioned earlier of this section, one of the tasks in this research is to examine how the DTA tool performs when using the calibrated matrix from other DTA tool. Therefore, in this study, the 15-minute uncalibrated and calibrated O-D matrices from the research by Hadi et al., (2013) were used as input matrices for VISUM analysis. Figure 22 presents the dynamic traffic assignment results for link volumes using the factorized demand matrix from the regional model, as well as the calibrated Cube demand matrix in VISUM. As shown in Figure 22, the  $R^2$  value when using the factorized matrix as an initial matrix to TFF was 0.47. It is also seen from Figure 22 that running VISUM DTA with the calibrated demand can produce link volumes that are relatively close to the observed values with a  $R^2$  of 0.82, which is similar to the Cube Avenue results. Figure 23 presents the results of simulated link volume after utilizing the ODME in VISUM. Significant improvements in the simulated link volumes can be observed in Figure 23. Compared to the results in Figure 22, the  $R^2$  value improved to 0.79 and 0.96 when using the uncalibrated and calibrated matrices to the VISUM ODME process, respectively. This indicates that the dynamic ODME procedure used in VISUM is more effective than the static assignment-based ODME in Cube that was implemented, as discussed earlier.

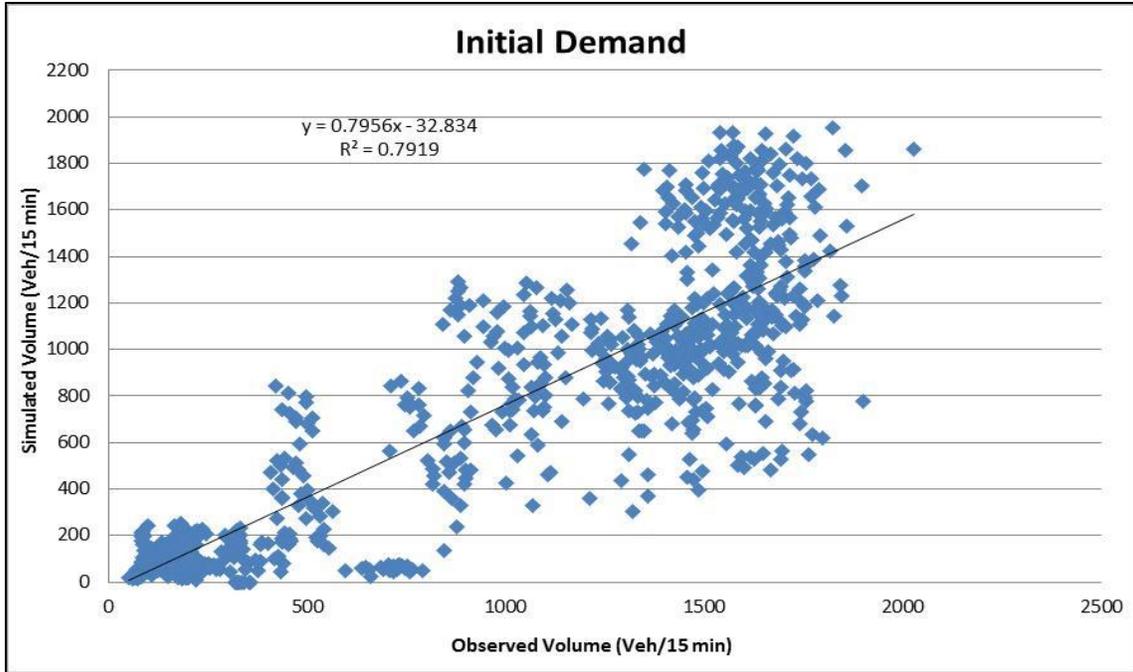


(a) Initial Demand

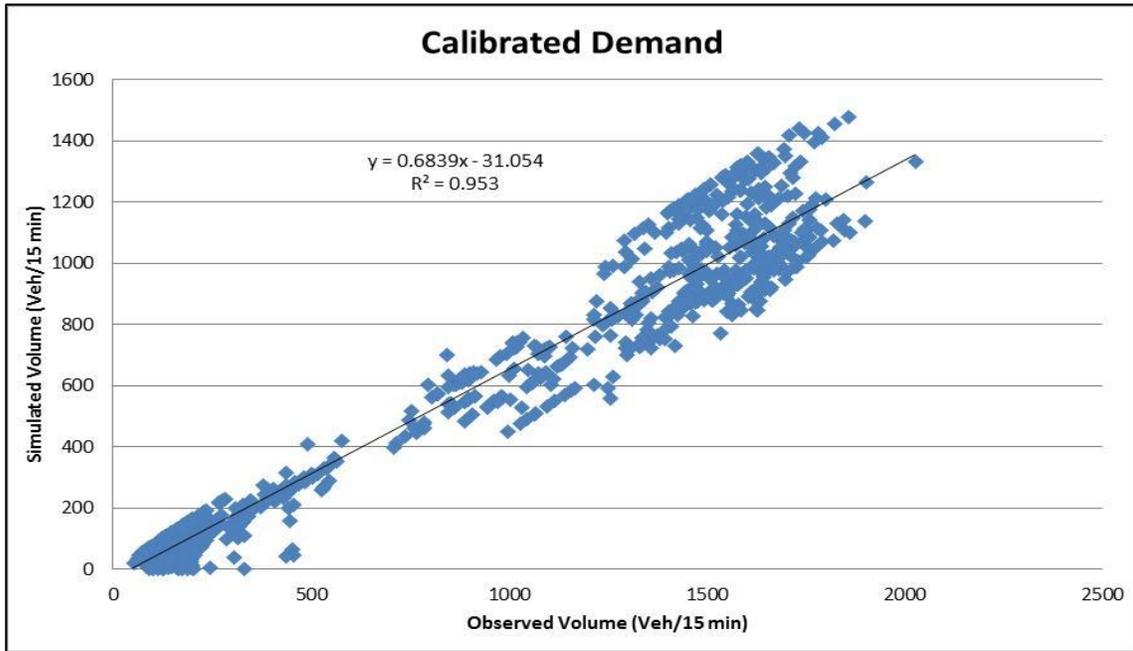


(b) Calibrated Demand

**Figure 22 Comparison of Simulated Link Volumes vs. Observed Link Volumes after Running DTA in VISUM**



(a) Initial Demand



(b) Calibrated Demand

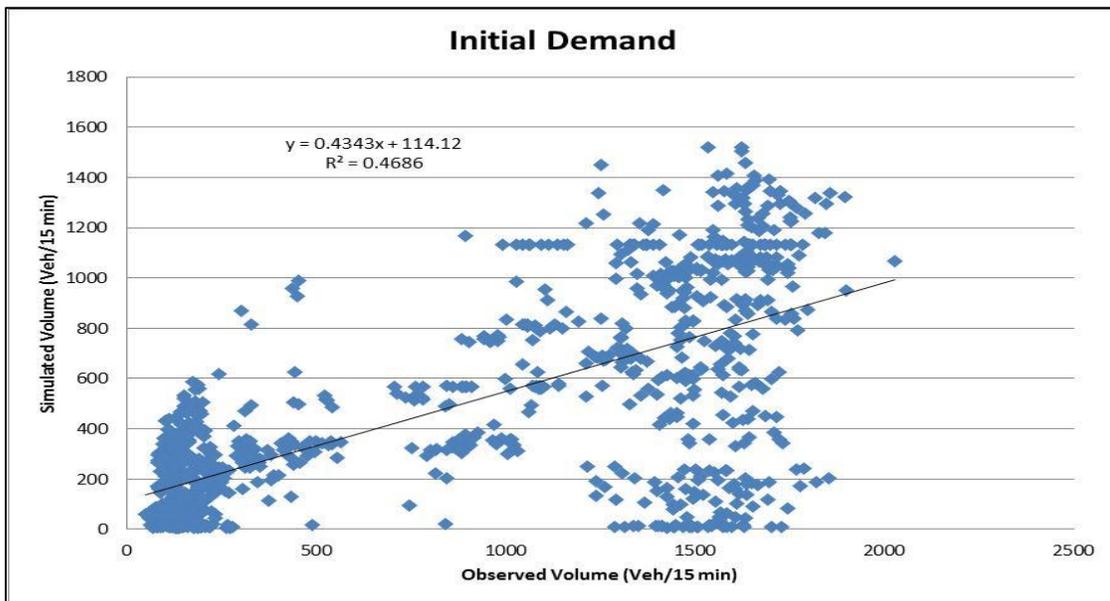
**Figure 23 Comparison of Simulated Link Volumes vs. Observed Link Volumes after Running ODME in VISUM**

#### **4.2.3.3. ODME Process in DTALite**

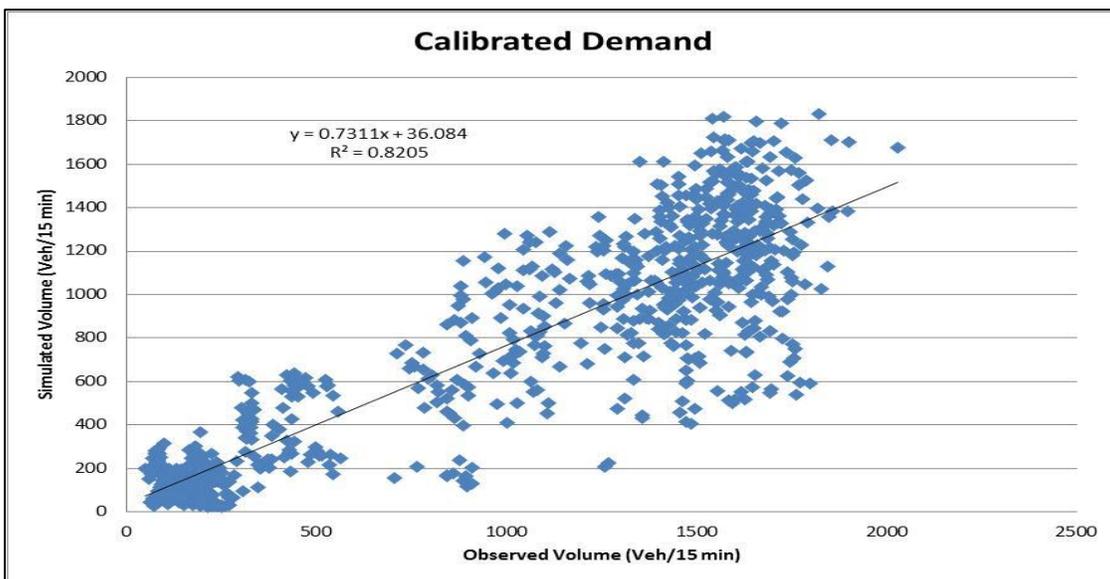
In NeXTA, the graphic user interface of DTALite, the user can run a dynamic ODME process by enabling the ODME mode in the “input\_scenario\_settings.csv” file and configuring the setups in the “ODME\_Settings.txt” file. The ODME parameters, such as the number of iterations, the amount of adjustment allowed per iteration, and the calibration time period which could be a portion of the modeling period, can be specified in these files. Figures 24 and 25 compare the simulated link volumes with the observed values without and with using the dynamic ODME process in DTALite. The results in these two figures are very similar to those obtained using VISUM software. When using the factorized demand matrix as an input, the implementation of ODME can improve the  $R^2$  value from 0.47 to 0.82, while the  $R^2$  value can increase from 0.82 to 0.96, with the use of the calibrated demand matrix as an input to the ODME. Again, these results emphasize the importance of dynamic ODME compared to the static ODME of Cube.

#### **4.2.3.4. Summary of Tool Assessment for Demand Estimation**

Demand matrix estimation is an undetermined problem as the number of equations for link counts is usually much lower than the number of unknowns O-D pairs. Hence, different O-D estimates may produce the same link volumes. It is important, therefore, to manage the estimation process to ensure the reasonableness and the correctness of the estimated demands. Tables 8 and 9 compare the goodness of fit for the simulated link volume based on the above results. The measures listed in these two tables show that DTALite can produce better volume results than other two tools, although the VISUM software results are also similar. A better demand matrix used as input to the ODME process (such as the previously calibrated demand matrix) can produce more realistic replication of real-world volume counts, compared to utilizing a simple factorized demand matrix. The implementation of the dynamic ODME in VISUM and DTALite can better capture the queue forming and dissipation than the static assignment-based ODME implemented in Cube, which can result in more accurate results of volume counts. As shown in Tables 8 and 9, the ODME module in Cube based on DTA does not improve the results significantly compared to that based on static assignment. However, the dynamic ODME in VISUM and DTALite are able to produce much better results because they enhance the model for congestion pattern replication than the ODME based on static assignment in Cube.

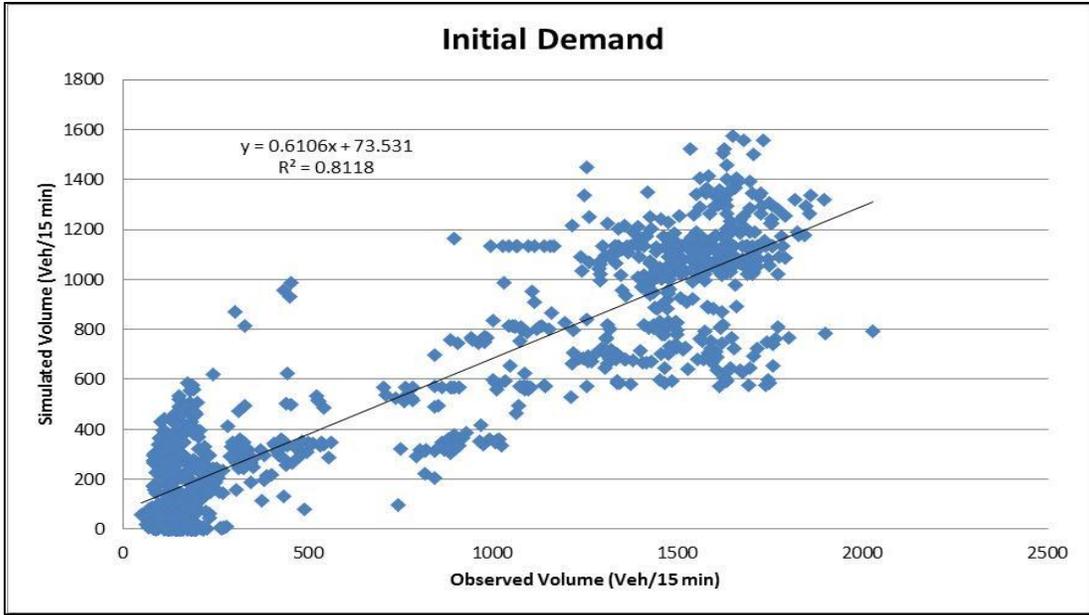


(a) Initial Demand

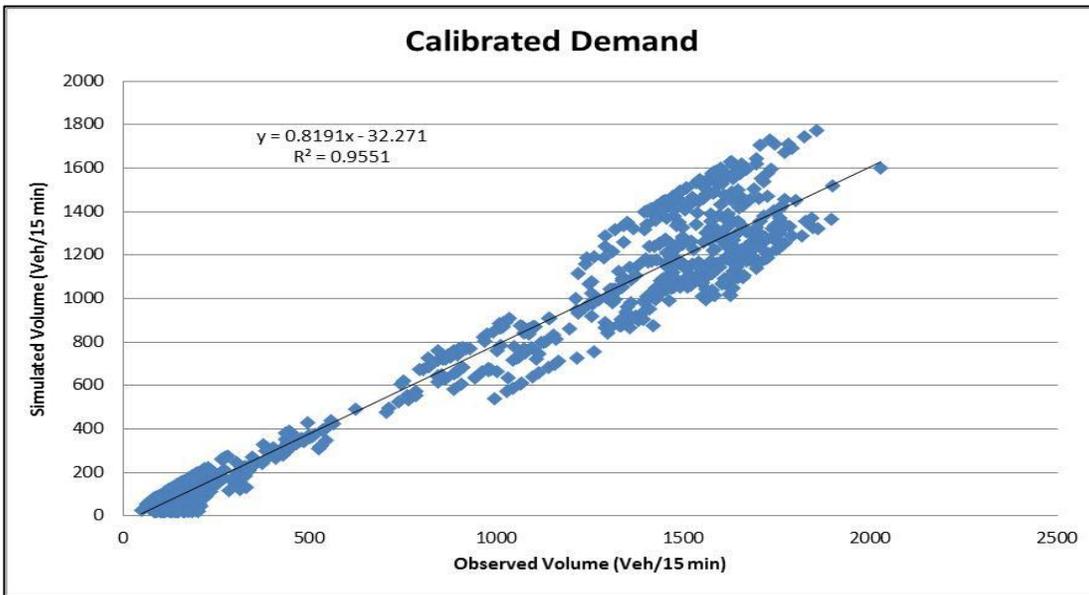


(b) Calibrated Demand

**Figure 24 Comparison of Simulated Link Volumes vs Observed Link Volumes after Running DTA in DTALite**



(a) Initial Demand



(b) Calibrated Demand

**Figure 25 Comparison of Simulated Link Volumes vs Observed Link Volumes after Running ODME in DTALite**

**Table 8 Goodness of Fit for Simulated Volume Based on Factorized Demand Matrix**

Goodness-of-Fit Statistics	Initial Demand					
	Running DTA without ODME			Running ODME Optimization		
	Cube	VISUM	DTALite	Cube	VISUM	DTALite
MAE	123.48	108.13	101.56	112.51	80.74	68.21
MAPE (%)	20.61	18.69	16.11	15.35	13.32	12.52
RMSE(veh/ln/15min)	181.32	158.79	149.14	165.21	118.56	100.16
R squared	0.29	0.46	0.47	0.39	0.72	0.81
Improved Demand Estimation Utilizing ODME Optimization (%)				8.88	25.33	32.84

**Table 9 Goodness of Fit for Simulated Volume Based on Calibrated Demand Matrix**

Goodness-of-Fit Statistics	Calibrated Demand					
	Running DTA without ODME			Running ODME Optimization		
	Cube	VISUM	DTALite	Cube	VISUM	DTALite
MAE	67.79	62.13	62.19	63.44	59.71	55.18
MAPE (%)	11.21	11.09	10.98	11.02	10.9	10.62
RMSE(veh/ln/15min)	95.15	91.24	91.33	93.15	87.68	81.03
R squared	0.80	0.821	0.832	0.81	0.95	0.96
Improved Demand Estimation Utilizing ODME Optimization (%)				2.09	3.9	11.27

#### **4.2.3.5. Assessment of Utilizing the Derived Demands in VISSIM**

As stated earlier, this task was supposed to be conducted if the VISSIM model for the I-95 corridor becomes available.

#### ***4.2.4. Modeling of Managed Lane Strategies***

In this study, a comparison is made of modeling managed lane strategies using a sketch planning tool, and mesoscopic simulation-based DTA (microscopic simulation will be used when available). Sensitivity analysis of the value of time, value of time distribution, value of reliability, and toll pricing policies were also conducted in this research to determine their impacts on the analysis.

#### **4.2.4.1. Value of Time (VOT) Consideration in ML Modeling**

When modeling managed lanes using a generalized cost function in the assignment process, the value of time is a critical parameter that affects the drivers' selection of managed lanes. VOT converts the monetary value of toll cost into equivalent time. This equivalent time can be then added to the utility function of the ML facility, as shown in Equation 8. If the summation of

route travel time and the added equivalent time is still smaller than the congested time in GPL, ML is more attractive to the user.

$$U = a_1 * TT + \times a_2 * TC \tag{8}$$

Where:

U: Utility function for route choice, f (time and cost)

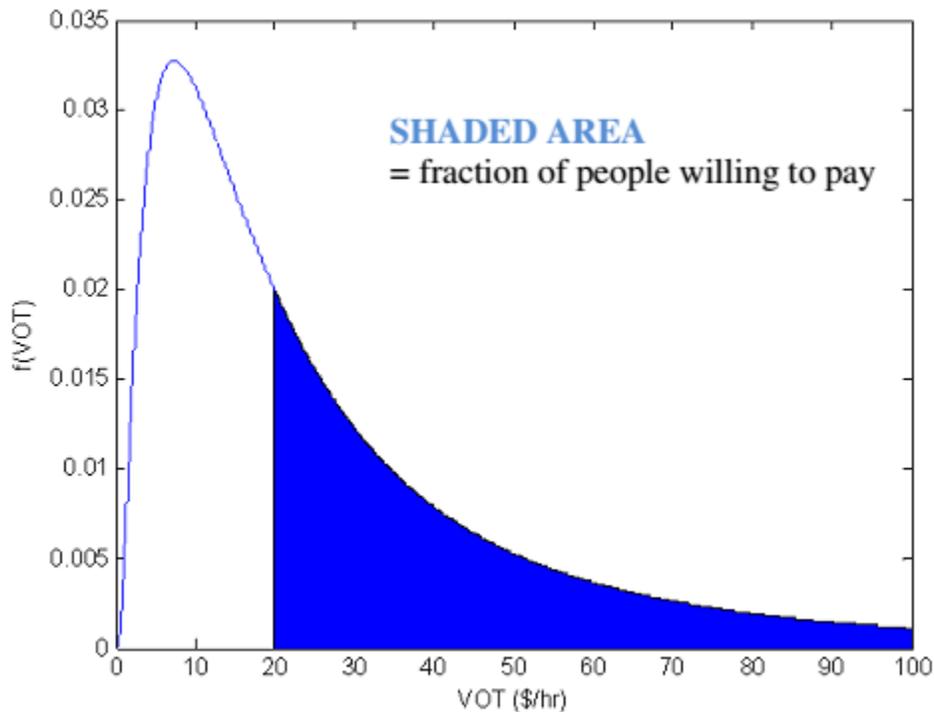
TT: Estimated travel time (minute)

TC: Toll cost (dollar)

$a_1$ : Travel time coefficient

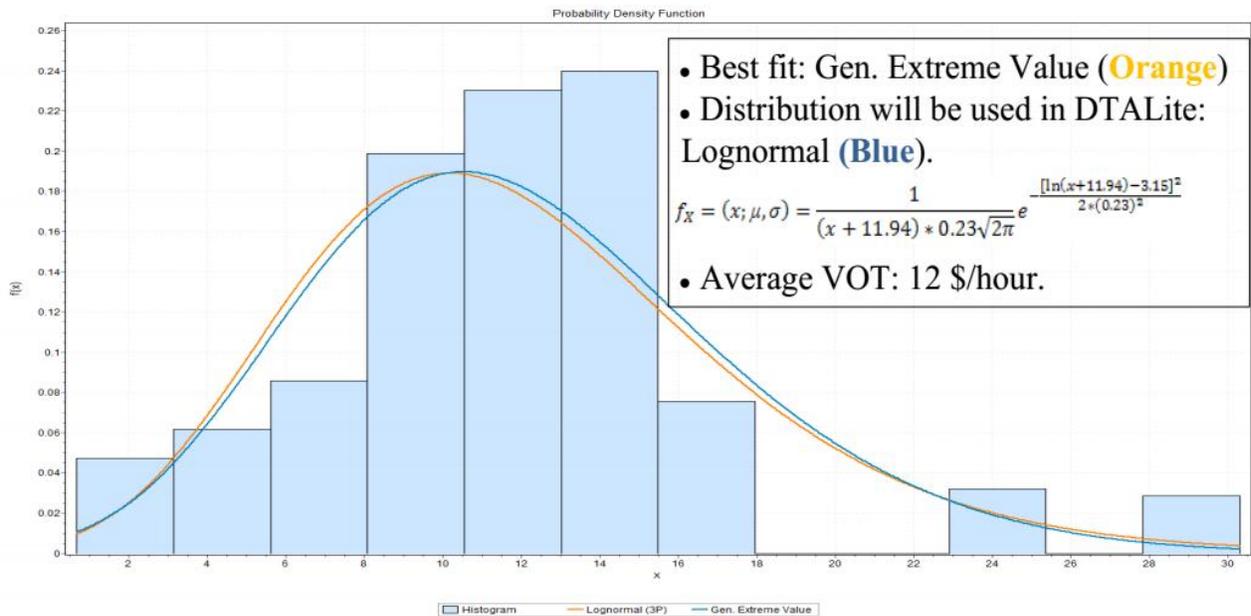
$a_2$ : Travel cost coefficient

The parameter  $a_2$  in the above equation is related to the value of time. A value of time of \$30 per hour means that the user is willing to pay \$30 to save one hour or 50 cents for every minute of saved time. In most of DTA tools and their applications, an average value of VOT is commonly used. However, a distribution of VOT, possibly combined with categorization of users by income and/or other measures, can better capture the preference of different road users. In the SHRP 2 C04 project, a lognormal distribution was recommended for the distribution of the value of time and the default mean VOT used in SHRP 2 C04 was \$20 per hour, as shown in Figure 26. In this figure, given a toll value of \$20, the proportion shown in the blue area are the people that have VOT savings exceeding the toll charged and would therefore pay it.



**Figure 26 Lognormal Distribution for VOT Based on SHRP 2 C04 Project (Parsons Brinckerhoff et al., 2013)**

In this study, using the fixed VOT and distribution of VOT was tested utilizing the DTALite because this tool allows the users to define a distribution for the VOT, which is not possibly or easily done in the other tools tested in this study. The default average VOT in DTALite is \$1 for every 5 minutes (that is, \$12/hour). Figure 27 shows the default distributions for VOT based on DTALite.



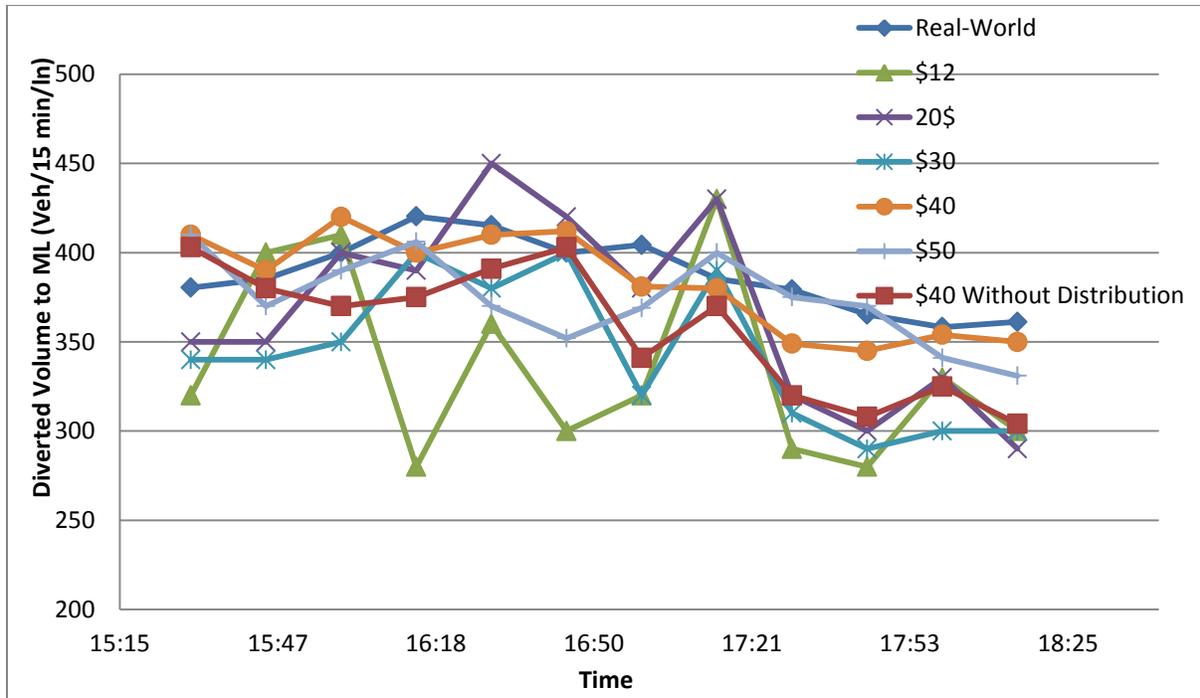
**Figure 27 VOT Distribution in DTALite (DTALite, 2012)**

In this study, the toll data for I-95 northbound in April, 2015 was also obtained from FDOT D6 TMC. Averaging the toll values over 10 weekdays shows that the average toll is between \$6 and \$7 during the congested PM peak period with an average value of \$6.30, as shown in Table 10. The time saved by travelers based on real-world detector data for non-incident days is usually between 6 to 10 minutes depending on the congestion level in the general-purposed lanes. Paying an average toll value of \$6.30 implies that the traveler’s value of time is about \$37 to \$63.

**Table 10 Real-World Toll Data for I-95 Northbound in April, 2015**

<b>Time (PM)</b>	<b>Day 1</b>	<b>Day 2</b>	<b>Day 3</b>	<b>Day 4</b>	<b>Day 5</b>	<b>Day 6</b>	<b>Day 7</b>	<b>Day 8</b>	<b>Day 9</b>	<b>Day 10</b>	<b>Average</b>
15:31	5.00	5.50	5.50	5.50	5.75	5.75	5.75	5.75	6.00	5.75	<b>5.63</b>
15:42	6.00	6.50	6.00	6.25	5.50	5.75	6.00	6.75	6.50	6.25	<b>6.15</b>
16:10	5.50	7.25	5.75	5.75	5.75	6.00	6.00	6.00	6.00	6.00	<b>6.00</b>
16:24	5.50	7.25	5.75	5.75	6.00	6.00	6.25	6.00	6.00	6.00	<b>6.05</b>
16:36	5.50	7.00	5.75	5.75	6.00	6.00	6.25	6.25	6.25	6.00	<b>6.07</b>
16:51	5.50	7.00	5.75	5.75	7.00	6.00	6.25	7.25	6.50	6.00	<b>6.30</b>
17:10	5.50	7.00	6.00	6.50	7.00	6.25	6.25	6.75	6.75	6.25	<b>6.42</b>
17:24	5.75	7.50	6.00	7.00	7.50	7.25	6.5	6.75	7.00	7.00	<b>6.82</b>
17:36	5.75	6.50	5.50	7.00	7.75	7.00	7.00	7.25	7.50	7.00	<b>6.82</b>
17:41	5.75	7.75	5.50	7.50	7.50	6.75	6.75	7.25	7.00	6.75	<b>6.85</b>
18:10	5.50	7.75	5.50	6.75	6.75	6.00	6.75	7.00	6.5	6.00	<b>6.45</b>
18:21	5.50	7.00	6.25	6.25	6.25	5.50	6.25	6.25	6.5	6.00	<b>6.17</b>

Based on the above discussion, a sensitivity analysis was conducted in this study to find the best value of time that produces the observed shift to the ML in the DTALite tool. An average VOT values of \$12, \$20, \$30, \$40, and \$50, were used in the sensitivity analysis (utilizing a distribution for VOT) and the results of the diverted volume to ML are presented in Figure 28 and Table 11. From Figure 28 and Table 11, it appears that the value of time of \$40 with lognormal distribution produces the closest results to the real-world diverted volume to ML, which is much greater than the value of \$13.44 used in the SERPM model. It should be noted that in addition to saved travel time, this VOT most likely accounts for other factors not considered in the generalized cost function such as travel time reliability, comfort, safety, and the travel time experience in past days, which could include more congested days and incident days compared to the present day. The next step was to examine if utilizing a distribution of VOT, instead of a fixed value produces better correspondence to real-world diversion.



**Figure 28 Comparison of Diverted Volume to ML for Different VOTs**

**Table 11 Diverted Volumes to ML for Different VOTs**

Time (PM)	\$12	\$20	\$30	\$40	\$50	\$40 without Distribution	Real-World
15:30	320	350	340	410	410	403	380
15:45	400	350	340	390	370	380	385
16:00	410	400	350	420	390	370	400
16:15	280	390	400	400	406	375	420
16:30	360	450	380	410	370	391	415
16:45	300	420	400	412	352	403	400
17:00	320	380	320	381	369	341	404
17:15	430	430	390	380	400	370	385
17:30	290	320	310	349	375	320	379
17:45	280	300	290	345	370	308	365
18:00	330	330	300	354	341	325	358
18:15	300	290	300	350	331	304	361

For each value of VOT, the differences between the simulated diverted volumes and the real-world observations were quantified in terms of mean absolute percentage error (MAPE) and root mean square error (RMSE), which are listed in Table 12. The MAPE and RMSE values in Table 12 confirm that the VOT with a lognormal distribution with an average VOT of \$40 produces better results compared to the real-world volumes of the ML. As indicated in Table 12, the corresponding RMSE and MAPE for this case are 18 veh/15 min/ln and 4.01%, respectively;

which indicates very well replication of the diversion. The results in Table 12 also confirm that the use of fixed VOT without utilizing the distribution of VOT does not produce as good results as when using a VOT distribution. The RMSE and MAPE values for the fixed \$40 VOT are 40 veh/mi/15min and 9.03%, respectively.

**Table 12 Goodness of Fit Statistics for Diverted Volume Replication Based on Different VOT**

Goodness-of-Fit Statistics	Value of Time \$ (VOT)					
	\$12	\$20	\$30	\$40	\$50	\$40 without Distribution
MAPE (%)	16.50%	9.70%	11.86%	4.01%	5.73%	9.03%
RMSE(Veh/mi/15min)	73.94	41.76	52.11	18.11	26.60	40.34

**4.2.4.2. Value of Reliability (VOR) Consideration in ML Modeling**

With the same average travel time for two different alternative routes, drivers generally prefer the more reliable alternative with the least day-to-day variability in travel time. However, travel time reliability has not been sufficiently considered in previous managed lane modeling. One of the important contributions of this project is to develop a function that estimates the reliability for inclusion in the generalized cost function of the assignment. In the modeling of ML to assess the impact of travel time variability in the diversion to the ML. Measuring reliability requires to be translated into measures represented by the 80<sup>th</sup> or 95<sup>th</sup> percentile of travel time indices versus the median. In this study, a methodology is proposed to incorporate the impacts of travel time reliability in the selection of managed lanes.

The methodology uses the general function proposed in the SHRP 2 L03 project (Margiotta et al., 2013) and shown in Equation 9.

$$TTI_{n\%} = e^{(k_n dc_{crit} + j_n LHL + l_n R_{0.05})} \tag{9}$$

Where,

- TTI<sub>n%</sub>: n<sup>th</sup> percentile TTI,
- LHL: Lane-hour lost,
- dc<sub>crit</sub>: Critical demand-capacity ratio, and
- R<sub>0.05</sub>: Hours of rainfall exceeding 0.05 inch.

It is recommended that the above equation with its default values are used, or if enough data is available be calibrated for local conditions. The parameters of this function for the case study of this project (I-95 northbound corridor in Miami) were developed using a regression analysis

utilized in the SHRP2 L38C project. The SHRP 2 L38C project developed a regression equation for the I-95 corridor that estimates travel time reliability as functions of demand/capacity (d/c) ratio, lane hour lost due to incidents, and weather conditions as shown in Equation 10 (Hadi et al., 2014):

$$TTI_{n\%} = e^{(b_1 * dc_{crit} + b_2 * LHL + b_3 * R_{0.05} + b_4 + b_5 * Length + b_6 * Length^2 + b_7)} \quad (10)$$

Where,

$TTI_{n\%}$ :  $n^{\text{th}}$  percentile TTI,

LHL: Lane-hour lost,

$dc_{crit}$ : Critical demand-capacity ratio,

$R_{0.05}$ : Hours of rainfall exceeding 0.05 inch,

*Length*: Segment Length (mi), and

$b_1, b_2, b_3, b_4, b_5, b_6,$  and  $b_7$  = Coefficients for  $n^{\text{th}}$  percentile TTI.

According to the above equations,  $TTI_{n\%}$  is the  $n^{\text{th}}$  percentile travel time index. The TTI is the ratio of the travel time at the specific percentile to the free flow travel time for the study segment. Then, the travel time of 80<sup>th</sup> and 95<sup>th</sup> percentiles are calculated. The following descriptions are the variables used in the equation based on SHRP 2 L38C (Margiotta et al., 2013):

- **“Lane hour lost:** The average number of lanes blocked per incident or work zone multiplied by the average duration of blockage and the total number of incidents or work zones during the time interval.
- **Critical demand-capacity ratio ( $dc_{crit}$ ):** The ratio of demand to capacity during the most critical hour of the study period.
- **Hours of rainfall exceeding 0.05 inch ( $R_{0.05}$ ):** The hours of rainfall when exceeding 0.05 inch during the study period.”

**Table 13 Coefficients for Different TTI Percentiles (Margiotta et al., 2013, and Hadi et al., 2014)**

SHRP 2 L03 Project								
Percentile <sup>th</sup>	$j_n$	$k_n$			$l_n$			
10	0.07643	0.00405			0.00000			
50	0.29097	0.01380			0.00000			
80	0.52013	0.01544			0.00000			
95	0.63071	0.01219			0.04744			
99	1.13062	0.01242			0.00000			
SHRP 2 L38C Project								
Percentile <sup>th</sup>	$R^2$	$b_1$	$b_2$	$b_3$	$b_4$	$b_5$	$b_6$	$b_7$
10	0.561	0.271	0.001	0.009	-0.952	0.034	-0.013	0.541
50	0.693	14.000	0.001	0.003	-14.681	-0.452	0.081	1.511
80	0.704	12.802	0.002	0.003	-12.991	-0.782	0.141	1.882
95	0.741	10.763	0.001	0.004	-10.433	-0.632	0.092	1.862
99	0.762	6.792	0.001	0.003	-5.864	-0.591	0.053	1.992
Mean	0.762	12.103	0.001	0.002	-12.631	-0.411	0.071	1.512

To add the reliability and associated values in the generalized cost function, Equation 11 is utilized to incorporate the travel time 80<sup>th</sup> and 95<sup>th</sup> percentiles as estimated from Equations 9 or 10.

$$U = a_1 * TT + a_2 * TC + a_3 * TT_{80\%} + a_4 * TT_{95\%} \quad (11)$$

Where:

U: Utility function for route choice, f (time, cost, reliability),

TT: Estimated travel time (minute),

TC: Toll cost (dollar),

$a_1$ : Travel time coefficient,

$a_2$ : Travel cost coefficient,

$a_3$ : Coefficient for reliability measure (80<sup>th</sup> percentile of travel time), and

$a_4$ : Coefficient for reliability measure (95<sup>th</sup> percentile of travel time).

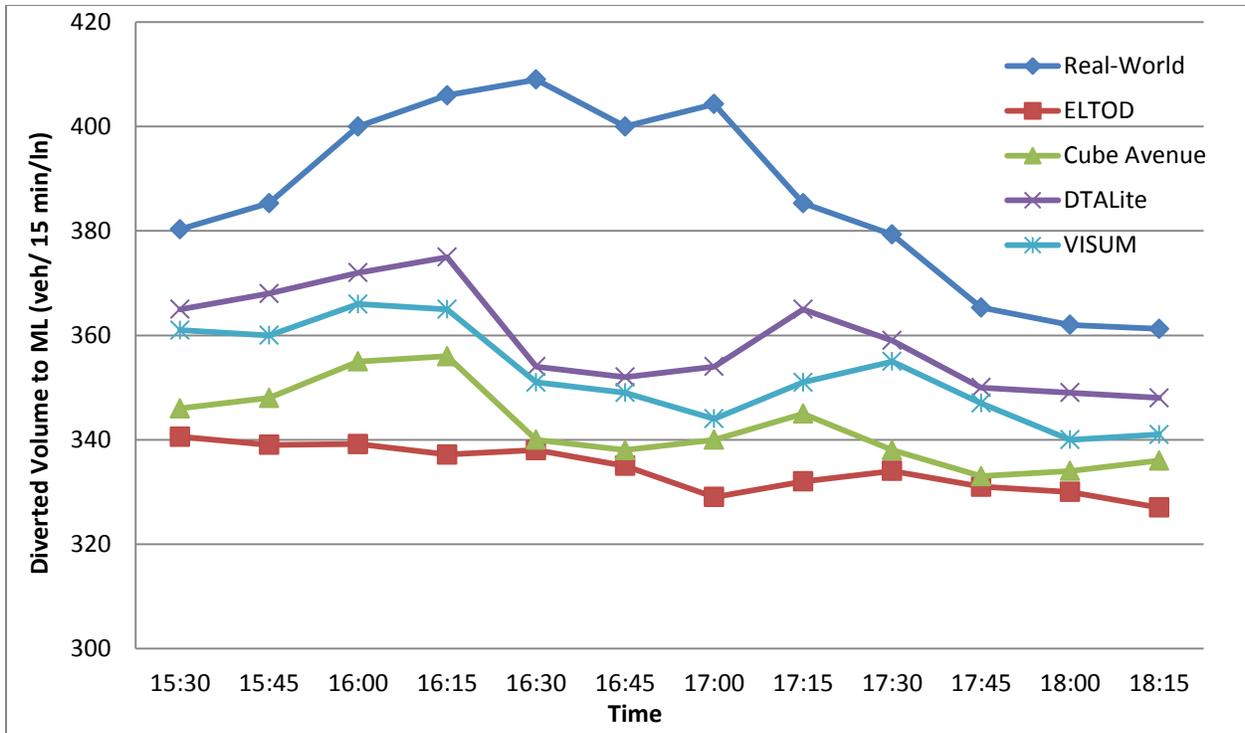
The VOR represents travelers' willingness to pay for reduction in travel time variability. The SHRP2 C04 project evaluated the reliability ratio (VOT/VOR) for an average trip distance and found that the ratio is in the range of 0.7 to 1.5 based on a stated preference (SP) survey conducted in that project (Parsons Brinckerhoff et al., 2013). In this study, a value of 1.1 is assumed for the ratio VOT/VOR, which is corresponding to  $a_1/(a_3+a_4)$  and  $a_1$  is calculated according to Equation 12.

$$a_1 = 1.1(a_3 + a_4) \quad (12)$$

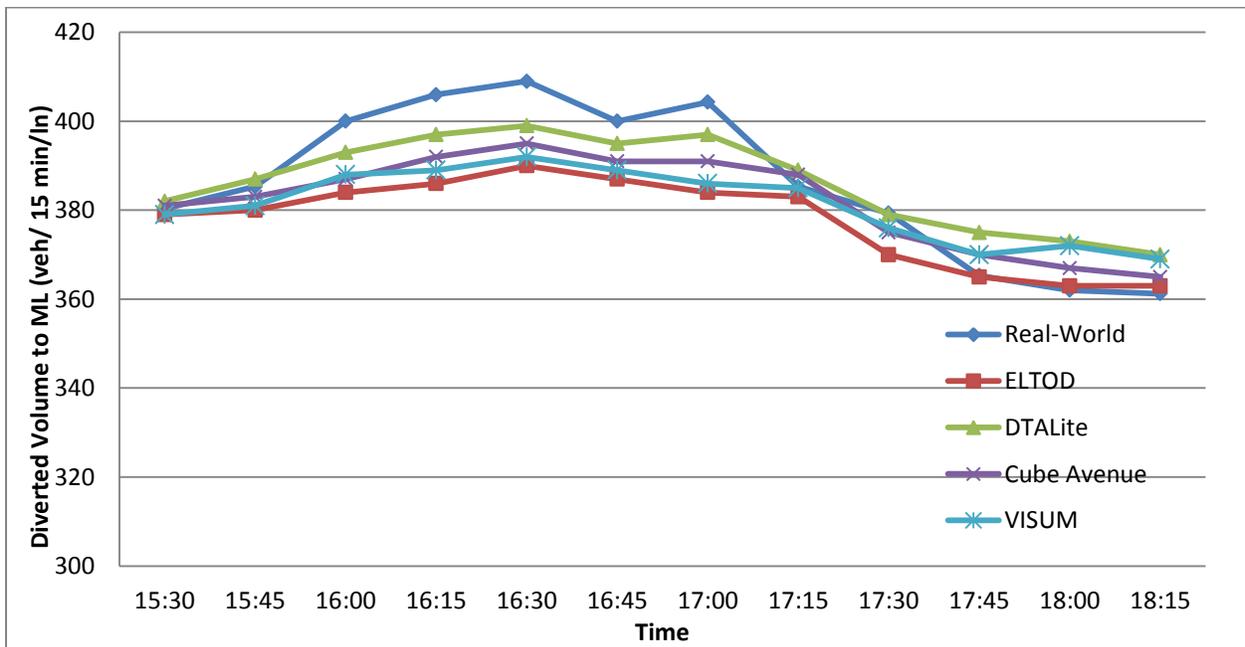
where  $a_3$  is assumed to be equal to  $a_4$  assuming that travelers put the same weight on the 80<sup>th</sup> and 95<sup>th</sup> percentile travel time. Based on Equation 12 and the above assumptions, and considering that the best VOT when not using reliability in the generalized cost function, is about \$42;  $a_1$ ,  $a_3$ , and  $a_4$  are estimated to be 22, 10, and 10, which results in a total VOT of \$22 and VOR of \$20.

As the travel time indices are calculated based on the real-world data, they may not be consistent with the modeled values. Therefore, instead of directly using these calculated values in the traffic assignment, the ratios of the 80th and 95th percentile travel time indices to the mean travel time index were calculated and these ratios were multiplied with the simulated mean travel times in the assignment to obtain the simulated 80th and 95th percentile travel time indices. These resulting indices are then incorporated in the generalized cost function utilized in the dynamic traffic assignment based on Equation 11.

Figures 29 and 30 show the diverted volumes to ML without and with the consideration of VOR, respectively. As shown in these figures, the results generated from different ML modeling tools are closer to the real-world observations when the VOR is considered in the ML modeling. Please note that because the modeling of dynamic pricing in DTALite requires the use of API code and is not explained in the program documentation, a fixed value is used for toll in the DTA modeling instead of using dynamic pricing. Fixed toll values were also used in VISUM. Dynamic pricing that replicates real-world tolling policy was used in Cube Avenue. Dynamic pricing based on volume/capacity ratio was used in ELToD.



**Figure 29 Comparison of Diverted Volume to ML without Consideration of VOR Utilizing Different Tools (Using Fixed \$40 VOT)**



**Figure 30 Comparison of Diverted Volume to ML with the Consideration of VOR Utilizing Different Tools (VOT of \$20, VOR of \$10 for the 80% TTI, and VOR of \$10 for 95% TTI)**

The corresponding MAPE and RMSE values to the results presented in Figures 29 and 30 are summarized in Table 14. All results are based on a \$40 VOT, which was presented in the previous section. The results show that DTALite with the consideration of VOR can produce better results compared to other tools, relative to the real-world diverted volumes to the ML. When the VOR is considered, the results from all tools are significantly improved.

**Table 14 Goodness of Fit Statistics for Diverted Volume Replication with and without the Consideration of VOR (Using \$40 VOT)**

Goodness-of-Fit Statistics		ELToD	Cube Avenue	DTALite	VISUM
With Consideration of VOR	RMSE (Veh/mi/15min)	12.00	9.18	8.23	10.77
	MAPE (%)	2.29	1.96	1.89	2.27
Without Consideration of VOR	RMSE (Veh/mi/15min)	54.30	46.22	31.02	37.03
	MAPE (%)	13.36	11.29	6.93	8.68

**4.2.4.3. Effect of Changing Dynamic Pricing**

The previous analysis assumed a fixed pricing to the modeling of ML. The benefit of modeling the dynamic toll policy used for the I-95 northbound managed lane in Miami, FL instead of an assumed fixed toll value was also investigated in this study. Instead of a fixed toll, the dynamic I-95 ML pricing is defined as a function of maximum traffic density along the managed lanes with a purpose of maintaining a desired level of service, as is done in the real-world. This toll policy was modeled in Cube Avenue using the script language of Cube. During each time interval in Cube Avenue, the maximum link density is calculated by comparing the densities of all the ML links in each direction. Once the maximum density is found, the corresponding toll cost (\$) is obtained by looking up a predefined toll policy table.

Table 15 shows the I-95 ML toll policy before March 1, 2014. In order to relieve the congestion along the ML, the FDOT D6 increased the minimum toll from \$0.25 to \$0.50 and the maximum toll from \$7.00 to \$10.50 as shown in Table 16. This study tested the ability of the ML models to estimate the increase in diversion when changing the managed lane pricing and other policies. The tested models utilized the VOT and VOR in the generalized cost function, as assumed in the previous section. Since VISUM and DTALite only allow a fixed toll rate, they are not included in this dynamic analysis.

**Table 15 I-95 ML Old Toll Policy (before March, 2014)**

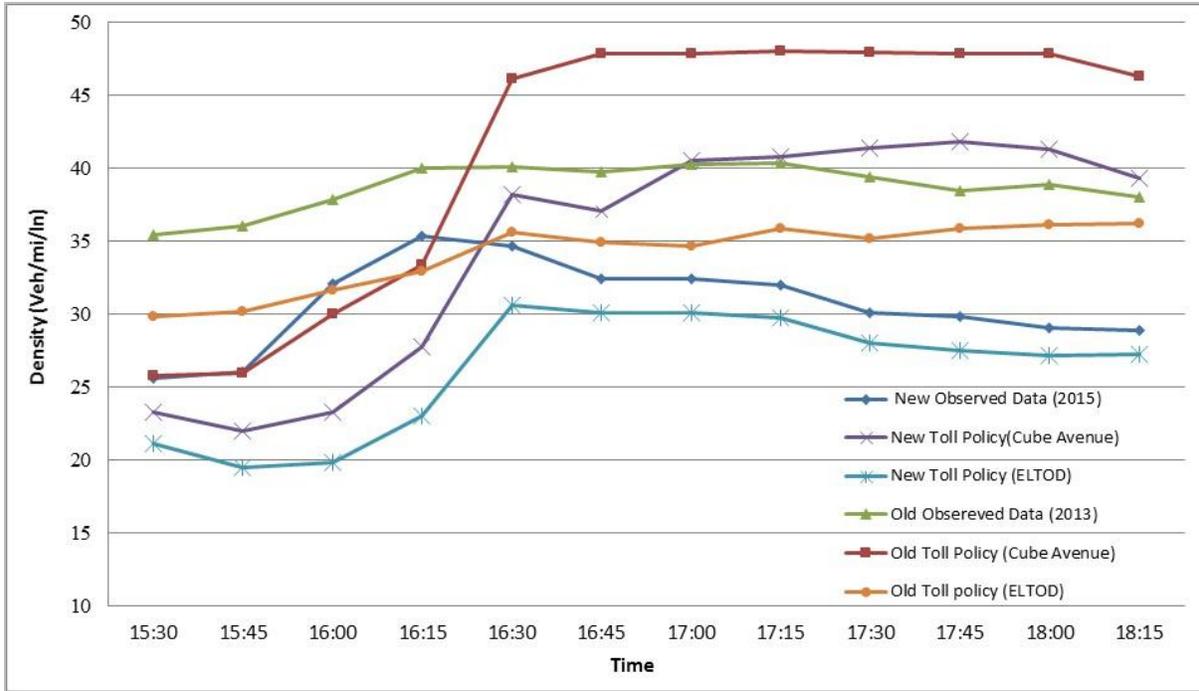
Level Of Service	Road Density (Veh/mi/ln)		Toll Cost (\$)	
	Minimum	Maximum	Minimum	Maximum
A	0	11	0.25	0.25
B	12	18	0.5	1.25
C	19	26	1.5	2.75
D	27	35	3	3.75
E	36	45	3.75	6
F	>45		6	7

**Table 16 I-95 ML New Toll Policy (after March, 2014)**

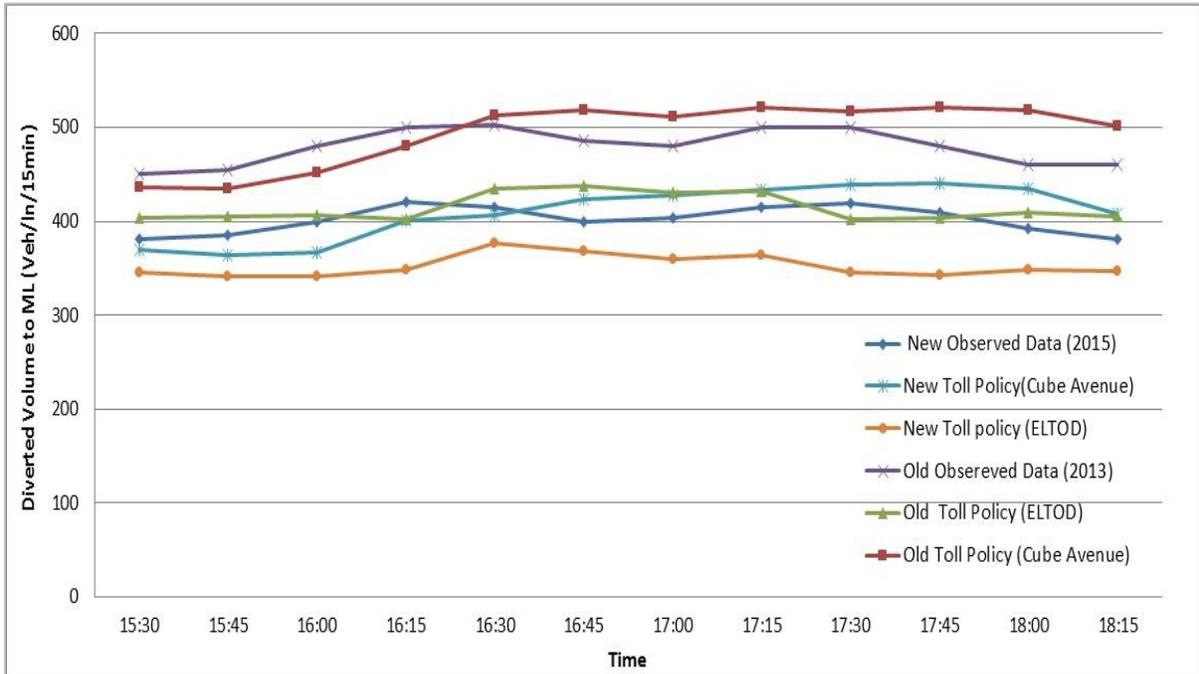
Level Of Service	Road Density (Veh/mi/ln)		Toll Cost (\$)	
	Minimum	Maximum	Minimum	Maximum
A	0	11	0.5	0.5
B	12	18	0.5	1.55
C	19	26	1.5	8.5
D	27	35	8.5	9.5
E	36	45	9.5	10.5
F	>45		10.5	10.5

Figure 31 shows the toll-density curve of the ML with the old and new toll policies for the I-95 ML based on utilizing dynamic pricing model in Cube Avenue and ELToD. It should be noted that the observed data in this figure refer to the density estimated from the real-world detector data. It can be seen from this figure that the new policy resulted in a reduction in the density of the managed lanes due to higher toll cost and this was also reflected in the utilized tool results.

Figure 32 presents the corresponding results for the diverted volume when using the old and new toll policies with different tools. It can be seen in this figure that ELToD, a static assignment-based ML model, underestimates the diverted volumes to the ML based on the old toll policy and the new toll policy. However, the dynamic assignment-based managed lane model implemented in Cube Avenue can produce better results of the diverted volume compared to the real-world measurements. It can also be seen that the differences between the diverted volume to the ML before and after implementing the policy are the same in the simulated and observed data, which indicates that the ML models in ELToD and Cube Avenue are able to capture the impacts of toll policy changes.



**Figure 31 Comparison of Density Using Old and New Toll Policies for I-95 NB**



**Figure 32 Comparison of Diverted Volume to ML Using Old and New Toll Policies for I-95 NB**

The results of the percentage share of ML volumes compared to total volumes along the corridor utilizing different tools for different toll scheduled policy are presented in Table 17. The percentage of ML share in this table is calculated as the number of vehicles diverted to managed lanes divided by total number of vehicles traveling along the corridor at the entrance of managed lanes.

**Table 17 Variation of Percentage of ML Share with Respect to Toll Scheduled Policy Utilizing Different Tools (%)**

Time	Old Toll Policy			New Toll Policy		
	ELToD	Cube Avenue	Real-World	ELToD	Cube Avenue	Real-World
15:30	32.44	35.10	36.21	27.78	29.70	30.60
15:45	32.57	34.97	36.61	27.52	29.28	31.00
16:00	32.71	36.34	38.62	27.42	29.53	32.18
16:15	32.32	38.68	40.23	28.04	32.20	33.82
16:30	35.02	41.31	40.47	30.30	32.69	33.42
16:45	35.17	41.66	39.10	29.61	34.03	32.18
17:00	34.70	41.20	38.62	28.98	34.44	32.53
17:15	34.77	42.00	40.23	29.30	34.92	33.42
17:30	32.39	41.59	40.23	27.78	35.32	33.73
17:45	32.53	41.98	38.62	27.63	35.48	32.93
18:00	32.93	41.68	37.01	28.01	35.00	31.56
18:15	32.63	40.39	37.01	27.90	32.83	30.60

#### ***4.2.5. Assessing the Impacts of CACC on Managed Lane Modeling***

This section presents the discussion of the impacts of CACC technology on managed lane modeling.

##### **4.2.5.1. Capacity Impact Estimation Based on Microscopic Simulation**

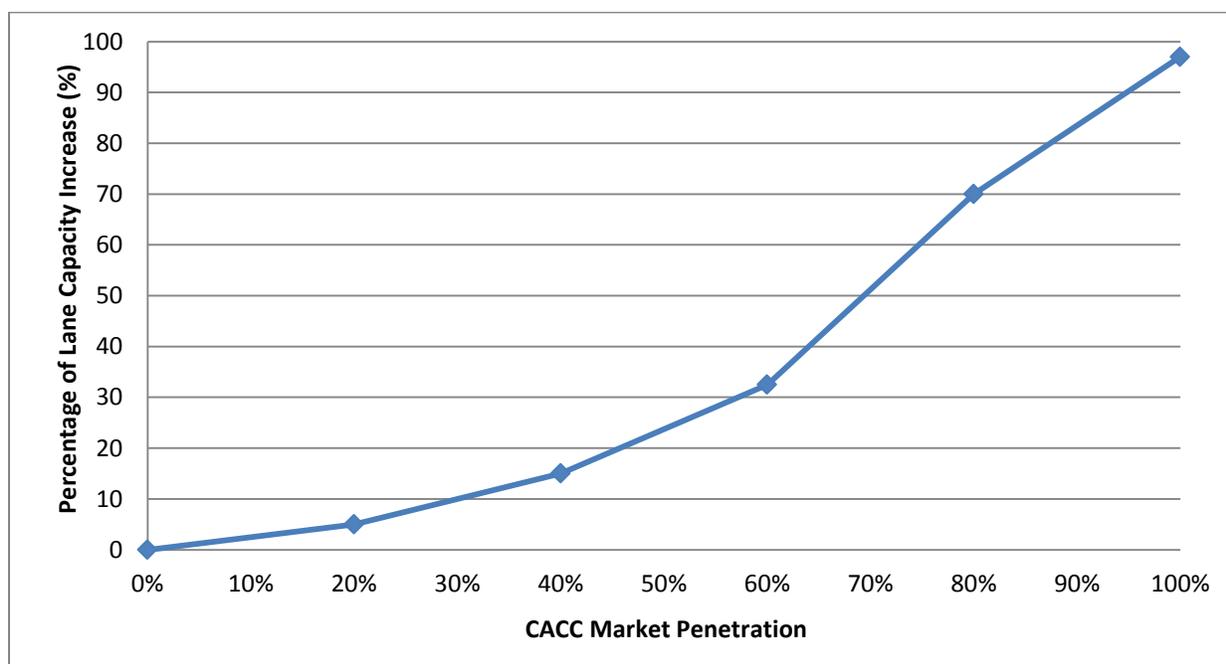
Shladover et al. (2012) applied a microscopic simulation model in AIMSUN to simulate lane capacity as a function of the proportions of CACC vehicles in traffic stream. The time gap distribution that was used in a real-world field test were used as inputs into the car-following model in AIMSUN. The parameters of the car-following models are the distance between vehicles, speeds of both the preceding and following vehicles, and vehicle lengths.

The scenario with all manually driven vehicles was used as the base scenario. The simulation of this base scenario resulted in an average capacity of 2,018 veh/ln/hr, in accordance with the Highway Capacity Manual (HCM) estimates.

The desired time gaps of ACC-equipped and CACC- equipped vehicles used in the simulation were identified from the gaps selected by drivers in the field test, as listed below:

- ACC: 31.1% at 2.2 sec, 18.5% at 1.6 sec, and 50.4% at 1.1 sec
- CACC: 12% at 1.1 sec, 7% at 0.9 sec, 24% at 0.7 sec, and 57% at 0.6 sec.

When basic ACC vehicles with the above time gaps were simulated in the traffic stream, the capacity increased within a narrow range from 2,018 veh/ln/hr to 2,100 veh/ln/hr, which is close to the base scenario capacity, regardless of the market penetration. This can be explained by noting that drivers of ACC-equipped vehicles use similar time gap setting to the time gaps that they set when they drive manually (the base scenario). However, when various combinations of manually driven and CACC vehicles were considered, the results showed that the capacity grew slowly the CACC market penetration was low, and then it grew more rapidly as the market penetration increased further. With 100% of CACC vehicles in the traffic, the lane capacity would increase from 2,018 veh/ln/hr to 3,970 veh/ln/hr, which means 97 % capacity increase, compared to the base capacity. Figure 33 shows the percentage of lane capacity increases with the different market penetration of CACC vehicle based on the results from Shladover et al. (2012).



**Figure 33 Impacts of CACC Vehicle Proportion on Lane Capacity (Shladover et al., 2012)**

The results from microscopic simulation, according to Shladover et al. (2012), indicate that the capacity is not significantly impacted by the introduction of ACC equipped vehicles into the traffic stream. However, the increase in the percentage of CACC technology increases the capacity significantly. If preferential treatment is given to CACC vehicles when using ML, this is expected to result in an increase in their percentage on ML and thus is expected to improve

mobility benefits of these devices by having more CACC vehicles concentrated on the lanes, which is an alternative way to improve capacity. These potential impacts are investigated in this study using static traffic assignment and mesoscopic simulation modeling based on DTA using the results from the microscopic simulation. This analysis approach can be considered as a multi-resolution modeling (MRM) approach since it uses results from macroscopic, mesoscopic, and microscopic models.

#### **4.2.5.2. Modeling the Impacts of CACC Vehicle Based on Macroscopic and Mesoscopic Simulation**

This study examined the assessment of the impacts of CACC vehicle technologies on the performance of ML and GPL in the exploration network using macroscopic and mesoscopic models based on capacity estimates from microscopic simulation models by Shladover et al. (2012), as described in the previous section. The assessment was based on the capacity estimated by Shladover et al. (2012). This capacity was coded as a variable in demand forecasting modeling tool with macroscopic traffic model and a mesoscopic simulation-based DTA tool. The capacity was allowed to vary in each assignment iteration, as a function of the percentages of CACC in traffic streams in that iteration, according to the findings from the microscopic simulation study.

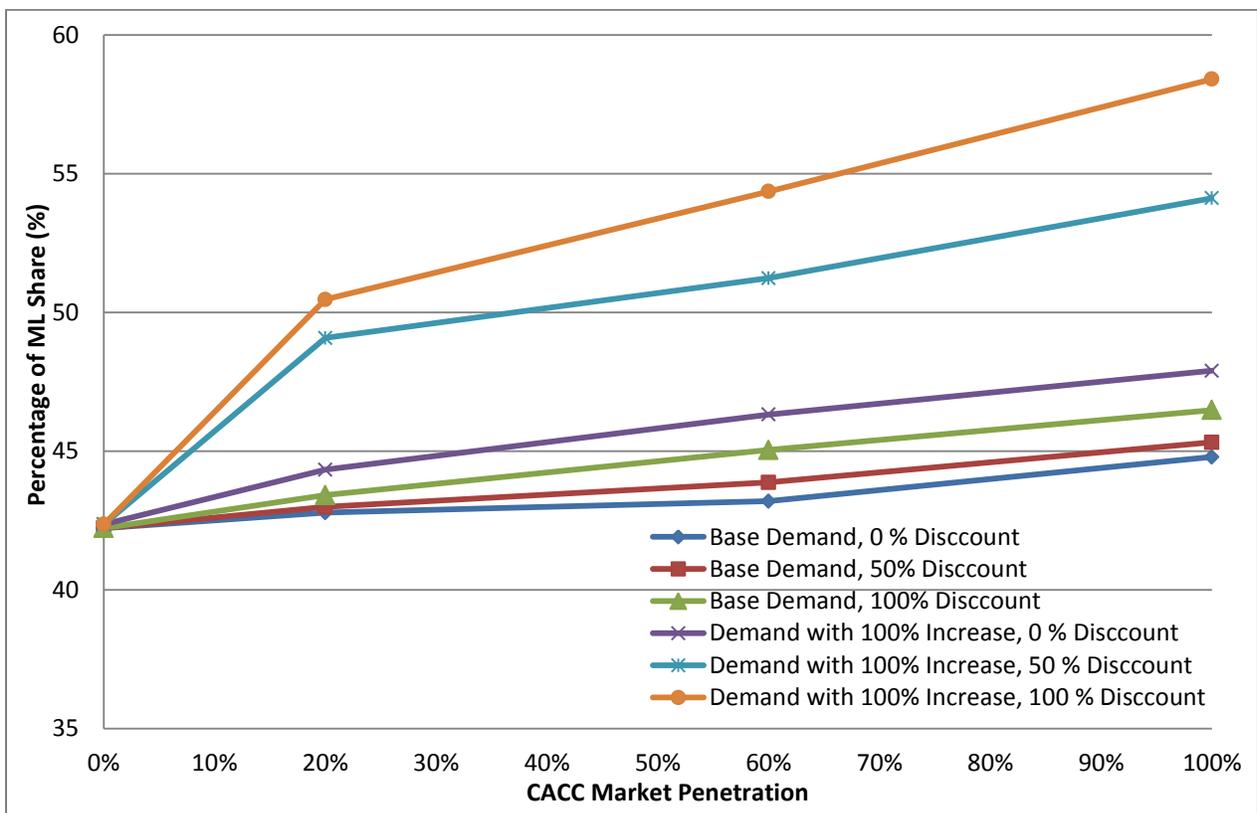
Macroscopic traffic flow-based STA and mesoscopic simulation-based DTA were used to assess diversions between GPL and ML, in response to different CACC-equipped vehicle market penetrations and different ML strategies in the exploration network, which includes eight miles of the northbound direction of the I-95 freeway corridor in Miami, FL with 288 nodes, 303 links and 57 zones. As described earlier in the methodology section, three different user groups of demand matrices were used in the model: Tolled Vehicles, Shared Ride of three or more occupants (SRP3), and Truck. SRP3 were allowed to use the ML without any cost or restriction, and trucks were not allowed to use ML.

In this research, the mobility impacts of CACC-equipped vehicles were modeled first based on the macroscopic traffic flow-based STA implemented in the SERPM. The same scenarios were also modeled in Cube Avenue, a mesoscopic simulation-based DTA tool. The results from STA and DTA were aggregated into peak period values for comparison purposes.

Although various projections have been reported in the literature to predict the market penetration of CACC vehicles from now until year of 2040, there is no consent yet on one specific projection. Therefore, a sensitivity analysis was conducted in this study to examine the impacts of CACC vehicle market penetration. Four values of market penetration were considered in the study, which were 0%, 20%, 60%, and 100%. Also, a tolling policy was tested in this study, to give incentive to the vehicles equipped with CACC and encourage them to use

the managed lanes by providing toll pricing discount to these vehicles. The rationale behind this policy is that for a given demand, the maximum managed lane throughput is expected to increase as the percentage of CACC vehicles traveling along the managed lanes increases due to smaller gaps between vehicles, which may help reduce congestion on the managed lanes and along the parallel general purposed lanes. In addition, two demand levels were included in the analysis, one corresponding to the existing travel demand and another with 100% increase in demand to represent an extreme case of increase in future demand.

The impacts of the CACC market penetration, toll discount rates and demand level on the portion of travelers that select the managed lanes under different scenarios was examined first using STA and the corresponding results are displayed in Figure 34.



**Figure 34 Variation of Percentage of ML Share with Respect to CACC Market Penetration Using STA**

As shown in Figure 34, based on the STA analysis, the percentage of ML share increases with the increase in the CACC market penetration for a given demand level and toll discount. It should be noted that the percentage of ML share in this figure is calculated as the number of vehicles diverted to managed lanes divided by the total number of vehicles traveling along the corridor at the entrance of managed lanes. The managed lane has two entrance points close to

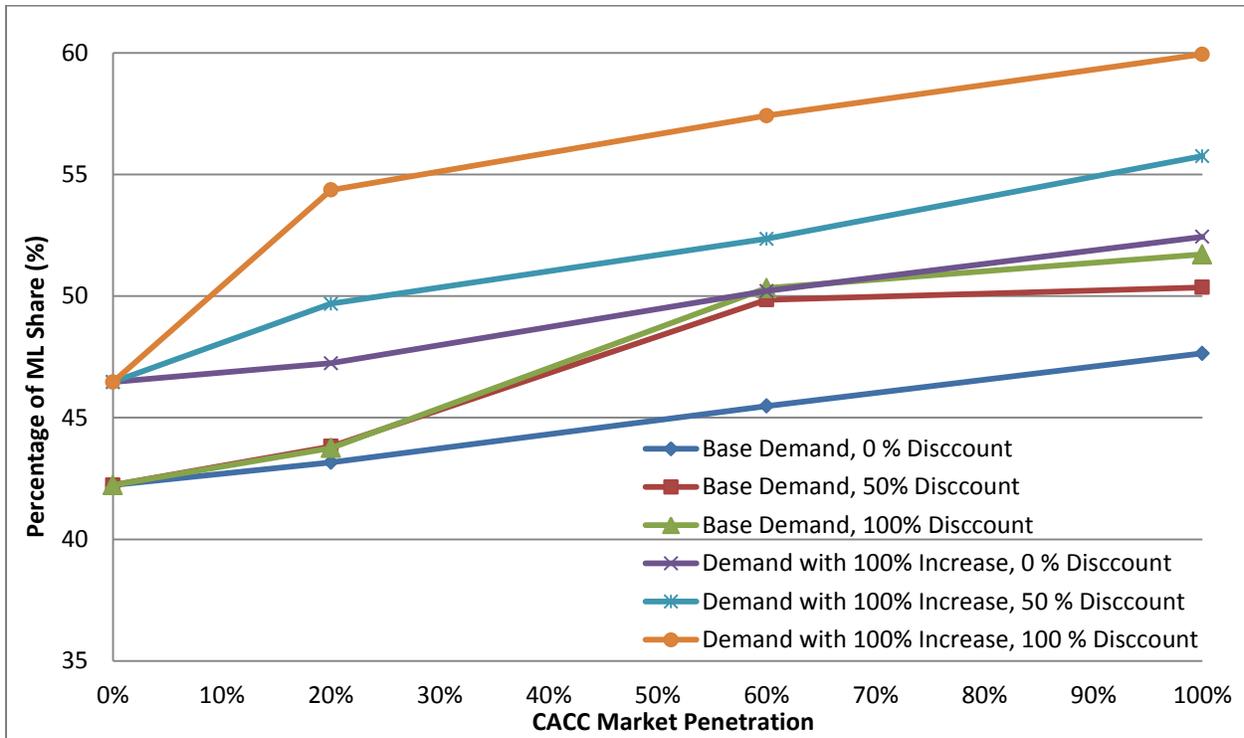
each other at the beginning of the system and the ML and GPL are separated until the end of the system. There are many ramps feeding the system and the higher percentages of vehicles that can be diverted to ML at the beginning of the system. It should be noted that due to the separation between ML and GPL, on-ramp vehicles have to use the GPL and cannot use the ML. In addition, all vehicles at the entrance of the system that are destined to off-ramps on the study segments are not able to use the ML due to the fact that they are not able to exit the ML to get to the off-ramps. Thus, the separation between GPL and ML creates a maximum limit on the number of vehicles that are able to use the ML.

With the base demand, this increase is from about 42% for 0% CACC market penetration to about 45%-46% for 100% CACC market penetration depending on the values of the toll discount rate. It appears that with the current demand, at small market penetrations of CACC, the increase in capacity due to CACC is small according to the relationship between the capacity and CACC vehicle proportion used in this study. Thus, as incentives are given to CACC vehicles and they divert to the ML in the assignment iterations.

At higher market penetrations and with the base demand level, the capacity increase on the GPL and ML is significant, reducing the congestion on the GPL and the ML, and thus results in the motivation to shift to the ML. As the demand doubled with an increase of 100% in demand, the percentage of the ML share shows a significant increase from about 42% for 0% CACC market penetration to 48%-58% for all CACC toll discount rates when the CACC market penetration is 100%. Also, it can be seen that the increase in the toll discount rate for vehicles equipped with CACC can attract more vehicles to use managed lanes, especially when the market penetration of CACC is high. For example, at 60% market penetration, the ML share increased from 46% to about 54% when 100% discount is provided.

Figure 35 presents the DTA-model based results of the percentage share of ML volumes compared to total volumes along the corridor. Again, the percentage of ML share in this figure is calculated as the number of vehicles diverted to ML divided by total number of vehicles traveling along the corridor at the entrance of managed lanes. It is interesting to note that the results in this figure show similar trends as those shown in Figure 34, described earlier. However, the increase in the ML percentage share with the increase in demand and toll discount is more in the DTA modeling compared to the STA modeling, reflecting the ability of DTA to better model congestion impacts. Compared to the STA modeling, simulation-based DTA considers the capacity constraint, as well as the queue propagation and thus produces more realistic results. It is seen from Figure 35 that for the scenarios with base demand, the percentage of ML share can be increased from 42% when CACC market penetration is 0% to 47%-52% for 100% CACC market penetration, which is higher than the percentage share of 45% - 46% resulted from the STA modeling. Similarly, for the high demand scenario (100% increase in demand), the percentage of ML share is about 42% for 0% CACC market penetration and

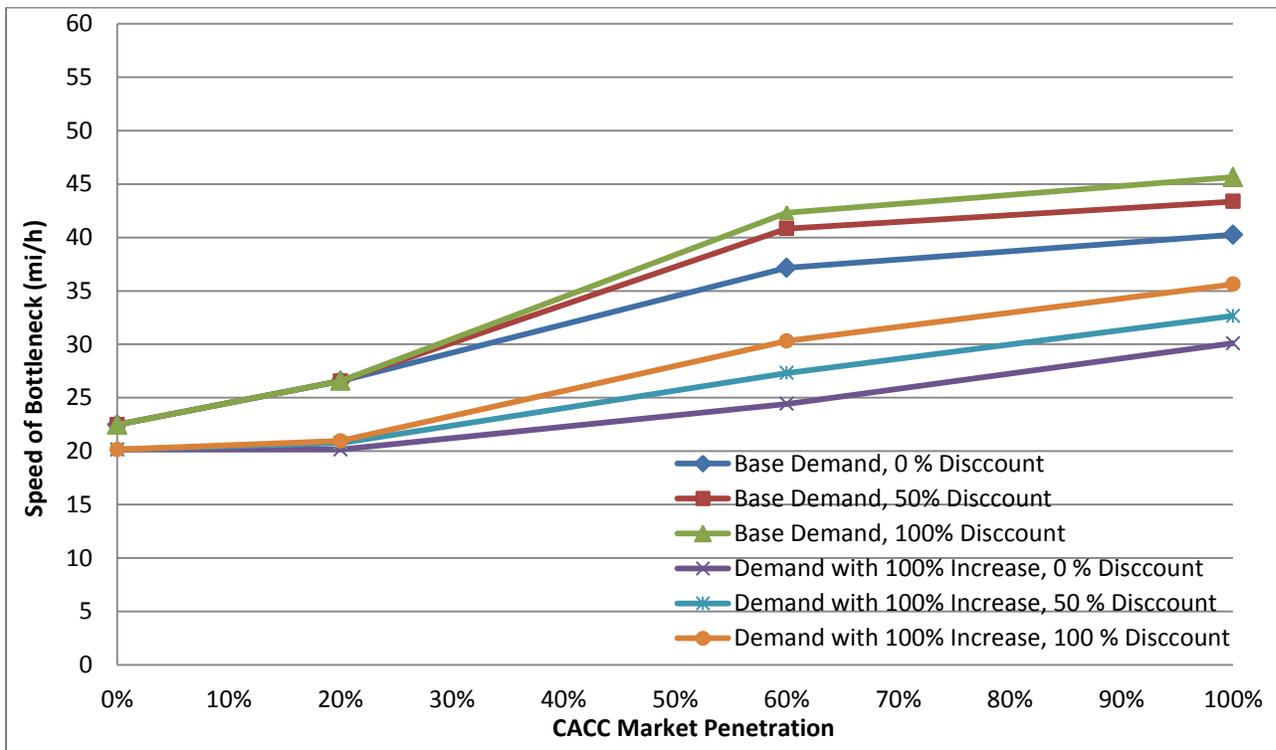
about 48% - 58% for 100% CACC market penetration based on the STA results. These values are 52% - 60% for 100% CACC market penetration according to the DTA modeling results. It should be noted that high demand causes higher congestion, which gives incentives for more drivers to use managed lanes and therefore results in a higher ML percentage share. Another example comparison is that at 60% CACC market penetration with the base demand, proving 100% discount increases market penetration from 43% to 45% according to the STA and from 45% to 50% according to the DTA.



**Figure 35 Variation of Percentage of ML Share with Respect to CACC Market Penetration Using DTA**

One of the bottleneck locations was at the NW 103<sup>rd</sup> St. interchange along the study corridor. Figure 36 presents the corresponding worst speed at this location along the GPL during the analysis period, according to the STA analysis. The results in this figure show that the speed at bottleneck location increases when the market penetration of CACC is increased and the discount rate is increased because of higher roadway capacity associated with the higher percentage of CACC and the increasing shift to ML. When the CACC market penetration is less than 20%, the toll discount does not show a significant impact on the bottleneck location speed. This can be explained again by the earlier discussion that with small market penetrations of CACC the increase in capacity due to CACC is small according to the relationship between capacity and CACC vehicle proportion used in this study. Thus, as incentives is given to CACC vehicles and they divert to ML in the assignment iterations, the congestion on the ML and the

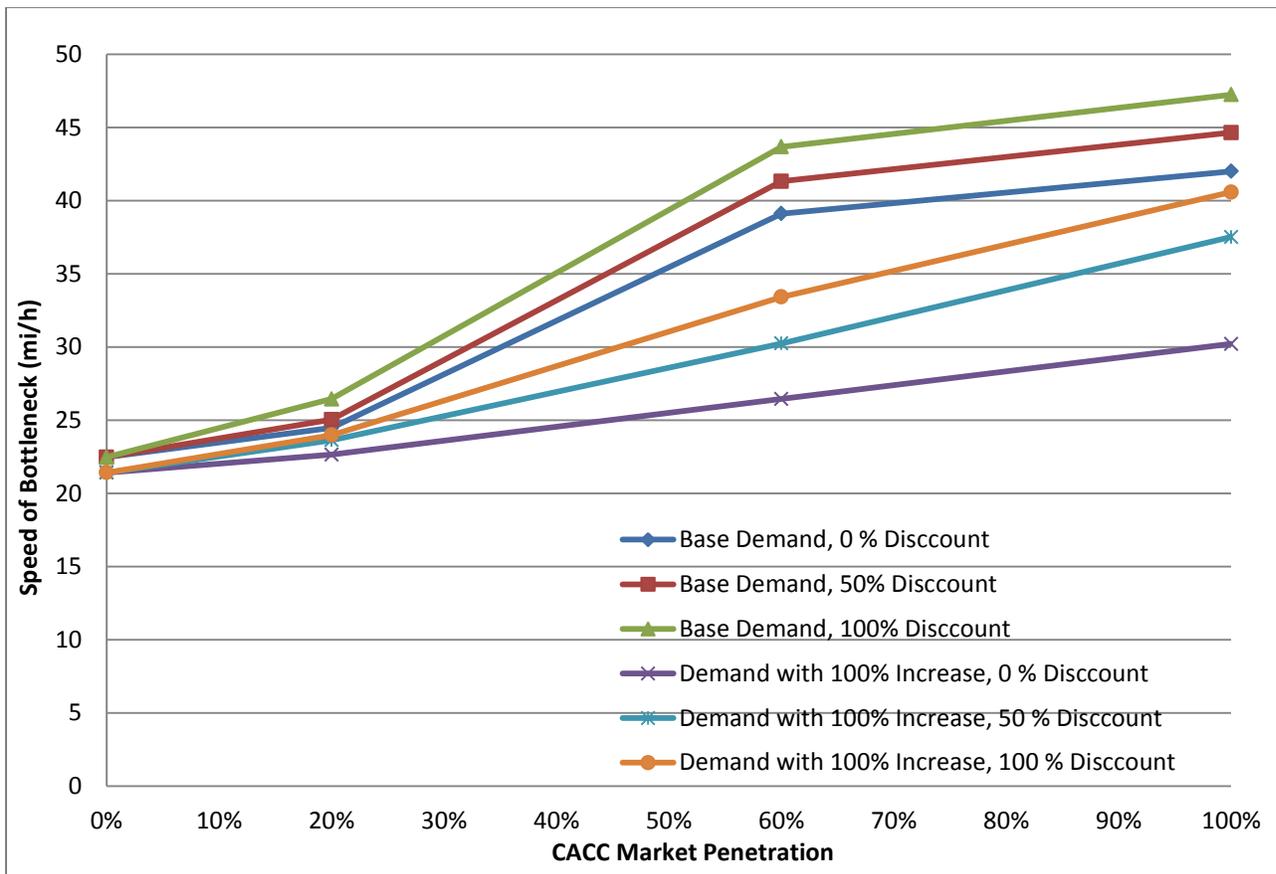
toll charged using a dynamic pricing algorithm increases, causing the CACC vehicle to shift back to the GPL. However, an about 5 mi/h increase in speed can be observed from Figure 36 due to toll discounts at higher CACC market penetrations. When the demand is increased by 100%, the speed at the bottleneck location becomes lower compared to the scenarios with base demand. However, the changes of bottleneck location speed with respect to CACC market penetration and toll discount rates are similar for these two demand levels.



**Figure 36 Variation of Speed at Bottleneck Location with Respect to CACC Market Penetration Using STA**

Figure 37 presents the corresponding DTA analysis for the speed at the worst bottleneck location along the GPL. As shown in this figure, the bottleneck location speed is improved with the increase in CACC market penetration, especially at the high CACC market penetrations. A close comparison of the results in Figure 36 and Figure 37 reveals that for the scenarios with the base demand, the implementation of different toll discounts can cause about 5 mi/h difference in the bottleneck location speed given a CACC market penetration of 100% based on both STA and DTA simulations. However, increasing the toll discount rate from 0% to 100% at the 100% CACC market penetration can improve the bottleneck location speed from 30 mi/h to 40 mi/h according to the DTA analysis, as shown in Figure 37, while such improvement in bottleneck location speed is only from 30 mi/h to 35 mi/h according to the STA results in Figure 36. This is consistent with the impacts of toll discount rate on the percentage of ML share utilizing STA and DTA, shown in Figure 34 and Figure 35, in which DTA modeling results show more vehicles

using the ML than the STA modeling results, which causes a higher speed at the bottleneck location in DTA modeling compared to STA modeling.



**Figure 37 Variation of Speed at Bottleneck Location with Respect to CACC Market Penetration Using DTA**

The results of this section demonstrate the benefit of using results from tools with different resolution of modeling to support each other's analyses. In general, the trends obtained based on results from the STA modeling of advanced vehicle technologies in terms of the market share of traffic in ML and the reduction in congestion on GPL are consistent with those obtained from DTA. However, DTA results show more significant shifts due to its better modeling of traffic congestion. The results also show that providing toll incentives for CACC-equipped vehicles to use express lanes is not beneficial at lower market penetration due to the small increase in capacity with these market penetrations. Such incentives are beneficial at higher market penetrations, particularly with higher demand levels.

### 4.3. Summary

As an example, the framework developed in this project was applied to model managed lanes. A list of managed lane modeling-related assessment criteria were developed in this study and applied to evaluate a number of tools. The assessment results are presented in Appendix A. It is seen that different managed lane modeling tools have different strengths. The Cube Avenue model for I-95 managed lanes developed in the previous study was converted into other tools including ELToD, DTALite, and VISUM utilizing the NeXTA interface. The impacts of traffic flow model and O-D matrix estimation on managed lane modeling results from different tools were also studied and compared based on real-world data. The supply calibration results show that the use of the calibrated capacity and jam density in the traffic flow model improves the simulation results, and reduces the deviations from the real-world speeds. The demand calibration results indicate that the dynamic OMDE can produce better estimates of O-D matrix than static-based ODME. The quality of the O-D estimation in all tools is found to be greatly dependent on the quality of the initial O-D matrix. The ODME process in DTALite can produce better link volume results than those obtained using Cube Avenue and VISUM although the quality of the VISUM ODME results is close to that of DTALite. Some fine-tuning of the matrices produced from the ODME can further improve the results.

The core of managed lane model is to accurately model travelers' preference to use managed lanes. Such preference greatly relies on the parameters of the value of time (VOT), value of reliability (VOR), and dynamic toll pricing. A sensitivity analysis was conducted in this study to examine the impacts of VOT. The results showed that the VOT of \$40 produced the best results in terms of predicting the utilization of managed lane. This value is much higher than the VOT commonly used in the assignment practices, for example, the VOT of \$13.30 used in the SERPM model. The results from this research also confirmed that utilizing a distribution of VOT, instead of a fixed value, produces better predictions of real-world utilization of managed lane.

This research developed a new method to assess reliability in macroscopic and mesoscopic simulation based on the equations developed in the SHREP 2 L03 and L07 projects. Previous reliability estimation studies used either a scenario-based approach that was too time-consuming to incorporate in the assignment iterations, or a simplified approach that did not account for important factors that affect unreliability such as incidents, work zones, and bad weather. In this study, an innovative methodology was proposed to assess travel time reliability in the traffic assignment process for managed lane modeling. It includes travel time reliability into the generalized costs, which is estimated based on regression equations developed as part of the SHRP 2 L03 project and later calibrated for the case study corridor (I-95 corridor in Miami) in the SHRP 2 L38C project. According to these equations, the travel time reliability is estimated as functions of demand/capacity ( $d/c$ ) ratio, lane hour lost due to incidents and work zones, and weather conditions. The equation allows the prediction of various percentile travel time index.

The analysis results also highlighted the importance of utilizing the VOR in the generalized cost function. There are significant differences between the simulated and real-world volumes of managed lane when the VOR is not included in analysis. The above discussion indicates the importance of selecting a tool that allows the inclusion of VOR in the assignment and the consideration of VOT variations between users.

When managed lane is congested, the toll rate may be increased to divert vehicles out of managed lanes in order to relieve the congestion in managed lanes, as what FDOT District 6 has implemented for I-95 Express Lane. The impacts of such changes in toll policy were also investigated in this study. The percentages of managed lane usage resulted from the DTA-based tools tested in this study are comparable with real-world data when dynamic pricing is modeled. However, static traffic assignment models were less successful in estimating the link volumes but they also produced reasonable results in terms of the amount of vehicles shifted to managed lanes. This clearly indicates that DTA-based mesoscopic and macroscopic models are preferred compared to STA-based models like ELToD and FITSEVAL. Further assessment of the use of microscopic model, as part of this framework will be discussed when the Miami-Dade I-95 VISSIM model is received from FDOT District 6.

This study also proposed one method to model the impacts of ACC and CACC combined with a toll policy that gives incentives to the vehicles equipped with CACC to encourage them to use the managed lanes by providing toll pricing discounts to these vehicles. This method was implemented in both static and dynamic assignment models based on capacity estimates from microscopic simulation models. For a given demand, the maximum managed lane throughput was expected to increase as the percentage of CACC vehicles traveling along a lane increases due to smaller gaps between vehicles.

## **5. ORIGIN-DESTINATION MATRIX ESTIMATION USING DATA FROM DIFFERENT SOURCES**

Origin-destination matrix estimation (ODME) modules have been developed by different vendors of static and dynamic traffic assignment tools to estimate the O-D matrices to better match real-world volumes, starting from initial O-D matrices that are normally obtained from demand forecasting models. An assessment of the tools provided by different vendors are presented in Section 3. These tools generally have optimization procedures to derive O-D matrices by minimizing the differences between the estimated volumes from the assignment results and the measured values. The traffic volumes are normally obtained from permanent and portable count stations installed by planning agencies, point sensors installed by traffic management agencies, traffic count tubes, or combinations of the above. Data are becoming available from new sources that can provide additional inputs to the optimization process to allow better solutions. These sources include O-D matrices collected using automatic vehicle location (AVI) technology, also known as automatic vehicle re-matching technologies, such as Bluetooth and Wi-Fi data and private sector data. It is recognized that the data from these sources may be for partial trips that do not cover the full trip, meaning that they identify trips between points located on the paths between the origins and destinations. This happens for example because the Bluetooth/Wi-Fi readers are not normally located at points that represent the origins and destinations used in the model or because the third party vendor O-D zones do not correspond to the modeling zones. It is also realized that the sample size obtained from these sources is not very high. Thus, data from various sources need to be combined to produce O-D matrices of good quality.

One of the tasks in this project is to explore how the inclusion of additional data sources into the ODME procedure will affect the accuracy of the ODME. To achieve this goal, the ability of dynamic traffic assignment-based ODME procedures utilizing traffic counts to improve the initial O-D matrix obtained from demand forecasting models was first examined. Then, the benefits of using partial trip data from a third party vendor and Bluetooth readers as well as turning movement counts in combination with volume count data as part of the ODME process was analyzed utilizing the capability of the Cube Analyst Drive module.

### **5.1. Review of Literature**

The O-D matrix estimation problem based on static and dynamic traffic assignment has been studied extensively in the literature (Cascetta et al., 1993; Mahmassani and Tavana, 2001; Shabaniyan, 2014). It is recognized, however, that the use of only link volumes from detector locations separated around the network results in an underdetermined optimization problem in O-D estimation, as the number of independent link counts is less than the number of time-

dependent O-D pairs. To overcome this issue, researchers proposed using data from other sources to supplement count data.

The most basic use of AVI data is to utilize them to validate and adjust the initial O-D matrices coming from the demand models. For example, the I-95 managed-lane modeling study in Broward and Palm Beach County, FL, used the Bluetooth data to verify and adjust the model's O-D patterns and trip lengths (Corradino Group, 2013).

Zhou and Mahmassani (2006) proposed a dynamic O-D estimation method that utilizes known O-D data for fractions of the trips between the trip end points, assuming that they can be measured using an AVI technology. The AVI readers are assumed to cover the entry/exit links of O-D demand zones. The study used synthetic AVI traffic counts and a simple small network to show that using AVI data with count data and initial demand information could improve the quality of O-D estimation. The Root Mean Square Error (RMSE) improved from 25% to about 10% with the use of AVI. The authors also showed that locating the AVI detectors on major O-D demand zones with large traffic attraction/production can capture the essential O-D distribution patterns in the network, and consequently improve the quality of O-D estimates.

Antoniou et al. (2004) introduced a methodology for the incorporation of AVI data into the ODME. They presented path-flow proportion matrices that relate O-D demand flows to sub-path AVI counts, and proposed framework to estimate static O-D flows. They showed that the quality of the ODME results improved with combination of synthetic AVI data and link counts.

Dixon and Rilett (2000) assumed that AVI readers are available at the boundaries of their network and used the generalized least squares and Kalman Filter algorithms to estimate the O-D demand. The study evaluated the algorithms on a freeway section with on- and off-ramps and showed that AVI utilization improved the estimation results.

Barceló et al. (2010) examined the use of Bluetooth and Wi-Fi data to estimate dynamic O-D matrices using linear Kalman Filter approach. The study utilized simulated data to prove the concept with a fixed proportion of equipped vehicles with AVI.

In addition to AVI-based data, automatic vehicle location (AVL) data using Global Position System (GPS) and phone data have also been proposed for O-D estimation. Zanjani et al. (2015) used truck GPS data as seed matrix and applied static ODME method with truck count for the estimation of O-D truck flows within, into, and out of Florida. They used Cube Analyst Drive for the ODME process, as part of this effort.

Alibabai and Mahmassani (2008) used turning movement counts as observation in dynamic ODME and compared the results with those obtained from the link volume counts. The main

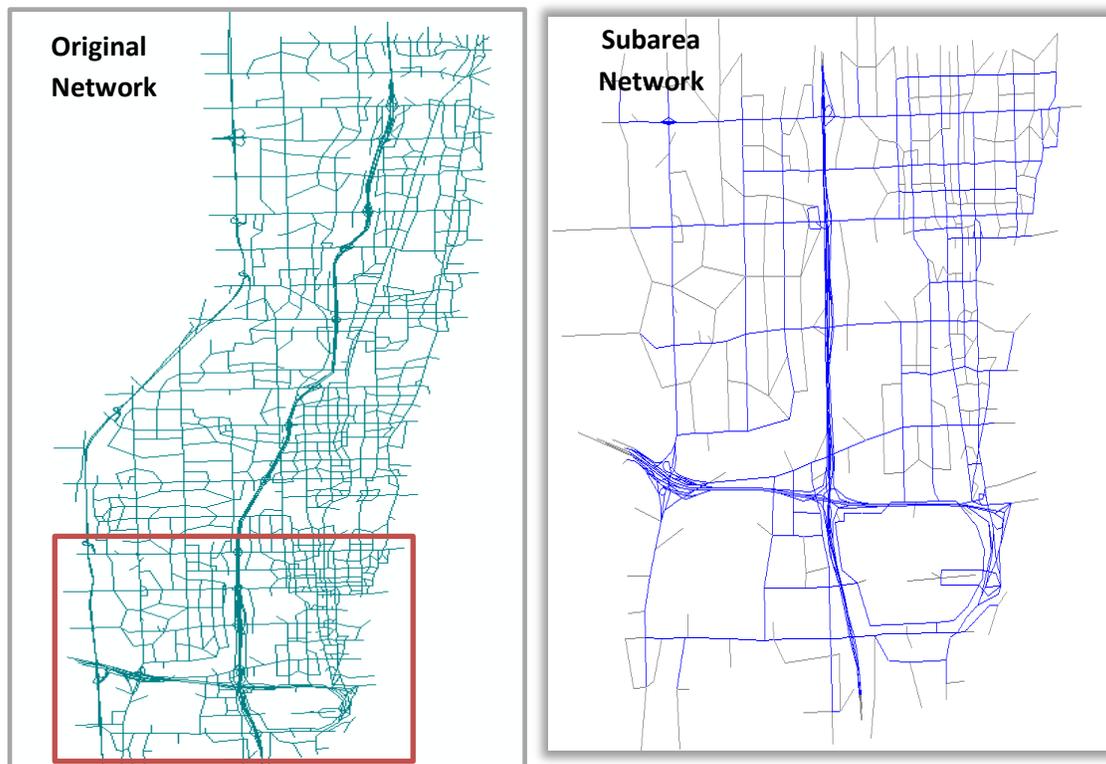
finding of the study was that intersection turning movement counts has considerable benefits in matching observed counts.

Based on the above review, it appears that researchers have recognized the need for using additional data such as AVI, AVL and turning movement counts to supplement traffic counts. However, some of these studies have used simple networks with synthetic data to prove the usefulness of the inclusion of AVI or AVL data in the ODME process. To the best of our knowledge, these studies have not examined the use of combinations of real-world AVI and AVL data or private sector data and turning movement counts to support the O-D estimation process for a real-world network. Also the capability of CUBE Analyst Drive to utilize partial trips and turning movement in the ODME process has not been well assessed.

## **5.2. Study Network Preparation**

The subarea network of the I-95 corridor in Fort Lauderdale, FL, as shown in Figure 38, was used as case study. The original network was extracted from a subarea of the Southeast Florida Regional Planning Model (SERPM) that was used by FDOT consultant in the modeling of the planned managed lanes for the corridor. The subarea network was modeled using both the STA in Cube and the DTA in the Cube Avenue software. The subarea network and an initial estimation of the associated trips were extracted from the original network.

Figure 38 shows the original network and the extracted subarea network. The subarea network has a total number of 198 zones, 1984 links and 913 nodes including two freeways (I-95 and I-595) and major arterials.



**Figure 38 Extracted Subarea Network for ODME Analysis**

The extracted subarea network was updated and cleaned before using it in analysis including adding network details, moving nodes and links to better represent the real-world network, and checking network connections. Link attributes, such as length, number of lanes, free-flow speed, capacity, facility type, and so on, were further checked and updated as necessary. The existing signal timing plans and intersection details were also added.

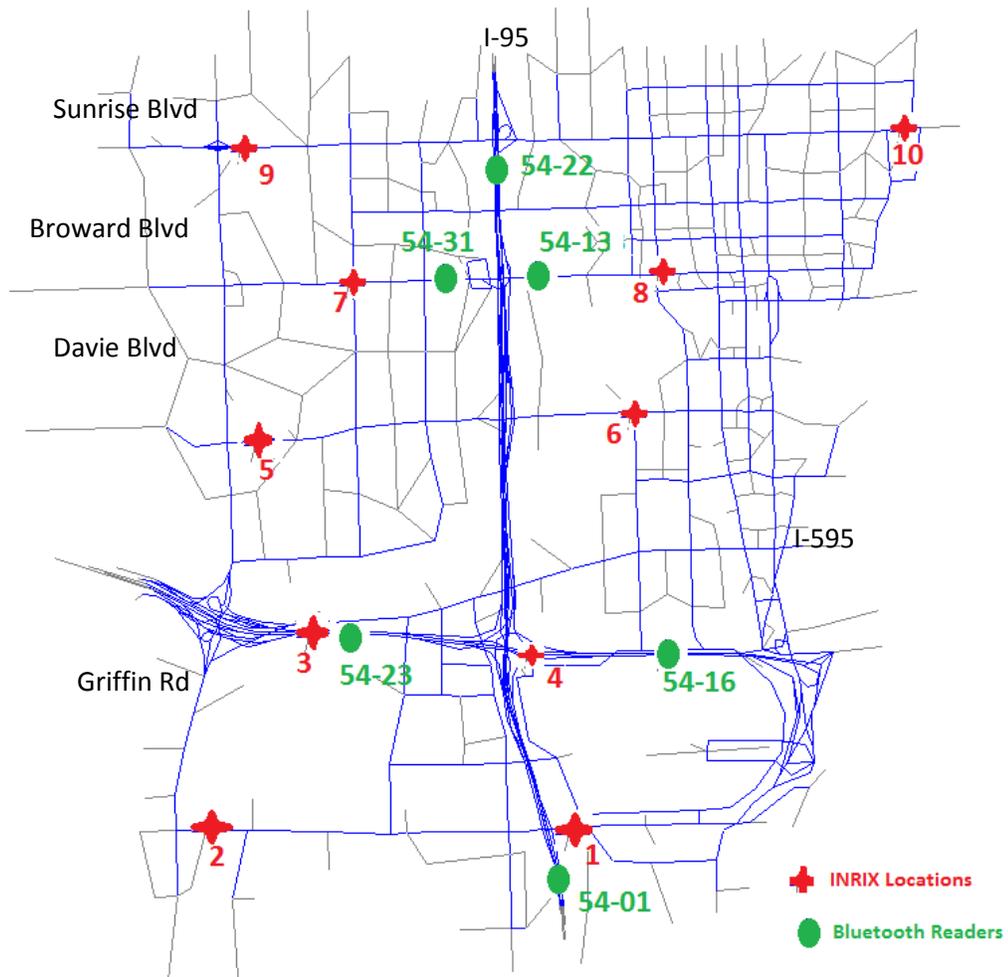
### **5.3. Data Processing**

The initial O-D matrix for the network was extracted for the PM peak period between 3:30 pm and 6:30 pm from the original network shown in Figure 38. This O-D matrix includes four travel modes: drive alone, shared ride with 2 persons, shared ride with more than 2 persons, and truck.

Link traffic volumes were estimated using three-day traffic counts obtained using Portable Traffic Monitoring Stations (PTMSs). These counts are collected every other year by the Statistics Office of the Florida Department of Transportation (FDOT) at major freeways, ramps, and arterials. In this study, a total number of 89 PTMS stations were identified to be within the network.

32 temporary Bluetooth readers were deployed by the FDOT consultant, as part of the I-95 managed lane project. Six of these readers are located in the network and used in this study, as shown in Figure 39. Each Bluetooth reader was operated for 12 or 13 days. The partial O-D matrices were determined based on matching the data generated by reading the unique Media Control Access (MAC) ID of vehicles as they pass the Bluetooth readers. The matched trips between two detection stations were aggregated into a trip table for every 15-minute time interval during the PM peak period.

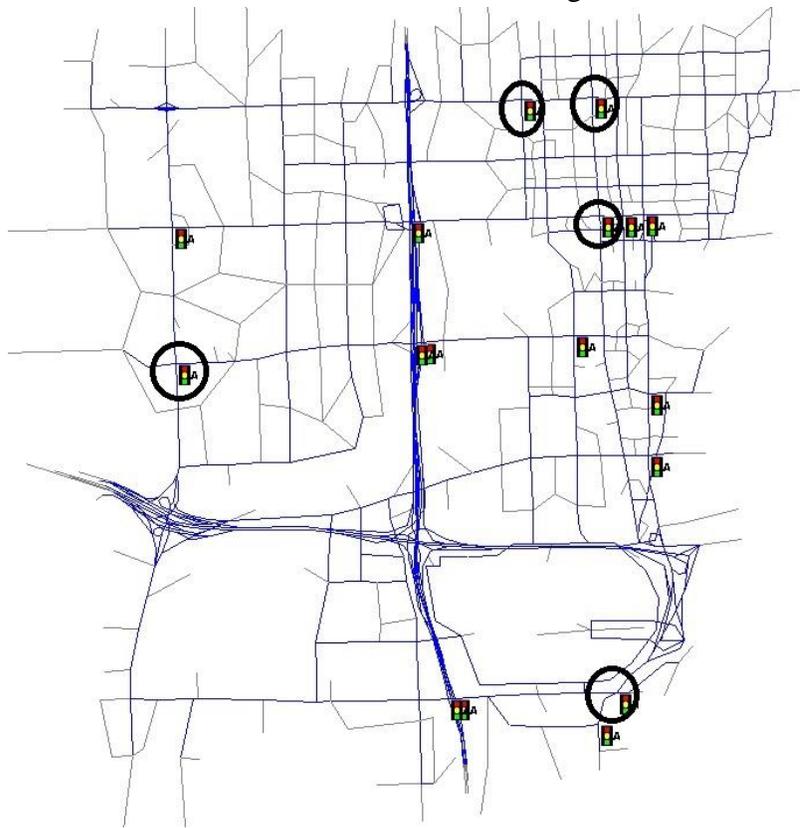
Additional partial trip data were obtained based on INRIX data. INRIX collects trip information based on probe data gathered from GPS-enabled vehicles, as well as from smart phones in vehicles. Trip records between zones in the study area were obtained from INRIX for one month. The data was used to generate partial trips between ten locations on the major arterials of the small network, as shown in Figure 39.



**Figure 39 Locations of Bluetooth Readers and INRIX**

As the Bluetooth readers and INRIX platform only capture percentages of the total traffic, the estimated Bluetooth and INRIX trip table obtained using the above procedures had to be expanded to reflect the total volume. The traffic counts at the nearest PTMS stations to a Bluetooth reader and the selected INRIX trip end locations were used to represent the total number of production and attraction from/to a point. This allowed expanding the estimated trips to the total volume utilizing an iterative matrix balancing method for each 15-minute time interval. This process continued until the error between the observed PTMS counts and the expanded Bluetooth and INRIX data was less than 10%. This was achieved at the 13th iteration.

Another data source is 15-minute turning movement counts. A total number of 15 signalized intersections were coded in the Cube network. Five of them have historical turning movement counts. The locations of these five intersections are shown in Figure 40.



**Figure 40 Locations of Intersections and Selected Ones for Inputting Turning Movement Counts**

#### **5.4. ODME Process and Results Analysis**

As stated before, this study investigates the impacts of using partial trip data and turning movement data in the ODME process on the quality of the ODME results. Cube Analyst Drive, a DTA-based ODME tool, has been used, as none of the other commercially available tools

examined in this study can use partial trips as inputs to the ODME process. It should be mentioned that the STA-based ODME module in the Cube 6.4 software also does not allow inputting turning movement counts and partial trips. The inputs to the Cube Analyst Drive module includes:

- A packet log file obtained from the output of Cube Avenue that tracks the movement of vehicle packets throughout the roadway network.
- Initial O-D matrices obtained by factorizing the O-D matrices for the whole PM peak period.
- Screen line data created from 89 PTMS throughout the network.
- Partial trip data from six Bluetooth readers and ten locations for private sector data (INRIX data).
- Turning count data from five signalized intersections for 12 15-minute intervals during the PM peak period.

Scenarios with and without the use of traffic counts and partial trip data along with turning movement counts were tested in this study. The estimated O-D matrix was evaluated by comparing estimated traffic volumes with observed traffic volumes at different locations. The Percentage Root Mean Square Error (PRMSE) was used as a measure to quantify the performance. The following equation provides the expressions for PRMSE:

$$PRMSE = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}} * \frac{100*n}{\sum \hat{y}_i} \quad (13)$$

Where,  $y$  is the simulated/estimated volume, and  $\hat{y}$  is the observed volume.

The analysis results show that the PRMSE between simulated and real-world volumes was 44.8% when utilizing the initial O-D matrices in the dynamic traffic assignment without the ODME process. The PRMSE dropped to 39.1% when utilizing O-D matrices estimated by the ODME based on traffic volume counts. The PRMSE dropped further to 29.56% when using turning movement counts in addition to the link traffic counts. The PRMSE dropped more to 22.9% when using the partial trips with traffic counts in the ODME.

The deviation between the simulation and the real-world estimation of the partial trip were estimated to be 116.3%, and 76.5% with the initial O-D matrices and matrices based on ODME with only partial trips, respectively. Increasing the weight of the partial trips contribution to the optimization objective function reduced the PRMSE, with partial trips only, to 57.2%. However, it increased the PRMSE from 22.9% to 29.16%, for the link volume comparison. Similarly, the deviation between the simulation and the real-world estimation of the turning movement counts were estimated to be 95.01%, and 46.12% with the initial matrices and matrices based on ODME with only turning counts, respectively. Increasing the weight of the turning counts contribution

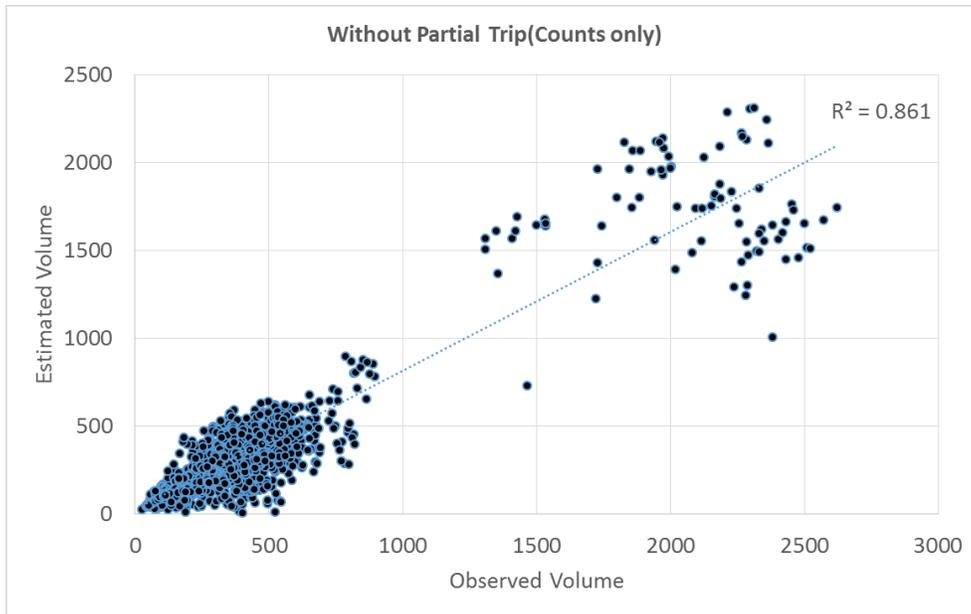
to the optimization objective function reduced the PRMSE. However, it increased the PRMSE for the link volume comparison.

The effect of partial trip utilization by different facility types was also examined in this study. Table 18 shows the PRMSE values by facility type. As can be seen from this table, the inclusion of the partial trips improved the results in all cases significantly. However, this inclusion had more effects on the arterial roads compared to freeways. As can be seen from the partial trip coverage in Figure 39, most partial trips estimated using INRIX private sector data are located on the arterial roads, while few Bluetooth readers are located on the freeways. This indicates that the estimation error decreases with the increase in partial trip coverage. It should be mentioned that the arterial network was the main focus of the research project, for which the O-D estimation was conducted.

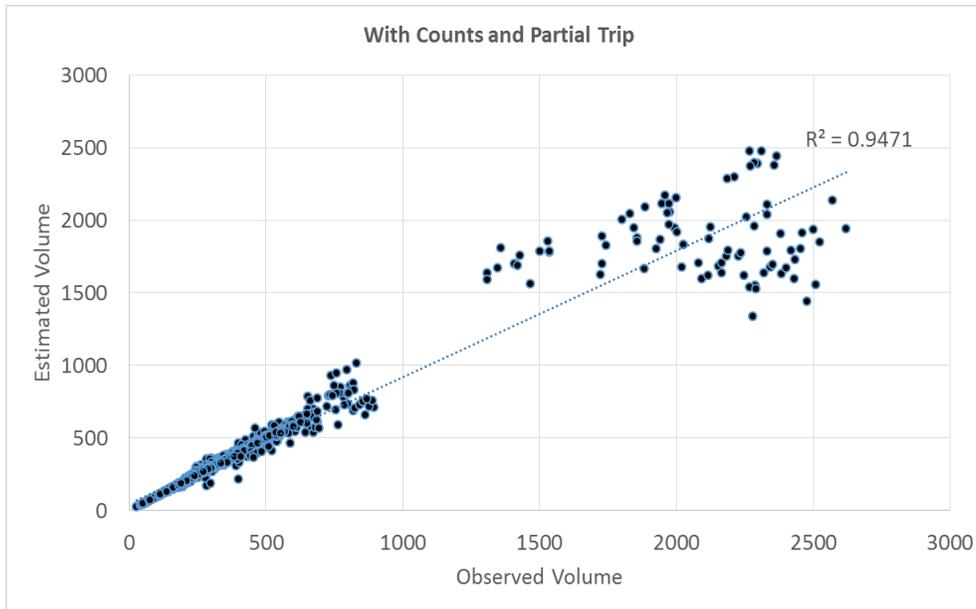
**Table 18 Comparison of PRMSE by Facility Type**

<b>Facility Type</b>	<b>Initial (Before ODME)</b>	<b>Counts-Only</b>	<b>Adding Partial Trip</b>
Freeway	28.43%	28.11%	22.01%
Freeway-Ramp	39.42%	37.86%	28.09%
Arterials	44.93%	34.69%	4.65%
Total	44.80%	39.10%	22.93%

It is also useful to look at the errors based on the count ranges. Figures 41 and 42 display a comparison of estimated volumes and observed traffic counts with and without using the partial trips in the ODME. Table 19 shows the PRMSE values for three different ranges of observed counts. These results demonstrate that the simulated volumes match reasonably well the simulated volumes when partial trip counts are added to the ODME, with better matches when the observed volumes are less than 1,000 vehicles per 15 minutes. Additional manual fine-tuning and calibration of the demand and supply sides are expected to improve the performance further.



**Figure 41 Observed Traffic Counts vs. Estimated Volume without Partial Trip**

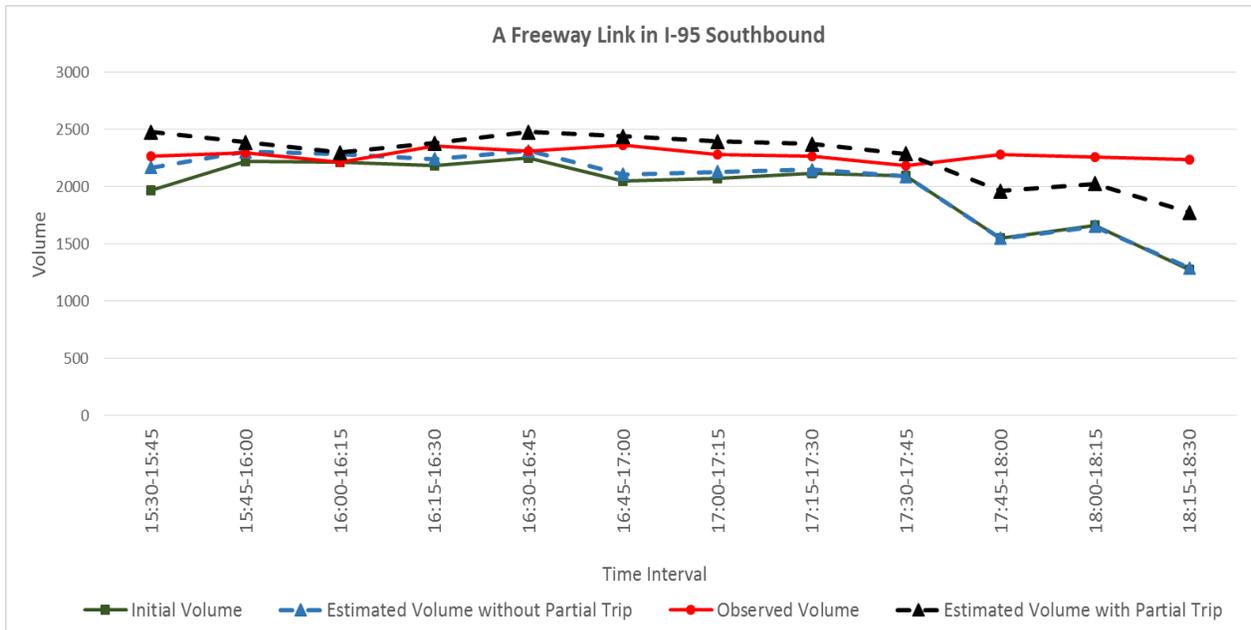


**Figure 42 Observed Traffic Counts vs. Estimated Volume with Partial Trip**

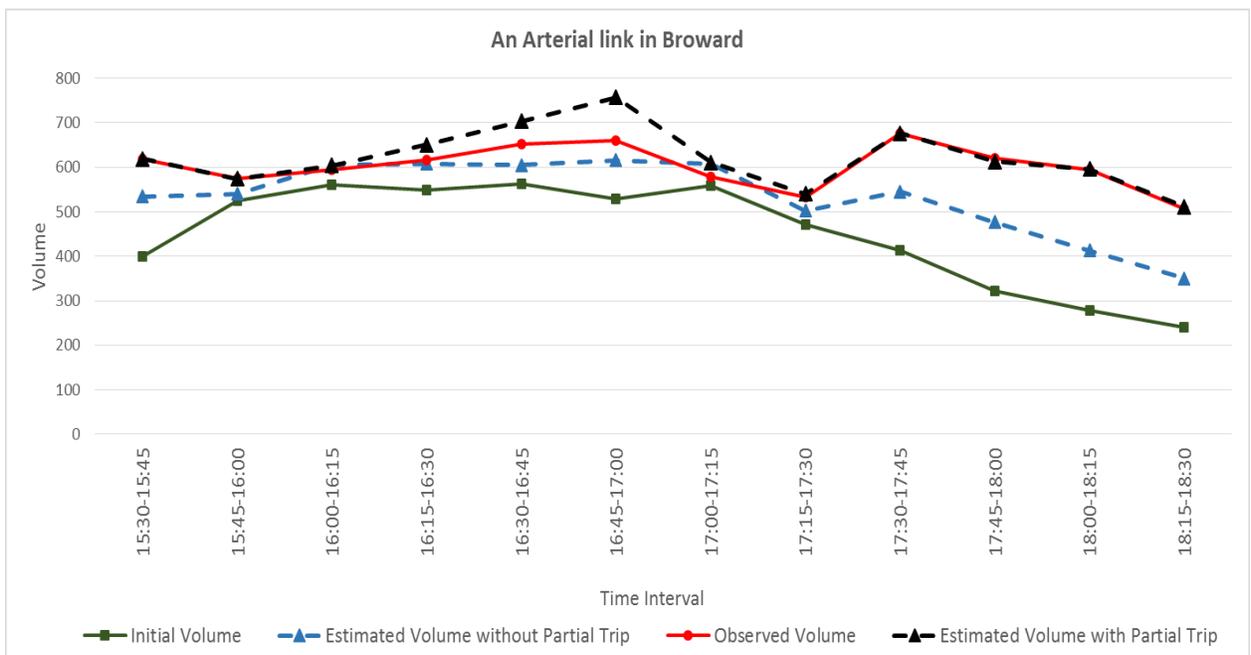
**Table 19 Comparison of PRMSE in Different Count Ranges**

<b>Observed Count volume</b>	<b>From Initial O-D Matrix without ODME</b>	<b>Counts Only</b>	<b>Adding Partial Trip</b>
26 ~ 894	44.75%	35.3%	6.81%
1308 ~ 2620	26.55%	26.18%	21%
Total	44.80%	39.10%	22.93%

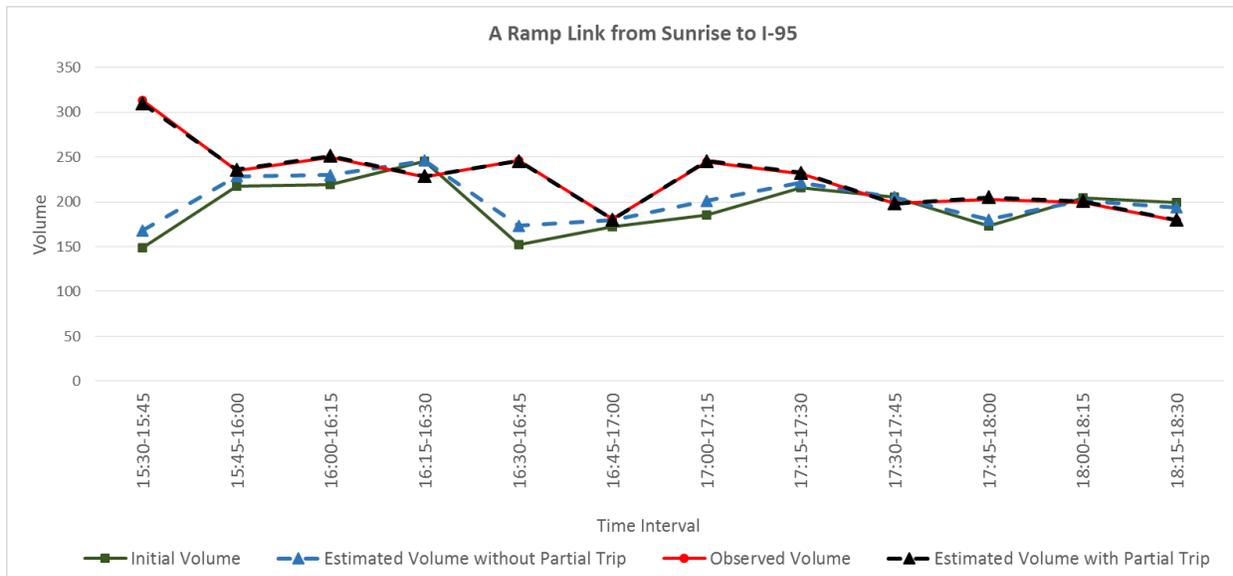
Examples of the effect of the incorporation of partial trip data in the ODME on the estimated volumes of a freeway link, an arterial link, and a ramp link during different time intervals are presented in Figures 43 to 45.



**Figure 43 Comparison of the ODME Results for a Freeway Link**

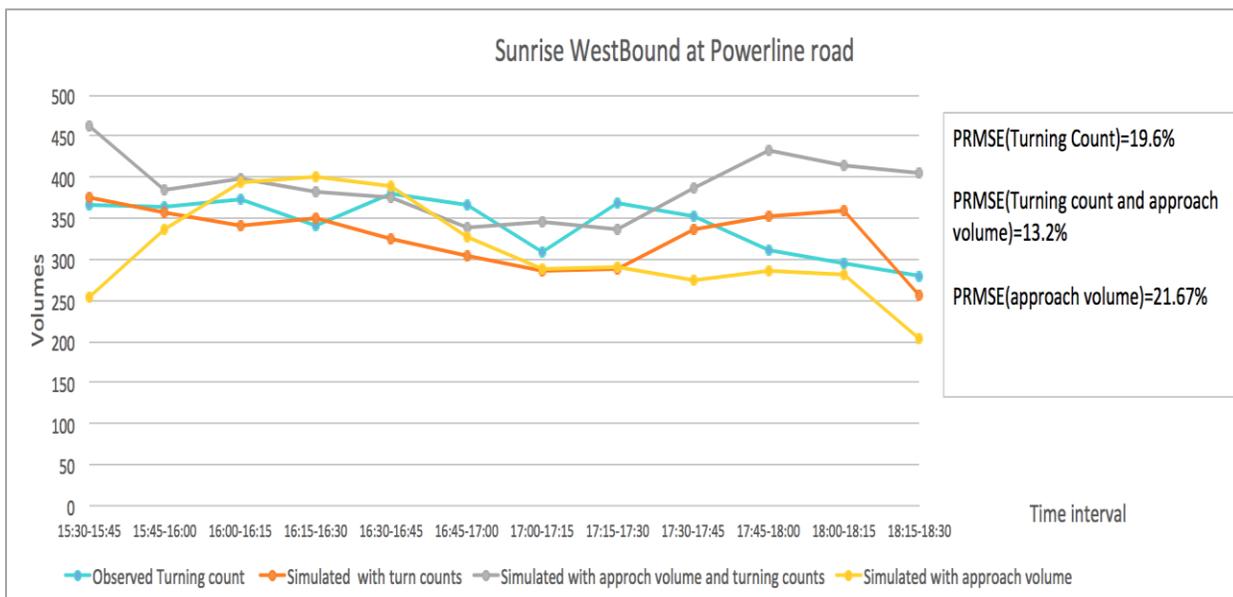


**Figure 44 Comparison of the ODME Results for an Arterial Link**



**Figure 45 Comparison of the ODME Results for a Ramp Link**

Figure 46 presents an example to illustrate the effect of the inclusion of turning movement count data on the results of an approach to an intersection. It can be seen from the figure that the estimated volume with the inclusion of the turning counts replicates the observed count data better than without turning counts. The PRMSE values for this approach for the ODME with turning counts only, count data only, and turning counts and count data combined are 19.6%, 21.67% and 13.2%, respectively.



**Figure 46 Comparison of the ODME Results with Different Inputs**

## **5.5. Summary of ODME Analysis**

This study assessed the benefits of using O-D data from a third party vendor and Bluetooth data as well as turning movement data in combination with traffic count data on the quality of the results of the ODME process. The analysis results showed that the inclusion of the partial trips improves the ODME results significantly, producing closer matches to the real-world counts compared to the ODME that utilizes traffic count data without partial trips. Also, the incorporation of turning movements improves the quality of O-D flow estimates compared to the ODME that uses traffic count data without turning movements. Increasing the weight of the partial trips (or the turning movement) contribution in the optimization objective function reduces the deviation of the modeling results from the partial trip data or turning movements. However, it can increase the deviation from count data. The analysts can set these weights based on their recognition of the relative accuracy of the partial trip or turning movements versus count data. It was found that the features of CUBE Analyst Drive in CUBE 6.4 that allow users to input partial trips and turning movements are a very useful in improving the performance of the ODME process.

## 6. APPLICATION OF MULTI-RESOLUTION MODELING TO DECISION-MAKING PROCESS IN HIGHWAY CONSTRUCTION PROJECTS

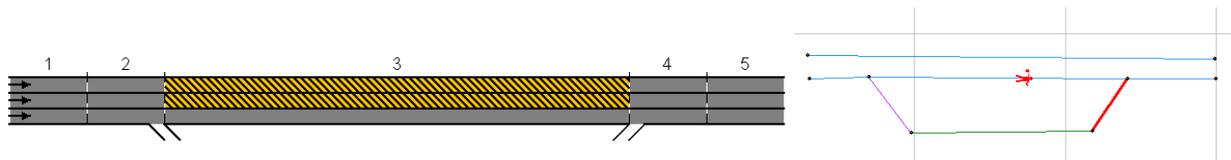
Construction projects can result in significant mobility, reliability, environmental and safety impacts to roadway users. In addition, the existence of work zones also induces inconvenience to local business and community, noise and environmental impacts. With the increasing needs to analyze and evaluate road user costs in transportation projects, various traffic analysis tools are available for the use at planning and operation stage of construction projects. Multi-resolution modeling can provide a powerful platform to evaluate the impacts of construction activities. The goal of this research is to develop a multi-resolution modeling methodology to estimate the impacts of construction projects on road users.

### 6.1. Work Zone Mobility Impacts Estimation Comparison

Various levels of tools can be used to estimate the mobility impacts of work zones. In order to compare their capabilities, a 3-mile work zone was assumed to be located along the I-4 corridor near the Graves Avenue in Orlando. It is assumed that the duration of working activity is 3 hours each day and 2 out of 3 lanes were closed during the construction. Table 20 summarizes the work zone information used in the case study and Figure 47 illustrates the geometry of the simple study network. It is also assumed that the work zone capacity is 1,000 vphpl in order to simplify the analysis.

**Table 20 Work Zone Information in Case Study**

Location	Length (miles)	FFS (mph)	Lane closure schedule	Working activity schedule
I-4, Orlando	3	65	2 out of 3 lanes	21:00~24:00

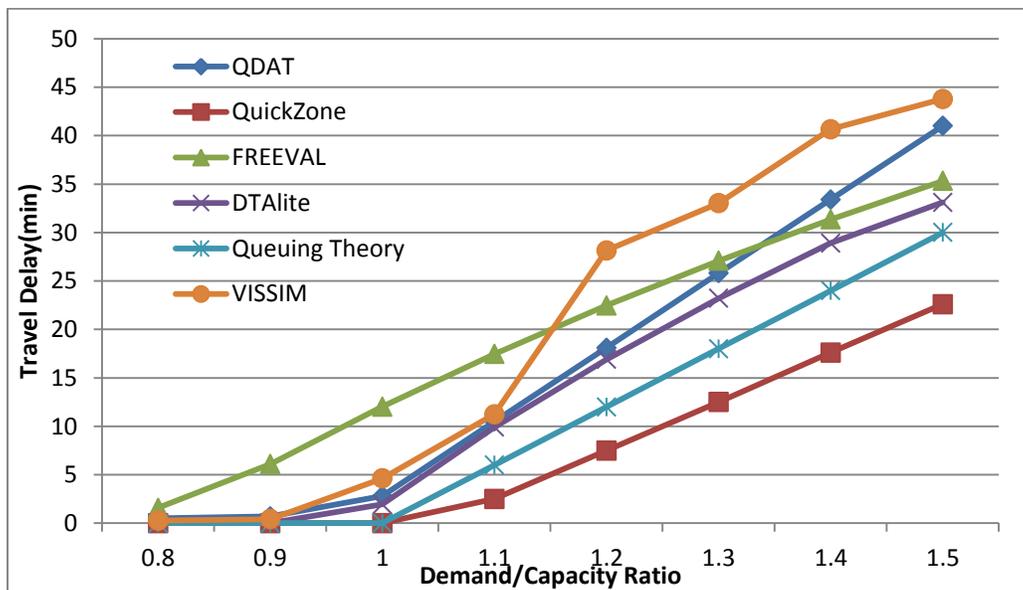


**Figure 47 Geometry of Study Network**

The delays due to work zones estimated by traffic flow models used in a number of traffic analysis tools were compared in this study to determine the differences in the obtained results. The assessed tools include two widely used analytical tools that are relatively easy to use for this purpose, Q-DAT and QuickZone, the Highway Capacity Manual (HCM) computational engine work zone module referred to as FREEVAL-WZ, a mesoscopic dynamic traffic assignment tool, DTALite, and a microscopic simulation tool, VISSIM. In general, these tools require different inputs and generate different outputs. The demand inputs for Q-DAT are the daily traffic

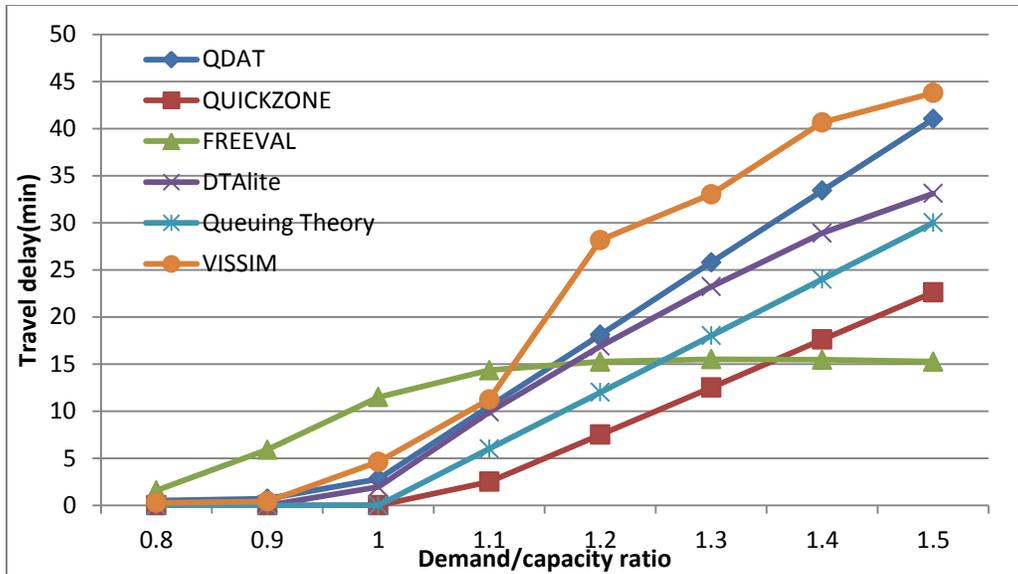
volumes. The inputs to the FREEVAL tools are 15 minute link volumes. QuickZone requires hourly link traffic volumes, and DTALite require travel demand matrices. The VISSIM software allows the input of either O-D matrix or demands at entrance links. These tools were compared based on the results from case study. It should be mentioned that route diversion was not considered in this comparison as some of the tools do not allow the consideration of the diversion to alternative route. The traffic diversion is being addressed in a separate task.

Work zone capacity and travel demand are important factors for work zone mobility analysis. To simplify the analysis, a capacity of 1000 vphpl was used for work zone in this case study, and a sensitivity analysis was conducted for travel demand. Figure 48 shows the case study results. It can be noted from this figure that the average travel delay increases significantly with the increase in travel demand (that is, demand/capacity ratio). However, the estimated delay by FREEVAL didn't change when demand/capacity ratio is over 1.2. This is because the queue extends beyond the boundary of the system, as explained next. It can also be noticed that all the results except FREEVAL show similar trends to the results obtained using simple queuing theory equations.



**Figure 48 Comparison of Travel Delay**

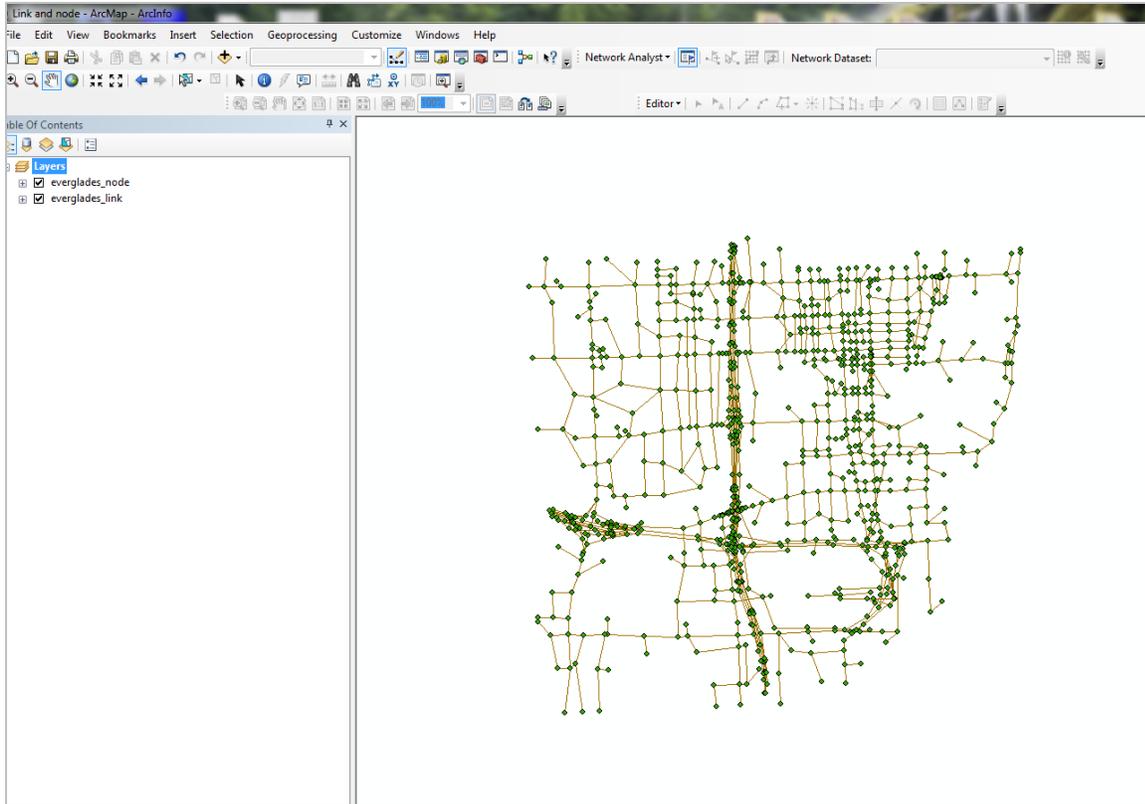
In order to capture the backup of queue, the upstream link of work zone was extended to 5 miles in each analysis tool. The corresponding new results are present in Figure 49. After changing the length of upstream link, the estimated delay from FREEVAL increases dramatically. This indicates that FREEVAL utilizes a true “horizontal queue.” As a microscopic simulation tool, the VISSIM software also considers the spatial distribution of queues. The other tools use vertical queues. Q-DAT, QuickZone, DTALite, and deterministic queuing theory analysis produce similar estimates of travel delay at the work zones, while FREEVAL and VISSIM produce higher delay.



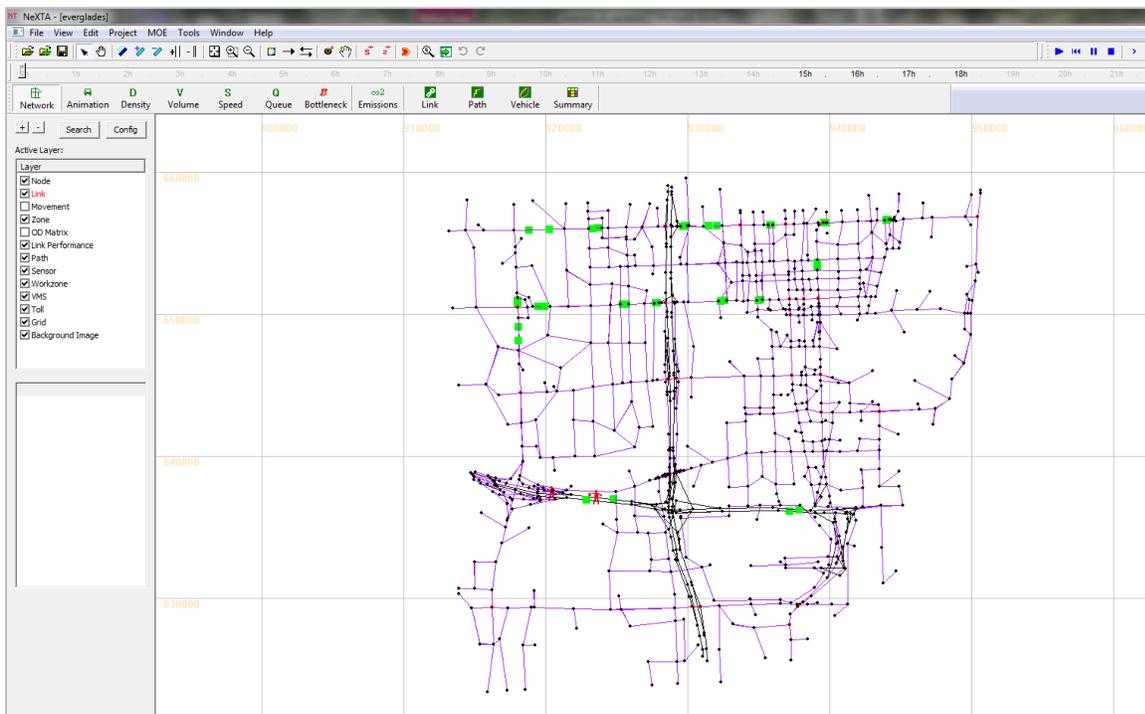
**Figure 49 Comparison of Travel Delay with Extended Upstream Link**

## 6.2. Traffic Diversion Analysis

A proportion of travelers may divert to alternative routes to avoid adverse traffic impacts resulted from construction activities. The rate of diversion is expected to vary with the duration of construction. In this study, a case study was used to demonstrate the traffic diversion modeling approach for the constructions along the I-595 corridor in Broward County, FL utilizing the DTALite tool and the associated DTALite data hub. The network used in the analysis was exported from an existing Port Everglades model coded in the Cube Avenue software, as shown in Figure 50. The first step in the network and demand conversions from the Cube software format to a format accepted by NeXTA. The network conversion contains the creation of link and node shape file that can be identified by NeXTA. With the conversion, the network is shown in Figure 51. The travel demand conversion involves the creation of 15-min travel demand matrices in csv format. The matrix used in this study is from 3:30 to 6:30 PM.



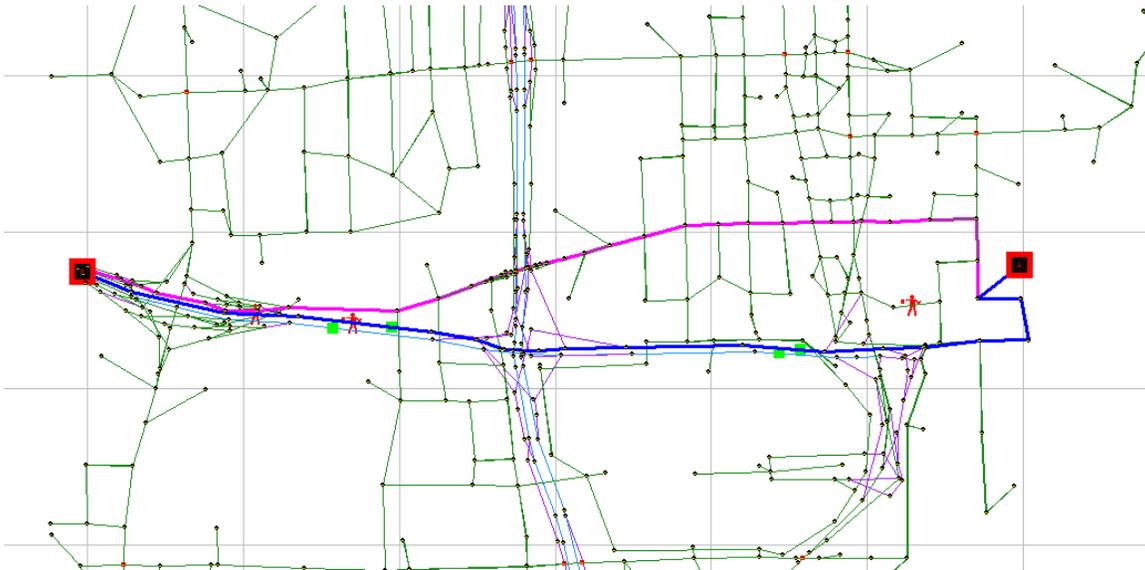
**Figure 50 Port of Everglades Network in ArcGIS**



**Figure 51 Port of Everglades Network in NeXTA**

Three methods of diversion behavior modeling were examined, that is, (1) diversion during a short-term construction utilizing a logit model developed in a previous study; (2) diversion during a long-term construction where the network reaches user equilibrium (modeled using a dynamic user equilibrium technique in DTALite); (3) diversion utilizing a day-to-day learning assignment in DTA modeling that accounts for the number of days that the construction zone is active (modeled using day-to-day learning assignment in DTALite).

In this study, a construction zone with 2-lane closure out of 4 lanes was assumed to be located along I-595 westbound in Broward County, FL. Figure 52 shows the location of the construction zone and its alternative main alternative route (SR 84). The demand from the Port of Everglades (Zone ID: 147) to the I-595 westbound (Zone Id: 165) that traveling along these routes were analyzed in this study. The corresponding lengths and free-flow travel times for these two paths are summarized in Table 21.



**Figure 52 Location of Work Zone and Alternative Route**

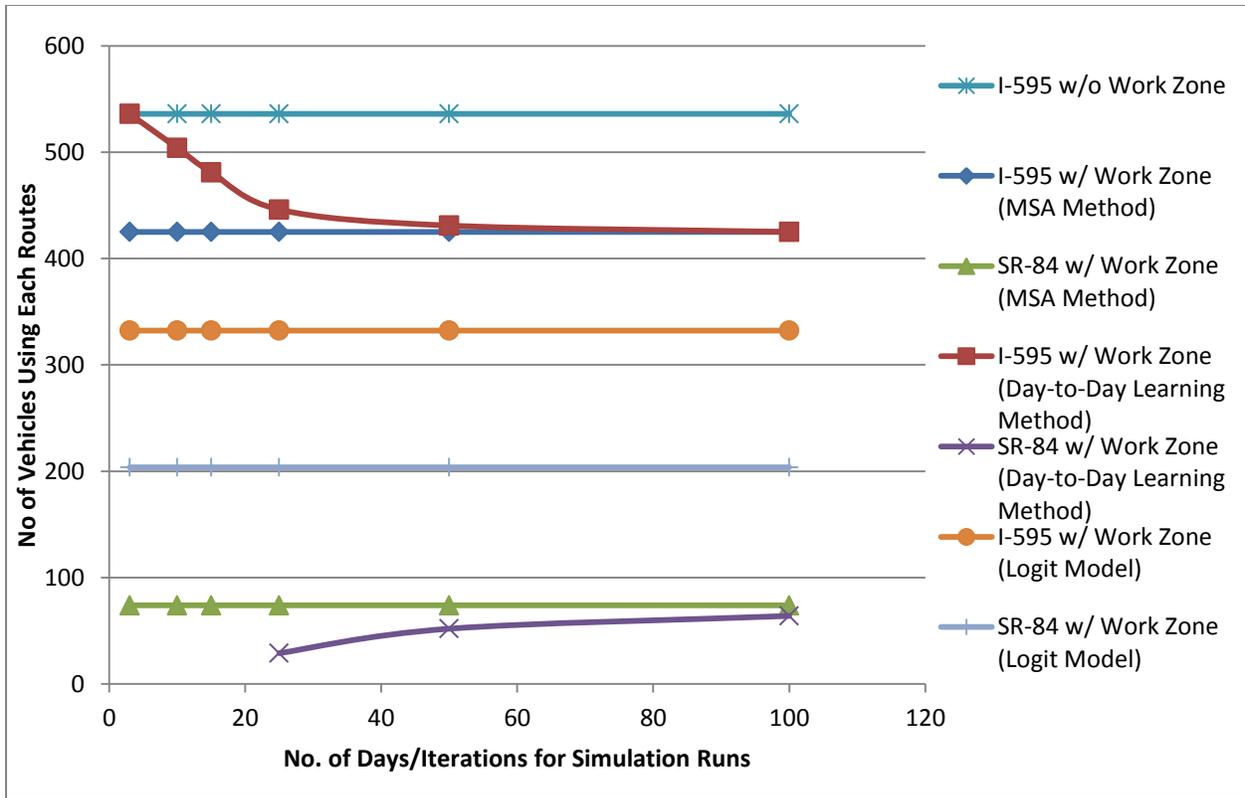
**Table 21 Length and Free-Flow Travel Time Information for Travelling Paths in Case Study**

From Zone	To Zone	Path	Length (mile)	Free-Flow Travel Time (min)
147	165	I-595	6.6	8.58
147	165	SR-84	6.4	11.03

Four scenarios were modeled in this study,

- Scenario 1: Simulation is conducted with 100 iterations to reach user equilibrium without work zone, which is a base case for comparison.
- Scenario 2: Simulation is conducted with 100 iterations to reach user equilibrium with the work zone.
- Scenario 3: Simulation is conducted for 100 days with work zone using the day-to-day learning assignment method.
- Scenario 4: Diversion is modeled using the logit regression model developed by Song and Yin (2008).

Figure 53 presents the results of traffic volumes on alternative routes between the origin-destination pair shown in Figure 52 for four study scenarios. This origin-destination pair starts from the zone located near the Port of Everglades to the zone located west of I-595. As shown in this figure, both the MSA method and day-to-day learning method produce similar results after 20-50 days of learning as traffic assignment reaches equilibrium in both cases. In the baseline scenario, all the drivers choose I-595 as their travelling route. In equilibrium, about 90 vehicles of the 520 vehicles using I-595 shift to SR 84 and 10 vehicles to other routes. In short-term work zones, modeled using day-to-day learning, the shift from I-595 is gradual as can be seen in the figures. It also appears that travelers choose other less favorable alternative routes compared to SR 84. This may not be totally realistic since a proportion of travelers are more informed travelers that can selected the best alternative routes. The logit regression model was also utilized to predict traffic counts in both routes. However, the logit model overestimated the portion of diverting traffic compared to the day-to-day learning and user equilibrium method. This could be in part due to the fact that the logit model does not consider the diversion from other O-D pairs. It can also be concluded that even though the final results for the MSA and day-to-day learning methods are close to each other (after about 20 days), the day-to-day learning method is able to better explain the process of drivers' route choice with shorter-term work zones.



**Figure 53 Traffic Count Comparison among Four Scenarios**

### 6.3. Modeling of Work Zone Mobility Impacts with Consideration of Route Diversion Using Microscopic Simulation Modeling

Microscopic simulation tools are usually used to model the detailed impacts of roadway design and traffic operation strategies. However, the accuracy of micro-simulation results greatly depends on the input of travel demands. Without correct input of travel demands, the simulation model cannot reflect the real-world traffic conditions. In this study, the travel demand after route diversion obtained from the mesoscopic tool, DTALite, was used as the input for microscopic simulation of work zone in VISSIM. The purpose of this analysis is to demonstrate the benefits of multi-resolution modeling of work zones. Another potential application of multi-resolution modeling approach to work zones is modeling the impacts of lane merging behaviors on work zone mobility and safety, is also discussed in this section.

#### 6.3.1. Microscopic Simulation of Work Zone Mobility Impacts

The diversion analysis results presented in the previous I-595 work zone case study shows significant traffic diversion due to the existence of a work zone. The work zone mobility performance with and without considering the diversion was further investigated in this section using the microscopic simulation software, VISSIM.

### **6.3.1.1. Work Zone Capacity Estimation**

Work zone capacity is an important input for traffic analysis tools to produce accurate results. Due to the lane closure and work zone activities, the roadway capacities for work zones are much lower than those under normal operations. A number of previous studies have been reported on work zone capacity. Dixon et al. (1996) measured speed-flow relationship at the end of the transition area and the area close to the actual working activities in order to estimate work zone capacity. Their report suggested that for a high intensity work zone with a configuration of 1 out of 2 lane closures, the capacity values at the activity area are around 1,200 vphpl and 1,500 vphpl for rural and urban areas, respectively. Sarasua et al. (2004) summarized the work zone capacity values estimated in different states, as shown in Table 22. It is seen from this table that work zone capacity varies with locations.

**Table 22 Variation of Work Zone Capacity across States**

<b>State</b>	<b>2 to 1 lane configuration</b>	<b>3 to 1 lane configuration</b>	<b>Units</b>
Texas	1,340	1,170	vphpl
Missouri	1,240	960	vphpl
Nevada	1,375 to 1,400	1,375 to 1,400	vphpl
Oregon	1,400 to 1,600	1,400 to 1,600	pcphpl
South Carolina	950	950	vphpl
Washington	1,350	1,350	vphpl

The Highway Capacity Manual (HCM 2010) defines capacity as the “maximum sustained 15-min flow, expressed in passenger cars per hour per lane that can be accommodated by a uniform freeway segment under prevailing traffic and roadway conditions in one direction of flow.” The capacity reduction due to construction activities can be divided into short-term and long-term work zone lane closures. HCM 2010 also stated that work zone capacity value should be modified by applying certain adjustment factors based on work zone intensity, effects of heavy vehicles and presence of ramps close to work zone. The following equation is utilized to estimate the capacity in vehicles per hour.

$$C = \{[(1600 + I) \times f_{hv}] \times N\} - R \quad (14)$$

Where,

*C*: Adjusted work zone capacity (vphpl)

*I*: Adjustment factor work zone intensity (ranges from -160 pcphpl to 160 pcphpl)

*f<sub>hv</sub>*: Heavy-vehicle adjustment factor

*N*: Number of open lanes through work zone

*R*: Manual adjustment for on-ramps

For long-term work zones, HCM 2010 suggests the capacity value can be 1,400 vehicle per hour (vphpl) for 2 to 1 lane closure (which means 1 out of 2 lanes is open within work zone). The capacity value can be 1,450 vehicle per hour (vphpl) for 3 to 1 lane closure. And the capacity value can be 1,350 vehicle per hour (vphpl) for 4 to 1 lane closure. Lane width factor is considered to be significant for work zone reduced capacity.

Sarasua et al. (2004) conducted studies on 22 work zone sites in South Carolina and estimated the base capacities for short-term work zone capacity was 1,460 pcphpl. The speed-flow-density data were fitted to a linear Greenshields model to estimate the capacity for work zone. A work zone capacity estimation model that is similar to HCM was proposed in this study.

$$Capacity \text{ (in veh)} = (1460 + I) \times N \times f_{hv} \quad (15)$$

where,

*I*: Work zone intensity adjustment factor that ranges from -146 vph to +146 vph

*N*: The number of open lanes

*f<sub>hv</sub>*: The heavy vehicle adjustment factor

Two types of regression models, additive and multiplicative models, were developed in a NCHRP report (2014) for freeway work zone capacity, as shown below. These two models take consideration of number of open lanes, barrier type used in work zone, work zone location, lateral distance, and time of day.

- **Additive type:**

$$C = 2093 - 154 \times f_{LSCI} - 194 \times f_{barrier} - 179 \times f_{area} + 9 \times f_{lateral-12} - 59 \times f_{day-night} \quad (16)$$

where,

*C*: Average queue discharge flow rate (pcphpl)

*f<sub>LSCI</sub>*: Adjustment factor for number of open lanes. It equals to the inverse of the multiplication of number of open lanes and open ratio

*f<sub>barrier</sub>*: Adjustment factor for barrier type. It is 0 for concrete barrier and 1 for cone or PE drum separation

*f<sub>area</sub>*: Adjustment factor for area type. It is 0 for urban areas and 1 for rural areas

*f<sub>lateral-12</sub>*: Adjustment factor for lateral distance

*f<sub>day-night</sub>*: Adjustment factor for time of day. It is 0 for daytime and 1 for night.

- **Multiplicative type:**

$$C = 2013 \times f_{LSCI}^{-0.1323} \times f_{barrier} \times f_{area} \times f_{lateral-12}^{0.0309} \times f_{day-night} \quad (17)$$

where the meanings of the symbols in Equation 17 are the same as those in Equation 16. However, the values are different. For example, the adjustment factor for barrier type is 1 for concrete barrier while it is 0.805 for cone or PE drum. The adjustment factor for urban areas is still 1 but it is 0.8836 for rural areas. The time-of-day adjustment factor is 1 for daytime while 0.9363 for night time.

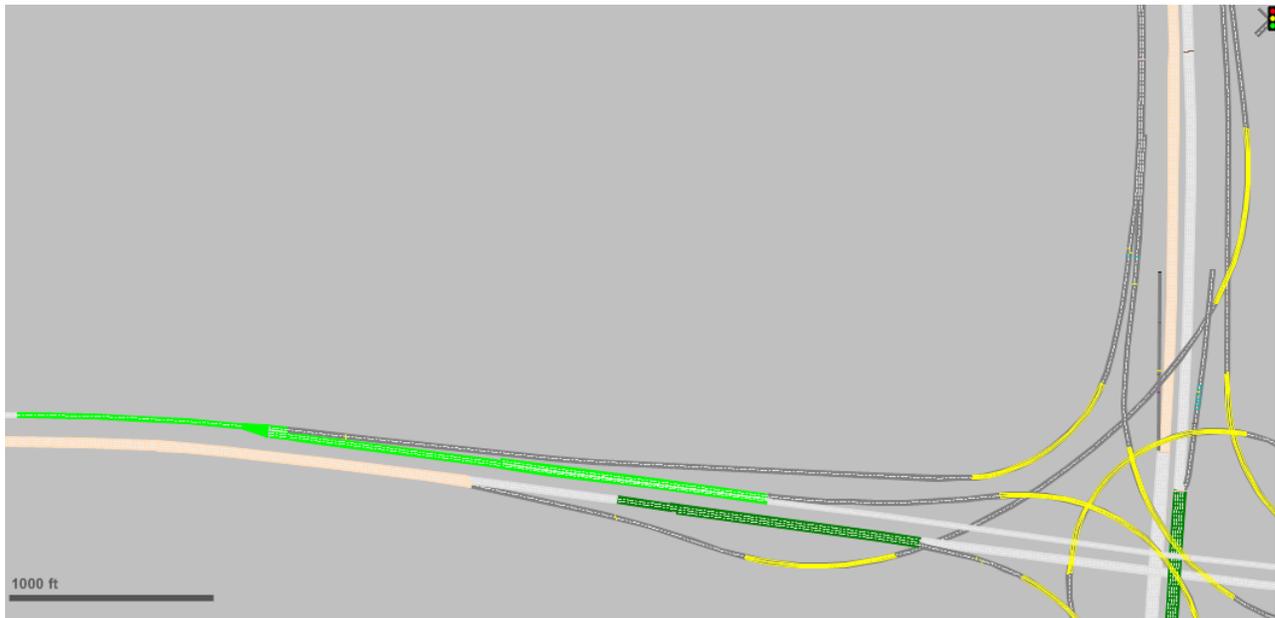
As discussed above, different methods are available to estimate work zone capacity. The selection of appropriate approach depends on user requirements and work zone location. In this study, both the HCM and NCHRP methods were utilized to calculate the work zone capacity. The resulting work zone capacity values are presented in Table 23.

**Table 23 Summary of Work Zone Capacity**

<b>Work Zone Capacity (vphpl)</b>	<b>HCM</b>	<b>NCHRP (Additive Model)</b>	<b>NCHRP (Multiplicative Model)</b>	<b>Previous Researches</b>	<b>Capacity Range</b>
<b>3 to 1 Lane</b>	1,187	1,258	1,307	950 to 1,400	1,000 to 1,300
<b>4 to 2 Lane</b>	1,275	1,453	1,480	1,450	1,200 to 1,500

### **6.3.1.2. VISSIM Model Calibration**

The I-595 work zone investigated in the previous case study was modeled in VISSIM, as shown in Figure 54. In order to accurately reflect real-world traffic conditions, the work zone capacity of this VISSIM model was calibrated based on the capacities estimated by HCM and NCHRP methods. In VISSIM, driver behaviors are modelled through the Wiedmann car-following and lane-change models. Table 24 summarized the relevant parameters. Their default values and possible ranges in VISSIM are also listed in this table.



**Figure 54 VISSIM Network for I-595 Work Zone**

**Table 24 Parameter Ranges and Default Values**

<b>Parameter</b>	<b>Description</b>	<b>Default value</b>	<b>Range</b>
CC0	Standstill distance between two stopped vehicle	4.92ft	
CC1	Desired time headway	0.9sec	0.9~1.8sec
CC2	Following variation	13ft	10~55ft
CC3	Threshold for entering "Following"	-8.00	
CC4	Following threshold	-0.35	
CC5	Following threshold	0.35	
CC6	Speed dependency	11.44	
CC7	Oscillation acceleration	0.82ft/s <sup>2</sup>	0.4~2.0ft/s <sup>2</sup>
CC8	Standstill acceleration	11.48ft/s <sup>2</sup>	
CC9	Acceleration at 80 km/h	4.92ft/s <sup>2</sup>	
SRF	Safety distance reduction factor	0.6	0.15~0.6

Gomes et al. (2004) utilized CC0, CC1 and CC4/CC5 pair to calibrate the value of field capacity in their VISSIM simulation study. CC1 value was changed globally from 1.5 to 1.7 seconds and this parameter was used specifically to calibrate queue length as it has more significance at low speed conditions. The overall selection of parameter values was conducted manually and based on visual interpretation of results.

Lownes et al. (2006) conducted a quantitative analysis of the impacts of VISSIM driving behavior parameters in estimating capacity. The impacts of the driving behavior parameters in

the Weidmann 99 car following model and the lane changing distance were investigated in the study. Each of the 10 behavior parameters were tested at four levels, namely, “low”, “medium”, “calibrated” and “high”, depending upon the values selected for each parameter. The results suggested that CC0 can only produce significantly different capacity at high CC0 values, but the CC1 values at all four levels have significant impacts on simulated capacity. Similarly, for CC2, as its value increases, a drop in the mean value of capacity was observed.

Based on the above literature review, four parameters in VISSIM were considered in the calibration, that is, CC0, CC1, CC2, and SRF. The values of these four parameters were tested through different simulation runs. The resulted work zone capacities were compared with those estimated using the HCM and NCHRP methods. After calibration, the capacity is 1,880 vphpl for the freeway segment without work zone and 1,144 vphpl for the freeway segment with work zone. Table 25 lists the values of the calibrated parameters.

**Table 25 Default and Calibrated Parameters**

Parameter	Default Value	Range	Calibration Value
CC0	4.92ft	-	4.92ft
CC1	0.9sec	0.9-1.8sec	1.1sec
CC2	13.2ft	10-55ft	22.5ft
SRF	0.6	0.15-0.6	0.6

### **6.3.1.3. VISSIM Results Analysis**

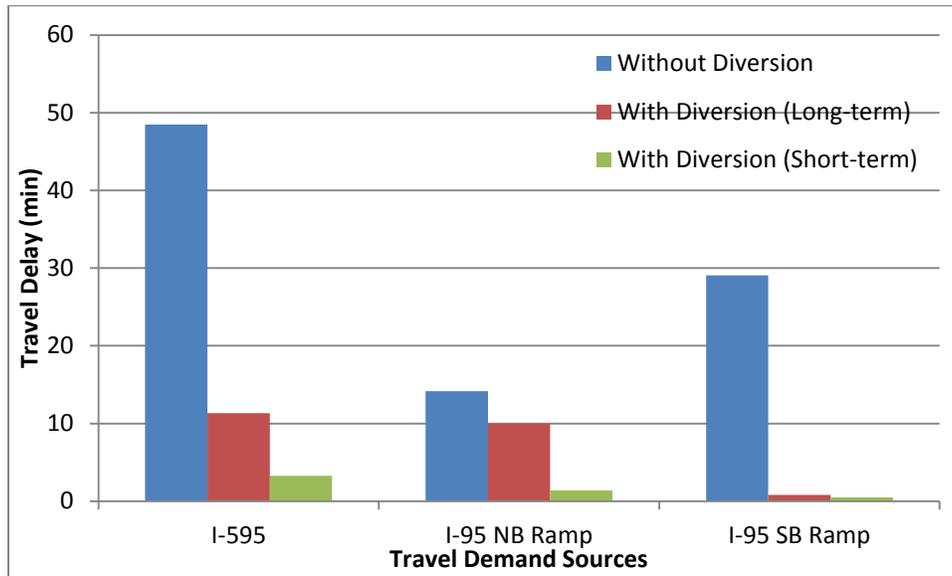
As mentioned above, the travel demand for the I-595 work zone segment was obtained using the mesoscopic analysis tool, DTALite, and used as an input to the VISSIM model. As shown in Figure 54, the work zone demands come from three upstream links, that is, I-595 WB, I-95 NB and I-95 SB. The corresponding demand values with and without diversion generated by DTALite are listed in Table 26. It can be seen from this table that the travel demand driving through the work zone area decreases for both short-term and long-term lane closure due to diversion. However, the diversion for the short-term construction is more, which is mainly due to the drivers’ overreaction to the existence of work zone.

**Table 26 Travel Demand with and without Traffic Diversion Obtained from DTALite**

Travel Demand (vph)	Without Diversion	With Diversion Short-term (10 days)	With Diversion Long-term (50-100 days)
I-595 WB	2478	1292	1480
I-95 SB Ramp	1210	114	320
I-95 NB Ramp	2728	987	1508

The VISSIM work zone mobility results are presented in Figure 55. As shown in this figure, the travel delay is much higher when route diversion is not considered in the analysis. Table 27

presents the simulated queue length and number of stops with and without the consideration of route diversion. Again, the queue length and number of stops for the scenario without route diversion is significantly larger than those with long-term diversion. The above results also indicate that the delay due to the work zone can be reduced significantly, if route diversion information is provided to drivers to encourage diversion. The impacts on the alternative routes can be also assessed using microscopic or mesoscopic tools.



**Figure 55 VISSIM Mobility Estimation Results**

**Table 27 VISSIM Queue Length and Number of Stops Results**

Queue Estimation	Queue Length (Maximum)	Queue Length (Average)	Number of Stops
<b>Without Diversion</b>	58,330 ft	40,812 ft	160,394
<b>With Diversion (Long-term)</b>	30,072 ft	23,707 ft	115,420
<b>With Diversion (Short-term)</b>	2,780 ft	2,027 ft	8,560

### 6.3.2. Impacts of Lane Merging Behavior at Work Zone

In the presence of work zone with lane drops, the merging of traffic at the taper area presents an operational concern. To improve traffic safety and mobility at work zones, researchers have proposed several traffic merging management methods, such as early merge (EM), late merge (LM), and dynamic lane merging (DLM). As a future work, the multi-resolution modeling framework developed in this study can be used to model the lane merging behaviors at work zone under different traffic merging management strategies. Mesoscopic models as described in the above section produce traffic volumes that are expected to pass through the work zones

considering the diversions to the alternative routes. These volumes can be used in the microsimulation models to further assess the impacts of different traffic merging management methods. For example, in VISSIM, partial decision routing can be used to imitate early merge (EM) strategy as drivers merge ahead of the work zone, while they stay in their lane until the taper when the late merge (LM) strategy is implemented. The resulting vehicle trajectories from VISSIM can be further imported to the Surrogate Safety Assessment Model (SSAM) to quantify the safety impacts. The output of travel time, throughput, and safety surrogate measures can be used to determine the optimal merging location at the work zones.

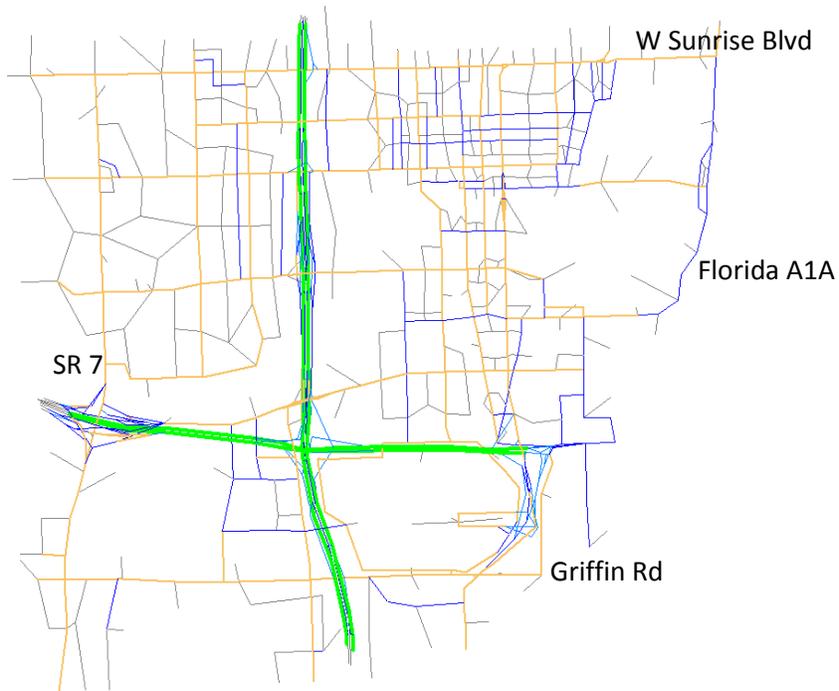
It should be mentioned that a feedback from the microscopic simulation to the mesoscopic simulation can be also included in the modeling, as the estimated work zone capacity with different merging behaviors can be estimated based on the microscopic simulation models and input to mesoscopic simulation in the upper level.

## **7. MODELING OF ACTIVE TRAFFIC MANAGEMENT ON URBAN STREETS**

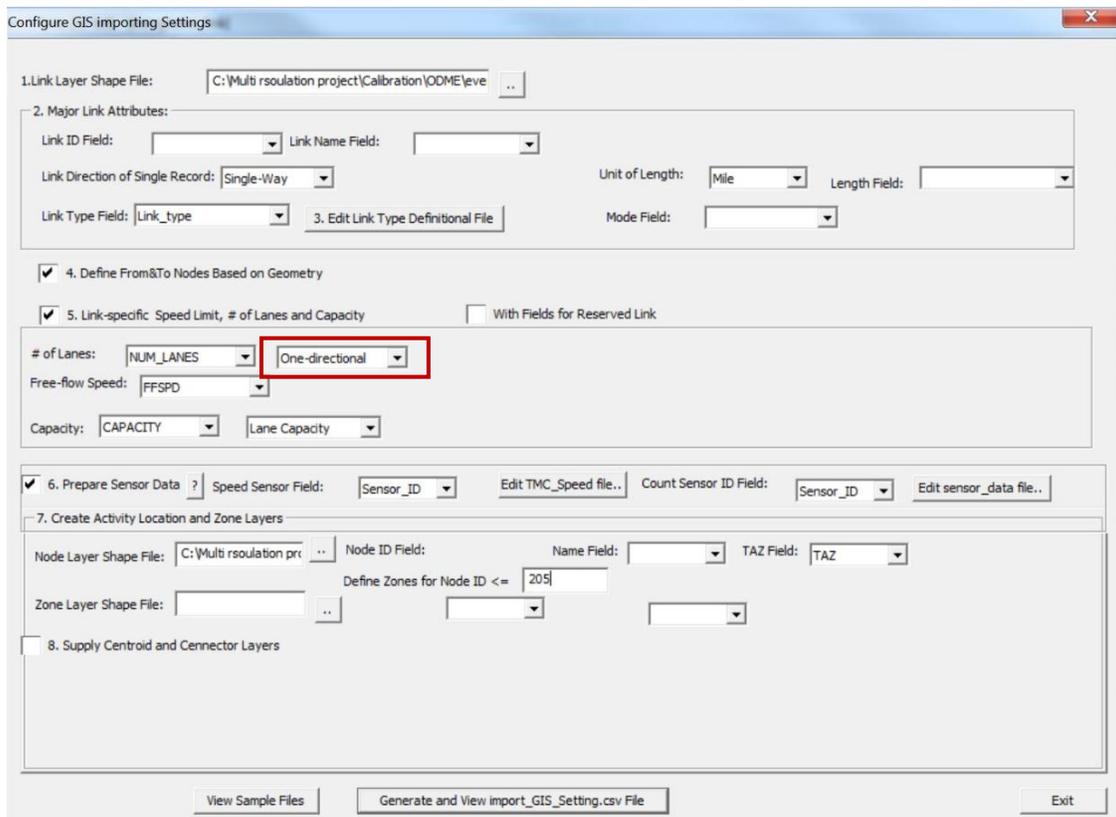
The implementation of active traffic management (ATM) strategies is an important consideration of transportation agencies. There is a strong trend to invest in ATM strategies on urban streets (signalized arterials) since such strategies have already been implemented on large proportions of urban freeway segments. The potential benefits of ATM strategies include mobility improvement, unreliability reduction, environmental impact reduction, and safety improvement. Methods are needed to assess these impacts of ATM strategies. This study demonstrates the utilization of combinations of data analytics, DTA modeling, and advanced simulation to assess the impacts of ATM strategies on urban streets traffic. The details of this demonstration are discussed below through a case study.

### **7.1. Network Preparation**

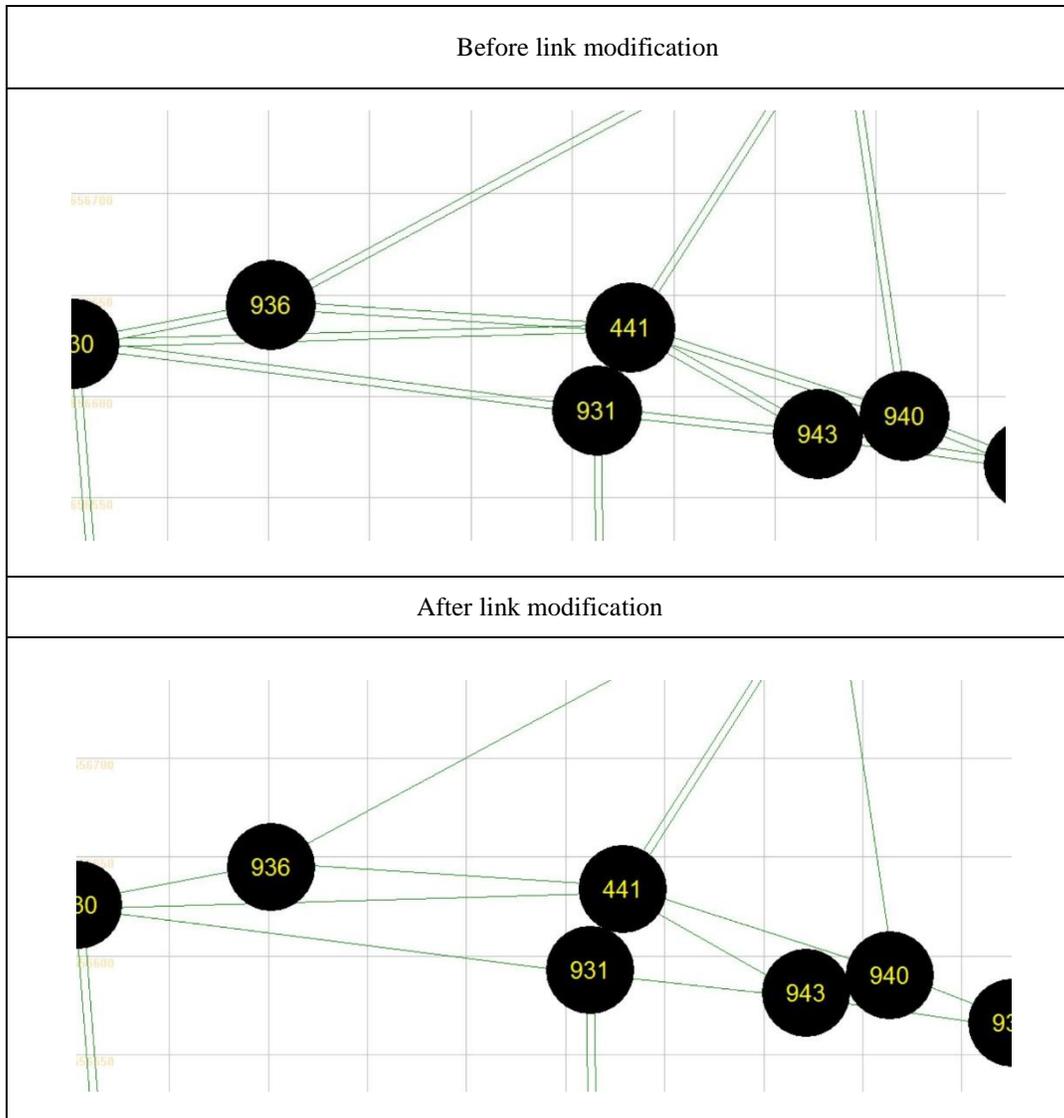
A subarea network around the Port of Everglades in Fort Lauderdale, FL, was used as a case study for demonstrating the benefits of ATM on urban street. As shown in Figure 56, this subarea covers the area between W. Sunrise Blvd and Griffin Rd in the north-south direction and between Florida A1A and SR 7 in the east-west direction. The original network was coded in the Cube Avenue software by Citilabs Inc. (Citilabs, Inc., 2016). In this study, this network was imported into the NeXTA/DTALite tool through the link and node GIS shapefiles that were exported from the Cube. The corresponding node and link attributes, such as the number of lanes, free-flow speed, lane capacity, link type, and so on, were configured in the “Configure GIS Importing Settings” file of NeXTA. The link types coded in the Cube Avenue model were also converted into the link types used in the DTALite, listed in Table 7, as shown in Figure 57. It should be mentioned that the original Cube network consists of both one-way and two-way links. However, the NeXTA importing interface can only handle the network with either one-way or two-way links but not both. Therefore, the network was first imported as two-way links and the extra links were manually deleted for those one-way links. Figure 58 shows an example of these modification.



**Figure 56 Port of Everglades Subarea Network**

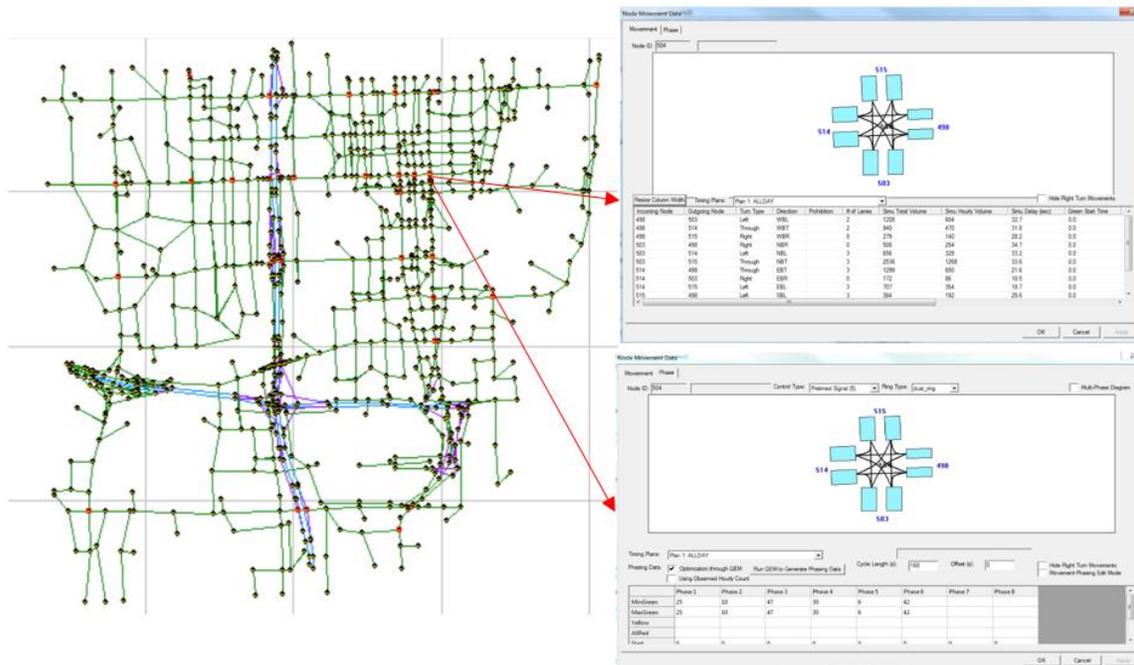


**Figure 57 GIS Importing Setting Interface in NeXTA**



**Figure 58 Example of Link Adjustment in NeXTA**

Correctly coding signal control is critical for assessing the impacts of ATM strategies along arterial. In this study, the junction data was obtained from the Cube Avenue model, which includes the signalized intersection geometry and signal timing data. Such information was coded in the DTALite model developed in this study through the “Node Movement Data” interface. Since the Broward Blvd is the corridor that this study focuses on in the microscopic-level simulation, the signal timing data for this corridor were further updated based on the more detailed information coded in a VISSIM model obtained from FDOT District 4. As an example of the signalized intersections coded in DTALite, Figure 59 shows the movements and signal timing for the intersection of Broward Blvd at US 1.



**Figure 59 “Node Movement Data” Interface for the Intersection at the Broward Blvd and US-1 in NeXTA**

## 7.2. Demand Data

The 15-minute O-D matrices during the PM peak period between 3:00 pm and 6:00 pm were extracted from the Cube Avenue model developed by Citilabs, mentioned earlier utilizing the “subarea analysis” process. Three travel modes were considered, auto, short-haul truck, and long-haul truck. The Cube demand matrices were then converted into csv files and imported into DTALite. Note that these demand matrices were obtained using the ODME procedure in Cube based on three-day PTMS traffic counts at midblock. Since this study focuses on arterial ATM, the accuracy of the estimation of turning movement counts is critical. The ODME process normally utilized is based on demand measures at subsets of the network links. Such process may not produce accurate estimates of the turning movement counts. Therefore, an additional ODME process had to be further conducted in this study based on turning movement counts and MVDS data to allow better estimates of turning movement demands as documented later. The matrices produced using PTMS as inputs to the ODME process were used as initial seed matrices in the additional ODME process, described later.

## **7.3. Data Acquisition and Traffic Pattern Identification**

### ***7.3.1. Data Acquisition***

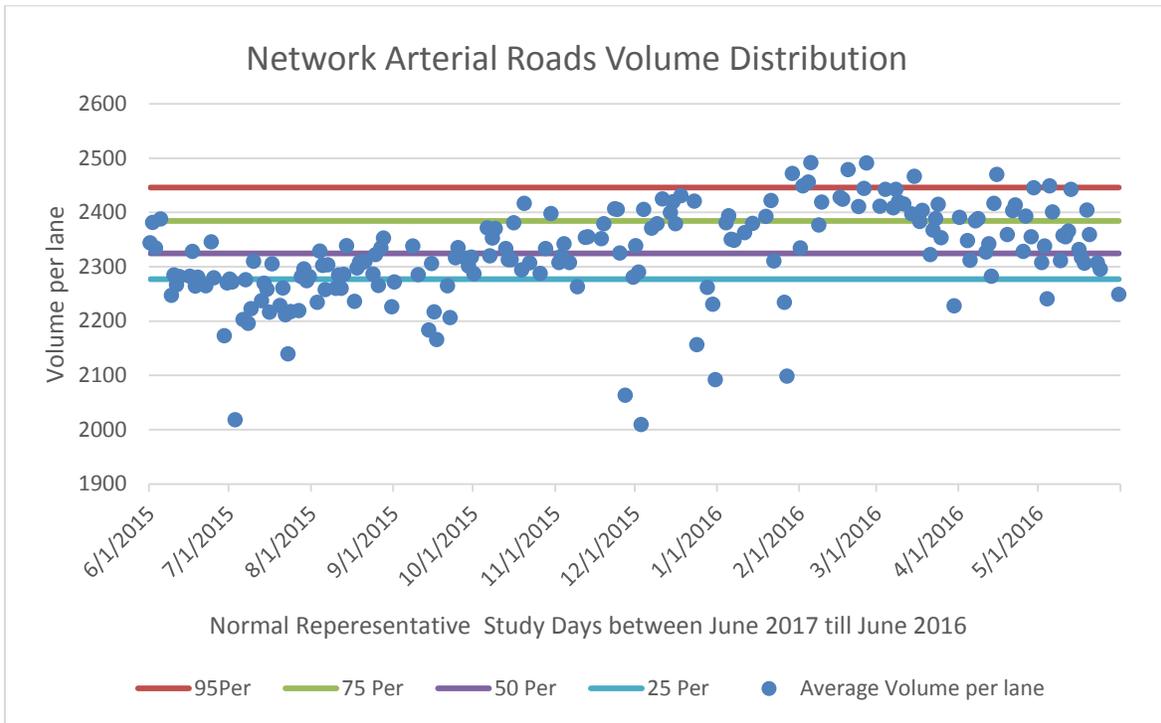
In this study, data from multiple sources were collected for the analysis of ATM strategies, including point traffic detector data along freeways, Microwave Vehicle Detector System (MVDS) along major arterials, turning movement counts, event data such as incidents, and weather data. MVDS data was collected by the FDOT District 4 TSM&O program, which was extensively used for the demand estimation, model calibration, and validation. The data contains records of traffic volumes, speeds, occupancies, and travel times aggregated at 15-minute intervals. The point traffic detector data for the two freeways within the study area, I-95 and I-595, was obtained from the Regional Integrated Transportation Information System (RITIS) website. One-year data from 06/01/2015 to 05/31/2016 between 3:00 pm and 7:00 pm was downloaded from this website. The locations of the detectors were identified and associated with links in the network that was modelled in DTAlite. Incident data were obtained from FDOT District 4 Transportation Management Center (TMC). This data include detailed event information, such as incident location, incident type, severity, duration, number of lane blockages, and so on. Archived turn movement counts were retrieved from the Broward County website. In addition, trips records that are within or passing through the study area in the month of January, 2016 were also extracted from Inrix data to obtain the number of partial trips. The validity of all these data were checked. The erroneous data or the data violating the spatial or temporal consistency were eliminated.

### ***7.3.2. Traffic Pattern Identification***

Traffic patterns vary day by day. As described earlier in this document, the recent guidance and demonstration projects funded by the FHWA have emphasized the need to model days with different patterns (such as different demand levels, incident conditions, and weather conditions). This is particularly needed when modeling advanced strategies of the type discussed in this chapter.

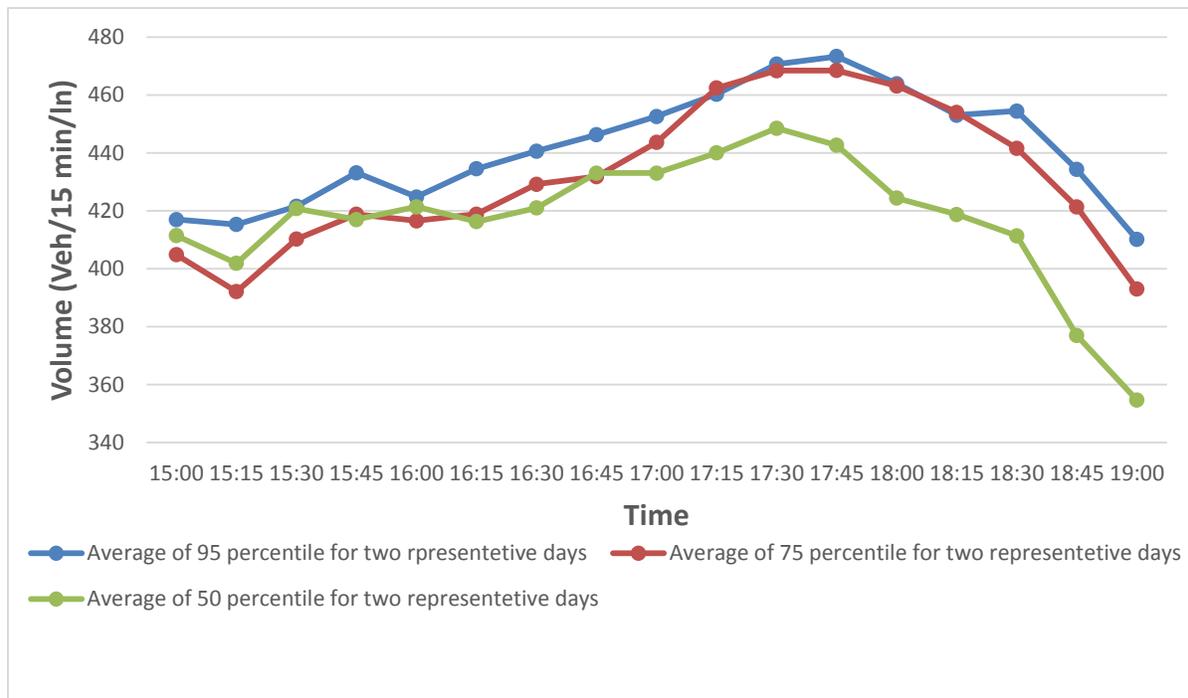
This study acknowledges the need to model different traffic patterns and demonstrate partially the consideration of different patterns in the analysis. More detailed considerations were done as part of the ATDM and DMA AMS project, funded by the FHWA and described earlier. In this study, representative days with different demand levels were selected for modeling. These days represent weekdays without incidents or abnormal external conditions such as heavy rain. In this study, the days with incident, special events, and bad weather were first filtered out, and also holidays and weekends were removed from the analysis. The remaining days were included in the next step analysis.

The 15-minute traffic counts between 3:00 pm and 7:00 pm for the remaining days were aggregated to obtain the PM peak period traffic counts. Since this study focuses on arterial streets, the average volumes of four critical arterials (that is, the Broward Blvd, Sunrise Blvd, SR7 and A1A) were used to identify the network traffic patterns with different demand levels. Figure 60 shows the average volume per lane during the PM peak period for normal days between June 1, 2015 and May 31, 2016.



**Figure 60 Average Volume during the PM Peak Period for Normal Days between June 1, 2015, and May 31, 2016**

Previous ATM evaluations have been done for one day that is assumed to be representative of the operations for the whole year. However, the impacts of ATM strategies vary between days due to the variations in demand, weather, capacity, work zone, incidents, and other events. To better capture the variations in demand and quantify the benefits of ATM strategies, the 50<sup>th</sup>, 75<sup>th</sup>, and 95<sup>th</sup> percentile volumes of normal days during the PM peak period were calculated and shown in Figure 60 as straight lines. The days with volumes that are close to these four percentile values were considered as representative days for these four demand levels and used in later analysis. Note that there may be no days with exact volumes as those percentiles. In this case, the average volume of two closest days were used in the analysis. Figure 61 shows the variation of average volume for different percentile days. Please, note that other methods such as clustering analysis could have been done to segregate days into different groups for analysis.



**Figure 61 Variation of Average Volume for Days with Different Percentiles**

#### 7.4. Supply Calibration

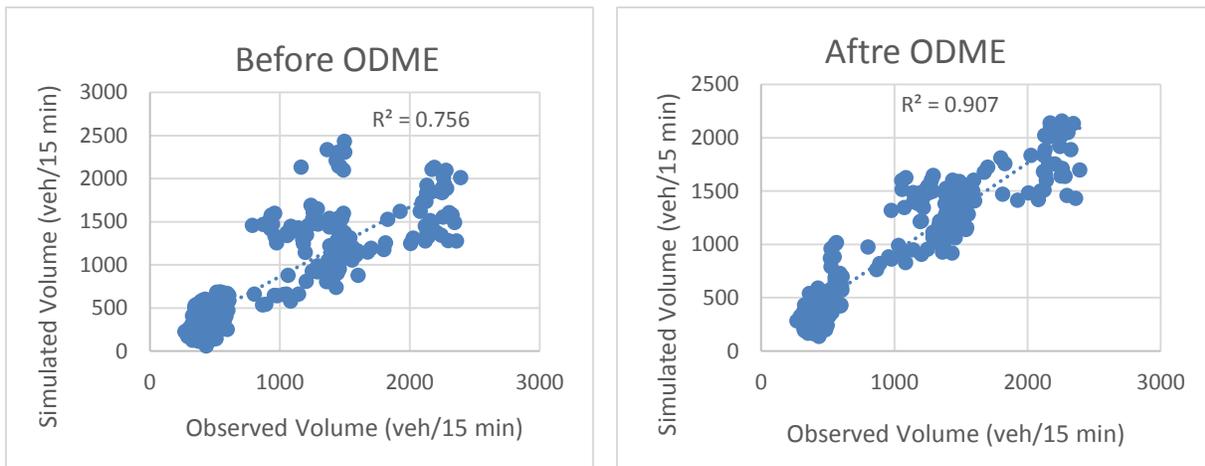
The network or supply calibration process estimates and modifies the network parameters such as capacity and traffic flow model parameters. In this study, updates were made to the signal timing operation plans for signalized intersections along the study arterial street, as mentioned above. The capacity of approaching links to these signalized intersections was also updated based on the saturation flow rate used in HCM 2010, that is, 1,800 passenger car per hour per lane for signalized intersections.

Zone centroid connectors are usually coded with a very high capacity in regional demand models to avoid their impacts on traffic assignment. However, it was found in this study that such high capacities for zone centroid connectors cause unrealistic traffic assignment in DTALite. When there are zone centroids located between two parallel streets, vehicles may use zone centroid connectors as a bypass to avoid congested streets due to their high capacities and thus shorter travel times. In order to overcome this problem, the capacities and speed limits of these zone centroid connectors were adjusted to lower values to prevent vehicles from using these links as a bypass.

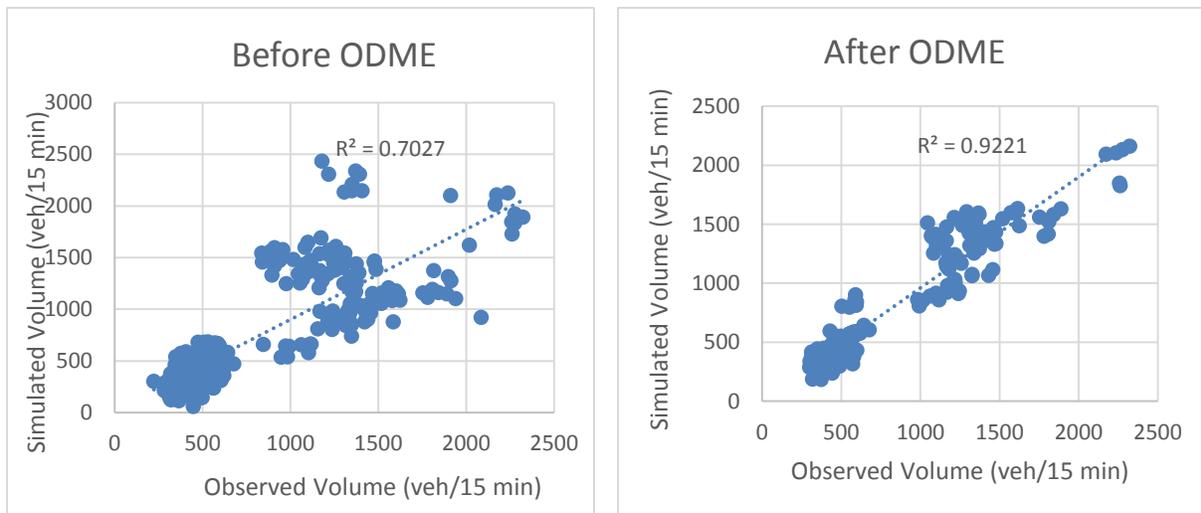
#### 7.5. Demand Calibration

A “traditional” ODME process was first conducted to calibrate the demand utilizing the available

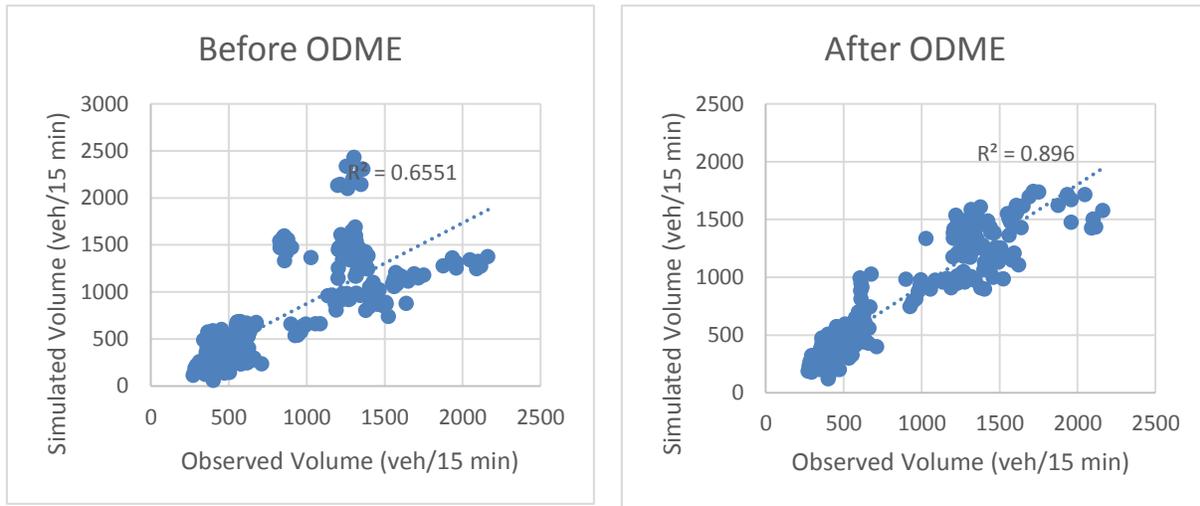
ITS detectors along the freeways and the midblock volume counts along the arterial streets. The initial demand matrix for this process was obtained through a PTMS-based ODME process implemented in Cube, as described in the previous demand data section. Figures 62 to 64 compare the simulated and observed link volumes without and with using the dynamic ODME process in DTALite for three demand levels. It is seen from these figures that the dynamic ODME process implemented in DTALite can greatly reduce the difference between simulated and observed link volumes. The  $R^2$  value increases from 0.756 to 0.907 in the case of the 50<sup>th</sup> percentile demand level, while the  $R^2$  value increases from 0.702 to 0.922 in the case of the 75<sup>th</sup> percentile demand level. For the 95<sup>th</sup> percentile demand level, the  $R^2$  value increases from 0.655 to 0.922.



**Figure 62 Comparison of Simulated Link Volumes vs. Observed Link Volumes Before and After Running ODME in DTALite for the Day with 50<sup>th</sup> Percentile of Demand**



**Figure 63 Comparison of Simulated Link Volumes vs. Observed Link Volumes Before and After Running ODME in DTALite for the Day with 75<sup>th</sup> Percentile of Demand**

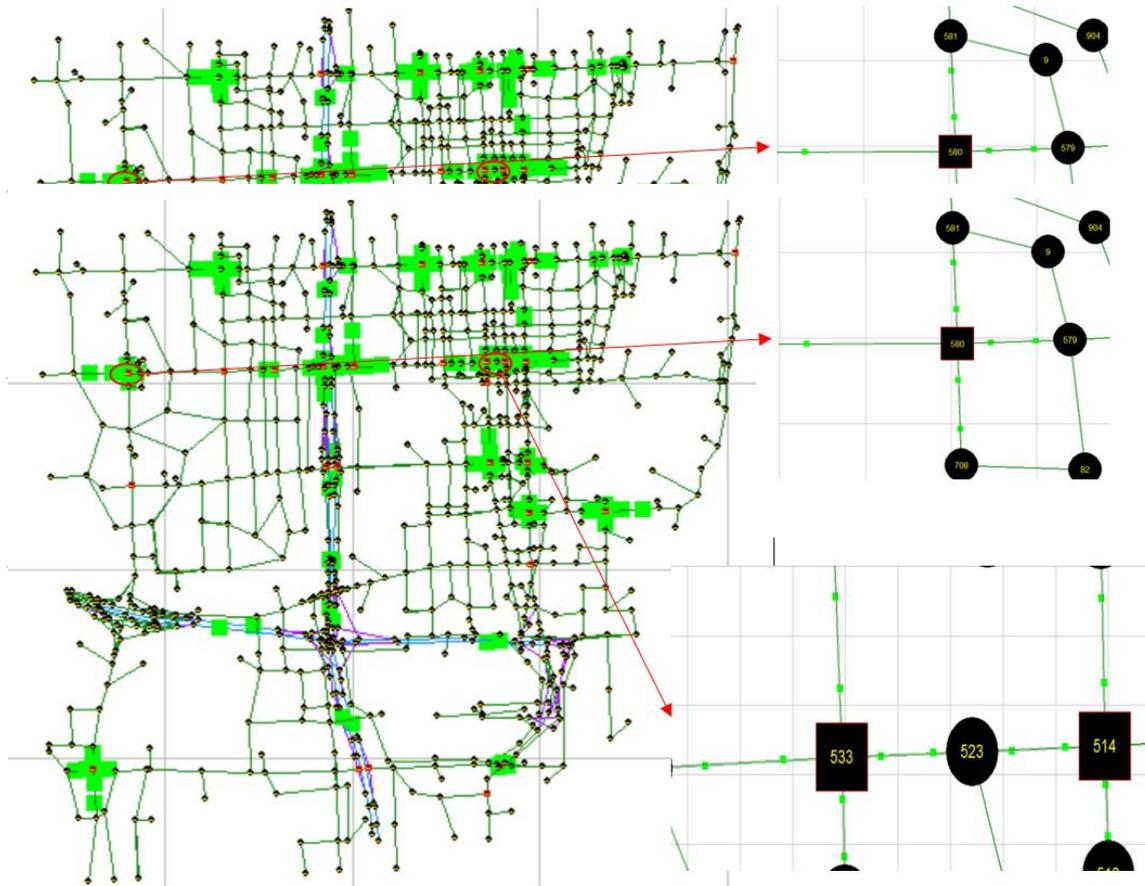


**Figure 64 Comparison of Simulated Link Volumes vs. Observed Link Volumes Before and After Running ODME in DTALite for the Day with 90<sup>th</sup> Percentile of Demand**

Even though the O-D matrix generated by the above ODME process produces very good  $R^2$  values for intersection approach volumes, there is significant errors at certain locations in terms of the turning movement percentages, which indicates that this model requires further calibration and validation. Therefore, an additional ODME process was conducted in this study for different percentile demand levels based on historical turning movement counts, in addition to the previously used midblock traffic counts.

Since the DTALite ODME process does not allow users to input turning movement counts, virtual sensors were added to each approaching and departing link at signalized intersections in this study with a purpose of minimizing the deviations from turning movement counts. Figure 65 shows the locations of the MVDS and virtual sensors in the study network. Two signalized intersections are enlarged to show the detailed coding of MVDS and virtual sensors. The traffic counts at each virtual sensor were calculated by summing up all the movements that can reach the corresponding link. However, the historical turning movement counts were only collected for one average day instead of one year. In order to produce the different turning movement counts for different demand levels, the ratios of MVDS counts at the 50<sup>th</sup>, 75<sup>th</sup>, and 90<sup>th</sup> percentile demand level to their average values were estimated and applied to the historical turning movements to generate the turning movements at each demand level. However, such turning movement counts may not reflect accurately the actual volumes at different demand levels. Therefore, these turning movement counts were further updated based on the MVDS data and the turning movement percentages calculated from the INRIX data at the intersections where the INRIX data is available. It should be pointed out that INRIX data has very limited sample size. Once the required turning movement counts were produced, the dynamic traffic assignment-based ODME procedure in DTALite was conducted again. It was noticed that the

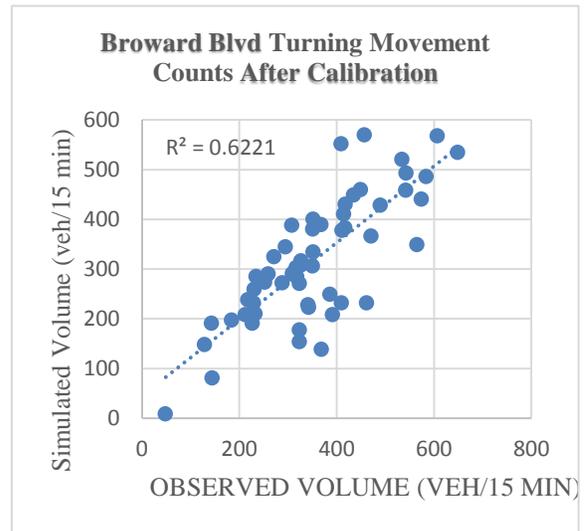
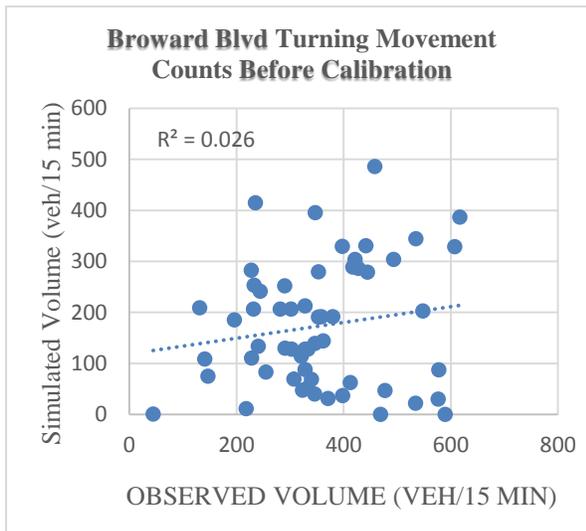
estimated O-D matrix still cannot produce reasonably good link volumes at certain locations compared to sensor data. A manual adjustment of the initial O-D matrix was made before running another ODME process. This process was conducted iteratively until reasonably good.



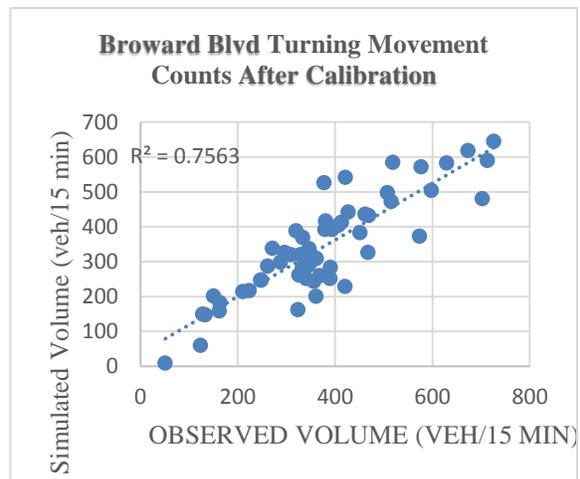
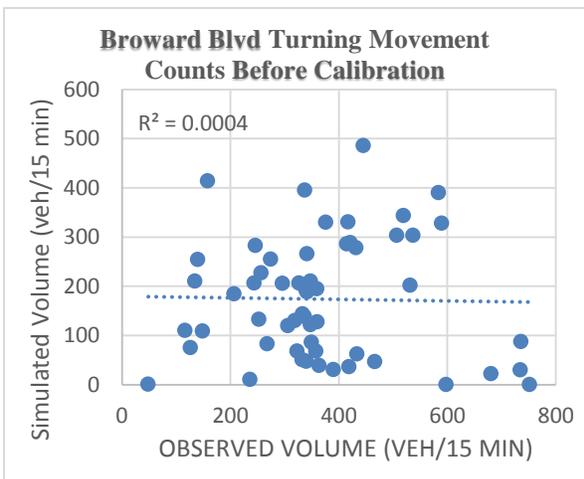
**Figure 65 MVDS and Virtual Sensor Locations in the Study Network**

The adjustment described above considered the fact that the zone connections to the network derived from the demand model do not reflect the real-world conditions. In the future, it is recommended that a method is developed to automatically disaggregate the zones into subzones with realistic connections to the network.

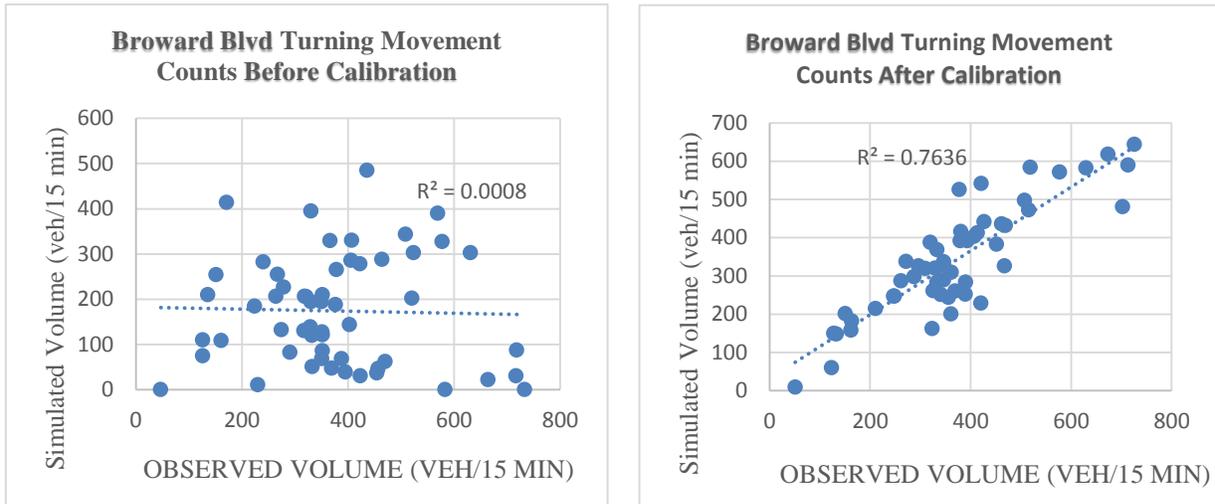
Figures 66 to 68 compare the simulated and observed turning movement counts along the Broward Blvd before and after implementing the above ODME process for different demand levels. As shown in Figure 66, the  $R^2$  value was 0.026 without demand calibration for the median day. This  $R^2$  value can be improved to 0.622 after the ODME process, which produces link volumes that are relatively close to the observed counts. Similarly, the results in Figures 67 and 70 show that the  $R^2$  value can greatly increase from 0.0004 to 0.764 for the 75<sup>th</sup> percentile of demand and from 0.0008 to 0.7636 for the 90<sup>th</sup> percentile of demand.



**Figure 66 Comparison of Simulated Link Volumes vs. Observed Link Volumes along the Broward Blvd Before and After Running ODME in DTALite for the Day with 50<sup>th</sup> Percentile of Demand**



**Figure 67 Comparison of Simulated Link Volumes vs. Observed Link Volumes along the Broward Blvd Before and After Running ODME in DTALite for the Day with 75<sup>th</sup> Percentile of Demand**



**Figure 68 Comparison of Simulated Link Volumes vs. Observed Link Volumes along the Broward Blvd Before and After Running ODME in DTALite for the Day with 90<sup>th</sup> Percentile of Demand**

Measures that include the RMSE and PRMSE between simulated and real-world volumes were also calculated to quantify the performance of the ODME. The expressions for the RMSE and PRMSE can be found in Equation 5 and Equation 13 in the previous sections. The corresponding results are listed in Table 28. As shown in this table, the RMSE is about 242 to 282 vehicles per 15 minutes and the PRMSE is 68% to 75% before the ODME process, while these values greatly drop to 79 to 89 vehicles per 15 minutes for the RMSE and 21% to 25% for PRMSE after the ODME process.

**Table 28 Comparison of Simulated Turning Movement Counts vs. Observed Turning Movement Counts for Broward Blvd for Different Levels of Demand**

Demand Level	RMSE Before Calibration (Veh/15 Min)	PRMSE Before Calibration	RMSE After Calibration (Veh/15 Min)	PRMSE After Calibration
50 percentile	241.85	68.07%	89.42	25.15%
75 percentile	277.86	75.60%	82.84	22.04%
95 percentile	282.43	75.01%	79.52	21.44%

It is also useful to look at the errors based on the count ranges. Table 29 shows the PRMSE values for three different ranges of observed counts. These values demonstrate that the simulated counts match reasonably well to the observed counts after the ODME steps, especially for the observed count range of more than 500 vehicles per 15 minutes. It is seen from this table that the errors follow almost the same pattern for different demand levels. Compared to the other

two demand levels, the 95<sup>th</sup> percentile demand level has the least PRSME. The 75<sup>th</sup> percentile demand level has a lower error in the count range of 250 to 5000 vehicles per 15 minutes.

**Table 29 Comparison of Simulated Turning Movement Counts vs. Observed Turning Movement Counts for Broward Blvd for Three Observed Volume Classes**

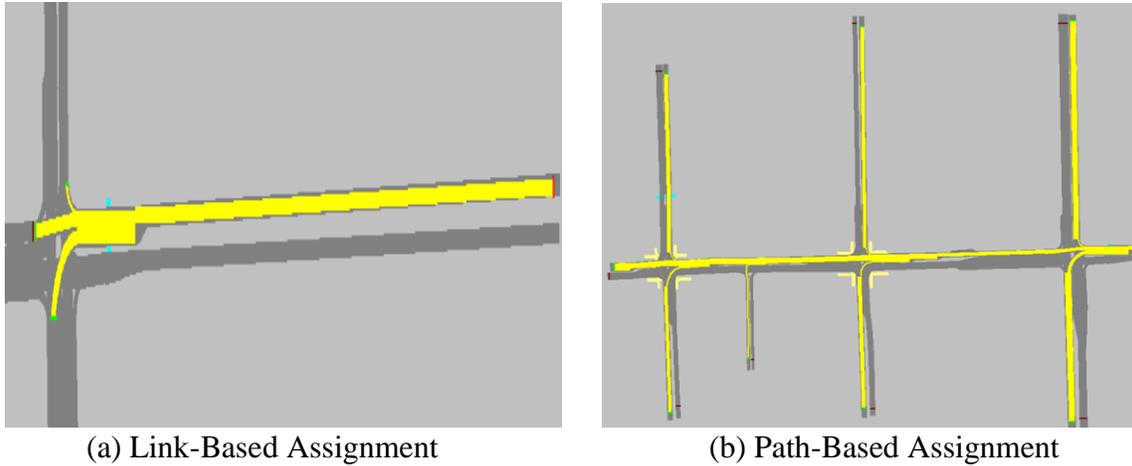
Observed Volume Count Range	50 Percentile (Medium day)		75 percentile (Heavy Day)		95 Percentile (Very Heavy Day)	
	PRMSE Before Calibration	PRMSE After Calibration	PRMSE Before Calibration	PRMSE After Calibration	PRMSE Before Calibration	PRMSE After Calibration
0 ~ 250	49.32%	18.33%	70.08%	19.42%	71.94%	19.08%
250 ~ 500	60.86%	26.53%	60.73%	22.91%	60.85%	23.03%
>500	73.95%	19.33%	79.23%	17.90%	78.94%	15.53%

## 7.6. ATM Strategy Modeling

Signal control was modeled as an example of ATM strategies, in this study. The mesoscopic DTALite model and microscopic VISSIM model were used in combination with a signal timing optimization tool, which allows the emulation of different signal timing strategies. In this study, part of the Broward Blvd between US-1 and Andrew Blvd was extracted from the mesoscopic DTALite network and modeled in VISSIM.

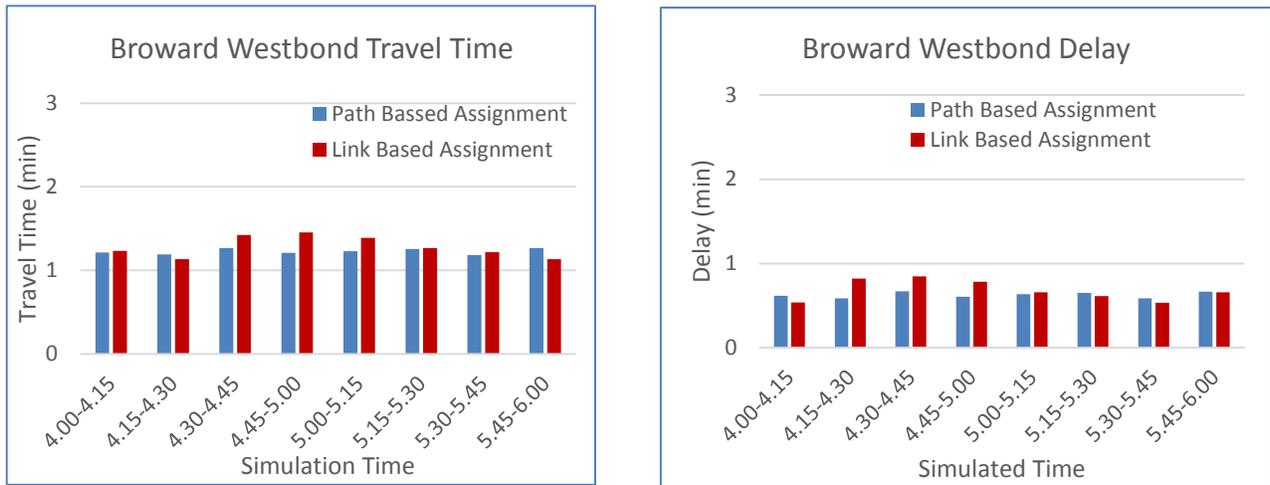
Two methods of traffic movement demand specification are included in VISSIM, link-based and path-based specification. In the link-based specification, vehicles are assigned based on the proportion of turning from an upstream link to its downstream links. This is the common approach used in microscopic simulations. The disadvantage of this approach is that VISSIM randomly assigns vehicles to turn left or right based on the given turning percentages. With this approach, a vehicle just entering the network may be immediately assigned to make turns and exit the network, which results in many short trips. Such random assignment may also affect the assessment of signal coordination impacts. In the path-based specification, vehicles are assigned from specific origin to specific destination on subpaths in the network. This approach avoids the short trip problem and can provide a more realistic replication of real-world traffic condition and traffic progression impacts. However, it is very difficult to estimate the routes from all the origins to all destinations manually particularly with a larger network size. A multi-resolution modeling provides a way to supply such routing information through a mesoscopic simulation that can be fed to the microscopic VISSIM model. Figure 69 shows an example of these two types of vehicle assignment. Figure 69(a) shows how the vehicles are assigned from the

westbound upstream link to its downstream turning movements at the intersection of Broward Blvd and US-1. Figure 69(b) shows how the vehicles are assigned to different destinations from the origin located at the Broward Blvd westbound.



**Figure 69 Link-Based Assignment vs. Path-Based Assignment**

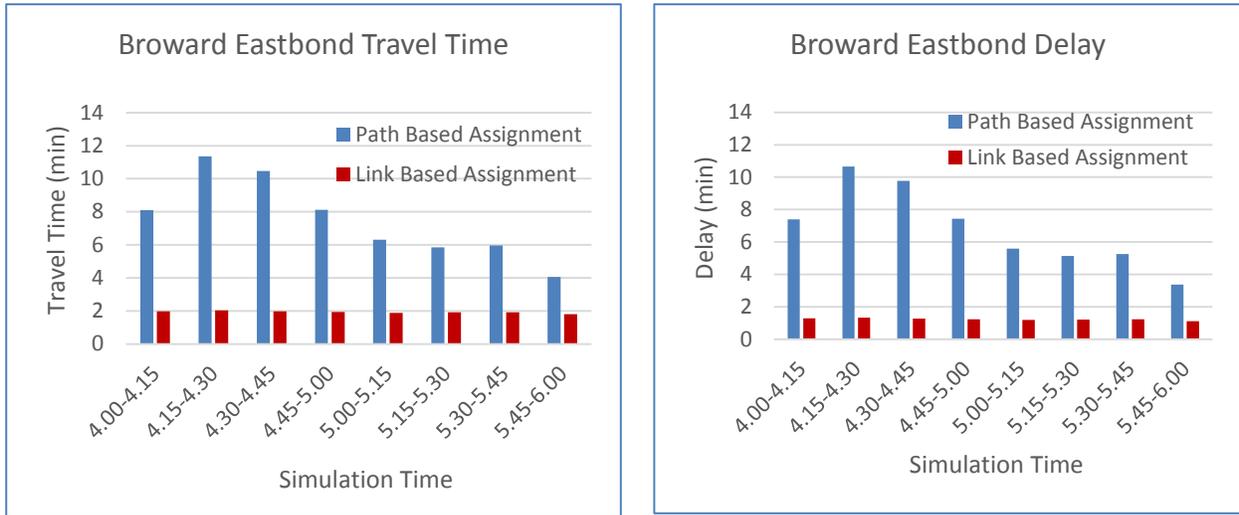
As mentioned above, the vehicle demands at the entrance links and the turning percentages along the routes were extracted from the DTALite model and used as inputs to the VISSIM model at 15-minute intervals. Figure 70 compares the resulted travel time and delays for Broward Blvd westbound traffic under a 50<sup>th</sup> percentile demand level using the two assignment methods.



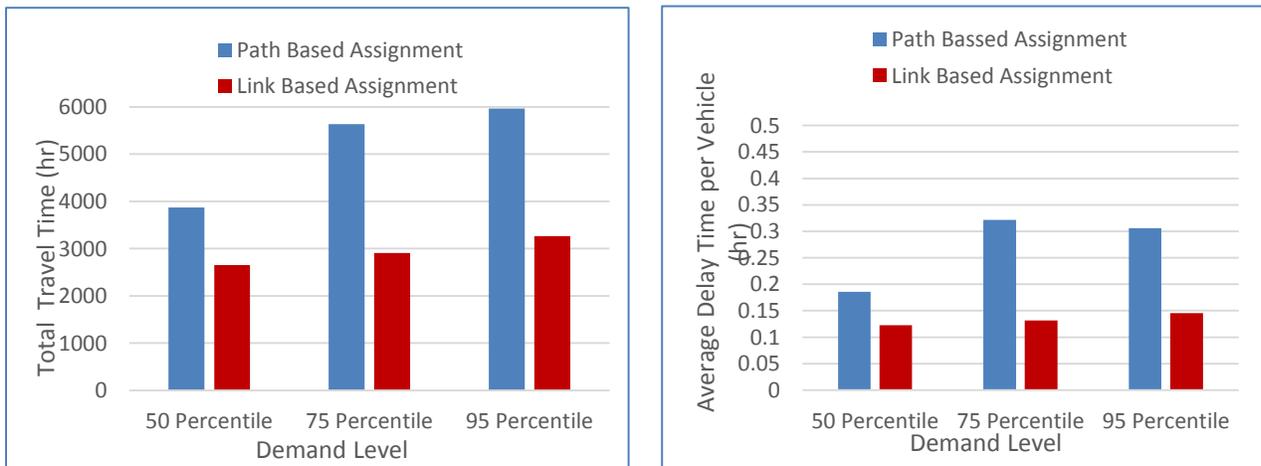
**Figure 70 Travel Time and Delays for Broward Blvd Westbound Traffic (Median Demand)**

Figure 71 shows the results for Broward Blvd eastbound traffic. As show in Figure 70, the travel time and delays for westbound traffic are slightly lower in a few time intervals when using the path-based specification. However, the eastbound traffic shows much higher travel time and delays when path-based specification is used. Figure 72 presents the comparison of the network-

wide travel time and delays for three demand levels. The results show that the path-based specification produces significantly different travel time and delays from those obtained with link-based specification. This demonstrates the importance of inputting all the routing decisions in a microscopic simulation model and the utility of using mesoscopic simulation for this purpose.



**Figure 70 Travel Time and Delays for Broward Blvd Eastbound Traffic (Median Demand)**



**Figure 71 Network-Wide Travel Time and Delays for Three Demand Levels**

## **8. ASSESSMENT OF LINK LEVEL VARIATION OF CONNECTED VEHICLE MARKET PENETRATION**

Connected vehicle (CV) and automated vehicle technologies promise significant safety, mobility, and environmental benefits. However, the benefits of these technologies largely depend on their market penetrations (MP) in the coming years. With regard to CV, the United States Department of Transportation's (USDOT) National Highway Traffic Safety Administration (NHTSA) released an advance notice of proposed rulemaking (ANPRM) and a supporting comprehensive research report on vehicle-to-vehicle (V2V) communication technology in 2014 (NHTSA, 2016). The draft Federal Highway Administration (FHWA) V2I Deployment Guidance (FHWA, 2015b) encourages V2I deployments, but it states that the USDOT will not require public agencies to implement V2I technology or applications, and recommends that these implementations should be done based on agency assessments. General Motors (GM) announced that it will release vehicle-to-vehicle (V2V)-equipped Cadillac by 2017 (U.S. News & World Report, 2016). Other car manufacturers are expected to equip their vehicles soon afterward. Thus, it is obvious that in the coming few years there will be an increase in the proportions of cars with connectivity features.

To assess the impacts of CV technologies, there is a need to estimate the MP of the vehicles in the coming years. The estimation of the CV market penetration, in the past, has provided an average estimate of the growth of CV for the nation. If the overall average market penetration of CV is at a given level, there is no guarantee that a certain link within a region will have that market penetration at any given period. This is because of the variations in the socio-economic characteristics of the regions compared to other regions, between the zones within a region, and the trip making characteristics of travelers with different socio-economic characteristics. In particular, the higher the income and new car ownership characteristics (vehicle age distribution) in a region or a zone, the higher is the ratio of new vehicles introduced into the traffic stream and thus the higher is the market penetration of connected vehicles. The market penetration of CV also varies between links as a result of the variation of inter-zonal socio-economic characteristics. This variation could be determined using the assignment of trips to the network and analyzing the output. The objective of this study is to develop a method to find the variations of the market penetration of CV between regions, zones within the region, and network links in a region, considering an average market penetration for the region. Although the focus of this study is on CV, the method presented in this document is also applicable to the estimation of market penetration of different levels of vehicle automation.

### **8.1. Application of Vehicle to Infrastructure (V2I)**

Connected vehicle data and the provision of messages to vehicles will play a major role in supporting the planning, operation, and management of the transportation system. The connected vehicle data and disseminated information will need to be transmitted using standardized

messages utilizing dedicated short-range communication (DSRC) or other communication technologies, such as cellular, Wi-Fi, and WiMAX. A connected vehicle will be equipped with an Onboard Unit (OBU), which consists of several components such as computer modules, display units, and a wireless communication module (either DSRC or cellular). The roadside infrastructure will be equipped with Roadside Units (RSU) that communicate with the OBUs and a central location when utilizing the DSRC option for communication. The connected vehicle (CV) message types and components are specified in the Society of Automotive Engineers (SAE) J2735 standards (SAE International, 2009).

The transmitted CV data could be used for a large number of applications (U.S. Department of Transportation, 2016) including safety, dynamic mobility, road weather management, and environment applications. The performances of these applications largely depend on the MP of CV. The estimated MP of CV is an important parameter for analyzing the impacts of connected vehicles on safety, mobility, and the environment (Olia et al., 2014). Previous studies have utilized the MP to assess the impacts of CV applications on mode choice (Minelli, 2015), traffic signal control (Smith et al., 2010; He, et al., 2012; Priemer and Friedrich, 2009), Freeway incident detection (Barria and Thajchayapong, 2011), lane-level speed estimation (Rim et al., 2011), arterial performance measurement (Li et al., 2008; Argote et al., 2011; Argote et al., 2012), intersection analysis (Ban et al., 2009; Ban et al., 2011; Hao et al., 2012), vehicle position detection (Goodall et al., 2016), transportation operation (Smith et al., 2007), and arterial queue spillback (Christofa et al., 2013). However, these studies have not considered the variations of the market penetration of CV between regions or in a region, as stated earlier.

## **8.2. Methodology**

The process of determining the MP distribution consists of three parts. The first part is to assume a scenario for CV implementation. The second part is to determine the MP of CV in different zones in a region depending on the socio-economic characteristics of these zones. The third part is to determine the variations of MP on different links in the region utilizing the traffic assignment procedures incorporated in the regional demand forecasting models.

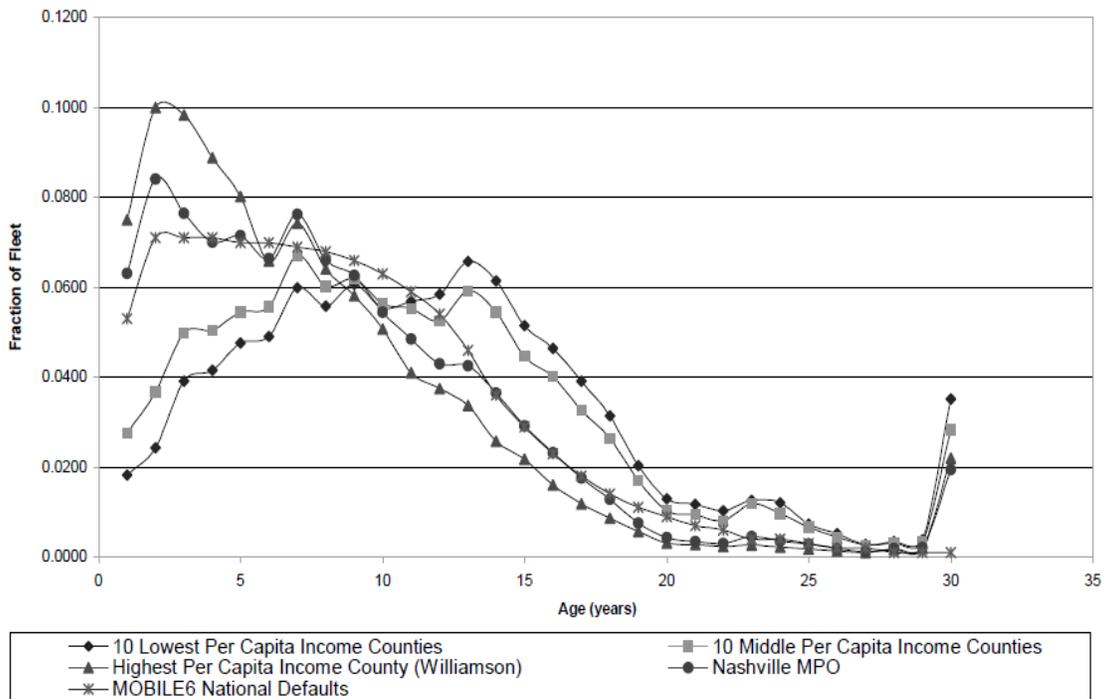
### ***8.2.1. An Assumption of One CV Implementation Scenario***

As stated in the previous section, NHTSA is expected to mandate connected vehicle technologies on all new vehicles. Apart from this mandate, after-market plug-in equipment will be available for installation on older cars but this is not expected to be mandated. However, it is not certain how many people will buy the after-market devices. Thus, the connectivity of the new cars will play the vital role in the determination of the market penetration of the CV and the after-market installations are not considered in this study to be on the conservative side in estimating the market penetrations. The USDOT (2008) conducted a study to estimate the benefits and costs of

CV implementations. For that purpose, the study predicted the probable market penetrations of CV in future years. In the estimation, the analysts considered the scenario where only new vehicles will use the CV technology with the assumption that in the first year 25%, second year 50%, third year 75% and afterward 100% of the new vehicles will have the connectivity. Wright et al. (2014) suggested three different scenarios for probable CV implementations. The most conservative scenario among the three is called the “15-year organic” scenario, which assumes that the CV will come into the fleet as organic sales of the new capability. The moderate one is called the “5-year mandate” scenario, in which manufacture would include OBUs into the new vehicles over a five-year period. The best-case scenario is the “1-year mandate” scenario where all the new vehicles will be equipped with OBU starting from the year that the CV is mandated. In this research, the “1-year mandate” scenario is assumed when producing the results. However, the methodology of this study could be applied to any of the above and other scenarios of CV implementations.

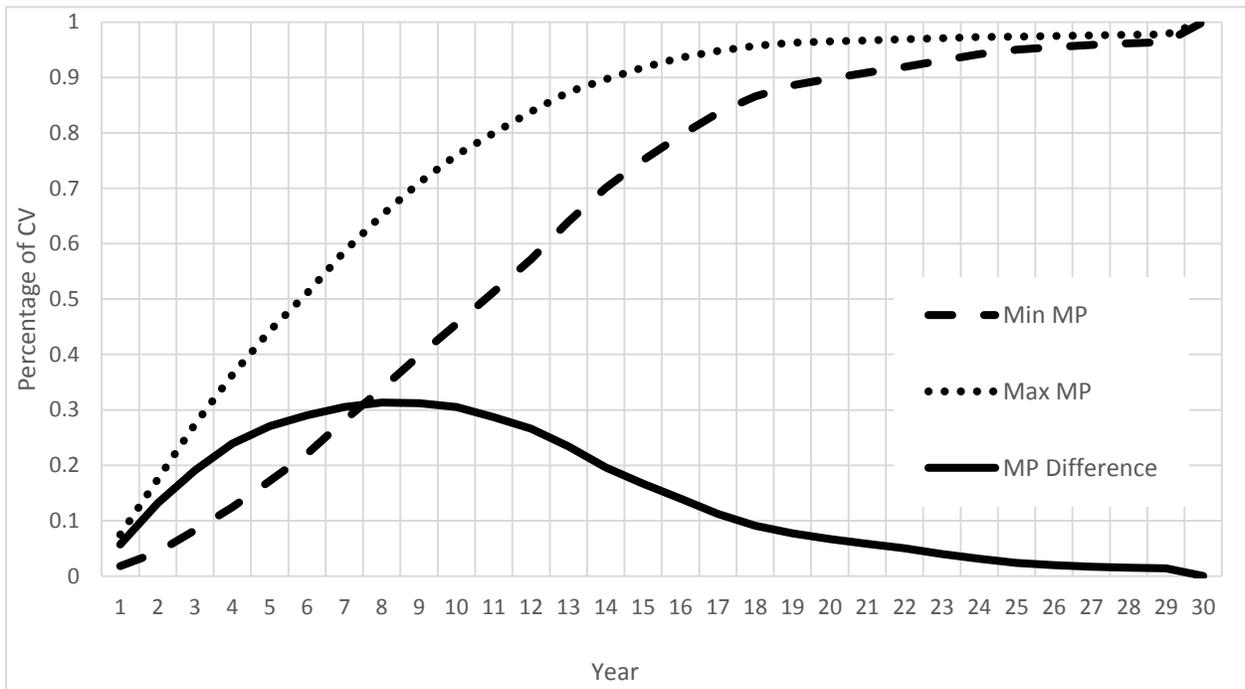
### ***8.2.2. Determination of Zone Specific MP***

The main objective of this study is to determine the variations of CV on different links in a region. These variations will occur due to the variations of the percentage of CV between zones in the region reflecting the associated socio-economical characteristics of the trip makers from/to these zones. Miller et al. (2002) showed that the vehicle age distribution is related to the per capita income in a county. They used the data from the state of Tennessee to illustrate the relationship. Country-by-country vehicle registration data and per capita income were used in their analysis. The per capita personal income information was collected from the United States Department of Commerce, Bureau of Economic Analysis (BEA) website. The vehicle age distributions for different income categories were developed for two vehicle types: light-duty vehicles (LDVs) referencing passenger cars and light-duty trucks (LDTs). The obtained age distributions of LDVs are shown in Figure 73 for counties with different income levels. The horizontal axis is the vehicle age and the vertical axis is the fraction of vehicles out of the total vehicles that have a certain age. The vehicles that have an age of thirty years or more are placed in the 30 years’ age group.



**Figure 72 LDV Age Distribution for Tennessee Counties (Source: Miller et al., 2002).**

Figure 73 shows that the fraction of one-year-old vehicles varies from 1.8% to 7.5% depending on the per capita income of an area. This means that if the connected vehicles are mandated for all new vehicles, then at the end of the first year the MP of CV will vary from 1.8% to 7.5% in a given area with an average value of 4.65%. This percentage will cumulatively increase each year as new vehicles are introduced in the market. This study uses the results from Miller et al. (2002) to produce cumulative percentage distributions of CV for regions or zones with the highest income area and lowest income area based on the results of Figure 73. Figure 74 shows the resulting distributions. Note that the results presented in this study are based on data from Tennessee due to the availability of this data to the researchers. However, the methodology is applicable to similar data, if available from other states and regions.



**Figure 73 Variation of the CV Market Penetration in Different Areas Based on the Information Presented in Figure 72**

Figure 74 shows the cumulative increase of CV each year for both the highest income area (Max MP) and the lowest income area (Min MP). The trend line shows that the increase in the CV market penetration is higher in the early stages and it slows down significantly after 12 to 18 years due to the market getting closer to saturation. The solid line in Figure 74 shows the difference between the maximum and minimum MP. An important observation from this graph is that the variability between areas increases for the first few years and reaches the maximum point around year 8 (3.1%). After that, the variability decreases and eventually becomes very low, as expected.

### 8.2.3. Determination of the Variation of MP between Links

This study used the cumulative MP of CV distribution described above to determine the MP of CV for each Zone in a region based on the socio-economic characteristics in the region. The determined MP was associated with each zone in a demand-forecasting model. Then, the assignment procedure of the model was exercised and the percentage of CV on each link is determined for each time period of the day based on the total volumes and CV volumes resulting from the assignment.

To demonstrate the application of the methodology to estimate the CV MP on the links, this study utilized the assignment step of four step demand-forecasting model in the southeast

Florida region, which is referred to as the Southeast Florida Regional Planning Model (SERPM6). This model covers Miami-Dade, Broward, and Palm Beach in southeast Florida. Unfortunately, the SERPM6 model does not include zone specific per capita income data. This information is available in other regional demand forecasting models but not in SERPM. Thus, the first step in this process is to identify the Southeast Florida income data per zone.

The income data is collected in this study using the American Community Survey (ACS) 5-year estimates (2010-2014). This data is available for download from the ACS website (United States Census Bureau, 2016) as a Geographic Information System (GIS) database shape file format. The income per capita in each census tract level is used in the analysis for this study. The income data downloaded at the census tract level is associated with the zone data using the ArcGIS software. There are a total 4,106 zones within the SERPM6 model. The minimum per capita income in the ACS database for southeast Florida is \$15,500 and the maximum per capita income is \$1,44,900. Using the income of each zone and the variation shown in Figure 74, the MP of a zone is calculated.

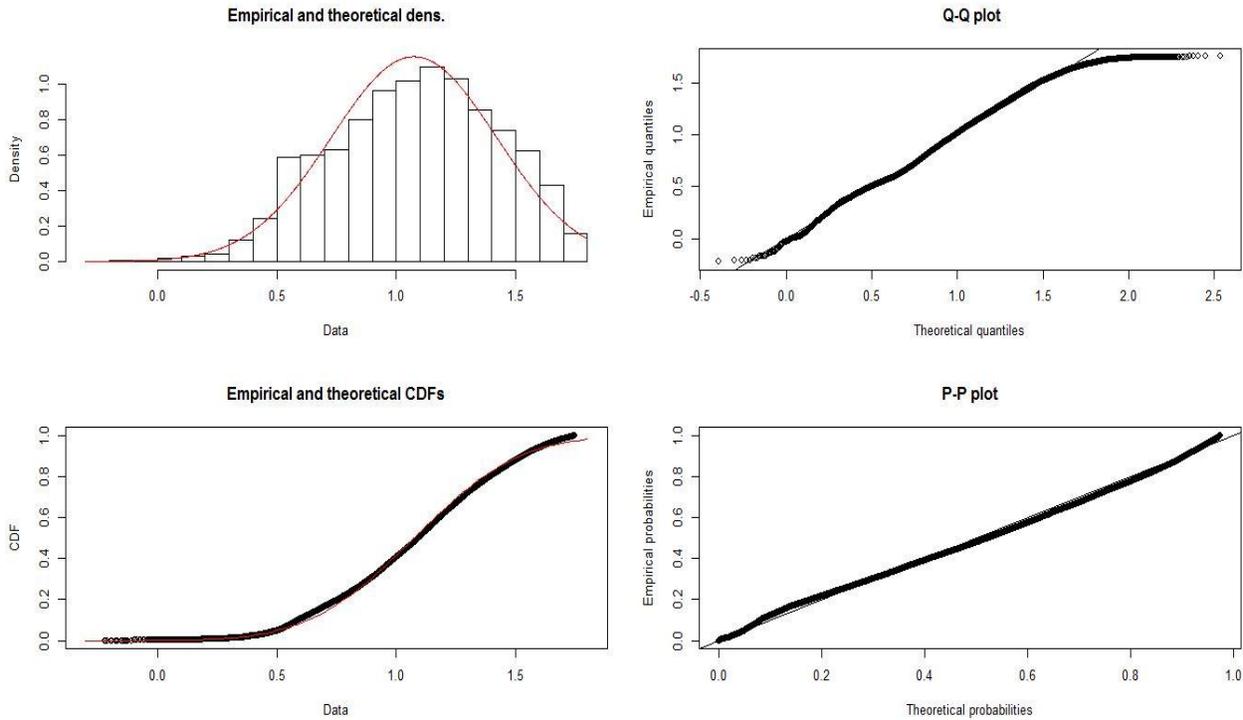
Once the MP for each Zone is identified, as described above, each O-D matrix in the demand model is divided into two matrices. The first O-D matrix is for the connected vehicles and the second one is for the non-connected vehicles. The total number of trips originating from each zone is multiplied by the MP of the CV associated with that zone to get the number of trips that are made by the CV. The remaining trips are considered as non-equipped vehicle trips. The two types of O-D matrices are then used as inputs to the trip assignment process. After the trip assignment, the link-level traffic volumes are analyzed and the percentage of CV for each link is calculated.

The study then uses the link level CV proportions in the region as determined above to identify the statistical distributions of these proportions. Analysts can use this type of distributions in lieu of using fixed CV proportions when assessing the performance of applications that are based on CV technologies.

### **8.3. Case Study Results**

For the Southeast Florida Case Study, there are about 45 thousand links, for each of which the CV percentages are identified based on the analysis of this study. As mentioned above, the next step is to determine the distribution of these proportions. First, this study investigated whether the distribution of the CV market penetrations on the links is normal or not. For a large sample, the most common practice of the normality confirmation is to check the normality test plots, as shown in Figure 75. After analyzing the data, it was found that the percentage of CV on different links follows a lognormal distribution rather than a normal distribution. The density plot of this variable is skewed to the right and it was found that the logarithm of the link CV percentage fits

better a normal distribution than does the original data. Figure 76 shows the plots to check the normality of the logarithmic value of the CV percentages for different links in year 1. Please, note that the results presented in this section is for the PM peak period. The analysis can be repeated for different peak periods to show the variations in MP by a period of the day. This will account for the difference in the distributions of the trips by time of day of users with different income levels.



**Figure 74 Different Plots to Check the Distribution of the CV Percentages for Various Links [Year 1]**

The plots show that the logarithm of the CV percentages is normally distributed. This same test was repeated for all future years. For all years, the distributions were found to be lognormal. Table 30 shows the mean and standard deviation of each year distribution.

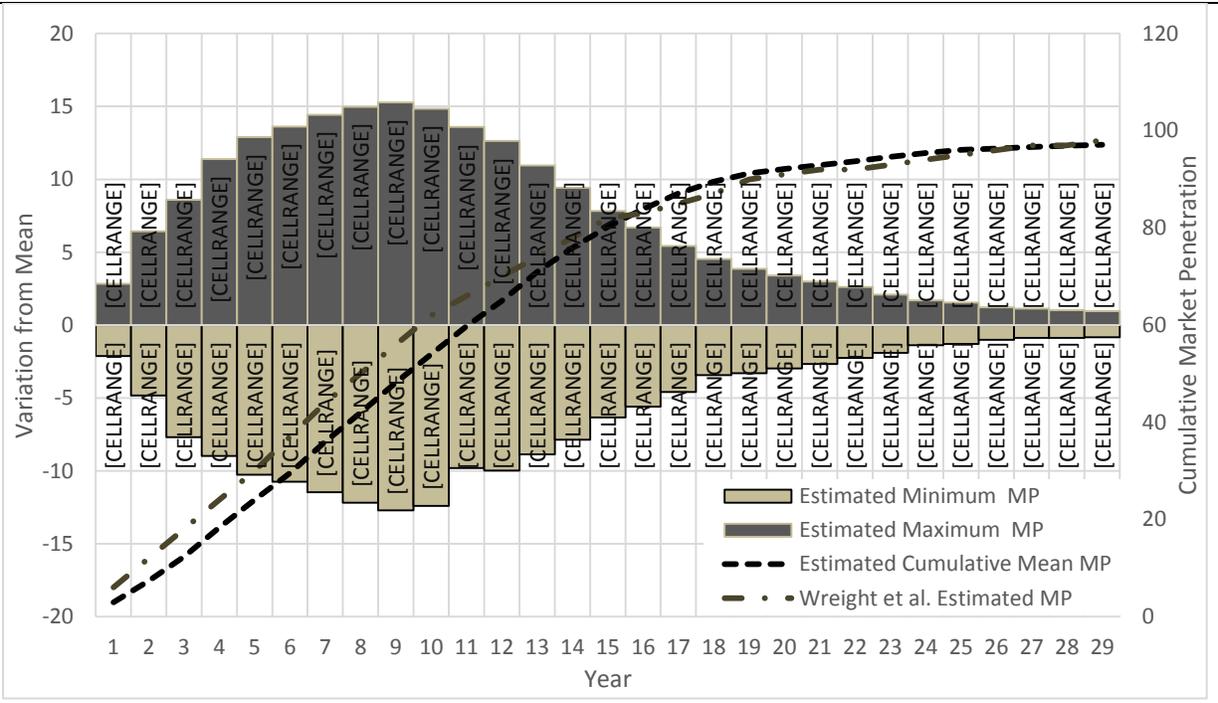
After analyzing the data for all the years following the methodology presented in the previous section, the mean market penetration and the variation level at each year are presented in Figure 76. In Figure 76, the left vertical axis shows the variation of the MP between links for each year and the right vertical axis shows the cumulative average MP of CV. The number inside each bar chart provides the maximum and minimum value of MP among the links in a region at a particular year of the analysis. The two dotted line represents the cumulative market penetration calculated in this study and the cumulative MP calculated by Wright et al. (2014).

**Table 30 Mean and Standard Deviation (SD) of Link-level MP Distribution by Year**

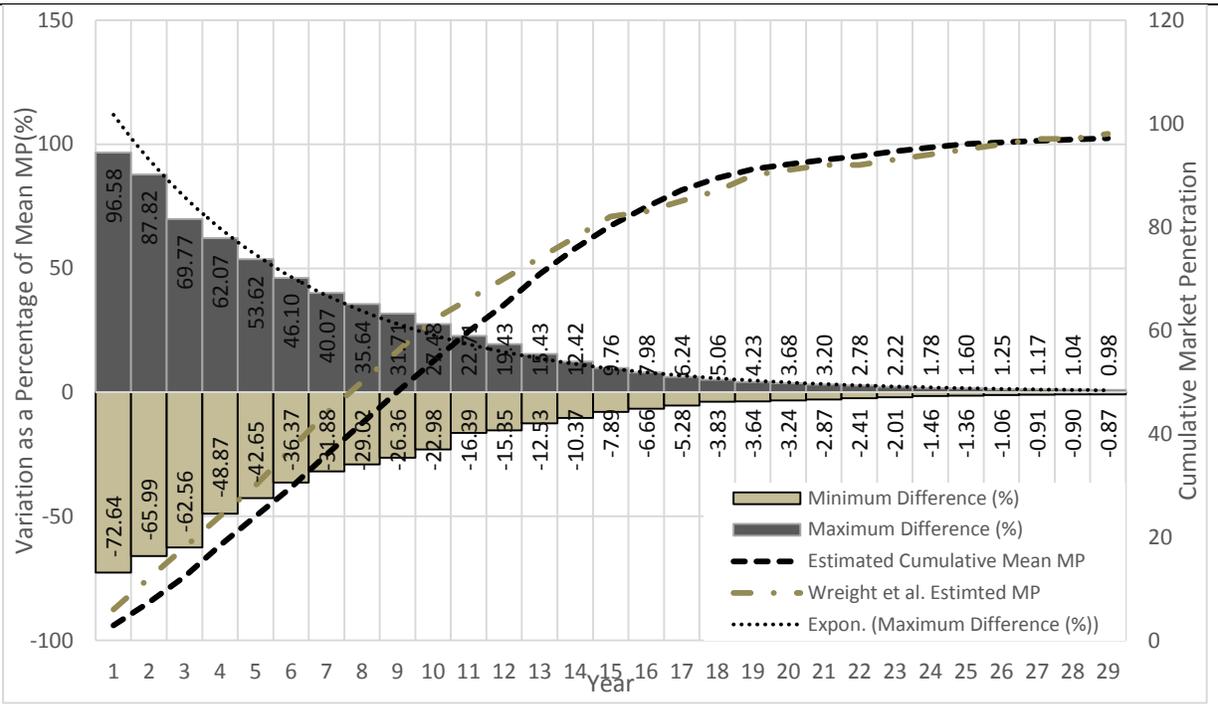
Year	Mean (log)	Mean (Actual)	SD (log)	Year	Mean (log)	Mean (Actual)	SD (log)
1	1.074	2.9	0.5460	16	4.429	83.8	0.0310
2	1.990	7.3	0.3230	17	4.467	87.1	0.0240
3	2.510	12.3	0.3000	18	4.494	89.5	0.0195
4	2.910	18.4	0.2300	19	4.513	91.2	0.0170
5	3.180	24.0	0.1960	20	4.523	92.1	0.0146
6	3.386	29.5	0.1720	21	4.532	92.9	0.0130
7	3.583	36.0	0.1480	22	4.540	93.7	0.0110
8	3.737	42.0	0.1330	23	4.550	94.6	0.0088
9	3.875	48.2	0.1190	24	4.558	95.4	0.0068
10	3.989	54.0	0.1060	25	4.565	96.1	0.0061
11	4.091	59.8	0.0860	26	4.568	96.4	0.0049
12	4.174	65.0	0.0740	27	4.571	96.6	0.0045
13	4.261	70.9	0.0600	28	4.574	96.9	0.0042
14	4.329	75.9	0.0470	29	4.576	97.1	0.0040
15	4.385	80.2	0.0380				

Figure 76(a) shows the actual variation and Figure 76(b) shows the variation as a percentage of the mean value. For lower market penetrations, the variations are lower but the percentage variations are higher. An exponential function that is fit to the data as shown in Figure 76(b) shows that the percentage of the MP variation decreases exponentially.

The average percentage increase of CV for each year is presented in Figure 77. Figure 77 shows that the MP increase rate grows up for the first several years and then it remains almost constant for the next few years before decreasing at a steep slope and finally becoming flat at a low value, due to reaching the oversaturation level.

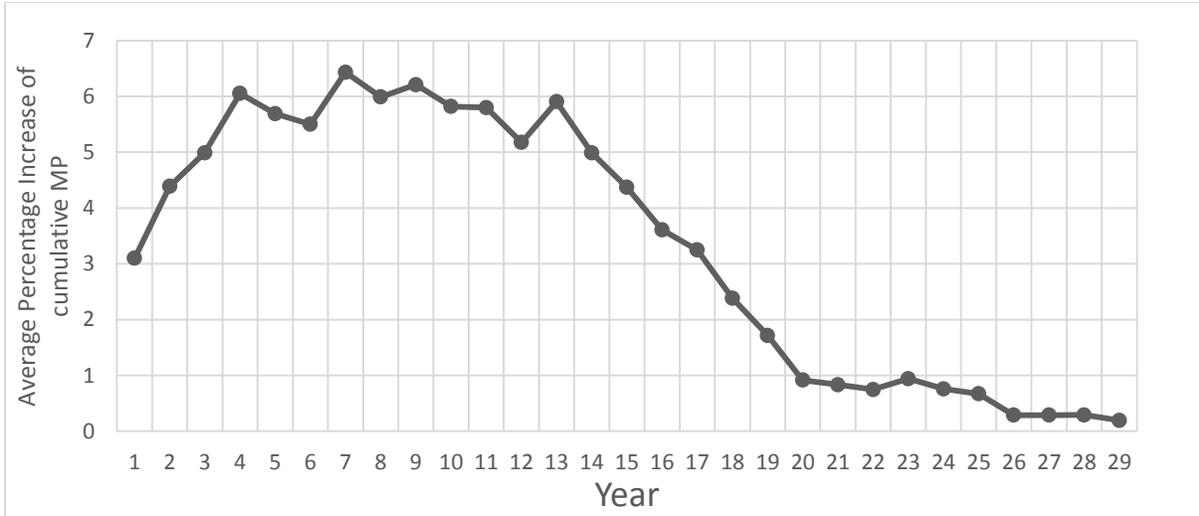


(a) MP variation values



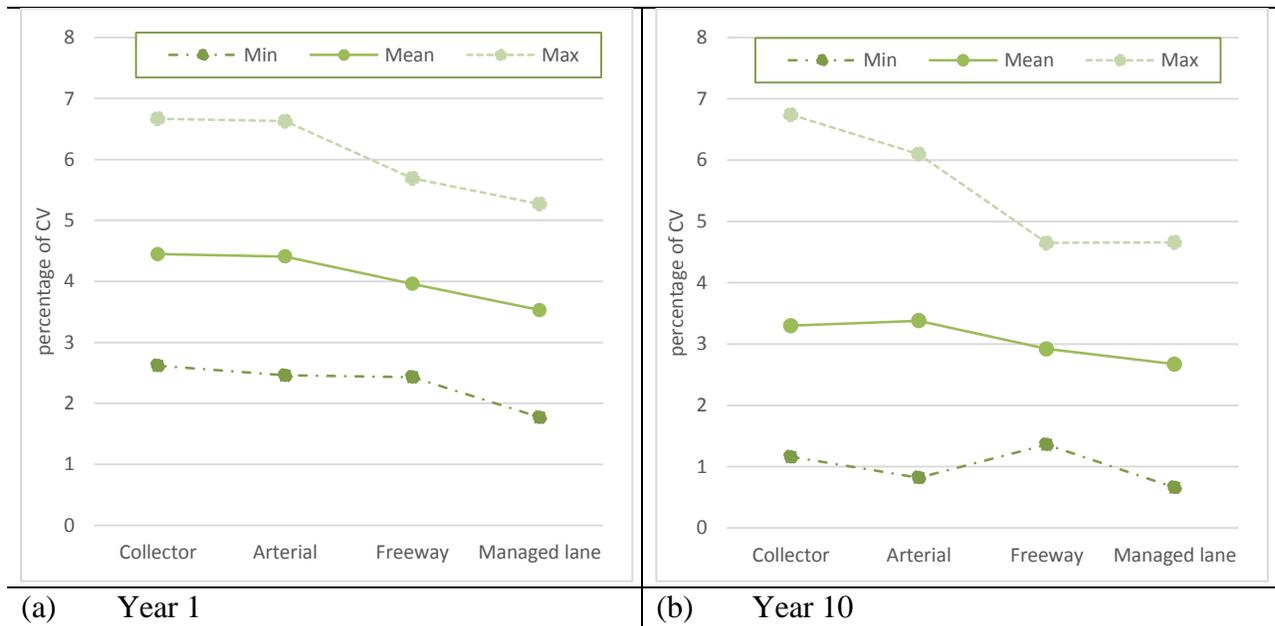
(b) Variation as a percentage of the mean MP

Figure 75 Variation of CV Market Penetration



**Figure 76 Average Percentage Increase of Cumulative MP of CV by Year**

This study also investigated the difference of MP variations on different facility types (Figure 78). Figure 78 shows that the variability decreases when moving from collector to arterial and from arterial to freeway and managed lane facilities. This is due to the mix of traffic from various zones that normally use freeways and to less extent arterials. Thus, it is recommended that these variations are considered separately by facility type with a different distribution is identified for each type.



**Figure 77 Variation of MP by Facility Type**

#### **8.4. Summary**

This study proposed a methodology to determine the variation of CV market penetration between regions, zones within a certain region, and links within the region. The methodology can be implemented with various CV implementation scenario assumptions and considers the variations in the socioeconomic characteristics between regions and zones. The analysis can be repeated for different peak periods to show the variations in MP by period of the day. This will account for the difference in the distributions of the trips by time of day of users with different income levels. Applying the methodology of this study to a case study indicates that the distribution of the link-specific CV MP follows a lognormal distribution. The percentage variation in the market penetration is shown to be the highest in the first year of CV implementation and decreases exponentially with the number of years passing since the implementation. The MP variations between links are the highest on collectors followed by arterials followed by freeways. It is recommended that the variations in MP are considered separately by facility type. The study also shows that the average percentage increase in the CV MP grows up in the first several years then remain almost constant before dropping sharply.

This study concludes that analyzing the impacts of CV implementation utilize a fixed forecasted MP for the whole nation will not be able to reflect the real-world conditions that involve variations in socioeconomic characteristics between regions and zones. It is recommended that the methodology developed in this study to forecast the CV market penetrations and their variations between regions, zones, and links are used when evaluating CV impacts.

## REFERENCES

Abdelghany, A., Abdelghany, K., Mahmassani, H., and Murray, P. (2000). "Dynamic traffic assignment in design and evaluation of high-occupancy toll lanes." *Transportation Research Record: Journal of the Transportation Research Board*, No. 1733, Transportation Research Board of the National Academies, Washington, D.C., pp. 39-48.

Alibabai, H., and Mahmassani, H. (2008). "Dynamic Origin-Destination Demand Estimation Using Turning Movement Counts." *Transportation Research Record: Journal of the Transportation Research Board*, No. 2085, Transportation Research Board of the National Academies, Washington, D.C., pp. 39-48.

American Association of State Transportation Officials. (2010). *Highway Safety Manual*. AASHTO, Washington, D.C.

Antoniou, C., Ben-Akiva, M., and Koutsopoulos, H. N. (2004). "Incorporating Automated Vehicle Identification Data into Origin-Destination Estimation." *Transportation Research Record: Journal of the Transportation Research Board*, No. 1882, Transportation Research Board of the National Academies, Washington, D.C., pp. 37-44.

Arem, B., and Van Der Vlist, M. J. (1992). *An On-line Procedure for Estimating Current Capacity* (Technical Report INRO-VVG 1991-17). TNO Institute of Spatial Organization, Delft, Netherlands.

Argote, J., Christofa, E., Xuan, Y., and Skabardonis, A. (2011). "Estimation of measures of effectiveness based on connected vehicle data." Proceedings of the 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), IEEE, pp. 1767-1772.

Argote, J., Christofa, E., Xuan, Y., and Skabardonis, A. (2012). "Estimation of Arterial Measures of Effectiveness with Connected Vehicle Data." Presented at 91<sup>st</sup> Annual Meeting Transportation Research Board, Washington D.C.

Arnaout, G. M., and Bowling, S. (2014). "A Progressive Deployment Strategy for Cooperative Adaptive Cruise Control to Improve Traffic Dynamics." *International Journal of Automation and Computing*, Vol. 11, No. 1, pp. 10-18.

Bahar, G., Masliah, M., Wolff, R., and Park, P. (2008). *Desktop Reference for Crash Reduction Factors* (Technical Report, FHWA-SA-08-011), U.S. Department of Transportation, Federal Highway Administration.

Ban, X., Hao, P., and Sun, Z. (2011). "Real Time Queue Length Estimation for Signalized

Intersections Using Travel Times from Mobile Sensors.” *Transportation Research Part C: Emerging Technologies*, 19(6), pp. 1133–1156.

Ban, X., Herring, R., Hao, P., and Bayen, A.M. (2009). “Delay Pattern Estimation for Signalized Intersections Using Sampled Travel Times.” *Transportation Research Record: Journal of the Transportation Research Board*, No. 2130, Transportation Research Board of the National Academies, Washington, D.C., pp. 109–119.

Barceló, J., Montero, L., Marqués, L., and Carmona, C. (2010). “Travel Time Forecasting and Dynamic Origin–Destination Estimation for Freeways Based on Bluetooth Traffic Monitoring.” *Transportation Research Record: Journal of the Transportation Research Board*, No. 2466, Transportation Research Board of the National Academies, Washington, D.C., pp. 19-27.

Barria, J. A., and Thajchayapong, S. (2011). “Detection and Classification of Traffic Anomalies Using Microscopic Traffic Variables.” *IEEE Transactions on Intelligent Transportation Systems*, 12(3), pp. 695–704.

Bassan, S., & Polus, A. (2010). Meaning of Actual Capacity of Freeways and its Estimation.” *Canadian Journal of Civil Engineering*, Vol. 37, No. 1, pp. 77-87.

Ben-Akiva, M., Palma, A.D., and Kanaroglou, P. (2009). “Dynamic Model of Peak Period Traffic with Elastic Arrival Rates.” *Transportation Science*, Vol. 20 (3), pp.164-181.

Bifulco, G. N., Pariota, L., and Di Pace, R. (2013). “Development and Testing of a Fully Adaptive Cruise Control System.” *Transportation Research, Part C: Emerging Technologies*, Vol. 29, pp. 156–170.

Caliper Corporation. (2011). *TransModeler 5.0*.

Calvert, S. C., a van den Broek, T. H., and van Noort, M. (2012). “Cooperative Driving in Mixed Traffic Networks — Optimizing for Performance.” IEEE Intelligent Vehicles Symposium, pp. 861–866.

Cambridge Systematics, Inc. (2012). *Value of Travel Time Reliability, Synthesis Report and Workshop Working Paper*. Prepared for SHRP 2 Workshops on ValueofTravelTimeReliability.<http://onlinepubs.trb.org/onlinepubs/shrp2/L35RF/DraftSynthesisValuingReliability.pdf>, Accessed Oct 12, 2013.

Cascetta, E. Inaudi, D., and Marquis, G. (1993). “Dynamic Estimators of Origin- Destination Matrices Using Traffic Counts.” *Transportation Science*, Vol. 27, No. 4, pp. 363–373.

Chao, C., Varaiya, P., & Kwon, J. (2005). "An Empirical Assessment of Traffic Operations." In Proceedings of International Symposium on Transportation and Traffic Theory, College Park, MD, July 2005, pp. 19-21.

Chiu, Y.C. (2012). *DynusT Online User Manual*. <http://wiki.dynust.net/doku.php>. Accessed December 12, 2016.

Chiu, Y. C., Bottom, J., Mahut, M., Paz, A. Balakrishna, R., Waller, T., and Hicks, J. (2011). *Dynamic Traffic Assignment: A primer*. Transportation Research E-Circular, (E-C153), Transportation Research Board of the National Academies, Washington, DC.

Chiu, Y. C., and Bustillos, B. (2009). "A Gap Function Vehicle Based Solution Procedure for Consistent and Robust Simulation Based Dynamic Traffic Assignment". Presented at the 88<sup>th</sup> Annual Meeting of the Transportation Research Board, National Research Council, Washington D.C., USA.

Christofa, E., Argote, J., and Skabardonis, A. (2013). "Arterial Queue Spillback Detection and Signal Control Based on Connected Vehicle Technology." *Transportation Research Record: Journal of the Transportation Research Board*, No. 2356, Transportation Research Board of the National Academies, Washington, D.C., 61-70.

Citilabs, Inc, (2013). *Citilabs Cube User Guide*.

Citilabs, Inc, (2016). *Port Everglades Area Cube Avenue Mesoscopic Simulation Model*. Prepared for Florida Department of Transportation. February 2016.

Corradino Group. (2013). *I-95 Broward and Palm Beach Origin-Destination Study*. Research Report, prepared for Florida Department of Transportation, Fort Lauderdale, FL.

Curry, D. A., and Anderson, D. G. (1972). *Procedures for Estimating Highway User Costs, Air Pollution, and Noise Effects*. National Cooperative Highway Research Program Report 133, Highway Research Board, National Research Council, Washington, D.C.

Davis, L. C. (2004). "Effect of Adaptive Cruise Control Systems on Traffic Flow". *Physical Review E*, Vol. 69, No. 066110, pp. 1-8.

Davis, P.K. and Hillestad, R. J. (1998). *Experiments in Multiresolution Modeling*. RAND Report. MR1004. RAND Corp.

DeCorla-Souza, P. (2003). "Evaluation of Toll Options Using Quick-Response Analysis Tools: A Case Study of the Capital Beltway." CD-ROM, Transportation Research Board, National Research Council, Washington, D.C.

Dehghani, Y., Adler, T., Doherty, M. W., and Fox, R. (2003). "Development of a New Toll Mode-choice Modeling System for Florida's Turnpike Enterprise." *Transportation Research Record: Journal of the Transportation Research Board*, No. 1858, Transportation Research Board of the National Academies, Washington, D.C., pp. 9-17.

Dervisoglu, G., Gomes, G., Kwon, J., & Varaiya, P. (2009). "Automatic Calibration of the Fundamental Diagram and Empirical Observations on Capacity." In Proceedings of 88<sup>th</sup> Annual Meeting of Transportation Research Board.

Deurbrouck, T., Glassco, R., Larkin, J., O'Hara, J., Wunderlich, K. (2015). *Trajectory Conversion Algorithm Software User Manual Version 2.3*.

Dixon, M. P., and Rilett, L. R. (2000). "Real-Time Origin-Destination Estimation Using Automatic Vehicle Identification Data." Presented at 79th Annual Meeting of the Transportation Research Board, Washington, D.C.

Dowling, R., Margiotta, R., Cohen, H., and Skabardonis, A. (2013). *Guide for Highway Capacity and Operations Analysis of Active Transportation and Demand Management Strategies* (FHWA-hop-13-042), June 2013.

DTALite. (2012). User Manual, <http://sites.google.com/site/dtalite/>, Accessed May 2012.

Duthie, J., Juri, N. R., Melson, C. L., Pool, C. M., & Boyles, S. (2012). *Guidebook on DTA Data Needs and Interface Options for Integration into the Planning Process*. Center for Transportation Research, University at Texas Austin No. 0-6657-P1.

Dixon, K. K., Hummer, J. E., and Lorscheider, A. R. (1996). "Capacity for North Carolina Freeway Work Zones." *Transportation Research Record: Journal of the Transportation Research Board*, No. 1529, Transportation Research Board of the National Academies, Washington, D.C., pp. 27-34.

Economic Development Research Group, Inc., Cambridge Systematics, Inc., ICF International, Texas A&M Transportation Institute, and Weris, Inc. (2014). *Development of Tools for Assessing Wider Economic Benefits of Transportation*. Transportation Research Record. Washington, D.C.

Elefteriadou,L., Martin,B., Simmerman, T., and Hale,D. (2011). *Using Microsimulation to Evaluate the Effects of Advanced Vehicle Technologies on Congestion*. Prepared for University Transportation Centers Program (UTC), by University of Florida, Gainesville, Florida.

Federal Highway Administration (FHWA). (2004). *Traffic Data Quality Measurement* (FHWA Report 14058), Washington, D.C., September 2004.

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2008a). *Value Pricing Pilot Program TRUCE 3.0 Users Guide, HOV Lane Performance*. [http://fhwa.dor.gov/tolling\\_pricing/value\\_pricing/tools/truce\\_model\\_guide.htm](http://fhwa.dor.gov/tolling_pricing/value_pricing/tools/truce_model_guide.htm), Accessed Oct. 10, 2013.

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2008b). *Managed Lanes: A Primer*. [http://fhwa.dot.gov/managedlanes/managed\\_lanes\\_primer.pdf](http://fhwa.dot.gov/managedlanes/managed_lanes_primer.pdf). Accessed Oct. 20, 2013.

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2012a). *Traffic Analysis Toolbox Volume XIV: Guidebook on the Utilization of Dynamic Traffic Assignment in Modeling* (Report No. FHWA-HOP-13-015) , Washington, D.C.

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2012b). *Managed Lanes*. [http://fhwa.dot.gov/managed\\_lanes.htm](http://fhwa.dot.gov/managed_lanes.htm). Accessed Oct. 20, 2012.

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2012c). *Traffic Analysis Toolbox Volume XIII: Integrated Corridor Management Analysis, Modeling, and Simulation* (Report No. FHWA-JPO-12-074), Washington, D.C.

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2013a). *The Effective Integration of Analysis, Modeling, and Simulation Tools* (Publication No. FHWA-HRT-13-036).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2013b). *Cooperative Adaptive Cruise Control, Human Factors Analysis* (Report No. FHWA-HRT-13-045).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2013c). *Analysis, Modeling, and Simulation (AMS) Testbed Requirements for Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs* (Report No. FHWA-JPO-13-098).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2013d). *Analysis, Modeling, and Simulation (AMS) Testbed Preliminary Evaluation Plan for Active Transportation and Demand Management (ATDM) Program* (Report No. FHWA-JPO-13-096).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2013e). *Analysis, Modeling, and Simulation (AMS) Testbed Framework for Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs* (Report No. FHWA-JPO-13-095).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2015a). *Connected Vehicles* (Publication No. FHWA-JPO-16-331).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2015b). *Vehicle-to-Infrastructure Deployment Guidance and Products* (Draft Report, FHWA-HOP-15-015).

Federal Highway Administration (FHWA), U.S. Department of Transportation. (2016). *CACC-VISSIM 2.0*. <https://www.itsforge.net/index.php/community/explore-applications#/31/96>, Accessed November 8, 2016.

Florida Department of Transportation (FDOT), (2013). *Southeast Florida Regional Planning Model, v. 6.5.3 (SERPM)*. Florida Department of Transportation, Florida, [http://www.fsutmsonline.net/index.php?/model\\_pages/](http://www.fsutmsonline.net/index.php?/model_pages/), Accessed Oct.20, 2013.

Florida's Turnpike Enterprise. (2005). *2005 Annual Customer Service Satisfaction Survey*, [http://www.floridasturnpike.com/downloads/CustomerSurveys/2005custsat\\_web.pdf](http://www.floridasturnpike.com/downloads/CustomerSurveys/2005custsat_web.pdf), Accessed Nov 4<sup>th</sup>, 2013.

Florida's Turnpike Enterprise. (2012). *Annual Customer Service Satisfaction Survey*, [http://www.floridasturnpike.com/downloads/CustomerSurveys/2005custsat\\_web.pdf](http://www.floridasturnpike.com/downloads/CustomerSurveys/2005custsat_web.pdf), Accessed Nov 4<sup>th</sup>, 2013.

Florian, M., Mahut, M., and Tremblay, N. (2008). "Application of a Simulation-Based Dynamic Traffic Assignment Model." *European Journal of Operations Research*. 189(3), pp.1381–1392.

Gettman, D., Pu, L., Sayed, T., and Shelby, S. (2008). *Surrogate Safety Assessment Model and Validation* (Final Report No. FHWA-HRT-08-051), Federal Highway Administration, Washington, D.C.

Gomes, G., May, A., and Horowitz, R. (2004). "Congested freeway Microsimulation Model Using VISSIM." *Transportation Research Record: Journal of the Transportation Research*

*Board, No. 1876*, Transportation Research Board of the National Academies, Washington, D.C., pp. 71–81.

Goodall, N. J., Smith, B.L., and Park, B.B. (2016). “Microscopic Estimation of Freeway Vehicle Positions from the Behavior of Connected Vehicles.” *Journal of Intelligent Transportation Systems*, 20(1), pp. 45-54.

Hadi, M., Ozen, H., Shabaniyan, Sh., and Xiao, Y. (2012). *Use of Dynamic Traffic Assignment in FSTUMS in Support of Transportation Planning in Florida*. Final Report, Prepared for Florida Department of Transportation, by the Florida International University Lehman Center for Transportation Research, Miami, FL.

Hadi, M., Shabaniyan, S., Ozen, H., Xiao, Y., Doherty, M., Segovia, C., and Ham, H. (2013). *Application of Dynamic Traffic Assignment to Advance Managed Lane Modeling*. Final Report, Prepared for Florida Department of Transportation, by the Florida International University Lehman Center for Transportation Research, Miami, FL.

Hadi, M., Xiao, Y., Ozen, H., and Alvarez, P. (2008). *Evaluation Tools to Support ITS Planning Process: Development of a Sketch Planning Tool in FSUTMS/Cube Environment*. Prepared for Florida Department of Transportation, by the Florida International University Lehman Center for Transportation Research, Miami, FL.

Hadi, M., Xiao, Y., Wang, T., Hu, P., Jia, J., Edelstein, R., and Lopez, A. (2014). *Pilot Testing of SHRP 2 Reliability Data and Analytical Products: Florida Pilot Site*. SHRP 2 Report.

Hadi, M., Xiao, Y., Zhan, C., & Alvarez, P. (2012). *Integrated Environment for Performance Measurements and Assessment of Intelligent Transportation Systems Operations*. Prepared for Florida Department of Transportation, by the Florida International University Lehman Center for Transportation Research, Miami, FL.

Hao, P., Ban, X., Bennett, K.P., Ji, Q., and Sun, Z. (2012). “Signal Timing Estimation Using Sample Intersection Travel Times.” *IEEE Transactions on Intelligent Transportation Systems*, 13(2), pp. 792–804.

Hardy, M., and Wunderlich, K. (2009). *Traffic Analysis Tools Volume IX: Work Zone Modeling and Simulation – A Guide for Analysts* (FHWA-HOP-09-001).

He, Q., Head, K. L., and Ding, J. (2012). “PAMSCOD: Platoon-Based Arterial Multi-Modal Signal Control with Online Data.” *Transportation Research Part C: Emerging Technologies*, 20(1), pp. 164-184.

He, R.R., Ran, B., and Choi, K. (2000). "Decision Support System for Value Pricing Strategies on I-394 Corridor Network." 79<sup>th</sup> Annual Meeting of the Transportation Research Board, National Research Council, Washington D.C., USA.

Holyoak, N., and Branko, S. (2009). "Benefits of Linking Macro-Demand Forecasting Models and Microsimulations Models." *ITE Journal*, Vol. 79, Issue 10, pp. 30-39

I. TranSystems and I. E.H. Pechan & Associates. (2012). *MOVES Operating Mode Distribution Generator Documentation Report*. Transportation and Climate Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, Washington D.C.

Janson, M., and Levinson, D. (2013). *HOT or Not, Driver Elasticity to Price on the MnPASS HOT Lanes*. <http://nexus.umn.edu/Papers/HOTorNOT.pdf>, Accessed Oct. 20, 2013.

Jeannotte, K., Chandra, A., Alexiadis, V., Skabardonis, A. (2004). *Traffic Analysis Toolbox Volume II: Decision Support Methodology for Selecting Traffic Analysis Tools*. FHWA-HRT-04-039.

Jia, A., Williams, B. M, and Roupai, N. M. (2010). "Identification and Calibration of Site Specific Stochastic Freeway Breakdown and Queue Discharge". *Transportation Research Record, Journal of the Transportation Research Board*, No. 2188, Transportation Research Board of the National Academies, Washington, D.C., pp. 148-155.

Jones, S. (2013). *Cooperative Adaptive Cruise Control: Human Factors Analysis*. Science Applications International Corporation. Sponsored by FHWA. Report No. FHWA-HRT-13-045.

Kerns, R., and Paterson, D. (2011). *Using a Simulation Environment for Dynamic Toll Analysis*. *TransModeler*, <http://www.caliper.com/Library/simulation-methods-for-analyzing-managed-lanes.htm>. Accessed 2011.

Kesting, A., Treiber, M., Schönhof, M., and Helbing, D. (2007). "Extending Adaptive Cruise Control to Adaptive Driving Strategies." *Transportation Research Record*, No. 1, pp. 16–24.

Khazraeian, S., Hadi, M., Xiao, Y., and Aghdasi, B. (2014). "Application of the Upcoming HCM Managed Lane Procedure to Pylon-Separated Managed Lane Analyses." In *Proceeding of Transportation Research Record: Journal of the Transportation Research Board*.

Kockelman, K., Fagnant, D., Nichols, B., and Boyles, S. (2012). *A Sketch-Planning Toolkit for Evaluating Highway Transportation Projects*. Prepared for Texas Department of Transportation, by the University of Texas at Austin, Austin, TX.

Koppelman, and GeoStats. (2013). *Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand*. Transportation Research Record. Washington, D.C.

Koupal, J., Landman, L., Nam, E., Warila, J., Scarbro, C., Glover, E. and Giannelli, R. (2005). *MOVES2004 Energy and Emission Inputs Draft Report*, Assessment and Standards Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, Washington D.C.

Lee, S. (2014). “Applications of TRANSIMS in Transportation.” *Procedia Computer Science*, Vol. 32, pp. 769–773.

Li, J., and Govind, S. (2003). “An Optimization Model for Assessing Pricing Strategies of Managed Lanes.” 82<sup>th</sup> Annual Meeting of the Transportation Research Board, National Research Council, Washington D.C., USA.

Li, M., Zou, Z., Bu, F., and Zhang, W.B. (2008). “Application of Vehicle-Infrastructure Integration Data on Real-Time Arterial Performance Measurements.” Presented at 87<sup>th</sup> Annual Meeting of Transportation Research Board, Washington D.C.

Lownes, N. E. and Machemehl, R. B. (2006). “Sensitivity of Simulated Capacity to Modification of VISSIM Driver Behavior Parameters.” *Transportation Research Record: Journal of the Transportation Research Board*, No. 1988, Transportation Research Board of the National Academies, Washington, D.C., pp. 102–110.

Luttrell, T., Sampson, W., Ismart, D., and Matherly, D. (2008). *Predicting Performance with Traffic Analysis Tools – Final Report* (Final Report, FHWA-HOP-08-055).

Ma, J., and Demetsky, M. J. (2013). *Integration of Travel Demand Models with Operational Analysis Tools* (Final Report, FHWA/VCTIP 14-R5), December, 2013.

Mahmassani, H. S., Dong, J., Kim, J. (2009). *DYNASMART-P 1.5 User's Guide and Programmer's Guide*. Transportation Center, Northwestern University.

Mahmassani, H. S., Kim, J., Chen, Y., Stogios, Y., Brimohan, A., and Vovsha, P. (2014). *Incorporating Reliability Performance Measures into Operations and Planning Modeling Tools*. Transportation Research Board of the National Academies

Mahmassani H. S., and Tavana. H. (2001). “Estimation of Dynamic Origin- Destination Flows from Sensor Data Using Bilevel Optimization Method.” Presented at 80th Annual Meeting of the Transportation Research Board, Washington, D.C.

Mahut, M., Florian, M., and Tremblay, N., (2007) Comparison of Assignment Methods for Simulation-Based Dynamic Equilibrium Traffic Assignment, Presented in 6<sup>th</sup> Triennial Symposium on Transportation Analysis.

Mahut, M., Florian, M., Tremblay, N., Campbell, M., Patman, D., and McDaniel, Z. K. (2004). “Calibration and Application of a Simulation-Based Dynamic Traffic Assignment Model.” *Transportation Research Record, Journal of the Transportation Research Board*, No. 1876, Transportation Research Board of the National Academies, Washington, D.C., pp. 101-111.

Mallela J. and Sadasivam, S. (2011). *Work Zone Road User Costs – Concepts and Applications* (Report No. FHWA-HOP-12-005), Federal Highway Administration, Washington, D.C.

Margiotta, R., Lomax, T., Hallenbeck, M., Dowling, R., Skabardonis, A., and Turner, S. (2013). “Analytical procedures for determining the impacts of reliability mitigation strategies.” 92th Annual Meeting of the Transportation Research Board, National Research Council, Washington D.C., USA, No. SHRP 2 Report S2-L03-RR-1.

Martin, P., Zlatkovic, M., Chaudhuri, P., and Tasic, A. (2011). *PTV Traffic Platform*. Research Prepared by Civil and Environmental Engineering University of Utah.

Milanés, V., Shladover, S. E., Spring, J., and Nowakowski, C. (2014). “Cooperative Adaptive Cruise Control in Real Traffic Situations.” *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, No. 1, pp. 296–305.

Miller, T., Davis, W., Reed, G., Doraiswamy, P., and Tang, A. (2002). “Effect of County-Level Income on Vehicle Age Distribution and Emissions.” *Transportation Research Record: Journal of the Transportation Research Board*, No. 1815, Transportation Research Board of the National Academies, Washington, D.C., pp. 47-53.

Minelli, S., Izadpanah, P., and Razavi, S. (2015). “Evaluation of Connected Vehicle Impact on Mobility and Mode Choice.” *Journal of Traffic and Transportation Engineering (English Edition)*, 2(5), pp. 301-312.

Murray, P.M., Mahmassani, H.S., and Abdelghany, K.F. (2001). “Methodology for Assessing High-Occupancy Toll-Lane Usage and Network Performance.” *Transportation Research Record: Journal of the transportation Research Board*, No.1765, pp. 8-15.

National Cooperative Highway Research Program (2014). *Capacity Models for Freeways/Multilane Highways, Urban Streets, and Two-Lane Highways* (NCHRP Project 03-107).

National Highway Traffic Safety Administration (NHTSA), U.S. Department of Transportation. (2016). U.S. Department of Transportation Issues Advance Notice of Proposed Rulemaking to Begin Implementation of Vehicle-to-Vehicle Communications Technology. Press release, <http://www.nhtsa.gov/About+NHTSA/Press+Releases/NHTSA-issues-advanced-notice-of-proposed-rulemaking-on-V2V-communications>, Accessed May 5, 2016.

National Transportation Operations Coalition. (2005). *National Transportation Operations Coalition (NTOC) Performance Measurement Initiative*. Final Report. [http://www.ite.org/M&O/ntoc\\_final\\_report.pdf](http://www.ite.org/M&O/ntoc_final_report.pdf)

Nava, E., Milster, K., Chiu, Y.C., (2013). “Modeling Managed Lane/Express Lane with Dynamic Traffic Assignment.” Submitted for presentation at the 93rd Transportation Research Board Annual Meeting, Washington D.C.

Ngoduy, D. (2013). “Instability of Cooperative Adaptive Cruise Control Traffic Flow: A Macroscopic Approach.” *Communication Nonlinear Science and Numerical Simulation*, Vol. 18, Issue 10, pp.2838–2851.

Nowakowski, C., Shladover, S. E., and Cody, D. (2010). *Cooperative Adaptive Cruise Control : Testing Drivers’ Choices of Following Distances* (Report No. UCB-ITS-PRR-2010-39). University of California PATH.

Olia, A., Abdelgawad, H., Abdulhai, B., and Razavi, S. N. (2014). “Assessing the Potential Impacts of Connected Vehicles: Mobility, Environmental, and Safety Perspectives.” Presented at 93<sup>rd</sup> Annual Meeting of Transportation Research Board.

Park, B. (2005). *Transportation Management System Performance Monitoring, Evaluation, and Reporting — A Technical Handbook* (Report No. FHWA-HOP-07-124), Produced for FHWA, Washington, DC, September 2005.

Parsons Brinckerhoff. (2013). *Managed Lane Modeling Application for FSUTMS, Phase II, Memorandum to Advanced Traffic Assignment Subcommittee*. Florida Department of Transportation, [http://www.fsutmsonline.net/images/uploads/ManagedLane\\_Phase\\_II\\_Draft\\_2\\_2.docx](http://www.fsutmsonline.net/images/uploads/ManagedLane_Phase_II_Draft_2_2.docx), Accessed Oct. 23, 2013.

Parsons Brinckerhoff, Northwestern University, Mark Bradley Research & Consulting, University of California at Irvine, Research System Group, University of Texas at Austin, Frank Koppelman, and GeoStats. (2013). *Improving Our Understanding of How Highway Congestion and Pricing Affect Travel Demand* (SHRP 2 Report S2-C04-RW-1). Transportation Research Record. Washington, D.C.

Parsons Brinckerhoff & San Francisco County Transportation Authority. (2012). *DTA Anyway, Final Methodology Report*. Transportation Research Record. Washington, D.C.

Pesesky, L., Ismart, D., Huffman, C., Chiu, Y., et al. (2012). *Strategic Approaches at the Corridor and Network Level to Minimize Disruption from the Renew Process* (Project No. SHRP 2-R11).

Potts, I. B., Harwood, D. W., Hutton, J. M., Fees, C. A., Bauer, K. M., Lucas, L. M., Kinzel, C. S., and Frazier, R. J. (2014). *Identification and Evaluation of the Cost-Effectiveness of Highway Design Features to Reduce Nonrecurrent Congestion*. Transportation Research Record. Washington, D.C.

Priemer, C., and Friedrich, B. (2009). "A Decentralized Adaptive Traffic Signal Control Using V2I Communication Data." In 2009 12th International IEEE Conference on Intelligent Transportation Systems (pp. 1–6), St. Louis, MO.

PTV Vision. (2013a). *VISUM 14 User Manual*.

PTV Vision. (2013b). *VISSIM 7 User Manual*.

PTV Vision. (2015). *VISSIM 8 User Manual*.

Rakha, H., & Mazen, A. (2010). "Calibrating Steady-State Traffic Stream and Car-Following Models Using Loop Detector Data." *Transportation Science*, Vol. 44, No. 2, pp. 151-168.

Reich, S. (2013). *Automated and Autonomous Vehicles and Managed Lanes*. Prepared for Tampa Hillsborough Expressway Authority, by Center for Urban Transportation Research, University of South Florida.

Resource Systems Group, (2012). *South Florida Expressway Stated Preference Survey Report*. Prepared for URS Corporation.

Rim, H., Oh, C., Kang, K., and Kim, S. (2011). "Estimation of Lane-Level Travel Times in Vehicle-to-Vehicle and Vehicle-to-Infrastructure-Based Traffic Information System." *Transportation Research Record: Journal of the Transportation Research Board*, No. 2243, Transportation Research Board of the National Academies, Washington, D.C., pp. 9–16.

Ruegg, S., Kulshrestha, A., and Puppala, S. (2013). *Phase I Managed Lane Assignment Model Testing I-95 Corridor, Orlando and Tampa Regional Model*. Memorandum to Advanced Traffic Assignment Subcommittee, Florida Department of Transportation, [http://www.fsutmsonline.net/images/uploads/ManagedLaneTesting\\_PhaseI.docx](http://www.fsutmsonline.net/images/uploads/ManagedLaneTesting_PhaseI.docx), Accessed Oct. 20, 2013.

SAE International. (2009). *Dedicated Short Range Communications (DSRC) Message Set Dictionary*, SAE J2735.

Safirova, E., Gillingham, K., Harrington, W., and Nelson, P. (2013). *Resources for the Future, Are HOT Lanes a Hot Deal?*. <http://www.rff.org/rff/Documents/RFF-IB-03-03.pdf>, Accessed Oct. 20, 2013.

Sallman, D., Jeannotte, K., Margiotta, R., and Strasser, J. (2013). *Operations Benefit/Cost Analysis TOPS-BC User's Manual: Providing Guidance to Practitioners in the Analysis of Benefits and Costs of Management and Operations Projects* (FHWA-HOP-13-041).

Sarasua, W., Davis, W., Clarke, Kottapally, J., and Mulukutla, P. (2004). "Evaluation of Interstate Highway Capacity for Short-term Work Zone Lane Closures." *Transportation Research Record: Journal of the Transportation Research Board*, No. 1877. Transportation Research Board of the National Academies, Washington, D.C., pp. 85-94.

Sbayti, H., and Roden, D. (2010). *Best Practices in the Use of Micro Simulation Models* (NCHRP Project 8-36, Task 90), National Cooperative Highway Research Program, Washington, DC.

Shabaniyan, S. (2014). *Advanced Methodologies in Dynamic Traffic Assignment Modeling of Managed Lanes*. Ph.D. Dissertation. Florida International University, Florida, United States.

Sheehan, B., Colyar, J., Hunt, J., and Jones, G. (2012). *ATDM Program Brief: Active Traffic Management* (FHWA-HOP-13-003).

Shelton, J. and Y.-C. Chiu. (2009). "Toward a Consistent and Robust Integrated Multi-Resolution Modeling Approach for Traffic Analysis." In TRB Planning Application Conference. Houston, Texas.

Shladover, S., Su, D., and Lu, X. (2012). "Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow." Proceedings of the 91st Transportation Research Board Annual Meeting, Washington D.C.

Smith, A., Bilotto, C., and Chang, M. (2008). *Policy Options Evaluation Tool for Managed Lanes (POET-ML) Users Guide and Methodology Description* (FHWA-HOP-09-031), December 2008.

Smith, B. L., Park, B. B., Tanikella, H., and Zhang, G. (2007). *Preparing to Use Vehicle Infrastructure Integration in Transportation Operations: Phase I* (Publication VTRC 08-CR1), Virginia Department of Transportation.

Smith, B. L., Park, H., Venkatanarayana, R., Goodall, N. J., Datesh, J., and Skeritt, C. (2010). *Development of New Traffic Signal Control Algorithms under IntelliDrive (No. 2)*. IntelliDrive Pooled Fund Study.

Song, Z. and Yin, Y. (2008). *Impact of Lane Closures on Roadway Capacity Part C: Modeling Diversion Propensity at Work Zones* (Florida DOT Research Report No. TRC-FDOT-59056-2007-C), Prepared by the Transportation Research Center, the University of Florida, Gainesville FL.

Tapani, A. (2012). "Vehicle Trajectory Effects of Adaptive Cruise Control." *Journal of Intelligent Transportation Systems*, Vol.16 (1), pp. 36–44.

Turner, S. (2006). *Quality Control Procedures For Archived Operations Traffic Data: Synthesis Of Practice and Recommendations*, Produced for FHWA, Washington, D.C., November 2006.

United States Census Bureau. (2016). American Community Survey 5-year Estimate – Geodatabase format. <https://www.census.gov/geo/maps-data/data/tiger-data.html>. Accessed May 23, 2016.

University of Maryland CATTI Lab. (2016). The Regional Integrated Transportation Information System (RITIS), <https://ritis.org/archive/traffic>, Accessed October 9, 2016.

U.S. Department of Transportation. (2016). *Connected Vehicle Technology*. [http://www.its.dot.gov/connected\\_vehicle/connected\\_vehicle\\_tech.htm](http://www.its.dot.gov/connected_vehicle/connected_vehicle_tech.htm). Accessed May 5, 2016

U.S. Department of Transportation. (2008). *Vehicle-Infrastructure Integration (VII) Initiative Benefit-Cost Analysis, Version 2.3 (Draft)*. Report for ITS Joint program office, USDOT, Washington, DC, 2008. [http://www.its.dot.gov/research\\_docs/pdf/7vii-benefit-cost-analysis.pdf](http://www.its.dot.gov/research_docs/pdf/7vii-benefit-cost-analysis.pdf). Accessed May 23, 2016.

U.S. Environmental Protection Agency (EPA). (2012). *Motor Vehicle Emission Simulator (MOVES) User Guide for MOVES2010b*. Washington D.C.

U.S. News & World Report. (2016). Car-to-Car Communication May Hit Roads Soon. Press release, <http://www.usnews.com/news/articles/2015/03/04/car-to-car-communication-may-hit-roads-soon>, Accessed May 5, 2016.

Van Driel, C. J. G., and B. van Arem. (2008). “Traffic Flow Impacts of a Congestion Assistant.” Presented at 87th Annual Meeting of the Transportation Research Board, CD-ROM. National Academies Press, Washington, D.C.

Wang, J., and Rajamani, R. (2010). “The impact of Adaptive Cruise Control Systems on Highway Safety and Traffic Flow.” Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, Vol. 218, No. 2, pp. 111–130.

Wright, J., Garrett, J. K., Hill, C. J., Krueger, G. D., Evans, J. H., Andrews, S., and Burkhard, B. (2014). *National Connected Vehicle Field Infrastructure Footprint Analysis* (Publication FHWA-JPO-14-125), FHWA, U.S. Department of Transportation.

Yeo, H., Shladover, S. E., Krishnan H., and Skabardonis, A. (2010). “Microscopic Traffic Simulation of Vehicle-to-Vehicle Hazard Alerts on Freeway.” *Transportation Research Record: Journal of the Transportation Research Board*, No. 2189, Transportation Research Board of the National Academies, pp. 68–77.

Zanjani, A., Pinjari, A., Kamali, M., Thakur, A., Short, J., Mysore, V., and Tabatabaee, F. (2015). “Estimation of Statewide Origin–Destination Truck Flows from Large Streams of GPS Data.” *Transportation Research Record: Journal of the Transportation Research Board*, No. 2308, Transportation Research Board of the National Academies, Washington, D.C., pp. 87-96.

Zhou, X., and Mahmassani, H. S. (2006). “Dynamic Origin–Destination Demand Estimation Using Automatic Vehicle Identification Data.” *IEEE Transactions on Intelligent Transportation Systems*, Vol. 7, No. 1.

Zhou, X., and Taylor, J. (2012). *NEXTA/DTALite User Guide Visualization*. <http://code.ooglr.com/p/NEXTA/>. Accessed September, 2012.

Zhou, X., and Taylor, J. (2014). *DTALite: A Queue-based Mesoscopic Traffic Simulator for Fast Model Evaluation and Calibration*. Cogent Engineering.

Ziliaskopoulos, A. K. (2000). “A Linear Programming Model of Single Destination System Optimum Dynamic Traffic Assignment Problem.” *Transportation Science*, 34(1), pp.37-49.

## APPENDIX A SUMMARY OF CRITERIA FOR TOOL ASSESSMENT

**Table 31 Summary of Criteria for Tool Assessment (Macroscopic/Analytical Tools)**

Criterion	Cube Voyager	ELToD	VISUM
<b>General Criteria (Hardware, Software, Interface, and etc.)</b>			
<b>Open Source</b>	No	Yes	No
<b>Utilization of Additional Hardware Computational Capabilities</b>	None	Requires Cube Voyager	Distributed computing for scenario calculations
<b>Flexibility in Modifying Procedures</b>	Cube scripting language can be modified	Implementation of Cube Voyager	Can use API utilizing Python script language, user defined delay functions can be coded in C++
<b>User Interface/Software Interface</b>	Make use of Cube environment powerful interface	Implementation of Cube Voyager	Complete menu driven GUI similar to any other GIS type tool, interfaces have been developed with ABM systems (DaySim, CT-RAMP etc.) as well as DynusT
<b>Shortest Path and Path Choice</b>			
<b>Assignment Type</b>	Static user equilibrium (UE). Several algorithms available including 1. Bi-Conjugate Frank-Wolf method, path-based gradient projection assignment 2. Gradient Projection Algorithm, origin based 3. Junction based	Use the static user equilibrium in Cube Voyager	Use different types of static and dynamic assignment including: <b>Static :</b> <ul style="list-style-type: none"> <li>• Incremental assignment</li> <li>• Path based Equilibrium assignment</li> <li>• Equilibrium _Lohse assignment(Frank-Wolfe variant)</li> <li>• Equilibrium assignment , Linear User Cost Equilibrium (LUCE) (OBA variant)</li> <li>• Assignment with Intersection Capacity Analysis (ICA) Stochastic assignment</li> <li>• TRIBUT (Time Based User Equilibrium)</li> </ul> <b>Dynamic :</b> <ul style="list-style-type: none"> <li>• Dynamic User Equilibrium (DUE)</li> <li>• Dynamic stochastic assignment</li> </ul>
<b>En-route Dynamic Routing (e.g., in-vehicle dynamic navigation system, DMS)</b>	No	No	No
<b>Specification of Fine-Grained Assignment Interval (e.g., 15-30 minutes)</b>	N/A	No	Yes
<b>Allows Fixing Paths for Parts of the Demands</b>	No. But can be emulated by restricting the link in the path. For specific demands (maybe difficult in some cases)	No. But can be emulated by restricting the link in the path. For specific demands (maybe difficult in some cases)	Yes
<b>Convergence Criteria</b>	Link based	Link based	Gap – as defined by Boyce et al.
<b>Outputting and Using Interval-based Convergence Gap</b>	N/A	N/A	Utilized gap is for the whole iteration rather than each interval. Individual interval gaps are not reported
<b>Assignment of Individual Vehicles</b>	No	No	No
<b>Assignment of Multiple Demand Types</b>	Yes. Different user classes for each demand type defined by user	Yes. Different user classes for each demand type defined by user	Yes (based on each user classes, by considering each demand type as type of PrT (Passenger car) system in link attribute). Unlimited demand classes
<b>Traffic Flow Model (TFM)</b>			
<b>Traffic Flow Model Type</b>	Macroscopic	Macroscopic	Macroscopic
<b>Queuing and Spillback</b>	No	No	Yes
<b>Modeling of Signalized Arterials</b>	Yes	No	Yes
<b>Modeling of Freeways</b>	Yes	Yes	Yes

**Table A-1 Summary of Criteria for Tool Assessment (Macroscopic/Analytical Tools)  
(Cont'd)**

Criterion	Cube Voyager	ELToD	VISUM
Modeling of Alternative Routes to Facilities	Yes	No. Only ML and GPL	Yes
Automatic Calculation of Signal Timing in Dynamic Traffic Assignment	Yes	No	Yes
Lane-by-Lane Simulation	No	No	No
Merging/Weaving Simulation	No	No	No
Modeling Turn Lane and Bay Length	No	No	No
<b>ML Modeling</b>			
Generalized Cost in Assignment	Various Variables using scripting language	Various variables using scripting language	Allows travel time and toll in the generalized cost function
Incorporation of Willingness-To-Pay (WTP) into Assignment	Yes	Yes	No
Link Access Restrictions/Prohibitions by Vehicle Type	Yes	Yes	Yes
Modeling Managed Lanes and Reversed Lanes	Yes, but fixed during period of time	Yes, but fixed during period of time	Yes, but fixed during period of time
Fixed and Time-of-Day Pricing by User Types	Yes	Yes	Yes
Dynamic Pricing	N/A	No	No
Inhomogeneous VOT and VOR	By user type, no randomization	By user type , no randomization	By user type and as lognormal distribution in TRIBUT assignment
<b>Advanced Vehicle Technology</b>			
Capacity as a Function of Proportion of Vehicle Types	Yes	Maybe emulated by coding PC <sup>1</sup> and trucks	Maybe emulated by coding PC and trucks
Fixed and Time-of-Day Pricing by different percentage of Advanced Vehicle Technology	Yes	Maybe emulated by coding PC and trucks	Maybe emulated by coding PC and trucks
<b>Work Zone Modeling</b>			
Capacity in Work Zone	Yes	N/A	Yes
Duration of work zone	No	N/A	Yes
Geometry features of work zone, e.g. length, No. of lanes	No	N/A	No
Queuing Warning System	No	N/A	No
Day-to-Day Learning	No	N/A	No
Specification of Traffic Diversion rates	No	N/A	No
<b>Other Advanced Strategies</b>			
Modeling DMS/HAR	No	N/A	No
Modeling Ramp Metering	Can be implemented using Cube Script or traffic signal	N/A	Yes
Modeling Variable Speed Limits	No	N/A	Yes
Modeling Traveler Information System	No	N/A	Yes – with interfaces to PTV-Optima
Modeling incidents and work zones	Yes	N/A	Yes
Modeling Traffic Response Systems	No	N/A	Yes – with interfaces to PTV-Optima
Modeling Traffic Adaptive Systems	No	N/A	Yes – with interfaces to PTV-Optima
Vehicle trajectory processor	No	N/A	No
Scenario generator	No	N/A	No

<sup>1</sup> PC: Passenger Car

**Table A-2 Summary of Criteria for Tool Assessment (Mesoscopic/Microscopic Tools)**

Criterion	DTALite	DynusT	Dynameq	Cube Avenue	VISSIM	VISSIM 8 (DTA) Mesoscopic	Trans Modeler	CORSIM
<b>General Criteria (Hardware, Software, Interface, and etc.)</b>								
<b>Open Source</b>	Yes	Yes	No	No	No	No	No	No
<b>Utilization of Additional Hardware Computational Capabilities</b>	None	None	None	None	None	None	None	None
<b>Flexibility in Modifying Procedures</b>	Open source. Codes can be modified. But difficult to modify.	Open source. Codes can be modified	Using a Python-based API to implement advanced strategies	Cube scripting language can be modified	Can use API utilizing Python script language	Can use API utilizing Python script language	Can use script language or API to implement advanced strategies	The Real Time Extension (RTE) facility allows coding of advanced strategies
<b>User Interface/Software Interface</b>	Use the NEXTA interface, which is a user friendly interface. Data in NEXTA can be converted to Cube and VISSIM	Use the NEXTA interface. The interface has been developed to convert DynusT files to VISUM, which can then be converted to VISSIM	Similar in design to the Emme 4 interface	Make use of Cube environment powerful interface	State of the art interface. There is no interface with other tools, general import /export via xml type format is supported	Same as VISSIM	State of the art. Interfaced with TransCAD	Good user interface but limited interface with other software
<b>Shortest Path and Path Choice</b>								
<b>Assignment Type</b>	Dynamic user equilibrium (DUE). Alternative methods are available including MSA, Fix Switching Rate (FSR), Day-to-Day learning, and OD Matrix Estimation (ODME)	MSA and recently introduced GFV-based method that performs significantly better	Dynamic user equilibrium (DUE) 1. Fastest path combined with regular MSA 2. flow balancing MSA Gradient-Like algorithm	Dynamic user equilibrium (DUE) utilizing MSA	N/A	Dynamic Stochastic assignment, initial path search (iteration 0) is based on distance and then continuously updated based on experienced travel time	Dynamic user equilibrium (DUE).	Use a static assignment before the simulation but this feature is not normally used.
<b>En-route Dynamic Routing (e.g., in-vehicle dynamic navigation system, DMS)</b>	Yes. In-vehicle and DMS <sup>2</sup> )	Yes. In-vehicle and DMS	No	No	No, but divert at DMS using API	En-route dynamic routing is supported based on fixed route guidance strategies and partial routing specified by user	Yes	No

<sup>2</sup> DMS: Dynamic Message Sign

**Table A-2 Summary of Criteria for Tool Assessment (Mesoscopic/Microscopic Tools)  
(Cont'd)**

Criterion	DTALite	DynusT	Dynameq	Cube Avenue	VISSIM	VISSIM 8 (DTA) Mesoscopic	Trans Modeler	CORSIM
<b>Specification of Fine-Grained Assignment Interval (e.g., 15-30 minutes)</b>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes.
<b>Allows Fixing Paths for Parts of the Demands</b>	Yes	Yes	Yes	No. But can be emulated restricting the link in the path. For specific demands (maybe difficult in some cases)	Can be done through API	Yes	Yes	No
<b>Convergence Criteria</b>	Trip based	Trip based	Trip based	Link based	Link or trip based	Absolute difference on – travel time on paths and edges. Also absolute volume difference on edges	Dynamic user equilibrium relative gap	N/A
<b>Outputting and Using Interval-based Convergence Gap</b>	Utilizes gap for the whole iteration	Utilizes gap for the whole iteration.	Utilizes gap for each interval.	Utilizes gap for the whole iteration.	N/A	Full information for all selected time slices is exported in a convergence text file	Interval-based relative gaps and uses only the average gap	N/A
<b>Assignment of Individual Vehicles</b>	Yes	Yes	Yes	No	Yes	Yes	Yes	N/A
<b>Assignment of Multiple Demand Types</b>	Yes. Allows only three different types of users: SOV, HOV, and Truck. However, the value of time can be specified as a random variable for each user type	Yes. Allow only three different types of users: SOV <sup>1</sup> , HOV <sup>1</sup> , and Truck	Yes. Different user classes for each demand type defined by user	Yes. Different user classes for each demand type defined by user	Yes (based on each user classes, by considering each demand type as type of PrT (Passenger Car) system in link attribute)	Yes, considered as multiple vehicle types each with their own generalized cost coefficients	Yes. Based on vehicle class, or driver group	N/A
<b>Traffic Flow Model (TFM)</b>								
<b>Traffic Flow Model Type</b>	Mesoscopic	Mesoscopic	Mesoscopic	Mesoscopic	Microscopic	Simulation based DTA with Event based simulation on vehicles	Microscopic	Microscopic
<b>Queuing and Spillback</b>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<b>Modeling of Signalized Arterials</b>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

**Table A-2 Summary of Criteria for Tool Assessment (Mesoscopic/Microscopic Tools)  
(Cont'd)**

Criterion	DTALite	DynusT	Dynameq	Cube Avenue	VISSIM	VISSIM 8 (DTA) Mesoscopic	Trans Modeler	CORSIM
Modeling of Freeways	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Modeling of Alternative Routes to Facilities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Automatic Calculation of Signal Timing in Dynamic Traffic Assignment	Yes	Yes	Yes	Yes	No	No	Yes	NA
Lane-by-Lane Simulation	No	No	Yes	No	Yes	Yes	Yes	Yes
Merging/Weaving Simulation	No	No	Yes	No	Yes	Yes	Yes	Yes
Modeling Turn Lane and Bay Length	No	No	Yes	No	Yes	Yes	Yes	Yes
<b>ML Modeling</b>								
Generalized Cost in Assignment	Allows travel time and toll in the generalized cost function	Allows travel time and toll.	Allows travel time, distance, and toll in the generalized cost function	Various variables using scripting language	Yes	Yes	Allows travel time and toll in the generalized cost function	N/A
Incorporation of Willingness-To-Pay (WTP) into Assignment	No	No	Yes	Yes	In ML modeling uses WTP with DTA	Ye	Yes	N/A
Link Access Restrictions/ Prohibitions by Vehicle Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Modeling Managed Lanes and Reversed Lanes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed and Time-of-Day Pricing by User Types	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Dynamic Pricing	No	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Inhomogeneous VOT and VOR	By user type and statistical distribution	By user type and statistical distribution	Utilizing INRO,by user type	By user type , no randomization	Yes	Yes	By user type and statistical distribution	N/A
<b>Advanced Vehicle Technology</b>								
Capacity as a Function of Proportion of Vehicle Types	Maybe emulated by coding PC and trucks	Maybe emulated by coding PC and trucks	Yes	Yes	Maybe emulated by coding PC and trucks	Yes	Can be emulated by coding PC and trucks	Maybe emulated by coding PC and trucks
Fixed and Time-of-Day Pricing by different percentage of Advanced Vehicle Technology	Maybe emulated by coding PC and trucks	Maybe emulated by coding PC and trucks	Yes	Yes	Maybe emulated by coding PC and trucks	Yes	Yes	Maybe emulated by coding PC and trucks

**Table A-2 Summary of Criteria for Tool Assessment (Mesoscopic/Microscopic Tools)  
(Cont'd)**

Criterion	DTALite	DynusT	Dynameq	Cube Avenue	VISSIM	VISSIM 8 (DTA) Mesoscopic	Trans Modeler	CORSIM
<b>Work Zone Modeling</b>								
Capacity in Work Zone	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Can be modelled as incident
Duration of work zone	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geometry features of work zone, e.g. length, No. of lanes	No	No		No	No	No		Can be modelled as incident
Queuing Warning System	No	No	No	No	No	No	No	No
Day-to-Day Learning	Yes	No	No	No	No	No	No	No
Specification of Traffic Diversion rates	No	No	No	No	No	No	No	No
<b>Other Advanced Strategies</b>								
Modeling DMS/HAR	Yes	Yes	No	No	Yes	Yes	Yes	No
Modeling Ramp Metering	Yes	Yes	Yes	Can be implemented using Cube Script or traffic signal	Yes	Yes	Yes	Yes
Modeling Variable Speed Limits	Can be implemented using API	Can be implemented using API	Can be implemented using API	Can be implemented using Cube Script	Yes	Yes	Yes	Can be implemented using API
Modeling Traveler Information System	Yes	Yes	No	No	Yes	Yes	No	No
Modeling incidents and work zones	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Modeling Traffic Response Systems	No	No	No	No	Yes – interfaces to PTV-Optima	Yes – interfaces to PTV-Optima	No	Can be implemented using API
Modeling Traffic Adaptive Systems	No	No	No	No	Yes – interfaces to PTV-Optima	Yes – interfaces to PTV-Optima	No	No
Vehicle trajectory processor	Yes	Yes	No	No	Internally included	No	Yes	Internally included
Scenario generator	Yes	Yes	No	No	No	No	No	No