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Martin O'Malley, *Governor*
Anthony G. Brown, *Lt. Governor*

Darrell B. Mobley, *Acting Secretary*
Melinda B. Peters, *Administrator*

STATE HIGHWAY ADMINISTRATION

RESEARCH REPORT

DEVELOPING MESOSCOPIC MODELS FOR THE BEFORE AND AFTER STUDY OF THE INTER-COUNTY CONNECTOR: PHASE-ONE

PRINCIPAL INVESTIGATORS
LEI ZHANG
GANG-LEN CHANG

ASSISTANT RESEARCH SCIENTIST
SHANJIANG ZHU

GRADUATE RESEARCH ASSISTANTS
CHENFENG XIONG
LONGYUAN DU
MOSTAFA MOLLANEJAD

UNIVERITY OF MARYLAND

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16. Abstract

This study developed a mesoscopic model for the before and after study of MD 200, the Inter-County Connector. It is in line with recent efforts by the Maryland State Highway Administration (SHA) in developing effective modeling tools for traffic analysis and travel forecasting. The integrated models are capable of capturing detailed traffic dynamics and the impacts of traffic operation improvements. At the same time, the scale of the integrated model is large enough to capture regional impacts.

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EXECUTIVE SUMMARY

This study developed a mesoscopic model for the before and after study of MD 200, the Inter-County Connector (ICC). It is in line with recent efforts by the Maryland State Highway Administration (SHA) in developing effective modeling tools for traffic analysis and travel forecasting. Examples include the I-270 microscopic traffic simulation model and the Maryland Statewide Transportation Model (MSTM). A comprehensive analysis of many emerging issues in transportation operations and planning at the corridor, multi-corridor, and even statewide levels requires the integration of both microscopic simulation model and macroscopic travel demand models. This study bridges such a gap by developing a mesoscopic model that draws strengths from both types of models.

The integrated models are capable of capturing detailed traffic dynamics and the impacts of traffic operation improvements. At the same time, the scale of the integrated model is large enough to capture any regional impacts. A route diversion model and an agent-based departure time choice model were developed and integrated to predict individual behavioral reactions to network changes, thus allowing the integrated model to reflect both spatial and temporal traffic demand adjustment and regional traffic dynamics.

This study benefited from previous data collection efforts by both SHA and the research team. Both individual travel behavior models and dynamic network supply models were calibrated against local data collected from the Washington, D.C., metropolitan area. The calibrated model was then applied to evaluate the network performance before and after the Inter-County Connector was opened as a tolling facility. The results indicated that after its opening, the new ICC would initially attract around 9,000 users during the morning peak period and would help reduce both delay and stopping time in the study area.

Applications of the integrated mesoscopic model go well beyond the before-and-after study of new network infrastructure. Given its sensitivity to changes in both network conditions and travel demand shifts, it can be applied to study a wide spectrum of transportation-related problems, including traffic operation improvement, dynamic pricing strategies, new travel demand management policies, and incident management policies.

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INTRODUCTION

The Maryland State Highway Administration (SHA) has successfully developed several effective modeling tools for traffic analysis and travel forecasting in recent years. Examples include the I-270 corridor meso/microscopic traffic simulation models and the Maryland Statewide Transportation Model (MSTM). The I-270 corridor traffic simulation model contains 399 sub-zones based on the Metropolitan Washington Council of Governments (MWCOG) and Prince George County traffic analysis zone systems, and it simulates traffic movements at 15-minute origin-destination (OD) demand intervals along the I-270/MD 355 corridor as well as on major roadways in the vicinity of the corridor. A working version of the MSTM was recently delivered to SHA by the model developers, and the statewide travel demand model is currently being calibrated and validated. The MSTM will soon be applied to analyze various transportation planning and policy scenarios relevant to land use and transportation decision-making in Maryland. These models provide necessary information needed for transportation operations and planning decision-making at the corridor, sub-area, and state levels. There are also other existing/upcoming traffic simulation models for various highway corridors (e.g. Synchro models for intersection analysis, a VISSIM model for MD 200, the Inter-County Connector (ICC) freeway, and travel demand models for metropolitan transportation planning in Maryland e.g. MWCOG and BMC models).

A recent synthesis of transportation operations and planning analysis needs in Maryland has identified a number of important transportation-related issues that require modeling analysis. Some of these issues include performance monitoring, congestion management, traffic operations, multimodal corridor improvements, freight transportation, land use and economic development. The comprehensive analysis of many of these issues requires the integration of microscopic traffic simulation models and travel demand models at the corridor, multi-corridor, and even statewide levels. For instance, the detailed impact of various traffic management strategies on corridor-level congestion is typically best modeled with a microscopic traffic simulator (e.g. CORSIM, TRANSMODELER, VISSIM, AIMSUN, or non-commercial traffic simulators). At the same time, these traffic management strategies can produce various demand responses such as peak spreading, modal shifts, and traffic diversions at the corridor and regional levels, which are best analyzed with travel demand models. In order to comprehensively analyze the traffic and demand impact of various operations and planning strategies, mesoscopic models are used. These models bridge the gap between microscopic traffic simulation and macroscopic travel demand models from both the methodological and application points of view. Moreover, the practical needs at SHA of analyzing highway and multimodal corridor projects with significant regional impact (ICC, I-270, I-495, etc.) also highlight the value and necessity of mesoscopic models. A good example is the before-and-after study of the Inter-County Connector project.

MD 200, the Inter-County Connector (ICC) may be the most significant and high-profile highway project in Maryland since the completion of the existing Interstate freeway system several decades ago. The ICC links existing and proposed development areas between the I-270/I-370 and I-95/US-1 corridors within central and eastern Montgomery County and northwestern Prince George's County. Existing project plans and design promise a state-of-the-art, multi-modal east-west highway that limits access and accommodates the movements of passengers and goods. The expected benefits of the ICC include: (1) Increased community mobility and safety; (2) More efficient and reliable movement of goods and people to and from economic centers in Maryland; (3) Cost-effective transportation infrastructure to serve existing and future development patterns that reflect local land use planning objectives; and (4) Restoration of natural, human and cultural environments in the project area. In order to comprehensively evaluate these potential benefits and to better understand the impact of the ICC on arterial roads and nearby freeways in the region such as I-95, I-270 and I-495, a mesoscopic model is needed. By doing so, both the changes in the local traffic pattern and the aforementioned behavioral reactions can be analyzed.

To bridge the gap between the needs in the field and the capacity of current modeling tools, this research developed a mesoscopic-modeling framework that integrates agent-based travel behavior models with large-scale microscopic traffic simulation models. Both the simulation model and behavioral models were calibrated using field data collected at the I-270/I-495/I-95 corridor in the North Washington, D.C., metropolitan area. The calibrated model was then applied to evaluate the base-year (2010) existing transportation network in the ICC corridor and the after-ICC scenario. The latter includes both the existing network and the new ICC freeway and ramp facilities. The final modeling product is capable of analyzing traffic operations, route diversion, peak spreading, and other major demand shifts under a variety of traffic operations and planning scenarios in the study area.

The next chapter will present the overall modeling framework, followed by a detailed description of each component in this integrated model. The data used in this study will be described and the calibration/validation process will be presented. Also, several potential applications of the integrated model proposed in this study will be discussed. This report will be concluded by a discussion of future research work.

CHAPTER 1: MODELING FRAMEWORK

1.1 INTRODUCTION

Microscopic traffic simulation models exhibit strong advantages. They are known for capturing detailed traffic dynamics and have been proven in practice as a valuable tool for evaluating corridor capacity expansion and traffic operation improvements. Their applications have recently been extended to address a broader range of transportation-related issues, including congestion management, multimodal corridor improvements, evacuation planning, land use and economic development. However, a comprehensive analysis of many of these issues requires models that can analyze various demand responses to various traffic management strategies. Included are peak spreading, modal shifts, and traffic diversions at the corridor and regional levels, all of which are conventionally taken as given in micro-simulation models. Another challenge of applying micro-simulation models to a large network is the difficulty of obtaining reliable travel demand data, usually as time-dependent origin-destination matrices.

Although planning models are traditionally used to address these demand-side problems, they are criticized for two reasons: (1) assigning traffic flow over capacity; and (2) inability to capture operational improvements, such as better signal timing. As planning models move from the aggregate four-step models into more realistic individual-based models, more details on travel experience (e.g. time-dependent travel time) are required to make these models operational in practice. Surveys based on hypothetical scenarios, which are relied on heavily during the model development and calibration process, can only support analysis for a limited number of OD pairs due to budget and manpower constraints. However, these inputs can be easily extracted from microscopic traffic simulation models. Therefore, it becomes attractive to develop integrated models to benefit from the strengths of both sides.

Figure 1 summarizes the general structure of the proposed mesoscopic modeling framework and how it connects with various ongoing data-collection/consolidation/modeling/application efforts at SHA. Various Agent-Based Modeling System (ABMS) modules, which capture the behavioral reactions and the resulting travel demand changes, form the modeling engine and play a central role in the comprehensive framework. The data hub synthesizes information from existing data sources, enhances them through data filtering and integration, and then informs the modeling engine. Existing models, such as the conventional four-step regional planning model, can also inform the modeling engine. If data is insufficient, conventional models can replace a subset of the multi-dimensional ABMS. The ABMS modeling engine has to interface with supply-side models (most of which are developed with various commercial software packages) to provide a full picture of the transportation system dynamics. To facilitate communications with practitioners, policy makers, and the public, a visualization module is needed to present system performance and its dynamics. Outputs from such a system will support various applications in both traffic operations and transportation planning. They will be discussed in detail in the following sections to demonstrate the potential of the system to benefit current practice.

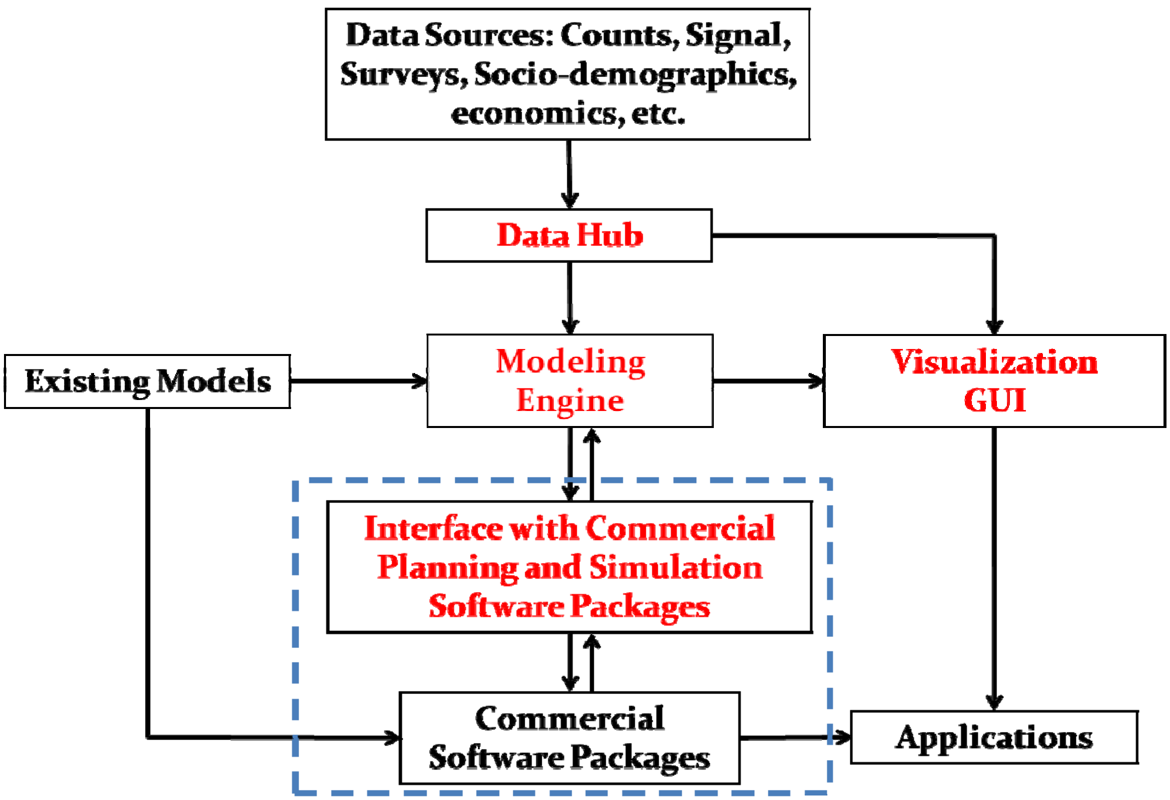

Figure 1. Overall Structure of Integrated Mesoscopic Models

1.2 MESOSCOPIC MODELING FRAMEWORK

The framework of the integrated model is presented in Figure 2. A microscopic traffic simulator was built with TransModeler, one of the major commercial software packages for micro-simulation. Models were constructed to build the origin-destination (OD) matrices for the simulator based on demand data from the regional planning model. The dynamic OD matrices and parameters for the micro-simulation model were then calibrated using field traffic counts. An agent-based departure time choice model was developed separately and then integrated to capture the behavioral reactions to network changes. The integrated model operated iteratively until no traveler was willing or able to adjust travel decisions and a stable network condition was reached. Details for each component of the model will be discussed in the following chapters.

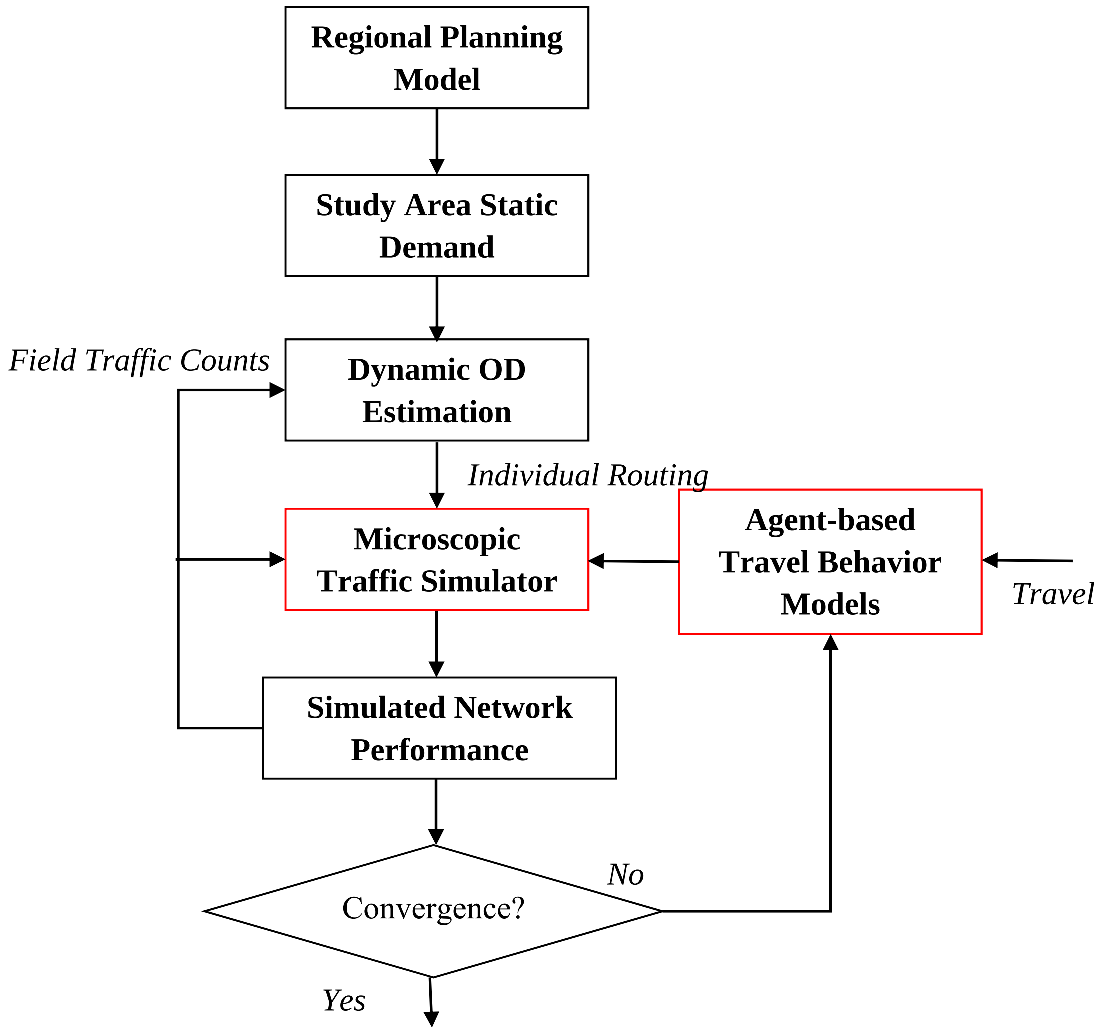

Figure 2. Overall Framework of the Integrated Model

CHAPTER 2: TRAFFIC SIMULATION MODEL

2.1 INTRODUCTION

Many microscopic traffic simulators (e.g. CORSIM, see Prevedouros and Wang, 1999; TRANSMODELER, see Wojtowicz *et al.*, 2011; VISSIM, see Gomes *et al.*, 2004, AIMSUN, see Barceló and Casas, 2005; or non-commercial traffic simulators, see Chen *et al.*, 2002) have been used in previous studies. These models differ in the underlining car-following models and the implementation of different traveler/driver modules. No consensus is reached on the superiority of any simulator in literature. TransModeler was selected in this study because it has a well-developed interface with Geographic Information System (GIS), which is necessary when working with multiple data sources.

A simulation model that includes all freeways, major arterials, most minor arterials, and some local streets along the I-270/I-495/I-95 corridor in the North Washington, D.C., metropolitan area was developed. It covers central and eastern Montgomery County and the northwestern Prince George's County of the State of Maryland, where several new developments, such as the Great Seneca Science Corridor (GSSC) in West Gaithersburg and military bases in Fort Meade, have been proposed. A new freeway currently under construction, MD 200, the Inter-County Connector (ICC), also traverses this area. The simulated network (see Figure 3), which includes 7121 links and 3521 nodes, was developed on top of satellite images provided by Google Earth and conforms to the true geometry with high accuracy.

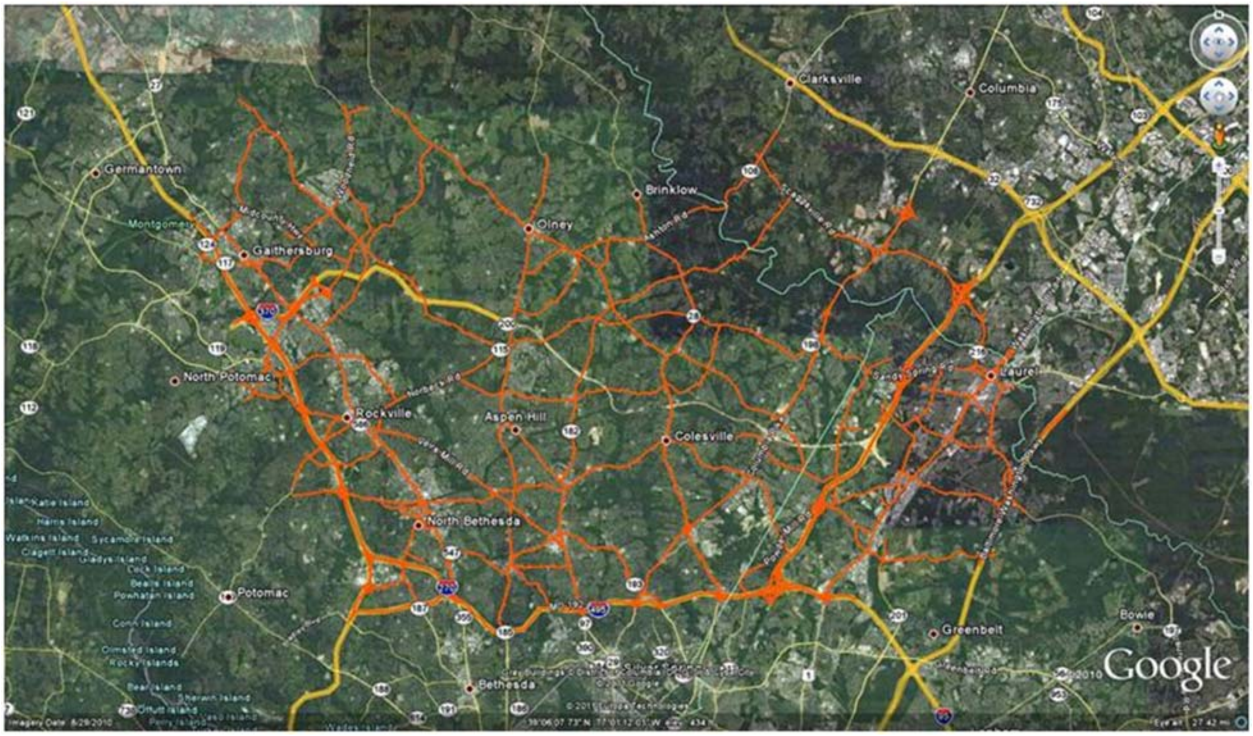

Figure 3. Simulated Network (in red) in the Study Area

2.2 OVERVIEW OF MODEL CALIBRATION

It has always been a great challenge to calibrate large-scale micro-simulation models. The reasons are three-fold: 1) it is extremely hard to obtain the dynamic origin-destination (OD) tables on large network; 2) complete information of traffic control strategies (such as signal timing plans) are usually not available; 3) the number of parameters is so large that it is hard to identify which one (or ones) should be adjusted to match the field counts.

Many previous research efforts have dedicated themselves to solving the first problem. Here, researchers sought to solve time-dependent OD tables based on two major information sources: static OD tables from regional planning models and traffic counts from field observation. For example, Van Zuylen and Willumsen (1980) estimated static OD trip table by using the entropy model. Fisk (1988) extended the entropy model under UE assumption, while Liu and Fricker (1996) investigated the same problem under SUE assumption. More recent examples include Cascetta *et al.* (1993), Ashok and Ben-Akiva (1993), Tavana and Mahmassanni (2001), and Lin and Chang (2006). Although there are abundant literatures in this field, many problems have not yet been addressed. Jintanakul *et al.* (2011) pointed out four common difficulties for existing studies: 1) high sensitivity to seed matrix; 2) non-uniqueness in link-path flow pattern; 3) lack of monotonicity between traffic counts and OD flows; and 4) lack of ground truth OD matrices for model validation. Given these difficulties, this study did not seek a comprehensive solution with high accuracy to the dynamic OD estimation problem. Instead, a systematic approach based on Gradient Projection (GP) algorithm was proposed to derive the seed matrix for the study area and an algorithm extended from a previous study by Nielson (1997) was used to obtain the dynamic OD matrices. Instead of focusing on a single mode as seen in previous studies, this research focuses on multi-modal traffic (Single Occupancy Vehicle, High Occupancy Vehicles, and Trucks). This difference is crucial because a HOV facility (I-270 HOV lane) exists in the study area.

Surprisingly, the second problem related to traffic control information was not widely discussed in previous studies on large-scale traffic simulation. Ideally, the signal-timing plan used in the field should also be used in simulation. However, complete information is usually not available for a large network such as the one in this study. Due to the complex geometric design of various intersections in the field, it is almost infeasible to apply the state-of-the-art optimization algorithms in literature, most of which require detailed inputs about demand patterns and turning movement designs. In this study, the field signal-timing plan was applied wherever it was available. There are 466 signalized intersections in total, 80 of which used the true signal plan. For the rest, a stylized ring-and-barrier plan with a cycle length of 150 seconds typically seen in field plans was applied. The length of green phases was assigned proportionately to the turning demand. Future research will explore more effective approaches to implement optimized signal plans on large network.

The third difficulty, the large number of parameters controlling both driving and traveling behavior, has been extensively studied in previous research by focusing on the development of microscopic traffic simulation models. This study adopted a hierarchical calibration strategy to avoid confounding facts at different levels. Parameters for driving behavior include free flow speeds, car-following models, distribution of critical gaps, and parameters that control lane-changing behavior (critical distance to start strategic lane changing and critical headway for gap acceptance model). The latter is critical for the traffic flow pattern at weaving segments. There are a total of six freeway bifurcations in our study areas, which occur where I-270 and I-95 interchange with I-495 Capital Beltway. Unfortunately, no fixed loop detector systems are available in the region and no speed contour is available. Instead, the major calibration objective was to replicate both the flow rate at these bottlenecks and the corridor travel time. After calibration, the largest hourly flow rate difference between the observation and model prediction was around 7% at the I-95/I-495 bifurcation area, while the numbers were smaller at other locations. These parameters for driving behavior were fixed once we moved from corridor to network level calibration, where the major concern was the network OD tables.

2.3 MULTI-MODAL STATIC OD ESTIMATION

Due to their dynamic nature, microscopic traffic simulation models require a set of time-dependent, multi-class OD tables as inputs. As discussed in the introductory sub-section, dynamic OD estimation challenges researchers and practitioners because it is infeasible to trace all vehicles between each OD pairs under current technology and with time and monetary constraints. Therefore, the research team had to rely on indirect measurements such as link flows to estimate dynamic OD demand - an under-determined problem because the number of OD pairs is usually much higher than that of link flow observations. To address this problem, some domain information about regional traffic demand patterns had to be explored. In this study, the best available source of regional travel demand information can be found in the MWCOG planning model, which has been constantly maintained and periodically recalibrated against field observations over the years.

Given the regional planning model, a sub-area analysis must be conducted to extract the demand pattern for the sub-network. This was achieved by capturing all the trips that would travel through one of the links in our study area. Conventional link-based assignment algorithms are insufficient for completing this sub-area analysis because they do not trace all the paths between each OD pair and it is impossible to tell which part of the OD demand travelled on the sub-network. Therefore, a path-based traffic assignment process must be introduced. Moreover, this model must be able to handle multiple traffic classes since the stratification of demand by user classes is common in regional planning models and is crucial in dealing with facilities such as HOV/HOT lanes.

Although the theoretical development of path-based traffic assignment algorithms has a long history, it is not considered as a viable option for early traffic assignment studies on large networks because of intensive memory requirement. Due to recent advancements in algorithms and computational capability, path-based traffic assignment algorithms have attracted increased interest from researchers. Two algorithms have proven to be promising for applications on large-network: the disaggregate simplicial decomposition (DSD) algorithm and the gradient projection (GP) algorithm. This study adopted the GP algorithm because of its efficiency due to the exploration of the second derivative of Hessian Matrix and its simplicity in implementation compared to the DSD algorithm. The rest of this subsection describes the GP algorithm and its implementation in this study.

A typical traffic assignment problem can be formulated as a mathematical programming problem:

$$minZ = \sum_{a\in A} \int_0^{x_a} t_a(w)dw \qquad (1)$$

Subject to flow conservation constraints:

$$\sum_{k\in K_{rs}} f_k^{rs} = d_{rs} \ \ \forall r \in R, s \in S \qquad (2)$$

Where x_a is the link flow and $t_a(w)$ is the link travel time. A is the set of all links in the network. d_{rs} represents the OD demand between origin r and destination s. K_{rs} is the set of all paths between OD pair r and s and the sum of path flows f_k^{rs}must equal total OD demand. The path flow and link flow patterns are summarized by the incident matrix δ_{ka}^{rs} where:

$$\delta_{ka}^{rs} = \begin{cases} 1 \ if \ link \ a \ is \ on \ path \ k \ serving \ r \ and \ s \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \qquad (3)$$

and

$$x_a = \sum_{r\in R}\sum_{s\in S}\sum_{k\in K_{rs}} f^{rs}\delta_{ka}^{rs}, \forall a \in A \tag{4}$$

and all path flows should be non-negative:

$$f_k^{rs} \geq 0, \forall k \in K_{rs}, r \in R, s \in S \tag{5}$$

The GP algorithm was first introduced by Bertsekas (1976) for general nonlinear multi-commodity problems and later applied to traffic assignment problems by Jayakrishnan *et al.* (1994). Chen *et al (2002)* provides a detailed analysis of its computational characteristics. The algorithm searches the optimal along the direction of negative gradient. The step size is decided by the second derivative Hessian and a projection to the non-negative domain is made whenever the search obtains an infeasible solution. To improve the efficiency and simplify the projection operation, the problem is reformulated by partitioning the path set K_{rs} into the shortest path $f_{\bar{k}_{rs}}^{rs}$ and the non-shortest path $f_{k_{rs}}^{rs}$. The flow conservation constraint (2) can now be expressed as

$$f_{\bar{k}_{rs}}^{rs} = d_{rs} - \sum_{k\in K_{rs}, k\neq \bar{k}_{rs}} f_k^{rs}, \forall r \in R, s \in S \tag{6}$$

This implies that the flow assigned on the current shortest path should be the difference between the OD demand and the total flow that has been assigned on other non-shortest paths. A new formulation can be obtained by embedding (6) into (1). This new formulation drops the linear constraint (2) and becomes a convex problem with only non-negativity constraints, which greatly simplified the projection operation.

The algorithm is operated in the following steps:

Step 0: Search the shortest path for each OD pair (r, s) and do an all-or-nothing assignment to get the initial flow pattern.

Step 1: Derive the link flow $x_a(0)$ based on current path flow pattern and calculate the corresponding link travel time $t_a(0)$.

Step 2: Conduct a new shortest path search based on current link travel time to get the shortest time path $\bar{k}_{rs}$. If this path does not exist in the previous path set K_{rs} for OD pair (r, s), then add it in the set. The path set is now divided into two sets: the shortest path and all the non-shortest paths.

Step 3: Calculate the new path flow for all the non-shortest paths by using formula (7) and project it to the non-negative domain (i.e. set it to 0 when the link flow becomes negative).

$$f_k^{rs}(n+1) = \left[f_k^{rs}(n) - \frac{a(n)}{s_k^{rs}(n)}\left(g_k^{rs}(n) - g_{\bar{k}_{rs}(n)}^{rs}\right)\right]^+, \forall k \in K_{rs}, k \neq \bar{k}_{rs}, r \in R, s \in S \quad (7)$$

Where n is the iteration number, $a(n)$ is the step size and $s_k^{rs}(n)$ is the diagonal element of the second derivative Hessian. $g_k^{rs}(n)$ and $g_{\bar{k}_{rs}(n)}^{rs}$ are the path travel time along path k and the shortest path $\bar{k}_{rs}$. This formulation implies that the path flow should be adjusted according to the travel time difference between current path travel time and the travel time on the shortest path. Less flow should be assigned to paths with longer travel time. However, the step size should also be adjusted according to the second derivative Hessian Matrix. For a full discussion of its mathematical property, please refer to Chen *et al.* (2002).

Step 4: Calculate the flow on the current shortest path by comparing the OD demand and total demand on all non-shortest paths.

$$f_{\bar{k}_{rs}(n)}^{rs}(n+1) = d_{rs} - \sum_{k \in K_{rs}, k \neq \bar{k}_{rs}(n)} f_k^{rs}(n+1), \forall r \in R, s \in S \quad (8)$$

Step 5: Derive the updated link flow $x_a(n+1)$ based on current path flow pattern $f_k^{rs}(n+1)$ and calculate the corresponding link travel time $t_a(n+1)$. Reevaluate path travel time and compare the current total travel time and the minimal travel time under the assumption that the shortest path is exclusively used. Decide if a convergence has been reached. If not, go to Step 2 to start a new iteration.

In this study, the conical volume delay function used by the MWCOG model was adopted to derive link travel time. All links were divided into 7 area types according to the built environment (e.g. downtown, suburban, rural, etc.) and 7 functional classes (centroid connector, freeways, major arterials, minor arterials, collectors, expressways and ramps). In total, 49 categories were defined and each category was assigned a unique set of parameters (e.g. free flow speed, capacity per lane, conical function parameters, etc.). For detailed definitions of each category, please refer to the MWCOG model user guide.

Three types of user classes were considered in this study: SOV, HOV, and truck. The iterative process described in this sub-section was operated iteratively among three user classes, each of which had a different OD demand table. Also, link properties had to be adjusted with a sub-loop for each user class (e.g. SOV cannot use HOV lanes). Figure 4 illustrates this iterative process.

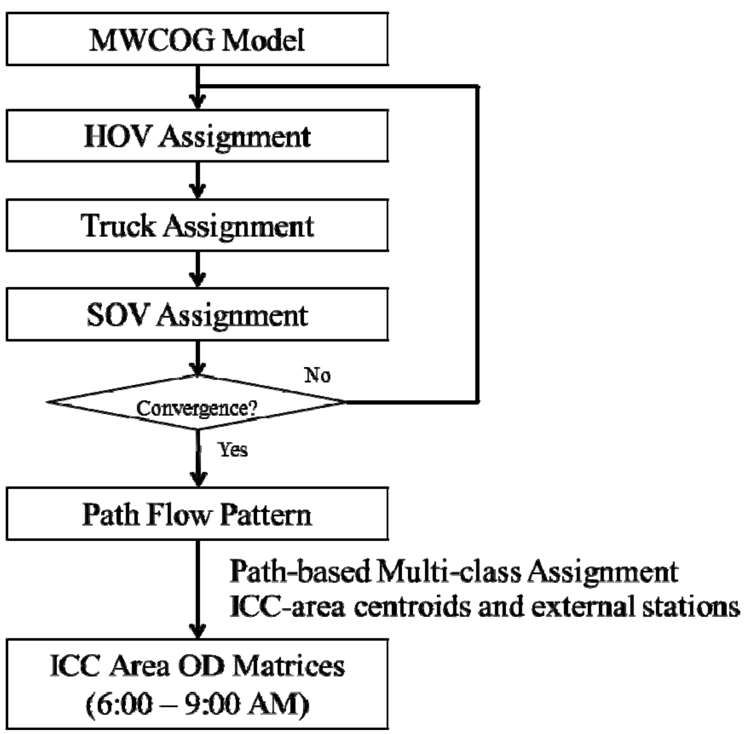

Figure 4. Path-based Multi-class Assignment

2.4 CALIBRATION OF DYNAMIC OD

Given the static OD matrices from previous steps, this sub-section seeks to match the spatial and temporal traffic pattern with field observations by adjusting the time-dependent OD tables. Twenty minutes will be used as the standard time interval for each OD matrix, which is consistent with the behavioral models to be integrated in the next section. A demand profile based on aggregated travel demand during each 20 minute time period was developed. It was then applied to divide the initial 3-hour static demand into a series of OD matrices, each of which represent OD demand by vehicle class for the corresponding time period. These matrices would serve as seed matrices for further adjustment.

The dynamic OD estimation algorithm is a variation of the Multiple Path Matrix Estimation Method (MPME) proposed by Nielsen (1997), which is designed for static OD estimation. The proposed algorithm first evaluates the OD demand adjustment factor $\alpha_{ij,r,t}$ associated with each path r between an OD pair i, j and for a given time slot t by the following:

$$\alpha_{ij,r,t} = \frac{\sum_{a \in S(ij,r,t)} \zeta_{ij,r,a,t} \frac{F_{a,t+\Delta t_{ij,r,a,t}}}{f_{a,t+\Delta t_{ij,r,a,t}}}}{\sum_{a \in S(ij,r,t)} \zeta_{ij,r,a,t}} \tag{9}$$

Where,

ij is the OD pair from origin i to destination j;

$r \in R(ij,t)$, where $R(ij,t)$ is the set of all used paths of OD pair ij, at time t;

$S(ij,r,t)$ is the link set of path r at time t;

$F_{a,t}$ is the actual link flow on link a at time interval t;

$f_{a,t}$ is the observed link flow on link a at time interval t;

$\Delta t_{ij,r,a,t}$ is the travel time from origin i to link a starting at time t;

$$\zeta_{ij,r,a,t} = \begin{cases} 1, \text{when a} \in S(ij,r,t) \\ 0, \text{otherwise} \end{cases} \tag{10}$$

With all factors $\alpha_{ij,r,t}$, the OD demand between each i to j was updated during iteration n based on demand of the previous iteration as follows:

$$d_{ij}^{n} = \sum_{t} \sum_{r \in R(ij,t)} \alpha_{ij,r,t} d_{ij}^{n-1} \tag{11}$$

The algorithm seeks to match the observed link flow by adjusting the OD demand, which uses this specific link along its path. If more than one observation is available, an average is taken. The algorithm then updates the OD demands by considering impacts of all paths. It differs from its static counterpart by considering the time required to reach the specific link along the path and mapping its impact to the OD demand with the corresponding departure time. Because the OD demand tables were discretized into slices of 20 minutes in this study, only the departure time slot of the majority of trips was considered. Starting from the seed matrices, the traffic pattern was first simulated with the model built in TransModeler and then the complete trip table for all paths was obtained. The time-dependent OD matrices were then updated by applying (9) and (10) for all OD pairs and for all time slots.

Field traffic counts provided by SHA were applied to calibrate the model. Freeway traffic counts can be accessed through the online interactive Annual Average Daily Traffic (AADT) Locator, while arterial traffic counts were collected in previous turning movement studies. In total, counts from 50 stations located on both freeways (15 stations) and arterial roads (35 stations) were used (see Figure 5 for their locations). Consistent with previous studies, Root Mean Square Error (*RMSE*) was used as the convergence measure. It is defined as below:

$$RMSE = \frac{\sqrt{\frac{\sum_{i,j}(f_{i,j} - \tilde{f}_{i,j})^2}{N}}}{\bar{f}} \tag{12}$$

where $f_{i,j}$ is the actual traffic flow count at station j, from time interval i. $\tilde{f}_{i,j}$ is the simulated traffic flow count and $\bar{f}$ is the average actual traffic flow count over time and locations.

After 10 iterations, the overall *RMSE* measure fell to 12.5%, while the *RMSE* based on 13 freeway stations was 8.7%. This calibration result is comparable to many corridor-level simulation studies where either turning movement tables were used or OD patterns could be easily identified from a limited number of entrances to the network. The problem becomes much more difficult when a large-scale network is considered and the only OD information available is assumed from the regional planning models. A better match to the field data could be reached by continuing this iterative process. However, given the size of the network, that would be very time consuming.

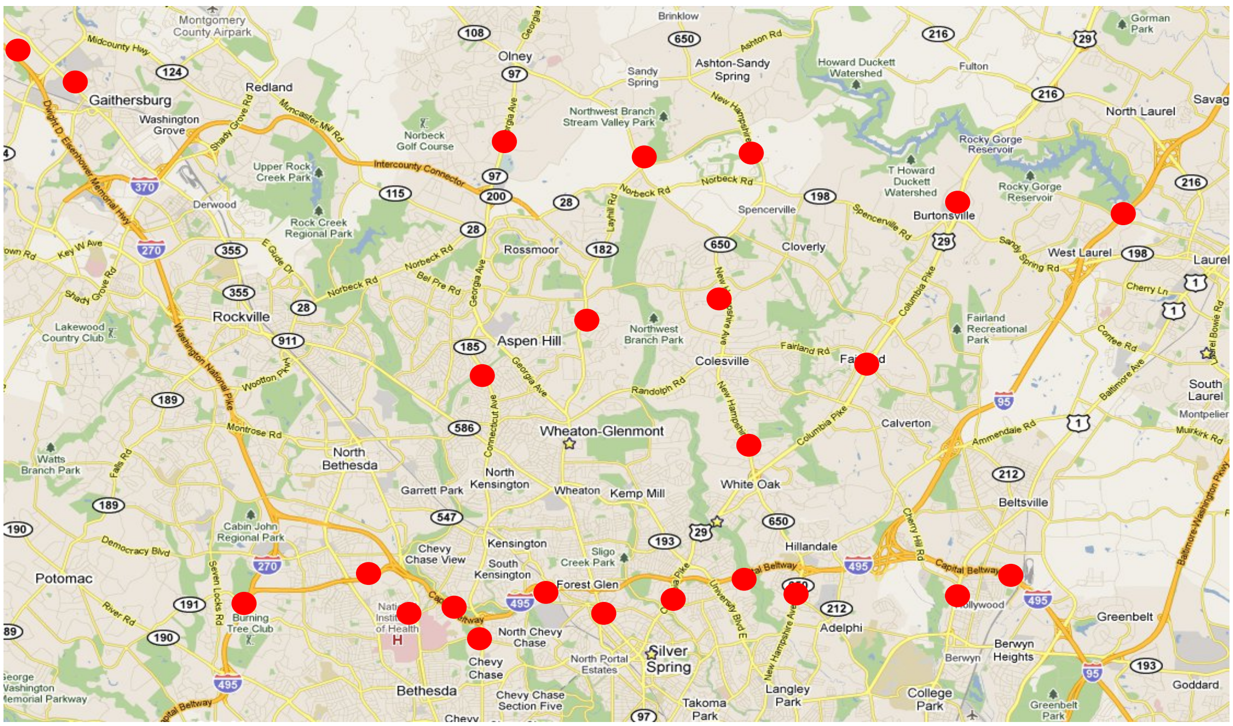

Figure 5. Traffic Count Stations Used in Calibration

CHAPTER 3: TRAVEL BEHAVIOR MODELS

3.1 INTRODUCTION

As discussed in the introduction chapter, travelers are adaptive and changes on network traffic condition will cause behavioral adjustments, which in turn help to shape future network flow patterns. Therefore, travel behavior models must be introduced and integrated with network supply models to obtain future demand and flow patterns. There are two major effects due to short-term behavioral changes: route diversion and peak spreading.

3.2 ROUTE DIVERSION MODEL

Travelers change their route to either avoid emerging bottlenecks or to benefit from travel time improvement on alternative routes. There have been many previous studies on route choice problems. For example, the normative route theory assumes that travelers are rational utility maximizers who would choose a route that minimizes travel time or other types of disutility. Models that follow this Random Utility Maximization (RUM) approach try to replicate route decisions by analyzing what constitute personal utility. Ben-Akiva *et al.* (1984) proposed a labeling approach to generate a choice set with favorable routes according to different utility definitions (e.g. minimum travel distance, travel time, generalized cost, the number of left turns, congestion time, or a combination of these functions) and estimate a Nested-logit model. Later studies expanded this framework to address the Independence of Irrelevant Alternatives (IIA) problem commonly associated with RUM models. For example, Cascetta *et al.* (2002) proposed the C-logit model and Ben-Akiva and Ramming (1998) proposed the Path-Size (PS) Logit model. More advanced RUM framework such as Logit Kernel or Mixed Logit Model has also been introduced.

Models under RUM framework have been criticized for three major reasons: 1) they predict what travelers should do instead of what they actually do; 2) they only predict the equilibrium flow pattern while ignoring how people adjust their route choices on a day-to-day basis; and 3) they assume everyone has complete knowledge about network conditions while ignoring heterogeneity in personal experience and knowledge. To address these problems, models based on learning-and-adaptation processes have been introduced. For example, Zhang (2007) proposed the Search, Information, Learning, and Knowledge (SILK) model to predict individual route choice while considering heterogeneity in personal knowledge and learning processes. This rule-based paradigm exhibits certain computational advantage on large networks because it generally does not require enumeration of all plausible routes between OD pairs. Moreover, this modeling paradigm allows further exploration of the day-to-day evolution of network flow patterns, which differs from equilibrium-based RUM framework.

After exploring several models from both alternatives, including the SILK route choice model previously developed by the research team, the team decided to adopt the built-in learning-and-adaptation model in TransModeler. This model assumes that travelers will learn the shortest time path with a specific departure time and choose to switch route according to a probability associated with personal preferences and extra delay on their current routes. All travelers will reevaluate route decisions and improve travel time iteratively. The network flow pattern stabilizes as most travelers have exhausted all alternatives and cannot improve route decisions any more. As a built-in model in TransModeler, it benefits from the consistent data structure of the simulator and exhibits significant advantage in computational efficiency when compared to other modeling alternatives.

3.3 DEPARTURE TIME CHOICE MODEL

3.3.1 Introduction

As previously discussed, travelers adjust their departure time in reaction to any changes in network conditions or management policies. Increasing congestion could force travelers to leave home either before or after the peak period, causing peak spreading in aggregate travel demand. Policies such as time-varying tolls may also encourage users to travel during shoulder hours of the peak periods, leading to a more efficient use of existing infrastructure. Therefore, it is crucial to incorporate departure choice models in the integrated model.

3.3.2 Existing Models

There are many departure time choice models in the literature. Similar to the route choice problem, departure time choice models can also be divided into two classes: normative and positive models. De Jong *et al.* (2003) provided a comprehensive literature review on RUM models. The multinomial logit (MNL) model is often criticized for its inability to account for possible correlation between similar alternatives. Small (1982) noted the problem of possibly correlated error terms and designed a test to study whether adjacent alternatives are closer substitutes (have a higher correlation) than pairs of non-adjacent alternatives. Bhat *et al.* (2003) estimated a MNL model for departure time choice of home-based trips. Socio-demographic and employment-related attributes were found to have significant impact on departure time decision. They emphasized the importance of differential sensitivities of socio-demographic groups to transportation system performance. Saleh and Farrell (2005) estimated a MNL model of departure time choice that accounts for variable congestion pricing and trip scheduling flexibility. Their result supports the fact that both work and non-work schedule flexibility affects departure time choice. Jin (2007) estimated a MNL model of departure time choice for long distance travel. The analysis found that trip characteristics along with other attributes, such as socioeconomic factors, have a significant impact on departure time choice. The study suggested a small-scale stated preference (SP) survey to capture traveler trade-off between the departure time and the related constraints, such as peak hour congestion, mode captivity, and work schedule. More advanced models under RUM framework include the ordered generalized extreme value model (OGEV) by Small (1987), the continuous cross-nested logit model (CCNL) by Lemp *et al.* (2010), and the mixed logit model (ML) by Börjesson (2008), among others.

Compared to the large number of models proposed in literature, their applications in traffic simulation on large-scale network are limited. In one example, Ettema *et al.* (2005) incorporated the MNL departure time choice model in the SIAS-PARAMICS micro-simulation study for N57 in the Netherlands. However, this normative modeling framework encountered similar challenges as their counterparts did in route choice problems. In most RUM models, the scope of alternatives and their generation mechanism remain unclear. Moreover, most RUM departure time models assume complete knowledge and perfect rationality, which may differ from reality. Due to its exhaustive nature, RUM models are not computationally efficient under the current integration framework. After exploring a few RUM alternatives, including the Conditional Logit Model, Mixed Logit Model and the Latent Class Model, the research team concluded that a positive approach based on SILK framework suits this project better.

3.3.3 Overview of Agent-based Departure Time Choice Model (ABDTM)

The novel positive model employed in this study theorizes departure time choice as a continual search process and tracks the departure time changes of each individual user in the transportation system. Therefore, it is especially suitable for integration with microscopic traffic simulators, simulation-based dynamic traffic assignment models and activity/agent-based travel demand models. The theoretical framework is illustrated in Figure 6.

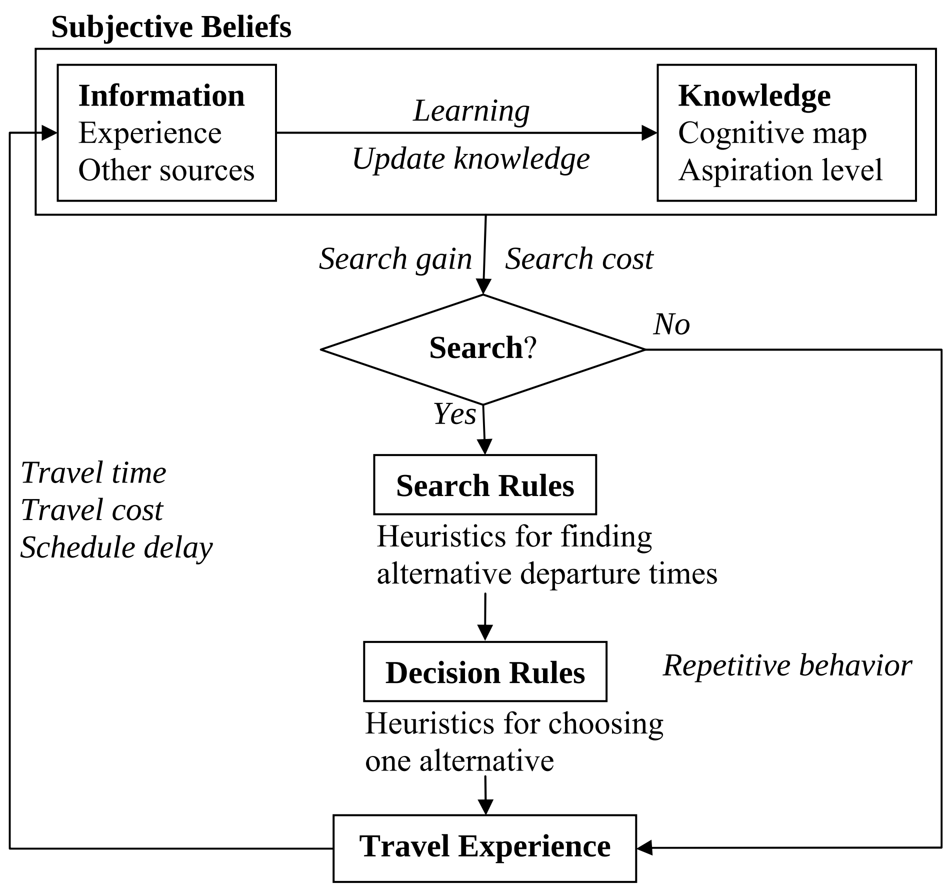

Figure 6. Flowchart of the Positive Departure Time Choice Model

As depicted in Figure 6, the individual accumulates information from prior travel experiences about travel conditions corresponding to different departure times. The individual forms a certain degree of spatial knowledge, which produces subjective beliefs. As a result, an individual at any given time has an aspiration level for potential gain, which influences travel decisions such as when to depart.

If an individual decides not to search, repetitive learned behavior or habitual behavior is executed. Otherwise, a search method (or heuristics) is employed to identify alternatives, which constitute a mapping from knowledge to decide one feasible alternative departure time. Then, the decision step employs decision rules to pick up an alternative option. The decision rules constitute a mapping from perceived attributes of alternatives to a choice. Influenced by these rules, the individual may prefer the currently used alternative due to habit, or choose a new one, moved by the desire of having, for instance, shorter travel time or fewer delays. The outcome of the decision step is a provisional trying behavior. The execution of it provides first-hand experience of the actual travel attributes in the temporarily chosen alternative at the time of the trial.

CHAPTER 4: CALIBRATION AND INTEGRATION OF ABM

4.1 DATA

Data used in this study was collected along the Maryland Capital Beltway (I-495) through a Revealed Preference/Stated Preference joint survey. The questionnaire was designed as a web-based survey and the recruitment was conducted by flyer distributions at several exit locations of I-495. The sample population consisted of car drivers traveling on I-495 during the following weekday extended peak periods: 8:00 a.m. - 11:00 a.m. and 3:30 p.m. -6:00 p.m. on March 21-25 and May 23-27, 2011. From a sample of 4,000 who received the flyer, a total of 200 responded to the questionnaire, resulting in an overall response rate of 5%. Within the 200 that completed the questionnaire, 150 submitted the survey, which results in an effective sample size of 150 observations.

The survey consists of two parts: revealed preference (RP) and stated preference (SP) questions. The description for each part of the survey is presented as follows:

4.1. 1 Revealed Preference (RP) Questionnaire

The RP questionnaire consists of two sections: respondents' socioeconomics and recent trip information.

4.1.1.1 Socioeconomic Information

The purpose of this section was to investigate socioeconomic data of the potential HOT lane users in I-495. The respondent was asked to describe the following socioeconomic information:

- Gender
- Age
- Household income range
- Education
- Occupation
- Number of workers per household

- Number of vehicles in the household
- Most used vehicle type by the respondent
- Number of years the vehicle owned
- Workplace zip code

4.1.1.2 Recent Trip Information

The recent trip information gathered data about the respondent's most recent trip on I-495. The purpose of this section was to use each respondent's experienced trip condition as the pivot point when designing the stated preference (SP) question. This ensured that the stated scenario in the SP part was realistic for each respondent. The respondent was asked to describe his/her most recent trip information on I-495 in the following categories:

- Mode choice
- Number of passengers
- Trip purpose
- Departure time (DT)
- Arrival time (AT)
- Preferred departure time (PDT)
- Preferred arrival time (PAT)
- Total travel time in minutes (TT)
- Total trip distance in miles (D)
- Fuel cost (FC)
- Parking cost ($)
- Toll cost ($)
- Entry and exit ramp locations
- Shortest (TT min) and longest (TT max) travel time experienced on the whole trip in minutes
- Shortest (ST) and longest (LT) travel time experienced on the beltway in minutes
- Number of departure time alternatives respondents have considered
- Corresponding departure and arrival time for the alternative departure time

- Work starting/ending time, work schedule flexibility (whether they can start working 30 minutes later)

4.1. 2 Stated Preference (SP) Questionnaire

The stated preference (SP) portion of the survey aims at investigating traveler departure time choice corresponding to time-of-day traffic condition and congestion pricing scheme. It presents respondents with 7 scenarios of stated experiment choices on the joint alternatives of departure time and lane choice.

The game consists of three alternatives and five variables. Each variable has up to five levels of variation per alternative. Three alternatives presented to respondents are: (1) Solo driver on normal lane, (2) High Occupancy Toll lane (HOT) and (3) High Occupancy Vehicle lane (HOV). The variables included in the departure time choice experiment include: (1) Departure time, (2) Travel time range, (3) Arrival time range, (4) Fuel cost and (5) Toll. These variables are designed to account for traffic conditions by time-of-day. They take into account observed respondents' departure time, where the peak period is defined as 8:00 a.m. to 10:00 a.m. and 3:00 p.m. to 7:00 p.m. (Crunkleton, 2008). The description of the variables used in the game is as follows:

- Departure time: Departure time is pivoted from respondent's reported departure time in the RP.
- Total travel time range: This variable is designed to account for both time-of-day conditions based on the respondent's reported departure time and travel conditions on toll lane. It is aimed to capture travel time uncertainty.
- Arrival time range: This variable is calculated by corresponding to the departure time and travel time range of the scenario provided to the respondent.
- Fuel cost: The fuel cost is designed to reflect higher expenses in the peak period and on the normal lane. The fuel cost is pivoted from the reported fuel cost in the RP part.
- Toll cost: The toll cost is designed as mileage-based using the Inter-County Connector toll rates. The toll rate for the HOT lane accounts varies if the respondents' reported departure time is in the peak or non-peak period.

The survey was designed with orthogonal design approach. Numerical evaluations in a wide range of parameter values were undertaken to guarantee sufficient efficiency of the design. The pilot study, in combination with expert judgments, was also used to arrive at the final levels of attribute in the SP experiment. Figure 7 shows the interface of the departure time choice on the website.

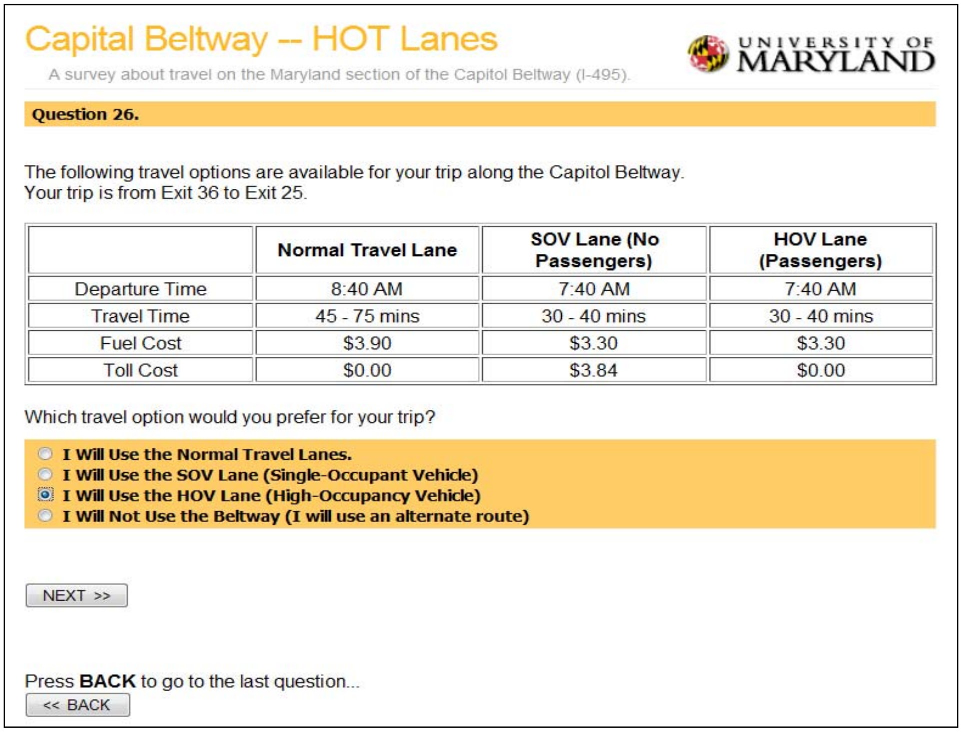

Figure 7. Departure Time Questionnaire

4.2 IMPLEMENTATION OF ABDTM

4.2. 1 Knowledge and Learning

It is assumed that an individual's perception about departure time is based on utility, which is separated into I categories based on prior perception, and that the utility u_i has been experienced n_i times. Therefore, the individuals' knowledge about departure times can be quantified as a vector $K(n_1 \dots n_i \dots n_I)$. According to Bayesian learning rules, the perceived weights of past observations are the same. Let vector $P(p_1 \dots p_i \dots p_I)$ represent an individual's subjective beliefs, where p_i is the subjective probability that an additional search would lead to an alternative departure time with utility u_i. Individuals' prior beliefs are assumed to follow a Dirichlet distribution. Thus, the posterior beliefs will also be a Dirichlet distribution (Rothschild 1974). This assumption is equivalent to Equation (13), where N denotes the total number of observations ($N = \sum_i (n_i)$).

$$p_i = n_i/N \tag{13}$$

4.2. 2 Search Gain Vs. Search Cost

The decision to search for a new alternative is based on the subjective search gain (which is hereby assumed to be based on the predicted utility improvement). It is assumed that an individual's utility associated with the current departure time is u. The expected gain (g) in terms of utility improvement per trip from an additional search is:

$$g = \sum_{i(u_i > u)} p_i(u_i - u) \tag{14}$$

Equation (14) shows how the subjective search gain is calculated as the search process continues in the model. In order to initiate the search process, the perceived search cost needs to be compared with the search gain. The perceived search cost is assumed to be constant for the same traveler. If an individual stops searching after n rounds of search, the perceived search cost for this individual must be lower than the expected search gain after $(n-1)$ searches such that search n is necessary, while it must be higher than the expected search gain after n searches such that search $(n+1)$ does not occur. These lower and upper bounds of search cost can be calculated using Equation (15). The average of these two bounds is used as an estimate of the perceived search cost (c):

$$c_{LOW} = g_n = \frac{u^* - u_{max,n}}{n+1} \tag{15-a}$$

$$c_{HIGH} = g_{n-1} = \frac{u^* - u_{max,n-1}}{n} \tag{15-b}$$

$$c = \frac{1}{2}(c_{LOW} + c_{HIGH}) \quad (15\text{-c})$$

The utility function adopted here was empirically estimated using survey data. More details about this survey can be found in Zhang and Xiong (2012). The function consists of three explanatory variables, including travel time, schedule delay early and schedule delay late. It is estimated following Small (1982)'s multinomial logit model specification. In the same survey, a number of individuals were asked about the order by which alternative departure times were sequentially searched. This information was used to empirically derive the distribution of perceived search costs.

4.2. 3 Search Rules

The search for alternatives is obviously not random because travelers first tend to adapt their choice to their schedule and then avoid extremely high congestion. If-then rules were selected to represent these departure time search heuristics given their capability of replicating human decision-making processes and minimum required computational resources. The latter is especially important for the microscopic traffic simulation model since a half million independent decision agents are involved.

The data set used to derive search rules was collected from commuters on the Capital Beltway. They were asked to recall the order of the alternative departure times they had first considered and then actually used for their commute trips. The variables used in the classifier included: arrival schedule delay early (*ASDE*), arrival schedule delay late (*ASDL*), travel time (*TT*) and free flow travel time (*TT**). The following equations define the delay variables (i.e. *ASDE*, *ASDL*, and *Delay*). In the equations, "*PAT*" denotes the preferred arrival time; "AT" denotes the actual arrival time; and "*Delay*" measures the difference between the actual travel time (*TT*) and the free flow travel time (*TT**), which indicates the congestion level.

$$ASDE = \max(0, PAT - AT) \quad (16\text{-a})$$

$$ASDL = \max(0, AT - PAT) \quad (16\text{-b})$$

$$Delay = (TT - TT^*)/TT^* \quad (16\text{-c})$$

Various machine learning algorithms (Witten and Frank, 2000) are able to derive if-then rules using the collected survey data. From four popular algorithms for deriving if-then classification rules, including C4.5 (Quinlan, 1986), PRISM (Cendrowska, 1987), PART (Frank and Witten, 1998), and RIPPER (Cohen, 1995), PART was chosen for its superior cross-validation accuracy.

Search 60+ min earlier, if

[*ASDL*> 70] (14.0/1.0) Rule 1

Search 30-60 min earlier, if

[45 <*ASDL*<= 70] (12.0/4.0) Rule 2

Search 0-30 min earlier, if

[*ASDL*> 0 AND *Delay*>0] (11.0/1.0) Rule 3

Search 0-30 min later, if

[0 <*ASDL*<= 30 AND *Delay*> 40%] (4.0) Rule 4

OR [*ASDL*<= 10 AND *ASDE*<= 40 AND *Delay*<=50% AND *TT*<= 65] (18.0/3.0) Rule 5

Search 30-60 min later, if

[*ASDL* = 0] (13.0/2.0) Rule 6

Search 60+ min later, if

[*ASDE*> 75] (12.0/1.0) Rule 7

OR [*ASDE*> 45 AND *Delay*>10%] (6.0/1.0) Rule 8

Otherwise, search 0-30 min earlier. Rule 9

4.2. 4 Decision Rules

As discussed in Section 4.2.3, a new departure time alternative is identified after each round of search. The alternative is either accepted or rejected. This decision is determined by a set of decision rules used to describe departure time switching behavior. Unlike the utility maximization theory, this assumption about the decision step does not presume complete information processing and allows for historical dependencies. The decision rules are again derived from a survey experiment conducted in Spring and Summer 2011. Subjects' actual departure time changing behaviors were observed from the survey. Decision rules were extracted using a machine-learning algorithm. A more detailed explanation about the experiment can be found in Zhang and Xiong (2012).

The final decision rule set consists of six rules, presented below. RIPPER is chosen for its better predictive performance based on dataset used in this study. The variables used in the decision rules include: preferred arrival time (*PAT*), departure time (*DT*), preferred departure time (*PDT*), travel time (*TIME*), household income (*INCOME*), trip purpose (*PURPOSE*), fuel cost (*FC*), and toll (*TC*). The variable *none-peak* is a dummy variable that equals one if the trip occurs in off-peak hours. "Δ" denotes changes or percentage changes (i.e. alternative departure time attributes – original departure time attributes).

Switch to the alternative departure time, if

[Δ*TIME*<=-35% and Δ*FC*<=-8%] (126.0/60.0) Rule 1

[Δ*TC* <= $2.5 and Δ*ASDL*<= -48%] (43.0/13.0) Rule 2

[Δ*TC*<= $2.4 and *INCOME*>= $150K and Δ*ASDL*<= -31%] (21.0/3.0) Rule 3

[*none-peak* = 1and *PURPOSE* = Other and Δ*TIME*<=-8% and Δ*ASDL*<= 53%] (17.0/0.0) Rule 4

[Δ*ASDE*<= -20% and Δ*TC*<=$0.7] (12.0/1.0) Rule 5

Otherwise, continue to use the current departure time. (1203.0/181.0) Rule 6

4.3 MODEL INTEGRATION

After individual travel demand models and dynamic network supply models were calibrated, models were integrated for impact studies of new infrastructure and network management strategies. Figure 8 illustrates the implementation process of the integrated model. Based on changes in network structure, operation strategies, or travel demand management policies, the calibrated dynamic traffic simulation model simulates vehicle movement under new network conditions, and predicts the updated network performance measures, such as link travel time. The model then updates the path travel time pattern and predicts route adjustments. This process continues until a stable path flow pattern is reached. Under the new path flow patterns, the time-dependent delay patterns between the same Origin-Destination pair change. Individual travelers may suffer additional delay, which prevents them from reaching their destination at the desired arrival time. The agent-based departure time model is then called to predict individual departure time adjustment based on factors such as the desired arrival time, penalty for late or early arrival, and disutility associated with travel delay. The time-dependent delay patterns predicted by the dynamic traffic simulation model are crucial inputs for the departure time choice model. This information is too coarse for application and may be completely unavailable with conventional regional planning models. Individual choices of departure time are aggregated into updated time-dependent OD demand tables and then a new iteration of simulation is conducted. This process simulates the learning-and-adapting process and stops when no travelers have incentive to adjust their departure time any further. At that time, network performance prediction under new conditions is obtained.

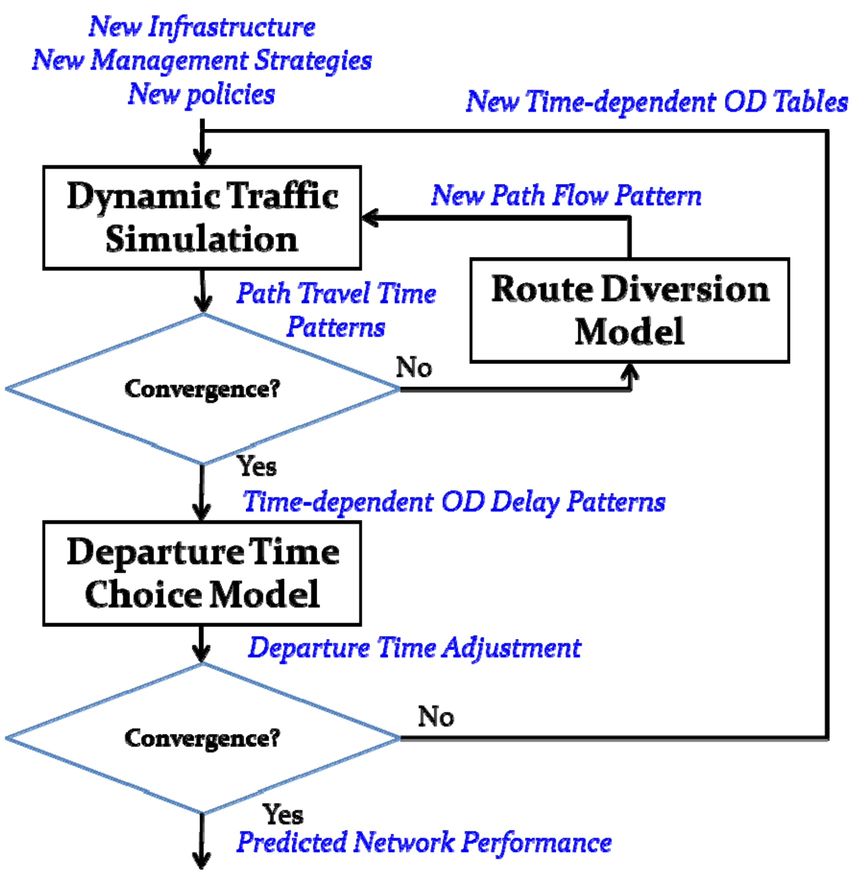

Figure 8. Flowchart of the Integrated Model

CHAPTER 5: BEFORE AND AFTER STUDY OF ICC

5.1 ICC IN TRANSMODELER

MD 200, the Inter-County Connector (ICC), was built in the TransModeler based on Google Earth Map and the ICC blueprint provided by SHA. Please refer to the purple line in Figure 9 for its location relative to the rest of the regional network. It was then integrated with the rest of the network, with interchanges properly connected according to the blueprint.

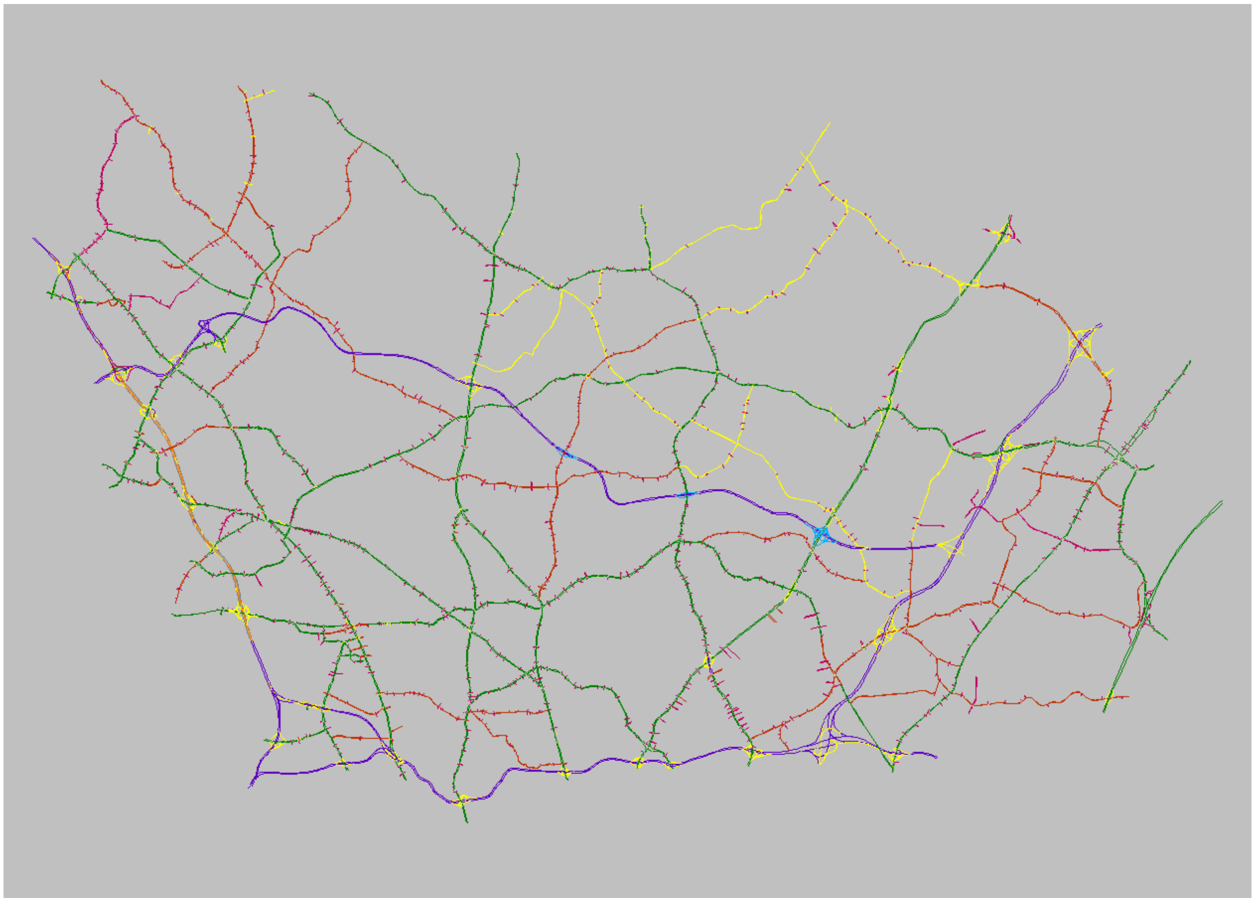

Figure 9. The Inter-County Connector Model (purple line in the middle) in TransModeler

5.2 ICC TOLL RATE

The ICC is a tolling facility. The pricing scheme for two-axle vehicles with E-ZPass, an electronic toll transponder, during different time periods is summarized in Table 1. If a vehicle without E-ZPass uses the ICC, a $1 video-processing fee is added to the total price and a bill is sent to the vehicle's registration address.

Table 1. Pricing Scheme of Inter-County Connector

Section:	I	II	III	IV	V
Peak	**$1.45**	**$0.60**	**$0.75**	**$0.65**	**$0.70**
Off-Peak	**$1.15**	**$0.50**	**$0.60**	**$0.55**	**$0.55**
Overnight	**$0.60**	**$0.40**	**$0.40**	**$0.40**	**$0.40**

5.3 BEFORE-AND-AFTER STUDY OF ICC

Given the pricing scheme and the value of time distribution among travelers in the study area, the choice decisions and the corresponding network condition can be simulated. Figures 9 and 10 present the average Level of Service (LOS) during morning peak hours on freeways and major arterials in the study area with and without ICC, respectively. All LOS levels are defined according to Highway Capacity Manual 2010. Green represents the free flow condition (LOS A), and red means very congested conditions (LOS F). As these figures show, the opening of ICC does not significantly change the congestion level on freeways. However, it does help to reduce the level of congestion on major parallel arterials corridors such as MD 28 and Randolph Road. It also helps to somewhat improve traffic conditions on major north-south arterial roads in the area, including MD 97, MD 182, and MD 650. The ICC itself is not congested under current toll rate and demand level.

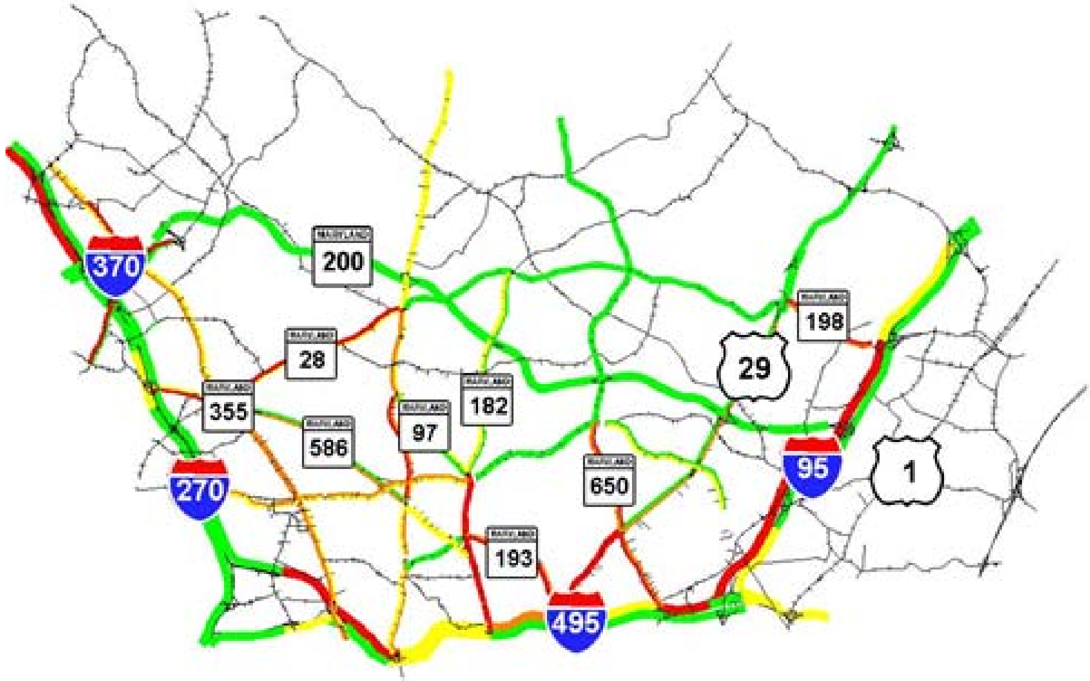

Figure 10. Level of Service Map with ICC

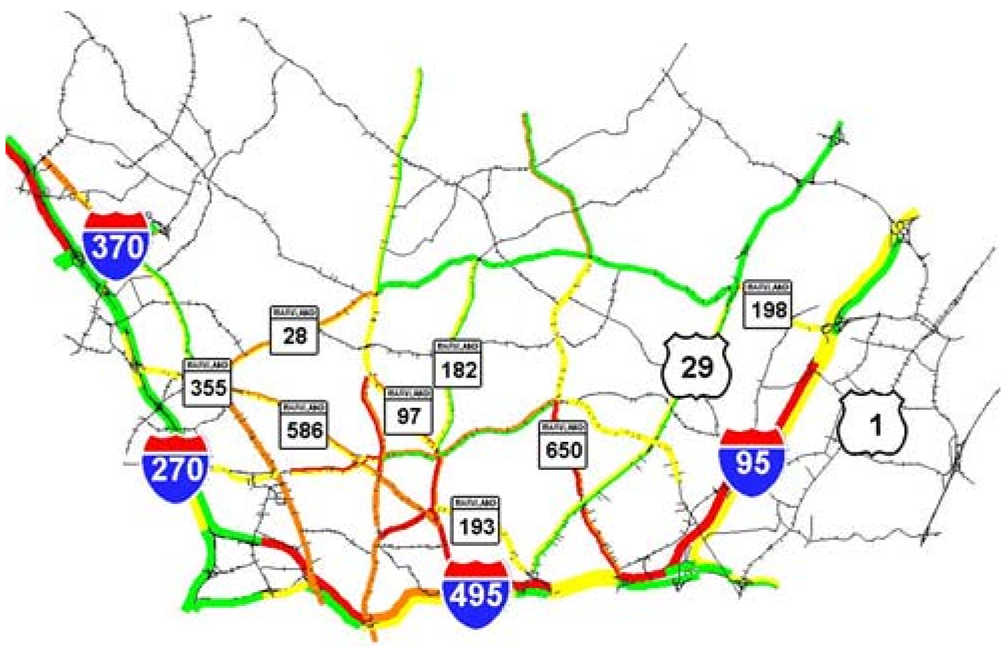

Figure 11. Level of Service Map without ICC

The quantitative network performance measures before/after ICC introduction and are summarized in Table 2. According to the model, ICC attracts about 9,000 trips during the extended morning peak period, which generate revenue of about $17,000. The ICC reduced both the average delay and the stop time. However, the total number of stop time increases slightly according to the model, potentially due to the fact that the ICC introduced several new signal-controlled intersections at the interchanges with local arterials.

Table 2. Network Performance and Revenue Comparison with and without ICC (Moring Peak 5:00AM – 10:00 AM)

Variables	Base Case		ICC Tolling	
	Mean	Std. Dev.	Mean	Std. Dev.
Delay (min.)	**10.97**	**14.43**	**10.40**	**14.48**
Stop Time (min.)	**6.33**	**11.99**	**5.86**	**11.00**
# of Stops	**9.58**	**14.45**	**9.74**	**16.06**
ICC Usage	**N/A**		**9,187**	
Toll Revenue	**N/A**		**$17,768.80**	

Compared to the conventional demand analysis based on regional planning model, the integrated model provides a more detailed comparison with a diverse set of measures. For example, measures such as the number of stops and stop time cannot be obtained through conventional models. Moreover, it allows researchers to focus on different sub-areas within the study area. For example, researchers can focus on one corridor, or one Traffic Analysis Zone, while still considering the impact of travel behavior changes in the larger area. However, to fully benefit from this mesoscopic model, more calibration and validation work on both individual travel behavior and aggregated network performance MOEs should be conducted in future research.

CHAPTER 6: CONCLUSIONS AND FUTURE STUDY

This study develops a mesoscopic model for the before-and-after study of the Inter-County Connector. It is in line with recent efforts by SHA in developing effective modeling tools for traffic analysis and travel forecasting. Examples include the I-270 microscopic traffic simulation model and the Maryland Statewide Transportation Model (MSTM). A comprehensive analysis of many emerging issues in transportation operations and planning at the corridor, multi-corridor, and even statewide levels requires the integration of both microscopic simulation model and macroscopic travel demand models. This study bridges such a gap by developing a mesoscopic model that draws strengths from both.

The integrated models are capable of capturing detailed traffic dynamics and impacts of traffic operation improvement. At the same time, the scale of the integrated model is large enough to capture any regional impacts. A route diversion model and an agent-based departure time choice model are developed and integrated to predict individual behavioral reactions to network changes This allows for the integrated model to reflect both spatial and temporal traffic demand adjustment and regional traffic dynamics.

This study benefits from previous data collection efforts by both SHA and the research team. Both individual travel behavior models and dynamic network supply models are calibrated against local data collected from the Washington D.C. Metropolitan area. The calibrated model is then applied to evaluate the network performance before and after the Inter-County Connector is opened as a tolling facility. The results indicate that after its opening, the new ICC would initially attract around 9,000 users during the morning peak period and would help reduce both delay and stopping time in the study area.

For a more robust prediction and policy evaluation, more research work is necessary. Signal timing plans have a significant impact on local traffic dynamics and network performance. Among the 466 signal-controlled intersections in the current model, only 80 of them have implemented real signal-timing plans. The model will be significantly enhanced if real signal-timing plans could be implemented at all signal-controlled intersections.

As this study demonstrates, it is a challenge to calibrate a large-scale microscopic traffic simulation model. In practice, the calibration process is usually divided into several steps in order to make it tractable. Researchers usually target a good match of traffic volume on freeways and major arterials and then move to minor streets. This usually involves a repetitive process. Researchers also have to go back and forth to improve the calibration results of volume and speed patterns. Results in this study reflect the best results the research team can achieve given current time and data availability. Given the size of the network and the number of unknowns, a more advanced calibration algorithm is needed for future studies and applications. Moreover, an efficient calibration may also involve good heuristics and engineering judgment. Findings from the current study may better inform future research efforts.

Applications of the integrated mesoscopic model go well beyond the before-and-after study of new network infrastructure. Given its sensitivity to changes in both network conditions and travel demand shifts, it can be applied to study a wide spectrum of transportation-related problems, including traffic operation improvement, dynamic pricing strategies, new travel demand management policies and incident management policies.

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