

ABSTRACT

Title of Document: TRAFFIC ANALYSIS ON CUMULATIVE LAND
DEVELOPMENT AND TRANSPORTATION
RELATED POLICY SCENARIOS

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Numerous methods have been developed to evaluate the impact of land developments and transportation policies on transportation infrastructures. But traditional approaches are either limited to static performance or a lack of behavior foundation. With only a few activity-based land development models in practice, this thesis integrates dynamic traffic assignment (DTA) with agent-based positive travel behavior model as a feasible tool for land development and transportation policy analysis. The integrated model enhances the behavior realism of DTA as well as captures traffic dynamics. It provides a low-cost approach to conduct new traffic analysis which emphasis on not only regional/local system mobility, but also individual behaviors. A land development analysis and a flexible work schedule policy analysis are illustrated in this paper. Unlike traditional land development impact studies, a great deal of travel behavior shift is obtained via this integrated model, which creates a new way for land development and policy analysis.

TRAFFIC ANALYSIS ON CUMULATIVE LAND DEVELOPMENT AND
TRANSPORTATION RELATED POLICY SCENARIOS

By

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Dedication

To my beloved mother Ling He, my beloved grandmother Liqun Zhao, and my dear wife Can Dong, my lasting spiritual home.

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Table of Contents

List of Tables.....	vii
List of Figures	viii
Chapter 1: Introduction	1
1.1 Background	1
1.2 Research objectives	4
1.3 Contribution	6
1.4 Thesis outline.....	8
Chapter 2: Literature review.....	10
2.1 Regional land use and transportation models	10
2.2 Application of Large-Scale Traffic Simulation.....	13
2.3 Behavior foundation in DTA	17
Chapter 3: ICC 24-Hour Simulation Model	21
3.1 Model development.....	21
3.2 PEA MOVES.....	23
3.3 Model Calibration and Validation	25
3.3.1 Model Calibration.....	25
3.3.2 Model Validation.....	31
3.4 Case Study of Inter-County Connector, Maryland.....	33
3.4.1 Regional Level Impacts	34
3.4.2 Corridor Level Impacts.....	38
3.4.3 Freeway Link Level.....	40
3.5 Discussion and Conclusion	42
3.5.2 Computational Time Issue.....	43
3.5.3 Network Gridlock Caused by Small Errors	44
3.5.4 Conclusion and Closing Remarks	45
Chapter 4: Cumulative land development analysis tool	48
4.1 From Land Development Model to Simulation Model	48
4.2 Introduction of DTALite	50
4.3 Mesoscopic Traffic Model and Model Calibration	52

4.4 <i>Integration with Behavior Model</i>	55
4.5 <i>Land Development Impact on Dynamic Traveler Behavior</i>	59
Chapter 5: Analysis on Potential Impact under Flexible Work Schedule Policy	67
5.1 <i>Positive Model</i>	67
5.2 <i>Proposed Model</i>	70
5.3 <i>Introduction of DynusT</i>	72
5.4 <i>Integration with DTA</i>	74
5.5 <i>Flextime Policy Analysis</i>	75
Chapter 6: Conclusion	84
6.1 <i>Integrated Tool for Cumulative Land Development Study</i>	84
6.2 <i>Flexible Schedule Policy Analysis</i>	85
6.3 <i>Limitations and Future works</i>	87
Bibliography	89

List of Tables

Table 3. 1 24-Hour Calibration Results.....	28
Table 3. 2 Validation results for AM Peak and PM Peak	32
Table 3. 3 Comparisons of the Two Scenarios using the Regional Level MOEs	34
Table 3. 4 Comparisons of the two scenarios using emissions and fuel consumptions ..	36
Table 4. 1 Income for Synthesized & Survey Population	58
Table 4. 2 Gender for Synthesized & Survey Population.....	58
Table 4. 3 Schedule Flexibility for Synthesized & Survey Population	59
Table 4. 4 Regional Performance	63
Table 4. 5 Route Choice Change	66

List of Figures

Figure 3. 1 ICC Microsimulation Network	22
Figure 3. 2 ICC Microsimulation Network	31
Figure 3. 3 Time-varying Average Delay per Mile	36
Figure 3. 4 LOS map before and after ICC	40
Figure 3. 5 I-495 EB space-time diagram of speed for the two scenarios	41
Figure 4. 1 Mesoscopic Network	53
Figure 4. 2 2007-2008 TPB/BMC Household Travel Survey Sample Map.....	54
Figure 4. 3 Validation Results	55
Figure 4. 4 2007-2008 TPB/BMC Household Travel Survey Sample Map.....	55
Figure 4. 5 Flowchart of the Integrated Model	57
Figure 4. 6 Land Use Changes 2010-2030.....	60
Figure 4. 7 Overall Demand Pattern Change	62
Figure 4. 8 Demand Pattern Change	63
Figure 4. 9 I-270/MD355 Travel Times	64
Figure 4. 10 I-270/MD355 Diverting Traffic	65
Figure 5. 1 Flowchart of Positive Departure Time Choice Model	68
Figure 5. 2 PATI v.s. PAT	71
Figure 5. 3 Flowchart of the Integrated Model	75
Figure 5. 4 A Real World Network: I-270/MD-355 Corridor	76
Figure 5. 5 Demand Pattern Change	79
Figure 5. 6 Demand Pattern Change for Both Traveler Groups.....	80
Figure 5. 7 Payoff Change Under 70% Scenario	82
Figure 5. 8 Travel Time Change for the Whole Population	83
Figure 5. 9 Network Average Travel Time.....	83

Chapter 1: Introduction

1.1 Background

Sustainable growth is an pervasive topic in the world of urban planning. Along with the increase in population, economy, and technology, urban development may also bring in problems such as pollution and traffic congestion. Schrank et al. (1) found that the congestion in US urban areas caused Americans to “travel 5.5 billion hours more and to purchase an extra 2.9 billion gallons of fuel”. Moreover, they claimed that congestion cost in 498 US urban areas was around \$121 billion in 2011, which is five times as that in 1982 (in 2011 dollars). Even though the congestion peak has remained relatively stable during recent economic recession years, the total congestion cost is on the rise because of the increase of commuters and freight shippers in the system. By predicting the nation would experience a congestion cost growth impact from \$121 billion (2011) to \$199 billion in 2020 (in 2011 dollars).

In order to make full use of this double-edged sword-- releasing people’s dream for modern urban life with the minimal social and individual cost, it is necessary for decision makers to have perspective on upcoming developments as well as policies. Transportation, which includes accessibility and mobility, is a referential vital measurement to urban developments. Traffic Impact Analysis (TIAs) is a tool that has

historically been used to evaluate the interplay between existing transportation infrastructure with proposed transportation related policies and transportation elements of land development projects. TIAs can provide a large amount of information that can assist with planning activities and policy adjustments, as well as make immediate adjustments during long term planning.

Over decades there have been numerous approaches to evaluate the impact of urban developments or demand management policies on transportation infrastructure. The ultimate goals of these analyses are to convert land developments/policies to transportation demand/supply changes for TIAs. That is, 1) based on local/regional economic situation, demographic condition and policies, the employment, population, and households in the future can be estimated; 2) these social-demographic data and policy assumptions are then incorporated into transportation demand models or behavior models to obtain new traffic demand patterns; and 3) with traffic assignment models, the changes in demand are finally reflected in roadways. However, there is still a weakness within current TIA on land development analyses and transportation related policies. Current methods for TIA represents traffic in a static phenomenon. The methods do not adequately account for traffic dynamics such as the building/discharging of traffic jam and time-dependent travel times along important corridors. Even though, dynamic traffic evaluation is conducted by Dynamic Traffic Assignment (DTA) model, the pursuit of a user equilibrium solution (UE) ignores

behavior changes that may lead to peak spreading. In addition, it is hard for these models to zoom in for detailed analysis in small areas, corridors, or even intersections.

Meanwhile, various planning policies have been implemented in terms of urban sustainable development, which includes expanding roadway capacity; encouraging public transit; and imposing restrictions on auto ownership/usage. These countermeasures neglect to deal with people's desire for travel at certain jammed time periods such as AM/PM peak period. As Anthony mentioned (2), traffic congestion will not ameliorate until travelers change their daily travel behaviors. An alternative way to gradually inspire distributed traffic demands is to popularize flexible work schedules. Traditionally, employees should be present at working places during some specific daily hours (usually 9:00 a.m. to 5:00 p.m.). Although traditional working policy results from several patterns (i.e., human's common habit of sleeping at night), it encourages commuters to centralize their trips during peak hours. Compared with the traditional 9 a.m. to 5 p.m. work hours, a flexible work schedule allows employees to choose their preferred arrival/departure times. For example, in one flextime situation, employees can arrive at offices anytime between 8 and 10 a.m. and leave for home anytime between 4 and 6 p.m.; or they can select one day off within weekdays, and finish an additional two-hours' work per day for the rest 4 days.

It is desirable and important for decision makers to understand the impact of urban developments or transportation policies, or the combination of them. For

example, how cumulative land developments along the same corridor influence regional traffic flow, and how purposed transportation related policies shift traveler's behavior. In a previous Maryland State Highway Administration (SHA) research project, the University of Maryland (UMD) research team successfully developed a mesoscopic model that integrates microscopic dynamic traffic simulation models and travel behavior models for the Inter-County Connector (ICC) corridor and a large region around the ICC corridor. The study area in that project covered the I-270 and MD-355 (Rockville Pike) corridor between the I-495 beltway and the ICC. In terms of more comprehensive TIAs, further developments are required for this mesoscopic tool to be utilized for this purpose. In the first place, the new tool is expected with the ability to capture demand pattern changes such as peak spreading, and route changes under cumulative land developments. Here, the word "cumulative" means that the traffic impact of the combination of two sector developments is larger than the sum of the individual traffic impact under both the two developments. Secondly, behavior models are required to be integrated to enhance the sensitivity of developments and policies.

1.2 Research objectives

In previous research, a mesoscopic TIA approach was developed by this UMD research team. Both microscopic simulation and travel behavior models are integrated for the analysis of regional traffic level of service (LOS) and behavior changes. The research team also integrates the Environmental Protection Agency's (EPA) emission

estimator Motor Vehicle Emission Simulator (MOVES) as a post-processing module for environmental analysis. The details of this previous project will be described in the next chapter.

To take a further step, the main purpose of this research is to continuously develop the ICC mesoscopic model to deliver an integrated tool for: 1) cumulative land development impact study along the I-270/MD-355 corridor, as well as the White Flint area; and 2) the potential impact of a flexible work schedule policy on travelers' departure time choice as well as the traffic congestion mitigation.

A number of cumulative land development plans have been proposed along the I-270/MD-355 corridor for next 20 to 30 years. Thus, it is necessary and interesting to adopt a tool to reflect traffic conditions under a series of purposed plans (i.e. regional traffic impact; dynamic queueing impact for specific roadways; destination changes; route choice for main corridor users; and turning movement changes at important diverting intersections). In addition, travel behavior models will be integrated into this tool to make it capable to recognize behavior shifts under these developments or some further policies. As an integrated model, it is interesting to gain perspective on how travelers change their travel behavior under a flextime policy, which is another feasible solution of traffic congestion. The thesis aims to capture how travelers will shift their travel times under different levels of flexibilities in their working schedule, and how the behavior change will influence the traffic..

During the development of this integrated model, a number of existing models and methods were reviewed. This included land development forecasting models, traditional and more advanced traffic demand models. Then the thesis selected DTA models and positive departure time choice model for the integration. Although there used to be challenges building the linkage between different models, this thesis has developed a convenient way and feasible tool for the whole analysis process.

In order to emphasize the value of this proposed TIA tool, it requires several features: 1) well incorporated land development models, making it sensitive to the changes of land use variables; 2) quick to conduct the TIA, as well as detailed analysis in subareas; and 3) good integration with behavior models.

1.3 Contribution

There are two major contributions towards this thesis. Firstly, this is an attempt to develop a traffic demand and behavior analysis tool. The integration of macroscopic land development forecasts, mesoscopic traffic simulation models, microscopic traffic simulation models and agent-based travel behavior models makes the tool capable of conducting analysis for both urban development and policy scenarios. One major advantage over current TIA models is its ability to capture both regional traffic congestion and individual level travel behavior changes. Based on dynamic mesoscopic Dynamic Traffic Assignment (DTA), microscopic DTA and

behavior choice models, it is possible to obtain a dynamic view of upcoming impacts.

Secondly, this thesis attempts to gain perception about travelers' reaction towards urban developments and flex work schedule policy. Unlike previous studies, an agent-based approach is applied to capture individual level behavior change. Moreover, the individual knowledge learning and decision making process is specified and empirically modeled to understand the potential influence of different scenarios on day-to-day traffic dynamics. The DTA model (DTALite or DynusT) is integrated with this agent-based positive departure time choice model. One remarkable advantage of this integrated model is its ability to provide a feedback between individual choice demand side and supply side network performance. The analysis in this thesis demonstrates the value of developing a software package for the integrated model.

The leading purpose of this thesis is to introduce and illustrate a theoretical framework to understand travelers' reactions towards various management policies, urban developments, and even road way incidents. Although departure time is the only variable in travelers' decision making process, this research presents the feasibility and necessity to include more behavior alternatives such as route choice, mode choice, lane choice, etc. The combination of departure time with other travel behaviors could be explored in future study.

1.4 Thesis outline

The remainder of this thesis is organized as follows. Chapter 2 mainly focuses on the literature reviewing work of this thesis. This will begin with regional land development forecast models, in which both the traditional four step models and modern models will be introduced. In this part, the author also includes some previous work to integrate DTA with behavior models (2.1). In 2.2, the review on behavior foundation in DTA models will be described. Then the author will talk about the review of current transportation policies in 2.3. At last in 2.4, the author will review the application of traffic simulation models on large scale networks.

The Chapter 3 of this thesis documents the model development, calibration, and case study in the hope that this document can serve as a useful reference for researchers and practitioners. In 3.1, the large-scale microscopic traffic simulation model is described including a brief description of the methodology for Origin Destination (OD) estimation and the calibration/validation. The emission estimation model would also be introduced in 3.2. In 3.3, detailed calibration process is introduced in a 24-hour time frame, which includes basis data, methodology and results. The validation process and results are also briefly mentioned. In 3.4, the case study of the new toll facility in Maryland is presented with various MOEs and comparisons obtained from the calibrated simulation model. The experiences learnt and challenges resolved when modeling and calibrating this large-scale 24-hour traffic simulation are discussed in the last section. The conclusions and discussions are

offered in 3.5.

The new approaches on cumulative land development study will be shown in Chapter 4. This chapter includes the major work and contribution in the thesis. 4.1 will briefly talk about the regional planning model. A more and more prevalent simulation based DTA modeler known as DTAlite will be introduced (4.2) and applied for cumulative land development study. In addition, 4.2 will also include the mesoscopic traffic simulation model in this thesis. The integration process between behavior model and DTA is described in 4.3. Then in 4.4, an application of land development impact analysis is showed to demonstrate the advanced features of this proposed tool on capturing behavioral changes and other traffic impacts.

The motivation and objective of Chapter 5 is to explore the potential impact of a flexible work schedule policy on congestion mitigation. The framework of this approach will be introduced which includes a positive departure time choice model (5.1), the improvements (5.2), and its integration with mesoscopic simulation-based DTA simulator (5.3). Then in 5.4, a real-world application for different levels of flexible schedule scenarios will be described. Both Chapter 4 and Chapter 5 are the core of this thesis. Conclusions and future work will be mentioned in the last chapter on: 6.1, integrated tool for cumulative land development study; 6.2, flextime policy; 6.3, limitations and future works.

Chapter 2: Literature review

The literature review chapter consists of three parts. Firstly, I would love to introduce the existing regional transportation models. Both the capability and limitation of these regional planning and transportation forecasting models will be discussed. Based on the discussion, I will claim the needs of an integrated model for regional transportation modeling. Secondly, since the goal of this thesis is to integrate current simulation based DTA models with agent-based behavior models, the difficulties and breakthroughs will be talked on the application of traffic simulation models. Here, I only focused on the application on large scale networks because the purposed integrated model is supposed to work in place of traditional transportation forecasting models. Finally, the behavior foundation of DTA models will be discussed to explore the feasibility of this integration. I will talk about the basic assumption and limitation of rational based traffic assignment theories, followed with some more behavior realized models.

2.1 Regional land use and transportation models

It is unrealistic to model the change of urban regions in every relevant aspect, because they are highly complex entities. Despite the associated difficulties, researchers have produced a variety of models forecasting interrelated processes of urban changes (3). Embodied in the concept of accessibility, it has been popular to model urban changes with the interaction between transportation infrastructure

improvement, land developments and the location of economic activities (3). The interaction between spatial patterns of land use and transportation networks is referred to transportation-land use “link” (4).

It is usually a double level problem when considering land development/policies related TIAs. The upper level is the urban planning and forecasting model, which includes: 1) spatial interaction/gravity-based models (4-9); 2) econometric models (10-16); 3) microsimulation models (17-18); and agent-based models (19-21). The lower level of urban development modeling is transportation models, e.g. 1) traditional four-step models, also referred as trip-based models (22); 2) advanced four-step models (23-25); and 3) tour/activity-based models (26-28); 4) dynamic traffic assignment models (29-33).

Spatial interaction models and econometric models are usually linked with four-step models for TIAs (3). Thus, most only have static traffic equilibrium models (34-36) which are incapable of capturing dynamic traffic performance. In addition, trip chaining and scheduling behavior, both of which are important for estimating demand responses to a variety of transportation-related policies, are unable to be modeled by these models due to the lack of a solid behavioral foundation (37). Microsimulation models and agent-based simulation models, on the other hand, usually contain the concept of “activity-based” for traffic activities modeling. With the emphasis on scheduling behavior, activity-based models theoretically promise a

stronger behavioral foundation for demand modeling. They are expected to provide more accurate time-dependent estimates of origin-destination (O-D) demand than the four-step model. The integration between activity-based models and dynamic traffic assignment techniques enforces this time-dependant advantage on both demand side and supply side (38-40).

However, two major reasons make behavior realism unavailable for most U.S. urban councils of governments (COGs): 1) there are only 11 activity-based models in practice, while most COGs are using traditional or advanced four-step models (37); 2) even though DTA enhances the capability to analyse traffic dynamics (41,46), it can hardly capture behavior responses such as peak spreading (46). Following rational behavioral rules, most dynamic traffic assignment models assume travelers have perfect network knowledge. Thus, they are able to identify the alternative routes with best payoff, and reach a Dynamic User Equilibrium (DUE) in the end. The considerations of travelers' cognitive and decision limitations have not been incorporated, even though travelers' rationality is proven to be bounded by a series of experimental studies (42-44) (see 2.2 for more details).

Zhang et al integrated positive travel behavior models (route choice model and departure time choice model) with DTA for a demand pattern study (45-46), and showed its application on large-scale networks. But only a fraction of the whole population is adopted with the behavior model. So far there is still a gap in the

exploration of the integrated DTA models for land development impact studies. This thesis is trying to fill this gap by illustrating a tool which is capable of conducting urban development TIA from a dynamic and behavior realistic point of view. The proposed tool successfully links the MWCOG planning model with a behavior-integrated DTA for TIA under future land development. In addition, with the adoption of a new DTA simulator DTALite (47), the tool can conduct quick analysis for both regional area and specific corridors where development happens.

2.2 Application of Large-Scale Traffic Simulation

Microscopic traffic simulation has gradually proved a powerful tool in transportation research. This trend moves slowly towards large-scale applications while the technology advancement makes the computational burden of microscopic simulation of less concern. From 1990s, most applications were on corridor analysis problems evaluating queue spillback, weaving, incidents, and signal control (67). Toledo et al. (68) presented a case study of a medium size simulation model (298 nodes and 618 links) in Irvine, California. The model was calibrated by comparing observed and simulated sensor counts for every time interval of 15 minutes. Similar studies were conducted but none of them ever dealt with large-scale networks (69-70). Here the term of “large-scale” indicates a scale that spatially covers multiple corridors and temporally covers multiple time periods. Rakha et al. (71) constructed and calibrated a 24-hour large-scale micro-simulation model (3365 nodes and 7926 links) for the Salt Lake metropolitan region. He applied the All-or-Nothing (AON) traffic

assignment algorithm for model calibration. Although the execution time is short, AON is unrealistic in capturing varying traffic dynamic. Jha et al. (72) developed a large-scale microscopic traffic simulation model for the entire Des Moines metropolitan area. Jha applied a route choice and simulation based assignment to calibrate time dependent OD matrices for 7:15 to 8:30 a.m. and 4:15 to 5:30 p.m. The time scale of Jha's model was much smaller than Rakha's. This is reasonable because simulation-based assignment required high computation cost in large-scale networks. Balakrishna et al. (73) adopted DTA and conducted the simultaneous calibration of a micro-simulation model with some 1,700 links for Lower Westchester County, New York. In Balakrishna's study, various measures of calibration goodness were used. Smith et al. (74) represented the most recent attempts in large-scale microscopic simulation.

Research gap exists in large-scale network calibration and simulation applications. While the spatial dimensions of the existing research sometimes involve large and complex network systems, very few studies calibrate and simulate multiple time periods. As the peak-hour demand grows and spreads to other time period, travelers' commuting departure time decision, as well as the aggregate peak spreading effect, become one crucial behavior response to excessive peak-hour congestion and time-varying toll policy. Zhang et al. (46) recently studied peak spreading using a microscopic simulation model. The study is limited by only allowing departure time shifts within the extended AM peak hours. Under this context, a 24-hour model is

necessary in order to simulate within-day behavior changes more realistically, in the future when behavior/demand models are available to be integrated into the modeling framework.

Studies that apply microscopic traffic simulation models to obtain MOEs for planning and management are insufficiently seen in literatures. Various performance measures in different levels were developed to quantify the impacts of transportation planning or management scenarios. Vehicle miles traveled (VMT) is an important MOE that indicates both auto usage demand and congestion level. Choo (75) investigated the impact of telecommuting on the VMT through a multivariate time series analysis of aggregate nationwide data. Nasri and Zhang (76) applied a multilevel mixed-effect regression model to study the impact of land use pattern on the VMT. Similarly, measures such as average trip time, average trip length, vehicle hours traveled (VHT), and gravity-based accessibility, which can be obtained from travel demand model (77-78), can also reflect regional-level performance. Although these MOEs are capable to evaluate the system, more detailed measures is necessary for a better understanding of impacts on specific and smaller study scales and can thus highlight the capability of a microscopic simulation model. Level of Service (LOS) proved to be a vital tool for agencies to consider a wider range of mitigation measures for congestion and growth (79). With graded evaluation, LOS can reflect full-scale information for freeway/arterial corridor evaluation, such as vehicle mobility and driver psychological comfort. While there is an increasing concern on environmental

issues, measures of emission estimation and fuel consumption have been indispensable in project planning evaluation. A number of studies have been carried out to link emission estimation models to traffic demand models. Haas et al. (80) calculated the total VMT and emission of carbon dioxide and analyzed greenhouse gases (GHG) reduction in both a single transit zone and whole region in Chicago. Similarly, Chen et al. (81) analyzed the change of mode shares, VMT and GHG on different land use development policies. As a strong tool for capturing traffic dynamics, microscopic traffic simulation models are able to generate all these MOEs as well as link with post processing models such as emission estimation models.

In previous work, a 24-hour large-scale microscopic traffic simulation model and a case study in Maryland are developed. The analysis differs from other papers in several ways. Firstly, one time-varying toll facility, three freeway corridors, and a total number of 7,121 links and 3521 nodes consist of our model. High-resolute roadway/intersection geometry and a complete set of signal timing information for a total number of 466 signalized intersections have been implemented in the model followed by a careful calibration procedure. Very few other studies have attempted a simulation of the scale and extent of the simulation in this study. Secondly, the study employs multiple data sources for validation and calibration. An independent process that compares simulated and observed corridor travel times have been done for model validation after the model is calibrated using 24-hour field counts data. Thirdly, a case study on the newly built toll facility in Maryland has been conducted to investigate

the before-and-after effect with various network-level, corridor-level, and freeway-level performance measures. After the simulation, Environmental Protection Agency (EPA)'s Motor Vehicle Emission Simulator (MOVES) (82) is integrated as a post processing model for the estimation of environmental impacts. This is among the first attempts to link EPA's MOVES to large-scale microscopic traffic simulations.

2.3 Behavior foundation in DTA

The concept of DTA was proposed in 1978 by Merchant and Nemhauser (87), who tried to model traffic dynamically in a discretized time-setting. Merchant and Nembauser formulated DTA as a deterministic, fixed-demand, single-destination, and single-commodity problem, System Optimal (SO) problem. A number of studies have been conducted about DTA (details can be found in 88), and researchers at that time were more interested in the analytical flexibility and convenience in DTA, such as the requirement of "first-in-first-out", multiple-destinations, the "holding-back" of vehicles on links, and how to represent link performance (88).

Janson (89) attempted to seek the temporal static equilibrium in terms of experienced path travel times for users. This attempt at applying User Equilibrium (UE) to DTA can be regarded as a behavior foundation in this study area (89). Most DTA models applied Deterministic User Equilibrium or Stochastic User Equilibrium (SUE) as their solutions (89). The behavior foundation of both DUE and SUE is based on rational behavior theory (90). Rational behavior theory was first proposed in 1947

in economics (91), which assumed: 1) the set of alternatives are open to choice; 2) utility is a function of alternative, and alternative is chosen with preference-ordering among utility. In the condition of DUE, travelers' experienced travel times are determined, and travelers have perfect information. The travel times are the same in all routes so that travelers share the same preference and no traveler would find another route with shorter experienced travel time (92). While in SUE, travelers no longer have perfect information. To model "imperfect" information, a random error component is added to the utility (travel time), and travelers are assumed to minimize their perceived travel time. The assumed distribution of the error component results in different preferences among travelers as well as different assignment models (i.e. Normal distribution for Probit model, Gumbel distribution for Logit model) (90).

One further progress with SUE over DUE is the way it generates the selection of alternative routes (90). The consideration of partial choice set overcame the behaviorally unrealistic in previous DUE approaches (Williams and Ortuzar 1982). However, SUE is still based on utility maximization, and it does not recognize historical dependencies of route searching behavior (90).

Another approach is Bounded Rational User Equilibrium (BRUE) developed by Mahmassani and Chang (93). BRUE is founded on Simon's famous bounded-rationality assumption and associated satisficing decision rules (93). Instead of seeking necessarily optimal alternative with the maximal utility, BRUE tries to

seek an acceptable alternative satisfactory to the traveler. In terms of a bounded rational based departure time choice model, an Indifference Band (IB) of tolerable schedule delay (SD) is applied to model if a SD is acceptable by traveler. IB is allowed to be indifferent among people, which enhances the capability of modeling heterogeneousness among individuals. However, the process of alternative departure time searching is only modeled using preferred arrival time subtracting perspective travel time, which lacks wayfinding behavioral realism (90, 95).

In order to improve the behavior realism in DTA, Behavior User Equilibrium (BUE) was developed by Zhang (92). BUE is based on the positive Search, Information, Learning, & Knowledge (SILK) theory that has overcome the limitations of rationality theory discussed previously. The historically dependent modeling is achieved by adopting a Bayesian learning to update travelers' network knowledge and subjective beliefs. Travelers' knowledge and beliefs are applied to determine their subjective search gain and perceived search cost, which will decide whether or not to conduct a new round of search and decision. Rule based searching increases the ease of observing individuals' wayfinding behavior. The searching process of one individual will stop if the perceived search cost exceeds the expected gain from an additional search. The BUE is reached on a network when all users stop searching for alternative routes. The BUE has more realistic assumptions about wayfinding behavior and empirical derivation of behavioral rules (90). Zhang claimed that the BUE meets the requirement to more accurately predict behavioral responses in a

complex decision environment. This thesis implied the departure time choice model under SILK theory. Details can be accessed in Section 5.1.

Chapter 3: ICC 24-Hour Simulation Model

3.1 Model development

Supported by Maryland State Highway Administration (SHA), a simulation model was developed, in which all the freeways (I-270, I-495, I-95 and I-370), major arterials (e.g. MD355, MD97, MD650, MD28), most minor arterials, and some important local streets in the central and eastern Montgomery County and the northwestern Prince George's County of the State of Maryland are included (Figure 3.1). With such a large-scale network, the simulation model could capture the impact of several new developments within this area, e.g. the new under construction toll road: the Inter County Connector (ICC); the Great Seneca Science Corridor (GSSC) in West Gaithersburg; the military base in Fort Meade (46).

Microscopic traffic simulator TransModeler was selected for the modeling. Transmodeler (83) has a well-developed interface with geographic information system (GIS), which is convenient dealing with various data sources of a large-scale network. The simulated network was developed with the accuracy satellite images provided by Google Earth and conformations to the true geometry of links and intersections. The completed network has a final size of 7,121 links and 3,521 nodes, which includes three freeway corridors and one time-varying tolling facility.

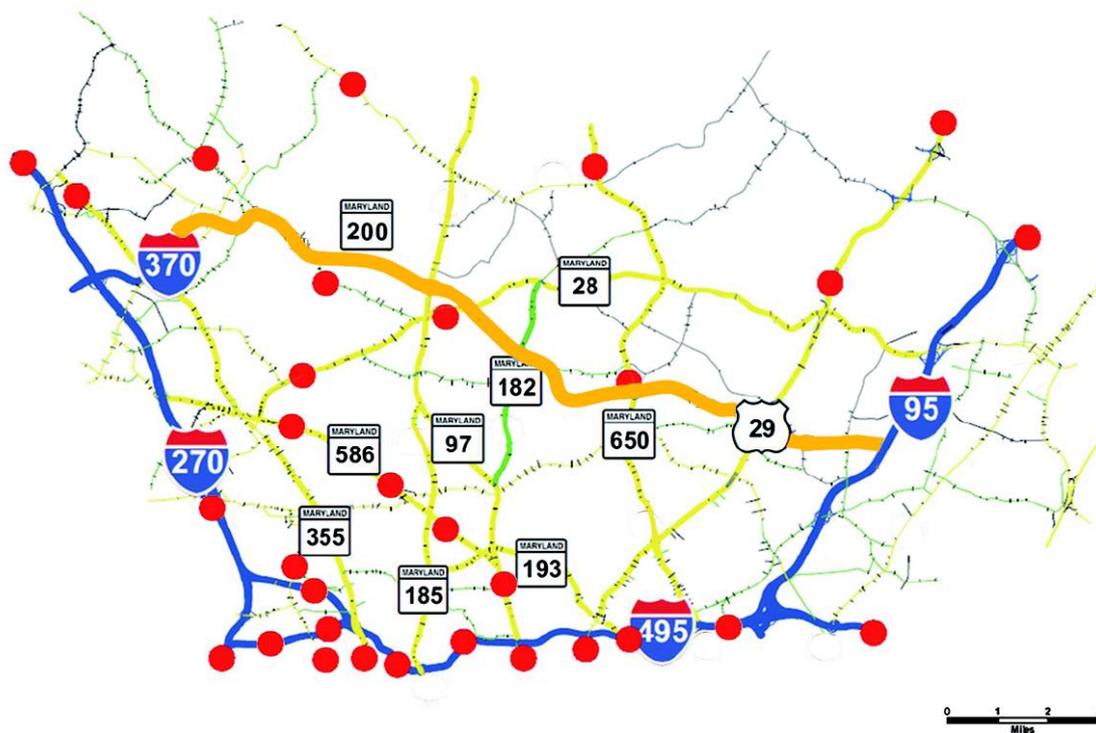


Figure 3. 1 ICC Microsimulation Network

In OD estimation procedure, the Metropolitan Washington Council of Government (MWCOC) planning model was used as the basis. MWCOC includes 27,743 links, 10,505 nodes, and 2,119 Traffic Analysis Zones (TAZs), while the case study contains 162 TAZ centroids within MWCOC area. 39 external centroids were divided through which the sub-network is connected with the rest of the MWCOC model. With the application of Gradient Projection (GP) path-based traffic assignment algorithm (84), hourly simulation OD has been extracted for 24-hour period by applying the method developed in the authors' previous work (46). Important steps of obtaining the OD are as follows:

1. Conduct assignment of HOV using the GP algorithm;

2. Conduct assignment of trucks by excluding HOV lanes and keep the path flow of HOV;
3. With the path flow of HOV and trucks, conduct the assignment of SOV;
4. Compare the difference between the shortest and longest OD travel time, if anyone exceeds the predetermined threshold, back to step 1;
5. Assign path flow between external stations and centroids to corresponding OD pair based on the path within the study area.

After deriving 24-hour OD, comprehensive calibration is conducted by adjusting the timely OD matrix to match the spatial and temporal traffic pattern with field observations. The “Before ICC” network is used for calibration since all the observed data was detected before the construction of ICC. After calibration, the model was validated with the comparison between observed and simulated travel times on some major corridors. More detailed calibration and validation work would be discussed in next section.

3.2 PEA MOVES

Another highlight of this study is the application of Motor Vehicle Emissions Simulator (MOVES) as a post-processing module to process simulation outputs and estimate emissions. MOVES is a reliable tool in emission estimation developed by the Environmental Protection Agency (EPA) (82). Compared with other models, MOVES has a couple of advantages. For example, it has a strong linkage with emission related

database for the whole United States which makes the calculation more convenient (82).

MOVES model is designed with different estimation scales: nation level, county level and link level scale for micro analysis. In this study, county level estimation is selected, which calculates the emission and energy consumption effort in one specified area during a given period of time. Simulated results and other data sources are required for county level estimation. These data requirements are described as follows:

1. Total VMT, available directly from simulated results;
2. The ratio of different vehicle types, obtained from the regional planning model (i.e. MWCOG model, version 2.2);
3. The ratios of different road types, obtained from the segments data in the simulation model;
4. Average speed distribution, calculated from the simulated counts and average speeds for every segment;
5. Vehicle age distribution and population. This has been obtained from 2007-2008 TPB/BMC Household Travel Survey, where daily number of trips, trip production per household and number of vehicles per household are used to estimate population;
6. Meteorology data (temperature and humidity), posted at weather website “The Weather Channel”;

7. Fuel formations are set as default.

After processing these data, MOVES estimates emissions such as greenhouse gas emissions, particular matters (PM), and energy consumption within the whole network and the corresponding time period.

3.3 Model Calibration and Validation

3.3.1 Model Calibration

As mentioned in the literature review, model calibration turns out to be the most time-consuming and critical step in model development. Before we move to calibration, complete 24-hour signal timing information for the 466 signalized intersections is obtained from SHA and local department of transportation and then implemented in the simulation model. In this paper, 24-hour field counts data from SHA are used for model calibration. The data comes from 24 freeway and 38 local arterial sensors (red dots in Figure 3.1), and are collected for multiple days. From the hourly OD, the calibration algorithm (details are listed in (46)) evaluates demand adjustment factor $\alpha_{ij,r,t}$ associated with each path r between an OD pair i, j and for a given time period t by using the following equation:

$$\alpha_{ij,r,t} = \frac{\sum_{a \in S(ij,r,t)} \zeta_{ij,r,a,t} \left[\frac{(F_{a,t} + \Delta t_{ij,r,a,t})}{(f_{a,t} + \Delta t_{ij,r,a,t})} \right]}{\sum_{a \in S(ij,r,t)} \zeta_{ij,r,a,t}} \quad (3.1)$$

where ij denotes OD pair from origin i to destination j ; $r \in R(ij, t)$ where R denotes

the complete set of all used paths of OD pair ij at time t ; $S(ij, r, t)$ denotes the link set of path r at time t . $F_{a,t}$ denotes the actual link flow on link a at time t ; $f_{a,t}$ denotes simulated link flow on link a at time t ; $\Delta t_{ij,r,a,t}$ denotes travel time from origin i to link a starting at time t . $\zeta_{ij,r,a,t}$ is an indicator which equals 1 if $a \in S(ij, t)$ and 0 otherwise.

When attempting to conduct the calibration on 24-hour period at a time, the model's DTA run time tends to be extremely long because during the first few iterations the assignment gridlocks the network and considerably slows the simulation. Thus, the authors address this by dividing the all-day study period into 6 sub-periods: early morning (0 - 6 a.m.), a.m. peak (6 - 9 a.m.), midday 1 (9 a.m. - 1 p.m.), midday 2 (1 - 4 p.m.), p.m. peak (4 - 7 p.m.) and night (7 p.m. to 0 a.m.) and calibrating them separately. The simulation state of the traffic condition by the end of each sub-period is saved as an initial state loaded to the simulation of next sub-period to make the simulation continuous and consistent.

Various performance measures have been applied to evaluate the accuracy of the match between field data and simulated counts:

1. Root Mean Square Deviation (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (f(\mathbf{x}^{(i)}) - \hat{f}(\mathbf{x}^{(i)}))^2} \quad (3.2)$$

2. Normalized Root Mean Squared Error (NRMSE)

$$\text{NRMSE} = \sqrt{\frac{\sum_{i=1}^N [f(\mathbf{x}^{(i)}) - \hat{f}(\mathbf{x}^{(i)})]^2}{\sum_{i=1}^N (f(\mathbf{x}^{(i)}))^2}} \quad (3.3)$$

3. Pearson correlation coefficient (PCC)

$$\text{PPC} = \left(\frac{N \sum_{i=1}^N \hat{f}(\mathbf{x}^{(i)})^2 - \sum_{i=1}^N f(\mathbf{x}^{(i)}) \sum_{i=1}^N \hat{f}(\mathbf{x}^{(i)})}{\sqrt{[N \sum_{i=1}^N f(\mathbf{x}^{(i)})^2 - (\sum_{i=1}^N f(\mathbf{x}^{(i)}))^2][N \sum_{i=1}^N \hat{f}(\mathbf{x}^{(i)})^2 - (\sum_{i=1}^N \hat{f}(\mathbf{x}^{(i)}))^2]}} \right)^2 \quad (3.4)$$

where N is the number of independent set data to be compared, $f(\mathbf{x}^{(i)})$ and $\hat{f}(\mathbf{x}^{(i)})$ denotes the observed and simulated count at sensor i . RMSE reflects the absolute deviation of counts; NRMSE indicates the relative deviation, where observed counts are weighted by volume; PCC is a measurement indicating the correlation between field counts and simulated counts. If $r^2 = 1$, the model is exactly predicting the test data, while $r^2 = 0$ indicates there is no correlation between the model results and the field measurements.

Finishing the calibration, the performance measures demonstrate a good calibration result (Table 3.1). RMSE indicates the average difference of counts was 595.2 for freeway stations, and 493.4 for all the stations (the average counts on freeway stations and all stations are 4,349 and 2,247 respectively). NRMSE shows the convergence of normalized relative errors for both freeway and all sensor stations are 12.95% and 16.77% respectively. The PCC results also imply that simulated counts

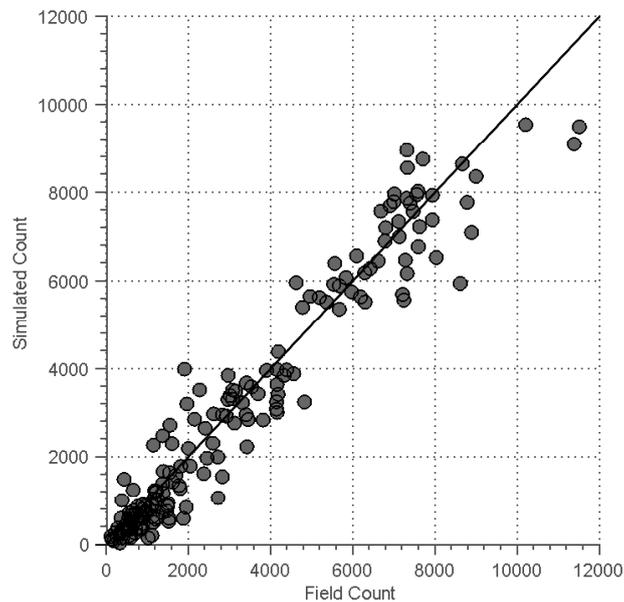
conform to the observed counts with high accuracy.

Table 3. 1 24-Hour Calibration Results

Time Period	RMSE		NRMSE (%)		PCC	
	Freeway	All	Freeway	All	Freeway	All
Average	595.2	493.4	12.95	16.77	0.927	0.974
0:00 to 1:00	72.3	101.2	6.59	14.52	0.978	0.980
1:00 to 2:00	106.7	86.5	15.58	20.02	0.923	0.974
2:00 to 3:00	99.0	74.4	17.61	21.06	0.886	0.966
3:00 to 4:00	94.9	77.8	15.14	19.79	0.914	0.976
4:00 to 5:00	195.9	155.3	14.40	18.16	0.946	0.982
5:00 to 6:00	390.9	366.2	9.36	13.90	0.973	0.984
6:00 to 7:00	899.5	650.5	14.05	15.80	0.918	0.976
7:00 to 8:00	1,108.7	871.6	16.28	19.54	0.877	0.964
8:00 to 9:00	1,030.8	844.8	15.33	19.14	0.881	0.962
9:00 to 10:00	1,134.1	847.1	17.85	20.56	0.866	0.957
10:00 to 11:00	805.8	585.1	13.99	15.81	0.921	0.977
11:00 to 12:00	613.6	507.1	11.08	14.21	0.924	0.980
12:00 to 13:00	513.2	498.8	8.99	13.52	0.946	0.983
13:00 to 14:00	562.5	507.5	9.59	13.41	0.954	0.984
14:00 to 15:00	986.0	758.3	14.57	17.42	0.910	0.977
15:00 to 16:00	1,128.2	901.4	16.18	19.95	0.877	0.964

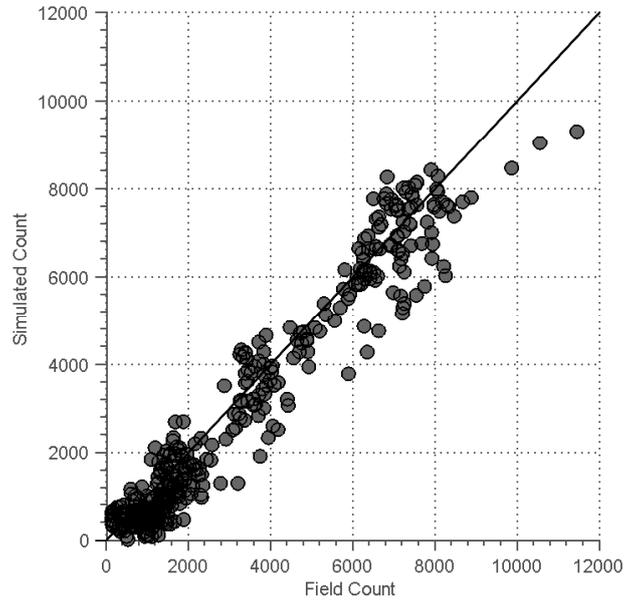
16:00 to 17:00	861.7	750.6	13.13	17.40	0.930	0.967
17:00 to 18:00	794.2	782.6	12.46	18.44	0.943	0.967
18:00 to 19:00	756.8	705.5	11.93	16.90	0.958	0.975
19:00 to 20:00	560.4	486.5	10.05	13.45	0.956	0.980
20:00 to 21:00	563.2	445.2	12.92	15.76	0.927	0.974
21:00 to 22:00	460.0	384.9	11.95	15.46	0.949	0.977
22:00 to 23:00	329.3	273.4	10.83	14.05	0.939	0.980
23:00 to 0:00	216.9	179.7	10.93	14.19	0.947	0.981

Figure 3.2 plots the final comparison of field and simulated traffic count data at all counting stations. After numerous rounds of error checking and calibration, the model appears to do a reasonably good job in replicating observed conditions. Most of the comparison points conform to the diagonal line. This implies an accurate calibrated model to simulate transportation planning scenarios.



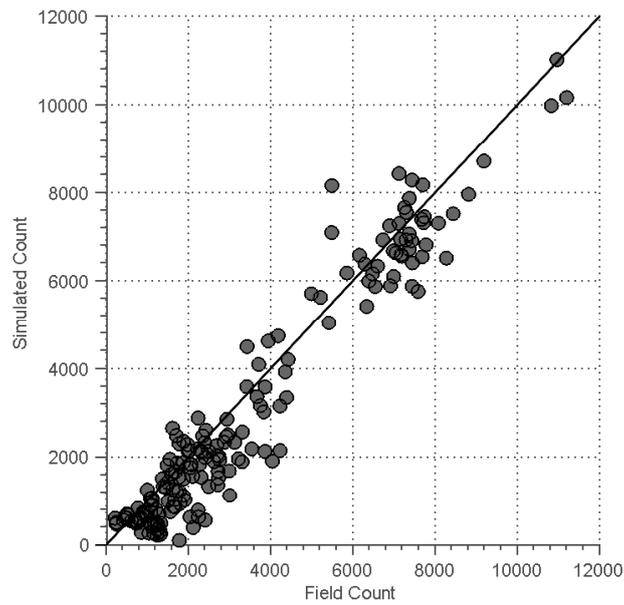
(a) AM Peak

(6 a.m. – 9 a.m.)



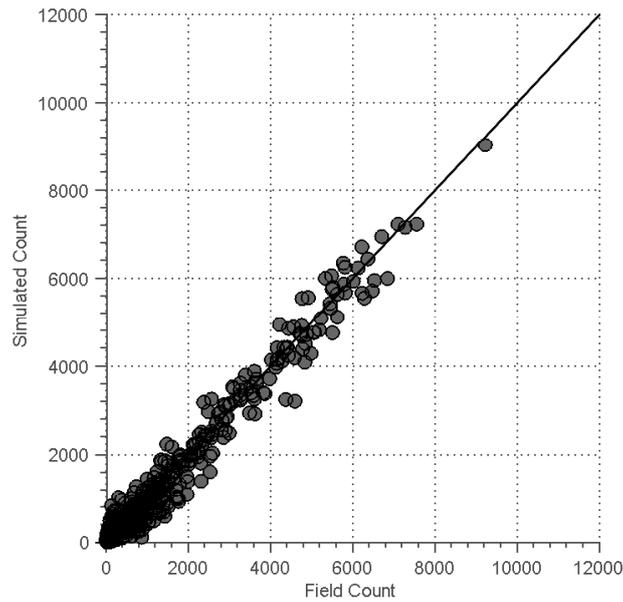
(b) Mid-Day 1 and Mid-Day 2

(9 a.m. – 4 p.m.)



(c) PM Peak

(4 p.m. – 7 p.m.)



(d) Night and Early Morning

(7 p.m. – 6 a.m.)

Figure 3. 2 ICC Microsimulation Network

3.3.2 Model Validation

The calibration results have demonstrated the consistency of the simulation model with the field measurements on most freeways and major arterials. The authors further validate the model's performance with an independent validation process. SHA collected corridor-level travel times using probe vehicle during the AM peak and PM peak periods. This paper employs this dataset as an independent validation dataset. A total number of 12 corridors (6 routes with both directions) have been included in this validation to inspect the model's consistency. The corridors are shown as the yellow curves in Figure 3.1.

As shown in Table 3.2, the overall differences between simulated and observed travel times are 12.6% and 11.2% for AM Peak and PM Peak, respectively. Validation results indicate that, the model calibrated by field counts data performs well on corridor travel times. Furthermore, the validation of link level travel speed can also be conducted once given related data.

Table 3. 2 Validation results for AM Peak and PM Peak

Corridor	Direction	AM Peak			PM Peak		
		Simulated	Observed	12.6%	Simulated	Observed	11.2%
Names		Time (min.)	Time (min.)	Difference	Time (min.)	Time (min.)	Difference
MD182	NB	13.9	15.3	-9.3%	17.4	14.0	24.0%
	SB	18.5	17.5	5.7%	11.5	12.8	-10.1%
MD28	EB	20.4	16.9	20.7%	21.9	22.3	-1.9%
	WB	26.2	23.9	9.6%	22.7	20.0	13.2%
MD355	NB	18.0	23.0	-21.8%	24.5	30.3	-19.2%
	SB	23.1	27.0	-14.5%	23.7	25.1	5.4%
MD650	NB	18.1	17.1	5.8%	20.1	19.3	4.0%
	SB	16.8	19.5	13.9%	17.4	16.9	3.0%
MD97	NB	15.2	12.8	18.8%	17.4	14.2	22.2%
	SB	15.1	17.2	-12.1%	14.7	14.0	5.2%
US29	NB	14.1	13.8	2.2%	18.9	20.7	-8.6%

SB	32.7	27.9	17.2%	15.4	13.1	17.1%
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3.4 Case Study of Inter-County Connector, Maryland

With the calibrated and validated model, the study aims at comprehensively investigating the impacts of a new toll road, MD-200 the inter-county connector (ICC, the orange link in Figure 3.1), on the overall traffic condition as well as the environment in Maryland. ICC was built since 2011, and now it is being expanded towards northeastern D.C. connecting a dense and mixed development urban area in Montgomery County, Prince George's County, and Baltimore metropolitan and BWI airport area. ICC is publicly expected to serve as a time-saving alternative route for the already high travel demand in these areas. How ICC could improve traffic safety and mitigate emissions pollutions is of research interests. In order to analyze various MOEs before and after ICC, both the traffic performances with ICC and without ICC are compared by microscopic traffic simulation. Taking advantage of the 24-hour large-scale microscopic traffic simulation model, MOEs on different levels of details are evaluated in this section. For example, the regional level evaluation, the corridor and freeway level analysis. Comprehensive MOEs for multiple time scales not only reveal the impacts of ICC, but also demonstrate the capability of the microscopic traffic simulation model for dynamic pattern studies, traffic management and policy analysis.

3.4.1 Regional Level Impacts

The regional level MOEs include VMT, VHT, delay per vehicle mile, stop time per mile, and average speed. These MOEs provide a general vision of network-level travel mobility and traffic congestion. The time-varying average delay analysis can be employed to capture travel dynamic and potentially used to evaluate broader peak spreading effect and departure time choice. Table 3.3 summarizes the traffic impacts of ICC at the regional level. For the early AM and night period, there is no obvious difference between the two scenarios. This may be due to the light demand (early AM only taking up only 8% of the whole day's demand). Most congestion mitigation effects are captured during the day time, especially the PM Peak. In terms of average delay per vehicle mile, the introduction of ICC causes a reduction of 7.62%. Better traffic condition is proven in ICC scenario from fewer delay and faster speed in the table.

Table 3. 3 Comparisons of the Two Scenarios using the Regional Level MOEs

		Early AM	AM Peak	Mid-Day	PM Peak	Night
		0 – 6 a.m.	6 – 9 a.m.	9 – 4 p.m.	4 – 7 p.m.	7 – 0 a.m.
VMT (k mi)	Before ICC	1,061.2	2,265.4	4,589.9	2,671.3	2,536.5
	After ICC	1,052.0	2,291.7	4,596.8	2,722.9	2,515.4
	(% change)	-0.87	1.16	0.15	1.93	-0.83
VHT (k hrs)	Before ICC	25.6	75.0	143.1	115.8	76.4
	After ICC	25.4	74.9	139.2	112.2	74.2

	(% change)	-0.78	-0.13	-2.73	-3.11	-2.88
Avg. Delay	Before ICC	30.4	61.4	54.3	97.1	50.2
(sec/mi)	After ICC	30.7	60.3	51.7	89.7	48.3
	(% change)	0.99	-1.79	-4.79	-7.62	-3.78
Avg. Stop	Before ICC	15.6	28.8	25.5	38.5	23.1
Time	After ICC	15.4	26.4	24.9	35.6	21.3
(sec/mi)	(% change)	-1.28	-8.33	-2.35	-7.53	-7.79
Avg. Speed	Before ICC	41.5	30.2	32.1	23.1	33.2
(mi/hr)	After ICC	41.4	30.6	33	24.3	33.9
	(% change)	-0.24	1.32	2.80	5.19	2.11

Figure 3.3 illustrates the average delay per network miles to better visualize the impact of ICC. From 8 a.m. to 1 p.m. and from 5 to 8 p.m., ICC helps reduce delay per mile by 6 seconds on average.

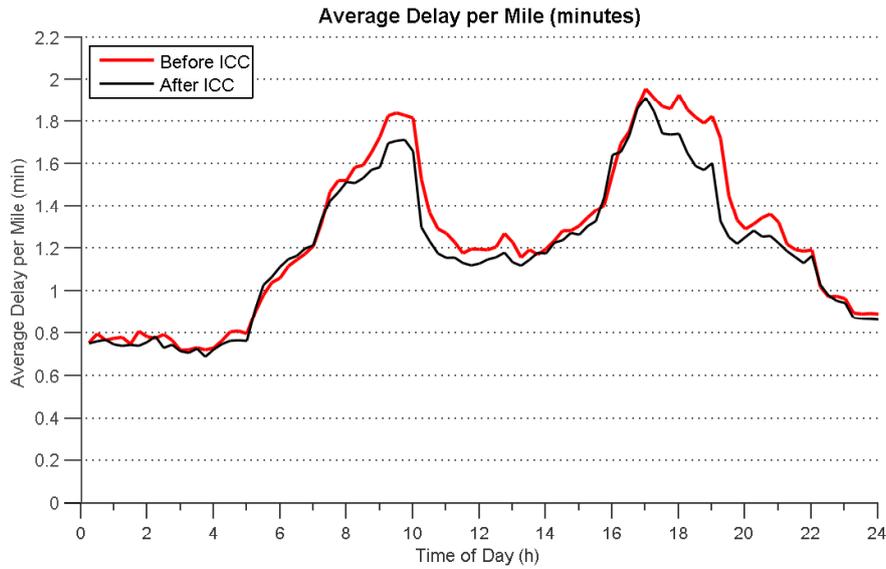


Figure 3. 3 Time-varying Average Delay per Mile

By integrating EPA’s MOVES model with microscopic simulation, the model is able to estimate environmental impact of ICC. The emissions and fuel consumptions before and after ICC are compared in Table 3.4. In general, with the improvement of regional traffic condition such as faster speed and less congestion, “ICC” scenario indicates a smaller emission rate on GHG, and higher energy utilization ratio. The most significant energy saving and GHG mitigation happens in PM Peak period. The total savings on fuel energy consumption per mile can be as large as 3.90 percent, while the total reduction on carbon dioxide per mile reaches 1.67 percent. For Particular Matters and other gaseous pollutants, the most significant improvement occurs in peak hours. For instance, PM10 can be reduced by 1.39 percent during PM Peak period.

Table 3. 4 Comparisons of the two scenarios using emissions and fuel consumptions

Emission	Early AM	AM Peak	Mid-Day	PM Peak	Night
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Per Vehicle Mile	0 – 6 a.m.		6 – 9 p.m.		9 – 4 p.m.		4 – 7 p.m.		7 – 0 p.m.	
	Before e ICC	After ICC								
GHG emissions										
CO₂ (g)	369.4	369.7	386.5	384.4	368.5	368.1	387.8	381.4	358.5	359.8
	8	8	4	0	8	8	5	0	4	4
NO_x (mg)	551.3	551.5	529.8	528.1	615.0	611.6	600.7	593.6	545.7	545.9
	1	3	2	7	5	6	7	6	1	2
CH₄ (mg)	15.93	15.99	34.76	34.49	33.94	33.58	34.12	33.31	26.39	26.58
Poisonous emissions										
NH₃ (mg)	30.81	30.77	29.99	29.79	30.70	30.07	30.30	30.14	30.11	29.91
CO (g)	6.098	6.120	10.17	10.10	10.61	10.51	10.70	10.48	8.795	8.827
			5	7	2	6	9	4		
SO₂ (mg)	7.27	7.27	7.52	7.48	7.17	7.16	7.54	7.41	6.95	6.99
Particulate matter (PM) contamination										
Total	25.35	25.43	27.67	27.58	27.96	27.84	27.98	27.59	25.14	25.36
PM10(mg)										
Total	23.51	23.59	25.53	25.44	25.78	25.67	25.79	25.44	23.18	23.38
PM2.5(mg)										
Energy consumption										
Petrol	4890.	4894.	5111.	5083.	4873.	4868.	5128.	5043.	4741.	4758.

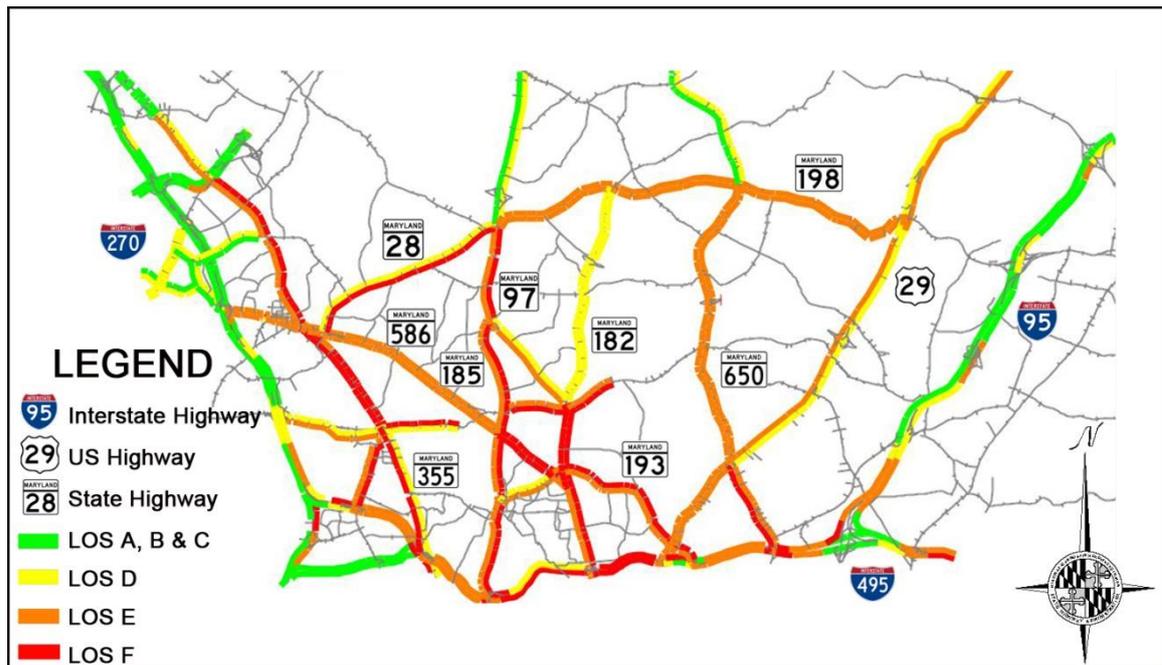
Energy	6	6	6	3	8	5	3	1	0	2
(KJ)										
Fossil	5136.	5141.	5377.	5347.	5127.	5122.	5395.	5306.	4988.	5006.
Energy	9	0	2	4	5	0	8	2	0	1
(KJ)										

3.4.2 Corridor Level Impacts

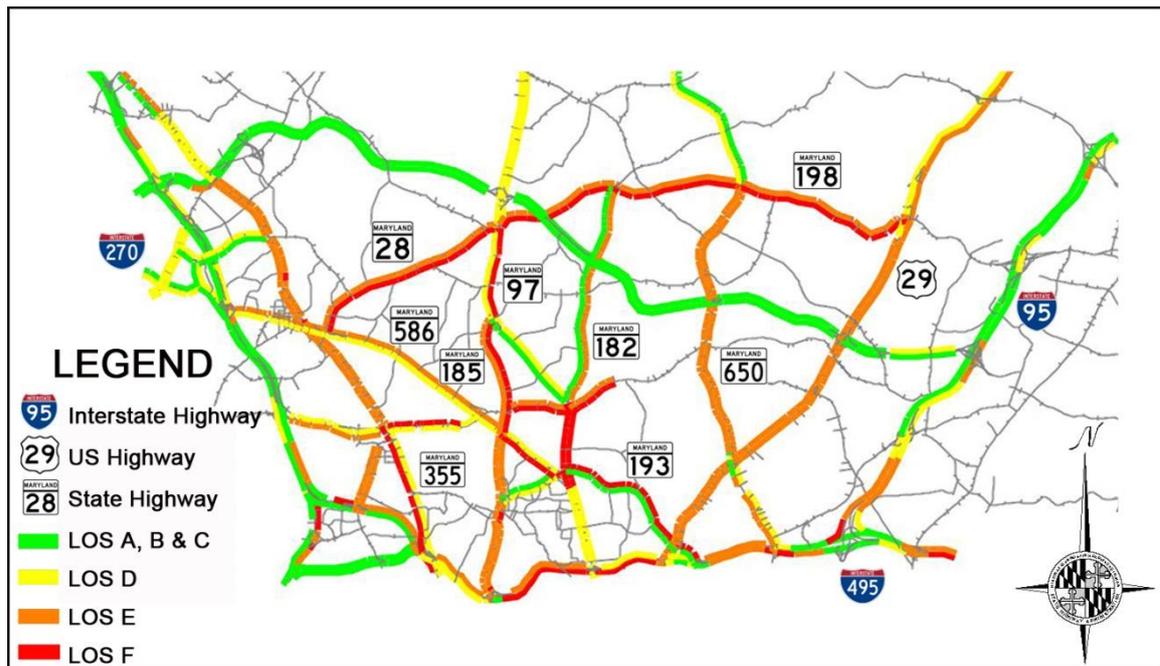
ICC leads to positive impacts on overall traffic condition as well as emissions control. The model can further evaluate performances of different corridors. Corridor LOS maps make it convenient to spatially assess congestion level and guide project planning and management. The LOS maps of PM Peak period before and after ICC are displayed in Figure 3.4 as an example of corridor level analysis. LOS A, B and C mean free and stable uncongested flow; D is an indicator of approaching unstable flow; E means the flow is operating at capacity; F suggests a breakdown flow.

LOS of all the freeways, arterials were presented. Predicted by the model, ICC would affect traffic on neighboring and crossing arterials as well as the parallel links. For example, the neighboring traffic conditions on MD-97 and MD-182 southbound are improved. Meanwhile, initially heavy congestion on segments of the parallel corridors (MD-355, I-270, and I-495) has been mitigated to some extent. While for some arterials such as US-29, MD-182, the north bound congestion gets worse, simulated traffic is observed to grow as more vehicles now access these segments via

ICC corridor. The model suggests more vehicles have been diverted from MD-355 and I-495/I-95 corridor, the most severely congested corridors in D.C. metropolitan area, to ICC heading northern sub-urban areas during PM Peak. Next subsection presents a freeway-level space-time analysis on I-495 to study this impact in depth.



(a) Before ICC



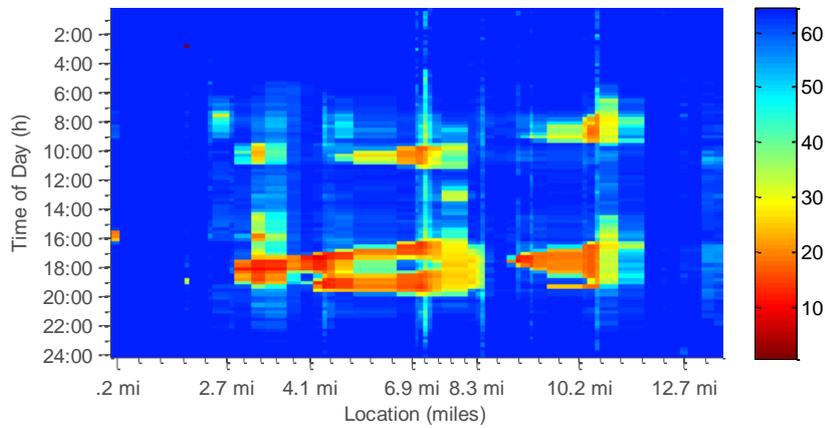
(b) After ICC

Figure 3. 4 LOS map before and after ICC

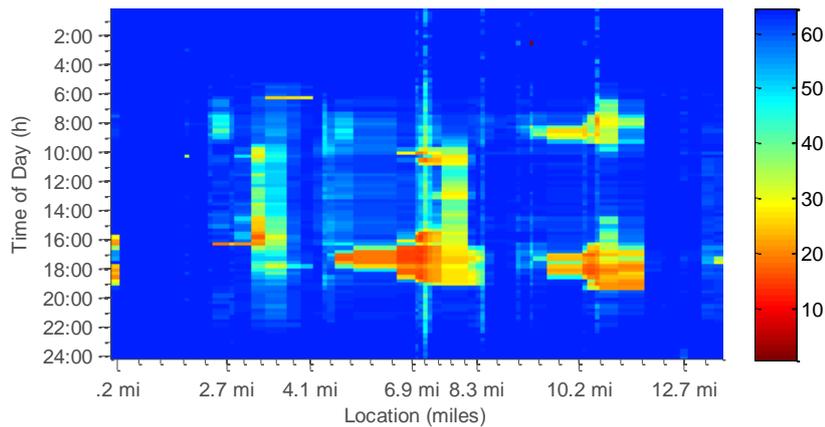
3.4.3 Freeway Link Level

The unique features of 24-hour simulation allow the authors to conduct a within-day freeway-level analysis on highway congestion assessment, traffic speed, and LOS. Before the construction of ICC, I-495, the Capital Beltway, has long been a highly congested corridor which carries intra- and inter-state travel demand from, via, and to the states of Maryland, Virginia, and Washington D.C. Once fully operational, ICC is believed to serve as an alternative corridor to remit congestion on I-495. To better understand the impact of ICC on I-495, comparison between space-time diagrams of speed is conducted (Figure 3.5). As the model predicts, ICC would cause noticeable effects to remit congestion level on I-495. A Spatial comparison implies that the most significant improvements on I-495 East Bound are at the joints of I-270 (3.2 mi in Fig. 5(a) and 5(b)), MD355 (4.2 mi), and I-95 (10.2 mi). Most significant

effects take place during PM Peak (the most congested period on I-495 EB, caused by tidal commuting phenomenon in the area), while AM Peak and Mid-Day also show noticeable improvement. This before-and-after comparison implies an important role of ICC in mitigating I-495 congestion. In the future, this analysis can also be extended to other arterial/freeway corridor scenarios, and similar analysis for intersection queue length can also be carried. Constrained to the length of the article, these analyses are not included in this paper.



(a). Before ICC



(b). After ICC

Figure 3. 5 I-495 EB space-time diagram of speed for the two scenarios

3.5 Discussion and Conclusion

A number of practical challenges emerge during the development of this multi-period large-scale microscopic traffic simulation model. Some of these issues and discussions are presented in the following subsections, along with the limitations of these approaches.

3.5.1 Data Collection

Developing a large-scale microscopic simulation model with multiple time periods requires unimaginable amount of detailed data. Firstly, building the network of this scale requires significant amount of workload and coordination. A great quantity of GIS data is indispensable to make sure the location of nodes and links, and the lane numbers on each segment. The geometry shape of particular areas (e.g. merging or separating of freeway and ramps) should be further examined to avoid even small geometry errors (which could be extremely troublesome). An early attempt of directly converting the network of the metropolitan of Washington (MWCOG) regional planning model was proven not successful since the planning model network does not define number of lanes for all links and has rough intersection geometry. In addition, adjusting the location and timing of signals also requires considerable time: all the 466 signalized intersections in our model were consisted with the field-signal timing.

Secondly, available traffic data like counts, speeds and travel times are often

insufficient to avoid the inconformity from the traffic pattern in reality. This type of problems makes it difficult to refine model calibration and validation. These problems are ubiquitous among microscopic traffic simulation modeling, and may lead to more serious troubles for large scale networks (72). Jha claimed that available data can be uncoordinated and cause more inconsistencies because they may be collected and measured by various agencies with different devices at different times. In this study, we face difficulties when trying to obtain counts data for after-ICC scenario. Relatively new field data is not readily available and maintained by different agencies. Once the data sources are complete, the calibration and analysis can be further justified.

3.5.2 Computational Time Issue

With strong dependence on technology such as computer configuration, the development and calibration of microscopic traffic simulation models with large scale networks can be time consuming.

In this study, neither advanced computational technology nor simplified method is dispensable to demonstrate the applicability of micro-simulation model to a large-scale, multiple-period network scenario. Having a huge network with over 2,150,000 trips (all-day period), the simulation model running 24-hour DTA demonstrated slow performance even on an Intel Xeon 24-Core CPU server with 12 GB memory. This computational difficulty is addressed by dividing the simulation period into 6 sub-periods as described in model calibration section. Thus, the time

spending on dynamic traffic assignment for a complete iteration of calibration has been greatly shortened. Even so, the comprehensive calibration framework required a number of iterations. The NRMSE of field traffic counts came to a convergence after around 8 iterations for each separate period, leading to approximate a total number of 400 hours for the whole calibration task.

3.5.3 Network Gridlock Caused by Small Errors

Single bottleneck at important intersections or merging areas may cause the entire network to become gridlocked. When developing and calibrating the model, various small errors were found which could lead to unreasonable bottlenecks. These issues are picked out and emphasized for microscopic studies. They may seem trivial but can cause serious problem for simulation.

- Missing important local links. It is time-consuming to include every local street within the study area. As a tradeoff, this may lead to insufficient network supply especially during the peak hours. Being a microscopic study restricting the link volume/capacity ratio, a considerable amount of travel demand is queued outside of the network and results in unrealistic delays. The authors' parallel study which applies DynusT mesoscopic DTA also experiences a similar issue. This paper prioritizes different locations using average delay measure and then includes a complete set of local links at the most congested regions in the study area. This increases the network supply at critical regions and effectively mitigates the gridlock.

- Signal timing problems. Limited real signal data may cause unrealistic and serious congestion. Optimizing the signals is not feasible given the size of the network. The paper employs real-world signal data of all intersections. A compromise when the actual signal data are not available can be using Synchro or similar programs to optimize the signal timing plan based upon the field turning movement information (Smith et al. 2008).

- Lane connectors and intersection geometry problems. In simulation, lane connectors and intersection geometry problems can cause the fact that the queue spillback block the path of other crossing vehicles at the intersection unrealistically and thus result in unreasonable congestion.

3.5.4 Conclusion and Closing Remarks

- This study develops a 24-hour large-scale network microscopic traffic simulation model for north Washington, DC metropolitan area. The model consists of over 7,000 links, 3,500 nodes, over 40,000 OD pairs, and over 2 million vehicles. Three freeway corridors, one new tolled highway, and all major/minor arterials are included in the simulation network. In addition, more than 400 intersections are signalized to simulate real dynamic signal control.

- Real-world signal timing information for all 466 signalized intersections has been obtained and implemented in order that the simulation model represents the actual situation. Then comprehensive calibration has been conducted for the

robustness and reliability of the model. 24-hour field counts at 62 sensor stations data are considered as calibration base. Then simulation-based DTA is applied to obtain simulated counts. To make the simulated counts converge to the observed counts, OD adjustments and signal optimization are applied. With some 2,150,000 demand of trips, the NRMSE comes to 16.77%. An independent validation has also been done via comparing simulated and observed corridor travel times. Through the time-consuming process of calibration/validation of large-scale microscopic traffic simulation models, challenges, important lessons, and the way to address these challenges have been learnt and offered for discussion.

- Another highlight of this paper is the emissions estimation using simulation outputs and EPA's MOVES simulator. County-level emission estimation has been conducted for environmental impact analysis of ICC. With the unique capabilities of the model developed in this research, various key conclusions on the policy implications of ICC tolling can be drawn from the simulation case study. Following the prediction of the model, ICC would save as much as 6 seconds per vehicle mile during peak hours. It also cuts down GHG emissions rate and energy consuming rate by 1.67% and 3.90% at most. For corridor level, ICC has benignly affected neighboring arterials such as MD-182, MD-97 and MD-650. Based on our simulation analysis, ICC also has some noticeable and beneficial impacts on the performance of I-495, especially during the two peak-hour period. The case study demonstrated the value of large-scale multiple-period microscopic simulation model for project

planning evaluation.

- The work contributes to the large-scale microscopic simulation research literature with a 24-hour model application and a before-and-after case study of a new tolled freeway (ICC). It contributes to the practice with empirical experiences and suggestions for future applications. Important issues such as data needs, computational burden, and simulation gridlocks are discussed and addressed. In particular, microscopic simulation network is more “congestible” as the volume/capacity ratio is restricted and each vehicle is simulated. Network gridlocks should be carefully dealt with before the calibration. Otherwise it is hard to clarify if, for instance, an underestimated simulation count is caused by insufficient OD demand or by the gridlocks. MOEs on different levels have been obtained for the case study to investigate the impact of ICC on dynamic traffic patterns. As one of the few studies that link the traffic simulation with emissions models such as MOVES, the paper demonstrates the feasibility of employing popular emission simulator as post-processor to analyze environmental impacts using simulation outputs. The model can be applied in a wide range of policy analysis, control and management, and decision-making processes. With the 24-hour traffic simulation, within-day and day-to-day behavior dynamics can be researched once agent-based dynamic behavior models are linked or integrated. This is a promising research direction to microscopically, dynamically, and behaviorally forecast the future.

Chapter 4: Cumulative land development analysis tool

4.1 From Land Development Model to Simulation Model

In the metropolitan Washington DC area, there is a regional planning and traffic demand model named the Metropolitan Washington Council of Governments (MWCOCG) planning model. However, the transportation model of MWCOCG is a trip-based four-step model, which can hardly acquire the dynamic/behavior interaction between traffic activities and transportation infrastructure. To gain a dynamic perspective on travel behavior change due to land development, such as route and departure time shifts, the land development model of MWCOCG (Round 8.2 Cooperative Forecasting model) is integrated with DTALite. The Round 8.2 Cooperative Forecasting model estimates population, households, and employment for the entire MWCOCG area on a Traffic Analysis Zone (TAZ) level. These land use data are converted to regional OD via the MWCOCG transportation demand model. The data hub feature of DTALite makes it applicable to convert and import the MWCOCG traffic network to mesoscopic simulation model. Then regional OD is derived for the study area based on traffic assignment and subarea cut procedure in DTALite.

The land development and transportation improvement information was obtained from MWCOCG regional planning model. We applied the 2010 MWCOCG static OD as

the travel demand for the base case, and the 2030 static OD as the demand for future case. One major effort to integrate these static OD to our mesoscopic simulation model is the time dependent OD estimation. The dynamic OD is estimated from previous approach. Zhang et al. proposed a Gradient Projection (GP) algorithm based systematic approach to derive subarea OD from regional OD matrix (46). In this thesis, this process was taken placed by applying “subarea cut” procedure in DTALite. That is, the whole transportation network of the regional planning model (MWCOG) is coded in DTALite. After the assignment of regional seed OD to the network, DTALite is capable to derive sub-OD cut for the study area.

When the static sub-OD is obtained, the overall OD is divided into time-dependent OD based on traffic volume. For example, if the static sub-OD for AM Peak period (6:00 a.m. to 9:00 a.m.) is derived from regional OD, we need to calculate the sum of field traffic hourly volume data from the sensor stations for 6:00 to 7:00 a.m., 7:00 to 8:00. a.m., and 8:00 to 9:00 a.m. respectively. Then, the time-dependent OD would be estimated based on the following equations:

$$\alpha_i = \frac{V_i}{V_{6-7} + V_{7-8} + V_{8-9}}, i \in \{6-7, 7-8, 8-9\} \quad (4.1)$$

$$p_{i,j,k} = \alpha_i \cdot P_{j,k}, i \in \{6-7, 7-8, 8-9\}, j, k \in S \quad (4.2)$$

where α_i is the factor by time period i , V_i is the sum of field traffic hourly volume data from the sensor stations during time period i , $p_{i,j,k}$ is the time-dependent OD

pair from TAZ j to TAZ k during time period I , $P_{j,k}$ is the static OD pair from j to k , S is the set of TAZs in the network. This simplified OD estimation process ignored the difference of time factors among different OD pairs. Such simplification method was used for the lack of ground traffic data for such a huge network. After the estimation of time dependent OD, comprehensive OD calibration and validation were conducted to enhance the robustness of the model.

4.2 Introduction of DTALite

DTALite is a light-weighted, open source simulation based mesoscopic DTA package (47). The “data hub” feature allows DTALite to import network files or transportation project files from a number of on fashion software, i.e. DYNASMART, and ArcGIS.

The traffic models in DTALite are queue-based models: point queue model, spatial queue model, and Newell’s simplified kinematic wave model (85). Point queue model assumes all the vehicles are queued at the end point of a link. When a vehicle is loaded to a link, it will travel at the speed limit until it reaches the end point of this link. Then, the remaining capacity would determine whether this vehicle would pass or queue at the link. There is no spatial constrains in point queue model. Spatial queue model adds a spatial queue constrain in point queue model, in which a link has a restore capacity defined by jam density multiplying number of lanes and then multiply link length.

Newell's simplified kinematic wave model uses cumulative arrival/departure volume to model traffic on road ways. The partial differential equation (equation 2) is applied to determine the spreading of traffic jam (traffic wave with 0 speed and jam density):

$$\frac{dq}{dx} + \frac{dk}{dt} = g(x,t) \quad (4.3)$$

where q is the volume, k is density, x is the spatial location, t is time, and g is the generation function. Based on the definition of wave speed, the change of cumulative volume, and the cumulative volume change on a link are:

$$dN(x,t) = \left(-k + \frac{q}{w} \right) \cdot dx \quad (4.4)$$

$$dN = k_{jam} \cdot l \cdot N \quad (4.5)$$

where l is the length, and N is the number of lanes. In order to speed up traffic assignment, as well as avoid unrealistic gridlock in early iterations, in DTALite, the first few iterations of DTA will be performed on point queue model, and then on Newell's simplified model.

The simplified traffic model allows DTALite to conduct high speed simulation. Another high light of DTALite is agent-based modeling: the travel information of every individual traveler (i.e. departure time, origin, destination, travel time, and route) is recorded as output, and it can also be loaded as input for simulation.

4.3 Mesoscopic Traffic Model and Model Calibration

Many DTA integrated traffic simulators, (e.g., DYNASMART, TRANSIMS, DynusT, and DTALite (85)) have been used in previous studies (46). They are all endowed with good features for real world applications, and there is no consensus superiority of any simulators. DTALite is selected for three main reasons: 1) it is a light-weight mesoscopic simulator with parallel computing for rapid simulations; 2) the embedded OD calibration system and subarea cut system allows detailed analysis for specific subareas; and 3) agent-based modeling is supported for the integration with behavior models.

Supported by SHA, a mesoscopic simulation model that includes all freeways, most major/minor arterials, and some local connectors/streets is developed for the all of Montgomery County, Maryland. The major commuting corridors: I-270, North I-495 and MD355 are located in the middle of this study area (Figure 4.1). The simulation network, which contains 470 TAZs, 5481 links and 1921 nodes, are directly imported and cut from the MWCOG traffic demand model.

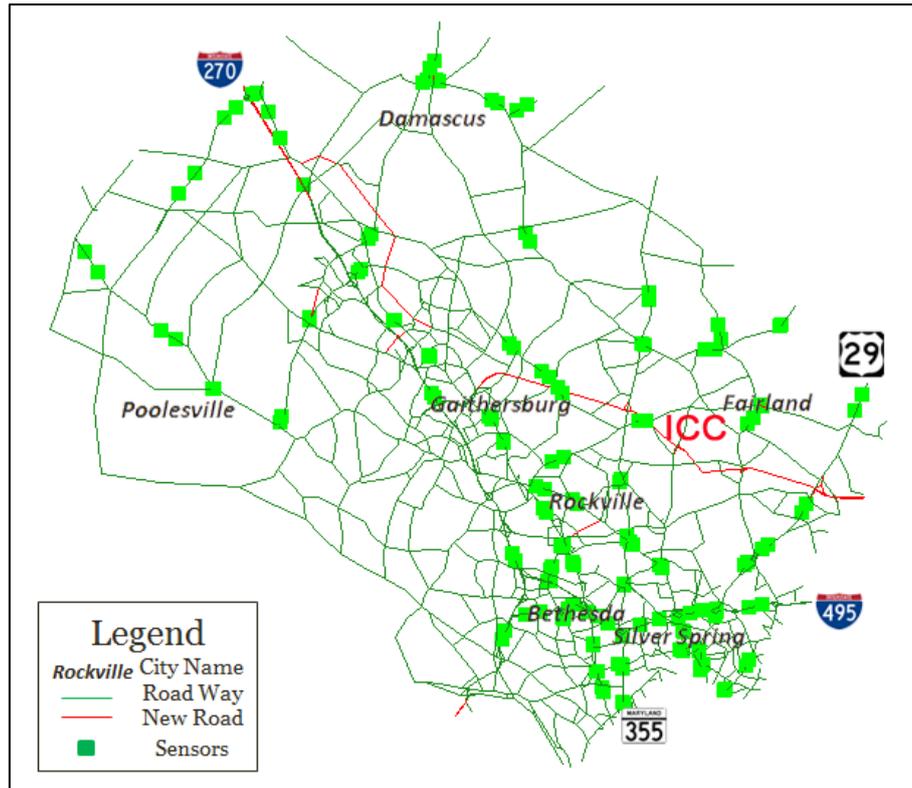


Figure 4. 1 Mesoscopic Network

The OD is jointly calibrated and validated with hourly volume data provided by 160 sensors from SHA’s traffic monitoring system and 2007-2008 TPB/BMC Household Travel Survey (map see Figure 4.2). The calibration and validation results are shown in Figure 4.3 and Figure 4.4. In Figure 4.3, each point represents a volume sensor. In Figure 4.4, the blue line denotes the cumulative demand rate (cumulative demand divided by total demand from 6:00 to 9:00) for the base case in the DTALite simulation model; while the red dash line denotes the cumulative demand rate in Figure 1 2007-2008 TPB/BMC Household Travel Survey.

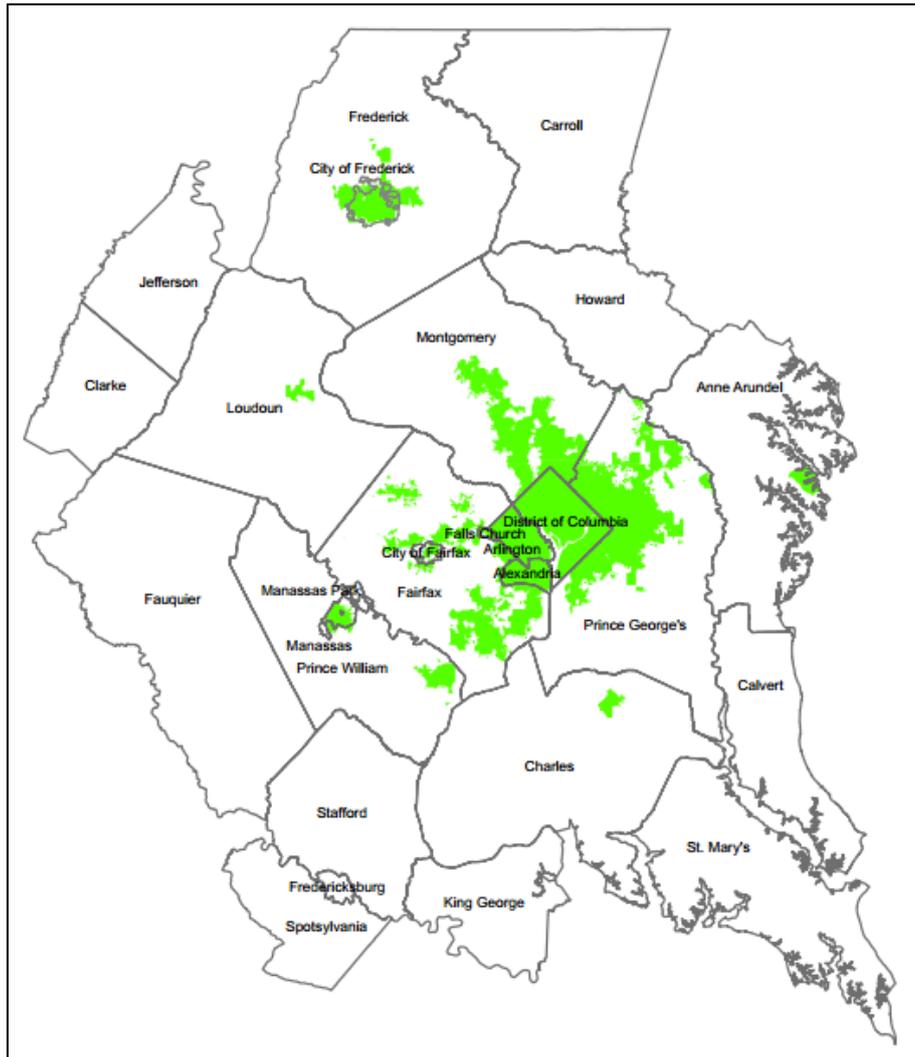


Figure 4. 2 2007-2008 TPB/BMC Household Travel Survey Sample Map

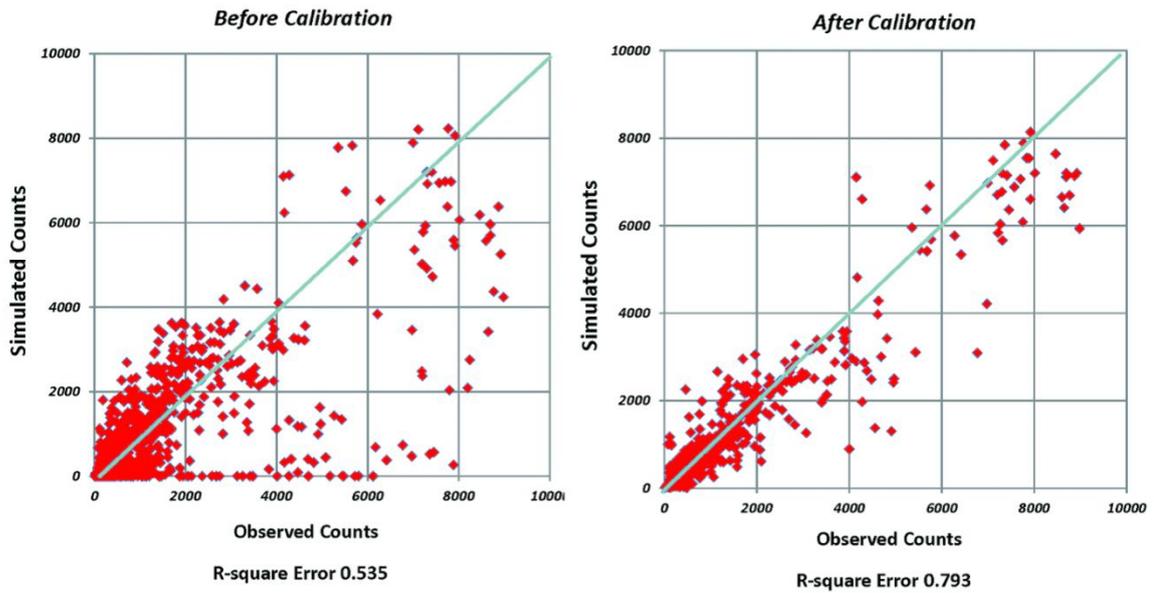


Figure 4. 3 Validation Results

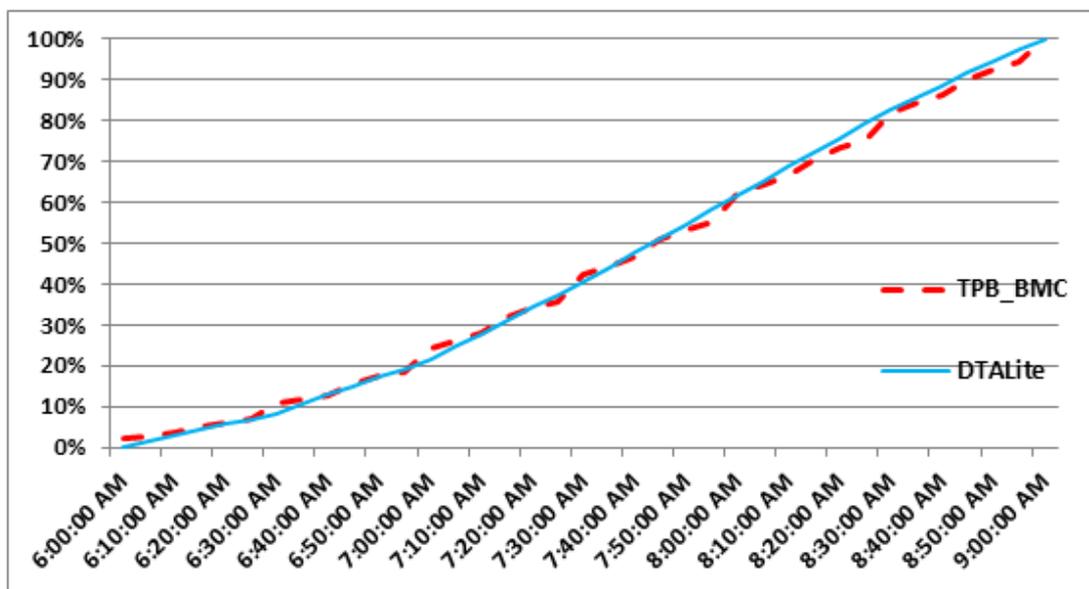


Figure 4. 4 2007-2008 TPB/BMC Household Travel Survey Sample Map

4.4 Integration with Behavior Model

In this study, an agent-based positive departure time choice model is integrated with DTALite for behavior analysis. The model was developed by Zhang and Xiong

(65), and simulates the goal, knowledge, learning, and search ability of the travelers in the system. Based on a series of the learning, searching process and behavior rules, the model attempts to estimate how people logically behave rather than a rational utility maximization. After modeling travelers' behavior changes, the individual decisions are aggregated for travel demand analysis. The framework of positive departure time choice model will be introduced in 5.1. More details of this model are available in literature (46) and (65).

The integration flowchart is shown in Figure 4.3. The agent-based modeling starts from the static OD estimated via the MWCOG planning model. This regional planning OD is loaded into DTALite for regional-level assignment, after which the subarea OD can be cut and calibrated through its own procedure. The process to estimate dynamic hourly OD is discussed in “additional work”. In order to calculate travelers' current experience, dynamic assignment is initially applied to pursue dynamic user equilibrium. This provides travelers' current travel time and routes. The routes are required to calculate free flow travel time (FFTT) as travelers' subjective believed ideal travel time. The subjective believed ideal travel time and current travel time will be used in positive model (see 5.1). Heterogeneity is then embedded by synthesizing these travelers with socio-demographic variables including: income, gender, flexibility of arrival times, search cost, etc. The population is synthesized based on 2007-2008 TPB/BMC Household Travel Survey. Under the initialization, dynamic assignment is adopted again to simulate the daily traffic for knowledge

learning process. Travelers' experience is updated in the positive model. Every traveler learns their travel experience from DTA results; they make a departure time choice following positive departure time choice model (5.1). The iterative loops of departure time modeling would not finish until only a small number of individuals are still searching for alternative departure times.

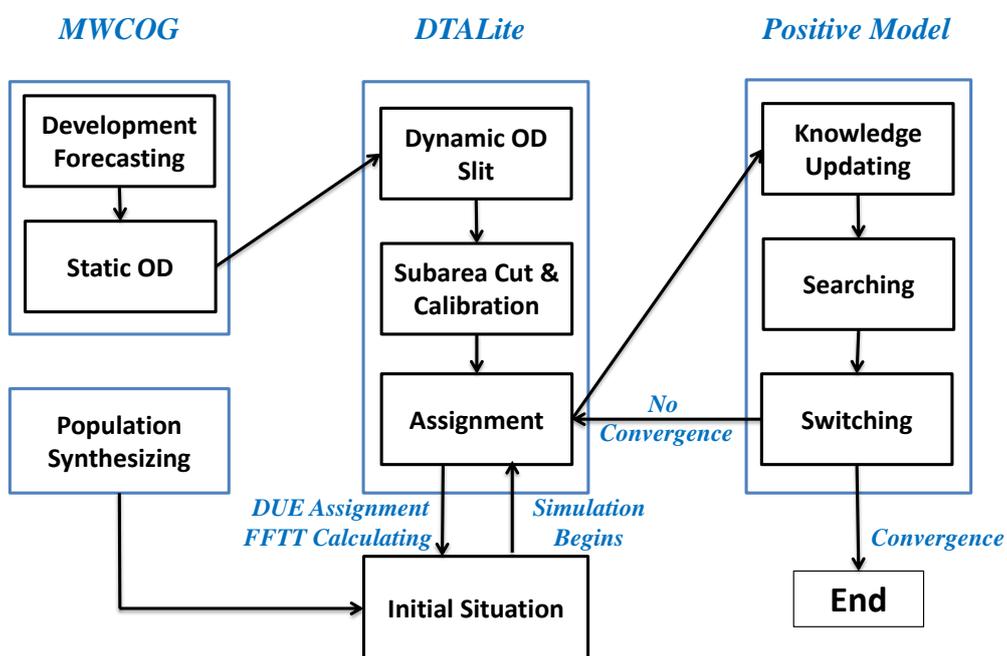


Figure 4. 5 Flowchart of the Integrated Model

In the thesis, the population was synthesized based on 2007-2008 TPB/BMC Household Travel Survey. The study area of the survey is shown in Figure 4.1. Several socio-demographic variables such as income, gender, flexibility of arrival times were used in search rule in positive model, and the distributions of these variables are the same with 2007-2008 TPB/BMC Household Travel Survey. Table 4.1 – Table 4.3 show the comparison between the survey sample set and the

synthesized population for cumulative land development analysis (2010).

The assignment of agents' socio-demographic variables was conducted using the random number function in Matlab. Firstly, several boundary numbers were calculated based on 07-08 TPB/BMC survey. These boundary numbers represented the cumulative frequency of different attributes. Secondly, for each agent, three random numbers were generated based on which the agent's income level, gender, and flexibility of arrival time were assigned. Take gender as an example: in 07-08 TPB/BMC survey, 47% of the population in the study area is male (table 4.2). Then the boundary number of gender is 0.47, if an agent gets a random number between 0 to 0.47, the agent will be assigned as a male; while if the random number is between 0.47 and 1, the agent will be assigned as a female.

Table 4. 1 Income for Synthesized & Survey Population

Income	2007-2008 TPB/BMC Household Travel Survey	Thesis Scenario 2010
0 – 29,999	1,806 (11.6%)	49,638 (11.6%)
30,000 – 59,999	3,405 (22.9%)	97,230 (22.8%)
60,000 – 124,999	5,996 (42.8%)	183,501 (43.0%)
125,000 - more	3,158 (22.7%)	96,588 (22.6%)

Table 4. 2 Gender for Synthesized & Survey Population

Gender	2007-2008 TPB/BMC	Thesis Scenario 2010
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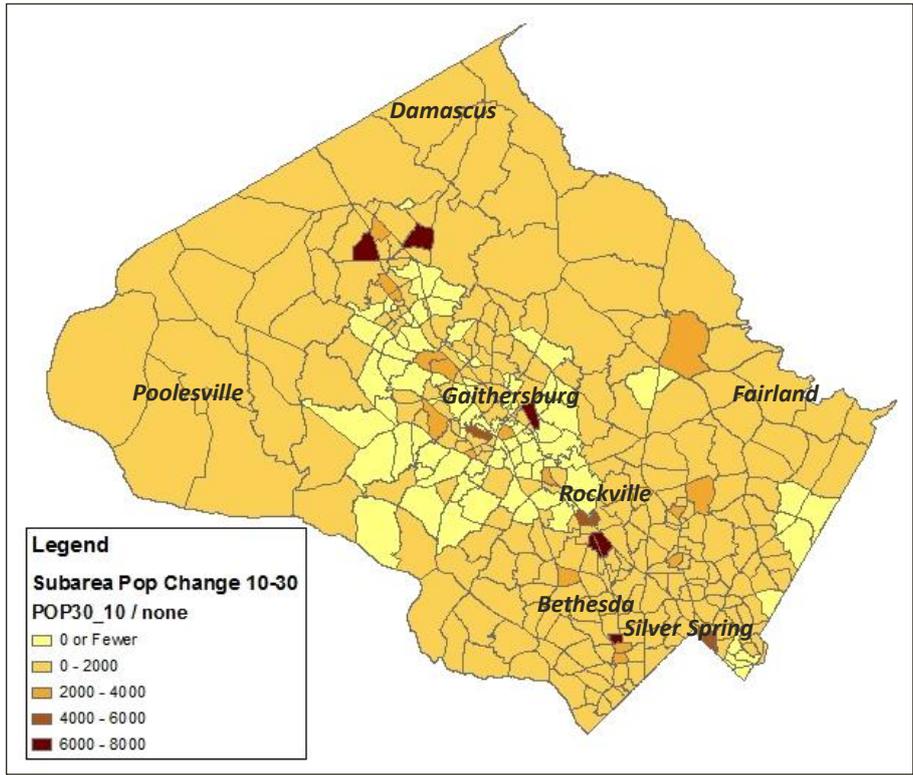
	Household Travel Survey	
Male	14,582 (47.0%)	200,997 (47.1%)
Female	16,748 (53.0%)	225,961 (52.9%)

Table 4. 3 Schedule Flexibility for Synthesized & Survey Population

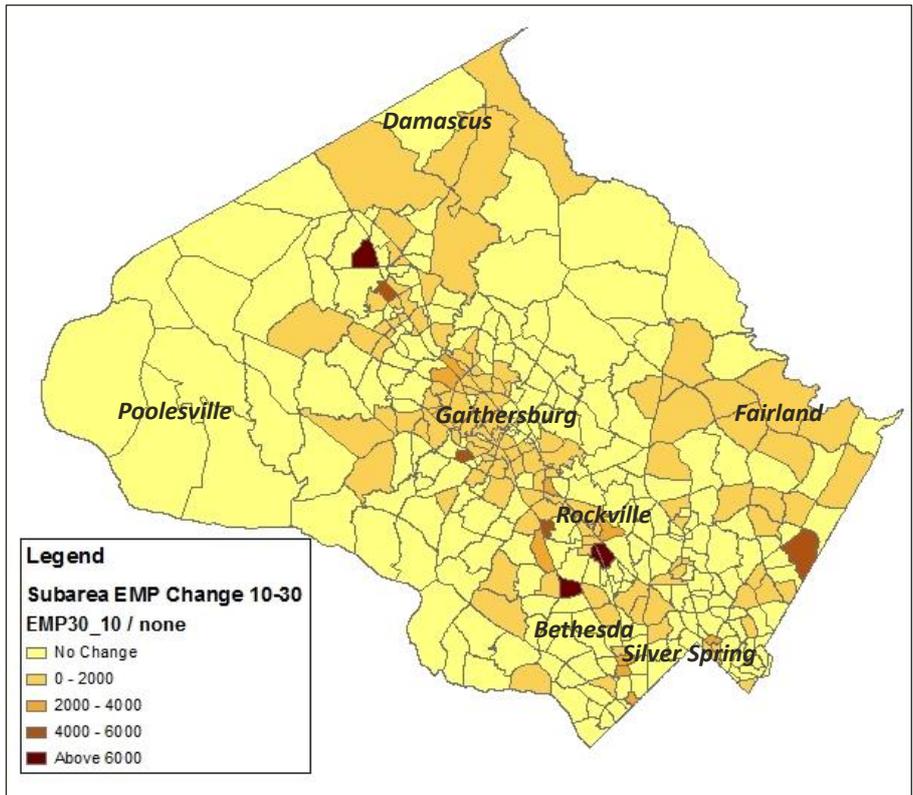
Flexibility of Arrival	2007-2008 TPB/BMC	Thesis Scenario 2010
Time	Household Travel Survey	
Flexible	9707 (29.1%)	124,831 (29.2%)
Not Flexible	21623 (70.9%)	302,127 (70.8%)

4.5 Land Development Impact on Dynamic Traveler Behavior

This section illustrates a land development case study via the proposed tool. Forecasted by MWCOG’s planning model, the population and employment of Montgomery County will increase by 18.6% and 24.4% respectively in 20 year (2010 to 2030), as shown in Figures 4.4 (a) and (b). Meanwhile, a number of land development plans are taking place surrounding the I-270 and MD355 corridors. The long term change makes it necessary for urban planners to focus on both region-level mobility and corridor-level travel behavior changes.



(a) 2010-2030 Population Growth



(b) 2010-2030 Employment Change

Figure 4. 6 Land Use Changes 2010-2030

Provided by the Round 8.2 Cooperative Forecast model, the zone level population/employment change is shown in Figure 4.4. In northern Gaithersburg, Rockville and the North Bethesda areas, there are several zones along I-270 and MD355 which will induce high population/employment growth. In addition, a new tolled freeway, the ICC, will be complete by 2015. Parallel to north I-495, the ICC is an alternative highway for travelers between Montgomery County and Prince George's County. With these highlighted developments, it is needful and interesting to forecast the change on both demand pattern and travel behavior along all these corridors (i.e., I-270, MD355, I-495, ICC).

Three scenarios are incorporated into this real world application: 1) 2010 scenario, which is referred to as the base case, uses the 2010 traffic network and demand provided by MWCOG. The base case TIA is only conducted by DTALite, and no behavior model is considered. 2) 2030 scenario, in which the differences between the 2030 scenario and the base case are the network and traffic demand. In 2030 scenario, both traffic network and demand are 2030. 3) 2030 departure time switch scenario. In this scenario, positive the departure time choice model is integrated with DTALite as illustrated in section 3. The last scenario well demonstrates the capability of this proposed tool for capturing dynamic behavior changes among users.

Figure 4.5 shows the overall demand change. Estimated by the static planning model, the first two scenarios share a similar demand distribution. However, when positive theory is integrated with travelers' behavior, the demand pattern shows an obvious shift: as the traffic situation gets worse in 2030, plenty of travelers will switch to earlier departure times to avoid being late. Even though a worse peak period shows up between 6:00 to 8:00, people tolerate the congestion to maintain being on-time for their work. Taking a further step than a single DTA model, this integrated model allows travelers to search for better alternatives based on their current experience. The new demand pattern results from individual behavior change, which also implies travelers' adaptation to their new behavior. After obtaining a BUE, the regional level traffic performance is summarized in Table 4.1. The land development leads to 6.64 minutes delay per traveler, but this delay may reduce to 4.49 minutes after they learn, search and finally adapt to new departure times.

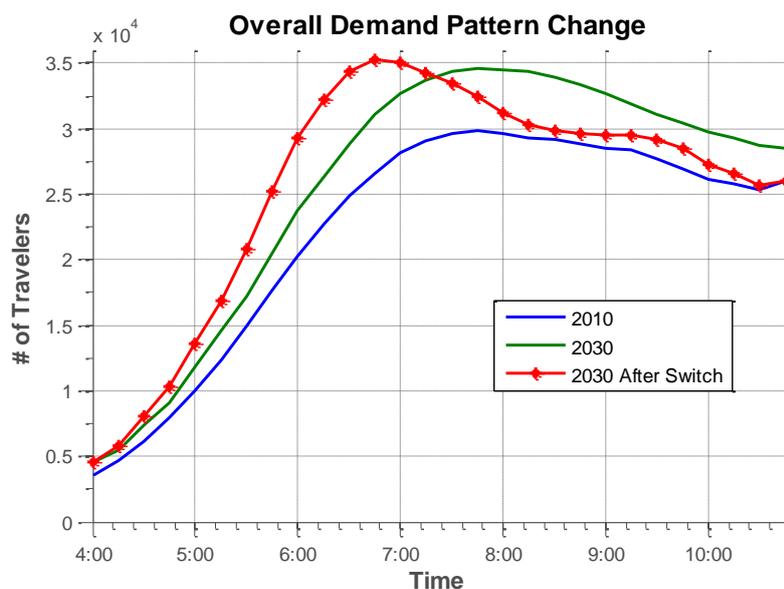
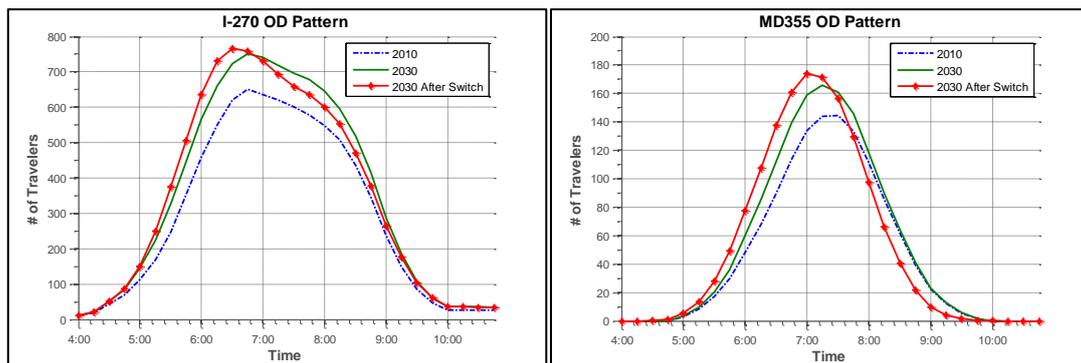


Figure 4. 7 Overall Demand Pattern Change

Table 4. 4 Regional Performance

Year	2010	2030	2030 After Switch
Num. of Trips	426,958	493,308	493,308
Avg. TT (min)	20.05	26.69	24.54
Avg. TTI	1.78	2.22	2.05
Avg. Speed (mph)	36.18	32.02	33.96

Meanwhile, from this integrated model, demand for specific OD pairs can be extracted for OD based demand analysis. Figure 6 displays the OD pattern change for I-270 and MD355. The demand pattern shown in Figure 4.6(a) and Figure 4.6(b) refer to the through traffic on I-270 and MD355 respectively. Similarly with the overall demand pattern, there is a shift for those who used to depart after 7:00 a.m. to depart earlier.



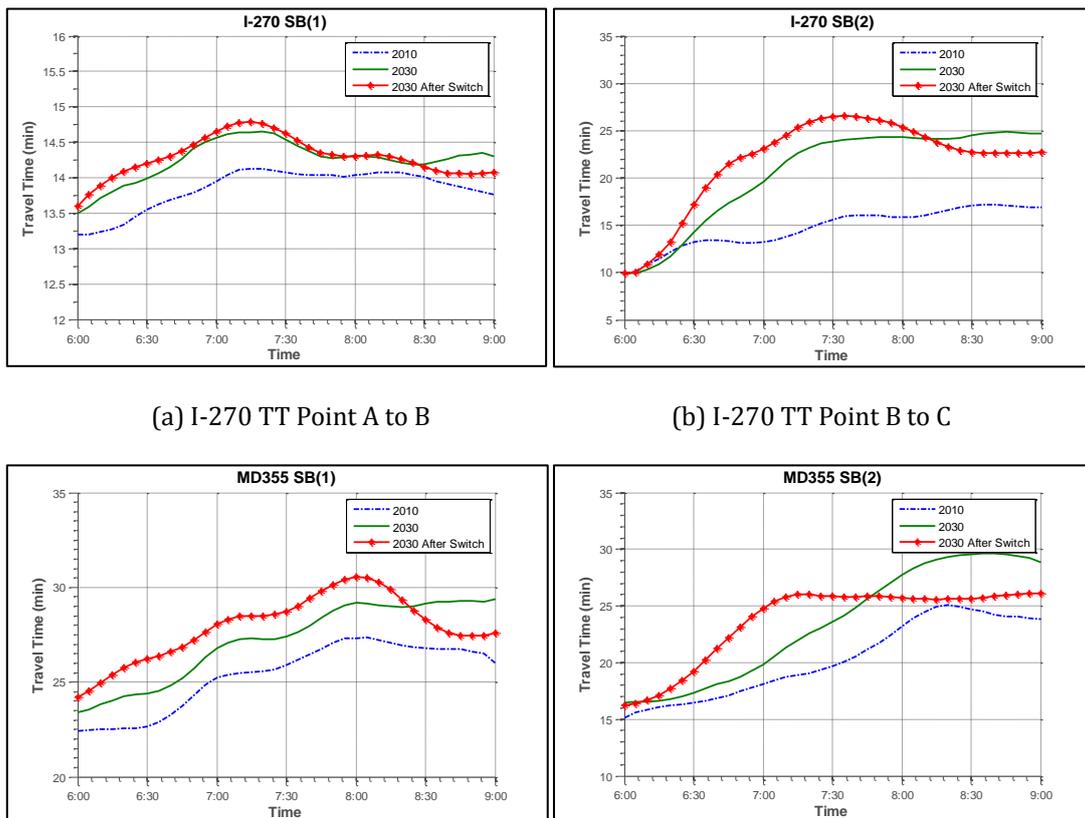
(a) I-270 OD Demand Pattern

(b) MD355 OD Demand Pattern

Figure 4. 8 Demand Pattern Change

The demand pattern changes along these two corridors results in the differences

of time-dependent travel time shown in Figure 4.7. Caused by the growth of population and employment, travelers commuting via I-270 and MD355 will encounter worse bottlenecks than base case. Comparing scenario 2010 with 2030, the travel time from the ICC diverting area (point B in Figure 4.8) to I-495 diverting area (point C) will increase by at least 5 minutes for both I-270 and MD355 users. However, the travel time of these corridors will change when allow departure time switches among travelers. In “2030 after switch” scenario, more people will depart earlier, building up earlier bottlenecks. The congestion will also encounter an earlier drop compared with 2030 scenario.



(a) I-270 TT Point A to B

(b) I-270 TT Point B to C

(c) MD355 TT Point A to B

(d) MD355 TT Point B to C

Figure 4. 9 I-270/MD355 Travel Times

In addition, the new demand pattern also influences travelers' route choices. The 2010 column and 2030 column in Table 4.2 imply an increase in through traffic at point B (Figure 4.8.). The construction of the ICC attracts over double the trips from I-270/MD355. While at point C, the increase of through traffic volume is not significant due to bottlenecks. Interestingly, the diverting traffic from I-270 to I-495 is shown to decrease by 6.7%. The increase of through traffic at point C indicates that a number of downtown-oriented travelers will switch from I-270 to MD355 in 2030. The last column claims that travelers tend to switch from MD355 to I-270 after they change departure time. This means travelers will take better advantage of the remaining capacity of I-270 for morning commuting, making more room on MD355 for users who depart later.

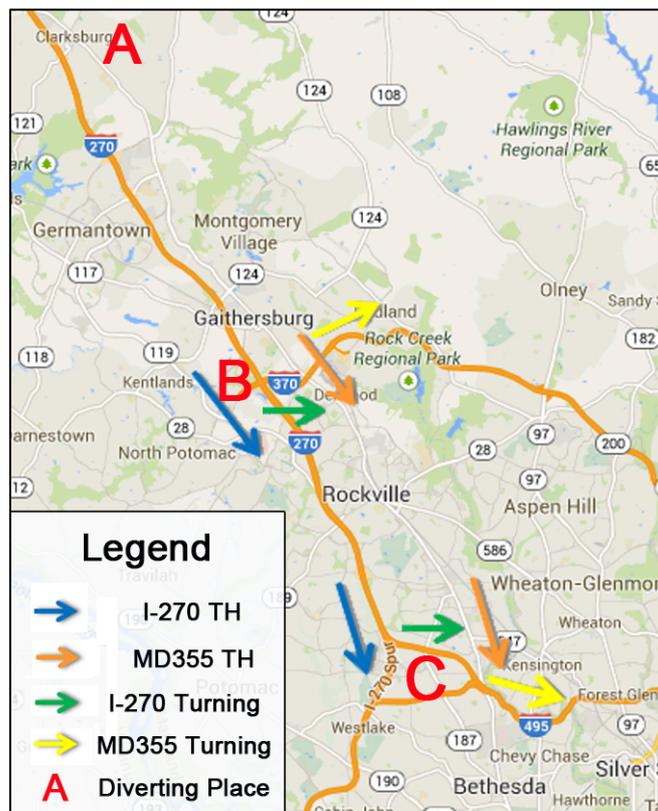


Figure 4. 10 I-270/MD355 Diverting Traffic

Table 4. 5 Route Choice Change

	2010	2030	2030 After Switch
Point B			
 Through	32,682	36,084 (10.4%)	37,260 (14.0%)
 Through	4,513	5,970 (32.3%)	6,528 (44.6%)
 Turning	4,333	9,659 (122.9%)	7,573 (74.8%)
 Turning	1,085	2,927 (169.8%)	2,991 (175.6%)
Point C			
 Through	25,201	25,800 (2.3%)	27,658 (9.7%)
 Through	9,323	10,479 (12.4%)	11,985 (7.1%)
 Turning	14,004	13,043 (-6.7%)	13,990 (-0.1%)
 Turning	409	639 (56.2%)	694 (69.7%)

Chapter 5: Analysis on Potential Impact under Flexible Work Schedule Policy

5.1 Positive Model

Positive travel behavior model is based on SILK theory, which models the process of searching, information, learning, and knowledge updating of travelers (45). Based on previous studies (46, 65, 66), the positive departure time model provides a framework for the flextime policy modeling. For each traveler in the model, he/she is able to acquire traffic information from his/her prior travel experience or other sources (e.g., traveler information systems). The individual's knowledge and subjective beliefs about traffic conditions are formed through a perception and learning process. With knowledge and subjective beliefs the model could determine personal attitude towards his/her current traffic conditions. That is, the amount the person expects to benefit from additional rounds of searches. Subjective search gain is defined to measure this benefit. It is theorized as the gap between the experienced best situation and the ideal situation. Correspondingly, search cost is defined to quantify a person's perceived loss in each round of search. This may result from a traveler's searching efforts (e.g., time, monetary, mental efforts, and risk involved). The trade-off between the subjective search gain and the perceived search cost determines the start and the end of an agent's searching process (Figure 5.1).

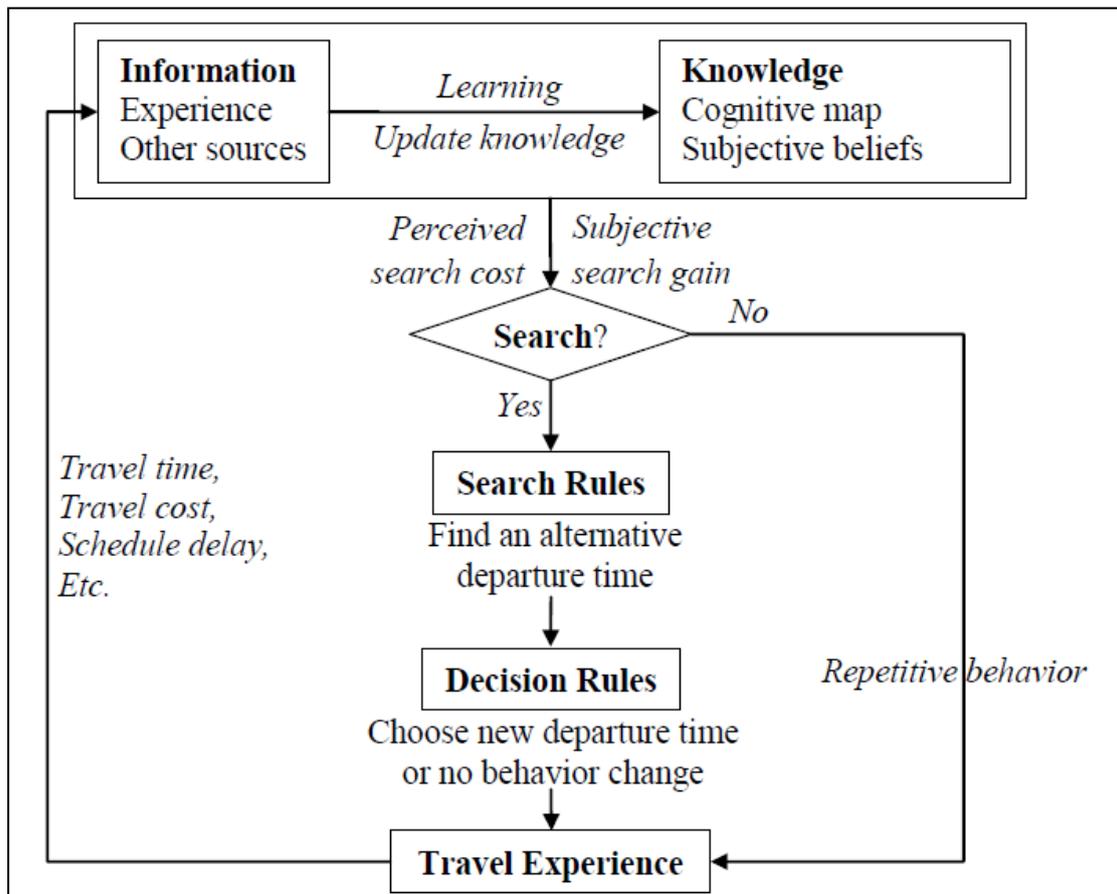


Figure 5. 1 Flowchart of Positive Departure Time Choice Model

Once a traveler stops searching, he/she would repeat his/her current departure time for the rest of the simulation. This assumption is to model either the traveler has found a good enough alternative or the traffic is so congested that he/she has already gotten used to the situation after days of search. Otherwise, the traveler would find a new departure time based on current knowledge and a set of search rules. The traveler needs to map his/her spatial knowledge to the traffic conditions of the alternative departure time. Then a binary decision is made based on a set of decision rules about whether or not to switch to the new departure time. After all the travelers have made decisions, the individual-level behaviors are aggregated for the traffic modeling of a new day. Veldhuisen et al (21) provides a full-scale view about the search rules and

decision rules.

To theorize a SILK model that captures how people make decisions, a number of assumptions of search gain/cost, and realistic mental rules and heuristics are made: 1) search gain is the gap between experienced best situation and ideal situation 2) search gain will decrease as people get tired of searching; 3) search cost is fixed for certain travelers; and 4) favored departure time alternatives are chosen based on preferred arrival time (PAT). The equations about search gain and search cost are as below:

$$g_n = \frac{V_{best} - V^*}{n+1} \quad (5.1)$$

$$c = \frac{1}{2} \cdot (g_{N+1} + g_N) \quad (5.2)$$

where g_n denotes the search gain for day n , V_{best} denotes the quantified attitude of the best travel situation that has been experienced, V^* denotes the quantified attitude of the believed best travel situation, n is the number of day. Here we assumed people's beliefs follow a Dirichlet distribution (divided by $n+1$ means every day contributes the same to subjective search gain). c denotes the search cost, which is fixed for an individual but different among travelers. We assume the search cost for an agent is the average between his/her last day's (the N th day) search gain and his/her $N+1$ th day's search gain. This is because on day $N+1$, the agent has stopped searching. The calculation of V will be introduced in 5.2.

5.2 Proposed Model

In this research, three major improvements were considered to enhance the robustness for flexible work modeling. Firstly, as individual-level decisions are made based on current travel experience, it is necessary to build a linkage between work flexibility and the quantitative attitude towards travel experience. In previous studies, this attitude was modeled following the rational behavior theory (equation 5.3).

$$V(t) = \alpha \cdot T(t) + \beta \cdot SDE + \gamma \cdot SDL$$

$$SDE = \max(0, (PAT - t - T(t))) \quad (5.3)$$

$$SDL = \max(0, (t + T(t) - PAT))$$

where t is the departure time, $V(t)$ is the payoff at t , $T(t)$ is the travel time associated with t ; PAT is the preferred arrival time, SDE/SDL represent schedule delay early/late, and α , β and γ are parameters. In this paper, PAT is replaced by preferred arrival time interval ($PATI$). Illustrated in Figure 5.2, a traveler arrivals earlier than PAT suffers some SDE ; however, after he/she has gained flexibility in schedule, the traveler no longer has SDE with the same behavior..

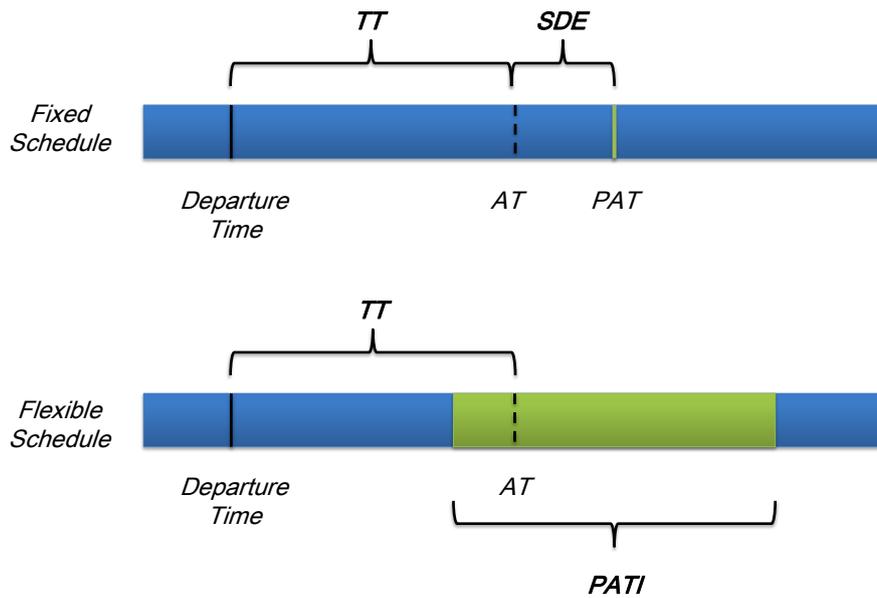


Figure 5. 2 PATI v.s. PAT

Secondly, uncertainty of both supply and demand sides is simulated in this paper to enhance the authenticity of the scenarios. Due to physical and operational factors, such as the road constructions and maintenance, incidents, and weather, some roadways may lose capacity or be blocked during certain time periods. In order to model supply side uncertainty, the whole 2013 incident data of the study area is obtained from Regional Integrated Transportation Information System (RITIS). Based on RITIS data, we assume the incident frequency follows Poisson distribution with rate 1.74 (times/day). The duration of incidents is assumed to follow Exponential distribution with rate 1/37 (1/minutes). The location of an incident is determined by a link's failure probability in direct proportion with its volume. Demand, also varies from day to day following the variation of social activities and events. The demand side uncertainty is introduced by randomness of the total travel demand from day to

day. The coefficient of variation (CV, defined as the demand standard deviation divided by the mean travel demand) can be used to measure the demand-side fluctuation. In this study, the day to day CV has an Uniform distribution from 0 to 0.15.

Thirdly multi-day knowledge updating is adopted instead of single-day learning and decision making. Before every round of searching and switching, 5 days' (one week) travel experience is simulated in DTA. Travelers cannot change their departure time during the 5 days. The average and standard deviation of travel time for every travel are calculated as a statistical travel experience. There are two concerns for this modification: to avoid simulation noise which may lead to unreasonable behavior changes; and to capture the impact of travel reliability on departure time choice.

5.3 Introduction of DynusT

DynusT is an open source simulation based mesoscopic DTA model. The traffic model built in DynusT is vehicle-based mesoscopic Anisotropic Mesoscopic Simulation (AMS) model (86). The simulation based DTA is solved through a gap function vehicle-based (GFV) algorithm. The relative gap function value will determine whether the travelers change routes or not. Compared with the widely used successive average method, GFV can avoid over adjustments of flow and thus lead to more consistent and robust assignment results. Meanwhile, DynusT adopts a method of isochronal vehicle assignment which divides analysis periods into epochs and

sequentially performs vehicle assignment in each epoch. This significantly improves the model scalability regardless of the total analysis period. In the newly released 2012 version, DynusT has been fully parallelized in simulation, time-dependent shortest path and assignment algorithms, and therefore boosts the computational speed dramatically. However, the current simulator does not address capacity drop due to congestion.

DynusT adopts a behavioral response system which assigns drivers to different response classes based on the percent distributions defined by the user. (1) Habitual users continue on the same path assigned to them unless there is a detour dynamic message sign that all cars must take. (2) System optimal users are assigned based on optimal system perspective, rather than the individual drivers'. In this system a vehicle may be assigned a longer path in order for the majority of vehicles to leave the system more quickly. This class of user will only respond to speed warnings or detour dynamic message signs. (3) User equilibrium users are assigned the paths that will reduce the travel time for the driver. Once the driver has reached user equilibrium the travel path is now the habitual path. (4) En-route information users. Two types of information are considered for this class: incident or disaster information is presented to drivers at the pre-defined frequency; new route information is presented based on updated travel time retrieved from the base station. The driver decides on whether the new route is chosen based on the bounded rational behavior. A driver considers switching routes whenever the en-route travel information is updated at each

predefined interval. (5) Pre-trip information users have best path information. They know in advance that there is road work or a closure before leaving, avoiding the congestion by choosing an alternate route and/or departure time.

5.4 Integration with DTA

In this study, the mesoscopic traffic simulator DynusT (86) is integrated with the positive departure time choice model to simulate travel experience for departure time choice. The integration flowchart is shown in Figure 5.3. The modeling of departure time shift begins from the static OD estimated via planning models. Multimodal static OD estimation and dynamic OD calibration are then conducted to obtain time-dependent OD tables for the study area. Details of these OD estimation approaches can be found in Ben-Akiva (23). In order to calculate travelers' current experience, DTA is initially applied to pursue DUE, after which travelers' travel times are collected. Meanwhile, their paths are extracted to calculate free flow travel time (FFTT) as their believed best travel condition. Here FFTT and current travel time are used to initialize their search gain. Heterogeneity is embedded when synthesizing these travelers with socio-demographic variables including: income, gender, flexibility of arrival times, search cost, etc. Under such initialization, one iteration path fixed dynamic assignment is adopted to simulate weekly traffic knowledge learning process. Travelers' a weekly travel time is updated, and a positive departure time choice model is employed for every traveler. In each run of the simulation, every traveler learns their travel experience from DTA results; makes departure time search

based on the trade-off between search gain and search cost; and adapts behavior via decision rules. The iterative loops of departure time modeling would not finish until only a few individuals are still searching for alternative departure times, which also means a BUE.

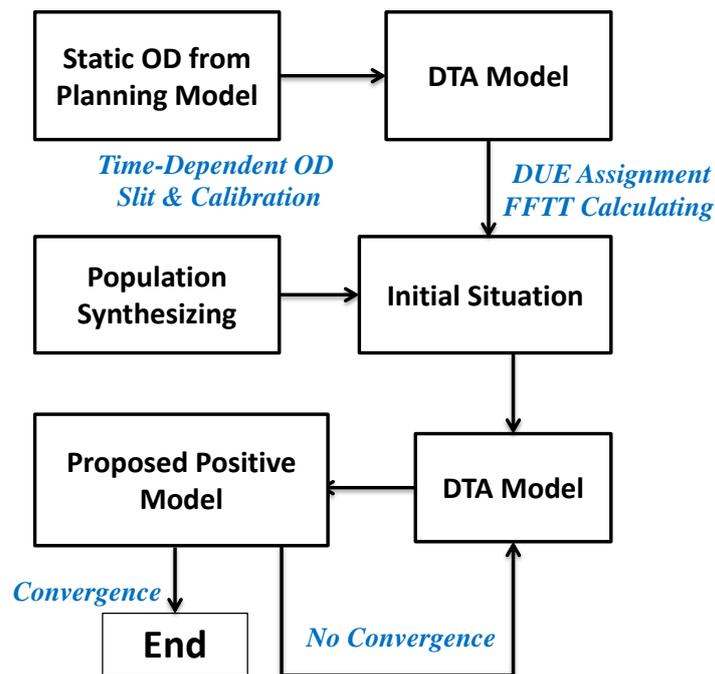


Figure 5.3 Flowchart of the Integrated Model

5.5 Flexitime Policy Analysis

In order to demonstrate the capability of the model for flexitime study, a real world application will be illustrated in this section. The selected study area is shown in Figure 5.4, which includes Rockville, North Bethesda, and Gaithersburg in Montgomery County, Maryland. Three major roadways (I-495, I-270 and MD355) and other minor/local roadways are coded via DynusT in this study. There are 61

traffic analysis zones, 201 nodes and 1077 links in total. Already containing the AM peak period, the simulation horizon is from 5:00 a.m. to 10:00 a.m. 237,903 vehicles were extracted from the previous ICC model (23) during the horizon. The demand has already been calibrated and validated in the previous work (46).

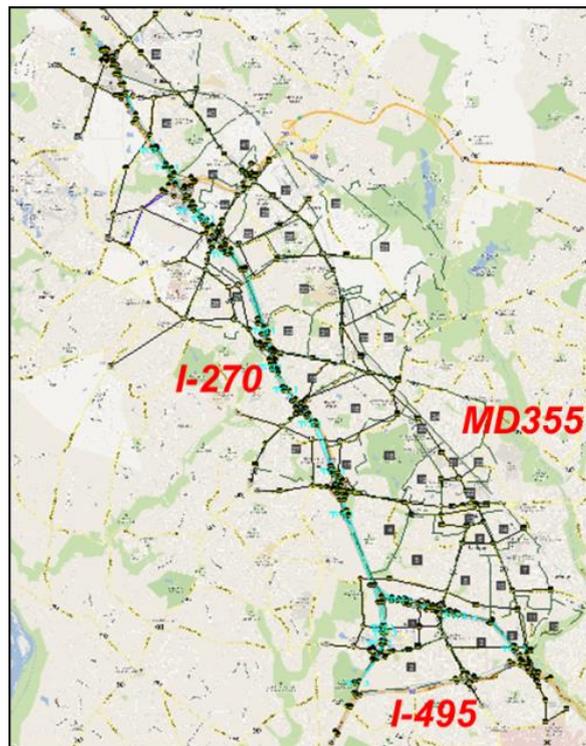
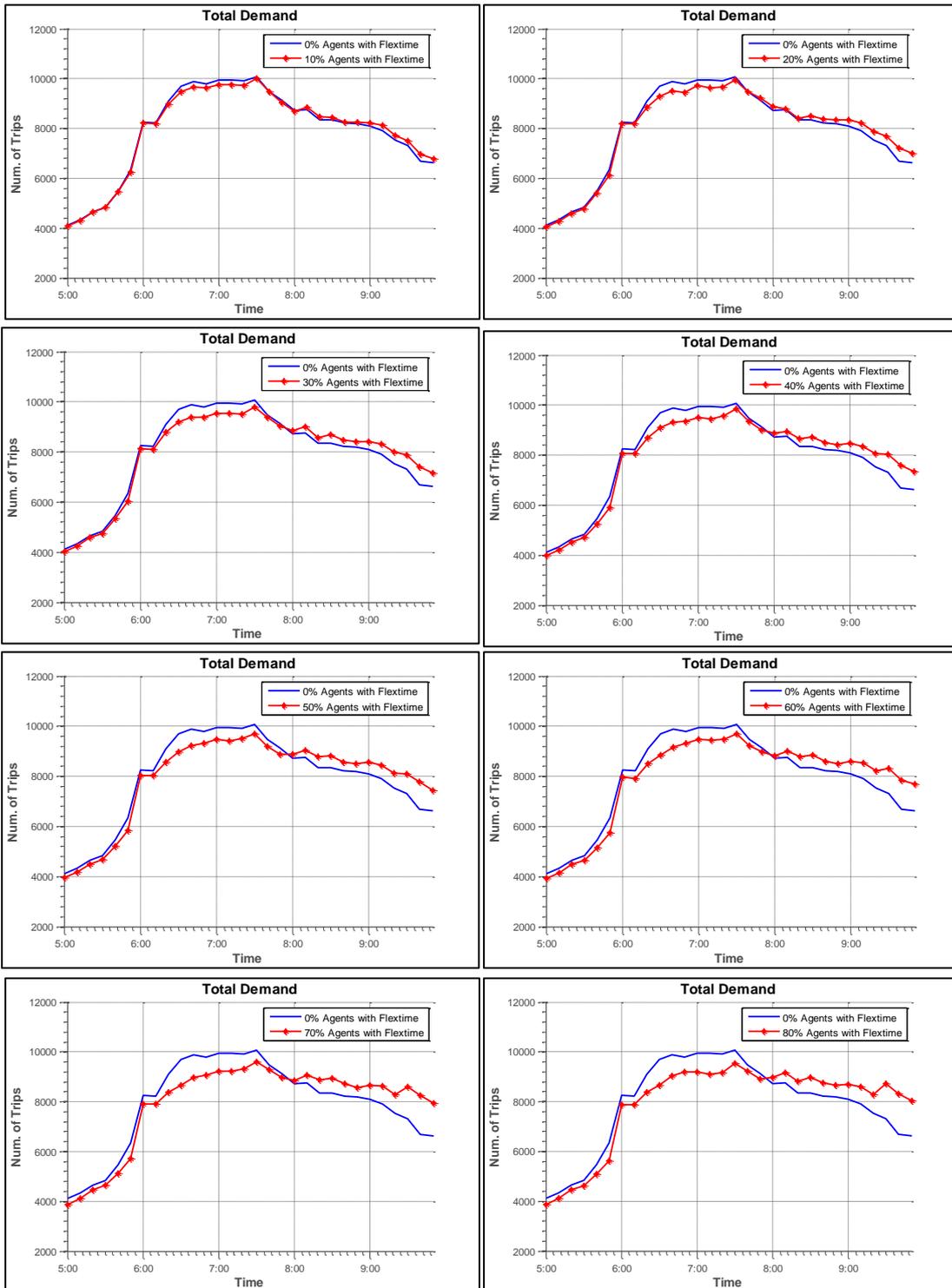


Figure 5. 4 A Real World Network: I-270/MD-355 Corridor

There are 11 scenarios designed in this paper with 0%, 10%, 20% to 100% of the travelers having flexible work schedule. People are randomly assigned with a flextime policy and the total number of flextime travelers will make up a certain percentage of the population (i.e. 10%, 20% ...100%). Socio-demographic variables such as gender and income level are generated by the same distribution with 2007-2008 TPB/BMC Household Travel Survey (65). In order to reduce the impact of simulation noise, 5

simulations are performed for each scenario with different flextime travelers (described in 5.2). The 0% scenario is considered as a base case. This base case is assumed to be the original traffic situation, in which all travelers have a habitual departure time and arrival time provided by DUE. In these scenarios, travelers assigned with flexible schedules can arrive any time within their PATI. The PATI is assumed to be a two-hour time window with their current PAT being the mean value. For example, if a traveler used to arrival at 9:00 a.m., his/her PATI should be 8:00 to 10:00 a.m.. It takes around 10 weeks (50 iterations) for each simulation to reach convergence, so there are around 2750 iterations in total.

At the end, only a fraction of travelers are still looking for new departure times. This stable situation among travelers is regarded as BUE. The impacts of flextime policy on demand pattern are displayed in Figure 5.5. The blue curves denote the base case situation, which means no agents have a flexible schedule; the red curves with dots denote the scenarios with different percentages of flexible agents. As the percentages of travelers with flexible schedule increase, the total demand during the AM peak period (6:00 to 9:00 a.m.) is shifting to later time periods. After the ratio of flextime travelers increases to 60%, there is no obvious peak period (compared with base case demand). The demand distributes smoothly from 6:00 to 10:00 a.m., which is consistent with Xiao's study (59). Using the integrated model, the step-by-step change of demand pattern is captured.



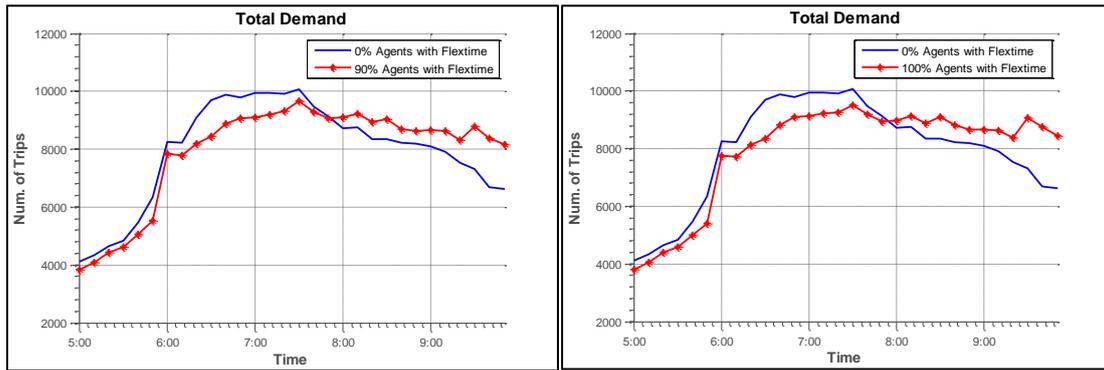
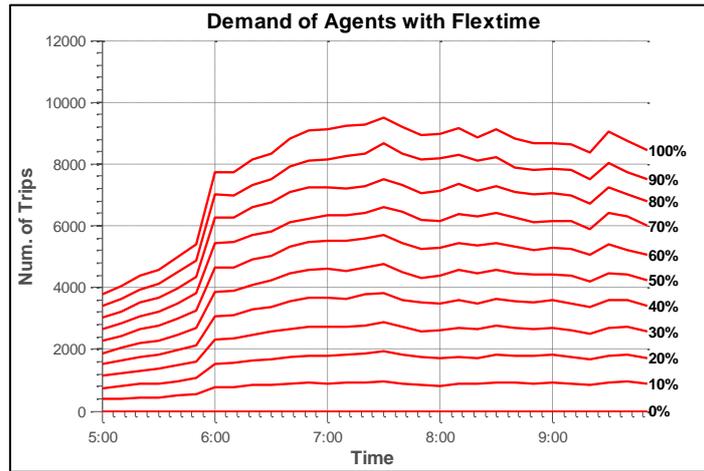
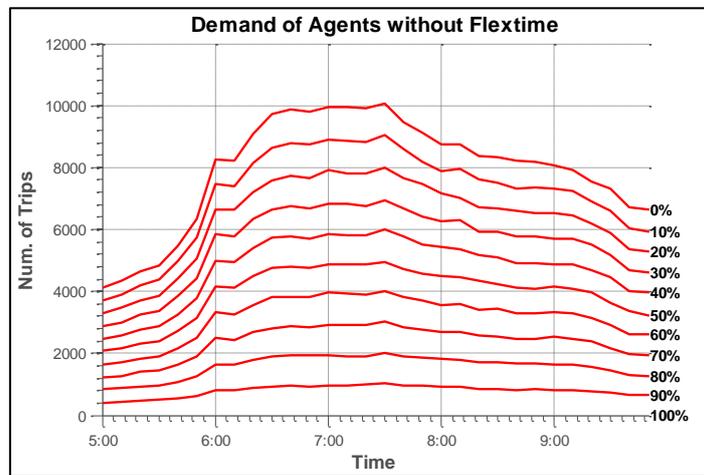


Figure 5.5 Demand Pattern Change

Having a better understanding of such demand pattern changes, Figure 5.6 separates the flex-agent demand and no-flex demand. Figure 5.6(a) summarizes the demand pattern change for travelers with flexible time. The 11 curves from lowest to highest refer to the increase in the percentage of travelers with flextime from 0% to 100%; while in Figure 5.6(b), the 11 curves from the lowest to highest refer to the decrease of this percentage (100% to 0%). For travelers who have flexible schedules, even though this ratio is low, there is no distinguished peak period; while, for travelers without the flexible policy, an obvious peak period can be found between 6:00 and 9:00 a.m. in nearly every scenario. This phenomenon implies that travelers with flexible schedules tend to depart later to avoid the peak hours. As the percentage of travelers with flextime increases, the absolute number of travelers who switch out of peak hours travel is also growing. This results in a difference in total demand pattern (Figure 5.4). It also this policy has little impact on the demand pattern of the travelers without a flexible schedule.



(a) Demand of agents with flexitime

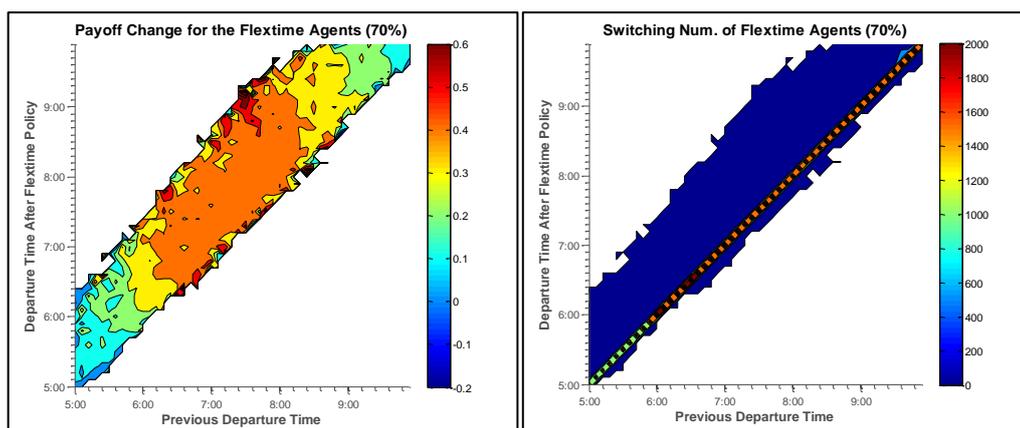


(b) Demand of agents without flexitime

Figure 5. 6 Demand Pattern Change for Both Traveler Groups

Figure 5.7 indicates the interesting finding that flexitime travelers choose to depart later while there is almost no change on the demand pattern of travelers without flexible schedules. The 70% scenario is selected for this analysis because: 1) although the total demand is evenly distributed from 7:00 a.m. to 10:00 a.m. (Figure 5.4); and 2) two groups of travelers obtain different changes in their payoff. Figure 5.7(a) illustrates the payoff changes of the travelers with flexible schedule: the horizontal axis represents the original departure time, while the vertical axis

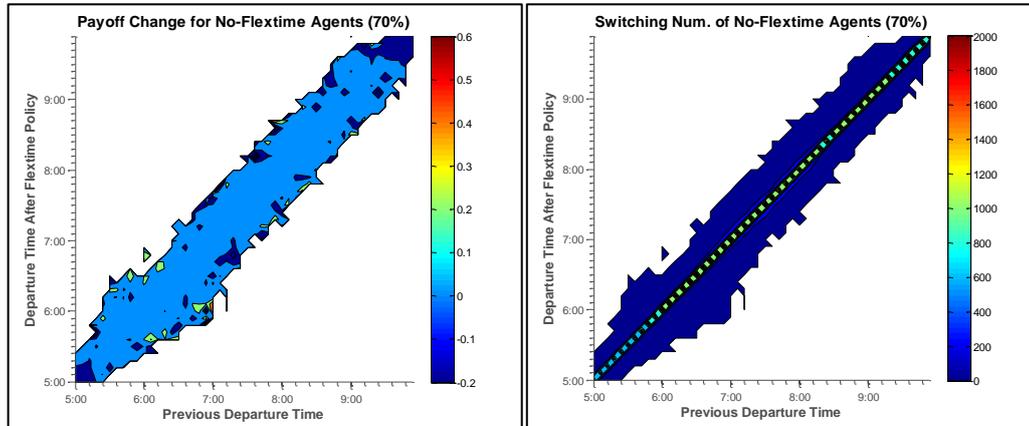
represents the departure time that travelers shifted to, and the color represents the payoff change. Obviously, thanks to this peak spreading effect (Figure 5.4) travelers who are used to depart during peak hours benefit the most. Figure 5.7(b) shows how many people have shifted departure time from/to different time periods. Even though these travelers have the flexibility to arrive later, the majority of them still use their original departure time. For those who changed behavior, a later departure time is much more preferred than an earlier one. When a minority of travelers departs later, traffic congestion is eased and there is less incentive for the rest of travelers to change their behavior. In Figure 5.7(c), the payoff changes of travelers without flextime are displayed: before 9:00 a.m., they may have a small increase in their payoff. Travelers departing after 9:00 a.m. will suffer a loss of payoff due to the demand increase. The majority of these travelers also stay unchanged (Figure 5.7(d)). And the number of travelers switching earlier/later is almost equal, leading to a stable demand pattern.



(a) Payoff Change for the Flexitime Travelers

(b) Switching Number of Flexitime

Travelers



(c) Payoff Change for the No-Flexitime Travelers (d) Switching Number of No-Flexitime

Travelers

Figure 5. 7 Payoff Change Under 70% Scenario

The average travel time diagram (Figure 5.8) shows the impact of aggregate network performance from individual behavior changes. The traffic during the AM peak improves greatly as the level of flexitime grows. However, the relationship between travel time and flex-share is not monotonic. Travelers departing after 9:30 am will suffer from some bottlenecks when this ratio surpasses 70%. Unlike the traffic congestion during the AM peak in base case, this slight bottleneck results from the trade-off between flexitime travelers' gain and non-flexitime travelers' loss in the payoff. For the whole simulation horizon, Figure 5.9 shows the overall average travel time for different policy scenarios. In this case study, every scenario performs better than the base case; the traffic system with 60% flexitime travelers reaches an excellent situation which can save 10,785 hours (22.3%) in total travel time.

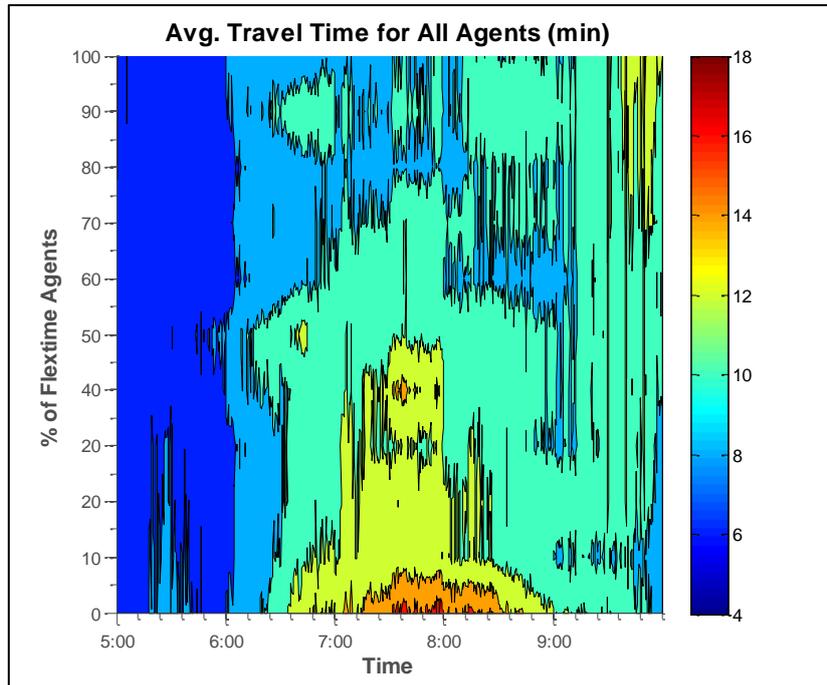


Figure 5. 8 Travel Time Change for the Whole Population

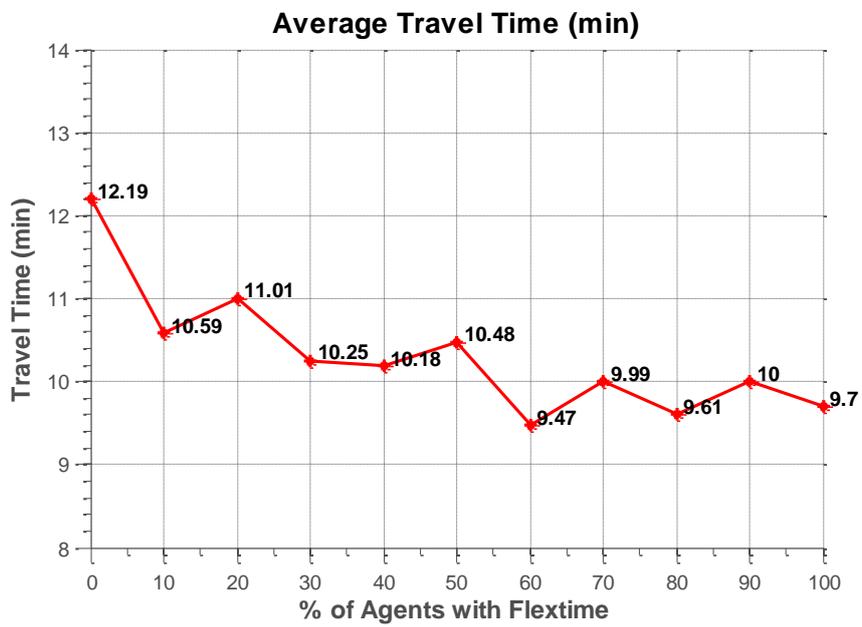


Figure 5. 9 Network Average Travel Time

Chapter 6: Conclusion

6.1 Integrated Tool for Cumulative Land Development Study

This study integrates DTA with an agent-based positive travel behavior model to estimate the transportation impact under land development. In the proposed model framework, travelers no longer have perfect network knowledge to maximize their travel utility. Instead, they are learning and searching for better choices to decline their costs due to delay, schedule delay early, and schedule delay late. The integration with a positive model enhances the behavior realism of DTA, resulting in the capability to capture dynamic travel behavior changes. This integration can be a valuable method for planning agencies to conduct studies on land development, traffic related policies and/or a combination of the two. It is also proven as a feasible tool to conduct new TIAs which emphasize not only regional/local system mobility, but also individuals' behavior.

A land development case study is illustrated in this paper. Various regional and local travel behavior changes are focused on to demonstrate the unique value of this tool on dynamic travel behavior analysis. The departure time shifts of travelers come from a series of rule-based logic evaluations, which may be biased due to the varying of travelers' attitudes such as value of time. But it still provides a low-cost resource for capturing individual reactions on their travel behaviors. Future research will focus

on integrating more choice dimensions such as mode choice and destination choice. In addition, comparisons between agent-based positive model and utility-based rational models are also expected in future efforts.

6.2 Flexible Schedule Policy Analysis

This thesis also attempts to gain perception about travelers' reaction towards flexible work schedule policy. Unlike previous flextime studies, the research goal in this paper is achieved through further developing the modeling framework of an agent-based positive departure time choice model. Individual knowledge learning and decision making process is specified and empirically modeled to understand the potential influence of this policy on day-to-day traffic dynamics. DTA is integrated with this agent-based positive departure time choice model. One remarkable advantage of this integrated model is its ability to build a feedback between demand-side individual choice and supply-side network performance. The disadvantage (we may also call it our future research opportunity) is that the agent behavior (search rules and decision rules) already built in this study area may be inapplicable for other study areas. Thus, the model requires further calibration before applying to other study areas or scenarios. One alternative calibration method is to apply simulation based optimization to adjust the probability distribution of the new departure time searching (39), which will be explored in future research.

Different scenarios of various percentages of flextime agents are tested in a real

world network in Montgomery County, Maryland. It has been found that travelers with schedule flexibility tend to make their travel later, which is the same as (12). This result is in accordance with the purpose of flextime policy, which aims at balancing the conflict between work and family. Travelers' individual level behavior change may lead to significant improvement on traffic system. As these flextime travelers switch from AM peak to post-peak periods, the congestion during peak hours is alleviated. However, the improvement of traffic condition has few influences on the demand pattern of agents without flexible schedules. The network with 60% flextime travelers performs the best. Under such condition, original AM peak in the base case will spread between 6:00 a.m. and 10:00 a.m.. Compared to the base case, 10,785 hours (22.3%) of traffic delay would be saved. Since the current flextime ratio is around 30%, the 60% or upper flextime ratio seems unpractical. In addition, results may not be the same for other areas or networks. This paper holds a theoretical analysis for prospect of future demand management policies.

In this research, the assumption in terms of flextime policy is strong: the PATI is a two-hour time window based on travelers' PAT. This is a shallow attempt to demonstrate the capability of this integrated agent-based model to capture departure time change under behavior related policies. Departure time flexibility modeling can be a complex problem because travelers' flexibility is determined by a variety of factors, i.e. travelers' ability to start work later/earlier, traveler's house responsibility, and social-economic characteristics. All these features can be taken into account for

future research. In addition, it will be more interesting and meaningful if monetary stimulus is considered in flextime policy study. That is, a traveler can get some monetary reward if he/she switches from peak period to off-peak period. Thus, it allows us to have perspective view on the monetary cost and welfare gain due to the introduction of flextime policy. Furthermore, comparisons can be conducted between traffic demand management and other congestion mitigation methods, such as roadway capacity extension.

Furthermore, this integrated model is also applicable for studying the impact of other management policies, demand increase, and even roadway incidents on travel behavior. Since departure time is the only dependent variable in its current framework, the model still requests further development to capture travelers' behavior change in route choice, mode choice, lane choice, etc. The authors expect to empirically estimate and embed other behavior rules into this framework for more comprehensive analysis.

6.3 Limitations and Future works

There are two major limitations of current approach. In the first place, the release of behavior foundation can be a double-edged sword. The good side is the model allows heterogeneity among travelers. The disadvantage is that the behavior pattern (search rules and decision rules) already built in this study area maybe inapplicable for other study areas. Thus, the model requires calibration before implying to other

study areas or scenarios.

Additionally, the dynamic OD estimation process lack theoretical foundation. In the current model, the dynamic OD is obtained by multiplying a “time factor” to the whole static OD table. In reality, different specific OD pairs may contribute differently by time. For example, a commuting OD pair (mainly connecting resident area with employment area) may have more trips during 6-7, while a shopping OD pair may contain more trips during 8-9 or even later. Thus, more advanced dynamic OD estimation approaches are required.

In terms of the limitation of current model as well as the interest, several considerations are made for future research: 1) the calibration process for the positive travel behavior model needs to be improved both theoretically and applicably. It is necessary to propose an easy-running behavior model calibration approach to enhance the robust of this integrated model; 2) other travel behavior models such as mode choice model, route choice model, destination choice model, will be considered to integrated into this model, resulting in a more behavior realism software package for a variety of applications such as the building of transit system, dynamic pricing policies, and the implement of ramp metering.

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