ABSTRACT

HU, HYEJUNG. Measuring the Effectiveness of Advanced Traveler Information Systems (ATIS). (Under the direction of Dr. Nagui Rouphail and Dr. Billy Williams.)

The objective of this study was to develop valid methodologies for addressing several limitations of the current Advanced Traveler Information Systems (ATIS) evaluation tools. This study was focused mainly on three enhancements. First, the queue propagation algorithm of the selected tool (DYNASMART-P) was modified to more realistically model traffic congestion. The author proposed the addition of transfer flow capacity and backward gated flow constraints for more accurately calculating transfer flow rate. Second, the study modeled the natural diversion behaviors of drivers who do not receive traveler information. Lastly, statistical models of user responses to traveler information were developed using binary and multinomial logit methods to understand and model the relationship between drivers' socio-economic characteristics and their responses to traveler information. Among these three enhancements, the first two (improved queue propagation and natural diversion behavior algorithms) were implemented in the enhanced model. The user behavior models, however, were not implemented because their predictive power was not acceptable due to limitations in the data set. The enhanced model was applied to two case studies: 1) verifying the capabilities of the model under a recurring bottleneck scenario on I-40 corridor in the Triangle region of North Carolina, and 2) demonstrating the capability of the enhanced model to measure the effectiveness of U-Transportation (similar to the Vehicle Infrastructure Integration [VII] program in the USA) which has been under development in Korea. The first case study results showed that the improved queue propagation algorithm simulated the bottleneck queue much closer to the real data than the original model. The simulation results also indicated that the actual diversion rate under recurring congestion in the study network was very low. The results of the second case study demonstrated that the enhanced model can evaluate the network impact of new advanced technology in flooding situations and can evaluate the effect of market penetration of the communication technology.

Measuring the Effectiveness of Advanced Traveler Information Systems (ATIS)

by
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DEDICATION

To

My Heavenly Father

and

My Family

BIOGRAPHY

Hyejung Hu was born on July 10th, 1976 in Seoul, South Korea. After graduating high school, she started her undergraduate study in the Department of Urban Engineering at the Hongik University in Seoul, Korea in March 1995 and received her Bachelor of Engineering degree in 1999. She started to study transportation engineering in the Department of Transportation Engineering at the University of Seoul, Korea in 1999. She received her Master of Engineering degree in 2001. After that, she worked as a researcher in the Seoul Metropolitan Government from May 2001 to July 2003. In July 2003, she came to Raleigh, North Carolina with her husband Jongdae Baek. Since the fall of 2004, she has been working on her Ph.D. degree under the supervision of Dr. Nagui M. Rouphail and Dr. Billy M. Williams in the Department of Civil, Construction, and Environmental Engineering at North Carolina State University. She will start working as a post doc at the Institute for Transportation Research and Education in January 2009. She lives in Raleigh, North Carolina with her husband Jongdae, daughter Seunghye, and son Seokju.

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CHAPTER 1. INTRODUCTION

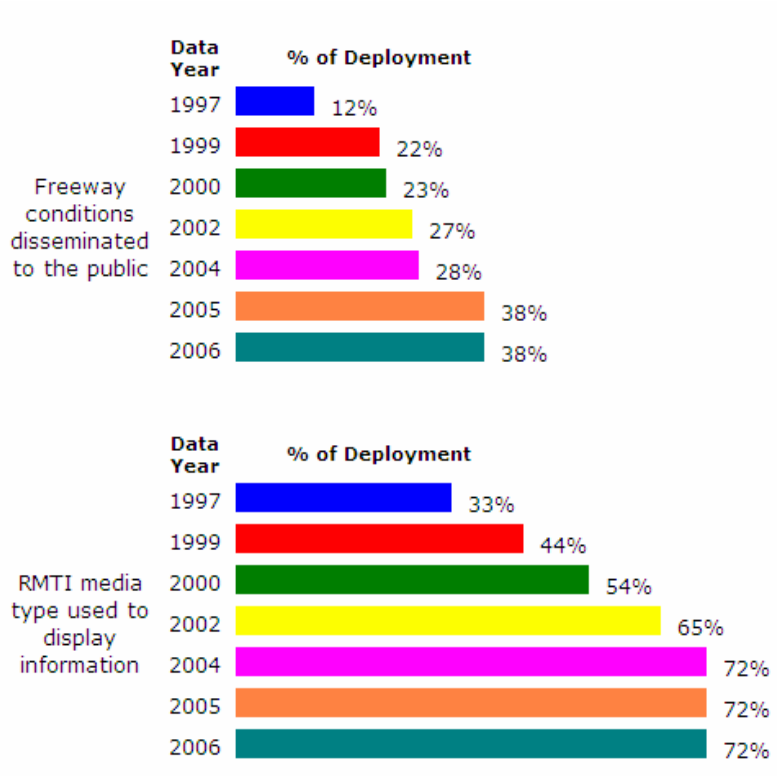
1.1 Background

It is well known that a traveler who is planning a trip must make many decisions - which destinations to select, which modes to use, which routes to take, and (if relevant) where to park their vehicles before the trip. Travelers undertaking this trip planning process find it useful to have access to real time information regarding their trip such as the traffic conditions, weather, or the occurrence of unanticipated incidents. The concept of Advanced Traveler Information Systems (ATIS) has been put forth to satisfy such needs. ATIS can be viewed as a data integration system that delivers accurate, reliable, and timely information to travelers. It disseminates traveler information through various technologies such as Variable Message Signs (VMS), internet websites, TV, Highway Advisory Radio (HAR), 511 phone service, or In-Vehicle Information System (IVIS).

ATIS provides individual travelers with opportunities to improve their travel plans in a timely manner, to avoid delays, to reduce uncertainty in arrival times, and to reduce travel stress and anxiety. In addition, traveler information contributes to the transportation system efficiency by reducing incident-induced congestion, increasing safety, enhancing accessibility to destinations and modes, reducing fuel consumption, and improving air quality. Those ATIS benefits can be found in a summary table in Appendix A. The table includes the ATIS benefits presented in the benefit database on the Intelligent Transportation System Joint Program Office (ITS JPO) website (ITS JPO, *2008*) and the ATIS benefits recently reported by several states.

In response to these evident ATIS benefits to individuals and the transportation system, many cities in the U.S. have deployed ATIS technologies. Figure 1.1 shows the growth trend in ATIS deployment from 1997 through 2006 based on the data from the 78 largest metropolitan areas surveyed in 1997, 1999, 2000, 2002, 2004, 2005, and 2006. In 2006,

information about freeway conditions were disseminated to the public in 38% of those cities and RMTI (Regional Multimodal Traveler Information) media were used to display information in 72% of those cities.



(Source: http://www.itsdeployment.its.dot.gov/Trends2006.asp?comp=RMTI)

Figure 1.1 ATIS Deployment Statistics-National Trend

Many cities in the U.S. have regional ITS deployment plan in which new or additional investments in ATIS technologies are included. In order to make good decisions regarding ATIS deployment and cost-effective investments, it would be essential to estimate the effect of ATIS on the performance of the transportation network. Although the experiences of transportation agencies and customer feedback on ATIS deployments have generally been positive, methodologies for quantifying the benefits and costs of ATIS are lagging behind. Thus, there are pressing needs for developing valid evaluation methodologies and tools to

quantify the costs and benefits of various ATIS deployment options. Recently, a NCDOT research project titled "Effectiveness of Traveler Information Tools" was carried out to meet the needs mentioned above (*Williams et al., 2007*). This pilot research assessed various ATIS evaluation tools to recommend an appropriate tool for North Carolina.

According to the literature review conducted in that project, there have been many attempts to quantitatively and qualitatively evaluate ATIS impacts. The summary table in Appendix A shows various methods in recent ATIS evaluation studies. ATIS evaluation methods are generally classified into four categories: field measurement, surveys, traffic simulation, and network-wide traffic assignment. Field studies investigate the differences in travel times of vehicles with and without ATIS on certain roadway sections. Surveys poll ATIS users to determine the type and value of perceived ATIS benefits. Traffic simulation-related studies aim to estimate the potential benefits that could occur if ATIS were to be used at certain locations or freeway or arterial corridors. Lastly, for study areas involving route diversion, dynamic traffic assignment models have attracted active research and development attention because it has strength on describing the dynamics of network flow propagation and dynamic travel behavior in response to real-time information.

In the NCDOT sponsored project, the capabilities of the ATIS evaluation tools currently in use were also investigated. One of the findings from the project was the identification of several limitations of the existing ATIS evaluation methods. To achieve better results in ATIS evaluations and to produce more effective and proper deployments of ATIS, it is a priority to solve these limitations to develop reliable and valid ATIS evaluation tools. In this study, methodologies to address some of the limitations of the current tools were addressed and applied to a mesoscopic network modeling and dynamic traffic assignment (DTA) tool, namely, DYnamic Network Assignment-Simulation Model for Advanced Road Telematics – Planning (DYNASMART-P, *Mahmassani and Jayakrishnan, 1991 and Mahmassani and Peeta, 1993*). The primary reason DYNASMART-P was selected for this study is that it has the capability to model real traffic condition using mesoscopic simulator applications and is

capable of reflecting users' response to ATIS (especially route diversion behavior) in dynamic traffic flow conditions using an integrated DTA tool. Without using dynamic assignment, it may be possible to evaluate different ATIS options, and produce useful benefit/cost ratio and net benefit reports for a simple corridor. However, static traffic assignment models or spreadsheet models do not and cannot realistically model traveler response to ATIS in a realistic, multipath traffic network.

Among the critical limitations of the current ATIS evaluation tools identified in the project mentioned above, three issues were thought to be most pressing to address and served as the basis for initiating this study. The first issue was that the original traffic simulator in DYNASMART-P does not reflect realistic queue propagation. The algorithm of the simulator, therefore, appeared to underestimate bottleneck-induced congestion. Because the effectiveness of ATIS is usually assessed under non-recurring congestion caused by non-bottlenecks caused by incidents or construction work, it is essential to improve the original queue propagation methodology to achieve more realistic and accurate estimation of the effectiveness of ATIS.

The second issue was that some of the existing ATIS evaluation tools that can simulate ATIS user's route diversion behaviors calculate the benefits of ATIS by comparing the network improvements before and after the route diversions. However, the tools assume that drivers who do not have access to any external travel information system would not change their original path. This assumption may be not very realistic. Travelers might visually identify the incident-induced queues by themselves on their routes and possibly divert if they had knowledge about the regional traffic patterns and alternate routes as commuters. If this is true, the current assumption could result in a possible overestimation of the ATIS effects by ignoring the possible route diversions under the no-ATIS scenario.

The third issue concerns identifying the class of users by ATIS access category. ATIS evaluation tools require input parameters related to ATIS technology usage rates and user

responses to the information in order to estimate the benefits of various deployable technology options in a certain area. These parameter values are difficult to measure, especially in such areas where ATIS has not been deployed yet. In this case, these parameters need to be calibrated using the data from areas where ATIS has been deployed.

1.2 Research Objectives

The main objective of this study was to develop valid methodologies for dealing with the limitations of current ATIS evaluation tools described above, so as to improve the assessment of ATIS benefits. In order to meet this objective, this study focused on the following concerns:

- Improving and if necessary replacing the queue propagation algorithm in ATIS modeling environments,
- Modeling path change behavior under severe congestion without information given to travelers in order to provide a more accurate baseline of ATIS benefits, and
- Understanding and modeling the relationships between driver's socio-economic characteristics on the one hand and ATIS usage and users' responses to ATIS on the other,
- Verifying the capabilities of the enhanced model which adopts the improved algorithms developed above using a regular bottleneck section on I-40 corridor in Triangle region, North Carolina, and
- Demonstrating the capabilities of the enhanced model under an advanced technology, u-Transportation which has been under development in Korea (similar system with Vehicle Infrastructure Integration (VII) program in USA), which is the next generation ITS.

This study is expected to produce more realistic measures of effectiveness for ATIS. It is also expected that the results of this study will contribute to a more robust benefit/cost (B/C)

analysis by providing reasonably estimated benefits that can support decisions about ATIS deployment plan and technologies.

1.3 Dissertation Outline

This dissertation consists of nine chapters. The background, objectives, dissertation outlines, and contributions are described in Chapter 1. The results of ATIS evaluations from several states and the ATIS evaluation methods and software tools recently used are reviewed in Chapter 2. Chapter 3 describes the four findings from the pilot study: First, tool selection methodology and results of tool selection are presented. Second, the recommended ATIS evaluation framework is depicted and explained. Third, the pilot case studies which examined the selected tools in incident and work zone scenarios on an I-40 section are partly described. Lastly, a section is presented to identify desirable functions that would improve the current ATIS evaluation tool.

Three of those selected topics and their enhancements are shown in Chapter 4, Chapter 5, and Chapter 6. Chapter 4 describes the enhanced model for Queue propagation Algorithm in DYNASMART-P. The problem definition, a proposed algorithm, and an implementation method are presented. A simple network for testing the implementation is depicted and the implementation results are given in this chapter. Chapter 5 dictates the proposed model for the natural diversion behavior. The problem definition, a proposed algorithm, and an implementation method are presented. A simple network for testing the implementation and the implementation results are described in this chapter. Chapter 6 presents the predictive models of ATIS use and travel decision. The TRM Survey data set and the developed models are shown in this chapter. The interpretation and prediction power of the models are discussed.

Chapter 7 describes the verification of the enhanced model, which adopted the enhancements A and B by applying the model to simulate recurring bottleneck situations on an I-40

corridor. The comparison between simulation results and field data are described. Chapter 8 describes the application of the enhanced model to evaluate the impact of u-Transportation using the assumed flooding scenarios in the Knoxville network, Tennessee. The simulation network, scenarios and results are presented. Summaries, conclusions, and findings are given in Chapter 9. The needs of further research are discussed in this chapter.

1.4 Contributions

The pilot study, the model verification study, and the application case study are good examples of various uses of the ATIS evaluation tool. The methodology and related difficulties in data collection, data preparation, simulation network building, scenario building, analysis of results, and comparison with field data were described in some detail in this dissertation.

While carrying out those simulation case studies, discussions with the developer and suggestions contributed to develop and improve some of other functions in the computer code beyond the three main topics of this study.

There were several previous trials for improving the queue propagation algorithm in the original DYNASMART-P, particularly for long links. Jayaskrisnan et al. (*1994*) suggested the method of dividing a link into smaller segments and Zilliaskopoulous and Lee (*1997*) tried to use the cell transmission model. Chiu and Zhou (*2006*) discussed the lack of anisotropic property in a long link and proposed Anisotropic Mesoscopic Traffic Simulation (AMTS) model. AMTS model will be implemented in the next version of DYNASMART-P. Even though the enhanced model proposed in this study does not change the structure of current program, it can model a reasonable and more realistic queue based on robust traffic flow theory without requiring a high computational burden or large memory. The proposed model could be one of the options for the traffic simulation in the next version of DYNASMART-P.

As the dissertation documents, the enhanced queue propagation algorithm models fixed the problems of queue position and slow queue propagation speed. Modeling natural diversion behavior yielded improved results than the original program, in which congestion in the "no information" scenario was overestimated and the benefit of information was overestimated. The enhanced model will assist planners in making better decisions based on valid evaluation results. Thus the method will yield more reliable information on the benefits and cost savings of ATIS deployment.

CHAPTER 2. REVIEW OF ATIS EVALUATION METHODS

The benefits of ATIS are known well, but it is not easy to define and document ATIS benefits, and quantifying ATIS benefits is especially difficult. Nonetheless, there have been many attempts to quantitatively and qualitatively evaluate ATIS benefits. The first part of this literature review presents the results of ATIS evaluation from other states. The results were extracted from recent evaluation research reports and the database provided by ITS Joint Program Office website (http://www.benefitcost.its.dot.gov). In next part, some of the methods and software tools recently used are introduced briefly along with a summary of key research findings from the literature.

2.1 The State of the Practice

The information about ATIS evaluation methods and effects of ATIS were gathered from the experiences of other states and ITS Joint Program Office (JPO) in USDOT. ITS JPO updates and provides ITS benefits and costs database through an organizational website (http://www.benefitcost.its.dot.gov). The database provides ITS unit costs and system costs in excel spread sheet files or PDF files. For the benefits data, the web site provides web links to relevant research summaries. The summarized data can be used for developing an ATIS evaluation methodology or adjusting default values in evaluation tools. Appendix A is a summary table of the evaluation results from other states and ITS JPO benefit database. It shows that ATIS have benefits in capacity/throughput, cost/savings, customer satisfaction, delay/time, energy/ environment, and safety. The benefits of ATIS in capacity and throughput are trivial in most studies, resulting from reduction in delay and the number of stops. The benefits of ATIS in cost and savings however are measurable and significant.

A simulation by Shah et al. (*2003*) found 40% of all ATIS users achieved an individual net positive benefit of $60 or more per year. Khattak et al. (*1994*) found that the benefits of incident-induced delay information could range from $124 to $324 per person (1992 dollars),

for 40% of the commuters who expressed a willingness to divert to alternative routes in the San Francisco Bay Area. A London Transport survey (*1998*) found that transit information changes behavior and creates revenue up to 14.5 million pounds, including 1.3 million for bus companies, 1.2 million for underground companies, 1 million for railway companies, and 11 million in societal benefits.

Most research on ATIS benefits investigated the level of customer satisfaction and user acceptance. Generally, researchers found that traveler information is useful for making travel decisions and that it reduces stress and travel time. However, research revealed low awareness of ATIS. For example, only 9% of households were aware of TravInfo – a regional traveler information system in California (*Yim and Miller, 2000*). Related studies showed that ATIS significantly reduced the amount of time spent on arrivals in the peak periods, with most studies reporting reductions in number of stops, travel time, and vehicle travel miles. In addition, ATIS has observable benefits in terms of environment, energy, and safety. Better traveler information results in changes in routes and departure time—changes found to reduce vehicle emissions and fuel consumption (*Tech Environmental, Inc., 1993, Jensen et al., 2000, Jeannotte, 2001, and Zimmerman et al., 2000*), as well as fatalities (*Jeannotte, 2001*).

Taken in the aggregate, the major benefits of ATIS lie in reducing uncertainty and delay. The key findings of a series of studies on ATIS include the effectiveness of personalized (route-specific) traveler information compared to general radio advisories and the value of pre-trip information, particularly in high congestion (*Vasudevan et al., 2004*). Individual ATIS users enjoyed benefits year-round, particularly in the afternoon peak period (*Shah et al., 2003*). Most benefit to travelers came not from shortened travel time, but from reduced incidence of early or late arrival (*Shah et al., 2003*). Thus, users need not shorten their trips to feel satisfied with the service, given other benefits, such as more precise travel planning and reduction of stress from congestion and uncertainty. Other relevant studies are presented in Appendix A.

2.2 Evaluation Tools

ATIS evaluation methods can be classified into three categories: field measurement, simulation, and survey studies. Field studies investigate the differences in travel times of vehicles with or without ATIS on a certain roadway section(s). Simulation studies estimate the potential benefits that could occur if ATIS were to be used at a certain location(s). Lastly, surveys poll ATIS users to determine what and how much ATIS benefits are being perceived.

2.2.1 Field observation

Field observation methods were used to evaluate the effectiveness of ATIS systems in areas where the system was already in use. System operators gathered data using their own detector systems and surveys for the assessment. Measuring ATIS benefits through field studies is often done with yoked trails, in which two vehicle groups (one equipped with ATIS and one not) travel between the same origin-destination (O-D) pair at the same time, each vehicle group with a different level or type of information including none. The time it takes these vehicles to travel between each O-D pair is then compared to determine whether the vehicle group with ATIS experienced travel times than the other driver group.

Schiesel and Demetsky (*2000*) attempted to determine the effect of a Dynamic Message Sign (DMS) system in the Hampton Roads area of Virginia. Data were collected on the DMS system and volume data was obtained using loop detectors, over a period from August 1998 to July 1999. Using this data the difference between the percentage of drivers turning towards the Hampton Roads Bridge Tunnel when the DMS system was and was not in use was calculated. This difference indicates the diversion percentage. Harder et al. (*2005*) used filed operation tests method for their research. They made the 117 participants actually drive real routes. Pre-trip travel-time information was provided in the field experiment to half the

participants. Various data collection techniques were used including in-vehicle GPS units, pre- and post-experiment surveys, and travel diary.

In other cases, the driver's responses to traveler information are inferred from the field operation results of a deployed ATIS system. Yim and Ygnace (*1996*) reported drivers' response to real-time traffic information under SIRIUS (Système d'Information Routière Intelligible aux Usagers). SIRIUS is the largest urban field operational test of the advanced traveler information and automated traffic management system in Europe. In this case, the research results might be more reasonable than one time field test result because long term effects were analyzed.

2.2.2 Simulation and assignment methods

2.2.2.1 Dynamic assignment model

Dynamic assignment models attempts to model traveler's behavior including route diversion, mode change, and departure time change depending on market penetration rate and quality of information. Because many of these models are still under development, developers usually test their new algorithms using a small sample network. Ge1 et al. (*2003*) built the framework consisted of two-level mathematical program. The upper-level program maximizes the reserve capacity multiplier subject to a link capacity constraint, and the lower-level program generates user equilibrium flow patterns under the influence of traveler information. In the lower level, they consider the dispersion parameter theta in the logit model as an indicator of the quality of information provided by ATIS. Yin and Yang (*2003*) classified three classes of drivers on a specific day: drivers without ATIS, drivers with ATIS but without compliance with ATIS advice, drivers with ATIS and in compliance with ATIS advice. All three classes of drivers make route choice in a stochastic manner, but with different degree of uncertainty of travel time on the network. They provided the function of the market penetration of ATIS and the probability of the ATIS compliance rate of equipped drivers. Lo and Szeto (*2004*) applied a stochastic dynamic model based on the cell-

transmission model. Two classes of drivers, those with ATIS and those without were considered. Both classes are modeled to follow the stochastic dynamic user optimal conditions, with the equipped drivers having a lower perception variation of the network travel time due to the availability of better information. ATIS market penetration is modeled. Srinivasan and Guo (*2004*) developed a simulation-based framework to analyze day-to-day dynamics by integrating an empirically calibrated model of route-choice decisions with a dynamic network assignment model. Computational experiments are used to investigate the effect of certain experimental factors—recurrent network congestion level, market penetration, nature of information, and frequency of information updates—on network performance stability and reliability.

2.2.2.2 Numerical simulators

IDAS (ITS Deployment Analysis System) is a sketch planning tool created for the FHWA by Cambridge Systematics (*2000*) to calculate the benefits and costs of implementing an ITS technology within a transportation network. It has a postprocessor and extender to the TDM (Mode choice and Assignment steps). Users can view and edit most of the model defaults works. The software uses imported data from the travel demand model to recreate the model network within the IDAS software then the user can build one or several ITS deployment alternatives to evaluate. It calculates the benefits and costs of deploying the specified ITS alternatives, performs internal network assignment and analysis to estimate impacts of ITS and reports outputs in terms of the incremental change in performance measures and the annual benefit/costs. The software can analyze over 60 types of ITS strategies, 11 of those related to traveler information. It maintains a database of system impacts and costs related to each type of deployment based on national evaluations.

VISTA (Visual Interactive System for Transport Algorithms) is introduced by Ziliaskopoulos and Waller (*2000*). VISTA has a simulator RouteSim that uses cell transmission rules. The VISTA website provides a program overview and tutorial. VISTA was applied to Chicago's

six county-area network. It is an innovative network-enabled framework that integrates spatio-temporal data and models for a wide range of transport applications: planning, engineering and operational. It can be accessed via a cross-platform Java client or a web page. The client software allows performing all basic transportation GIS type operations, such as zooming, displaying multiple layers, adding intersections, street segments, signal controls, ITS devices, etc. as well as run the modules, access the data warehouse and see some reporting (mostly graphical, such as 2-D animation). The groundbreaking innovation of VISTA is that it runs over the network on a cluster of UNIX machines. This makes it universally accessible without worrying about available computational power of the client machine to run sophisticated dynamic traffic assignment, control and simulation models.

Mahmassani and Jayakrishnan (*1991*); Mahmassani and Peeta (1993) described the DYNASMART (DYnamic Network Assignment-Simulation Model for Advanced Road Telematics) developed at the University of Texas at Austin. DYNASMART-P is a mesoscopic traffic simulator, meaning that it simulates the movement of individual vehicles moving through a network in accordance with macroscopic flow rules (e.g., speed-density relationships.) It simulates several different route choice rules including dynamic system optimality, dynamic user optimality, and a bounded rationality rule in which drivers receiving enroute information about path conditions will only switch paths if the expected improvement exceeds a threshold amount. DYNASMART has been widely used for investigations of route guidance.

DYNAMIT (Dynamic Network Assignment for the Management of Information to Travelers) Ben-Akiva et al. (*1998*) developed the mesoscopic traffic simulation model DynaMIT. DynaMIT is explicitly designed for route guidance applications and is a simulation-based real-time system designed to estimate the current state of a transportation network, predict future traffic conditions, and provide consistent and unbiased information to travelers. DynaMIT combines real-time data from a surveillance system with historical travel time data in order to predict future traffic conditions and provide travel information

and guidance through an ATIS. Yang et al. (*2000*) develop the microscopic MITSIMLab tool for testing and evaluation of dynamic traffic management systems. Subsequently, Sundaram (*2002*) developed a methodological framework for such applications and implemented this framework in DynaMIT. He modeled traveler behavior and network performance, in response to special events and situations such as incidents, weather emergencies, sport events etc. The resulting new planning tool DynaMIT-P consists of a supply (network performance) simulator, a demand simulator and algorithms that capture their interactions. The supply simulator captures traffic dynamics in terms of evolution and dissipation of queues, spill-backs etc. The demand simulator estimates OD flows that best match current measurements of them in the network, and models travel behavior in terms of route choice, departure time choice and response to information. DynaMIT-P is particularly suited to evaluate Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS) at various levels of sophistication. Florian (*2004*) provides an empirical study of the impact of ATIS on transportation network quality of service using an application of DynaMIT in his thesis. An understanding of the relationship between transportation system performance and ATIS market penetration provides important insights into a sustaining market structure for the ATIS industry.

INTEGRATION was conceived during the mid 1980's as an integrated microscopic traffic simulation and traffic assignment model (*Van Aerde, 1985; Van Aerde and Yagar, 1988a and b; Van Aerde and Yagar, 1990*). It models routing and assignment, thus allowing for the modeling of traffic re-routing in response to real-time traffic information. It allows for the integrated modeling of freeway and arterial systems. This capability allows for modeling of traffic diversion between the freeway/arterial facilities. It has been utilized in the evaluation of the TravTek route guidance system (*Van Aerde and Rakha, 1995*) and the Intelligent Transportation Systems (ITS) architecture study.

Prepared by Khattak and Rouphail (*2005*) recently, IMAP is a decision support tool that allows easy planning and operational assessment of existing and potential service patrol sites

in North Carolina. IMAP uses FREEVAL as a traffic simulation tool. FREEVAL replicates the freeway facility methodology in Chapter 22 of the Highway Capacity Manual 2000 (TRB, *2000*). It can model the effects of incidents / work zones on traffic operations macroscopically and also model route diversion effects by shifting diverted demand to alternative route.

VISSIM (PTV, http://www.ptvamerica.com/) is a microscopic, behavior-based multi-purpose traffic simulation program. VISUM is another tool provided by PTV. It is for transportation planning, travel demand modeling and network data management. VISSIM networks can be exported from VISUM. Therefore, after editing large networks in VISUM, then users can export the data to VISSIM for simulation. It is able to assess ATIS options such as VMS effects in network by applying dynamic assignment feature in VISSIM.

2.2.2.3 Driving simulation experiments

Driving simulators represent an attractive alternative to field observation in terms of costs, participant safety, and data collection difficulty. Fox and Boehm-Davis (*1998*) evaluated driver compliance with ATIS advice using a high-fidelity driving simulator. Participants drove through a simulated with network the goal of avoiding congestion. A simulated ATIS made route recommendations. They carried the experiments to test user compliance depending on accuracy of information. Their results show that 40 percent accuracy would not support user trust and compliance, but that 60 percent accuracy probably would. Liu and Mahmassani (*1998*) collected data from laboratory experiments using a dynamic interactive traveler simulator that allows actual commuters to simultaneously interact with each other within a simulated traffic corridor. Given real-time information provided by the system, commuters determine their departure time and route at the origin and select paths en route at various decision nodes along the trip. Also, Bogers et al. (*2005*) used interactive travel simulator to collect data for their model estimation.

HOWLATE (Heuristic On-line Web-Linked Arrival Time Estimation, Jung et al., *2002*) was developed by Mitretek Systems. HOWLATE uses simulated yoked pairs traveling between specified origin and destination (O-D) pairs, one of which has ATIS and one that does not. The simulation extracts traffic data every 5 minutes from an Internet service provider that records link travel times on various roadways. The first step of the simulation is to establish the routes and departure times for the ATIS traveler and the non-ATIS traveler. Once the routes and departure times have been chosen, the second step consists of using the archived data to construct actual travel and arrival times in traffic conditions during the date and time used for simulation. While many yoked-pair studies have drivers depart at the same place and time, HOWLATE focuses on the destination and target arrival time of the yoked pairs. HOWLATE allows conducting controlled experiments based on travel times for different driving trips at different times on different days in the archive. In this simulated environment, we could determine the effectiveness of ATIS for freeway trips across the region by comparing the outcome of an ATIS user who may leave earlier or later or change route in response to real-time traffic information and a "habitual" commuter who maintained the same time of departure and route from day to day. Jung et al. (*2002*), Toppen and Wunderlich (*2003*), Jung et al. (*2003*), and Toppen et al. (*2004*) employed this simulation technique for estimating ATIS effects. Due to high data collection costs, analysts are commonly faced with the problem of limited data in the evaluation of ITS systems. Vasudevan et al. (*2004*) suggested and applied an analog of statistical resampling ("experimental resampling") to generate a large sample of days over.

OTESP (Orlando Transportation Experimental Simulation Program, *Abdel-aty, 2003*) is a powerful interactive computer simulation tool. It creates a simulated roadway environment and presents a human subject with several travel scenarios between trip origin and destination. Abdel-aty (*2003*), and Abdel-aty and Abdalla (*2004*) used OTESP as data collecting tools for route choice modeling purposes under ATIS. A subject has the ability to move the vehicle on different segments of network using the computer's mouse. Different levels of information are provided to the subjects, including transit and route information,

pre-trip and en-route information, and information with and without advice. Different travel congestion levels are also provided. All the travel decisions are captured and coded to a database for analyses.

2.2.3 Survey

Survey is one of the most common methods for ATIS Evaluation. Surveys conducted after installing and operating an ATIS are designed to estimate user satisfaction and the effects of ATIS operation. Appendix A shows benefit evaluation results from other states. Many of the benefit evaluations used survey methods. Various kinds of collecting methods such as telephone, mailing, e-mail, and on-line survey were used. Question selection will depend on the research objectives and the level of compliance desired. Pierce and Lappin (*2002*) investigated the usage of Web, Radio, and TV in Seattle, Washington and users' response to ATIS. They found 3.2% of respondents consulted traveler information: Radio 56%, pre-trip radio 22%, TV news 13%, traffic website 6%, and transit website 6%. Also, their survey results showed 37% of information users changed their travel decisions (1.1% of total trips): changing departure time 13%, making small route change 11%, taking whole different route 9%, postponing or canceling trip 2%, and changing mode 1%. Appendix A includes other survey research and result.

CHAPTER 3. PILOT STUDY

3.1 Tool Selection

Recent ATIS evaluation tools were reviewed in the literature. IDAS is a popular evaluation tool as an ATIS sketch planning tool and has been used in several States. Both DYNASMART-P and DYNAMIT have capabilities to simulate various situations including recurring congestion and non-recurring congestion and evaluate the network effects of various ATIS options under the simulated traffic condition because they contain a dynamic assignment and traffic simulation models. However, DYNAMIT is less applicable than DYNASMART-P because the former uses UNIX system for operation system, while the latter uses the Window operation system. INTEGRATION has been commonly used as an ATIS evaluation tool. Recently driving simulators including HOWLATE and OTESP have been introduced as a substitute method for field operation tests, but these tools are not appropriate because these are designed for specific locations. IMAP tool was developed as an incident management tool in North Carolina State and has potential capabilities as an ATIS evaluation tool. VISSIM is a popular Micro-simulation software but it is able to assess ATIS options in network by applying its own dynamic assignment feature. Accordingly, IDAS, DYNASMART-P, INTEGRATION, IMAP, and VISSIM were considered as ATIS evaluation tools for North Carolina State.

Evaluation criteria were selected in terms of functional requirement in the states of North Carolina. Sixteen main criteria plus sub criteria are shown in Table 3.1 Criteria 1 through 8 assess the aspects of tools' capabilities. Criteria 9 to 11 are about data acquisition use. Criteria 12 to 15 evaluate the "user-friendliness" of the tools. Finally Criterion 16 evaluates the tools' robustness. The grading scale is 0 to 4, with 0: tool does not meet the stated criterion and 4: tool fully meets the criterion.

Total score for each tool is shown in the last row of Table 3.1. All points of each criterion or each sub-criterion were summed up. No weighting factors were given in each criterion but if a criterion has more sub-criteria, it could be interpreted that criteria has larger weighting factor than others.

As shown in Table 3.1, DYNASMART-P received highest grade, and INTEGRATION, IDAS took second and third place respectively. IMAP and VISSIM received two grades, one for current or off-the-shelf capabilities and one for extended capabilities. IMAP received 43 for current capabilities; 80 for extended capabilities through additional programming. VISSIM received 36 for off-the-shelf capabilities; 61 for extended capabilities through API programming.

According to functional requirement evaluation, DYNASMART-P, IDAS, and extended IMAP were deemed appropriate ATIS evaluation tool for North Carolina. DYNASMART-P is considered the best alternative for the ATIS evaluation tool. It has robust ATIS evaluation method and it is also relatively easy to use and transfer input data from other tools. The Project team recognized the potential capability of IMAP. IMAP is currently in use at NCDOT, so program edition and extension are relatively straightforward from the project team prospective. IDAS is equipped with an evaluation module for various ATIS options as a sketch planning tool. However, IDAS has the big limitation of ATIS benefit estimation that the method can not model the traveler's response to ATIS (e.g., route diversion, or departure time shift) under a given condition. IDAS estimates benefits based on simple formula with several assumed values. Thus, the two ATIS evaluation tools, i.e., DYNASMART-P and FREEVAL were suggested by the project technical committee as more appropriate tools for ATIS evaluation in North Carolina.

Table 3.1 Functional Requirements for ATIS Tools

	CRITERIA (0= no value; 4= perfect value)	DISCUSSION	IDAS	DSP*	INTEGRATION	IMAP		VISSIM	
						Existing	Extension	Existing	API
1	Ability to cover broad geographical area	What tool covers: point, facility, corridor or network	4	4	4	2	3	4	4
2	Ability to incorporate multiple travel modes	minimum car pool and transit options	4	3	3	0	1	4	4
3	Ability to incorporate the effects of various ATIS components such as	pre-trip affects departure							
	-pre-trip information	time and mode, in-vehicle	4	4	4	1	2	0	2
	-in vehicle information	affects route choice so does	4	3	0	0	3	0	2
	-en-route information	en-route (CMS)	4	3	0	2	3	0	3
4	Ability to EXPLICITLY model ATIS technologies	some tools just 'emulate' the							
	-Internet, 511, TV/Radio, PDA, Kiosks (pre-trip)	effect of technologies, others	2	2	2	1	3	0	1
	-In Vehicle, 511, Radio, PDA, CMS	may be more explicit	2	3	3	0	3	0	1
	-Other: Parking Management; ETC; Tourist Information System.)		2	0	0	0	2	0	1
5	Ability to model the effect of ATIS under BOTH recurring and non-recurring congestion	ATIS provide max value during incidents, work zones, evacuations, etc.	2	4	3	3	3	0	2

* DSP: DYNASMART-P

Table 3.1 Continued

	CRITERIA (0= no value; 4= perfect value)	DISCUSSION	IDAS	DSP*	INTEGRATION	IMAP		VISSIM	
						Existing	Extension	Existing	API
6	Ability to model various traveler responses to ATIS, including	This criterion looks at the diversity in the travelers' response that the tool can accommodate.							
	-pre-trip route diversion		0	4	3	2	3	0	0
	-pre-trip mode shift		0	0	0	0	1	0	0
	-en-route route diversion		0	3	2	0	3	0	4
	-en-route modal shift		0	1	0	0	1	0	0
	-departure time shift		0	2	0	0	2	0	2
	-destination choice shift		0	1	0	0	2	0	2
	-induced demand		0	0	0	0	2	0	2
	-foregone trip		0	0	0	0	3	0	2
7	Ability to generate benefit-related statistics from ATIS deployment, such as:	These are critical since the benefit would be calculated as the difference in system performance with and without ATIS presence							
	-reduction in network travel time or delays		4	4	4	3	4	4	4
	-reduction in network VMT		0	3	4	0	4	4	4
	-reduction in queue lengths		0	4	4	1	3	4	4
	-revision to modal split, including car-pool		0	0	0	0	1	0	0
	-reduction in crashes		0	0	0	0	2	0	0

* DSP: DYNASMART-P

Table 3.1 Continued

	CRITERIA (0= no value; 4= perfect value)	DISCUSSION	IDAS	DSP*	INTEGRATION	IMAP		VISSIM	
						Existing	Extension	Existing	API
8	Ability to model the impact of market penetration of the technologies to be assessed	E.g., is the tool sensitive if CMS are deployed every 10 vs 50 miles?	3	4	3	4	3	1	2
9	Tool is autonomous or requires interface with other tools?	e.g., IDAS requires interface with TDM output	0	4	2	4	4	4	4
10	Amount and availability of local data to execute the ATIS assessment tool, including the availability of defaults	How 'data-hungry' is the tool, are defaults readily available, how much it will cost to provide local data?	3	3	4	3	3	2	2
11	Ability to transfer input data from other tools and data post-processing requirements	Data management issue	4	4	2	2	2	3	3
12	Availability of tech support, adequate documentation.	Long-term usability of the tool	4	3	2	3	3	2	2
13	Ease of use and training	Data preparation, run time	3	3	2	3	3	2	2
14	Track record on the use of the tool, including	Have there been similar applications	4	3	3	4	3	0	0
15	Previous successful applications to NC for that specific tool?		0	3	2	4	4	0	0
16	Robustness	Traffic flow model, Theoretical base	0	2	2	1	1	2	2
	TOTAL SCORE BY EACH TOOL (MAX= 124 POINTS)		**53**	**77**	**58**	**43**	**80**	**36**	**61**

* DSP: DYNASMART-P

3.2 Recommended ATIS Evaluation Framework

The pilot study developed a recommended framework for conducting ongoing evaluation of ATIS/ITS effectiveness. Figure 3.1 depicts the recommended ATIS evaluation framework. Individual components are classified into three categories, namely inputs, processes, and outputs. Inputs into the ATIS evaluation tool are the physical network context, the travel demand, the ATIS alternatives under consideration, and driver response conditions. The evaluation results in turn provide decision support for ongoing ATIS deployment and enhancement decisions directly. A discussion of the individual components follows.

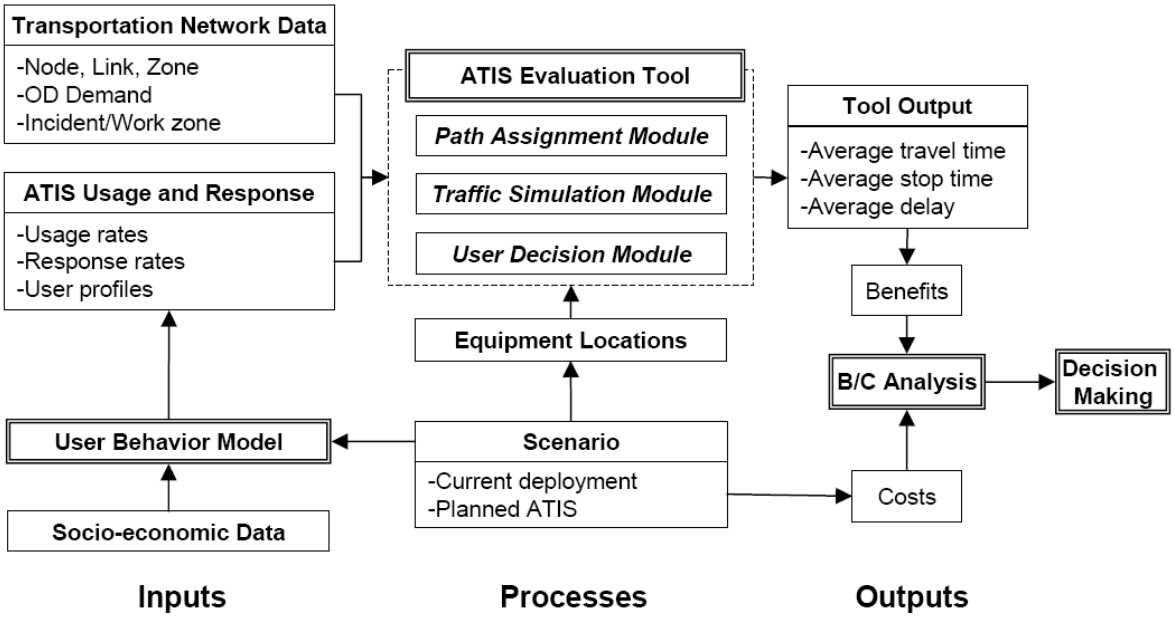


Figure 3.1 ATIS Evaluation Framework

3.2.1 Inputs

Transportation network data - The physical transportation network and its operational characteristics are required data elements. The additional data (on the supply side) should include network impacts for any capacity reduction configurations due to work zone or

incident that may be the subject of evaluation. An accurate representation of the travel demand during the time period or periods to be evaluated also has direct impact to the final quality of the evaluation results.

ATIS usage and responses – Although future research may provide driver response models that can be embedded in integrative evaluation tools, in the current state of the practice, driver response to travel information must be determined and defined separately, requiring assumptions about individuals' behavior. Direct or indirect parameters determine the type and level of driver response for the various ATIS devices and technologies to be evaluated.

ATIS deployment alternatives – Full specification of this element involves the definition of all ATIS deployment alternatives that are being considered both in the case of new deployments where no ATIS components are currently in place or in the case where enhancement of current ATIS systems are being contemplated.

3.2.2 Processes (ATIS evaluation tool)

The evaluation methodology involves modeling of traffic operations under the various scenarios selected for analysis. The ideal ATIS evaluation tool must include robust modules for traffic simulation, user decisions, and path assignment. The pilot study selected DYNASMART-P as the integration tool for an institutional ATIS evaluation framework for several reasons. Above all, DYNASMART-P is a mesoscopic simulation tool which integrates the two classes of tools: network assignment models and traffic simulation models. In particular, mesoscopic traffic simulation models can allow a richer representation of traveler behavior decisions, an explicit description of traffic processes and their time-varying properties, and a more complete representation of the network elements, including signalization and other operational controls. In addition, DYNASMART-P provides rich capabilities for modeling and evaluating problems which have traffic operation and route planning characteristics. In this study, this dynamic assignment system is specifically used to

evaluate traveler information supply strategies such as pre-trip information, real-time en-route information, and varying types of variable message signs (VMS). Other important features in the data preparation stage include the relative ease of incorporating network and origin-destination data from regional travel demand models and dynamic traffic assignment.

3.2.3 Outputs

The primary outputs will be network measures of effectiveness under the various operational scenarios defined for comparative analysis. These measures of effectiveness, such as average travel time and vehicle delay, will provide direct support to ATIS deployment decisions (both new deployments and system enhancements) and can also be incorporated into comparative analyses of benefits and costs.

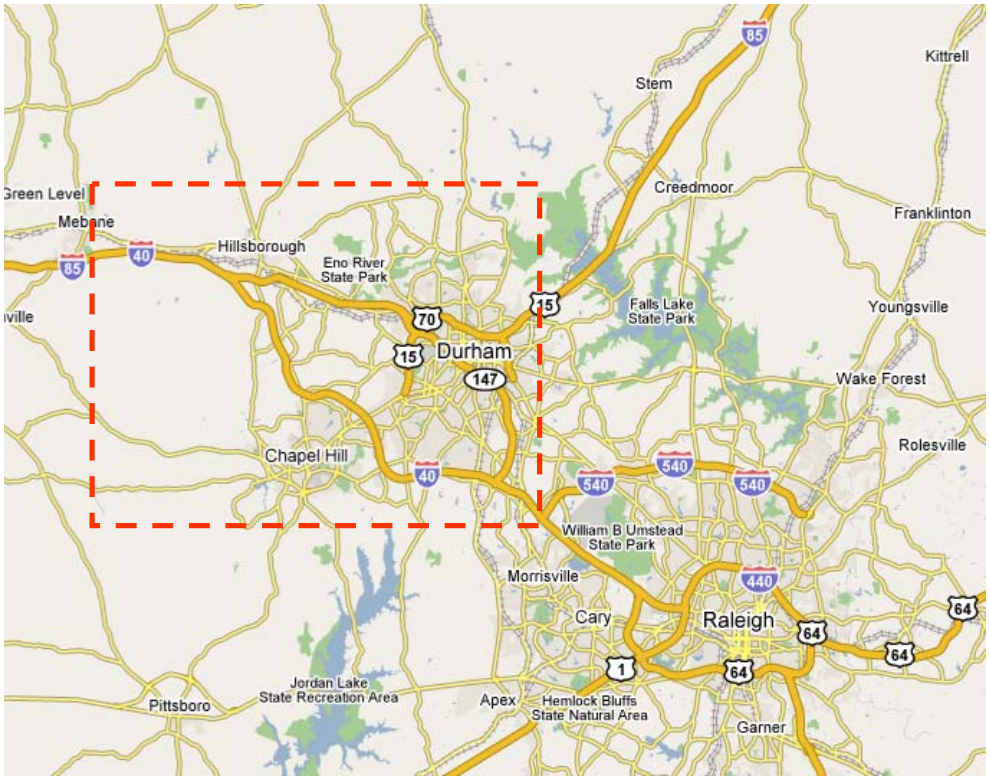
3.3 Case Study Approach with Selected Tool

In an earlier phase of the NCDOT project, the two ATIS evaluation tools, i.e., DYNASMART-P and FREEVAL were suggested by the project technical committee as appropriate tools for ATIS evaluation in North Carolina. By using the two tools, real effects of several ATIS deployments on selected study area were captured. However, in this study, the case study using DYNASMART-P was used for examining the current ATIS evaluation tools. This section explains the scenarios used in these case studies, and the results from the case studies using DYNASMART-P. In the end of this section, findings from the case study and desired improvements are presented.

3.3.1 Network description

Figure 3.2 shows the location of the study area which is highlighted by a dotted rectangle. I-40, I-85, and NC-147 carry heavy through traffic and commuters in the Triangle region. Raleigh, Durham, and Chapel Hill are the major cities in the study area. RTP (Research

Triangle Park) in the study area is a major source of producing large trip demands especially during AM and PM peak hours.



Map Source: Google map (http://maps.google.com)

Figure 3.2 Case Study Area

NCDOT has made extensive efforts to manage traffics in this area. As one of their efforts, they installed CCTVs and speed detectors to collect information and have been providing traveler information by internet, 511, HAR, and VMS. The selected area is an appropriate location for evaluating the effect of ATIS. One of the reasons is that route diversion behavior and the effects of the diversion can be measured explicitly because I-40 and I-85 are the best alternative routes for each other. Another reason is that as NCDOT began re-pavement

works for some segments on I-40 in this area at April, 2007, a validation of estimating ATIS effects on work zone became possible.

Four incidents and two work zones were chosen for the case study. Figure 3.3 shows the locations of the incidents and the work zones in the simplified network of the study area.

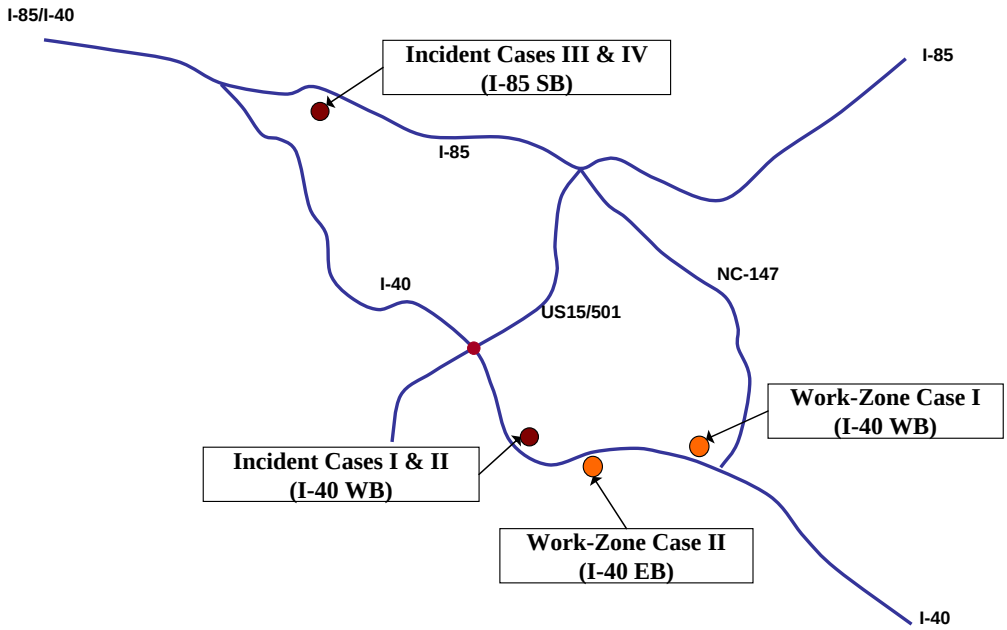


Figure 3.3 Simplified Network (I-40, I-85, and NC-147) and Case Locations

Table 3.2 presents the incident parameters used in the case studies. The incident cases were studied during the morning peak hour (7 AM ~ 8 AM) to simulate the most severe impact of an incident. To understand the sensitivity of different levels of ATIS deployment, incident cases with different severities and durations were modeled. Note that Incident I and II affect traffic headed from the southeast to the northwest. Incident III and IV affect traffic headed from the northwest to southeast.

Table 3.2 Incident Parameters Used in the Case Studies

Case No.	Time	Location	Severity*	Incident Duration
Incident I	AM peak time (7 am-8 am)	WB I-40, East of US-15/501	0.40 (60% capacity remaining)	30 minutes
Incident II			0.75 (25% capacity remaining)	45 minutes
Incident III		EB I-85, West of I-40 split	0.50 (50% capacity remaining)	30 minutes
Incident IV			0.75 (25% capacity remaining)	45 minutes

*Severity means capacity reduction ratio due to an incident. The meanings of the severity levels used in the incident studies are as follows:
Severity 0.40: one of the two lanes is closed, 60% of normal capacity remains
Severity 0.50: one of the two lanes is closed, 50% of normal capacity remains
Severity 0.75: two of the three lanes are closed, 25% of normal capacity remains

The construction work was performed in each direction separately and one lane of the three lanes remained open to traffic. In other words, the work zone section lost 75% of its capacity. Table 3.3 shows work zone parameters used in the work zone case studies. The two work zone cases were assumed to have the same capacity reduction and duration, but opposite in directions on I-40. Because weekdays have heavier traffic than weekend days, we chose weekday constructions to model more severe impacts of a construction work on traffic.

Table 3.3 Work Zone Parameters Used in the Case Studies

Case No.	Effective Time	Location	Severity	Duration
Work Zone I	Weekdays 8 pm-6 am	WB I-40, just E of NC-147	0.75 (25% capacity remaining)	10 hours
Work Zone II		EB I-40, just W of NC-147	0.75 (25% capacity remaining)	

Each of the six cases has five scenarios. One of them is 'no incident or work zone' scenario which doesn't have incident nor work zone in network. Each case has four ATIS level scenarios, i.e., No ATIS (no path change), Existing ATIS, Planned ATIS Alternative I, and Planned ATIS Alternative II.

No ATIS scenario refers to a situation that there is incident / work zone on the study network without ATIS deployment. Although travelers might identify incident-induced queues by themselves and take the diversion route if they were familiar with the regional network, we assumed, in this study, that there was no diversion if there was no ATIS service provided.

For the scenario with existing ATIS service, we modeled the effect of existing ATIS around the service area provided either by the private sector (commercial radios, TV channels, Internet etc.) or by the public sector (SMARTLINK, VMS, HAR, 511 etc.). We used a 10% diversion rate to conservatively represent the effect of existing ATIS service. For scenarios with different planned ATIS alternatives, we assumed 20% and 30% diversion rate for Alternative I and II, respectively.

3.3.2 Network preparation

The TRM (Triangle Regional Model) provides network data such as nodes, links, zones information, and OD demands for building a DYNASMART-P network. Figure 3.4 depicts a TRM network. It has 11,218 nodes, 15,078 Links, and 2,389 zones. TRM has three OD matrices: AM peak 4 hours, PM peak 4 hours, and off peak 16 hours. Each OD matrix is constituted of the demands by three vehicle types, i.e., HOV (High Occupancy Vehicle), SOV (Single Occupancy Vehicle), and CV (Commercial Vehicle).

TRM network is developed using TransCAD. TransCAD network data can be transferred to DYNASMART-P network through DYNASMART-P network preparation steps described in Figure 3.5. Before transferring TRM network data, study network was carved using the sub area analysis feature in TransCAD because our study area is a part of TRM network as shown in Figure 3.4. Then, sub-network data were exported from TransCAD to Microsoft Excel files or text files. A database program such as Excel and a text editor program help to edit these files to make an input file for DynaBuilder which is a tool for transferring GIS network data such as TransCAD data to DYNASMART-P. Using DynaBuilder, we can

generate DYNASMART-P input files. Next, we need to fix some errors and edit input data using DSPEd which is a very useful tool for calibrating DYNASMART-P network.

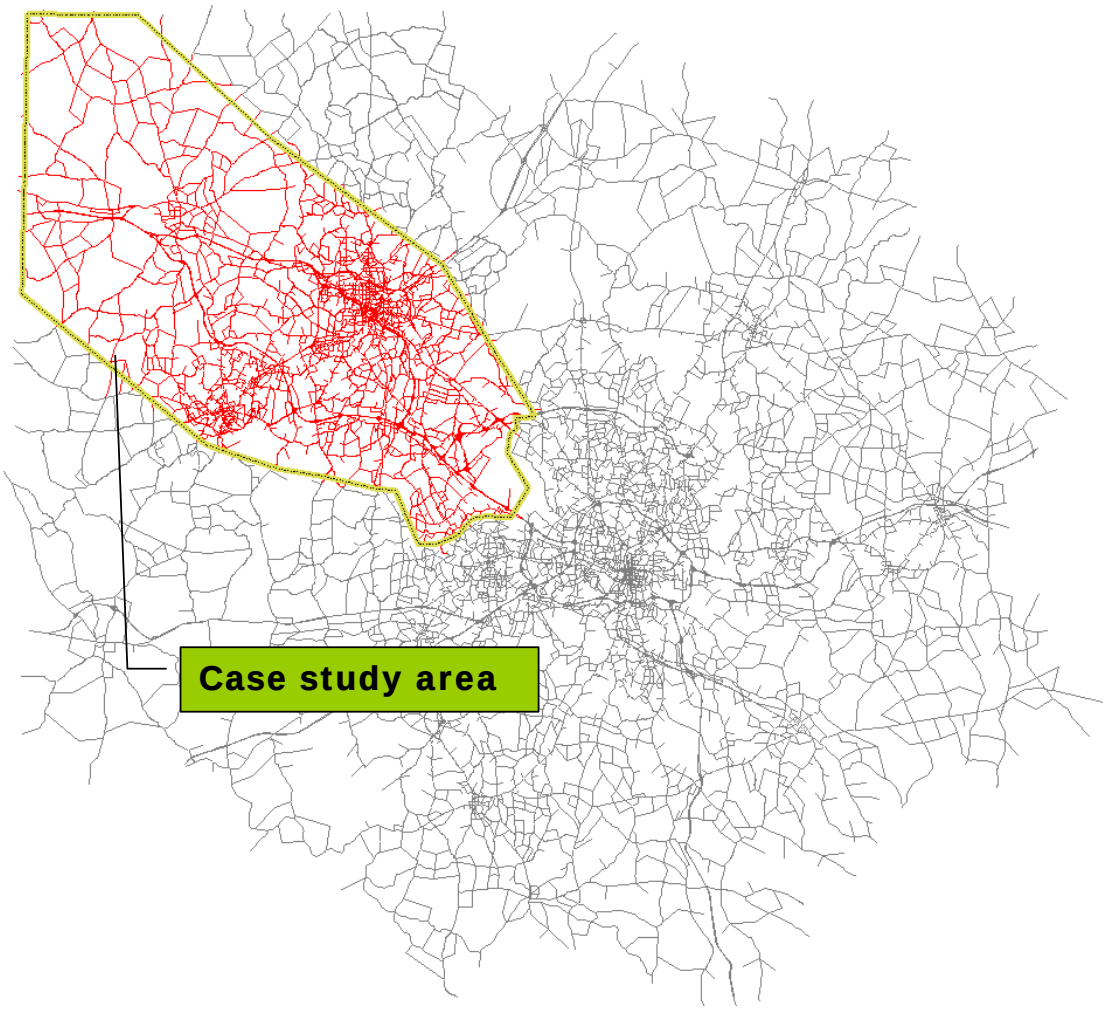


Figure 3.4 TRM Network

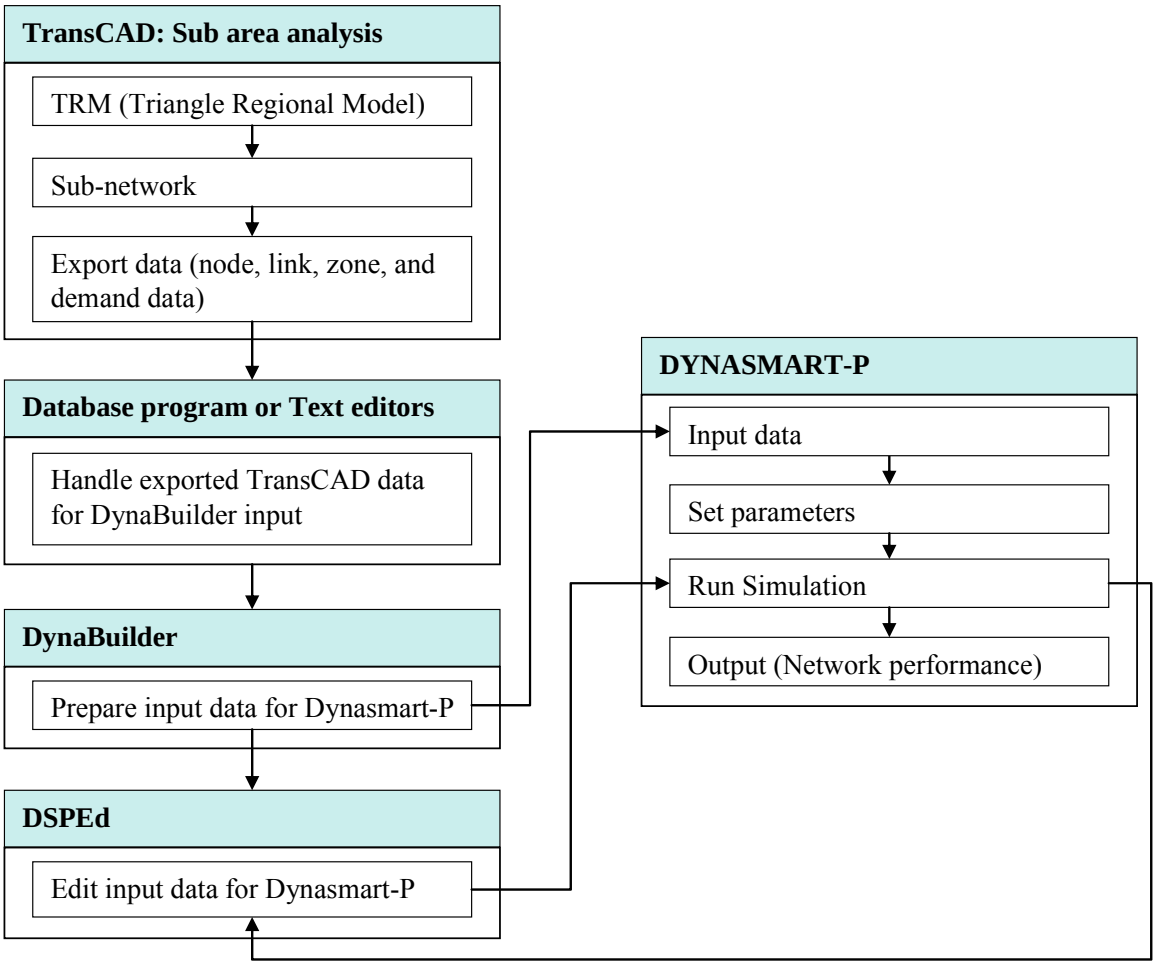


Figure 3.5 DYNASMART-P Network Preparation

Network characteristics

The sub-network consists of 806 zones, 3,985 nodes, and 9,508 links. Figure 3.6 shows this network. Two time periods of demand profile were prepared; AM peak demand for the incident cases and off peak demand for the work zone cases. Two vehicle types of OD matrix were prepared. Passenger Car demand was the sum of HOV and SOV demand and truck demand was identical with CV demand.

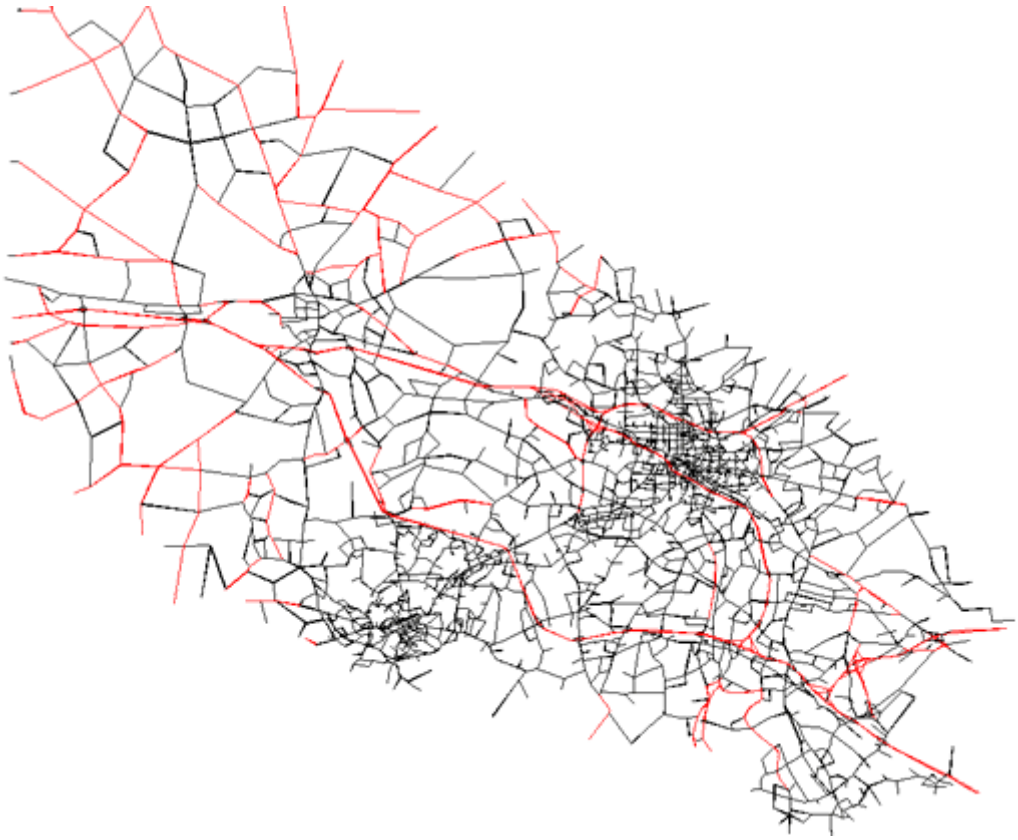


Figure 3.6 DYNASMART-P Network

Among 3,985 nodes, 534 nodes were signalized and 3,451 nodes were unsignalized intersections. The 534 signalized intersections were set as actuated traffic signals. DynaBuilder generated traffic signal plans for all the signalized intersections. We used default values given by DynaBuilder; 100 sec of Maximum green, 10 sec of Minimum green, and 5 sec of Amber. The number of the two link types and the settings for those are as follows:

- 973 Freeway links (posted speed limit >=55)
    - Maximum service flow rate: 2000 pcphpl
    - Saturation flow rate: 2200 vphpl
    - Speed limit 65 (+5) mph

- 8, 535 arterial links (posted speed limit <55)
    - Maximum service flow rate: 2000 vphpl
    - Saturation flow rate: 1800 vphpl
    - Speed limit 45 (+5) mph

The maximum service flow rate was the maximum capacity of a given lane providing the upper limit of the flow rate through a section under any conditions. The saturation flow rate applied to downstream vehicles discharging from a queue. Actual free-flow speeds were assumed base on the posted speed limits; in this study, the free flow speeds of the freeway and arterial links were set to be 70 mph and 50 mph, respectively.
Some geometric configurations were also assumed as follows:

- All links allow u-turn movements
- All links have one left turn bay and no right turn bay, and
- All links have 0% grade.

To increase the capacity of the generation or destination links, we set the number of lanes of the centroid connectors to be nine.

Preparing Origin Destination Demand

The two time periods (AM peak and off peak time) and two vehicle types (passenger car and truck) were considered. Thus, four OD demands matrices were developed:

- AM peak time demand for passenger cars,
- AM peak time demand for trucks,
- Weekday night time (off peak demand) for passenger cars, and
- Weekday night time (off peak demand) for trucks.

The AM peak period demand profile has three OD matrices each of which was made by multiplying hourly distribution factor to the TRM four hours AM peak demand matrix. The Hourly distribute ratios were derived from the traffic count data from the I-85 ATR station A3101.

Table 3.4 and Figure 3.7 explain how the AM peak period demand profile was developed. An incident occurs during the most congested time period, i.e., between 7:00 AM and 8:00 AM. To measure the exact incident and ATIS policy effects, we generated vehicles one hour before the incident times and one hour after incident period ended. The first period generated vehicles for filling the network. The second period had incidents and generated vehicles by the highest demand level among the four periods. The third period generated vehicles for preventing incident effect disappearing due to zero demand. The fourth period did not generate any vehicles. This period was for waiting until all generated vehicle finished their travel.

Table 3.4 Demand Profile for the Incident Cases

Period	Time	Hourly Ratio	Simulation Time	Multiplier	Others
1	6:00~7:00	0.175	0~ 60 min	0.175	For filling network
2	7:00~8:00	0.295	60~120 min	0.295	Incident I (60~90 min) Incident II (60~105 min)
3	8:00~9:00	0.268	120~180 min	0.268	Keep feeling network
4	9:00~	0	180~300 min	0	For clearing network

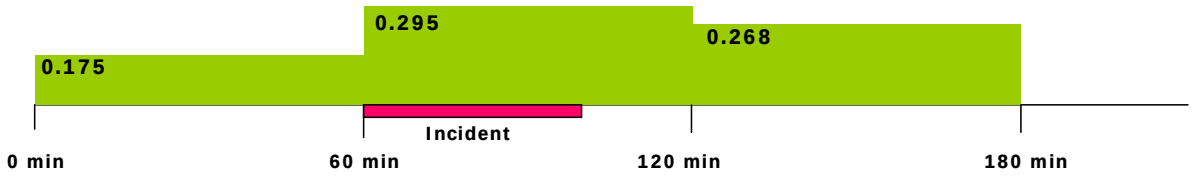


Figure 3.7 Demand Profile for the Incident Cases

The demand profile for the work zone cases was prepared in a similar way as that for the demand profile of the incident case study. Weekday night time demand profile had four OD matrices; each matrix was made by multiplying hourly distribution factor to the TRM 16 hour off peak demand matrix. The hourly volume distributions were derived from traffic count data from the I-85 ATR Station A3101.

Table 3.5 and Figure 3.8 explain how the off peak period demand profile looks like. The construction work was scheduled to be active between 8:00 PM to 6:00 AM. We generated vehicles for one hour before construction work begins, which was the first period. The second, third, and fourth periods were work zone period, which had aggregated demand level for two hours (8:00 pm to 10:00 pm), another two hours (10:00 pm to 12:00 am), and six hours (12:00 am to 6:00 am), respectively. Figure 3.8 shows average hourly demand level. For example, the multiplier of the second period was 0.143 for two hours, which meant that the hourly demand level of this period was 0.0715. In the work zone case, additional vehicle generation periods were not required. Since from midnight on the demand was very low, work zone impacts were not supposed to transfer to the next time period. The fifth period did not generate any vehicles. This period was designed to clear the network.

Table 3.5 Demand Profile for the Work Zone Case

Period	Time	Hourly Ratio	Simulation Time	Multiplier	Others
1	19:00~20:00	0.094	0~ 60 min	0.094	For filling network
2	20:00~21:00	0.077	60~180 min	0.143	Construction (60~660 min)
	21:00~22:00	0.066			
3	22:00~23:00	0.050	180~300 min	0.091	
	23:00~24:00	0.041			
4	00:00~06:00	0.140*	300~660 min	0.140	
5	06:00~	0	660~800 min	0	For clearing network

*: Sum of hourly ratio for six hours = 0.028+0.019+0.018+0.019+0.022+0.034 =0.140

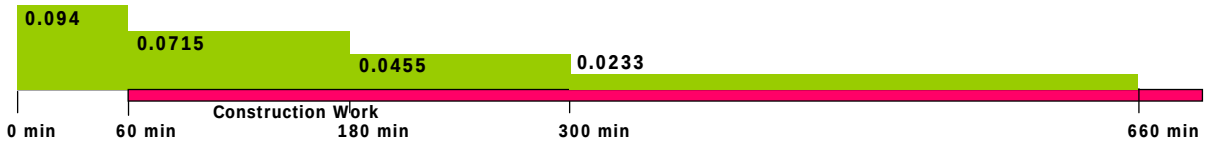


Figure 3.8 Demand Profile for the Work Zone Study

Modeling incident/work zone and ATIS deployments

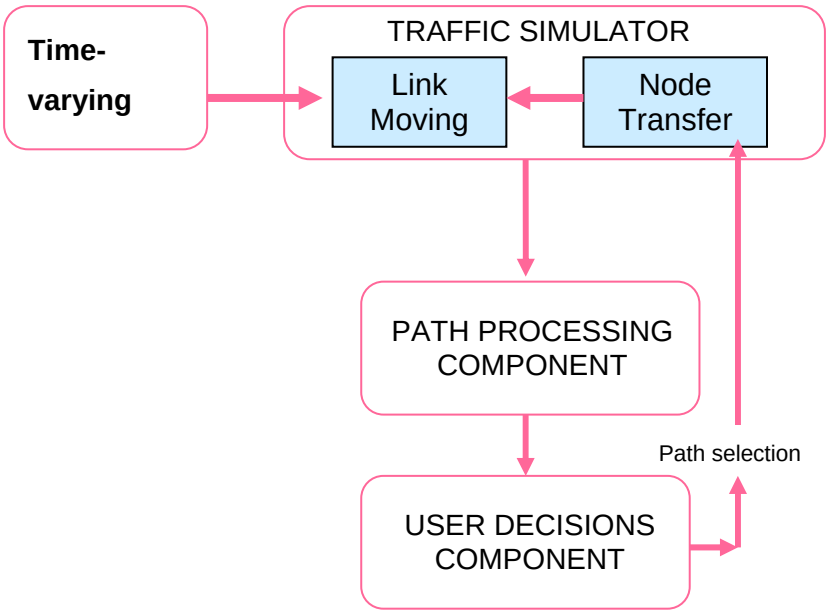
Four incident cases and two work zone cases were designed for this study. Each case had 5 scenarios. The five runs for these scenarios using DYNASMART-P were as follows:

- The first run: no incident/no work zone,
- The second run: incident/work zone without ATIS (no path change),
- The third run: incident/work zone with existing ATIS (max 10% diversion),
- The fourth run: incident/work zone with planned ATIS (max 20% diversion), and
- The fifth run: incident/work zone with planned ATIS (max 30% diversion).

DYNASMART-P integrates two classes of tools: network assignment models and traffic simulation models. Through these two models, DYNASMART-P can be used to model and evaluate the problems which have traffic operation and transportation planning characteristics; ATIS evaluation is good example of the problem.

Figure 3.9 shows the framework of DYNASMART-P. The required input data are time-dependent OD matrices and network data (node, link, zone information). DYNASMART-P consists of traffic simulator, path processing, and user decisions component. Traffic simulator moves individual particles according to robust macroscopic traffic flow relations (mesoscopic). The traffic simulation component has two major modules: link movement and node transfer. Network links are subdivided into smaller sections for simulation purpose. Link movement module calculates inflow, outflow, the vehicle concentration from the solution of the finite difference form of the continuum model, and estimate speed according

to speed-density relationship. Node transfer module performs the link to link transfer of vehicles at node. It determines the number of vehicles that are traversing each intersection in the network at each simulation time step as well as the number of vehicles entering and exiting the network according to the control strategy at the node. It represents traffic processes at signalized junctions, under a variety of operational controls (critical for urban congestion and ITS). Path processing component determines the route-level attributes (e.g. travel time) for use in the user behavior component from the given the link-level attributes obtained from the simulator. A multiple user class K-shortest path algorithm model is used for calculated K different paths for every origin-destination pair. User behavior component models traveler's route-choice decision. It applied micro-simulation of individual trip-maker decisions, particularly route, departure time and mode, including user responses to varying types of information. Iterative algorithms for computation of mutually consistent flow patterns and user decisions, e.g. time-varying user equilibrium where applicable.



Source: DYNASMART-P user's guide

Figure 3.9 Basic Framework of DYNASMART-P Model

Multiple user information classes in DYNASMART-P segment broadly into three groups in ATIS application, i.e., unresponsive user class, enroute information user (IVIS), and VMS user. Unresponsive user class can be divided into the two groups who has pre-trip information or no traveler information depending on whether user use path file or not when they select their travel route. Vehicles that receive real-time en-route information via in-vehicle equipment are allowed to re-route at any intersection. Re-routing is based on the boundedly rational behavior mechanism, namely the fraction of travel time improvement and the time improvement (in minutes) are criteria for route switching decisions. When any of these two criteria is exceeded the threshold, the user will switch routes at the next intersection. There are three types of VMS, i.e., congestion warning VMS, optional detour VMS, and mandatory detour VMS. The traveler's response rule to VMS has defined based on the selected VMS types. Followings are the brief explains about the three VMS types:

- *Congestion Warning VMS* (multiple alternate routes): alerts travelers of potential downstream congestion, allows the user to switch to better (faster) paths, and provides multiple route switching possibilities
- *Optional Detour VMS* (two alternate routes): advises travelers of lane closures, and allows all travelers to either keep their original path (through detoured link) or follow pre-specified detour
- *Mandatory Detour VMS* (single route): advises travelers of lane closures, and mandates all travelers to follow a (user-specified) detour

Figure 3.10 presents how to set these five scenarios in DYNASMART-P. There were two possible options to do traffic assignment. Iterative consistent assignment (equilibrium) might give us better results than those of one-shot simulation assignment. In our case study, however, the network size was too large to run the former option because it required a huge amount of memory. One-shot simulation assignment, therefore, was the recommended option for ITS evaluation by DYANSMART-P. The first run was made assuming the original vehicle path with no incident or work zone. To extract the impacted vehicle analysis

results, however, a very small capacity reduction was input on the locations which were planned for incident/work zone in other runs. In the third, fourth, and fifth run, incidents and work zones were included as shown in Table 3.2 and Table 3.3.

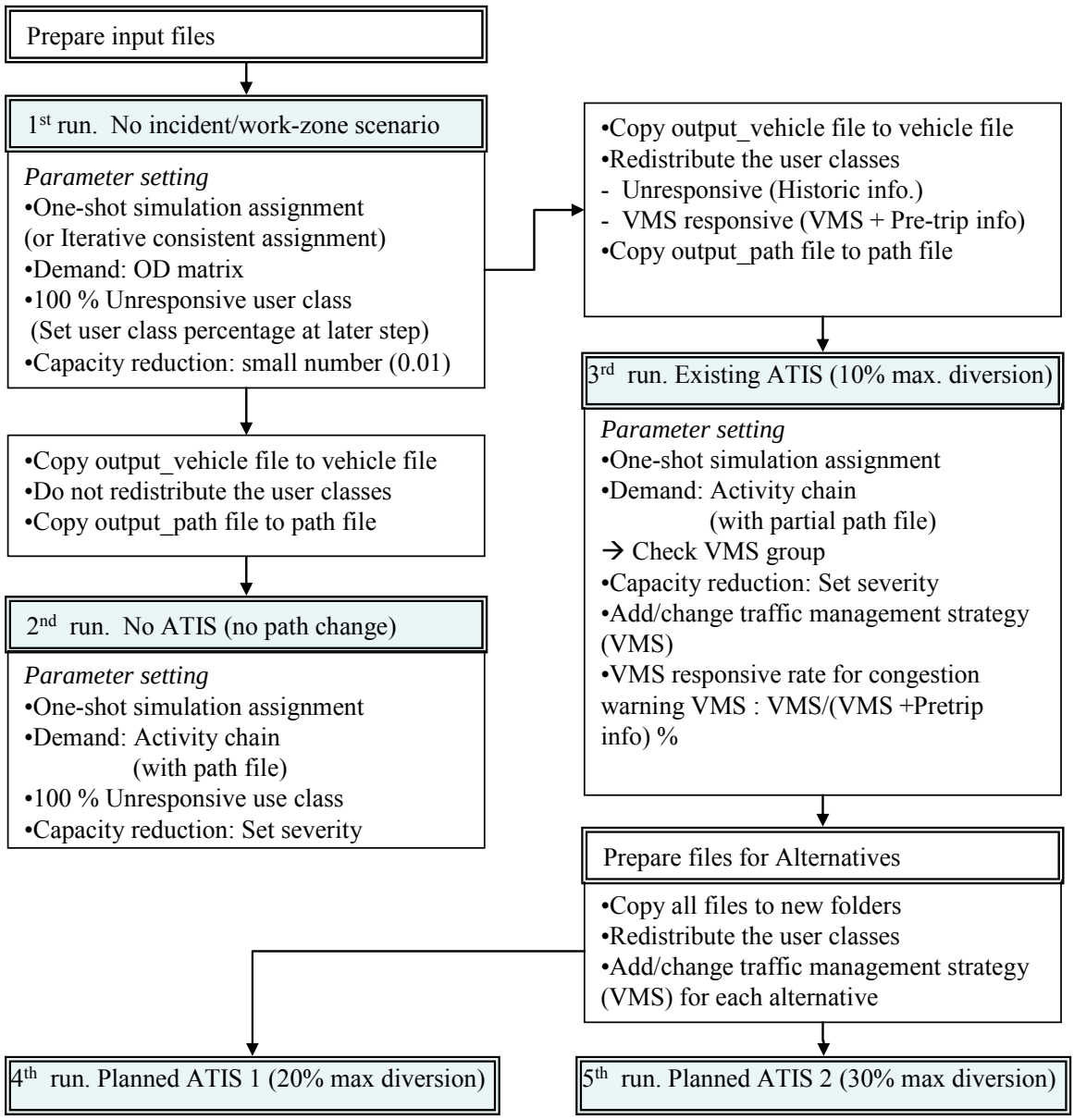
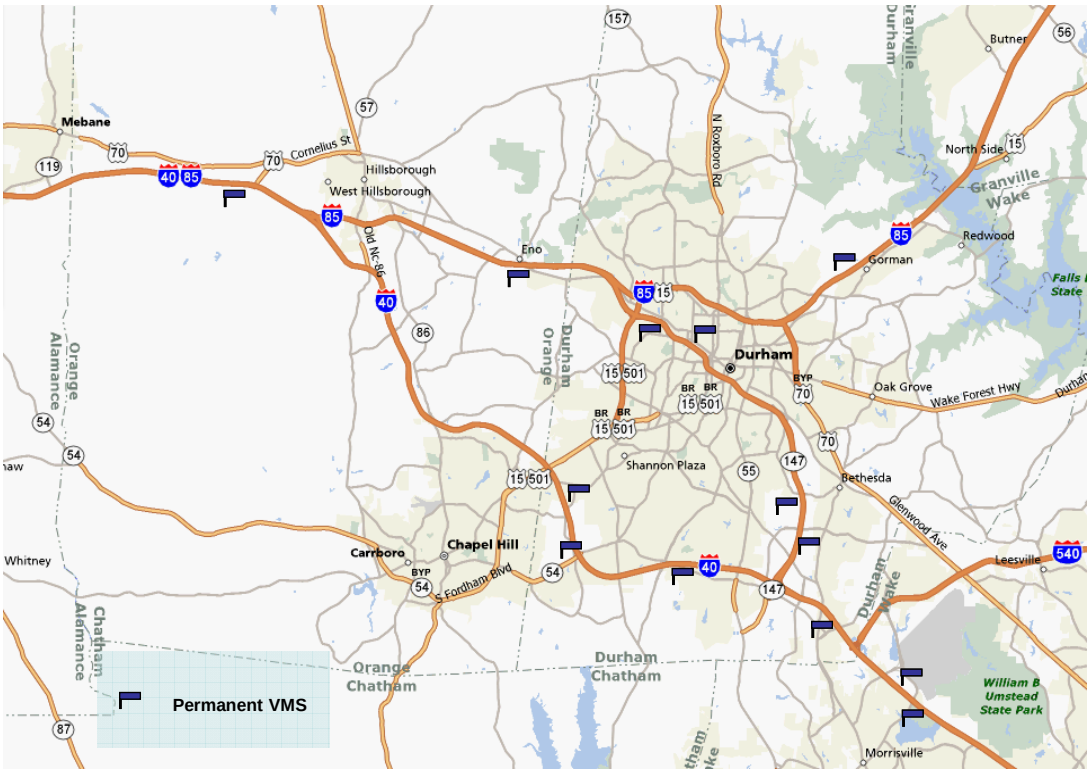


Figure 3.10 DYNASMART-P Simulation Steps

In the first and second run, all of vehicles were classified into an unresponsive user group. This group didn't have ATIS or didn't comply with the information. It was assumed that any vehicle wouldn't change their path in the second run. From the third run, some vehicles were assumed to have ATIS and respond to it. In this study, we used a 10% diversion rate to conservatively represent the effects of the existing ATIS service. We assumed 20% and 30% diversion rates for ATIS alternative I and II, respectively. However, we couldn't handle diversion rates directly in DYNASMART-P. It followed the user's path change rule and route diversion was decided by network condition. We modeled assumed diversion rates by adjusting the combination of information user group and VMS response rate. This diversion rate is not an actual diversion rate but can be considered as the rate of willingness to divert. Existing VMS locations shown in Figure 3.11 were inputted into the DYNAMSART-P network.



Map source: Google map

Figure 3.11 VMSs in Case Study Network

We classified various information sources into two groups; pre-trip information and VMS. We set the percentages of the user groups as 10% (8% pre-trip and 2% VMS), 20% (15% pre-trip and 5% VMS), and 30% (15% pre-trip and 15% VMS) for existing ATIS, planned ATIS I, and planned ATIS II, respectively.

3.3.3 Case study results

The results of DYNASMART-P simulation are reported in three aspects, namely, (a) behavior of the impacted vehicles, (b) overall network, and (c) travel time saving benefits.

First of all, we examined the effects of ATIS on the impacted vehicles generated during statistics collection period. The impacted vehicles were defined as these vehicles that have paths passing through any incident or work zone link. DSPEd has an "impacted vehicle analysis tool" which identifies the impacted vehicles and reports their paths and travel times. The improvements on the impacted links were estimated by comparing the number of the impacted vehicles and their travel times in each scenario. Another major function of the tool is to report the route diversion behavior of the initial impacted vehicles of which the path through the impacted links in the first run. Some of the initial impacted vehicles had traveler information, so parts of them changed their route to a new optimal path. Others who had no information stuck to their original path. So, this function helps the user understand ATIS effects on the initial impacted vehicles' route diversion and travel time saving.

Second, the effects of the several ATIS alternatives on the entire network during the analysis period were compared. The 'Summarystat.dat' file includes simulation statistics which reports statistics for all vehicles generated during statistics collection period. The time period for filling the network was excluded in the statistics collection period. Average travel time, stop time, and average trip distance were chosen as MOEs for evaluating network performance.

Third, the benefits of ATIS were estimated. In this case study, travel time savings were considered among the various benefits of ATIS and calculated using the following equation:

$$\text{Travel time savings} = \mathrm{N} \times \Delta t \times W \qquad \text{(Equation 3.1)}$$

Where,

N: the number of vehicles in network

Δt : travel time reduction per vehicle

W: average hourly wages

The hourly wages of North Carolina was available in the website of U.S. Department of Labor (Bureau of Labor Statistics) of which the web address is 'http://www.bls.gov/'. The most recent available data was selected for the benefit estimation. The followings are examples of the mean hourly earnings of several cities in North Carolina: Raleigh - Durham - Chapel Hill, NC, March 2004: $21.74/hr

The results from all the cases are not shown in this proposal. The results of the revised work zone II case are shown because they represent the most meaningful case. We modified the work zone location to be identical with the location of the real construction work to compare the simulation results using speed data. According to the I-40 construction report given by NCDOT, June 6th was chosen for the work zone scenario. The location and direction of the work at that day were similar to those of Work zone II, but the lane closure section length was about 1 mile from Exit 274 to 275 (EB).

Table 3.6 shows the ATIS effects on the impacted vehicles. A total of 7, 447 vehicles use a path where the planned reconstruction work took place. When there is no capacity reduction, the average travel time of those vehicles is 20.7 minutes. However, when lanes were partly closed and traveler information was not provided, their travel time increased to 71minutes, a 50 minute (or 233%) increase. As ATIS usage increased through the various scenarios, the

diversion rates increased. The modeled diversion rates are less than specified the ATIS usage rate because route diversion is not advantageous throughout the entire simulation period. Furthermore, as drivers began to use alternate routes, the impacted vehicles' travel time on the original route began to reduce dramatically thereby lessening the need for diversion. Since the primary alternative route taken by the diverted is lightly traveled at night, the average travel time for the diverted vehicles is about 24 minutes. The slightly longer length of the detour results in the 4 minute difference from the normal travel time. The non-diverted vehicles' average travel time also decreases as the lower volume reduces the congestion through the work zone, which results in reducing the difference between diverted and non-diverted travel time.

Table 3.6 Impacted Vehicle Analysis Results for the Revised Work Zone II

Scenarios / MOEs	No Work Zone	Work Zone (No Diversion)	Existing ATIS (Pre 8%, VMS2%)	Planned ATIS I (Pre 15%, VMS5%)	Planned ATIS II (Pre 15%, VMS15%)
Number of vehicle					
Total Impacted vehicles	7,447	7,447	7,447	7,447	7,447
Non-diverted vehicles	..	7,447	6,900	6,382	5,979
Diverted vehicles	..	0	547	1,065	1,468
Diversion rate	..	0%	7.3%	14.3%	19.7%
Average Travel Time (min)					
Total Impacted vehicles	20.7	70.96	59.89	47.39	36.36
Non-diverted vehicles	..	70.96	62.71	51.72	39.28
Diverted vehicles	..	..	24.38	24.12	24.44

* Data collection period: 8:00 pm ~6:00 am

The network wide performance is presented in Table 3.7. The simulation results include information for all vehicles generated during statistics collection period, excluding the initialization time period required for filling the network. Average travel time and stop time were selected as the MOEs for evaluating network performance. The impacted vehicles' detour behavior is primary cause of the difference in the network performance. Because the

number of total vehicles in the network is extremely large, the difference in average travel time and stop time is relatively small. However, the network performance measures show that the ATIS alternatives did produce lower average travel and stop times. The values in the parentheses represent the percentage changes in comparison to the No work zone case. As ATIS usage % increase, 14% additional average travel time decreased to 3% and 79% additional average stop time decreased to 16%.

Table 3.7 Network-wide MOEs for the Revised Work Zone II

MOEs \ Scenarios	No Work Zone	Work Zone (No Diversion)	Existing ATIS (Pre 8%, VMS2%)	Planned ATIS I (Pre 15%, VMS5%)	Planned ATIS II (Pre 15%, VMS15%)
Average Travel Time (min)	8.97	10.19 (14%)	9.83 (10%)	9.50 (6%)	9.27 (3%)
Stop time (min)	1.11	1.99 (79%)	1.72 (55%)	1.46 (32%)	1.29 (16%)
Average trip distance (mile)	6.96	6.96	6.96	6.96	6.96

* Data collection period: 8:00 pm ~6:00 am

3.3.4 Initial benefit cost analyses from case study

This benefit cost analysis presented here is intended to illustrate how the simulation results can be used to estimate the value of the ATIS benefits on the one-year resurfacing work. ATIS benefits from other conditions such as recurring congestion or a car accident were not included in the benefit estimation. The benefits of ATIS alternatives were estimated by calculating the travel time savings of the ATIS alternatives in comparison with the No ATIS scenario.

Table 3.8 shows the estimated benefits for one year of the ATIS implementation for the case study area. Because the resurfacing work was a night time construction work in low traffic volume condition, the work rarely affected to the non-impacted vehicles. Therefore, only the travel time savings of the impacted vehicles were included in the estimation of the ATIS benefits. The travel time savings were changed into monetary values using Equation 3.1

Table 3.8 ATIS Benefits of the Revised Work Zone II

Scenarios / Travel time savings	No Work Zone Case	Work zone scenarios			
		No ATIS (No Diversion)	Existing ATIS (Pre 8%, VMS2%)	Planned ATIS I (Pre 15%, VMS5%)	Planned ATIS II (Pre 15%, VMS15%)
Impacted vehicles on network*	7,447	7,447	7,447	7,447	7,447
Average Travel Time (min)	20.70	70.96	59.89	47.39	36.36
Travel time savings per vehicle (min)			11.07	23.57	34.60
Total travel time savings (hour)			1,374	2,925	4,294
Total travel time savings ($)			29,870	63,599	93,361
Total travel time savings per year ($)			4,480,521	9,539,827	14,004,158
Benefit of additional investment per year ($)				5,059,306	9,523,637
Benefit/Cost Ratio				18.0	33.9

Note: 1. Average wage in the study area is $21.74
2. The number of work zone activities is set to 150 days per year.
3. Data collection period is 8:00 pm ~6:00 am
4. Annualized cost is $281,027 (0)
* Out of 454,199 vehicles on the entire network.

For the prototype analysis, one day of the actual I-40 resurfacing work days was modeled. Throughout the reconstruction work, the work location changed day by day. However, the work zone duration, the number of lanes left open, and the approximate lane closure length was consistent. Therefore, it can be assumed that the effect of the one-day case study is representative of the ATIS effects for the entire I-40 resurfacing work days. The re-pavement work was planned as a one year project. The number of construction work days was assumed to be 150 days. The winter season (about 4 months) and the expected rainy days were excluded. In Table 3.8 , the third row from the bottom shows the total benefits for each ATIS alternative. As the next step, the benefits of the alternative investment options were estimated by calculating the increase in the benefits of planned alternatives in comparison to the benefits of the existing ATIS. In Table 3.8, the second row from the bottom shows the total estimated benefit of the additional investment options. The benefit of

Planned ATIS I was about 5 million dollars, and the benefit of Planned ATIS II was about 9.5 million dollars.

Recently, 29 speed detectors, 10 permanent VMSs, and 6 portable VMSs (auxiliary equipment was not considered) were additionally deployed in the Triangle Region. The capital cost was calculated by multiplying the number of unit and the initial investment cost per unit. However, the capital costs were annualized because the investment was not for the one year work zone. There could be benefits of the facility on the recurring and non-recurring congestion during the rest of the facility life cycle. The annualized capital costs were estimated based on the capital costs and the life cycles of the equipments and 5% interest rate. The annual operations and maintenance (O&M) costs were calculated by multiplying the O&M costs per unit by the numbers of units. Total annual costs which are the sum of the annualized capital costs and the annual O&M costs of these equipments were estimated as $281,027 as shown in Table 3.9. For Planned ATIS I and II, the 0.28 million dollars of investment produced 5 or 9.5 million dollars of benefits in one year of the I-40 resurfacing work. The benefit/cost ratios were about 18.0 and 33.9 for Planned ATIS I and II, respectively.

Table 3.9 Costs of Additional Investment for Planned ATIS II

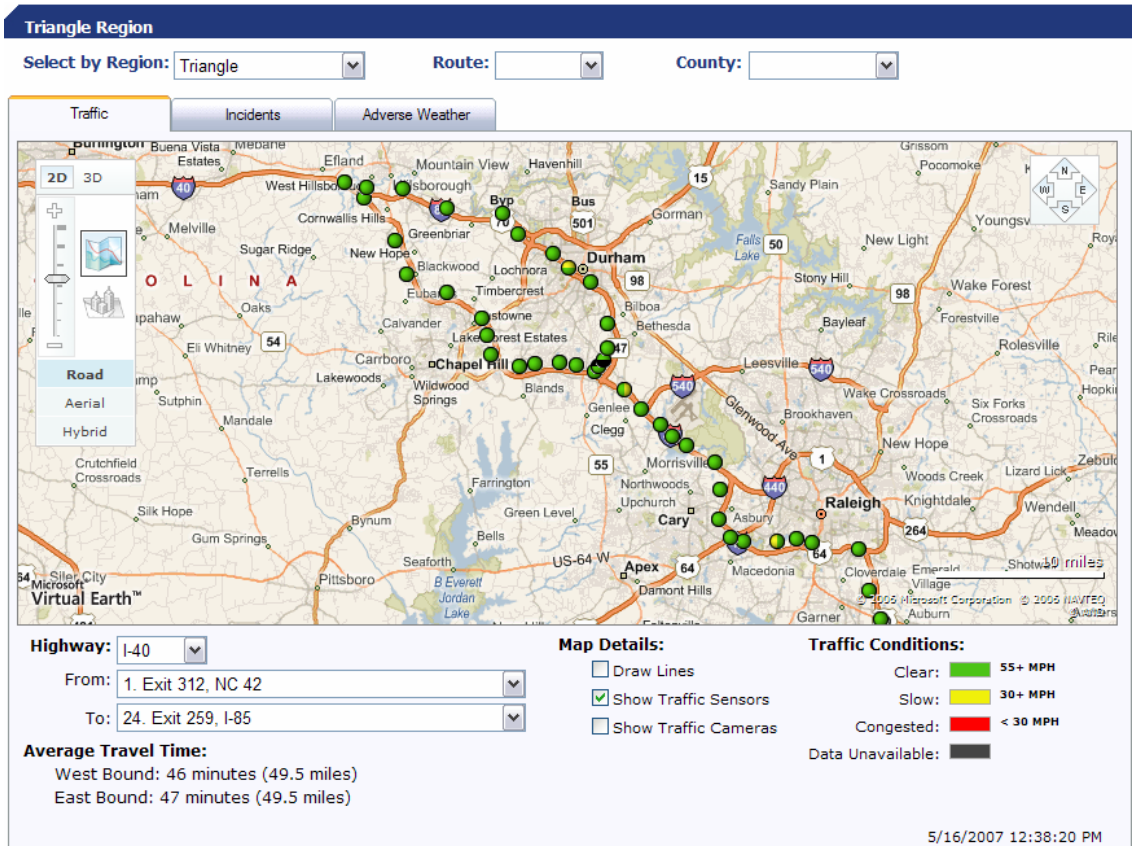
Devices	Number of Units	Initial Investment Cost per Unit ($)	Annual Operation and Management Cost per Unit ($)	Life Cycle (year)	Capital Cost ($)	Annualized Capital Cost ($)	Annual O & M Cost ($)	Total Annual Cost ($)
Speed detector	29	8,500	200	10	246,500	**31,922**	**5,800**	**37,722**
Permanent VMS	10	150,000	5,000	12	1,500,000	**169,200**	**50,000**	**219,200**
Portable VMS	6	25,000	500	9	150,000	**21,105**	**3,000**	**24,105**
Total annual cost								**281,027**

Note: 1. Estimations of initial investment, annual O&M costs are based on NCDOT cost data and cost database from ITS Joint Program Office (http://www.benefitcost.its.dot.gov).

2. Annualized Capital cost = P(A/P, i, n), where, P: first cost of equipment, A: annualized capital cost, i: interest, and n: life cycle of equipment. (A/P, 5%, 10) = 0.13, (A/P, 5%, 12) = 0.11, (A/P, 5%, 9) =0.14

3.3.5 Speed validation

NCDOT Traveler Information Management System (TIMS) provides real time information about travel, incident, and adverse weather through their website. TIMS has been managing and distributing travel information to ten ITS regions (Asheville vicinity, Eastern Mountains, Metrolina, Northern Coastal, Rural Piedmont, Southern Coastal, Triad, Triangle, and Western Mountains). Our case study area is in the Triangle region. Traveler information panel shows traffic condition by speed detector information and video images from CCTVs. Figure 3.12 shows the location of speed detectors in the Triangle region. NCDOT allows us to download the raw speed data which is one minute average speed. Hence, we can compare measured speed from the field and the simulators.



Source: http://apps.dot.state.nc.us/tims/RegionSummary.aspx?re=1

Figure 3.12 NCDOT TIMS Web Service

As mentioned in a previous section, June 6th, 2007 was selected for modeling the revised work zone II case. This day's lane closing direction was eastbound and two of three lanes were closed from mile marker (MM) 274 to 275. To examine the effect of ATIS on the upstream and downstream of the work zone, speed data from MM 270 to MM285 were collected during construction period (June 6th 8:00 PM ~ June 7th 6:00 AM). One minute average speeds for every 15 minute interval were picked out (8:00~8:01 pm, 8:15~8:16 pm, 8:30~8:31 pm,…, 5:30~5:31 am, and 5:45~5:46 am). The link performance export tool in DSPEd was used to extract speed data from the DYNASMART-P results. Because the speeds of the selected links were considered as speeds from the locations where the detectors were installed, links on the same locations where the detectors were installed were selected. Figure 3.13 shows the locations of the speed detectors around the revised work zone case II.

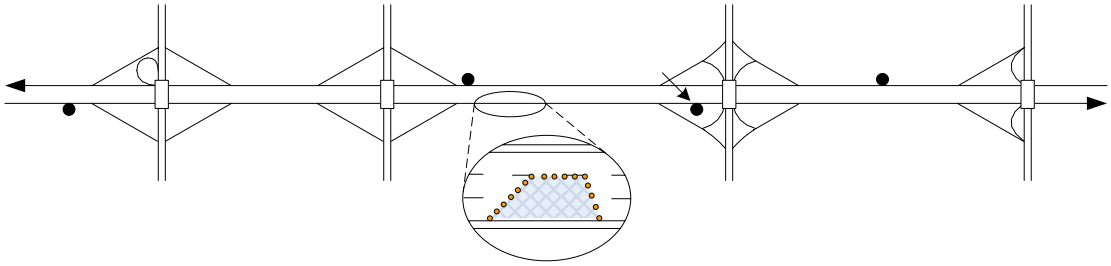


Figure 3.13 The Locations of the Speed Detectors around the Work Zone II

Figure 3.14, Figure 3.15, Figure 3.16, and Figure 3.16 were depicted to compare the field speeds and DYNASMART-P link speeds in the revised Work zone II. The scale of y axis is % of Free Flow Speed (FFS). Most of the field speeds showed some fluctuations. One of the reasons of these fluctuations is that the detector locations were near exit ramps (on or off ramps). Most of detectors in the Triangle area are installed near exit ramps because it is easy to find a post to mount detectors around interchanges.

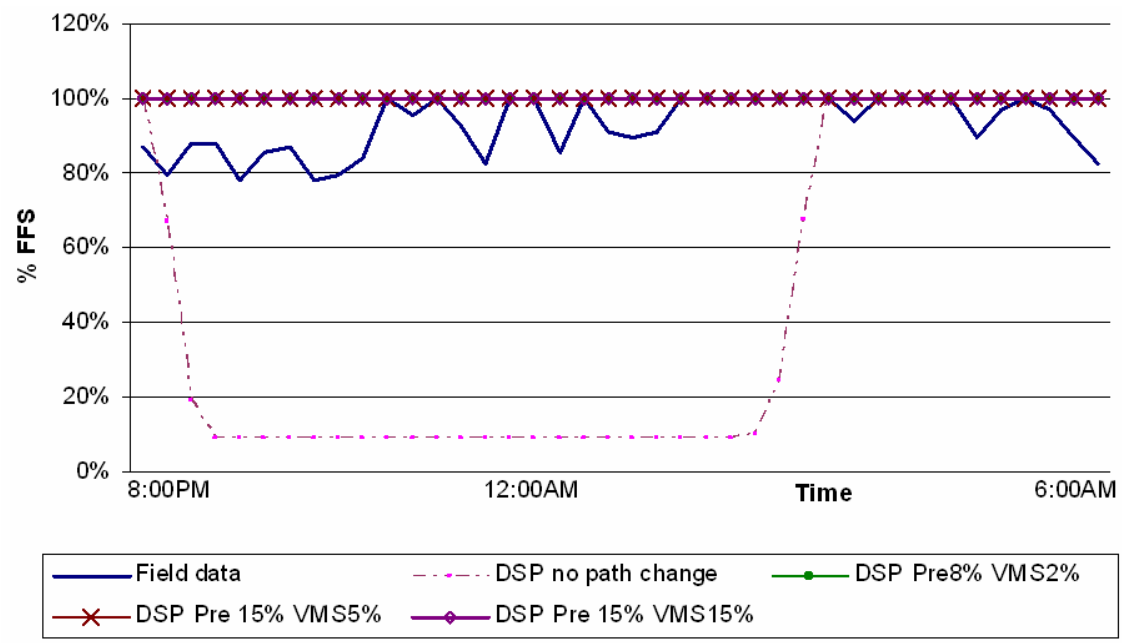


Figure 3.14 Speed Measurements on MM 273 from Field and DYNASMART-P

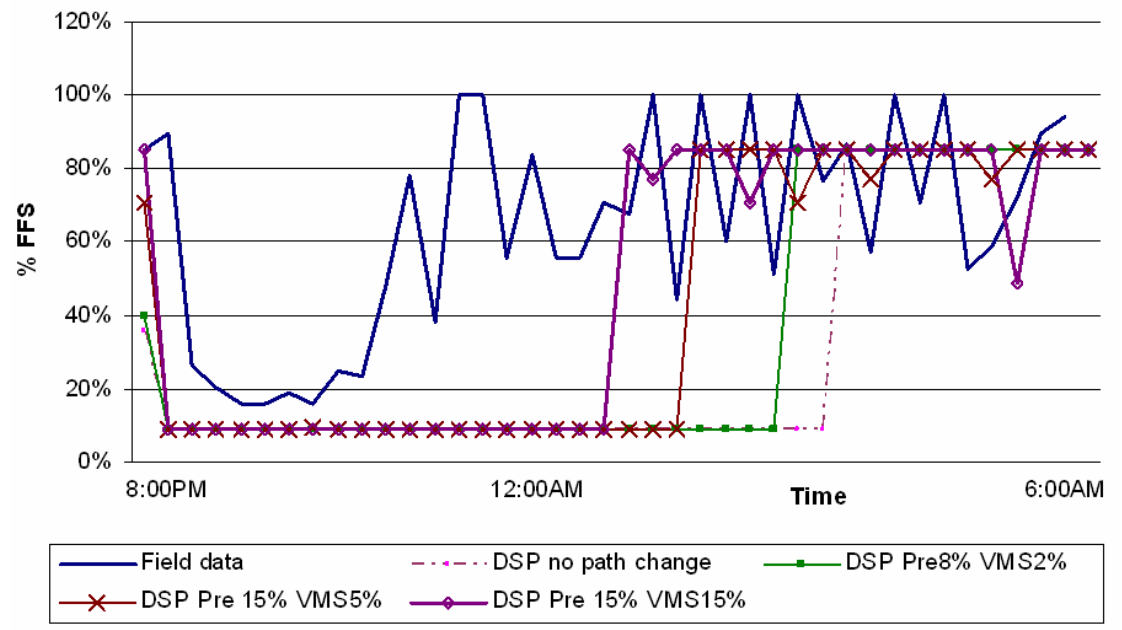


Figure 3.15 Speed Measurements on MM 274 from Field and DYNASMART-P

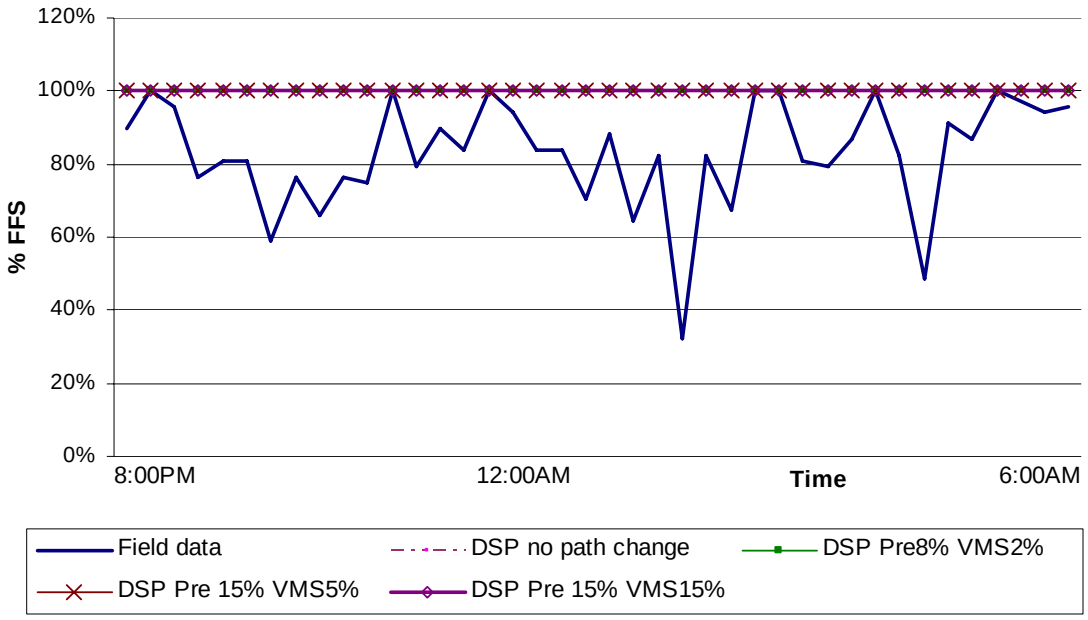


Figure 3.16 Speed Measurements on MM 276 from Field and DYNASMART-P

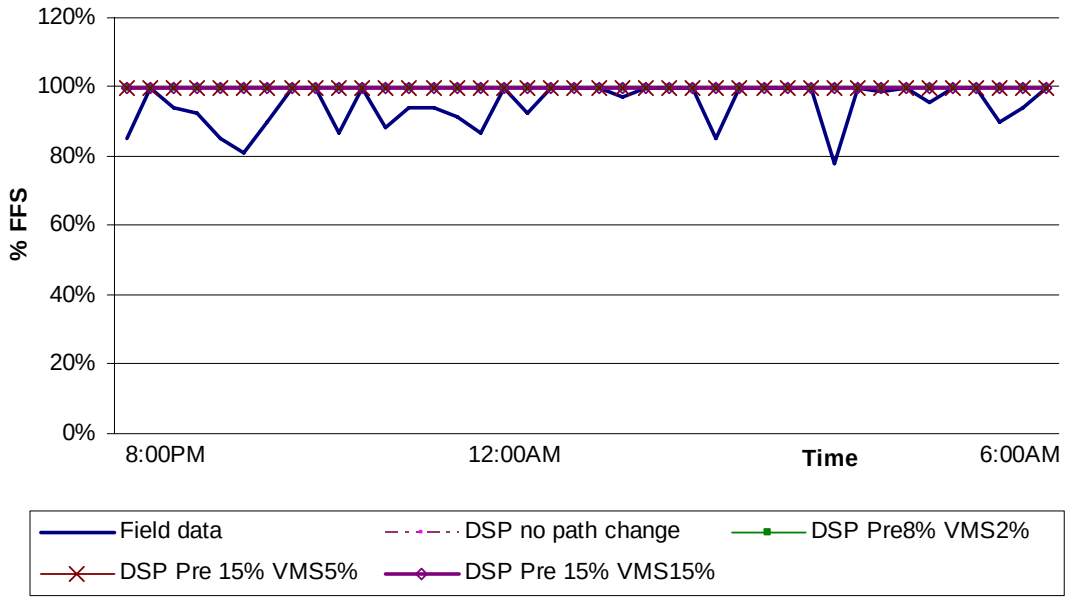


Figure 3.17 Speed Measurements on MM 277 from Field and DYNASMART-P

MM 273 is located upstream of the work zone. 'DYNASMART-P no path change' scenario in Figure 3.13 shows very low speeds during the work time period. It means this upstream link had big congestions and queues. The congestion disappeared at about 3:00 AM. Very low demand helps dissipate the queues. The congestions due to the construction work were not found in DYNASMART-P ATIS scenarios. Field speeds fluctuated near the FFS as expected because ATIS was deployed in the study area at that time. Field speeds could be compared to the results from an ATIS scenario.

The construction work occurred around MM 274. Figure 3.14 shows the speeds on this location. The MM 274 detector was also located on right after the on-ramp. This fact could be a reason for the large speed fluctuation during the time period of lane closure. The speed data showed the congestion due to the lane closure and the time these congestions began to be mitigated. As the percent of information user increased, the speeds were recovered earlier. 15% pre-trip information and 5% VMS scenarios gave the similar results to those from the field data.

Figure 3.15 and 3.16 present the speeds on the downstream of the work zone. The speeds from DYNASMART-P on downstream of the work zone were at free flow speed. Because the bottleneck reduced the throughput, even the speeds of the no path change scenario reached free flow speed. However, the field speeds on MM 276 showed some speed reduction. In fact, the speeds of MM 276 should be less than free flow speed because vehicles needed acceleration time. DYNASMART-P cannot reflect this fact. However, the field speeds on MM 276 showed severe fluctuation. There is a possibility that one of the three lanes was closed in this area to make a temporary taper.

3.4 Discussion

This research investigated ATIS effects on reduced capacity due to a major reconstruction work zone using a DTA-based mesoscopic network modeling tool. Using the operational

results of the case study, a prototype example was presented for the translation of the quantified ATIS benefits to monetary values.

Speed data was acquired for a time period for the I-40 resurfacing work zone during which the extents of the work zone were known. These field speed data were compared with simulation results. Although this did not represent a rigorous validation, it provided further support for the conclusion that DYNASMART-P simulation provided reasonable results and therefore could be applied to predict ATIS benefits.

The case study has several modeling limitations. First, even though TRM provided a valid network data set for the simulation network, those inputs are not sufficient for DYNASMART-P. Since the case study network is quite large, the operational level data such as traffic signal plans, left turn lanes, and grades were assumed. Second, the traffic flow models which are the core of traffic simulations could not be calibrated due to the lack of field traffic data. Third, in developing the time dependent demand profile, hourly volume distribution of just one location having ATR data were used. Finally, linking ATIS investment and the ATIS usage and response rate is not simple, which makes the interpretation of the benefit cost analysis results complicated.

Overall, however, DYNASMART-P performed well in evaluating various levels of ATIS deployment in the work zone case study. DYNASMART-P is an excellent tool to investigate driver's response to ATIS. It could model driver's path change behavior according to their information type and network condition. Also, it provides various outputs to help interpret the simulation results from multiple prospective including network wide performance, selected link's performance, and also impacted vehicle's diversion behavior and travel time savings. In the case study, DYNASMART-P seemed to generate quite reasonable results. Route diversion rate was increased by increase of percentage of ATIS users. Generally ATIS reduced congestion due to incident or work zone.

However, the case study did reveal and suggest several areas for further improvement. It required significant input data. It was not easy to prepare network data, calibrate demand level, and to calibrate traffic flow model. The OD demand matrix should be included or developed. It was difficult to calibrate demand level and observed link volumes. It took a long time to run simulation large network and long simulation duration like our work zone cases (it took about 5 hours for actual 12 hour duration to simulation). Also, it was difficult to get actual information usage rate and response rate in a network. While carrying the case study, several items were revised and added to assist network preparing and calibrating:

- Function for increasing capacity of centroid connectors: To increase the capacity of generation or destination link, it set centroid connectors have 9 lanes.
- Function for demand level calibration: It compares observed link volume and simulated one and calculates MSE and MAE.

In addition, the following two tools were developed with support from an external consultant to extract output and understand the simulation results:

- Export link performance tool: This tool makes analysis work for two major routes and speed measurement a lot easier.
- Impacted vehicle analysis tool: This tool help us to investigate the route diversion behaviors of impacted vehicle and travel time savings of the impacted vehicles under ATIS.

Specifically, this study focused on the following concerns:

- Developing a realistic model of link-based queue and shock wave propagation that can be efficiently implemented in a mesoscopic model,
- Understanding and modeling the relationships between drivers' socio-economic characteristics and ATIS usage and user responses to ATIS, and

- Developing a realistic model of driver response to visual recognition of downstream congestion, that is, even without accessing en-route or VMS information provided by GPS or TMC, drivers would be expected to change routes after detecting the tail of a queue.

The enhancements of these three topics are explained in Chapters 4, 5, and 6, respectively. Each chapter describes the problem definition, a proposed method, and the implementation method and results in detail.

CHAPTER 4. ENHANCEMENT A: QUEUE PROPAGATION ALGORITHM IN DYNASMART-P

DYNASMART-P has been used in several applications related to ATIS and ATMS and is considered to produce reasonable results for overall network evaluation. However, it was also found that the traffic simulator in DYNASMART-P did not realistically reflect queue propagation in a freeway bottleneck congestion area in the pilot study described in Chapter 3. Because the effectiveness of ATIS is usually investigated under non-recurring congestion (e.g., temporary bottlenecks caused by incidents or construction), it is important to improve the original queue propagation methodology to achieve a more accurate evaluation. This chapter provides background on related software, a review of the original network traffic simulation model of DYNASMART-P regarding queue propagation, the proposed enhancement methodology, and an implementation test of that enhancement.

4.1 Background

Macroparticle Simulation Model (MPSM) (*Chang et al., 1985*) is the predecessor of DYNASMART-P. MPSM is a macroscopic traffic simulation model which uses pre-specified traffic flow relationships to simulate the vehicle movements. It shared the common assumptions of macroscopic traffic simulation models in that: (a) time is divided into small, equal intervals (Δt), (b) the highway facility is divided into sections (Δl), and (c) traffic demand and system performance are effectively constant over a given time interval. However, unlike most macroscopic simulation programs, the traffic flow was not modeled as a compressible fluid, but is viewed as a collection of vehicle groups or bunches, termed macroparticle (5 to 20 vehicles).

MPSM further uses speed-concentration equations, rather than the flow relation ($q = kv$). Each section speed is specified by a speed-concentration equation. Vehicles (macroparticles)

in a section move in accordance with the mean section speed. Then the concentration (density) of each section can be updated at every time step by tracing the actual physical positions of the macroparticles.

The initial concept of the traffic simulator in DYNASMART-P was documented by Mahmassani and Peeta (*1993*), building on the MPSM model. A significant difference between the two simulation programs is that the simulator of DYNASMART-P tracks the movements of individual vehicles in a network and vehicle queues in links. Another difference is that links in DYNASMART-P do not have to be divided into smaller segments. Thus, DYNASMART-P models individual vehicle movements in a network based on the macroscopic traffic flow relationships. This level of simulation is called as mesoscopic traffic simulation. Even though a mesoscopic traffic model can track individual vehicle movements, it does not require an inordinate computation power as microscopic traffic simulators do, because the underlying traffic stream models are less complex than the car-following and lane-changing algorithms used in microscopic traffic simulation. Therefore, mesoscopic traffic simulators are considered to be appropriate for application in the Dynamic Traffic Assignment (DTA) tool. However, the author found that the traffic simulator of DYNASMART-P does not realistically model queue propagation in a freeway bottleneck section and performs particularly poorly with long links in this study.

Several previous attempts have been made to solve this problem in DYNASMART-P. Jayaskrisnan et al. (*1994)* suggested a method of dividing a link into smaller segments, while Zilliaskopoulous and Lee (*1997*) tried to use the cell transmission model. However, both of these approaches greatly increased the calculation and memory requirements. Chiu and Zhou (*2006*) discussed the lack of anisotropic property in a long link and proposed Anisotropic Mesoscopic Traffic Simulation (AMTS) model. In this model, a vehicle's prevailing speed is determined by using a macroscopic v-k relationship based on the density in the Speed Influencing Region (SIR). As another effort to improve DYNASMART-P, this study

proposed a method for modeling more realistic queue propagation and dissipation based on the Kinematic Wave theory suggested by Lighthill and Whitham (*1955*).

4.2 Queue Propagation Algorithm in DYNASMART-P

DYNASMART-P models individual vehicle movements in a network based on macroscopic traffic flow relationships. The following procedures and equations explain the original traffic simulation algorithm of DYNASMART-P. Variable notation is provided after Equation 4.7.

Step 1: Update link density.

$$k_{i,t+1} = NV_{i,t+1} / (l_i \times nol_i) \qquad \text{(Equation 4.1)}$$

Step 2: Calculate link speed according to the traffic flow model in DYNASMART-P. The Modified Greenshields model is applied to represent the speed-density relationship.

if $k_i < k_b$, $v_{i,t+1} = v_f$

else, $v_{i,t+1} = (v_I - v_0)(1 - k_{i,t+1}/k_j)^{\alpha} + v_0$ (Equation 4.2)

Step 3: Estimate the vehicle location based on the current link speed.

$$d_{m,t+1} = \Delta t \times v_{i,t+1} \qquad \text{(Equation 4.3)}$$

if $R_{i,m,t} \geq d_{m,t+1}$,

then $R_{i,m,t+1} = R_{i,m,t} - d_{m,t+1}$ (Equation 4.4)

else, add the vehicle in the queue list for the link.

Step 4: Calculate the transfer flow from Section *i* to Section *i*+1.

$$q_{i,t+1} = Min\,[VQ_{i,t}, \{k_j \times l_i \times nol_i - (NV_{i,t} - VO_{i,t})\}, k_j \times l_i \times nol_i) \qquad \text{(Equation 4.5)}$$

Step 5: Update the individual vehicles' location and queue list.

If the order of the vehicles in the queue list is less than or equal to $q_{i,t+1}$, then

$$R'_{i+1,m,t+1} = [\Delta t - \{R_{i,m,t} / v_{i,t+1}\}] \times v_{i+1,t+1} \qquad \text{(Equation 4.6)}$$

However, if the order of the vehicles in the queue list is greater than $q_{i,t+1}$, then update the queue list.

$$R_{i,m,t+1} = 0 \qquad \text{(Equation 4.7)}$$

where,

$k_{i,t}$ = mean density in section i during the tth time step

$NV_{i,t}$ = number of vehicles on link i during the tth time step

l_i = length of ith link

nol_i = number of lanes of link i

$v_{i,t}$ = mean speed in section i during the tth time step

v_f = free flow speed

v_I = speed intercept

v_o = minimum speed

k_b = density breakpoint (density at capacity)

k_j = jam density

α = a parameter used to capture the sensitivity of speed to the density

$d_{m,t}$ = distance of the vehicle can advance during the tth time step

Δt = simulation time interval

$R_{i,m,t}$ = distance from vehicle's current position to the beginning of the next (downstream) link

$q_{i,t}$ = transfer flow from section i to section i+1 during time step t

$VQ_{i,t}$ = number of vehicles in the queue list of link i during time step t

$VO_{i,t}$ = number of vehicles exit link i during time step t

Each link speed is specified by a speed-concentration equation based on the identified density from Step 1. Equation 4.2 in Step 2 shows the speed-density relationship which is currently used in DYNASMART-P. In Step 3, the vehicle location is estimated based on the link speed. In Step 4, the number of vehicles that should be transferred to the next link is

investigated. In Step 5, vehicles move in accordance with the link speed. Then the density of each link can be updated at every time step by tracing the actual physical positions of the vehicles in Step 1.

The traffic simulator in DYNASMART-P tracks vehicle queues in links using the queue lists as shown in Step 5 above. Equation 4.5, the vehicle transfer algorithm, handles queues in a link. The algorithm decides how many vehicles should shift to the next link. There are two constraints for the transfer flow - forward gated flow and backward gated flow. These describe the number of vehicles arriving at the end of a link (or stop line) and the space capacity of the downstream link, respectively. If a vehicle arriving at the end of a link cannot transfer to the next link due to the lack of the downstream link space capacity, it contributes to the link queue. Since queued vehicles don't have space to occupy in the link, the queued vehicles are stacked vertically on the downstream end (or stop line) of the link by the algorithm (*Vickery, 1969*). Vickery's original model assumed that a queue does not take any physical space. Therefore, the vertical queue model never predicts a queue spill-back situation in which a queue propagates across the link entrance and thereby blocks the intersection. In DYNASMART-P, queue propagation can be modeled using the downstream link space capacity constraint.

The original DYNASMART-P model assumes that any queue on a link is at the jam density level. Even though the traffic flow model in DYNASMART-P captures the propagation of queues across links, queue spill back in the simulation could be different from those in real traffic, since the queue density assumption is inconsistent with both theoretical and empirical evidence. While queues at a signalized intersection link are considered to be at jam density levels, queues in a freeway bottleneck can have a range of densities, depending on the severity of the congestion.

Another deficiency in Equation 4.5 regarding the transfer flow is that it does not have a flow rate capacity constraint, and the simulation results therefore produce unreliable results when

the downstream link has a lower capacity. Figure 4.1 depicts a simple network constructed for checking the queue propagation phenomenon in DYNASMART-P. The link between Nodes 2 and 3 represents a bottleneck segment in a four-lane freeway section. The capacity of the freeway is assumed to be 2,200 vphpl. Figure 4.2 shows the traffic volume on the upstream link between Nodes 1 and 2, based on the simulation results. It is apparent that the flow rate is greater than the bottleneck link capacity (4,400 vph) for the first 25 minutes of the simulation, which is not theoretically feasible.

In addition, if the downstream link is very long, the congestion in the downstream link affects the upstream link at a very slow rate. The second term of Equation 4.5 is used for building backward propagation in a cell-based traffic simulation model such as the Cell Transmission Model (Daganzo, 1994). However, since the term has higher value than the other terms for a long link, it becomes a nominal term. In other words, even though the downstream link is congested and has a standing queue, most of vehicles in the queue list of the upstream link can still transfer to the next (downstream) link until the queued vehicles fully occupy the downstream link.

Figure 4.3 shows the percent queue length on the bottleneck link. The bottleneck link becomes fully congested at about 25 minutes. As shown in Figure 4.2, the traffic demand from the upstream link is transferable into the bottleneck link until this time. Thus, the bottleneck link itself has a queue, as depicted in Figure 4.3. The queue start point is Node 3 in this algorithm. Based on traffic flow theory, however, the queue should begin at Node 2 if the link between Nodes 3 and 4 has no extra capacity reduction (*Lighthill and Whitham, 1955*).

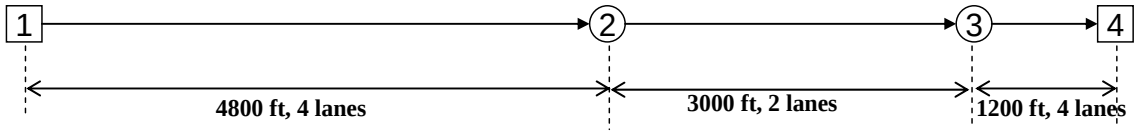


Figure 4.1 A Simple Network for Testing the Queue Propagation in DYNASMART-P

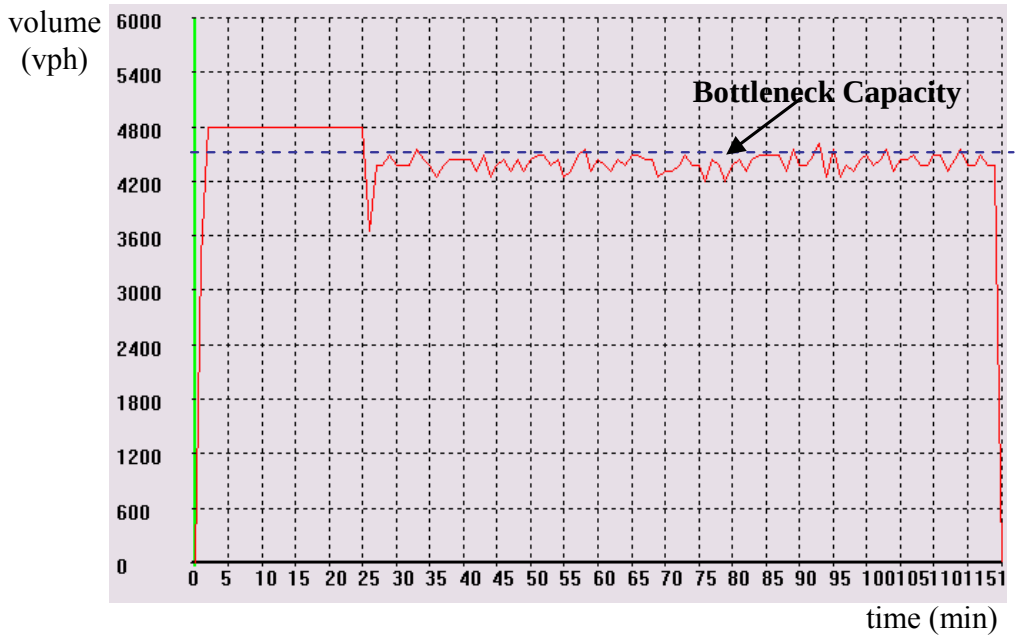


Figure 4.2 Volume on Upstream Link

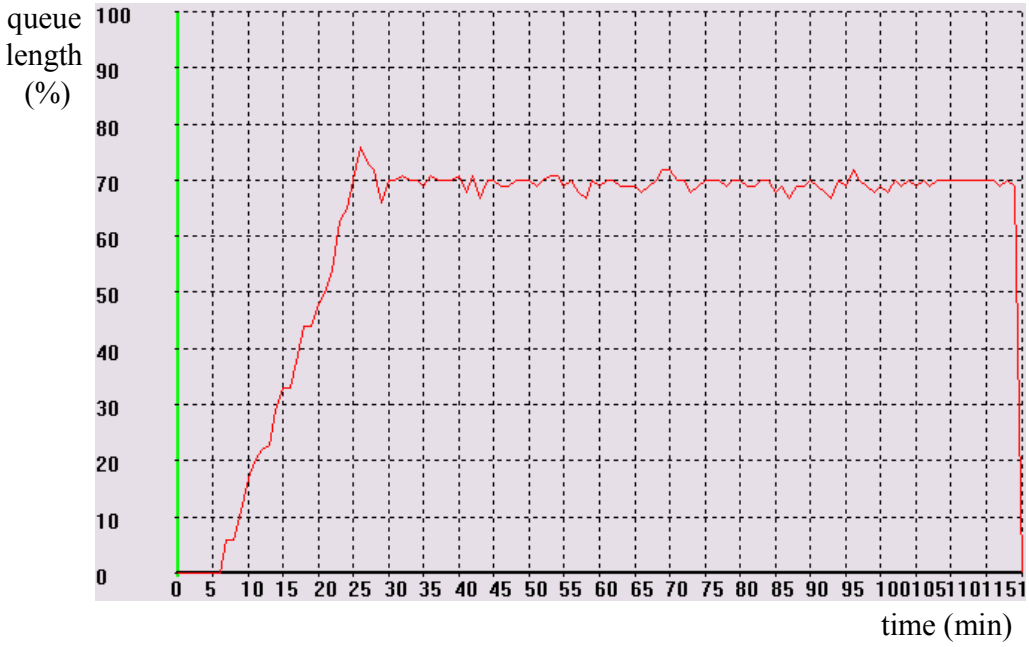
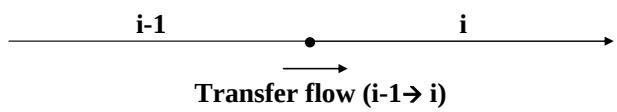


Figure 4.3 Percent Queue Length on Bottleneck Link

4.3 Proposed Queue Propagation Algorithm

The original queue propagation logic produced reasonable results in the MPSM which is the predecessor to DYNASMART-P. This model requires network links to be divided into smaller segments, where segment length is calculated according to the size of the simulation time interval and vehicle speeds. Thus, the downstream link space capacity term is comparable to the flow rate and can be used as backward gated flow constraint in the MPSM. However, the downstream link space capacity is not an appropriate constraint to serve as the backward gated flow constraint in the original link-based model since it depends only on the link length and could take on a higher value relative to the forward gated flow constraint. This is one of the main reasons why the original model produces the three unreasonable queue propagation results discussed earlier.

Figure 4.4 depicts the proposed improvement to the vehicle transfer algorithm using two additional flow constraints. The first is a transfer flow capacity constraint. The other constraint is a new backward gated flow constraint to limit transfer flow rate when the downstream link is in the over-saturation regime.



Transfer flow (i-1→ i, t) = Min {Demand (i-1→ i, t-1), Space capacity constraint (i,t-1)}

If density (i,t-1) ≤ density breakpoint (i)
Transfer flow (i-1→ i, t) = Min {Demand (i-1→ i, t-1), Space capacity constraint (i,t-1),
Transfer flow capacity (i-1→ i, t**)**}

If density (i,t-1) > density breakpoint (i)
Transfer flow (i-1→ i, t) = Min {Demand (i-1→ i, t-1), Space capacity constraint (i,t-1),
Transfer flow capacity (i-1→ i, t**)**,
Backward gated flow (i, t-1)}

Figure 4.4 Transfer Flow Algorithm Enhancement

Transfer flow capacity

The transfer flow capacity was included in Equation 4.5. In the case that the flow rate capacity of the current link is different than that of the downstream or upstream link, this constraint is essential. The equation for this constraint can be expressed as follows:

Transfer flow capacity (i-1→i, t)

= Min {flow rate capacity (i-1, t), flow rate capacity (i, t)} (Equation 4.8)

Backward gated flow

In cell-based macroscopic simulations, the space capacity constraint, $k_j \times l_i \times nol_i - (NV_{i,t} - VO_{i,t})$ in Equation 4.5 has a major role in building backward queue propagation. However, in link-based mesoscopic simulations, this term is not effective, especially when the link length is long. The proposed new backward gated flow rate was estimated from the simplified flow density curve for the oversaturated region. The software tool FREEVAL (based on Chapter 22 in Highway Capacity Manual, *2000*) uses a similar way to simulate oversaturated traffic on freeway facilities. Figure 4.5 depicts a flow-density curve and a simplified curve of the oversaturated region. If the density of the next link i is in the oversaturated flow region, the flow rate (transfer flow) $Q_{i,t}$ is calculated by Equation 4.9.

$$\begin{aligned} Q_{i,t} &= Q_{\max}(k_j - k_{i,t-1})/(k_j - k_c) \\ &= \{Q_{\max}/(k_j - k_c)\}(k_j - k_{i,t-1}) \\ &= w(k_j - k_{i,t-1}) \end{aligned}$$ (Equation 4.9)

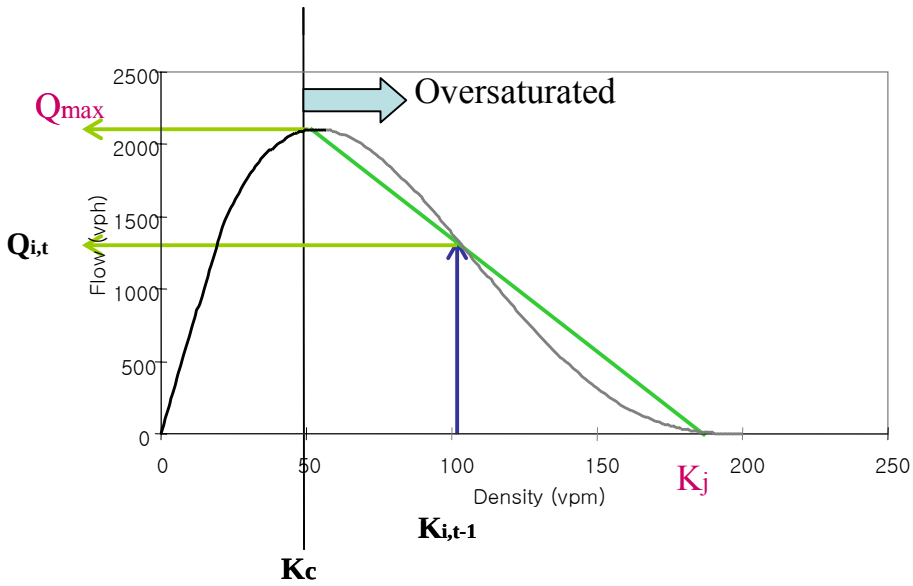


Figure 4.5 Flow-Density Curves

Examination of the proposed model

Transfer flow rates can differ as a function of the geometry and traffic conditions on the downstream and upstream links. The proposed enhanced model was applied to eight possible cases classified by the geometry and traffic condition factors as shown in Table 4.1. Figure 4.6 through Figure 4.13 depict the flow-density curves for each case to examine whether the transfer flow rates based on the proposed model are theoretically valid. $Q_{i,t}$ in these figures represents the transfer flow rate based on the proposed model. Based on the figures, the proposed algorithm successfully predicted theoretically valid transfer flow rates in the eight cases.

Table 4.1 Transfer Flow Rates of the Various Cases

Cases	Downstream Link Capacity Change	Downstream Link Condition	Transfer Flow Rate	Validity Check	Reference figures
1	No change	$k_{i,t} \le k_c$	**Min {Demand , Flow rate capacity}**	√	Figure 4.6
2	No change	$k_{i,t} > k_c$	**Min {Demand , Backward gated flow rate}**	√	Figure 4.7
3	Reduced	$k_{i,t} \le k_c$ (demand<downstream link capacity)	**Min {Demand , Flow rate capacity}**	√	Figure 4.8
4	Reduced	$k_{i,t} \le k_c$ (demand≥downstream link capacity)	**Min {Demand , Flow rate capacity}**	√	Figure 4.9
5	Reduced	$k_{i,t} > k_c$	**Min {Demand , Backward gated flow rate}**	√	Figure 4.10
6	Increased	$k_{i,t} \le k_c$	**Min {Demand , Flow rate capacity}**	√	Figure 4.11
7	Increased	$k_{i,t} > k_c$ (downstream link is slightly congested)	**Min {Demand , Flow rate capacity}**	√	Figure 4.12
8	Increased	$k_{i,t} > k_c$ (downstream link is severely congested)	**Min {Demand , Backward gated flow rate}**	√	Figure 4.13

√ represents that transfer flow rate based on the proposed model is theoretically valid.

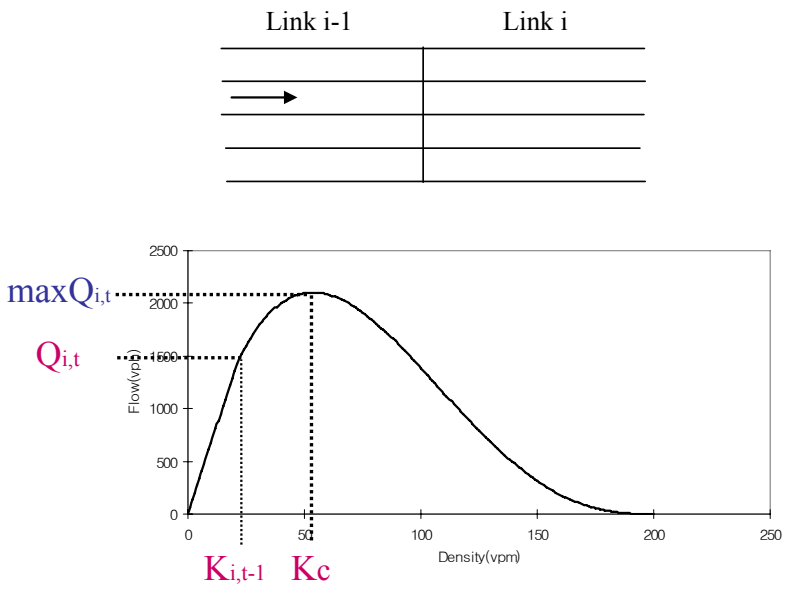


Figure 4.6 Transfer Flow Rate - Case 1

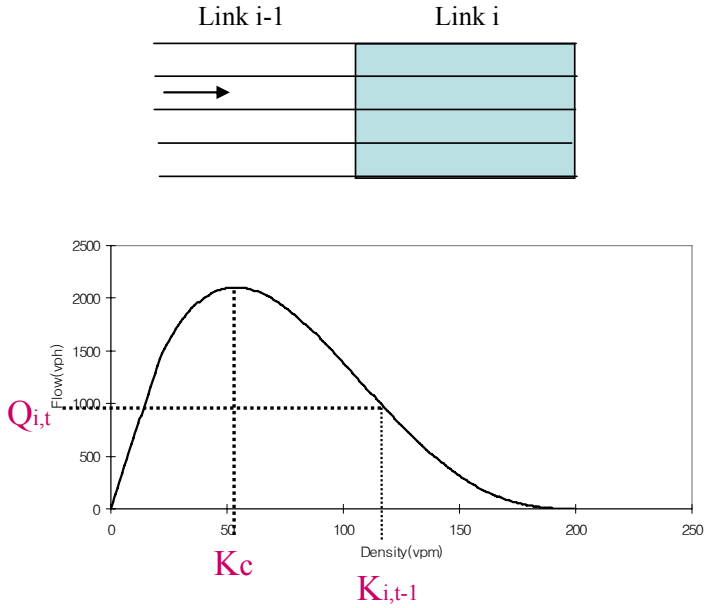


Figure 4.7 Transfer Flow Rate - Case 2

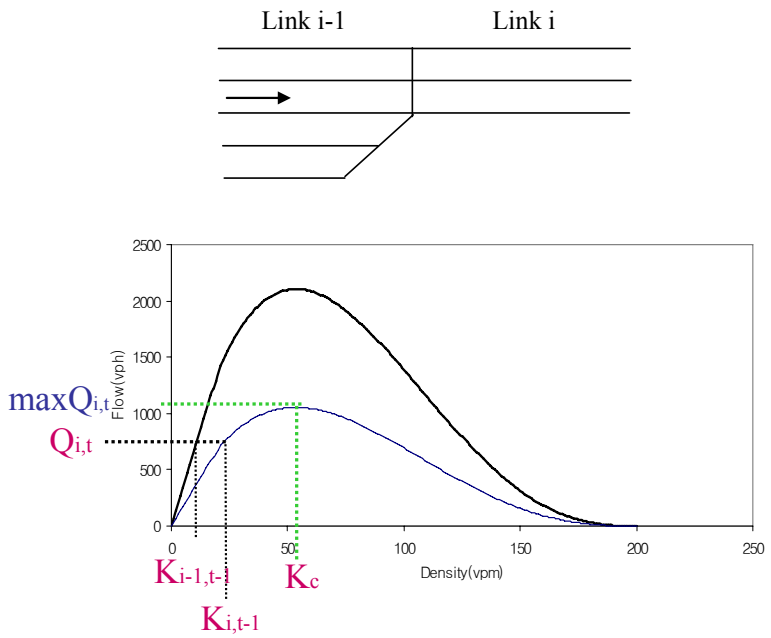


Figure 4.8 Transfer Flow Rate - Case 3

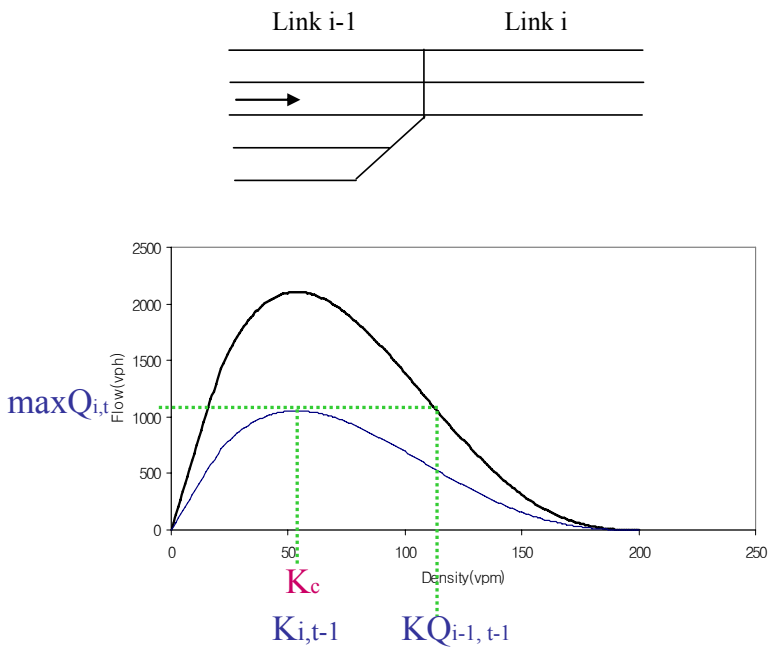


Figure 4.9 Transfer Flow Rate - Case 4

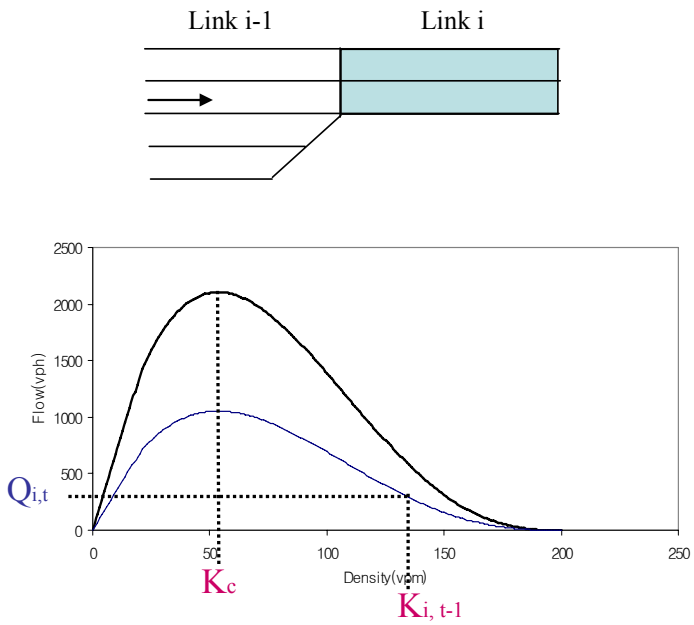


Figure 4.10 Transfer Flow Rate - Case 5

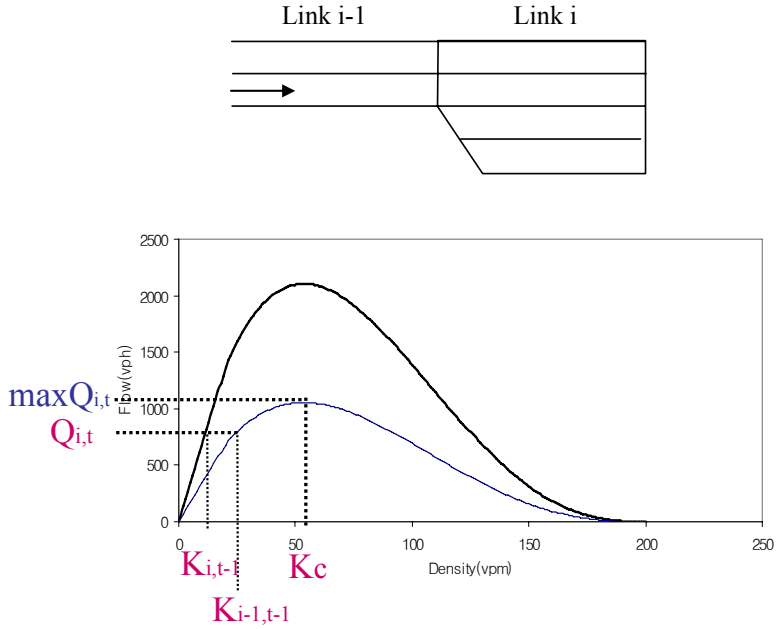


Figure 4.11 Transfer Flow Rate - Case 6

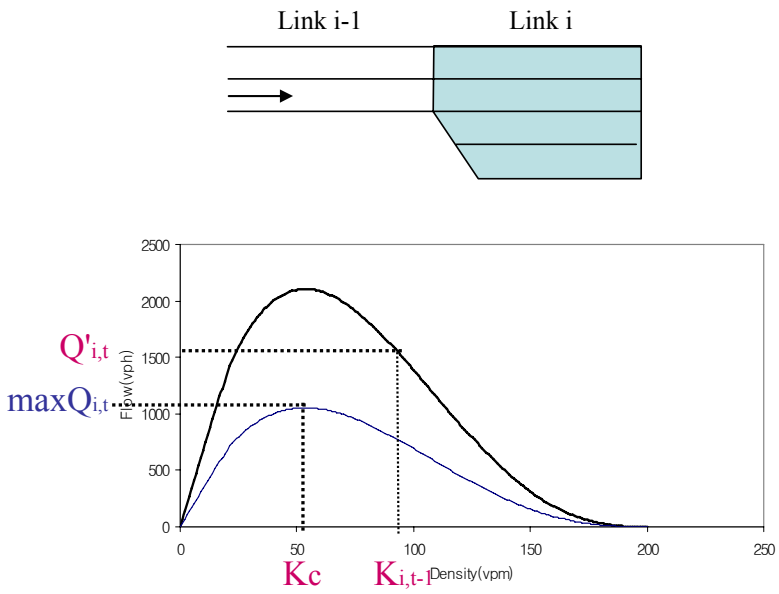


Figure 4.12 Transfer Flow Rate - Case 7

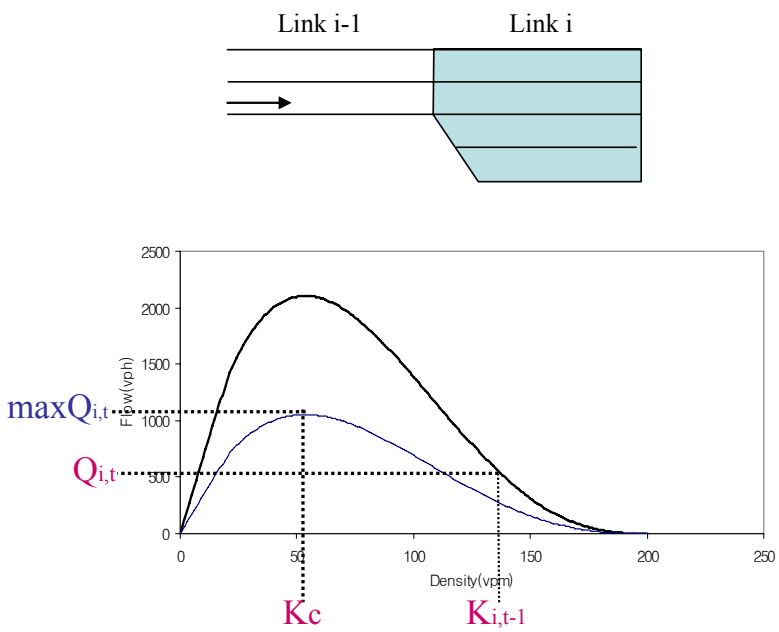


Figure 4.13 Transfer Flow Rate - Case 8

4.4 Implementation and Results

4.4.1 Network and input parameters

The proposed enhanced model with the two additional constraints was implemented in DYNASMART-P and tested on a very simple network containing a bottleneck link. Figure 4.14 shows the test network. The link between Nodes 4 and 5 is a bottleneck link. The simplified traffic flow model has following characteristics:

- Free flow speed = 60 mph
- Density breakpoint (density at capacity) = 30 vpmpl
- Jam density = 180 vpmpl
- Link Capacity =1800 vphpl

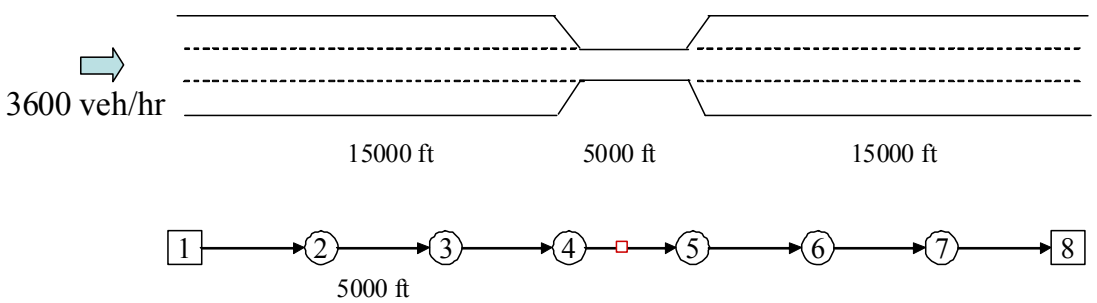
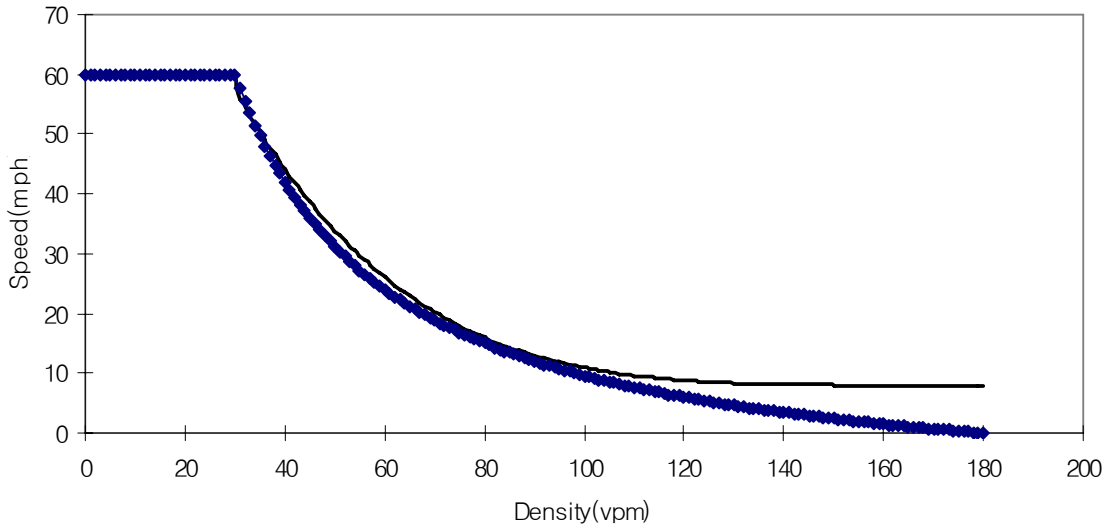
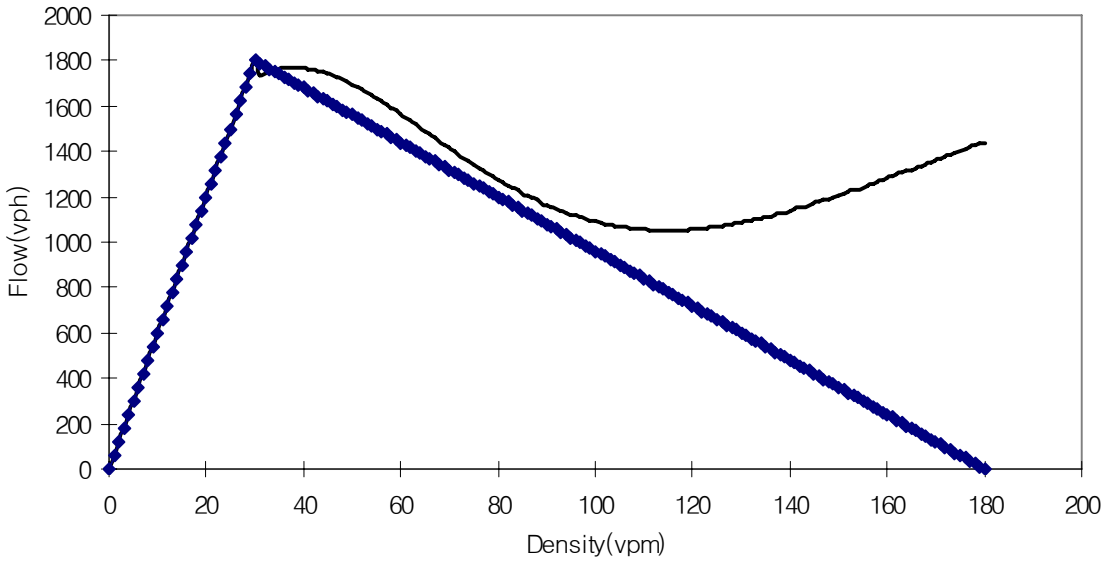


Figure 4.14 Simple Network for Test Implementation of Enhancement A

As shown in Figure 4.15, the traffic flow model in DYNASMART-P was calibrated to fit the characteristics mentioned above. The solid lines represent the fitted model and the dotted lines represent the simplified traffic flow model.



(a) Speed-Density Curve



(b) Flow-Density Curve

Figure 4.15 Traffic Flow Model for the Simple Network

Figure 4.16 presents the traffic flow curve on the bottleneck link and the upstream link of the bottleneck link. The traffic flow model showed that the transfer flow rate for the bottleneck link was 1,800 vph. The upstream flow rate was 3,600 vph. The density of the bottleneck link was 30 vpmpl and the density of the queue was 130 vpmpl. The shock wave speed (about 16.4 mph) is also depicted in Figure 4.16.

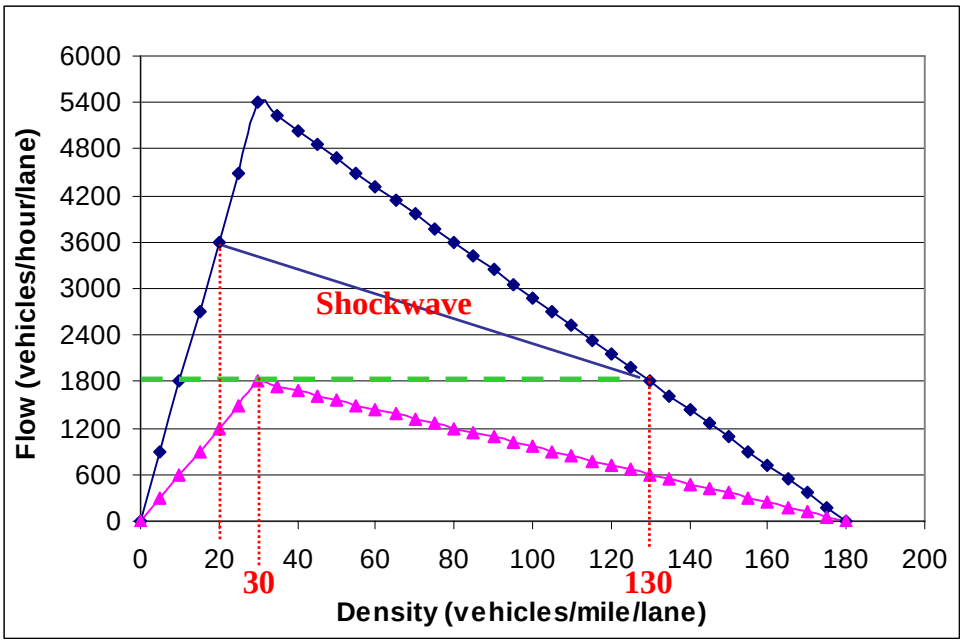


Figure 4.16 Traffic Flow Model for a Bottleneck Point in the Test Simple Network

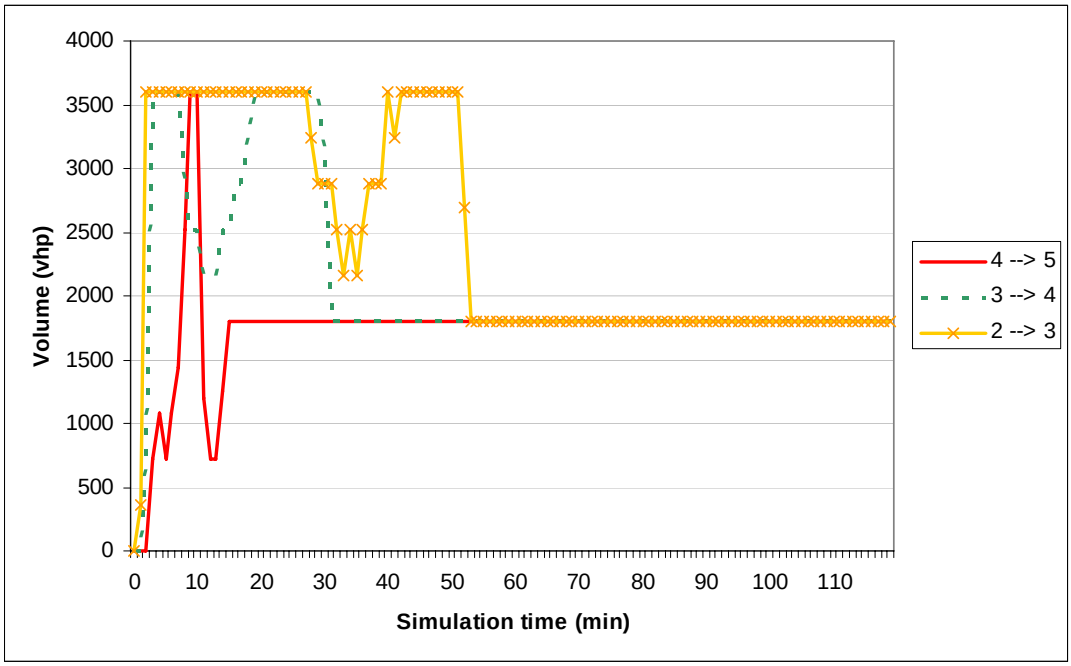
4.4.2 Results

The simulation results using the original and proposed models were compared. Link performances were compared for three links: the bottleneck link between Nodes 4 and 5, and the two upstream links between Nodes 2 and 3 and between Nodes 3 and 4. Figure 4.17 through Figure 4.20 show the volume, density, speed, and queue length results for the two models.

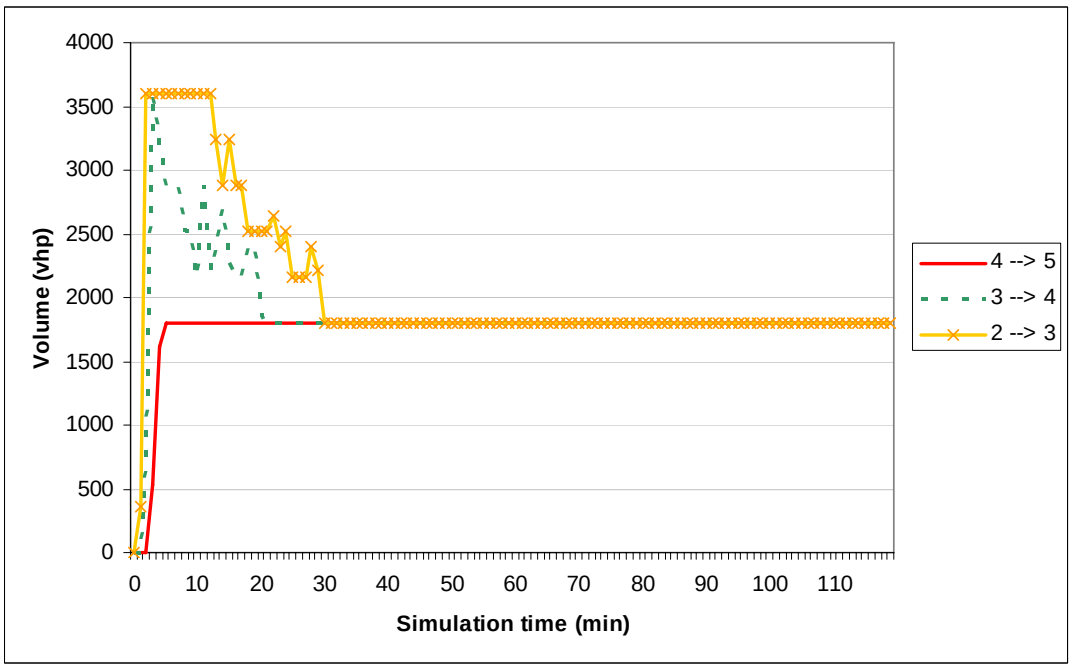
The simulation results showed that the proposed model remedied the shortcoming of the queue propagation model in the original simulator. The proposed model provided reasonable queue propagation simulation results based on traffic flow theory. Figure 4.17(b) shows that the transfer flow rate of the bottleneck link is not greater than the bottleneck link capacity, which is not true for the original model. Figure 4.18(b) shows the bottleneck link density was about 30 vpmpl which is the capacity density (or density breakpoint). The queue density was about 125 vpmpl which is near 130 vpmpl. The results are very close to the expected value presented in Figure 4.16.

The bottleneck link speed in Figure 4.19(b) and the bottleneck queue length in Figure 4.20(b) indicate that the bottleneck link didn't have queue. It implies that the proposed model solved the problem in the original model where the queue started in the wrong position.
In Figure 4.20, the queue forming speeds are compared. From Figure 4.20(a), the queue start time of the link between Nodes 2 and 3 was found to be about 25minutes in the original model. The queue start time of the same link was about 10 minutes in the proposed model, which is much faster than the original model.

From Figure 4.20(b), the difference between the queue start time of the link between Nodes 2 and 3 and the queue start time of the link between Nodes 3 and 4 was found to be about 6 minutes. It was supposed to take 3.5 minutes until the queue end reaches to 5,000 ft back because the shockwave speed was 16.4 mph as shown in Figure 4.16. One of the possible reasons for this difference is that the fitted model was not exactly the same as the assumed simplified model. However, even though the result was not entirely consistent with the theoretical result, it showed much improvement in comparison to the original model where it took a much higher 20 minutes as shown in Figure 4.20(a).

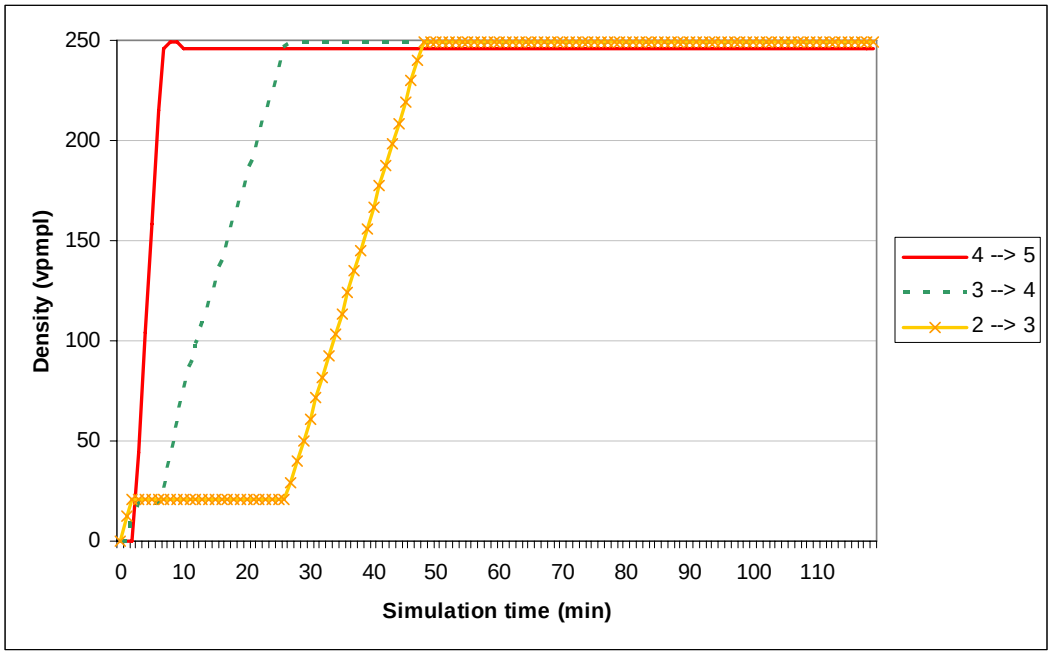


(a) Original Model

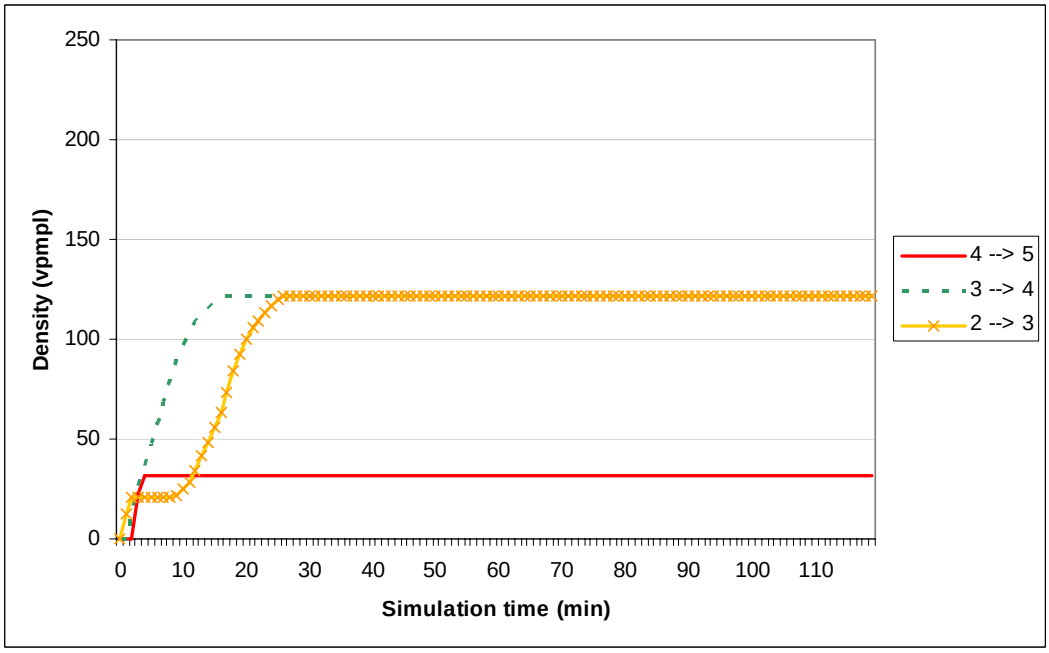


(b) Proposed Model

Figure 4.17 Comparison of the Original and Proposed Models - Volume

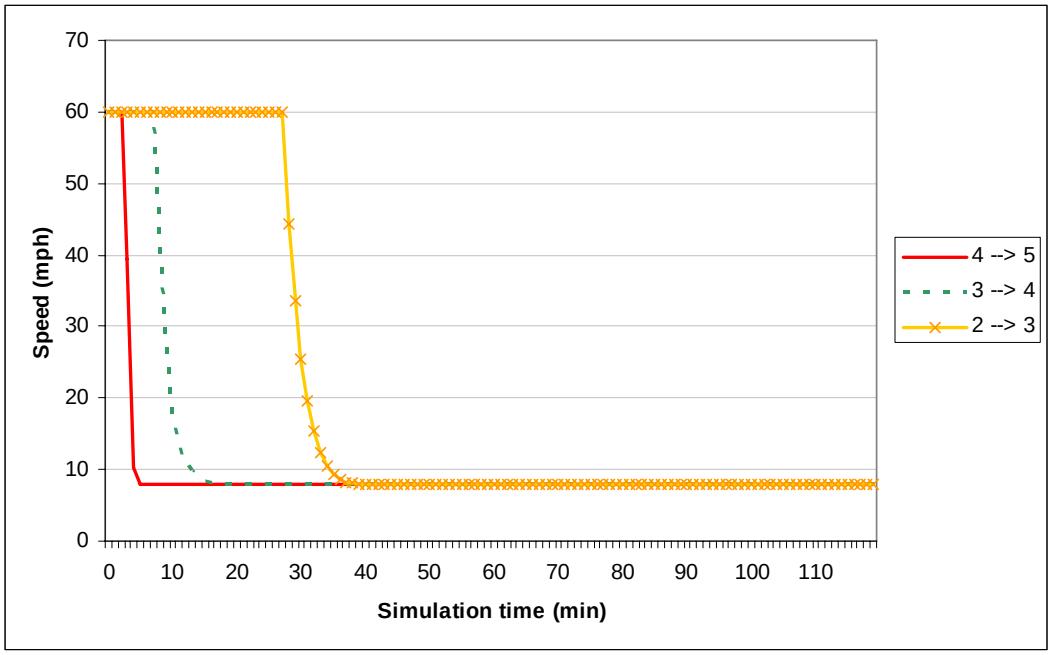


(a) Original Model

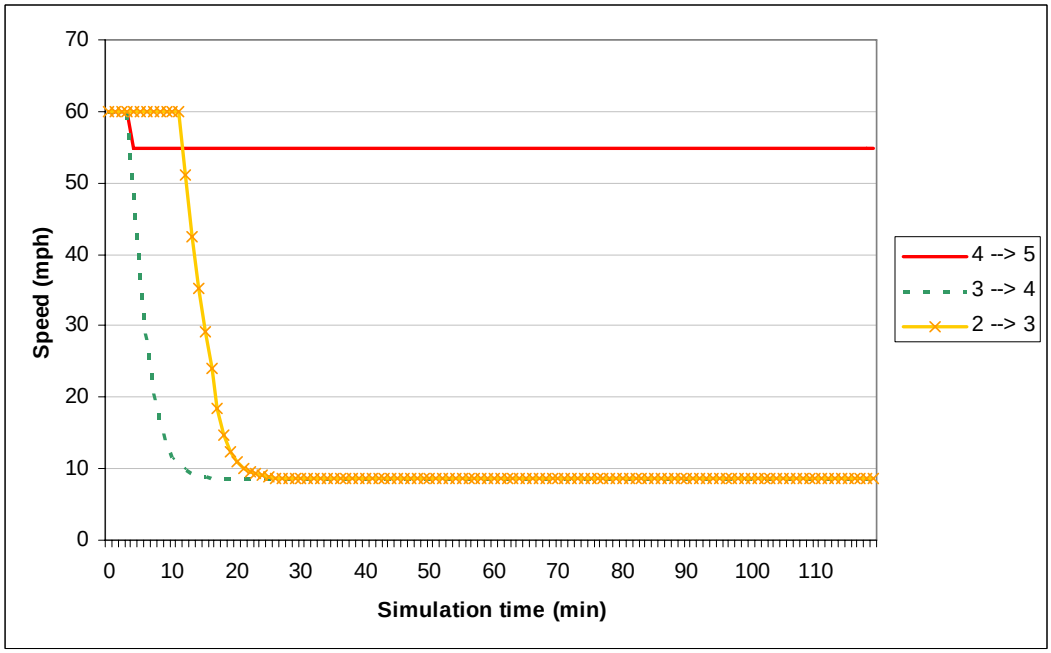


(b) Proposed Model

Figure 4.18 Comparison of the Original and Proposed Models – Density

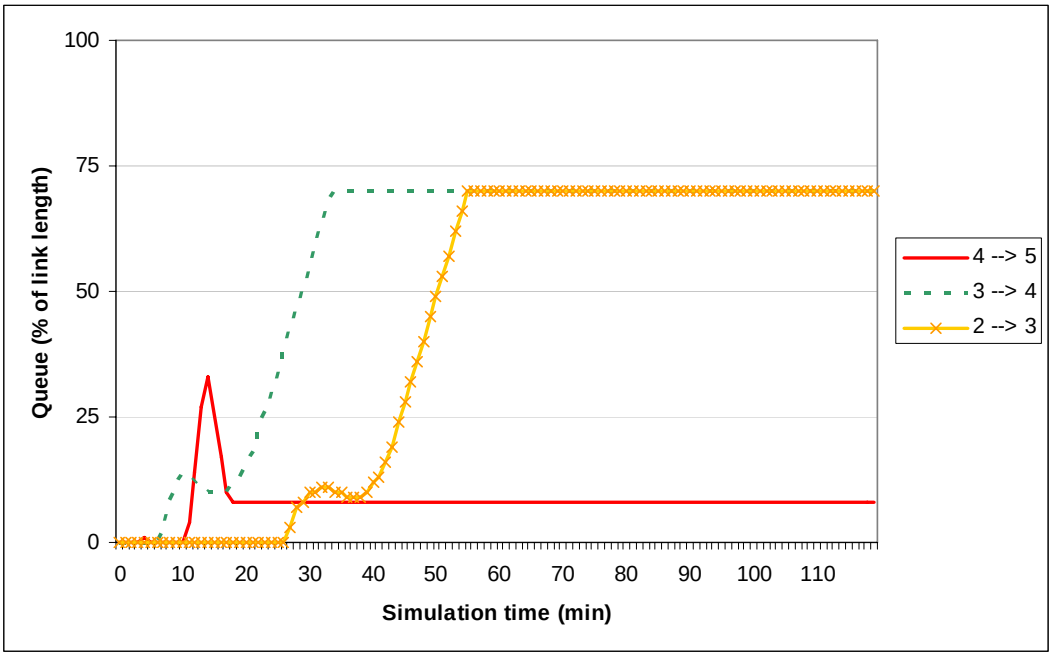


(a) Original Model

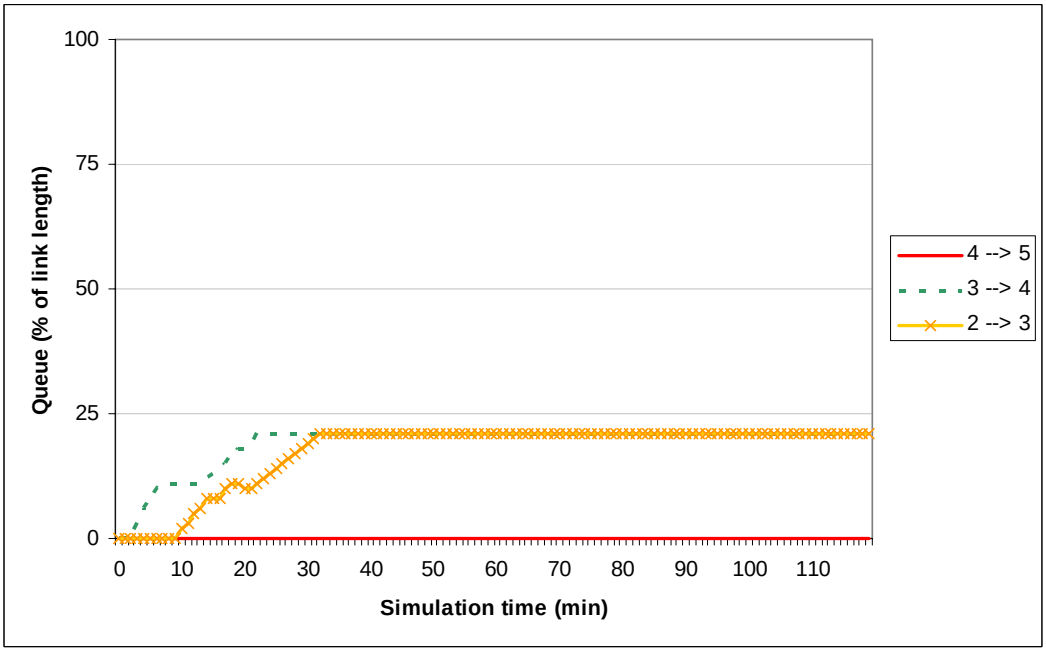


(b) Proposed Model

Figure 4.19 Comparison of the Original and Proposed Models – Speed



(a) Original Model



(b) Proposed Model

Figure 4.20 Comparison of the Original and Proposed Models – Queue (%)

4.4.3 Sensitivity analysis

A sensitivity analysis of the model results to link length was conducted. The implemented network in Figure 4.14 was reconstructed with various link lengths: 5,000, 2,500, 1,250, and 1,000 feet. Table 4.2 summarizes the results of the sensitivity analysis. The volume (veh/hr), density (veh/ml/ln), and speed (ml/hr) in 4 links were compared. As shown in Table 4.2, the simulation results, as was hoped for, did not show large sensitivities to the selected link lengths.

Table 4.2 Link Length Sensitivity – the Enhanced Model

	Length / Links	5000ft	2500ft	1250ft	1000ft
Volume (veh/hr)	Link 2-3	2297	2250	2231	2231
	Link 3-4	1951	1904	1883	1881
	Link 4-5	**1686**	**1679**	**1675**	**1674**
	Link 5-6	1656	1649	1643	1645
Density (veh/ml/ln)	Link 2-3	92.2	91.3	91.4	91.7
	Link 3-4	107.2	107.5	108.0	108.6
	Link 4-5	**29.9**	**26.9**	**29.8**	**29.7**
	Link 5-6	8.8	9.8	9.7	8.8
Speed(ml/hr)	Link 2-3	21.7	22.8	23.4	23.6
	Link 3-4	14.1	14.7	15.1	15.1
	Link 4-5	**55.2**	**57.6**	**53.7**	**55.2**
	Link 5-6	60.0	60.0	60.0	60.0

4.5 Discussion

As shown in Equation 4.8, the transfer flow capacity in a node is the smaller of the flow rate capacities of the current and downstream link. In this study, the former was not included in the model implementation because this term is meaningless. When a downstream link has more capacity (see Cases 6, 7, and 8 described in section 4.3), the transfer flow rate could be estimated correctly, even though this term is not included. In Cases 6 and 7, however,

demand can not exceed upstream link flow capacity; therefore, demand becomes the transfer flow rate. In Case 8, demand could be greater than the upstream link flow capacity if the upstream link has a queue, which means the backward gated flow is less than the demand; therefore, the backward gated flow becomes the transfer flow rate. Thus, even though the flow rate capacity of the current link was not included in the transfer flow rate constraints, the proposed model could provide valid results.

CHAPTER 5. ENHANCEMENT B: DRIVER'S NATURAL DIVERSION BEHAVIOR

When drivers, especially commuters, meet an unexpected long queue or unusually severe congestion on a road section, they can guess from their experience with that road section whether the congestion is caused by an incident or a work zone, even if they have no other information from any external source. Some may change their originally planned route if they are aware of the alternate routes available and if they believe that those alternatives are acceptable from a travel time respective. However, most current ATIS evaluation tools do not consider this "natural" diversion behavior in the driver behavioral models. This chapter suggests a proposed method for modeling this behavior so as to enhance the realism of ATIS evaluation tools, without such addition, the benefits of ATIS technologies may be overestimated.

5.1 Background

Experienced travelers can recognize an incident-induced congestion intuitively by observing unusual long queues or by experiencing long delays on congested links, even without receiving information from any other source. Some of them may try to divert their route to avoid the problem area. Ullman (*1996*) named this behavior "natural diversion" and explored the effects of this behavior on traffic conditions and travel patterns upstream of temporary work zone lane closures on high-volume urban freeways in Texas. He found that the average volumes exiting ramps during the lane closure increased at four sites. The amounts were 1% 11%, 16% and 1% of the mainline volume for the four sites, respectively. Ullman and Dudeck (*2003*) pointed out that the current traffic analysis tools for work zones are limited in that this natural diversion behavior is ignored. They calibrated a model to reasonably represent the magnitude of the traffic queues developing upstream of actual work zone lane closures on urban freeways in Texas. Chen et al. (*2008*) observed that the volumes on some exit ramps increased by as much as 12% at four work zone sites. They developed a

logistic regression model using the field data and a combination of micro-simulation and logistic regression methods to emulate natural diversion behavior dynamically near a work zone. The developed logistic regression model indicated that queue length had significant effect on natural diversion behavior.

Current ATIS evaluation tools estimate ATIS benefits by calculating network improvements when a subset of drivers changes their originally planned routes after receiving travel information. In other words, the network improvement is calculated by comparing the performances of two scenarios: ATIS vs. No ATIS. The No ATIS scenario refers to a situation where there is an incident or an active (more likely short term) work zone on a network without any ATIS deployment. For this baseline scenario, the evaluation tools generally assume that drivers will not change their original path without some external information regarding the prevailing congestion level.

Under this assumption, severe congestion may occur in this baseline scenario simulation, since drivers would remain in the queue and not seek an alternate route. Figure 5.1 shows an example of this phenomenon. The screenshot captured during the simulation is the result of the work zone case II scenario described in Chapter 3. The work zone closure began at 8 PM and lasted until 6 am. The queues from the work zone link blocked the neighboring arterial and local roads (under the assumption mentioned above) as depicted in the figure. This severe congestion was still present on the network at around 4 AM (shown in the time frame at the bottom of Figure 5.1). Obviously, this situation is not very realistic. As a result, the simulator overestimated the congestion severity and duration for the No ATIS scenario and subsequently overestimated the congestion reduction value of ATIS.

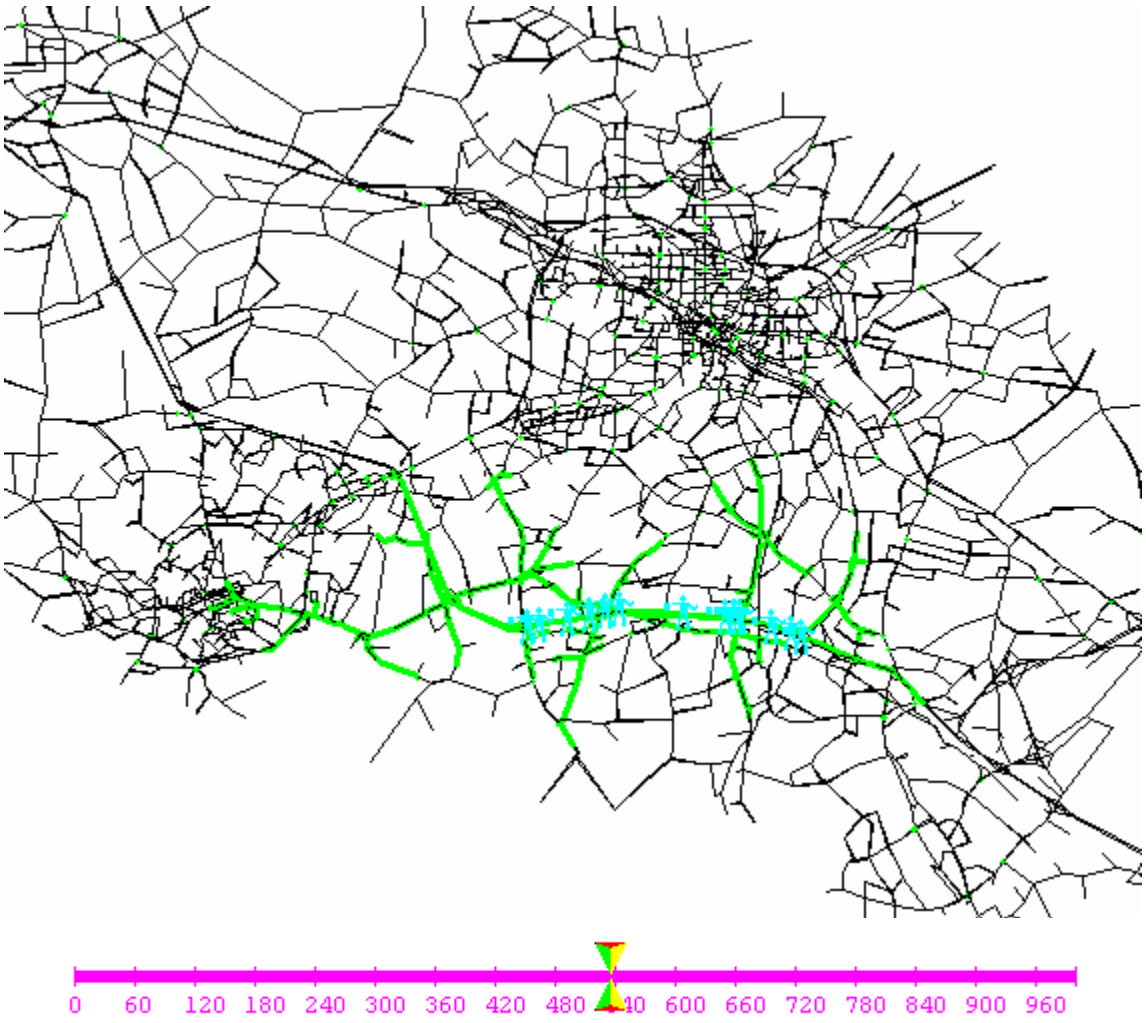


Figure 5.1 Example Congested Network without ATIS

Figure 5.2 presents the proposed ATIS evaluation framework described in Chapter 3. The user Decision Module in the ATIS evaluation tool emulates the behavior of driver travel decision (path selection or path change) corresponding to the information types that drivers access. As mentioned above, the natural diversion behavior was not included in the most of current ATIS evaluation tool. This study proposed a method to incorporate the model of natural diversion behavior in ATIS evaluation tools and implemented it in DYNASMAR-P.

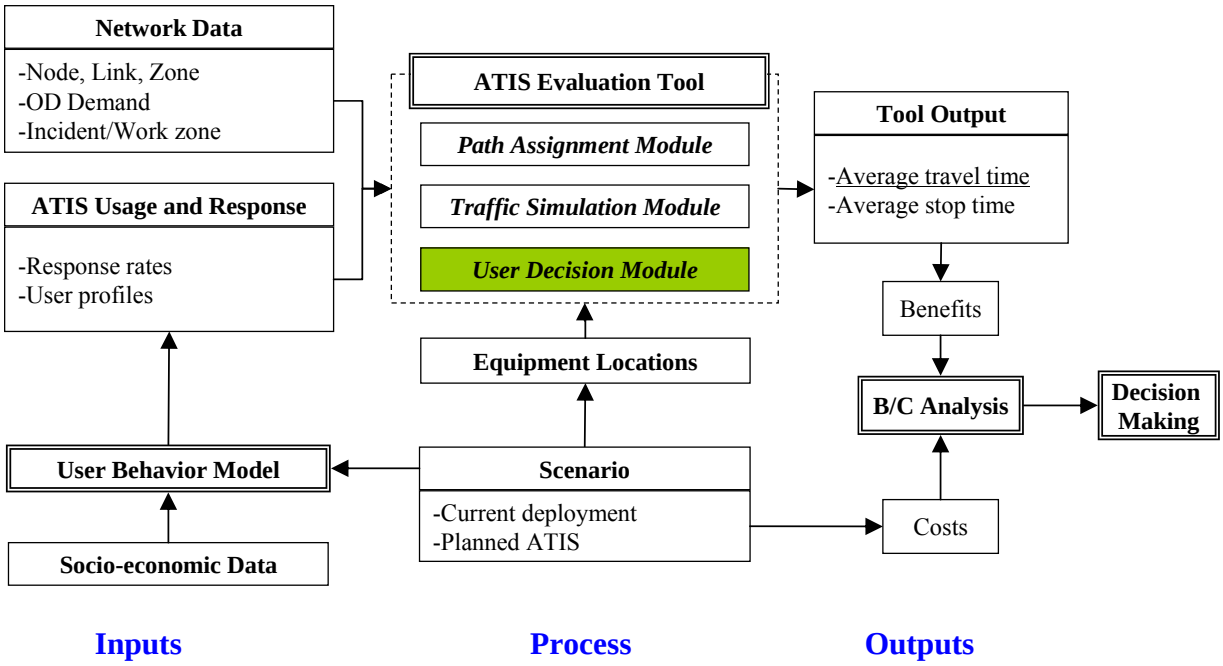


Figure 5.2 ATIS Evaluation Framework

5.2 Emulating Natural Diversion Behavior

Every driver who sees an unusually long queue downstream can reasonably assume that significant congestion lies ahead. However, only a fraction of drivers may consider alternate routes to avoid the congestion, and only some of those may actually change their routes. In order to model this behavior, a simple natural diversion decision tree was proposed as shown in Figure 5.3. First, drivers must recognize the presence of downstream congestion. Next, some will consider diverting, assuming there is a nearby exits. If these conditions are met, then again only those who benefit from diverting to an alternate route will select the new path.

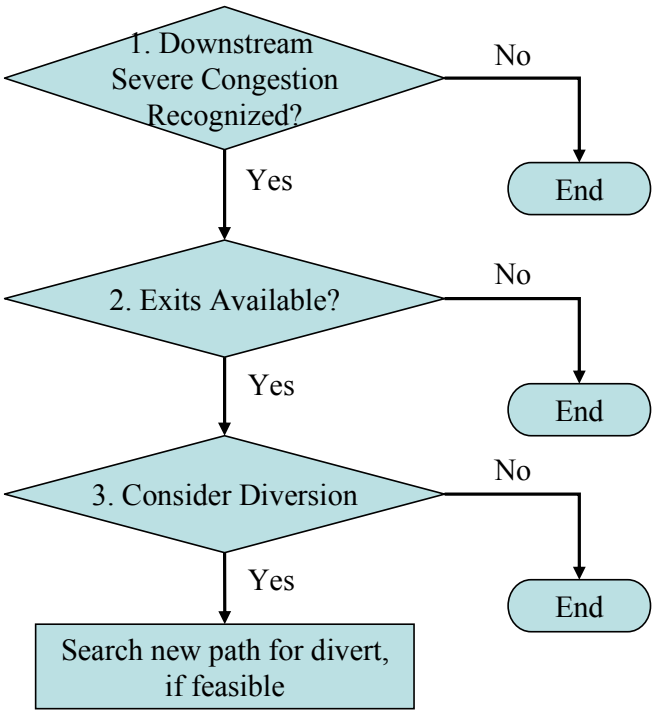


Figure 5.3 Natural Diversion Decision Tree

Each step may include complex decision rules. The decision rules are most likely very different depending on the facility types. In the proposed model, only uninterrupted flow facilities and decision rules for that facility were considered.

In addition, the decision tree could be simplified by assuming that modelers can make informed decisions the locations where natural diversion behavior are likely to occur. That is, because the existence of available exits could be examined by the modeler, the second decision in Figure 5.3 can be omitted.

Also, this assumption can solve a major limitation of implementation of the proposed natural diversion model in the selected tool. This limitation is that when a driver judges whether the downstream congestion is severe, only the traffic condition of the very next link could be examined in DYNASMART-P, even though the driver could be aware of the traffic

conditions of further downstream links in some cases. By this assumption, the modeler will consider the traffic conditions of further downstream links for drivers in modeling network. In the following sections, Steps 1 and 3 of the natural diversion decision tree in Figure 5.3 are described in detail.

Step 1. Downstream severe congestion recognized?

Even though a queue is one of the prime indicators of downstream congestion, queue length was not chosen as a congestion severity indicator because the estimated queue length is not accurate in the selected tool due to its vertical queuing system. Hence, in order to define whether severe congestion exists on a downstream link, link density rather than the queue length of the link was used.

For the enhanced model it was proposed that if next downstream link density is greater than a critical density for a detour decision, the downstream link is considered to have a severe congestion and natural diversion behavior could occur. Downstream link density varies depending on the traffic condition. For the critical density, the minimum of the two density thresholds was suggested to be used; one is the mid value of the optimal density and jam density as shown in Figure 5.4, and the other is the downstream link queue density estimated from the initial run. This can be expressed using the following equations:

critical density = MIN (density threshold 1, density threshold 2) (Equation 5.1)

density threshold 1 = optimal density + (jam density-optimal density)/2 (Equation 5.2)

density threshold 2 = α * downstream link queue density ($0 \leq \alpha \leq 1$) (Equation 5.3)

In Equation 5.3, α is a sensitivity parameter. Using 1 for α means that natural diversion behavior occurs when next link is fully occupied by queued vehicles. If $0 \leq \alpha \leq 1$, natural diversion behavior occurs before the next link is fully occupied by queued vehicles.

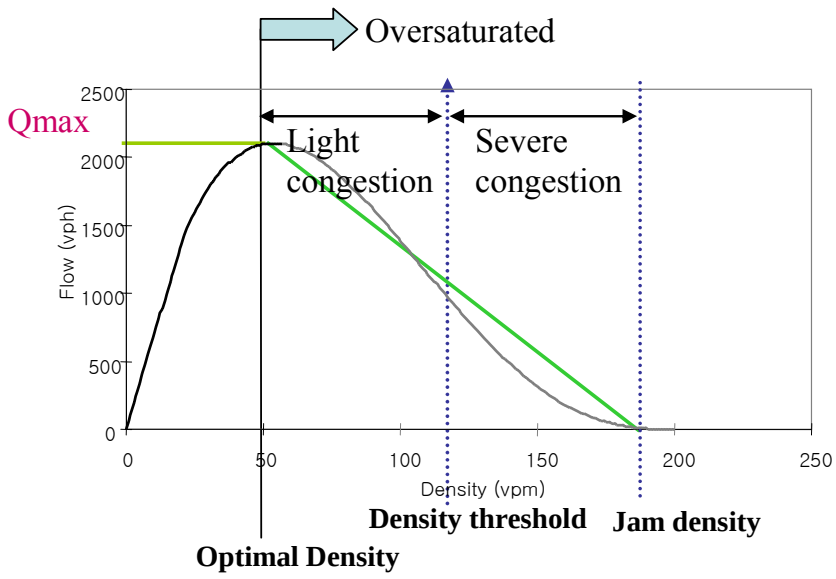


Figure 5.4 Concept of Dividing Light and Severe Congestion

Step 3. Consideration of diversion

The proportion of travelers who use detour routes depends on the travelers' characteristics. For instance, someone may not tolerate being in a queue for more than a few minutes, while others might tolerate remaining in the queue for much longer. Many other factors may affect this proportion, which will also be referred to as the "natural diversion rate". One of the most important factors is congestion severity. If drivers observe long downstream queue or expend a considerable amount of time in the queue, their willingness to divert increases. Drivers' familiarity with the roadway network is another important factor. The drivers who are familiar with the roadway may feel less apprehensive about taking other routes in the network. Distance to the destination and socio-economic characteristics of drivers also may be factors affecting the willingness to divert.

In the proposed model, congestion severity was used to estimate the natural diversion rate. The congestion severity index is taken as the value of the downstream link density divided by

the maximum downstream link density. The natural diversion willingness rate can be calibrated using the following equation:

Natural diversion willingness rate (%)
= maximum natural diversion willingness rate (%)
* congestion severity
= maximum natural diversion willingness rate (%)
*(downstream link density / jam density) (Equation 5.4)

Because the maximum natural diversion willingness rate value is unknown, modelers need to calibrate this value for their networks. It could be acquired from surveying methods.

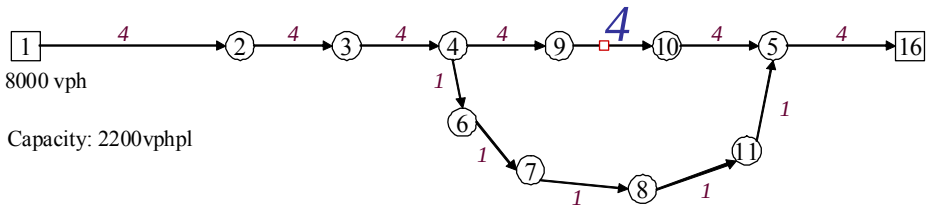
5.3 Implementation and Results

To implement the proposed method, the congestion warning VMS feature in DYNASMART-P was used. Natural diversion behavior was implemented by adding a condition option for specifying when the congestion warning VMS should be activated. The revised congestion warning VMS is activated when the downstream link is severely congested, that is, the downstream link density exceeds the critical density. This study used maximum natural diversion willingness rate (%) as an input parameter representing the response rate for the activated congestion warning VMS.

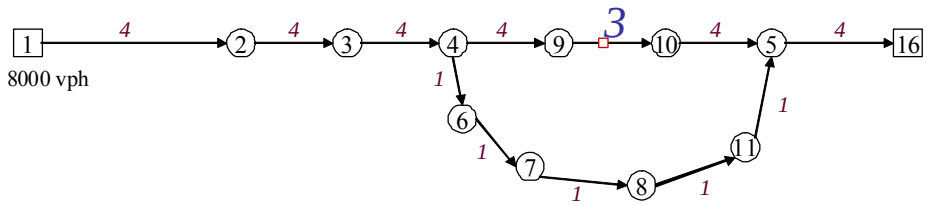
Figure 5.5 depicts an implementation test network. Numbers on links indicate the number of lanes. The traffic flow model used in this network has the following characteristics:

- Free flow speed = 70 mph
- Optimal density (density at capacity) = 30 vpmpl
- Jam density = 200 vpmpl
- Link Capacity = 2,200 vphpl

Two scenarios were prepared for demonstrating how the natural diversion behavior was modeled. One scenario was for a normal condition and the other was for a capacity reduction condition. In the first scenario run, the network without any capacity reduction, as shown in Figure 5.5 (a), was used to generate vehicles and their normal paths. The network includes a main path (Nodes 4 → 9 → 10→ 5) and a diversion path (Nodes 4 → 6 → 7 → 8 → 11→ 5). The main route had sufficient capacity under normal conditions and the alternate route was longer than the original route. Thus, all drivers would typically select the main route under normal traffic conditions.



(a) Normal condition



(b) Capacity reduction on Link 9-10

Figure 5.5 Implementation Test Network

The second scenario modeled a situation of capacity reduction on Link 9-10 as shown in Figure 5.5(b). It was assumed that all drivers had no information about the capacity reduction in the two scenarios. Thus, normal paths generated from the first run were assigned to all vehicles. The second scenario was run twice - once by the original model and once by the proposed model. Because the number of lanes of Link 9-10 (the bottleneck link) was reduced from four to three lanes, the link's capacity was reduced from 8,800 vph to

6,600 vph. Were all traffic to remain on the original route, the traffic demand of 8,000 vph would exceed capacity.

Figure 5.6 shows the density of Link 4-9, which is the link upstream of the bottleneck link in the second scenario. Because of the bottleneck, the upstream link was fully occupied by a queue and the link density was about 92 vpmpl.

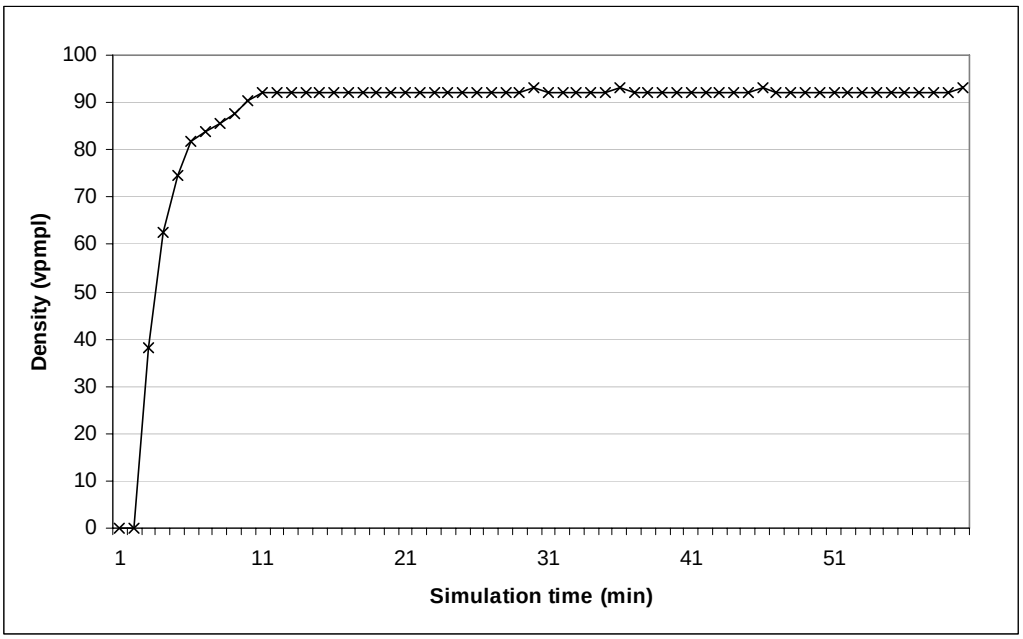


Figure 5.6 Queue Density of Link 4-9 from the Second Scenario

The revised congestion warning VMS was located on Link 3-4 because natural diversion behaviors were likely to occur at Node 4. The maximum natural diversion willingness rate was set at 20%. The calibrated critical density was 90 vpmpl. The calculations using the proposed method were as follows:

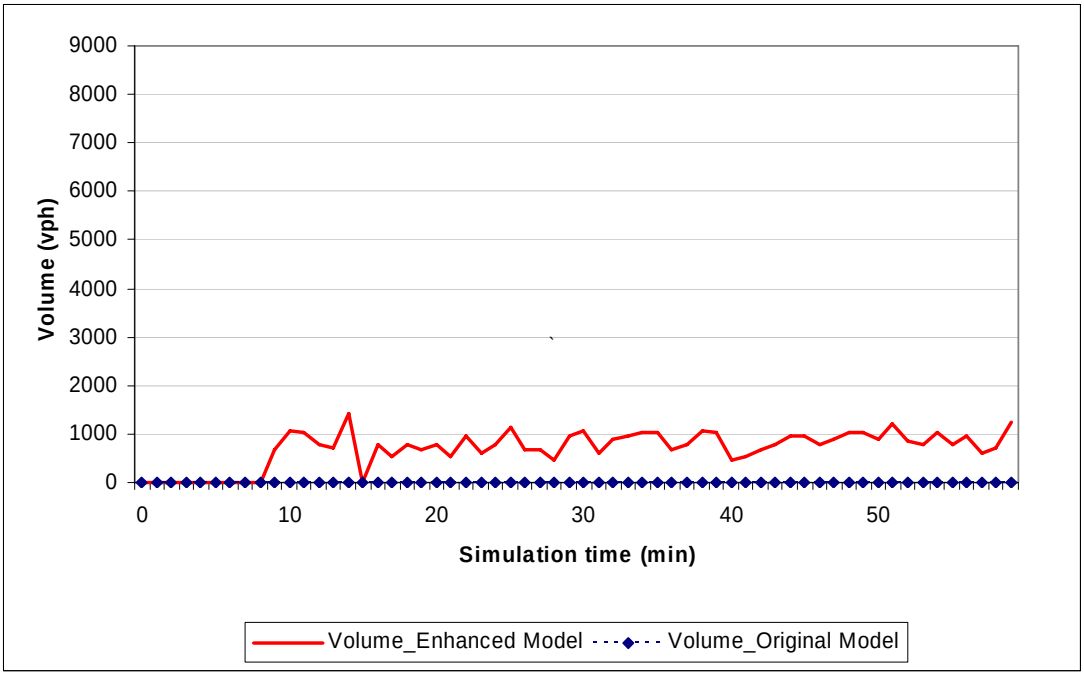
- density threshold 1 = optimal density + (jam density-optimal density)/2
  = 30+(200-30)/2 =115 vpmpl

- density threshold 2 = α * downstream link queue density (here, α = 0. 978)
  = 90 vpmpl
- critical density = MIN (density threshold 1, density threshold 2)
  = 90 vpmpl

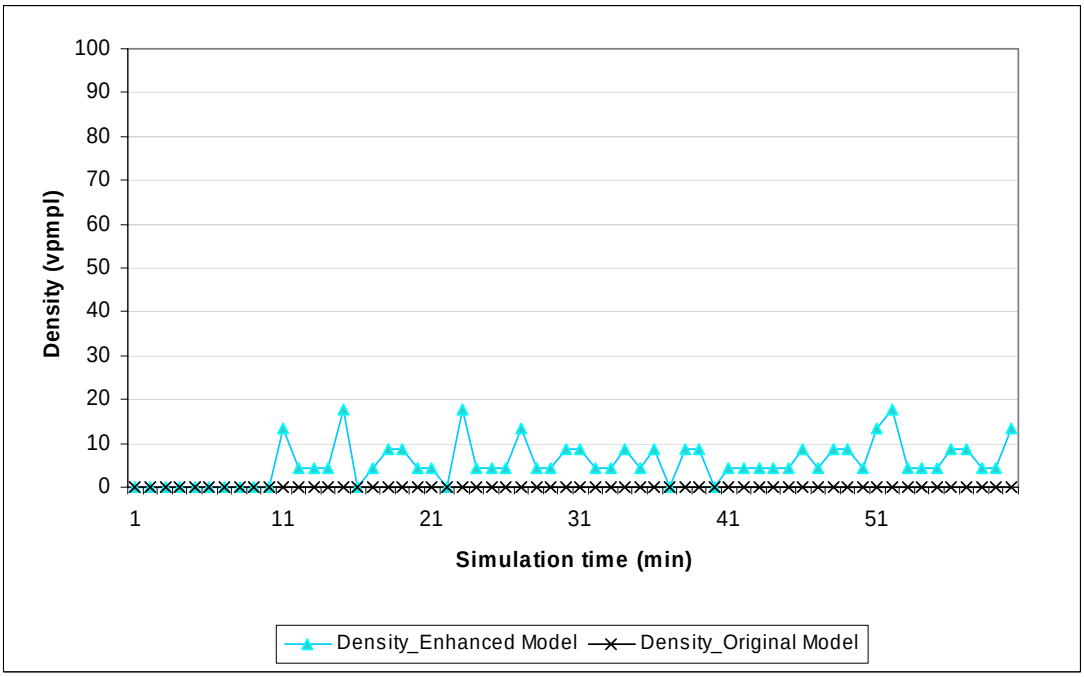
In the original model, even if the main route is congested because of an incident, no drivers used the alternate route if they had no access to traveler information. In the suggested enhanced model, however, some vehicles observed the queue diverted based on a defined model representing the natural diversion behavior.

Figure 5.7 shows a comparison of the modeling results from the original and proposed models for Link 4-6. As shown, no vehicles used the alternate route in the original model, while some vehicles diverted to the alternate route in the proposed model. Thus, the volume and density on Link 4-6 produced by the proposed model were higher than those produced by the original model; a result that can be attributed to natural diversion behavior.

Figure 5.8 shows the effects of natural diversion on the volume and density of Link 3-4. As shown, the volume on link 3-4 in the proposed model was about 6,500 vph, while that in the original model was about 6,000 vph. The density of the link in the proposed model was less than 80 vpmpl, while that in the original model was around 90 vpmpl. This implies that the network congestion due to the bottleneck was slightly improved by the natural diversion behaviors. In conclusion, this implementation study showed that the proposed model can properly emulate natural diversion behavior.

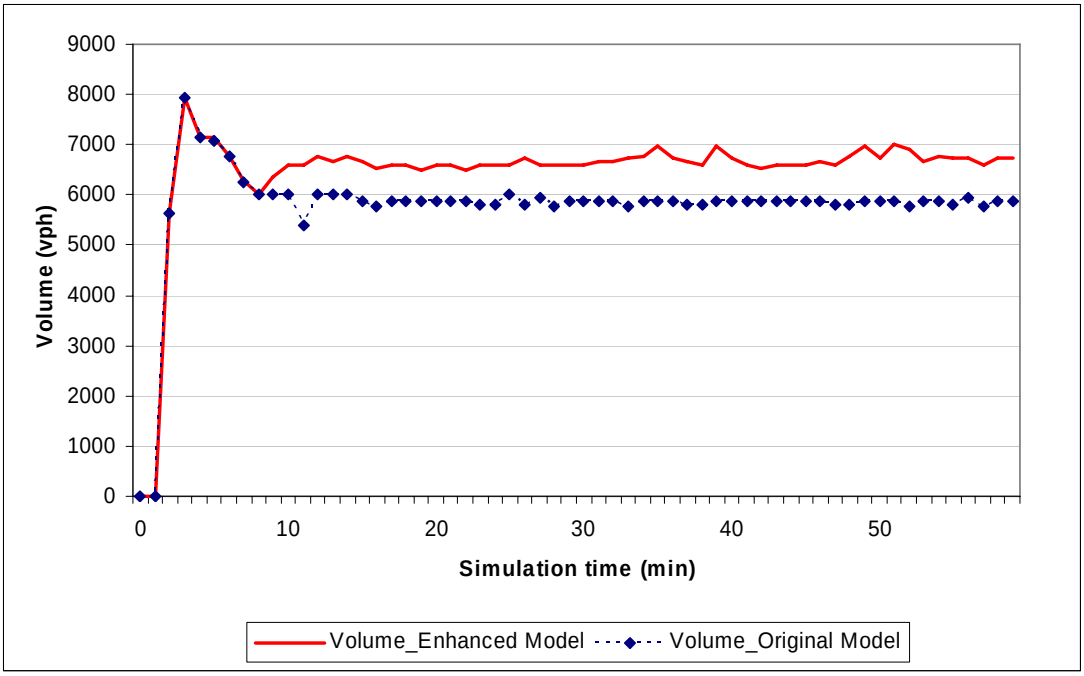


(a) Volume

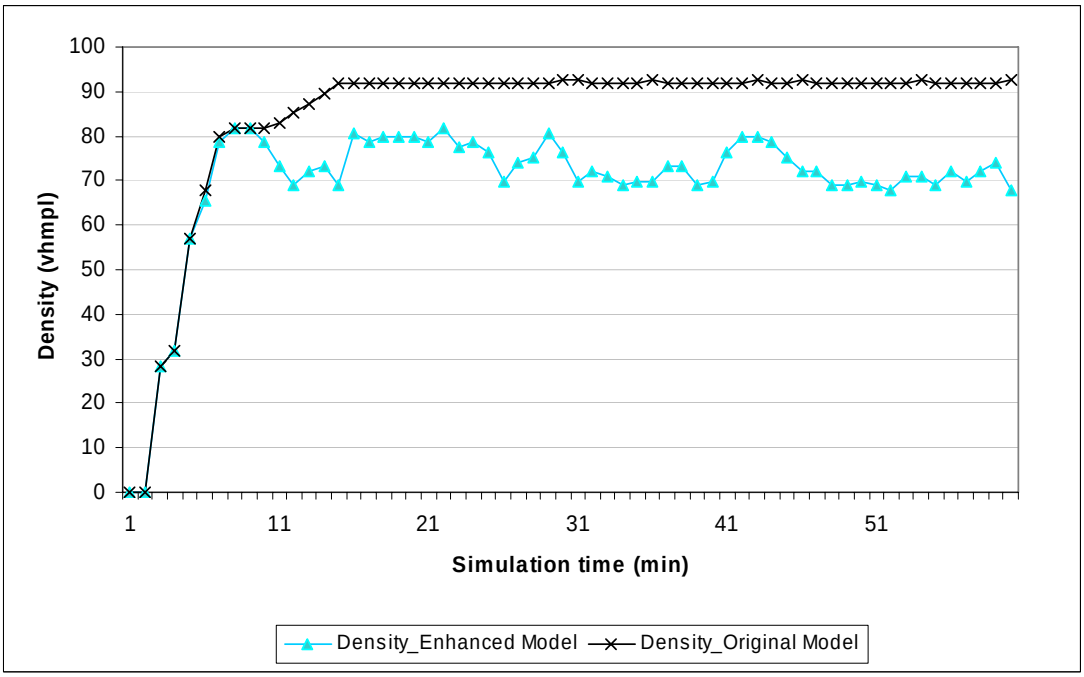


(b) Density

Figure 5.7 Comparison of the Results by the Original and Proposed Models – Link 4-6



(a) Volume



(b) Density

Figure 5.8 Comparison of the Results by the Original and Proposed Models – Link 3-4

5.4 Discussion

This chapter discusses the concept and implementation of a 'natural diversion behavior' algorithm, intended to emulate the effect of observing downstream queues on driver diversion behavior, particularly under non-recurring congestion or incidents. The method is rooted in the definition of a critical density on the downstream link, above which diversion is considered but not necessarily undertaken. The algorithm was implemented in a simple network in DYNASMART-P and the results were found to generate reasonable traffic patterns on the effected links.

When drivers compare alternative routes in the final step of the decision tree in Figure 5.3 and do not have access to traveler information, they will select an alternative route based on their estimate of the remaining travel time to the destination. In this study, these estimated travel times were taken from the real time traffic conditions in the simulation network. Thus, drivers behaved as if they had access to an en-route dynamic travel information device. This obviously violates the assumption that drivers have no travel information access. In future studies, the estimated travel times of alternate routes under normal (recurring) conditions should be used to avoid violating this assumption.

The task remains to calibrate the key parameters for the model, namely the maximum willingness to divert (expressed as a fraction of all drivers in the network). Direct observations of the parameters are virtually impossible to gather in uncontrolled field settings. Rather, a stated or revealed preference survey may be an appropriate tool to assist in estimating them. A survey would show the factors affecting the natural diversion preference, such as remaining travel distance, familiarity with the network, and availability of a navigation system. These could then be used for estimating a natural diversion rate. This is left for future research.

CHAPTER 6. ENHANCEMENT C: PREDICTIVE MODEL OF ATIS USE AND TRAVEL DECISION

ATIS evaluation tools require several input parameters related to ATIS technology usage and the potential users' responses to the ATIS services, in order to assess the effects of ATIS implementations. In order to predict such input parameters, ATIS user behavior models were developed using data from the 2006 Greater Triangle household travel survey (*NuStats, 2006*) in this study. Responses to survey questions related to access to travel information, acquisition technology of information, and travel change decision for each information acquisition technology type were expressed as discrete variables, i.e., binary or nominal responses. Consequently, logistic regression techniques were used to analyze the data. This chapter describes the data sources, binary and multinomial logit model forms, and a discussion of the modeling results.

6.1 Background

ATIS provides information about traffic conditions to users through various sources of information. As a result, some users alter their travel behavior based on the information through route changes, mode changes, departure time changes, or trip cancellation. These travel changes can alter the traffic patterns in the network. For example, some travelers who are scheduled to travel on a congested link are aware of the traffic congestion and therefore may use alternate routes, thereby decreasing the demand on the link. As a result, delay on this link will be reduced. On the other hand, the traffic demands on the detour routes will be increased and as a result, traffic conditions on these detour routes may deteriorate. In other words, travel changes triggered by ATIS services induce changes in the performance of the transportation network, which can be evident by changes in average travel time, delay, stop time, etc.

ATIS evaluation tools model drivers' response to the information and resulting path diversion, with the goal of quantifying the effect of the ATIS implementation. ATIS evaluation tools require input parameters related to the usage of the ATIS technologies (TV, Internet, Radio, and so on) and user responses to such information. These parameters dictate how many travelers are willing to change their travel decisions based on the traveler information received from each information acquisition technology. Since the ATIS effectiveness depends on the magnitude of those travel changes, estimating the values of these parameters is essential for a realistic evaluation of ATIS. However, it is impossible to obtain actual information usage rate and response rates before initiating an ATIS service in an area. Therefore, such parameters have usually been transferred from previous research or experiences in other cities, where ATIS has been deployed. The problem with this practice is that these parameters are likely to be strongly dependent on the local conditions and may not be transferable from one site to another.

Local conditions may be represented through socioeconomic data such as age, gender, income level, employment, etc. Such statistics are gathered and updated periodically for the purpose of developing regional travel demand models at various levels of government, from local municipalities to the state level. If relationships between these socioeconomic factors and the usage of ATIS technology and user responses to the information can be estimated, these socioeconomic data can be used to calibrate the input parameters for ATIS evaluation models. For example, Williams et al. (*2007*) conducted a cross-classification analysis and developed a statistical ATIS user behavioral model by using data from the 2006 Greater Triangle household travel survey (*NuStats, 2006*). The authors defined a relationship between the driver's socioeconomic characteristics and ATIS usage and users' responses to the ATIS.

Using those same data, statistical ATIS user behavioral models were developed in this study. The major difference between this study and the previous study is that the modeling goal was to predict the input parameters for ATIS evaluation models as well as to define the

relationships between the driver's socioeconomic characteristics and ATIS effects. Therefore, model validation was conducted using a subset of the full sample not used for model development. Another important difference is in the data samples used for model development. The earlier research included all survey responses from 12 counties in the Greater Triangle area, while this study included only the responses from the Triangle metropolitan area counties (Wake, Durham, and Orange). This was done because the ATIS services provided in these counties are different from the services in the remaining counties. The three selected counties are using the state-of-the-art technologies to collect and disseminate real-time traffic information.

Figure 6.1 presents the proposed ATIS evaluation framework described in Chapter 3 and shows how the ATIS user behavioral model could be applied in the ATIS evaluation tools (see shaded cells). The user behavior model calibrates the ATIS input parameters, including the information acquisition technology types and the response rate for each information acquisition technology. This is different from the current state of the practice, in which driver responsiveness to information must be determined prior to modeling the network in the ATIS evaluation tool.

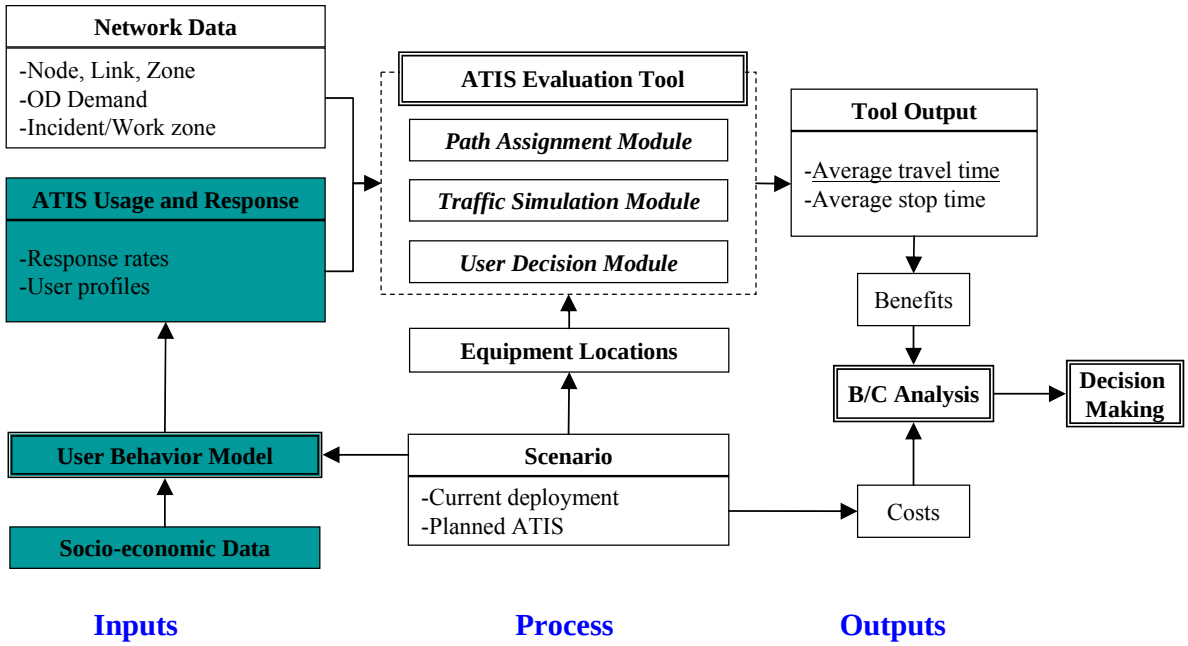


Figure 6.1 ATIS Evaluation Framework

The above framework can be enhanced as shown in Figure 1.2, where the driver behavioral models are integrated in the evaluation tool. In this case, the inputs would be the demographic distribution of the area to be evaluated. Accordingly, the ATIS evaluation tool distributes the driver's demographic characteristics consistent with these input data, and the user behavioral model can predict driver behavior changes resulting from the ATIS. In the integrative evaluation tools, every vehicle generated in the simulation has attributes matching the driver's demographic characteristics, selected ATIS information acquisition technology, and the resulting change in travel behavior. The user decision module in the tool emulates the user travel behavior in a way that path selection and travel changes are based on those attributes.

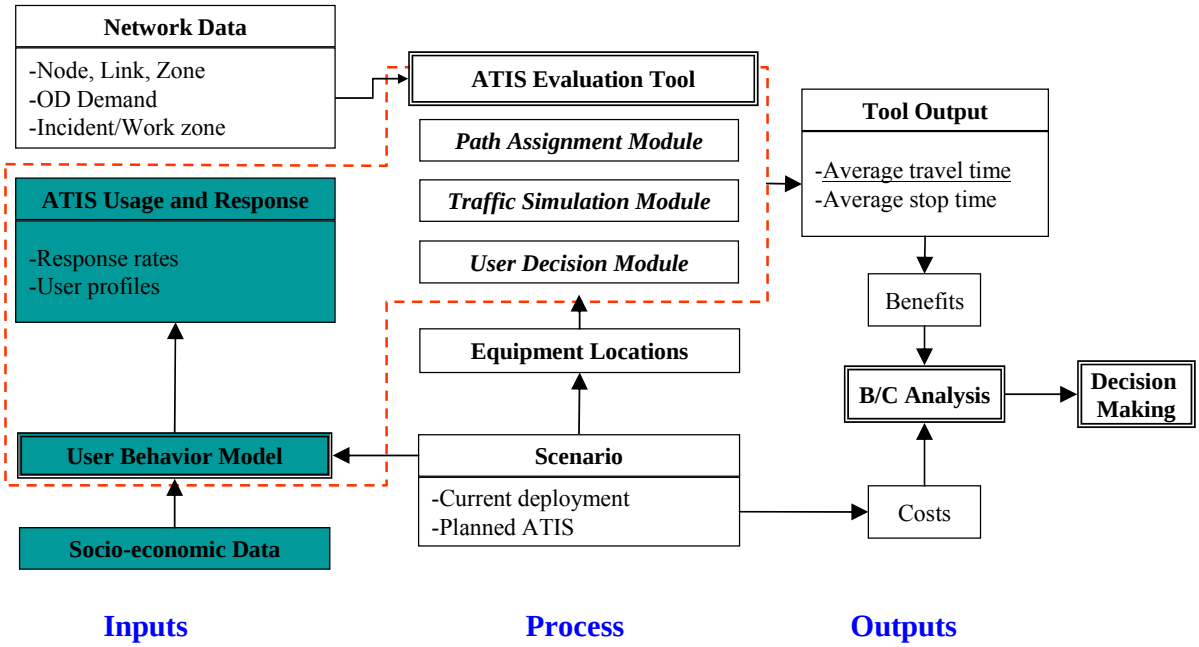
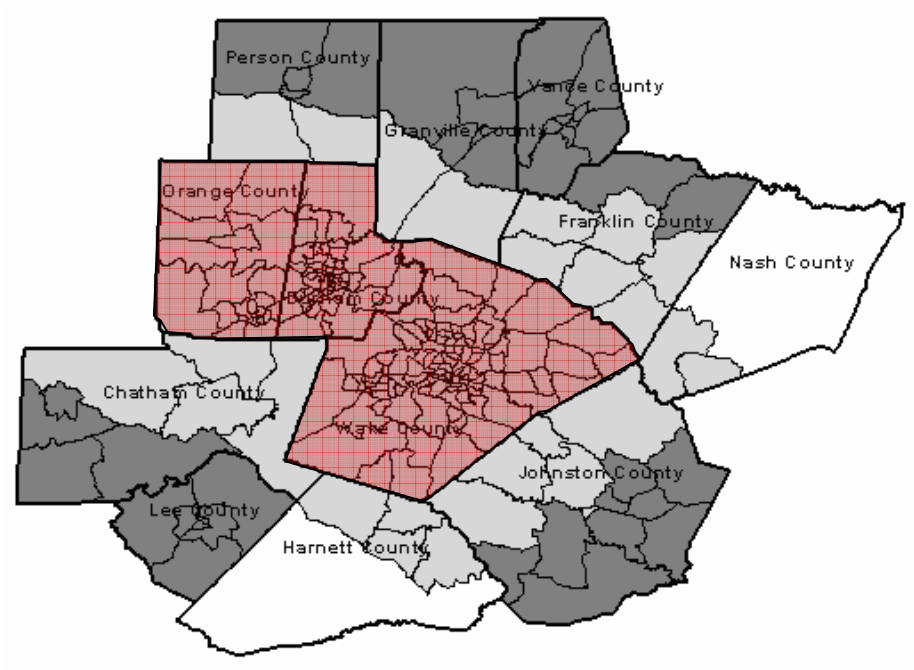


Figure 6.2 ATIS Evaluation Framework with Embedded User Behavior Model

6.2 Survey Data

The 2006 Greater Triangle household travel survey was conducted using state-of-the-art travel survey methods and computer-aided telephone interviewing (CATI) technology. The surveyed data included questions about demographic characteristics and travel behavior of regional travelers with the goal of updating the current regional model. The data were also intended to develop a new and more robust travel demand model for the 12-county region in North Carolina, including Durham, Orange, Wake, Chatham, Lee, Harnett, Johnston, Nash, Franklin, Vance, Granville, and Person County, shown in Figure 6.3 as shaded area. In total, 7,300 households were recruited to participate in the study, but only 5,107 households provided all details required for the final data set. The 5,107 surveyed households are a representative sample of the 548,539 total households in the region.



Source: Nustat (2006)

Figure 6.3 Map of the Survey Area

6.2.1 Socioeconomic data

The 2006 survey collected socioeconomic characteristics of the respondents. Among the collected socioeconomic characteristics, seven variables were selected to develop the ATIS user behavioral model: gender, age, education level, work status, house hold income level, transit use on regular basis, and length of time lived in area. These variables represent those socioeconomic characteristics having a potential relationship to the usage of ATIS technology and the user responses to the information.

As mentioned earlier, only the responses from the three-county Triangle metropolitan area were employed for the statistical analysis conducted in this study. The sample size of respondents with information for all seven socioeconomic characteristics mentioned above in the Triangle metropolitan area was 3,216. Table 6.1 shows the distributions of these

variables in the sample. As shown in Table 6.1, about 58% of the respondents were females. The respondents were evenly distributed in terms of age group, except for the group less than 20 years old, and the group greater than 65. About half of the respondents were 50 or older. Over 87% of the respondents had at least some college-level education. About 77% of the respondents had a job. About 36.7% of the respondents had lived in the area more than ten years.

Table 6.1 Socio Economic Characteristics of the Respondents (N=3,216)

Attribute	Range	Count	%
Gender	Male	1,350	42.0%
	Female	1,866	58.0%
Age	<20	5	0.2%
	20 ~ 29	292	9.1%
	30 ~ 39	613	19.1%
	40 ~ 49	735	22.9%
	50 ~ 64	1,042	32.4%
	>65	529	16.4%
Education level	<High School	81	2.5%
	High School graduate	326	10.1%
	Some College	380	11.8%
	Associate or technical school degree	237	7.4%
	Bachelor	1,096	34.1%
	Graduate	1,096	34.1%
Work status	Work	2,475	77.0%
	Do not work	741	23.0%
Household Income	<$15,000	186	5.8%
	$15,000 ~ $24,999	184	5.7%
	$25,000 ~ $34,999	241	7.5%
	$35,000 ~ $49,999	449	14.0%
	$50,000 ~ $74,999	637	19.8%
	$75,000 ~ $99,999	550	17.1%
	$100,000 or more	969	30.1%
Transit use on regular basis	Use	412	12.8%
	Not use	2,804	87.2%
Length lived in current address	<1 year	307	9.5%
	1 ~ 2 years	309	9.6%
	2 ~ 5 years	724	22.5%
	5 ~ 10 years	696	21.6%
	More than 10 years	1,180	36.7%

6.2.2 ATIS questionnaire

In addition to the socioeconomic characteristics, a set of questions intended to gather the users' response to traveler information was appended to the survey. Four questions were asked about usage frequency, user preference for the selection of traveler information acquisition technology, and travel behavior changes in response to traveler information. Table 6.2 lists those ATIS-related survey questions.

Table 6.2 Key Questions for Stated Preference Study about Traffic Information

Variable Name	Question Asked in Survey
Frequency of traffic information use (n = 5107)	S6. How often do you and others in your household seek information about traffic and general travel conditions in the region? never At least once a week 2-4 times per week 5+ times per week
Information acquisition technologies (n = 2584)	S7. Where do you go to get this information? (multiple response) Internet Commercial radio Television Variable message signs (signs on the side of the road) Highway advisory radio Traveler information hotline (511) Others (specify)
Travel decision changes (Yes/No) (n = 2584)	S8. Have you ever changed your travel plans based on the information you got? Yes No DK/RF (refuse)
Type of travel decision changes (n = 2584)	S8a. If YES: How? (multiple response) Changed route of travel Changed Time that you started trip (departure time) Changed mode of travel Cancelled trip

Source: The 2006 Greater Triangle Household Travel Survey

Table 6.3 through Table 6.5 show the survey results for questions on the frequency of information access in a week, the selection of information acquisition technology, and the

travel decisions based on the information, respectively. As shown in Table 6.3, about one-half of the respondents (1,724, 53.6 %) reported that they acquire travel information from different types of electronic sources. Among those who acquire traffic information, 81.1% changed their travel decisions based on the information received, which is 43.5% of the total respondents. Moreover, 37.1% of the total survey respondents (1,194 out of 3,216) had changed their travel route after receiving travel information.

Table 6.3 Frequency of Information Access on a Weekly Basis

Range	Count		%	
Never	1,492		46.4	
At least once	355	1,724	11.0	53.6
2-4 Times	297		9.2	
5+ Times	1,072		33.3	
Total	3,216		100	

Regarding the information acquisition technology, Table 6.4 shows that people are most likely to access travel information through television, followed by commercial radio and the Internet. Specifically, 46.5% of the total respondents used TV for traffic information acquisition, wile 32.8% used commercial radio, and 20.4% used the Internet. The reported use of other public information acquisition technologies, including VMS, HAR, and 511 was relatively rare, and so those information acquisition technologies were not considered in the data for model development.

Table 6.4 Information Acquisition Technology

Type	Count	%
Internet	351	20.4
TV	801	46.5
Radio	566	32.8
Traveler Information Radio	6	0.3
Total	1,724	100

Table 6.5 Travel Decisions Based on the Information

Decision type		Count		%	
No change		325		18.9	
Change	Departure time	121	1,399	7.0	81.1
	Travel mode	20		1.2	
	Cancel Trip	64		3.7	
	Route	1,194		69.2	
Total		1,724		100	

6.3 Statistical Modeling Methods

6.3.1 Choice levels

Figure 6.4 depicts the structure of the choices and responses for the four questions in Table 6.2. For modeling purposes, this structure needed to be simplified. The response types of the first choice level, i.e., information access, were classified into binary responses, Yes or No. In the second choice level on information acquisition technology, the response Highway Advisory Radio (HAR) was combined with the response Radio, and the response Variable Message Signs (VMS) and other information acquisition technologies were excluded in the samples because the number of those responses was very small. Even though TV and

Internet are both pre-trip information acquisition technologies, those were not combined because the relationship between the two information acquisition technologies and socio-economic variables showed very different tendencies in a cross-classification analysis (*Williams et al., 2007*). Thus, the second choice level has three types of responses about information acquisition technology, TV, Internet, or Radio. The response on the third choice level, i.e., the travel change decision, was also binomial with yes or no outcomes for each selected information acquisition technology type. The fourth choice level, i.e., travel modification was not considered in the modeling, because the sample size for each response was not enough. Based on this procedure, a simplified choices and responses structure was constructed as depicted in Figure 6.5.

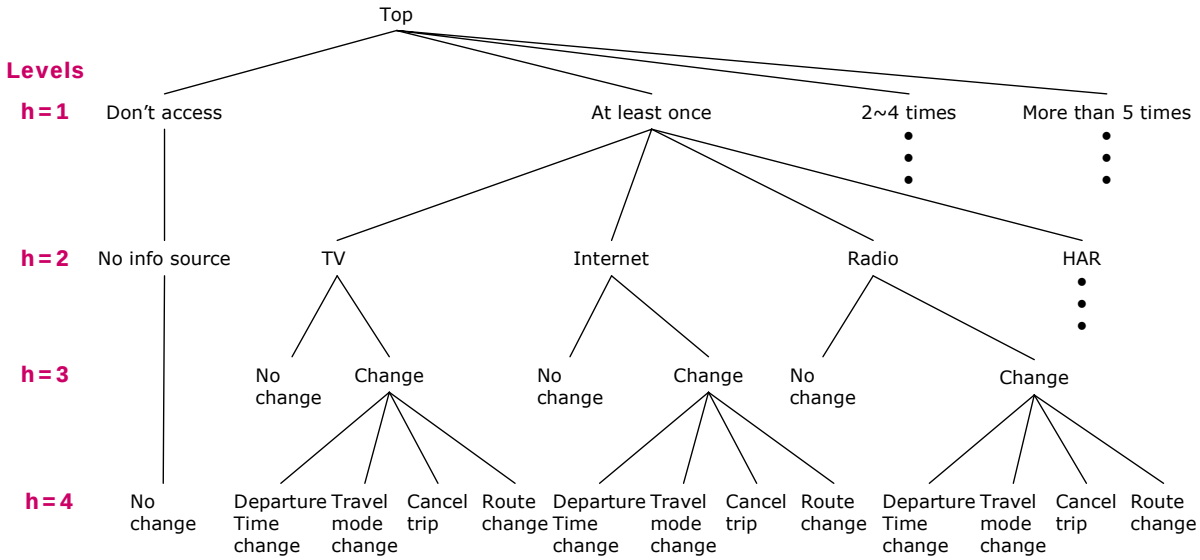


Figure 6.4 Original Choice Levels and Responses in the Survey Data

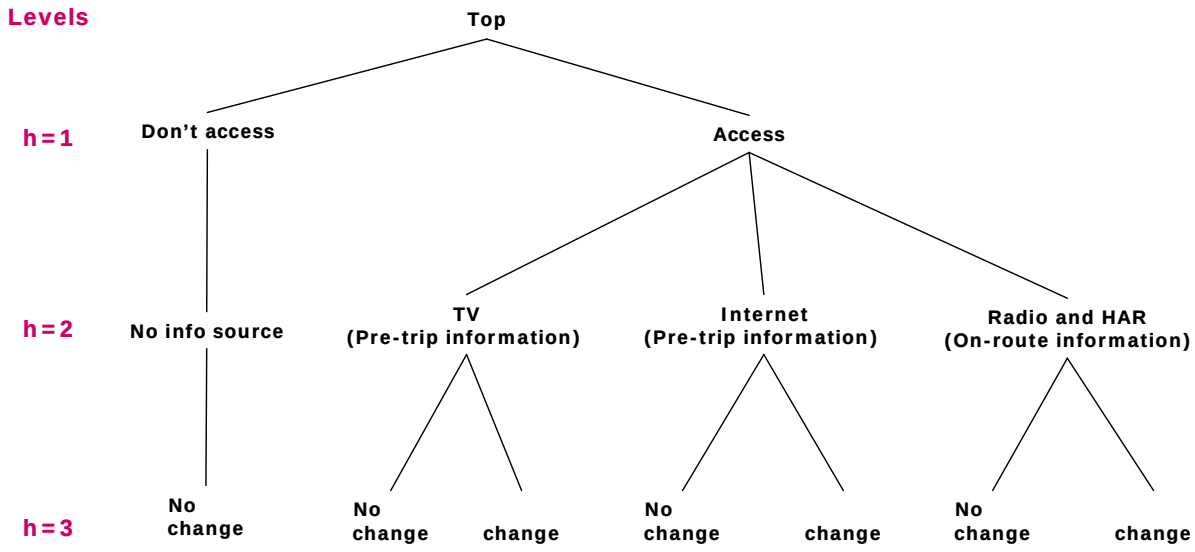


Figure 6.5 Simplified Choice Levels and Responses

6.3.2 Modeling methods

Based on the response structure, there were two possible options for modeling these three choice levels. The first option is to assume that a traveler simultaneously decides on the information access, information acquisition technology type, and travel decision. To develop a model this option, a multinomial logit modeling for the third level which has 7 types of responses must be used. However, this multinomial model violates the Independence from Irrelevant Alternative (IIA) assumption. To overcome this problem, a nested logit model was considered. To develop a nested logit model, additional explanatory variables which can explain the different attraction of the selection in the second and third choice levels must exist. For example, in the second choice level, the cost for or accessibility of a selected information acquisition technology could be the extra variable. In the third choice level, travel time savings or travel distance increase could be considered as the extra variables. However, the survey data didn't include any information about such variables. Hence, a nested logit model method was not appropriate for this study.

The second option is to assume that the three choices are made sequentially. In other word, each choice level has a separate choice model. This option was selected in this study because the modeling procedure for this option is simple and the survey data satisfy the requirement for this option. To satisfy the Independence from Irrelevant alternative (IIA) assumption, subsets of samples out of the entire data set were used for the model developments in the second and third level. For example, to develop an information selection model, the subset of samples which have only yes responses to the information access was used.

Because the response variables in each level were discrete and categorical, methods of categorical data analysis were considered. A binary logit regression model was selected when the responses were binary. A multinomial logit regression form was applied when the responses consisted of more than two choices. The selected models for each choice level are as follows:

- Level 1 : Information access (1: yes, 2: no) - binary logit model

  For a binary response variable Y and explanatory variable X,

  let $\pi(x) = P(Y = 1 \mid X = x) = 1 - P(Y = 0 \mid X = x)$,

  $$\pi(x) = \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)} \qquad \text{(Equation 6.1)}$$

  where, α is intersept and β is coefficient of explanatory variable.

- Level 2: Information acquisition technology type (1: TV, 2: Internet, and 3: radio) - multinomial logit model

  Response probability $\{\pi_j(x)\}$ is,

  $$\pi_j(x) = \frac{\exp(\alpha_j + \beta_j{}' x)}{1 + \sum_{h=1}^{J-1} \exp(\alpha_h + \beta_h{}' x)} \qquad \text{(Equation 6.2)}$$

  J = number of response choice (J=3 in this context)

  If model has multiple explanatory variables,

$$\pi_j(x) = \frac{\exp(\alpha_j + \beta_{1j}{}' x_1 + \beta_{2j}{}' x_2 + \ldots + \beta_{pj}{}' x_p)}{1 + \sum_{h=1}^{J-1} \exp(\alpha_h + \beta_{1h}{}' x_1 + \beta_{2h}{}' x_2 + \ldots + \beta_{ph}{}' x_p)} \qquad \text{(Equation 6.3)}$$

- Level 3: Travel decisions (change or retain travel condition)
  - Level 3-1: TV users (1: yes, 2: no) - binary logit model
  - Level 3-2: Internet users (1: yes, 2: no) - binary logit model
  - Level 3-3: Radio users (1: yes, 2: no) - binary logit model

  Because the response variable is binary, Equation 6.1 was applied to the model level 3.

The logistic procedure in SAS program provides estimation values of intercepts α_i, coefficients β_i, and the Wald Chi-Square test for the null hypothesis $\beta_i = 0$. In the Wald Chi-Square test, if the p-value for a variable x_i is less than 0.05, the null hypothesis is rejected, which implies that the variable x_i is a meaningful variable in the model. The interpretation of β_i is not simple due to the exponential form of the logit equation. A one-unit increase in the independent variable results in the increase in the odds ($\frac{\pi}{1-\pi}$) of the response variable by the odds ratio, e^{β_i} .

6.3.3 Modeling process

The modeling process is shown in Figure 6.6. First, random data sampling was conducted to construct a training set containing 80% of the entire data set for model developments, and a test set that consists of the remaining 20% of the entire data set for validation purposes. The data mining tool in SAS program was used to randomly classify observations into the two sets. Figure 6.7 shows the number of observations for each response subset in the training set.

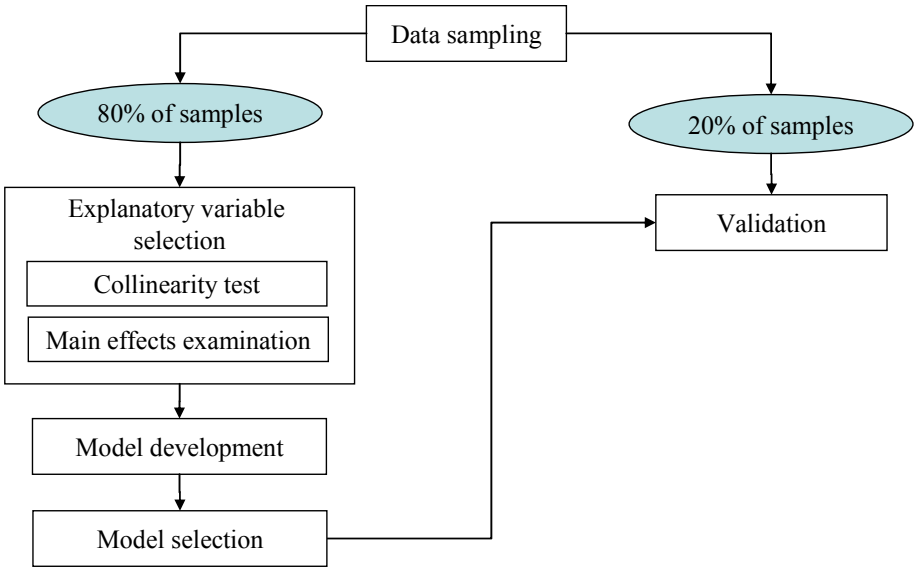


Figure 6.6 Modeling Process

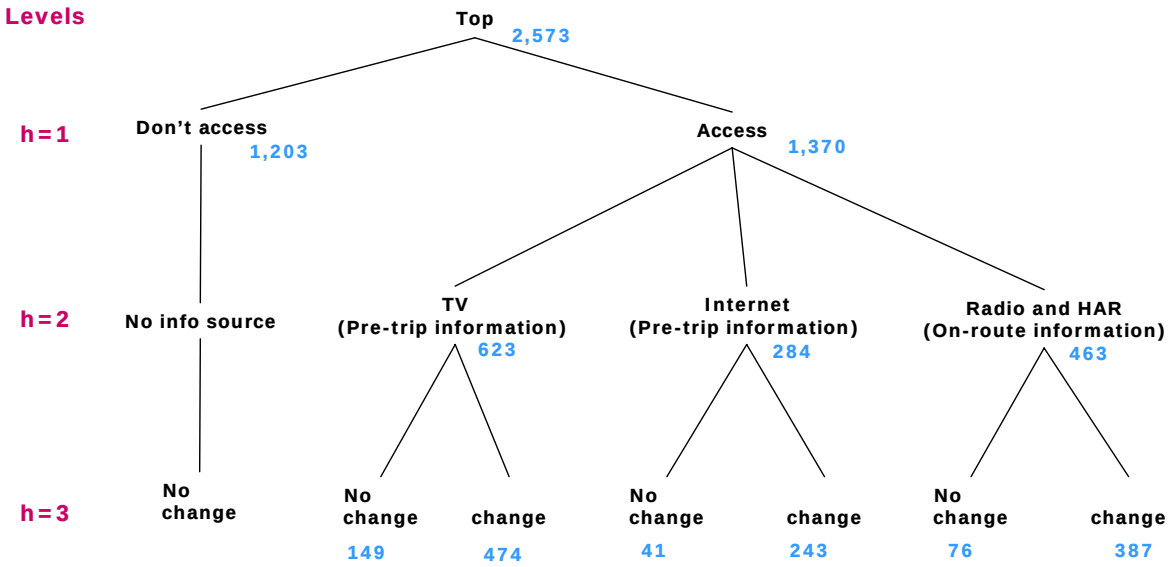


Figure 6.7 Number of Responses in Training Set – 80% of the Entire Sample

To test for interaction effects between explanatory variables, a collinearity test was conducted. Because all models used the same seven socioeconomic variables, the collinearity test was performed only once. The results in Table 6.6 show no significant correlations between the explanatory variables. The relationships between the variables age and length lived in area and between income level and education level were relatively strong but still negligible. The variables income, education level, and work status presented relatively strong relationships between each other.

Table 6.6 Collinearity Test Results

	Gender	Age	Income Level	Education Level	Work Status	Length Lived	Regular Transit User
Gender (0: Female 1: male)	1.00	0.00	0.14	0.10	0.07	-0.02	0.00
Age (1-99)		1.00	-0.05	-0.15	-0.34	0.42	-0.12
Income Level (1-7)			1.00	0.39	0.29	0.11	-0.15
Education Level (1-6)				1.00	0.24	-0.05	-0.07
Work Status (0: don't work 1: work)					1.00	-0.05	0.01
Length Lived (1-5)						1.00	-0.13
Regular Transit User (0: don't use 1: use)							1.00

The effect of each independent variable on the dependent variable was examined in order to pick the significant ones to be used in the model. Specifically, variables with a p-value less than 0.05 were selected. Based on the result of the main effect test, the order of introducing the selected independent variables into the model was determined using the Chi-square

values, with variables having higher Chi-square values introduced first. The order of variable introduction can affect the model selection results because the forward selection algorithm was applied in this study. The main effect examinations were conducted for every choice level. The main effect test results are shown in the model development and selection section.

To compare the developed models in the model selection step, the deviance statistic was used. It is expressed as follows:

$$\text{Deviance} = -2 \log \text{likelihood} \qquad \text{(Equation 6.4)}$$

The reduction in the deviance value between two models is compared using the Chi-square statistic with degrees of freedom equal to the difference in the number of parameters between the two compared models. Because the forward selection method introduces variables to the model one by one, the degrees of freedom in the Chi-square tests were always 1 for the binary logit model. For the multinomial logit model, the degrees of freedom in the Chi-square tests were 2 because the multinomial logit model uses a different β coefficient for each response level other than the base level. In other words, the selected three-response model adds two β parameters for each variable added to the model.

As another criterion for model selection, the Akaike information criterion (AIC) can be used, which is a version of the -2 log likelihood statistic that applies a penalty for the number of parameters in the model. Using this information criterion, non-nested models can be compared for selecting the best model. In this study, however, one of the two models in comparison was always an extension of the other model because the forward selection method was applied as mentioned above. Therefore, the AIC was not useful as a model selection criterion in this study.

In the validation step, the selected final models were applied to predict the responses using the test data set prepared in the data sampling step as mentioned earlier in this section. Then,

the predictive power of the developed models was examined by comparing the reported and predicted values for the test set. Classification tables were constructed by cross-classifying the responses according to the estimated probabilities. For the binary logit models, the prediction is $\hat{y}=1$ when $\hat{\pi}_i > \pi_0$ and $\hat{y}=0$ when $\hat{\pi}_i \le \pi_0$, some cutoff π_0 , where $\pi_0 = 0.5$ was applied. For the multinomial logit models, the prediction selected the response which has the highest estimated probabilities.

In binary logit model, $\pi_0 = 0.5$ is typically used to make classification tables. But Agresti (*2002*) describes a limitation of this approach that collapses the continuous predictive value $\hat{\pi}$ into binary one, where the choice of π_0 is arbitrary, and it is highly sensitive to the relative numbers of times $y=1$ and $y=0$. The way to overcome this limitation is to use the Receiver Operating Characteristic (ROC) curve. The ROC curve is a plot of sensitivity as a function of (1-specificity) for the possible cutoffs π_0 . Where, $Sensitivity = P(\hat{y}=1 | y=1)$ and $Specity = P(\hat{y}=0 | y=0)$. The area under a ROC curve is identical to the value of another measure of predictive power, the concordance index (c) that estimates the probability that the predictions and the outcomes are concordant. A value of c=0.5 means that the predictions were no better than random assignment.

6.4 Level 1 Results: Information Access (1: yes, 2: no)

6.4.1 Main effects examination

Table 6.7 presents the summary of the model results of the main effect examination for the choice level 1, i.e., information access choice. As shown in Table 6.7, the variables age, income level, and work status showed statistically significant relationships with the information access choice. The variable income level had the biggest Chi-square value, and the variables work status and age took the second and third place, respectively as shown in Table 6.7.

Table 6.7 Main Effects Examination for Level 1 (Information Access)

Variable	Intercept	Estimated Beta	Chi-square	pr>Chi-square
Gender	0.1839	-0.1298	2.6216	0.1054
Age	0.7828	**-0.0132**	**24.3743**	**<0.0001**
Income Level	-0.6007	**0.1440**	**41.8067**	**<0.0001**
Education Level	0.2477	-0.0254	0.8454	0.3579
Work Status	-0.2838	**0.5391**	**32.6367**	**<0.0001**
Length Lived	-0.0250	0.0424	1.9860	0.1588
Transit User	0.1147	0.1224	1.0416	0.3074

6.4.2 Model development and selection

According to the main effects examination results, the variables income level, work status, and age were selected as the independent variables for the Level 1 model development. The variables were introduced into the model one by one until any additions do not improve the model fit. In other words, if the difference of deviance between the models with and without the newly introduced variable is not statistically significant (based on the p-value), the model with the additional variable was not considered. The variable introducing order was determined using the descending order of Chi-square values of the selected variables in Table 6.7. In this case, the variables income level, work status, and age, in that order, were introduced into the model individually.

Table 6.8 summarizes the results of fitting and comparing the different logit models to the information access with the independent variables, income level, work status, and age. The fourth model including all the three independent variables was selected to be the best model based on the model selection criteria mentioned earlier.

Table 6.8 Developed Models and Selection Criteria for Level 1 (Information Access)

Model		Deviance (-2 log L)	Deviance Difference	df	pr>Chi-square
1	None (intercept only)	3556.089			
2	Income	3513.556	42.533	1	<0.0001
3	Income + Work	3496.968	16.588	1	<0.0001
4	Income + Work+ Age	3484.618	12.35	1	0.0004

Table 6.9 shows the result of the parameter estimation for the selected model. According to the estimated coefficient values shown in Table 6.9, the probability that a person accesses traveler information increases with the person's income level and when the person is employed. Conversely, the probability decreases with age. The final model can be expressed as follows:

$$P(Y=1)=\frac{\exp(-0.2129+0.1229income+0.2785work-0.01age)}{1+\exp(-0.2129+0.1229income+0.2785work-0.01age)} \qquad \text{(Equation 6.5)}$$
$$P(Y=2)=1-P(Y=1)$$

Table 6.9 Estimated Parameters for Level 1 (Information Access)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-square
Intercept	1	**-0.2129**	0.2050	1.0784	0.2990
Income	1	**0.1229**	0.0233	27.7635	<.0001
Work Status	1	**0.2785**	0.1046	7.0905	0.0077
Age	1	**-0.0100**	0.0029	12.3123	0.0004

6.4.3 Validation

Table 6.10 shows the results of the prediction when applied to the test data set using the information access model developed above. According to the results, the model predicted

the “yes” responses more than the reported values by about 15%, and therefore, there were 15 % fewer “no” responses. Overall, however 58% of the responses were correctly classified.

Table 6.10 Classification Table for Level 1 (Information Access)

		Predicted Response		Total
		YES	NO	
Reported Response	YES	267 (41.52%)	87 (13.53%)	354 (55.05%)
	NO	181 (28.15%)	108 (16.80%)	289 (44.95%)
Total		448 (69.67%)	195 (30.33%)	643 (100.00%)

Figure 6.8 shows the ROC curve produced from the validation result for the information access model. As shown in Figure 6.8, the ROC curve is above but close to the 0.5 line, which means the model is slightly better than a random assignment of the responses.

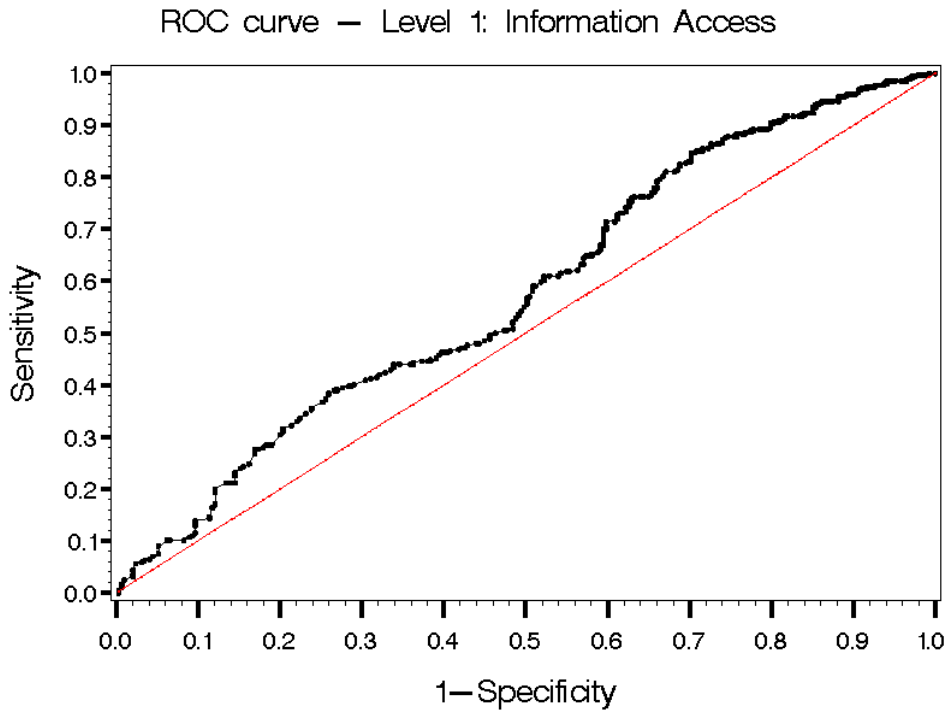


Figure 6.8 The ROC Curve - Level 1: Information Access

6.5 Level 2 Results: Information Acquisition Technology

6.5.1 Main effects examination

The results of the main effect examination for the choice level 2, i.e., the information acquisition technology type indicated that all variables except the variable transit user showed statistically significant relationships with the information acquisition technology selection as shown in Table 6.11. The order of those six variables based on their Chi-square values was age, work status, income level, education level, gender, and length of time lived in the area.

Table 6.11 Main Effects Examination for Level 2 (Information Acquisition Technology)

Explanatory variable	Information Acquisition Technology	Intercept	Estimated Beta	Chi-square	pr>Chi-square
Gender	TV	0.4599	-0.4257	**23.5934**	**<0.0001**
	Internet	-0.5985	0.2369		
Age	TV	-1.3993	0.0352	**69.5972**	**<0.0001**
	Internet	-0.4821	-0.00015		
Income Level	TV	1.0230	-0.1383	**26.9832**	**<0.0001**
	Internet	-0.8751	0.0699		
Education Level	TV	1.0763	-0.1705	**26.6730**	**<0.0001**
	Internet	-0.8579	0.0769		
Work Status	TV	0.9227	-0.7704	**29.5555**	**<0.0001**
	Internet	-0.4895	0.000918		
Length Lived	TV	-0.3864	0.1837	**21.0254**	**<0.0001**
	Internet	-0.3711	-0.0333		
Transit User	TV	0.2804	0.1379	5.7476	0.0565
	Internet	-0.5590	0.4999		

6.5.2 Model development and selection

Table 6.12 summarized the results of fitting and comparing the several multinomial logit models for the information acquisition technology type with the independent variables age, work status, income level, education level, gender, and length lived. The sixth model with

four variables, age, work status, income level, and gender, was selected as the best model for the information acquisition technology type.

Table 6.12 Developed Models and Selection Criteria for Level 2 (Information Acquisition Technology)

Model		Deviance (-2 log L)	Deviance Difference	df	pr>Chi-square
1	None (intercept only)	2880.233			
2	age	2805.728	74.505	2	<0.0001
3	age+work	2794.646	11.082	2	0.0039
4	age+work+income	2773.026	21.620	2	<0.0001
5	age+work+income+educa	2767.091	5.935	2	0.0514
6	age+work+income+gender	2756.399	16.627	2	0.0002
7	age+work+income+gender+lived	2752.715	3.684	2	0.1585

Table 6.13 shows the result of the parameter estimation for the selected model. According to the estimated coefficient values shown in Table 6.13, the probability that a person choose TV as an information acquisition technology increases as the person's age increases. Conversely, the probability that a person chooses TV decreases as the person's income level increases, if the person is a male, or the person is employed. The variables age, income level, and gender showed opposite effect to the probability that a person choose Internet. The final model can be expressed as follows:

$$V1 = -0.2892 + 0.0331age - 0.3346work - 0.1121income - 0.3647gender$$
$$V2 = -0.7794 - 0.0019age - 0.0995work + 0.0656income + 0.219gender$$
$$P(Y=1) = \frac{\exp(V1)}{1+\exp(V1)+\exp(V2)} \qquad \text{(Equation 6.6)}$$
$$P(Y=2) = \frac{\exp(V2)}{1+\exp(V1)+\exp(V2)}$$
$$P(Y=3) = \frac{1}{1+\exp(V1)+\exp(V2)}$$

Table 6.13 Estimated Parameters for Level 2 (Information Acquisition Technology)

Parameter	Information acquisition technology	DF	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-square
Intercept	TV	1	**-0.2892**	0.3418	0.7162	0.3974
	Internet	1	**-0.7794**	0.4203	3.4394	0.0637
Age	TV	1	**0.0331**	0.0050	44.0824	<.0001
	Internet	1	**-0.0019**	0.0062	0.0986	0.7536
Work Status	TV	1	**-0.3346**	0.1780	3.5347	0.0601
	Internet	1	**-0.0995**	0.2309	0.1857	0.6665
Income	TV	1	**-0.1121**	0.0392	8.1914	0.0042
	Internet	1	**0.0656**	0.0496	1.7477	0.1862
Gender	TV	1	**-0.3647**	0.1315	7.6872	0.0056
	Internet	1	**0.2190**	0.1535	2.0351	0.1537

6.5.3 Validation

Table 6.14 shows the results of the prediction to the test data set using the information acquisition technology model selected above. According to the prediction results, the model predicted the TV and radios responses more than the reported value by about 17% and 2%, respectively. The Internet was not predicted at all by the model for the test data set. Overall, about 51 % of all the response were properly classified.

Table 6.14 Classification Table for Level 2 (Information Acquisition Technology)

		Predicted Response		Total
		1 = TV	3 = Radio	
Reported Response	1 = TV	138 (38.98%)	40 (11.30%)	178 (50.28%)
	2 = Internet	35 (9.89%)	32 (9.04%)	67 (18.93%)
	3 = Radio	65 (18.36%)	44 (12.43%)	109 (30.79%)
Total		238 (67.23%)	116 (32.77%)	354 (100.00%)

6.6 Level 3-1 Results: Travel Decision for TV Information Users

6.6.1 Main effects examination

Table 6.15 shows the results of the main effects examination for the choice level 3-1, i.e., travel decision change of TV users. As shown, all variables except gender and length of time lived in the area had statistically significant relationships with travel decision change of the users who received traveler information from TV. The order of those five variables based on their Chi-square values was income, education level, age, work status, and transit user.

Table 6.15 Main Effects Examination for Level 3-1 (Travel Decision for TV Users)

Variable	Intercept	Estimated beta	Chi-square	pr>Chi-square
Gender	1.2144	-0.1665	0.7168	0.3972
Age	2.1185	-0.0184	**7.3529**	**0.0067**
Income Level	0.0084	0.2372	**22.1278**	**<.0001**
Education Level	0.2417	0.2138	**11.6272**	**0.0006**
Work Status	0.8411	0.4338	**4.3780**	**0.0364**
Length Lived	0.7001	0.1198	2.6600	0.1029
Transit User	1.2304	-0.5186	**3.9659**	**0.0464**

6.6.2 Model development and selection

Table 6.16 summarized the results of fitting and comparing the several logit models to the travel decision change of TV users with the independent variables selected to be considered, i.e., income, education level, age, work status, and transit user. The fourth model with the independent variables income and age was selected to be the best model.

Table 6.16 Developed Models and Selection Criteria for Level 3-1 (Travel Decision for TV Users)

Model		Deviance (-2 log L)	Deviance Difference	df	pr>Chi-square
1	None (intercept only)	685.444			
2	income	663.148	22.296	1	<0.0001
3	income+educa	661.207	1.941	1	0.1636
4	income+age	657.459	5.689	1	0.0171
5	income+age+work	657.447	0.012	1	0.9128
6	income+age+usetr	656.275	1.172	1	0.2790

Table 6.17 presents the result of the parameter estimation for the selected model. According to the estimated coefficient values shown in Table 6.17, the probability that a TV user changes travel decisions increases as the person's income level increases. On the contrary, the probability decreases with age. The final model can be expressed as follows:

$$P(Y=1)=\frac{\exp(0.871+0.2302income-0.0159age)}{1+\exp(0.871+0.2302income-0.0159age)} \qquad \text{(Equation 6.7)}$$
$$P(Y=2)=1-P(Y=1)$$

Table 6.17 Estimated Parameters for Level 3-1 (Travel Decision for TV Users)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-square
Intercept	1	**0.8710**	0.4481	3.7771	0.0520
Income	1	**0.2302**	0.0509	20.4527	<.0001
Age	1	**-0.0159**	0.00669	5.6200	0.0178

6.6.3 Validation

Table 6.18 shows the results of the prediction on the test data set using the selected travel decision change model for TV users. According to the result shown in Table 6.18, the model predicted the yes responses more than the reported value by about 16%, and therefore, 16 % less no responses. Overall, 81% of the responses were properly classified.

Table 6.18 Classification Table for Level 3-1 (Travel Decision for TV Users)

		Predicted Response		Total
		YES	NO	
Reported Response	YES	143 (80.34%)	2 (1.12%)	145 (81.46%)
	NO	31 (17.42%)	2 (1.12%)	33 (18.54%)
Total		174 (97.75%)	4 (2.25%)	178 (100%)

Figure 6.9 shows the ROC curve produced from the validation result for the travel decision change model for the ATIS users who perceived travel information from TV. As shown in Figure 6.9, the ROC curve is above but close to the 0.5 line, which means the model is slightly better than a random assignment of the responses.

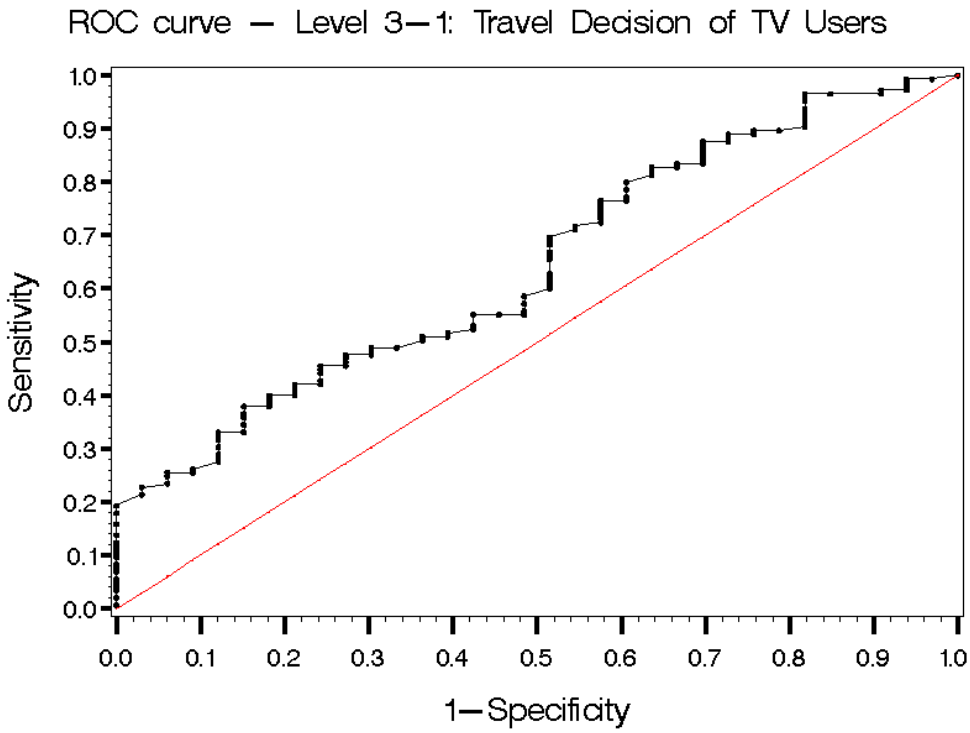


Figure 6.9 The ROC Curve - Level 3-1: Travel Decision for TV Users

6.7 Level 3-2: Travel Decision for Internet Information Users

6.7.1 Main effects examination

Table 6.19 presents the summary of the results from the main effect examination for the choice level 3-1, i.e., travel decision change of Internet users. As shown in Table 6.19, the variables age and income level showed statistically significant relationships with the travel decision change of Internet users. The variable income level had the higher Chi-square value than age.

Table 6.19 Main Effects Examination for Level 3-2 (Travel Decision for Internet Users)

Variable	Intercept	Estimated beta	Chi-square	pr>Chi-square
Gender	2.0108	-0.4354	1.6205	0.2030
Age	3.1041	-0.0284	**4.6023**	**0.0319**
Income Level	-0.5742	0.4469	**17.7549**	**<.0001**
Education Level	1.2167	0.1174	0.9190	0.3377
Work Status	1.3218	0.5430	1.5253	0.2168
Length Lived	1.3984	0.1108	0.7664	0.3813
Transit User	1.7769	0.0148	0.0011	0.9737

6.7.2 Model development and selection

Table 6.20 summarizes the results of fitting and comparing the different logit models to the travel change of Internet users with the independent variables, income and age. The third model including both independent variables was selected to be the best model.

Table 6.20 Developed Models and Selection Criteria for Level 3-2 (Travel Decision for Internet Users)

Model		Deviance (-2 log L)	Deviance Difference	df	pr>Chi-square
1	None (intercept only)	234.477			
2	income	216.500	17.977	1	<0.0001
3	income+age	212.113	4.387	1	0.0362

Table 6.21 shows the result of the parameter estimation for the selected travel change of Internet users model. According to the estimated coefficient values shown in Table 6.21, the probability that an internet user changes travel decision increases as the person's income level increase. On the contrary, the probability decreases with the person's age. The final model can be expressed as follows:

$$P(Y=1)=\frac{\exp(0.6558+0.4499income-0.0269age)}{1+\exp(0.6558+0.4499income-0.0269age)} \qquad \text{(Equation 6.8)}$$
$$P(Y=2)=1-P(Y=1)$$

Table 6.21 Estimated Parameters for Level 3-2 (Travel Decision for Internet Users)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-square
Intercept	1	**0.6558**	0.8252	0.6316	0.4268
Income	1	**0.4499**	0.1083	17.2496	<.0001
Age	1	**-0.0269**	0.0130	4.2967	0.0382

6.7.3 Validation

Table 6.22 shows the results of the prediction to the test data set using the selected travel decision change of Internet users model. As shown in Table 6.22, the model predicted the yes responses more than the reported value by about 15%, and didn't predict any no response. Overall, 85% of all observations were properly classified.

Table 6.22 Classification Table for Level 3-2 (Travel Decision for Internet Users)

		Predicted Response		Total
		YES	NO	
Reported Response	YES	57 (85.07%)	0 (0.00%)	57 (85.07%)
	NO	10 (14.93%)	0 (0.00%)	10 (14.93%)
Total		67 (100%)	0 (0.00%)	178 (100%)

Figure 6.10 shows the ROC curve produced from the validation result for the travel decision change model for the ATIS users who perceived travel information from the Internet. As

shown in Figure 6.10, the ROC curve is very close to the 0.5 line, which means the model is not much better than a random assignment of the responses.

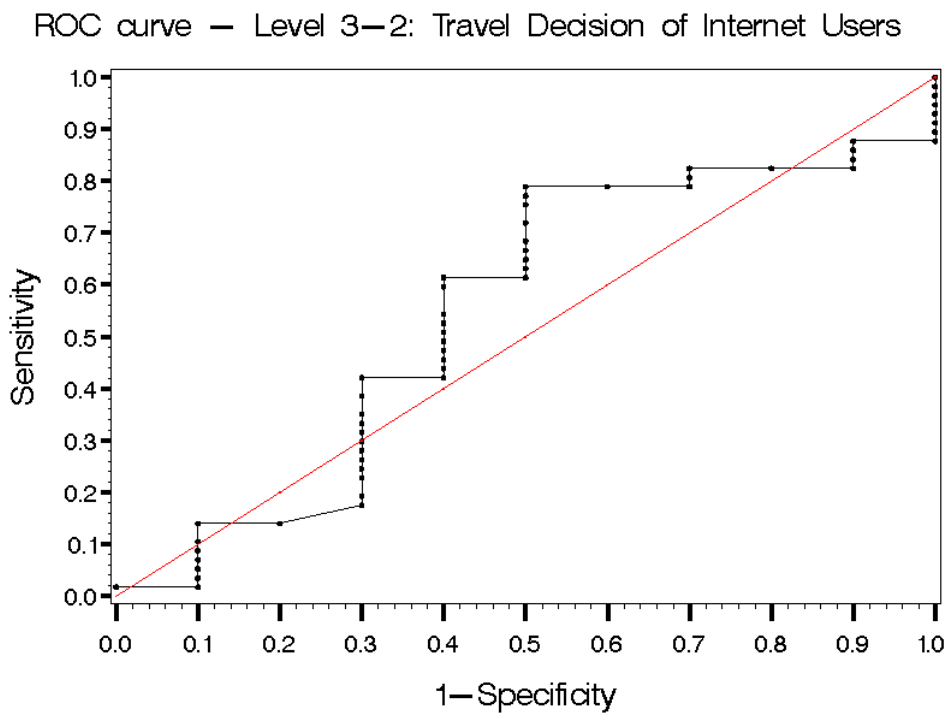


Figure 6.10 The ROC curve - Level 3-2: Travel Decision for Internet Users

6.8 Level 3-3: Travel Decision for Radio Information Users

6.8.1 Main effects examination

Table 6.23 presents the summary of the results from the main effect examination for the choice level 3-3, i.e., travel decision change of radio users. As shown in Table 6.23, the variables income level, work status, and length lived showed statistically significant relationships with the travel decision change of radio information users. Among them, the variable income level had the highest Chi-square value and the variables length lived and work status had the second and third highest Chi-square values, respectively.

Table 6.23 Main Effects Examination for Level 3-3 (Travel Decision for Radio Users)

Variable	Intercept	Estimated beta	Chi-square	pr>Chi-square
Gender	1.7138	-0.1914	0.5782	0.4470
Age	1.4898	0.00307	0.0965	0.7560
Income	0.2488	0.2639	**12.2765**	**0.0005**
Education Level	1.2250	0.0860	0.8716	0.3505
Work Status	0.8938	0.8835	**7.9291**	**0.0049**
Length Lived	0.6355	0.2920	**9.7477**	**0.0018**
Transit User	1.6721	-0.3567	0.9526	0.3290

6.8.2 Model development and selection

Table 6.24 summarizes the results of fitting and comparing the different logit models to the travel decision change of radio users with the independent variables income level, length lived, and work status. The fourth model with all the three independent variables was selected.

Table 6.24 Developed Models and Selection Criteria for Level 3-3 (Travel Decision for Radio Users)

Model		Deviance (-2 log L)	Deviance Difference	df	pr>Chi-square
1	None (intercept only)	413.443			
2	income	401.414	12.029	1	0.0005
3	Income+lived	394.859	6.555	1	0.0105
4	income+lived+work	387.827	7.032	1	0.0080

Table 6.25 presents the result of the parameter estimation for the selected model. According to the estimated coefficient values shown in Table 6.25, the probability that a person changes his or her travel decision increases as the person's income level increase, the person has a job,

or the person lived at the region for a long time. The final model can be expressed as follows:

$$P(Y=1)=\frac{\exp(-1.1351+0.1969income+0.9127works+0.287lived)}{1+\exp(-1.1351+0.1969income+0.9127works+0.287lived)} \qquad \text{(Equation 6.9)}$$
$$P(Y=2)=1-P(Y=1)$$

Table 6.25 Estimated Parameters for Level 3-3 (Travel Decision for Radio Users)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-square
Intercept	1	**-1.1351**	0.5480	4.2910	0.0383
Income	1	**0.1969**	0.0776	6.4316	0.0112
Work Status	1	**0.9127**	0.3321	7.5520	0.0060
Length Lived	1	**0.2870**	0.0982	8.5316	0.0035

6.8.3 Validation

Table 6.26 shows the results of the prediction to the test data set using the selected travel decision change of radio users model. As shown in Table 6.26, the model predicted the yes responses more than the reported value by about 14%. Overall, 86% of all responses were properly classified.

Table 6.26 Classification Table for Level 3-3 (Travel Decision for Radio users)

		Predicted Response		Total
		YES	NO	
Reported Response	YES	93 (85.32%)	0 (0%)	93 (85.32%)
	NO	15 (13.76%)	1 (0.92%)	16 (14.68%)
Total		108 (99.08%)	1 (0.92%)	109 (100%)

Figure 6.11 shows the ROC curve produced from the validation result for the travel decision change model for the ATIS users who perceived travel information from the radios. As

shown in Figure 6.11, the ROC curve is higher than the 0.5 line, which means the model is much better than a random assignment of the responses.

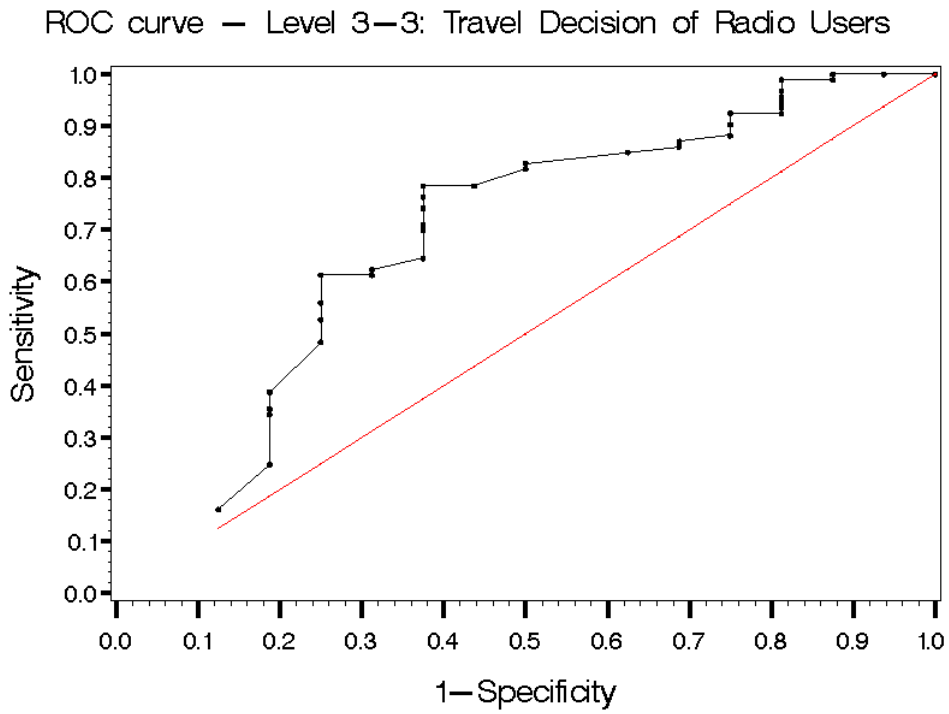


Figure 6.11 The ROC curve - Level 3-3: Travel Decision for Radio Users

6.9 Discussion

Five logistic models were developed for the three response levels: one binary logit model for level one, one multinomial logit model for level two, and three binary logit models for level three. The developed models were useful for investigating which socio-economic factors were more related to the responses. However, based on the validity test results, the prediction results were not considered to be representative of the real response rate. Only 58% and 51% of the responses were correctly classified in the levels one and two, respectively. Because the predictive power is not acceptable, the predictive models developed in this chapter were not used for the enhanced model, which was applied to the

two case studies described in Chapters 7 and 8. Thus, the enhanced model included only Enhancements A and B described in Chapters 4 and 5, respectively.

One of the reasons why the predictive power is not acceptable may be that it is not easy to predict human behavior using a statistical model with limited number of factors. There might be many other factors affecting the ATIS users' decision. Another reason may be that no other set of explanatory variables which can explain the different attribute according to the response types in each choice level were considered. For example, in choice level 1 (information access), factors such as travel distance, travel purpose, and travel starting time can be considered as possible explanatory variables in addition to socio-economic variables. The lower level choices can include the cost for or accessibility to a selected information acquisition technology or the travel time saving or travel distance increase of a selected travel decision change. A model with additional explanatory variables may be able to increase its prediction power and explain the role of the socio-economic variables on the information acquisition technology selection or travel decision change. Moreover, with additional explanatory variables, nested logit modeling method can also be used to develop a user behavioral model.

As the technologies for collecting traffic information data and providing traveler information are improved, the user behavioral model needs to be recalibrated because some information acquisition technology types need to be modified and the response rate can be affected.

CHAPTER 7. VERIFICATION OF ENHANCED MODEL

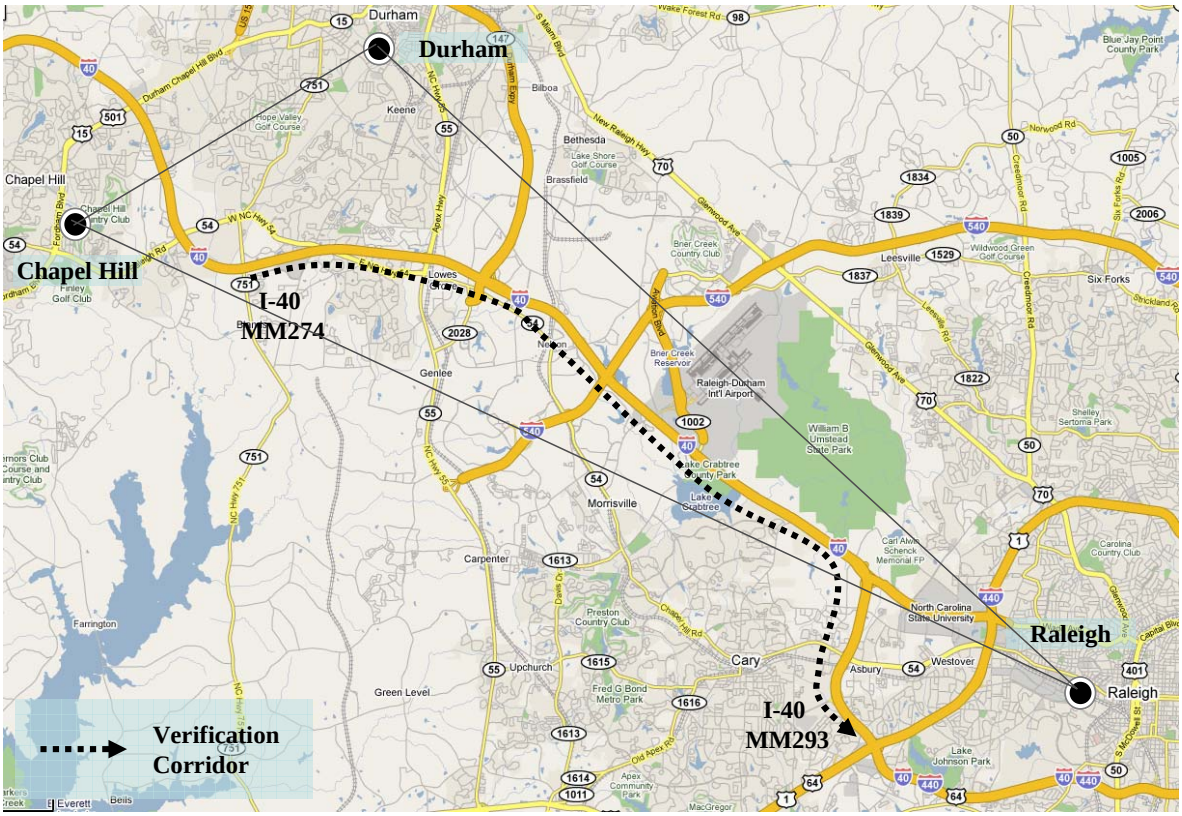
This chapter describes the verification of the model which adopted the enhancement A (a revised queue propagation algorithm) and Enhancement B (a natural diversion algorithm) mentioned in earlier chapters. The verification was conducted by applying the enhanced model to simulate recurring bottleneck situations on the I-40 corridor in the Research Triangle Park region in North Carolina. The simulation results were compared with field data in an effort to investigate the validity of the enhanced model. The field data collection efforts, the simulation network modeling procedures, and the verification results are described in this chapter.

7.1 Scope of Model Verification

Figure 7.1 depicts the location of a 20 mile-long I-40 section between exit 274 (NC-751) and 293 (US-1) in North Carolina used for field validation of the proposed model. The dotted line in Figure 7.1 depicts the corridor. The corridor is located in a virtual triangle connecting three primary cities; Durham, Chapel Hill, and Raleigh-Cary. This triangle circumscribes many business and research facilities which are heavy traffic generators along the I-40 corridor. This area is known as the Research Triangle Park (RTP) and is located near the center of the corridor, i.e., between Exit 278 and Exit 280.

During the PM peak hours of a typical weekday, it is not unusual for recurring congestion to take place on the eastbound direction, especially on some segments between Exit 279 and Exit 290, due to increased demand during this time period. Generally, recurring congestion is more severe and occurs almost everyday on the segments between Exit 285 and Exit 290, while congestion is relatively less severe and occurs less frequently on the segments between Exit 279 and Exit 285. The congestion occurring between Exit 285 and Exit 290 are initiated from two points, i.e., Exit 289 which are the Wade Avenue split and the first on-ramp of Exit 290. The two points are recurring bottlenecks during the PM peak hours because of the

increased demand and the geometric characteristics, i.e., the presence of lane drops. The enhanced model was applied to simulate this recurring bottleneck situation on the corridor. Figure 7.2 shows the geometric characteristics of the corridor - number of lanes, exit ramps locations, and the length of acceleration, deceleration, and auxiliary lanes.



Map source: Google map

Figure 7.1 Location of the Test Corridor

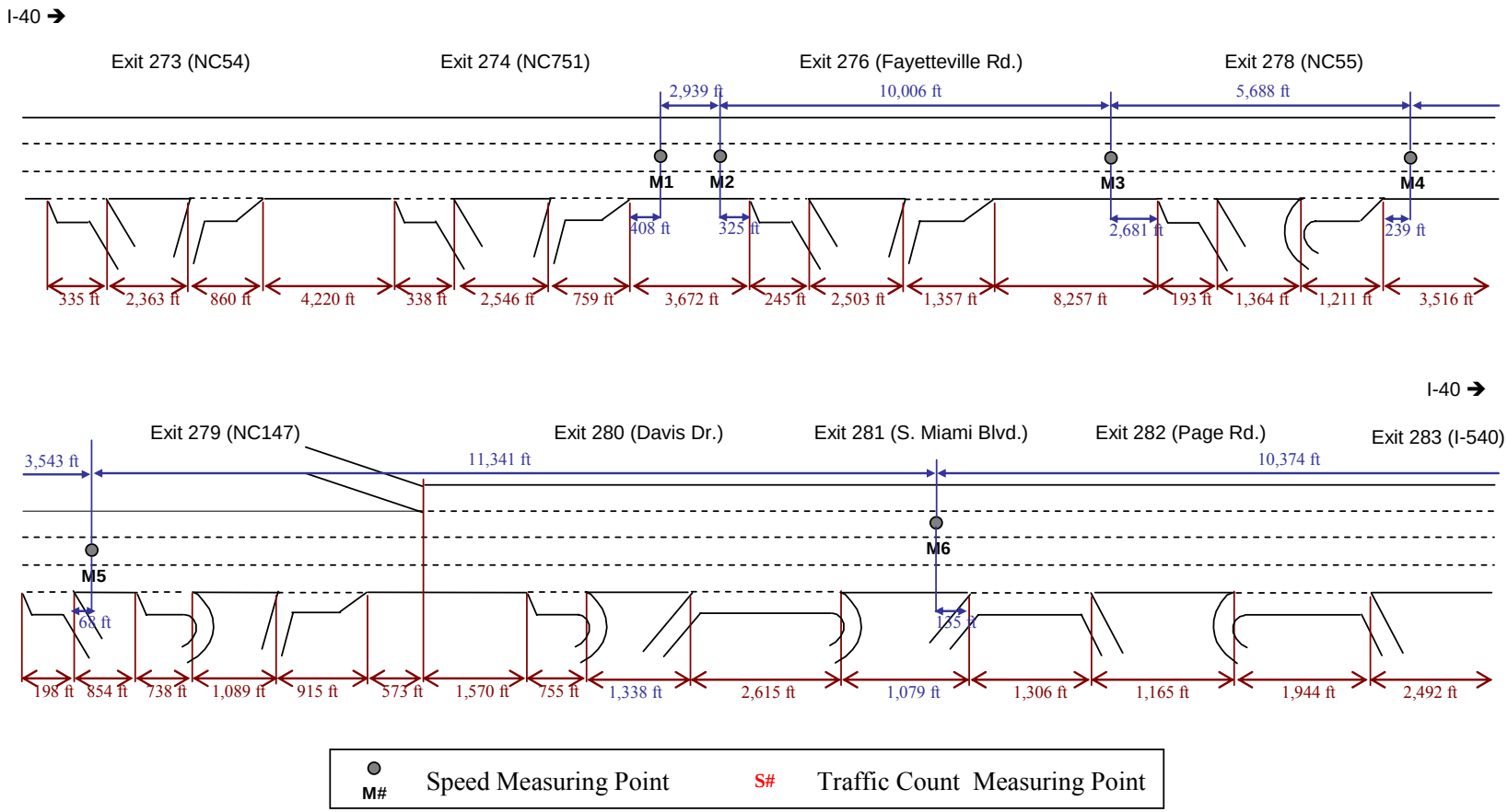


Figure 7.2 Geometry of the Test Corridor

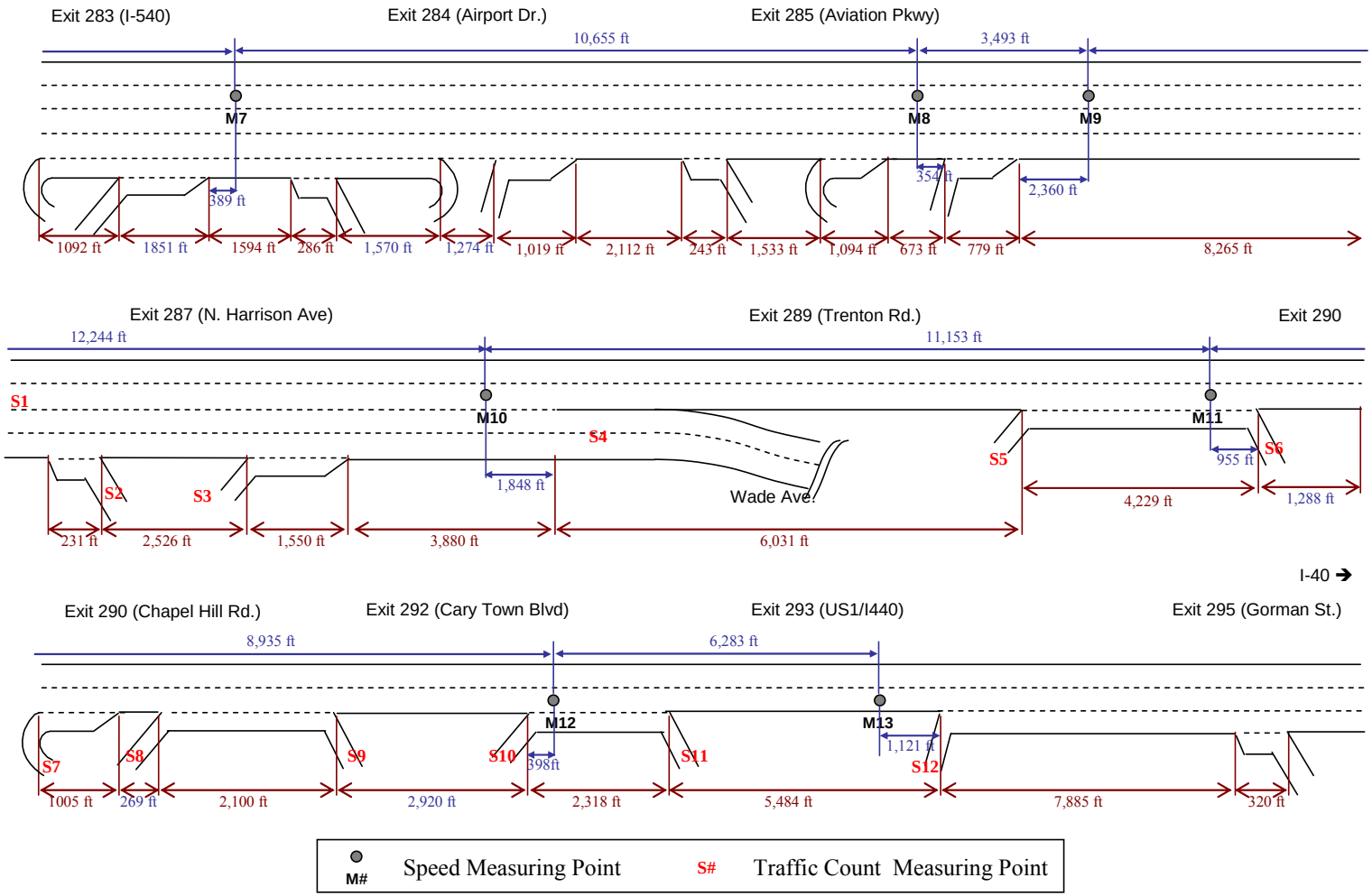


Figure 7.2 Continued

7.2 Verification Method

7.2.1 Verification procedure

Figure 7.3 illustrates the model verification procedure. The procedure involves field data collection, modeling, and verification. The left side of Figure 7.3 depicts the procedure for field data collection of travel times and traffic counts. Travel times were measured using a Global Positioning System (GPS) device installed in a probe vehicle traveling the corridor. To check the validity of the GPS data, the speeds measured by the GPS device were compared with the speeds measured by the SpeedInfo's fixed Doppler radar sensors and archived in NCDOT Traveler Information Management System (TIMS) database. Traffic counts on the corridor were measured by using video recorded from an overhead vantage point. This video was then used in conjunction with an automated video data collection method using an Autoscope Rackvision Card (Image sensing system, Inc., *2008*). In some instances a manual count was necessary particularly in congested time periods. Speed data were collected prior to the bottleneck using this same video and a predefined distance between two points on the ground.

The right side of Figure 7.3 depicts the modeling procedure. The Triangle Regional Model (TRM) network provided network data including zone, node, link, and origin-destination demand data for the modeled network. The geometry data from the TRM network such as number of lanes, traffic controls, and lane configurations for the intersections of the modeling network were updated based on the satellite photo images from Google Maps. Census data were used for calibrating the overall demand level. A demand profile for the peak hour was built from the field traffic counts collected along the corridor. Based on the measured speeds and flow data along the freeway segment on the verification corridor, the traffic flow model for the modeled network was calibrated.

To conclude the procedure, the travel time and counts from the field data and simulation results were compared. In the following sections, the field data collection, the modeling processes, and the verification results are described in detail.

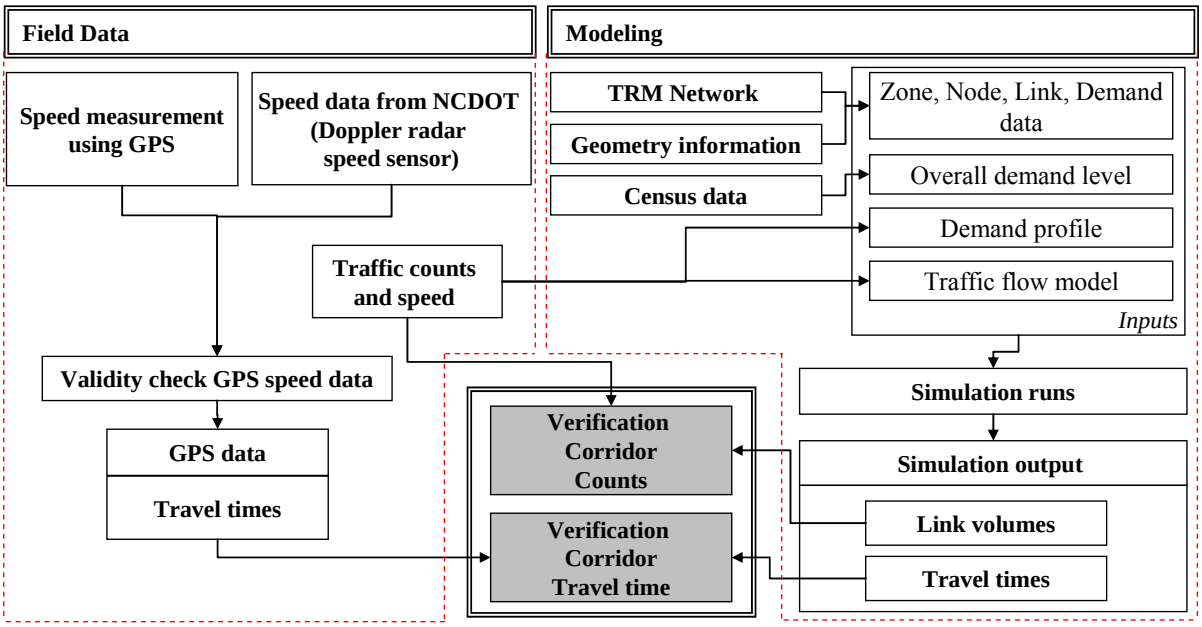


Figure 7.3 Model Verification Procedures

7.2.2 Field data

7.2.2.1 Speed measurement and verification

GPS data collection

A GPS device was installed in a probe vehicle to measure travel times. That is, while a probe vehicle equipped with the GPS device was traveling the test corridor, the GPS coordinates of the vehicle location were recorded in the memory of the device in one second intervals. Therefore, the travel time between specific locations on the corridor could be calculated directly using the coordinates and the times at which the probe vehicle passed the locations.

The probe vehicle traveled only the eastbound portion of the corridor from Mile Marker (MM) 274 to MM 293 during the PM peak hour (5:00~6:00 PM) of a typical weekday. For consistency purposes, the driver attempted to pass MM 274 around 5:00 PM during each day of measurement. The data collection was performed on Tuesdays, Wednesdays, or

Thursdays from April to July, 2008 excluding days that had crashes, incidents, football games, etc. that may affect the normal traffic demand. The GPS field measurements were conducted for 31 weekdays using the following procedure:

- Place the receiver of the GPS device on the dashboard of the probe vehicle and turn on the power of the device.
- Allow the device about one minute to find satellites and communicate with them before entering the study section.
- Drive with the average traffic flow along the corridor and stay in the middle lane of traffic. After completing each travel time run, download the data (time, longitude, latitude, speed, etc.) recorded in the memory card of the GPS device.

Speed Data from SpeedInfo's Detectors

NCDOT installed SpeedInfo's Doppler radar speed detectors almost every mile on I-40 in the Triangle region to collect real-time spot speed data. Figure 7.4 is a screenshot of the NCDOT TIMS site that providing real time traveler information including mean speeds measured from the SpeedInfo's detectors for NCDOT maintained roadways. The variously colored dots on the corridors in Figure 7.4 represent the mean speeds on the speed detecting spots. The detectors are placed on the various road facilities using poles or signs along the freeway. The measurement spot of a SpeedInfo's sensor is set up typically around 1,000 feet from the sensor in the sensor pointing direction. The distances between the sensors and the measurement spots, however, can be longer or shorter than 1,000 feet to avoid detecting the speeds on the auxiliary lanes in the ramp area. The small solid dots on the mainline tagged by M1~M13 in Figure 7.2 indicate the approximate locations of the speed measurement spots according to the facts mentioned previously. The speed detectors measure the speeds of all cars passing its measuring zone on all lanes on both sides of the road every 30 seconds. The detectors transmit the rolling average of the last four measurements every minute. The measurement accuracy is 0.1 mph for each individual car measured. NCDOT TIMS archived the measured speed data in the TIMS database. The speeds collected from the detectors on

MM 274, MM 276, MM 277, MM 278, MM 279, MM 281, MM 283, MM 285, MM 287, MM 288, MM 290, MM 292, and MM 293 for the study days were obtained from the NCDOT TIMS database.

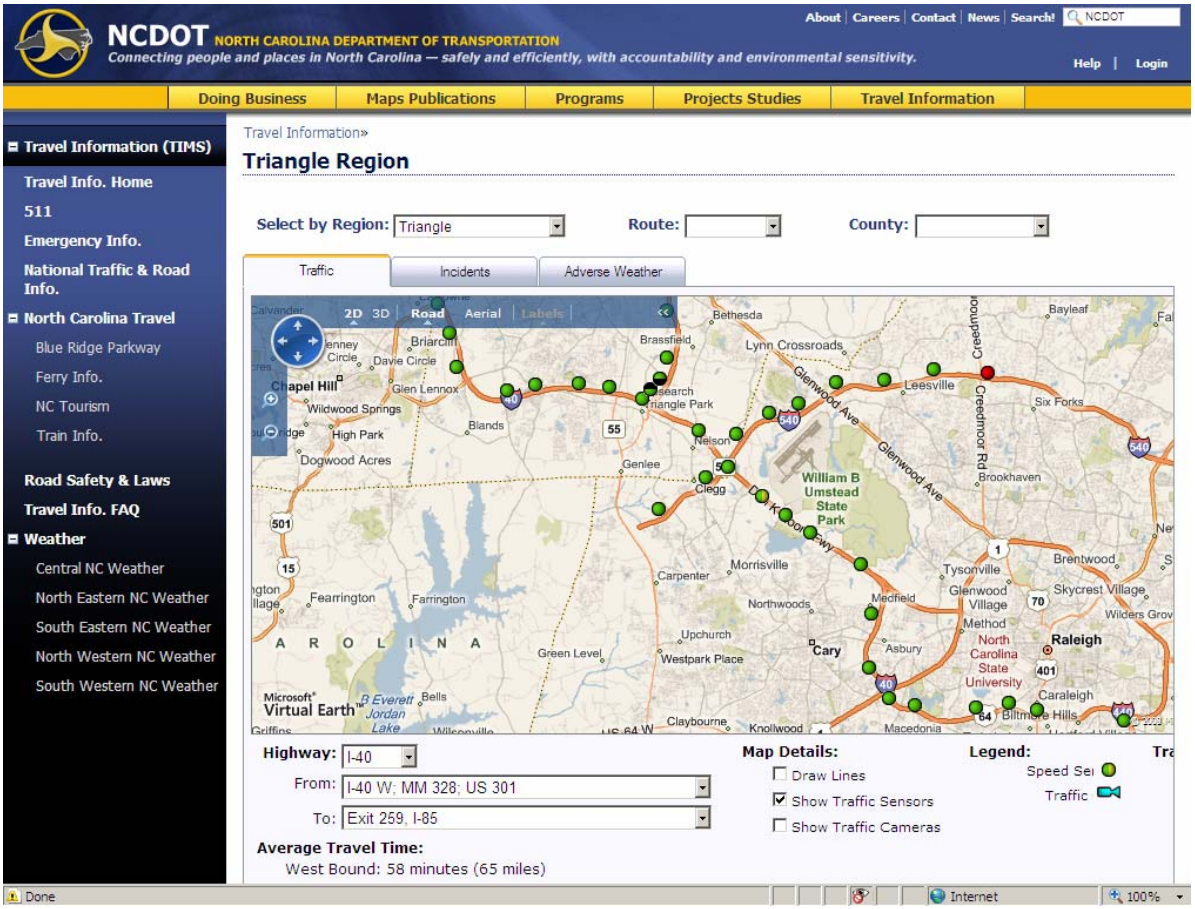


Figure 7.4 Screenshot of NCDOT TIMS Site

Validity check of the GPS speeds

The validity of the GPS speed data was investigated to check whether the GPS data collected by a probe vehicle driver is representative of the average travel of the vehicles on the corridor. The verification of the GPS data was done by comparing the spot speeds from the GPS measurement and the corresponding spot speeds from the NCDOT TIMS database. For the

comparisons of the two data sets, it was necessary to synchronize the locations and times of the speed measurements from the two data sets by conducting the following procedure:

- Locate the longitudes and latitudes of the approximate locations of SpeedInfo's (NCDOT's) speed measuring spots, M1 through M13, which were estimated based on the information gathered from a technician from SpeedInfo.
- Extract the GPS speeds corresponding to the speed measuring spots obtained in the above step. A tolerance distance of about 200 ft (i.e., 100 ft upstream and 100 ft downstream of each speed measuring spot) was applied because the author could not confirm the exact locations of the speed measuring spots. At a speed of 70 mph, it takes about 2 seconds to travel a distance of 200 ft, while at a speed of 10 mph, it takes more than 10 seconds. The average of those GPS speeds measured every second was used as the speed to compare to the SpeedInfo's speed.
- Identify the times at which the GPS speeds were measured.
- Extract the SpeedInfo's speeds corresponding to the times identified above.

The speeds measured from M6 (Exit 281), M8 (Exit 285), and M10 (Exit 288) were not included in the comparison because the two data sets show large differences in measured speeds. The mean speed from SpeedInfo's detectors on M6 was lower than the mean GPS speed by about 8.9 mph. One of the possible reasons is the presence of extensive weaving movements in the outer two lanes caused by the increased entering and exiting traffic demands around the Exit 281 area. These weaving movements reduce the speeds in the outer two lanes compared to the inner two lanes and, therefore, reduce the mean speed of all four lanes compared to the GPS middle lane speed. On the other hand, the mean speed from SpeedInfo's detectors on M10 was higher than the mean GPS speed by about 5.7 mph. M10 is located just ahead of the Wade Avenue split as seen in Figure 7.2. Most of the traffic using Wade Avenue uses the outer two lanes, while most of the traffic utilizing the I-40 mainline use the inner two lanes and usually the mean speeds of the outer two lanes are higher than the mean speeds of the inner two lanes. As already mentioned, the mean speed

from SpeedInfo's detectors included the four lanes and the mean GPS speed was only from the second lane from the median, which is responsible for the differences between the two mean speeds. The mean speed from SpeedInfo's detectors on M8 was higher than the mean GPS speed by more than 20 mph. In this case, the accuracy of the NCDOT speeds on M8 was suspect because the 15 days' speeds among the total 31 days' measured speeds were virtually at 68 mph, but the mean GPS speed for those 15 days was 39.9 mph, a difference of over 28 mph.

Table 7.1 shows the statistical summary of the speeds from the two data sets. The mean speed of the GPS data set (58.84 mph) is about 1.9 mph higher than the mean speed of the data set from SpeedInfo's detectors (56.91 mph). One of the possible reasons for the difference, as mentioned earlier, is that the GPS speeds were collected strictly from the middle lane, while the speeds from SpeedInfo's detectors were measured from all lanes and usually speeds of middle lanes are higher than the outer lanes because they are less affected by entering and exiting traffic. Although the result of a paired two sample t-test represented that the difference was considered to be statistically significant (the two-tailed P value was 0.000142) at a 5% significant level, the high Pearson correlation value of 0.86 meant the speeds from the two measuring sources indicated a strong linear relationship. This strong linear relationship was also evident from linear regression. As shown in Figure 7.5, the slope of the linear regression model was 1.0037 which is very close to 1. The results of linear regression and the hypothesis test that the slope is 1 (shown in Appendix C) indicated that the slope was significantly close to 1 with a p-value = 0.9135. Based on the statistical analysis results, the GPS speeds appear to be an adequate representation of spot speeds in the corridor.

Table 7.1 Summary of the Paired t-test (GPS vs. SpeedInfo's Detectors)

	Speed from SpeedInfo's detectors	Speed from GPS
Mean (mph)	56.91	58.84
Std. Dev. (mph)	14.91	17.32
Number of observations	304	304
Pearson Correlation	**0.86376**	
Hypothesized Mean Difference	0	
df	303	
t Stat	-3.85332	
P(T<=t) two-tail	**0.000142**	
t Critical two-tail	1.967824	

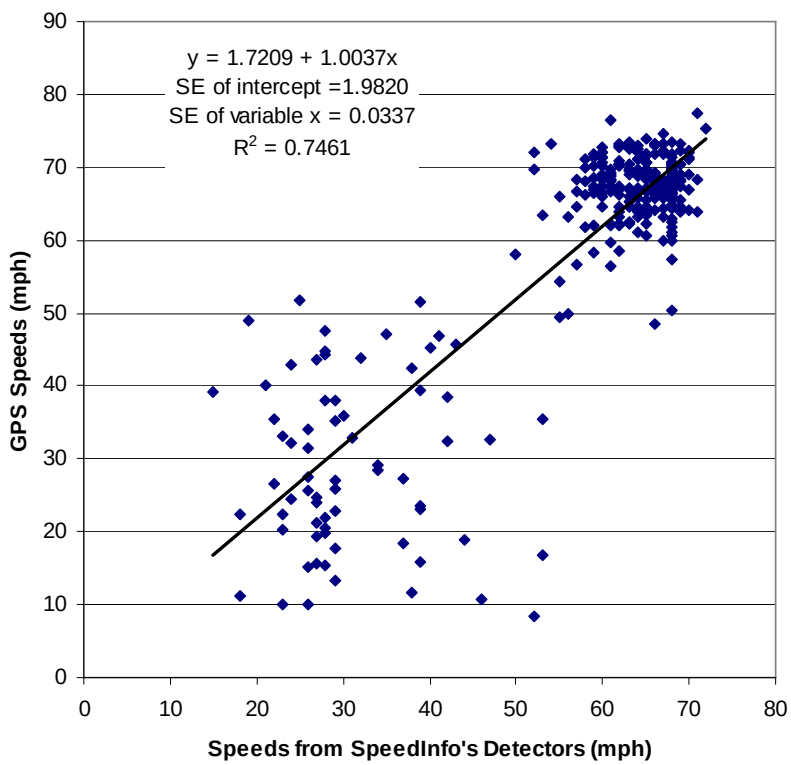


Figure 7.5 GPS Speeds vs. Speeds from SpeedInfo's Detectors

7.2.2.2 Field travel times

The GPS device recorded the vehicle's location every second and time stamped each record. The travel times between two measurement points, therefore, were simply calculated from the difference of the recorded times when the probe vehicle passed the measurement points. Table 7.2 shows the segments between each speed measurement point for which the travel times were measured. The locations of each speed measurement point, M1 through M13, are depicted in Figure 7.2.

Table 7.2 Segments for Travel Time Measurement

Segment ID	Segment	Distance (mile)
1	M1-M2	0.56
2	M2-M3	1.90
3	M3-M4	1.08
4	M4-M5	0.67
5	M5-M6	2.15
6	M6-M7	1.96
7	M7-M8	2.02
8	M8-M9	0.66
9	M9-M10	2.32
10	M10-M11	2.11
11	M11-M12	1.69
12	M12-M13	1.19

During the data reduction process, 10 days of measurements were eliminated from the 31 total days of field measurements. Some of those days were influenced by an incident and some days had too early or too late departure time in comparison with the mean departure time, 5:05 PM. The remaining 21 days of trips were thought to represent normal conditions (no incidents and relatively equivalent departure times of 5:00-5:10 PM) and were used to calculate the travel times. Table 7.3 shows the 21 days of travel time measurements for each segment.

Table 7.3 The 21 Daily Travel Times on the Test Corridor by Segment (min.)

Days \ Segment ID	1	2	3	4	5	6	7	8	9	10	11	12
Day 1	0.53	1.68	1.00	0.57	2.02	1.75	1.80	0.60	3.70	4.98	1.98	-
Day 2	0.47	1.65	1.00	0.58	1.93	1.68	1.77	0.57	5.45	5.58	2.13	-
Day 3	0.50	1.60	0.90	0.58	2.05	2.15	1.80	0.63	5.15	6.13	2.33	1.08
Day 4	0.48	1.55	0.93	0.55	2.23	2.10	3.87	1.27	5.08	6.88	1.95	-
Day 5	0.50	1.70	0.95	0.57	2.27	2.10	5.12	1.62	6.97	5.30	2.02	1.13
Day 6	0.48	1.60	0.90	0.55	2.08	1.98	3.38	1.03	6.22	6.62	2.10	1.13
Day 7	0.48	1.60	0.88	0.57	2.50	2.00	2.40	0.93	6.07	4.97	2.33	1.12
Day 8	0.47	1.65	1.02	0.58	2.37	2.17	4.75	1.42	7.72	6.75	2.23	1.07
Day 9	0.48	1.67	0.95	0.57	1.92	1.78	2.97	2.13	7.25	6.18	2.05	1.15
Day 10	0.47	1.60	0.92	0.57	1.88	1.78	1.92	1.05	2.93	4.70	2.50	-
Day 11	0.48	1.65	0.97	0.60	1.92	1.73	5.47	1.37	5.50	-	-	-
Day 12	0.48	1.58	0.93	0.62	1.98	1.93	4.52	1.55	8.28	6.00	2.08	1.05
Day 13	0.48	1.63	0.92	0.57	1.98	2.47	7.10	1.98	7.75	5.75	2.57	1.17
Day 14	0.48	1.65	1.00	0.63	2.58	2.17	3.07	1.08	7.00	6.58	2.30	-
Day 15	0.47	1.62	0.95	0.57	2.97	2.40	2.30	1.55	6.00	6.18	2.05	1.20
Day 16	0.50	1.63	0.95	0.55	2.62	1.97	1.90	0.90	6.27	3.88	2.10	1.07
Day 17	0.50	1.63	0.95	0.67	4.48	1.70	2.17	1.18	5.92	6.20	2.13	1.08
Day 18	0.48	1.73	1.02	0.65	2.15	1.80	1.88	0.60	4.10	4.93	2.13	1.15
Day 19	0.50	1.67	0.93	0.58	2.00	1.88	3.15	1.60	8.47	6.20	1.72	1.08
Day 20	0.47	1.63	0.95	0.57	2.52	2.05	2.75	0.92	3.97	3.62	2.58	1.08
Day 21	0.52	1.75	1.02	0.57	2.25	1.98	1.82	0.68	3.03	4.35	2.45	1.12
Mean	**0.49**	**1.64**	**0.95**	**0.58**	**2.32**	**1.98**	**3.14**	**1.17**	**5.85**	**5.59**	**2.19**	**1.11**
Median	**0.48**	**1.63**	**0.95**	**0.57**	**2.15**	**1.98**	**2.75**	**1.08**	**6.00**	**5.88**	**2.13**	**1.12**
Std. Dev.	**0.02**	**0.05**	**0.04**	**0.03**	**0.57**	**0.22**	**1.49**	**0.46**	**1.64**	**0.96**	**0.22**	**0.04**

* Segment IDs are shown in Table 7.2

7.2.2.3 Traffic counts and speed measurements

Field traffic counts needed to be collected for several purposes. First, counts were needed to verify the enhanced model by comparing the traffic counts from the model and the field. The locations where the traffic counts were collected are shown in Figure 7.2 by and labeled S1 through S12. These data were recorded between 5:00-6:00 PM on Tuesday, Wednesday, or Thursday by counting in the field manually or recording video images for easier counting later in the lab.

The second purpose of the field traffic counts was to use them along with the field speed data to calibrate the traffic flow model in DYNASMART-P. Of the field traffic counting locations, S1 is a basic freeway segment (as shown in Figure 7.2), so it is an appropriate place to collect flow and speed data for calibrating the traffic flow model. The flow and speed data for this purpose were collected by video recording between 2:00 and 7:00 PM, which included both under-saturated and oversaturated traffic conditions. An automated video data collection method using an Autoscope Rackvision Card was used for counting vehicles during the under-saturated condition. The vehicles traveling during the oversaturated condition, however, were counted manually since the error rate of traffic counting by the video data collection method increases sharply in the case of oversaturated conditions. Times taken by the vehicles to travel a certain distance between two points on segment S1 were measured to calculate space mean speeds by dividing the distance by the times. The calibrated traffic flow model using the field traffic and speed data is described in section 7.2.3.4.

The third purpose of obtaining field traffic counts was to calibrate the PM peak overall demand level and peak hour demand profile. The traffic counts on S1 were used for this purpose. The demand calibration results based on the traffic counts is described in section 7.2.3.3.

7.2.3 Modeling

7.2.3.1 Simulation network

The DYNASMART-P simulation network is shown in Figure 7.6. The simulation network includes the test corridor and the surface streets abutting the corridor in the Durham, Cary, and Raleigh area. This simulation network was based on the Triangle Regional Model (TRM) network and calibrated using the latest geometry information from Google satellite images, the census data from Real Estate Center at Texas A&M University, and the traffic count and speed measurement data from the field. The TRM network provided information about attributes of nodes, links, and zones. The TRM network, however, did not have detailed data about traffic control and lane configuration. The satellite images provided by Google map were a good source for updating the geometry data such as newly constructed roadways and numbers of lanes. In addition, the satellite images helped identify the intersection control types. Since it was difficult, however, to distinguish whether an unsignalized intersection has yield or stop signs or no signs and whether a signalized intersection has pre-timed control or actuated control, intersection control types were modeled by two types only; no control or actuated control. Information about lane configuration such as turning lanes was also obtained using the satellite imagery, since lane configuration is very important in modeling the link capacity of a signalized intersection. The acceleration and deceleration lanes at ramps were not considered as one of the mainline lanes. The auxiliary lanes in weaving sections were coded as extra lanes. Summary information about the network nodes, links, and zones of the modeling network is as shown in Table 7.4.

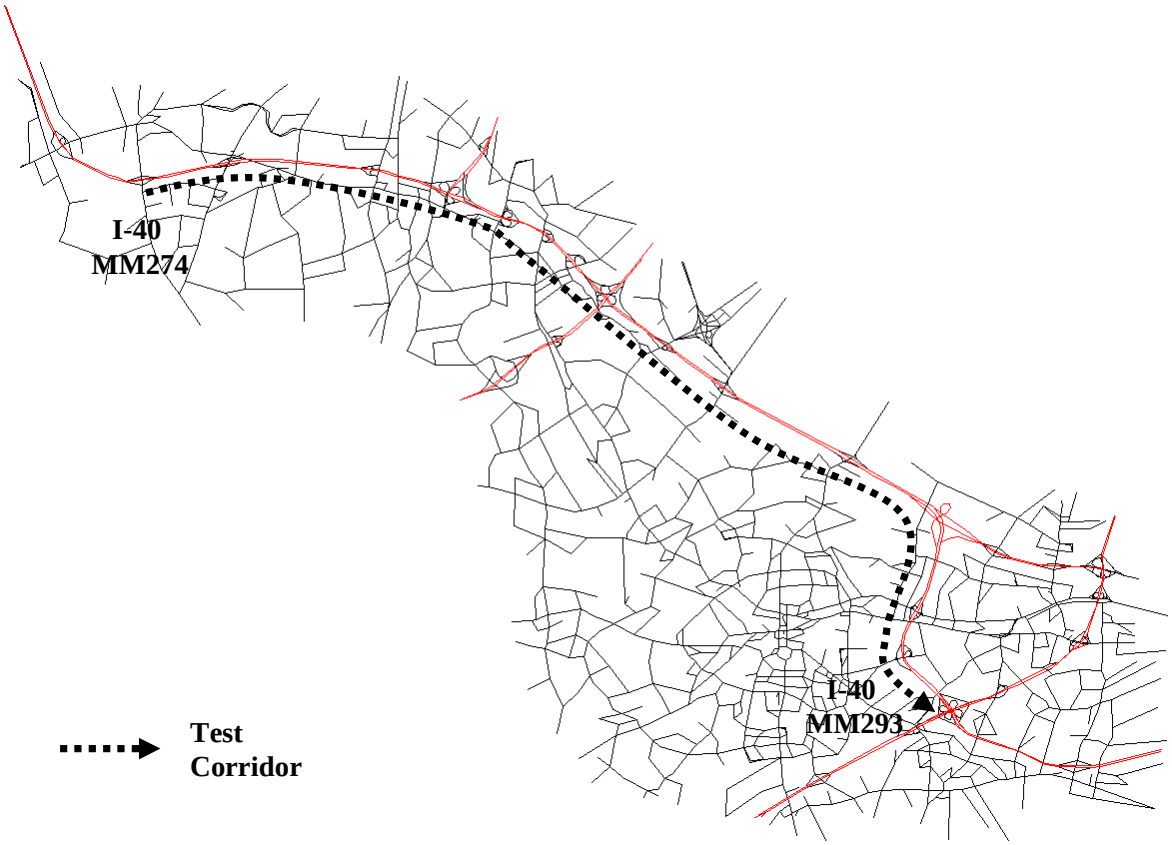


Figure 7.6 The DYNASMART-P Simulation Network

Table 7.4 Summary Information about the Simulation Network

Network data	
Number of nodes	1,563
Number of Links	3,609
Number of OD zones	348
Intersection Control Data	
Number of no controls	1,364
Number of actuated control	199
Overall Statistics (results from the model with Enhancement A)	
Simulation time (min)	120
Number of vehicle	199,988
Average travel time (min/veh)	12.59
Average stop time (min/veh)	3.34
Average trip distance (mile)	5.52

7.2.3.2 Calibration of the overall demand level

Population and employment growth

Since the base year of the TRM network was 2005, the network data needed to be calibrated. The OD demand matrix of 2005 was increased using population and employment growth factors in the network area, which was provided by Real Estate Center at Texas A&M University.

Table 7.5 and Table 7.6 depict the historical data on population and employment in the Raleigh-Durham-Chapel Hill area, respectively, acquired from Real Estate Center at Texas A&M University (http://recenter.tamu.edu/). As shown, the growth rates of the population and employment between 2005 and 2007 are about 8%. Therefore, the overall demand level was increased by a factor of 1.08.

Table 7.5 Raleigh-Durham-Chapel Hill, NC MSA Population

Year	Population	Change
2001	1,235,652	-
2002	1,270,546	34,894 (2.8%)
2003	1,301,540	30,994 (2.4%)
2004	1,334,758	33,218 (2.6%)
2005	**1,378,351**	43,593 (3.3%)
2006	1,432,692	54,341 (3.9%)
2007	**1,489,897**	57,205 (4.0%)
Increase from 2005 to 2007	**111,546 (8.1%)**	

Source: Real Estate Center at Texas A&M University (http://recenter.tamu.edu/)

Table 7.6 Raleigh-Cary, NC Employment

Year	Employment	Change
2005	**482,607**	**-**
2006	510,101	27,494 (5.70%)
2007	**520,592**	10,491 (2.06%)
Increase from 2005 to 2007	**37,985 (7.87%)**	

Source: Real Estate Center at Texas A&M University (http://recenter.tamu.edu/)

PM peak hours travel demand distribution

The PM peak OD matrix from the TRM network provides an average PM peak 4 hour demand from 3:00-7:00 PM. Because the simulation time periods occurred from 4:30-6:00 PM, overall demand level needed to be calibrated. The measured flow rate (vphpl) of the field traffic count point S1 is shown in Figure 7.7. As shown in the figure, travel demands during the simulation time period (4:30-6:00 PM) were higher than the average demand of the entire peak 4 hours. According to the distribution, the overall demand calibration factor for the simulation time period was (1.07+1.35+1.17)/3 = 1.2.

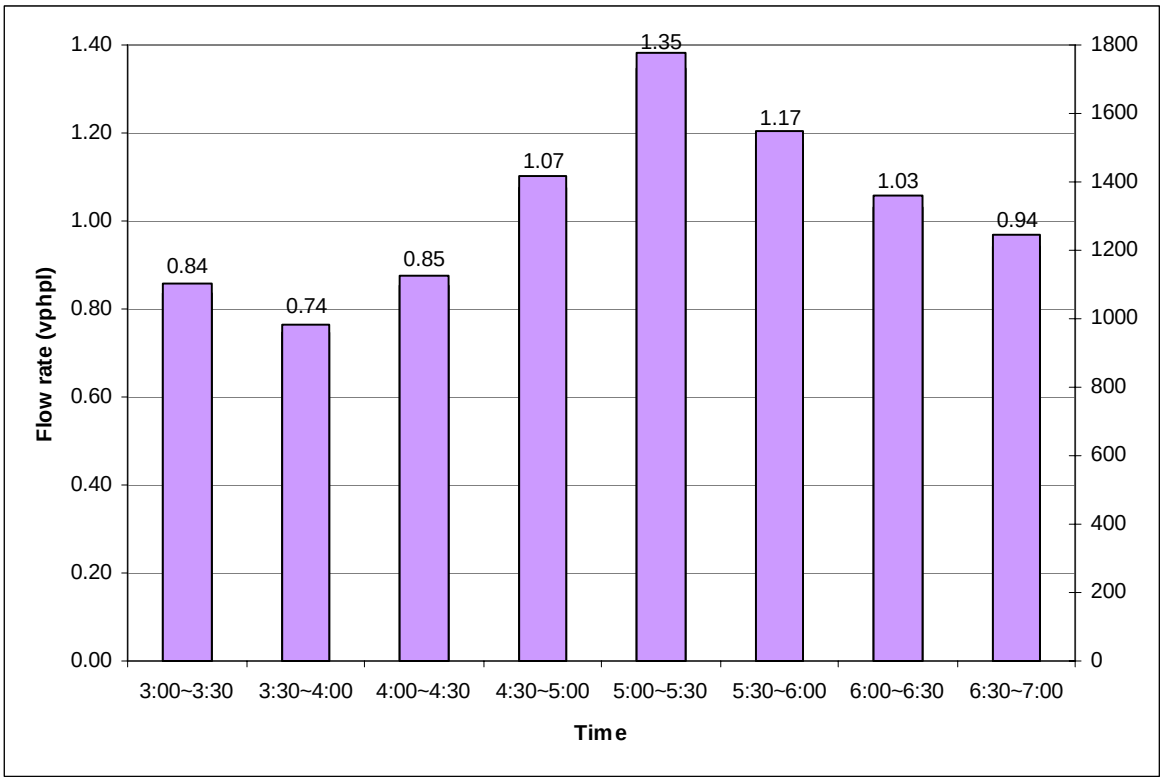


Figure 7.7 PM Peak Period Travel Demand Distribution

7.2.3.3 Demand profiles

From the measured flow rate (vphpl) of the traffic counting point S1, the 10-minute interval demand profile was constructed. The measured rate (vphpl) and the ratios to the average peak period rates are shown in Figure 7.8. It is evident that the flow rate was highest during the 30 minutes from 4:50 to 5:20 PM.

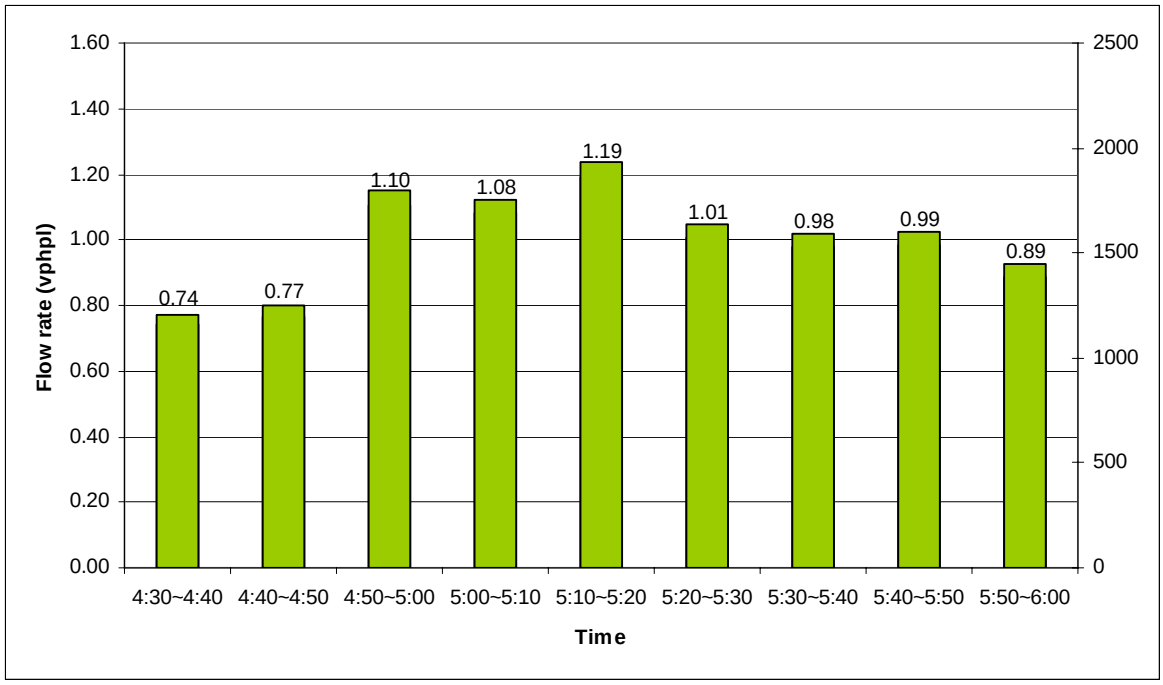


Figure 7.8 Travel Demand Profile

7.2.3.4 Traffic flow model calibration

Equation 7.1 shows the speed-density relationship for the traffic flow model in the simulation network.

$$\text{if } k_i < k_b,\ v_{i,t+1} = v_f$$

$$\text{else, } v_{i,t+1} = (v_I - v_0)(1 - k_{i,t+1}/k_j)^{\alpha} + v_0 \qquad \text{(Equation 7.1)}$$

Where,
$v_{i,t}$ = mean speed in section i during the tth time step
v_f = free flow speed
v_I = speed intercept
v_o = minimum speed
k_b = density breakpoint (density at capacity)
k_j = jam density

$k_{i,t}$ = mean density in section i during the tth time step
α = a parameter used to capture the sensitivity of speed to the density

The traffic count and speed data of the test corridor were used to calibrate the parameters in Equation 7.1. By applying this calibrated traffic flow model, the enhanced queue propagation model described in Chapter 4 was able to simulate the traffic on this network more realistically. Figure 7.9 shows the speed-density relationship of the field data set and the fitted model. Speeds and flows were acquired in one minute intervals for five hours. A total of 288 data points was used in fitting the parameters in Equation 7.1. The calibration results were as follows:

- v_f = 68 mph
- v_I = 122.6 mph
- v_o = 8 mph
- k_b = 30 vpmpl
- k_j = 154.4 vpmpl
- α = 4

The estimated speeds from the calibrated model were compared with the field measured speeds. Those two data set showed an R-square value of 0.9978 and a standard error of 3.07 (mph). Figure 7.10 depicts the flow-density curve from the field data set and fitted model. As shown in Figure 7.10, the model fits the field data set well. Capacity was found to be around 2,016 vphpl based on the calibrated traffic flow model.

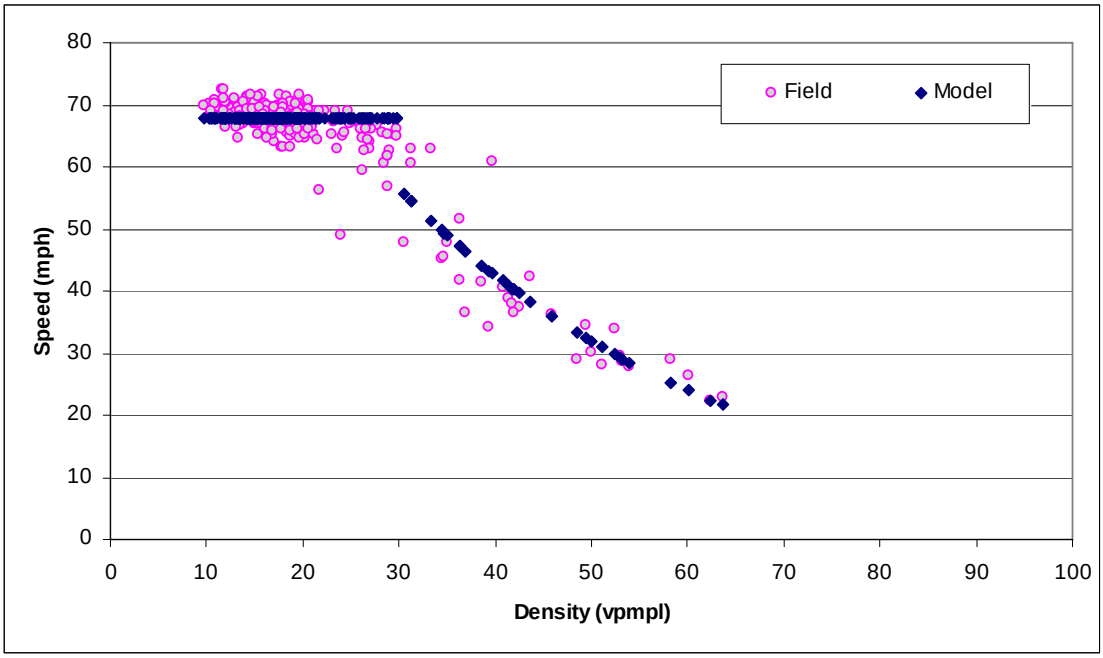


Figure 7.9 Speed-Density Curve on the Test Network

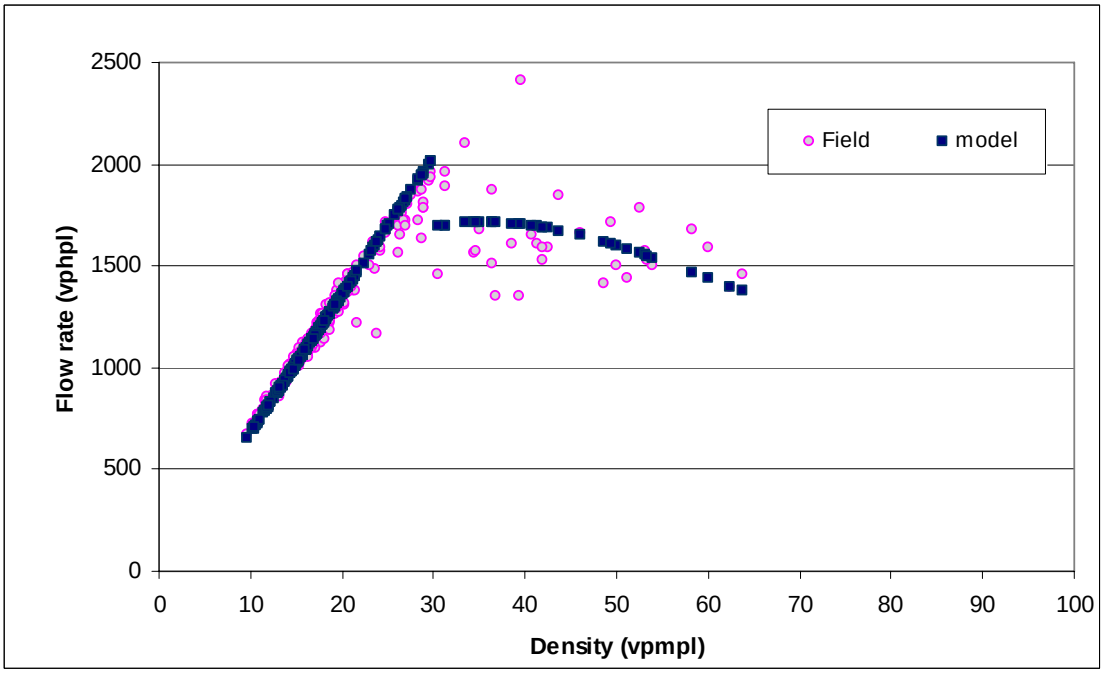


Figure 7.10 Flow-Density Curve on the Test Network

7.2.3.5 Simulation scenarios

The original model, the model with Enhancement A (enhanced queue model), and the model with Enhancements A and B (natural diversion behavior) were used for running the simulation network to test the proposed queue propagation algorithm and the natural diversion behavior model. Table 7.7 shows the simulation scenarios and settings for the model verification runs. The original model was used for Scenario 1. The enhanced queue model was implemented in Scenarios 2, 3, 4, and 5. The natural diversion behavior was implemented in Scenarios 3, 4, and 5. A natural diversion VMS was placed upstream of the off-ramp of Exit 287. Maximum natural diversion willingness rates (see section 5.2) of 1%, 5%, and 25% were tested. The critical density (see section 5.2) was 90 vpmpl, which is the midpoint between the density at capacity and the jam density. The corresponding speed at the critical density was about 11 mph. User Equilibrium assignment mode was applied in all simulation scenarios, since the driver's path selection as well as the natural diversion behavior in a recurring bottleneck situation were iterative.

Table 7.7 Simulation Scenarios and Settings for Runs

Scenario ID	Vehicle Generation Mode	User Class	Enhanced Queue Model	Natural Diversion VMS	Density Criteria	Max Diversion Rate
1	OD demand	User equilibrium	No	No	-	-
2	OD demand	User equilibrium	Yes	No	-	-
3	OD demand	User equilibrium	Yes	Yes	90	1%
4	OD demand	User equilibrium	Yes	Yes	90	5%
5	OD demand	User equilibrium	Yes	Yes	90	25%

7.2.3.6 Data extraction from model

The peak hour link volumes on the traffic counting points S1 through S12 were simply acquired from the simulation results using the sensor tool in DYNASMART-P. However,

the travel times of the corridor segments could not be obtained directly from the simulation results. The vehicle trajectory file, one of DYNASMART-P output files, provided the origin and destination nodes, the nodes encountered on the travel path, and the nodes passing times for each vehicle. Based on the vehicle trajectory file, most of the vehicles traveling from the origin node 340 (Chapel Hill) to the destination node 337 (Raleigh) in the network passed through the test corridor. Those vehicles arriving at M1, which is the starting point of the corridor, between 5:00 and 5:10 PM were selected to extract their travel times for comparison with the field travel time data from the GPS.

7.3 Results

The model verification results showed that the model with Enhancement A provided more accurate network performance results than the original model. The comparison between the results from the model with Enhancement A only and the model with Enhancements A and B revealed the existence of the effect of modeled natural diversion behavior. Maximum natural diversion willingness rates (see section 5.2) of 1%, 5%, and 25% were tested. However, interestingly, there was no difference in the simulation results between the scenarios applying the maximum willingness diversion rates of 1%, 5% and 25%. This indicates that the actual diversion rate under recurring congestion conditions will converge into a very low value, and in a sense is reflected in the equilibrium assignment process.

Travel times from the simulator were compared with the GPS field travel times. The corridor was divided into 12 sub-segments (see Table 7.2) based on the spot speed measurement points. Because the lengths of the 12 segments were different, the travel times for the segments could not be compared directly. For comparison purposes, the travel times were standardized by adjusting all the lengths of each segment to a standard length. In this study the standard length was decided to be 2.26667 miles which is the distance a vehicle needs to travel for 2 minutes at the free flow speed of 68 mph.

Figure 7.11 through Figure 7.13 depict the travel time comparison results from between the models and field travel times. To investigate the validity of the simulation results, drawing a field travel time distribution plot like Figure 7.11, Figure 7.12, or Figure 7.13 was a useful approach because the severity and position of the recurring bottleneck congestions varied widely day by day, even for the same peak hour period as shown in those figures.

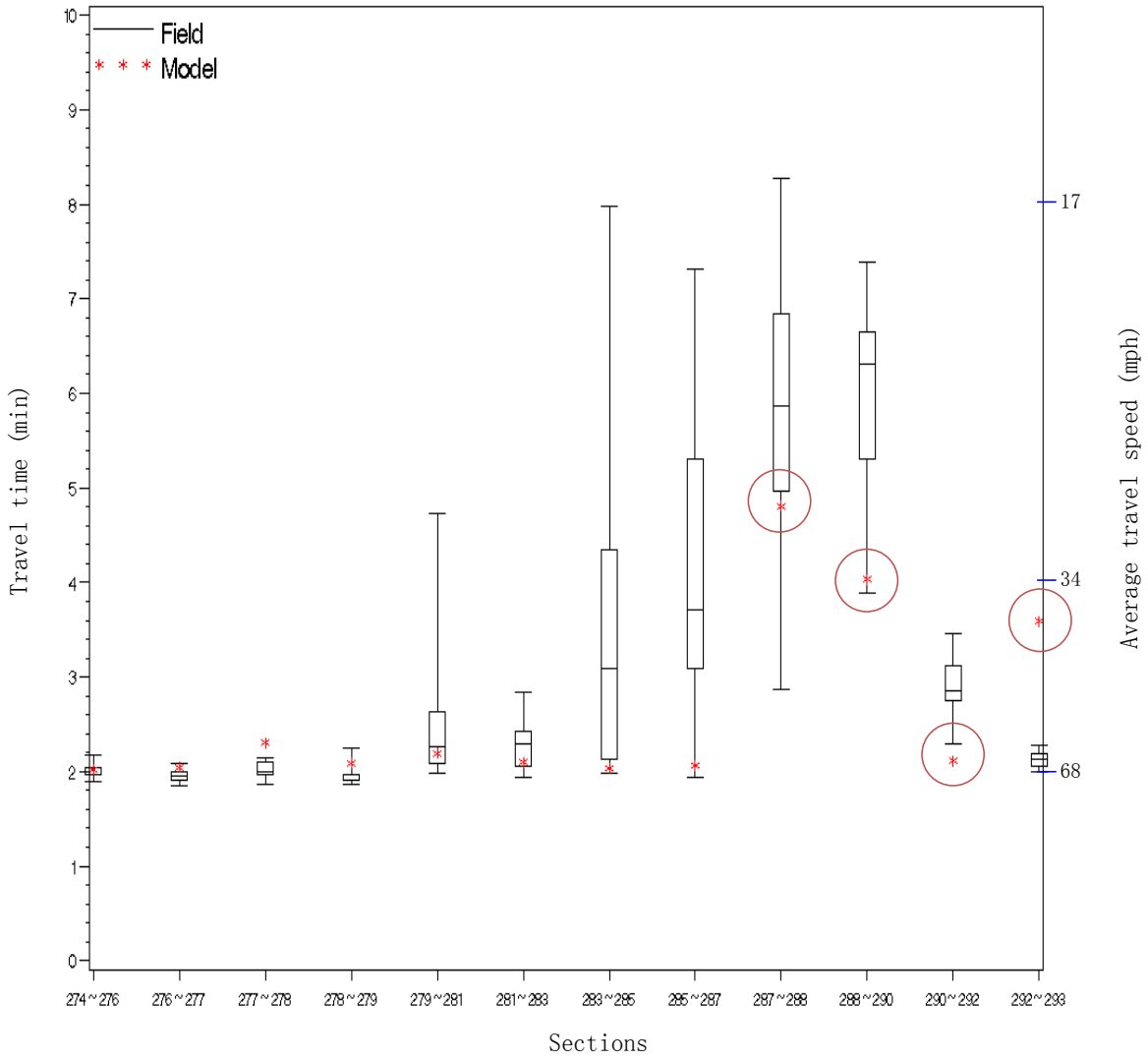


Figure 7.11 Travel Times from Original Model with Distribution of Field Travel Times

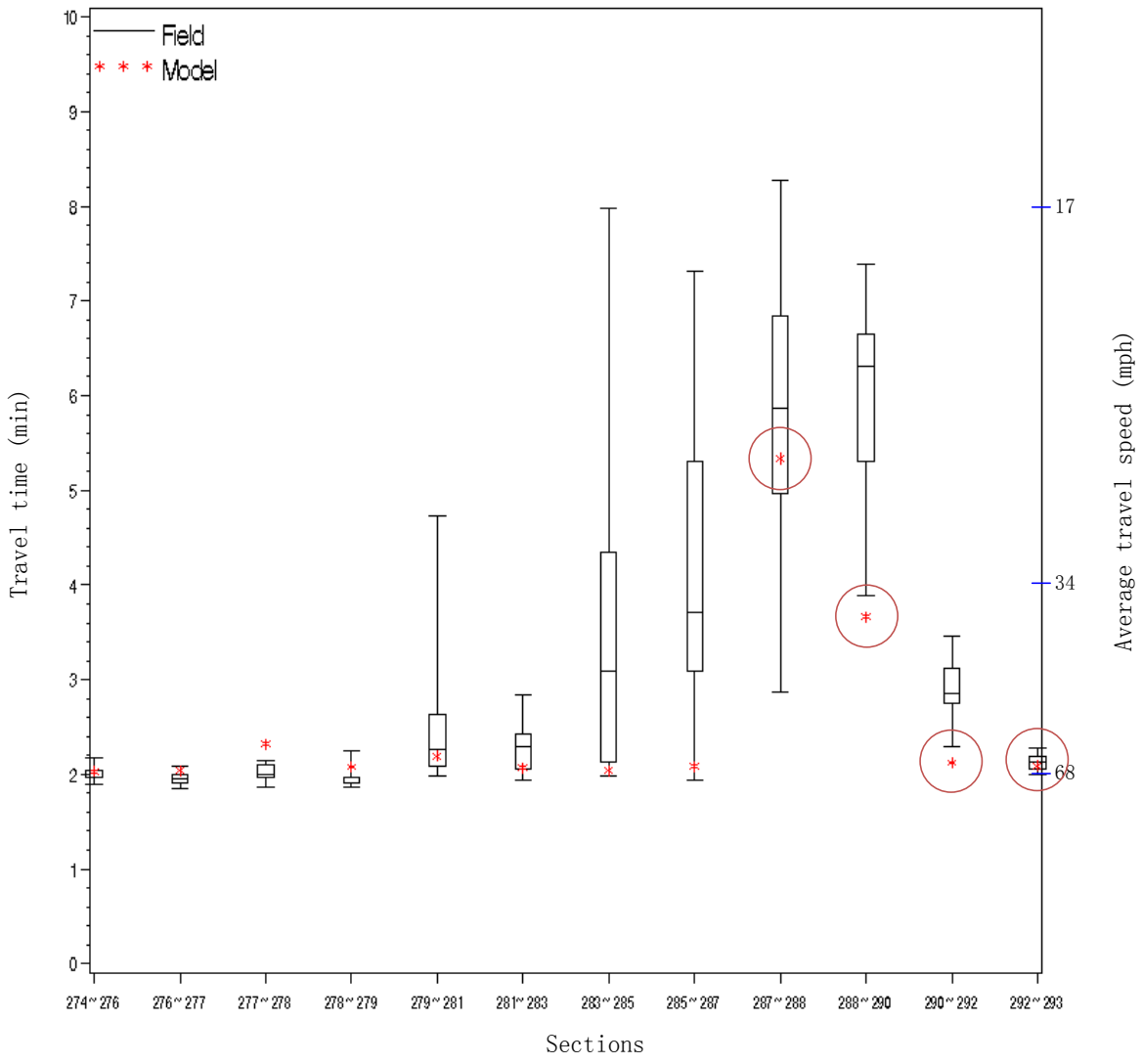


Figure 7.12 Travel Times from Model with Enhancement A with Distribution of Field Travel Times

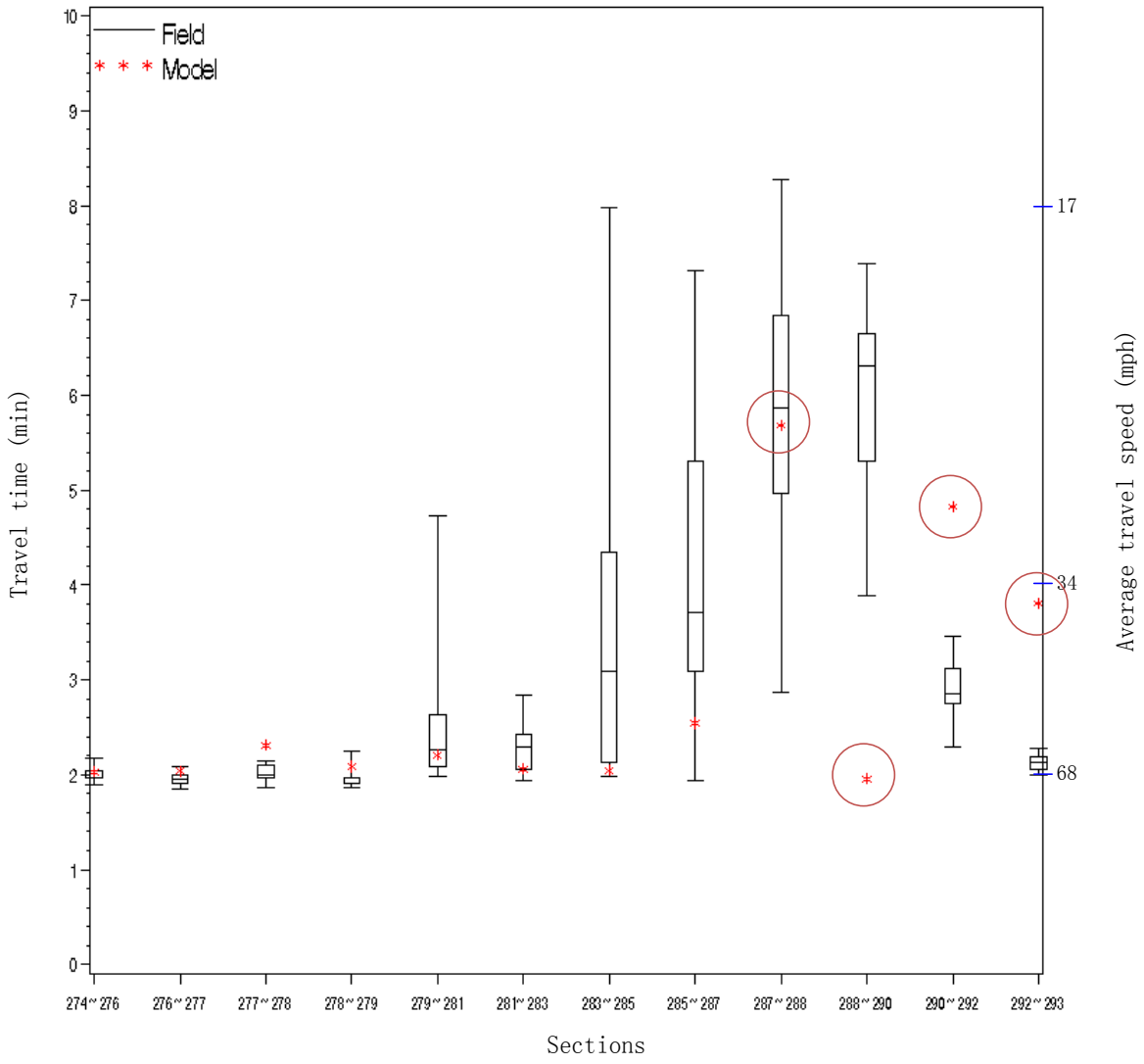


Figure 7.13 Travel Times from Model with Enhancement A+B with Distribution of Field Travel Times

From Figure 7.11 through Figure 7.13, the congested segments could be identified. The field travel times indicated that Segments 7 (MM283~285) through 10 (MM288~290) had recurring congestion which caused by the bottleneck segment from MM 289 to MM293. However, as shown in Figure 7.11, Segment 12 was defined as the congested segment in the original model even though this segment was not a congested segment according to the field

travel times. This was because queue began from downstream end of the bottleneck segment (Here, MM293) in the original model as discussed in Chapter 4. As presented in Figure 7.12, the travel times with Enhancement A scenario showed that Segments 9 and 10 were congested. Queue beginning point in the model with Enhancement A was much closer to the field data in comparison with the original model. As shown in Figure 7.13, the travel times from Enhancement A plus B scenario simulation showed that Segments 9, 11, and 12 were congested. Due to natural diversion, the congestion on Segment 10 was actually reduced. Consequently, traffic flow of the downstream of Segment 10 was somewhat increased and this increased flow changed Segments 11 and 12 from hidden to active bottlenecks. This is why Segments 11 and 12 became congested.

Table 7.8 shows the comparison between the mean travel times from the field data and the travel times from the models for each segment. The Mean % Absolute Deviation (MPAD) in travel times of the model with Enhancement A decreased from 24% to 17% in comparison with the original model. However, the downstream hidden bottleneck became an active bottleneck and made severe congestion. Thus, the MPAD in travel times increased from 17% to 30%.

The results from the model with Enhancement A only were closer to the field travel time data in comparison with the results from the model with Enhancements A and B. It implies that the actual diversion rate might be near 0% under recurring congestion in the study network. However, the natural diversion rate could be higher under non-recurring congestion such as work zones or highway incidents.

Table 7.8 Mean Standardized Travel Time Comparison

Segment ID	Mean Field Travel Time (min)	Travel Time by Model (min)			Difference from Field		
		Original	Enhancement A	Enhancement A+B	Original	Enhancement A	Enhancement A+B
1	1.98	2.02	2.04	2.04	0.04	0.05	0.05
2	1.96	2.05	2.04	2.04	0.08	0.08	0.08
3	2.01	2.31	2.32	2.31	0.30	0.32	0.31
4	1.97	2.09	2.08	2.09	0.12	0.11	0.12
5	2.45	2.20	2.20	2.21	-0.25	-0.25	-0.24
6	2.28	2.10	2.07	2.06	-0.18	-0.21	-0.22
7	3.52	2.04	2.04	2.05	-1.48	-1.48	-1.47
8	4.02	2.07	2.08	2.55	-1.96	-1.94	-1.48
9	5.72	4.81	5.34	5.69	-0.90	-0.38	-0.03
10	5.71	4.04	3.67	1.96	-1.68	-2.05	-3.75
11	2.79	2.12	2.13	4.83	-0.67	-0.66	2.04
12	1.99	3.59	2.10	3.81	1.61	0.11	1.82
RMSE		1.04	0.96	1.48	-	-	-
MAE		0.77	0.64	0.97	-	-	-
MPAD		24%	17%	30%	-	-	-

$$RMSE(Root\ Mean\ Squared\ Erro) = \sqrt{\frac{(a_1 - c_1)^2 + (a_2 - c_2)^2 + \ldots + (a_n - c_n)^2}{n}}$$

$$\text{MAE (Mean Absolute Error)} = \frac{|a_1 - c_1| + |a_2 - c_2| + \ldots + |a_n - c_n|}{n}$$

$$\text{MPAD (Mean \% Absolute Deviation)} = \frac{|a_1 - c_1| / a_1 + |a_2 - c_2| / a_2 + \ldots + |a_n - c_n| / a_n}{n} \times 100$$

Where, c_i is computed value and a_i is its corresponding correct value

As shown in Table 7.9, the mainline traffic counts from the original model were greater than other scenarios. This is because queue begins from downstream end of bottleneck segment (Here, MM293) and queue propagation speed is slow in the original model as discussed in Chapter 4. With Enhancement A, the mainline traffic counts at upstream of the bottleneck decreased in comparison with the original model. The Mean % Absolute Deviation (MPAD)

in travel counts of the model with Enhancement A decreased from 28% to 1.4% in comparison with the original model. With natural diversion behavior model (Enhancement A+B), the mainline traffic counts at upstream of the bottleneck decreased in comparison with Enhancement A model. The mainline traffic counts decreased from 4,659 to 4,481 vph. Because the volumes of the exit ramps were affected not only by the detour behaviors but also by the traffic congestion, it is difficult to tell whether natural diversion behavior caused the difference in ramp volumes.

Table 7.9 Traffic Counts from the Model and the Field (vph)

Count Point	Traffic Counts				Difference		
	Field	Model			Model		
		Original	Enhancement A	Enhancement A+B	Original	Enhancement A	Enhancement A+B
Mainline*	4,391	5,187	4,659	4,481	796	-268	-90
Off-Ramps	5,642	5,811	5,716	5,922	169	74	280
On-Ramps	5,797	6,505	6,357	6,392	708	560	595
RMSE		311.37	180.49	191.60		-	-
MAE		139.42	75.17	80.42		-	-
MPAD		28%	1.4%	1.4%		-	-

* Mainline traffic count position is mainline between off-ramp and on-ramp at Exit 287

7.4 Discussion

This chapter has presented a method for testing the validity of two proposed enhancements to the DYNASRMART-P model: a revised queue propagation algorithm and a natural diversion algorithm. The implementation of the first algorithm required the development of a calibrated speed density model, which was fitted using field data gathered at a representative segment on the test facility. Testing of the validity consisted of comparing traffic counts, speeds, and travel times on various points, segments, and the entire facility. In general, the

results obtained were quite promising, particularly as they relate to the queue propagation algorithm.

However, the proposed natural diversion algorithm did not show much sensitivity in terms of improving the model fit. One hypothesis for this finding is that there is not likely to be much *additional* diversion when drivers encounter a recurring bottleneck situation, which by definition is anticipated and expected. Such natural diversions are likely to occur more frequently under non-recurring congested conditions of incidents, crashes, etc. where unanticipated congestion drives the process of path modification. So, the value of incorporating a natural diversion algorithm will be left to other researchers to investigate in that context. The empirical data required to make that judgment was simply unavailable in the course of this research.

CHAPTER 8. APPLICATION OF ENHANCED MODEL TO ASSESS U-TRANSPORTATION IMPACT

A case study was carried out to demonstrate the capability of DYNASMART-P with the enhanced model described in Chapters 4 and 5 to measure the potential mobility benefits derived from implementing Ubiquitous Transportation (U-Transportation) technology. U-Transportation system has been under development in Korea since 2005 (*Kang et al., 2005*) and is considered as the next generation ITS. Its concept is similar with that of the Vehicle Infrastructure Integration (VII) program in USA (*FHWA, 2005*). The case study conducted used a network in a flooding-prone area in Knoxville, Tennessee. The modeling assessed the U-Transportation impact on a non-recurring congestion progressive situation induced by incidents that include natural disasters like flooding.

8.1 Capability of U-Transportation

The core of U-Transportation technology is real time communication between vehicles, the transportation infrastructure, and pedestrians equipped with Ubiquitous Vehicle Sensors (UVS), Ubiquitous Infrastructure Sensors (UIS), and Ubiquitous Pedestrian Sensors (UPS), respectively. A Ubiquitous Transportation Center (UTC) will collect traffic data and transmit traffic information through UIS's. The following describes the two way communications data considered to be developed and transmitted:

- V2V (Vehicle to Vehicle): Vehicles will transmit and acquire position, speed, type, observed incident and congestion and etc. with other equipped vehicles.
- V2I (Vehicle to Infrastructure): Vehicles will transmit position, speed, type, observed incident and congestion and etc. to the infrastructure. The infrastructure will acquire the data from multiple vehicles and provide traveler information such as incident, work zone, congestion information, alternate routes, and so on to equipped vehicles.

- V2P (Vehicle to Pedestrian): Vehicles will transmit position, speed, and type to pedestrians. Pedestrians can send warning alerts when they wish to cross at designated crosswalk.
- I2P (Infrastructure to Pedestrian): The infrastructure will provide many types of information related to transit services and directions outdoors or indoors. Pedestrians can send a signal when they want to cross or board a specific transit vehicle.
- I2I (Infrastructure to Infrastructure): The information for coordination such as traffic control and management status will be transmitted between the various traffic management centers

The U-Transportation Sensor Network (U-TSN) will be developed based on the concepts of vehicle and road ad-hoc networks for the U-Transportation communication protocol. The conversion of U-TSN with current data collection systems will produce more seamless, accurate, and reliable traffic information.

Various services for pedestrians, transit users, and drivers and many strategies for operation, management, and safety were proposed at the ITS level, but some were not feasible because of lack of timely information and technical limitations. Ubiquitous computing is expected to resolve some of the limitations in conventional ITS strategies. Hence, some limited ITS services will be possible to realize, and of course, new services and strategies will be additionally provided.

8.2 Modeling Information User Classes of u-Transportation in DYNASMART-P

DYNASMART-P was the selected tool for evaluating the effect of information because it can model different route choice and assignment rules under different information sources. Modeling travel mode change, departure time change, or trip cancellation is not feasible in current DYNASMART-P. Therefore, the team assumed that U-Transportation will not

impact those characteristics. The five user classes available in DYNASMART-P are described in the paragraphs below. The information user groups for V2V communication and V2I communication were modeled using Class 4 and Class 2 users, respectively. Other communication types were not considered in the pilot studies.

Class 1 (Historical info): This class represents drivers who have no access to any information source except for historical knowledge of the network, and in route variable message signs (VMS). Thus, drivers in this class select routes (normal paths) based on their historical experience, in other words, their travel choice under recurring traffic conditions. Those drivers adhere to those normal paths throughout the entire trip, when not encountering VMS. Normal paths are provided from an initial run which generates vehicles and paths based on OD demand under normal conditions, using the user equilibrium assignment rule. Vehicles specified as Class 1 follow paths derived from the initial run.

Class 2 (System Optimal, SO): This class follows the system optimal assignment rule. To minimize the overall network travel time, a small fraction of users (the fraction of Class 2 users) may be assigned to sub-optimal routes, from the driver perspective. This assignment method requires multiple iterations until an optimal solution is reached. This class emulates users who follow the recommended path proposed by the UTC using V2I communications.

Class 3 (User Equilibrium, UE): This class follows user equilibrium assignment rule. Every driver in this class tries to select the best path to minimize his/her own travel time. Depending on other drivers' path selections, this route might not be the best path. Then, some of those drivers will try other routes in the next iteration. These trials continue until no driver can benefit by switching to another route. We call this route assignment a user equilibrium. This assignment rule is meaningful for modeling long term planning effects. This assignment method requires iterating convergence in OD travel times is achieved.

Class 4 (In vehicle information system, IVIS): This class models drivers and vehicles that can receive real time travel information in a ubiquitous fashion. Thus, these users can update paths at each intersection based on the real time shortest path. This behavior is very similar to drivers who capture link and network travel information via V2V communication.

Class 5 (pre-trip info): This class represents pre-trip information users. These users select the best path at the start of their travel, then adhere to this path unless they encounter and respond to VMS alerts which may prompt them to divert.

It should be noted that every information user group responds to VMS. There are three types of VMS in DYNASMART-P: congestion warning VMS, optional detour VMS, and mandatory detour VMS. The traveler's response rule to VMS is defined based on the selected VMS types. VMS Responses in case of:

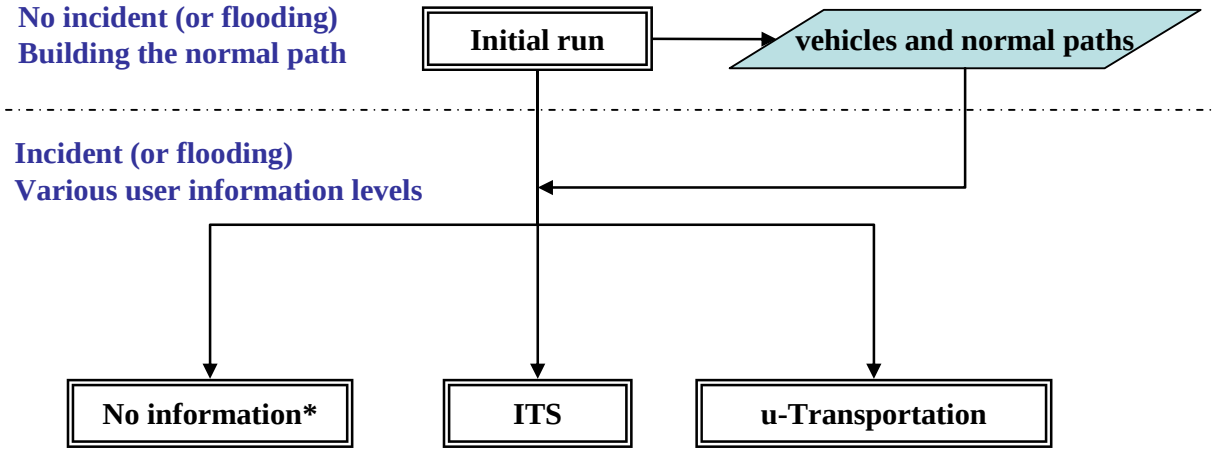
- Congestion warning VMS (multiple routes): alerts travelers of potential downstream congestion. It allows a certain percentage of users that encounter the VMS the opportunity to determine a new best path at that time and position to their ultimate destination.
- Optional detour VMS (two routes): advises travelers of lane closures, and allows all travelers to either keep their original path (through detoured link) or follow a pre-specified detour
- Mandatory detour VMS (single route): advises travelers of lane closures, and mandates all travelers to follow a (user-specified) detour

In the pilot studies, congestion warning VMS represents the conventional way information is provided. Mandatory detour VMS are used to emulate evacuation assistance by enforcement personnel as in the case of a flooding situation. Optional detour VMS was not used. As a general rule, re-routing was based on the bounded rational behavior mechanism. Thus, both the fraction of travel time improvement and the magnitude of travel time improvement (in minutes) dictated route switching decisions. When either of these two criteria exceeded the

threshold, the user switched routes at the next decision point (in most cases that meant the next intersection or interchange).

8.3 Defining user Information Levels in the Case Studies

The U-Transportation network will provide real time information for vehicles capable of transmitting and receiving data from other vehicles and from the infrastructure. Users will be able to avoid non-recurring congestion by altering their routes. Those travel changes will produce network-wide benefits. The magnitude of the benefit will depend in part on the level of U-Transportation market penetration. Figure 8.1 depicts the structure of evaluation scenarios. It shows four groups of scenarios from an in information provision perspective.



* In the flooding case, mandatory detour VMS are deployed (representing enforcement personnel) even for the No information case.

Figure 8.1 Structure of U-Transportation Evaluation Scenarios

Initial run

In the initial run vehicles and paths are generated based on the Origin-Destination demands for the entire network under normal traffic conditions assuming a user equilibrium (UE) assignment. The initial run does not consider any pre-trip information or VMS presence because such information is not critical under recurring (or known) congestion patterns. The generated vehicle information is archived, along with the paths derived from this run, which are considered to be the "normal" paths. By using the archived vehicle information and assigning those same paths to the historic information group (class 1) for every scenario, reasonable comparisons between scenarios are possible.

No information scenario

This scenario represents the incident (or flooding) effect on the network under a no information condition. It is not a very realistic situation, but it does represent the worst case scenario. No drivers have access to any information type. Thus, all drivers continue to use the normal paths and adhere to them throughout the simulation. However, in the flooding scenario, mandatory detour VMSs are used to emulate the presence of enforcement personnel in the vicinity of the flooded area.

ITS scenarios

These scenarios assess the current ITS devices' effectiveness in relieving the congestion due to the flooding. In fact, these scenarios represent the baseline cases which describe traditional network controls (conventional ITS). ITS technologies include pre-trip information such as internet, radio, and TV, as well as en route VMS. Here, we assume that users with access to pre-trip information will select the best path before the start of travel. Other drivers are assumed to have no access to any information. They use and adhere to their normal path. In this series of scenarios, VMS devices are always available on the network. Every driver can respond to the VMSs if they encounter one and a certain percentage of users (response rate specified by the modeler) will look for the shortest path to their destination when and if they

encounter a VMS. The VMS operation time is set up to activate 15 minutes after the start of the flooding occurs in order to distinguish between the conventional ITS response time and the faster information service of U-Transportation information acquired via V2V or V2I protocols.

U-Transportation scenarios

These scenarios are developed to demonstrate how much improvement U-Transportation can affect the network when a flooding occurs. Equipped vehicles are presumed to have access to two real time information types based on communications with other vehicles (V2V) and the infrastructure (V2I). In V2V communication, users can receive travel information everywhere any time from other vehicles and can avoid congestion due to the timely acquisition of the information. However, such users can't coordinate their route with other users based only on this information. With V2I communication, the network infrastructure control gathers global or sectional traffic information and sends it to equipped vehicles and recommend alternate routes if appropriate. This alternate route is presumed to be developed using a system optimization algorithm. Vehicle equipped with U-Transportation will be able to receive both types of information. However, only apportion of the users will follow the suggested infrastructure control paths. Others who do not choose the system provided paths will find their own paths with no consideration of system optimization.

Vehicles or trips are assigned to the various DYNASMART-P information user classes described in Section 8.2 according to the information levels indicated in Figure 8.1. Table 8.1 includes detailed user classification according to the evaluation scenarios for the flooding case. Scenario 1 simulates the normal network condition without flooding. Every scenario except Scenarios 1 and 2-1 included natural diversion behavior. Scenario 2-1 was intended to show the flooding effect on the network when ignoring natural diversion behavior. The mandatory detour VMSs for emulating enforcement personnel are included in every scenario which has flooding effect (all Scenarios except Scenario 1). Scenario 3 and 4 model

conventional ITS information effects on the network when the flooding occurs. Scenario 3 is intended to assess the combined effect of VMS and pre-trip information.

Table 8.1 Distribution of User Classes for U-Transportation Evaluation Scenarios in DYNASMART-P (Flooding Scenarios Only)

Scenarios		Historical Route (Class 1)	ITS		U-Transportation		
			VMS	Pre-trip Information (Class 5)	V2I (Class 2)	V2V (Class 4)	Total
1	Initial run (no flooding)	100%	-	0%	0%	0%	0%
2-1	**Flooding-MDV-no ND**	100%	-	0%	0%	0%	0%
2-2	**Flooding-MDV**	100%	-	0%	0%	0%	0%
3	Flooding-VMS	100%	√	0%	0%	0%	0%
4	Flooding-ITS	80%	√	20%	0%	0%	0%
5	Flooding-u-T 20%/VMS	80%	√	0%	5%	15%	20%
6	Flooding-u-T 25%/ITS	60%	√	15%	6.25%	18.75%	25%
7	Flooding-u-T 50%/ITS	40%	√	10%	12.5%	37.5%	50%
8	Flooding-u-T 75%/ITS	20%	√	5%	18.75%	56.25%	75%
9	Flooding-u-T 100%/VMS	0%	√	0%	25%	75%	100%
10	Flooding-u-T100%/VMS	0%	√	0%	0%	100%	100%
11	Flooding-u-T 20%/VMS	80%	√	0%	15%	5%	20%
12	Flooding-u-T 25%/ITS	60%	√	15%	18.75%	6.25%	25%
13	Flooding-u-T 50%/ITS	40%	√	10%	37.5%	12.5%	50%
14	Flooding-u-T 75%/ITS	20%	√	5%	56.25%	18.75%	75%
15	Flooding-u-T 100%/VMS	0%	√	0%	75%	25%	100%
16	Flooding-u-T 100%/VMS	0%	√	0%	100%	0%	100%

√ means VMS are activated in the simulation scenario.
MDV: Mandatory detour VMS (this represents enforcement personnel)
ND: Natural Diversion behavior
VMS: Congestion warning VMS and Mandatory detour VMS
ITS: VMS and Pre-trip information

Scenarios 5 through 16 model the effect of U-Transportation information on the network when a flooding occurs, under various U-Transportation market penetrations. Five U-

Transportation market penetrations (20, 25, 50, 75, and 100%) were modeled. Scenario 5 to 16 can be divided in two groups, considering the users' information preference (V2V or V2I). U-Transportation users in Scenario 5 through 10 are more likely to rely on information from other vehicles, or V2V. We assumed a compliance rate of 25%, meaning that only 1 out of 4 drivers will execute a route diversion suggestion based on V2V communications. Conversely, U-Transportation users in Scenario 11 through 16 are more likely to comply with information disseminated through V2I.

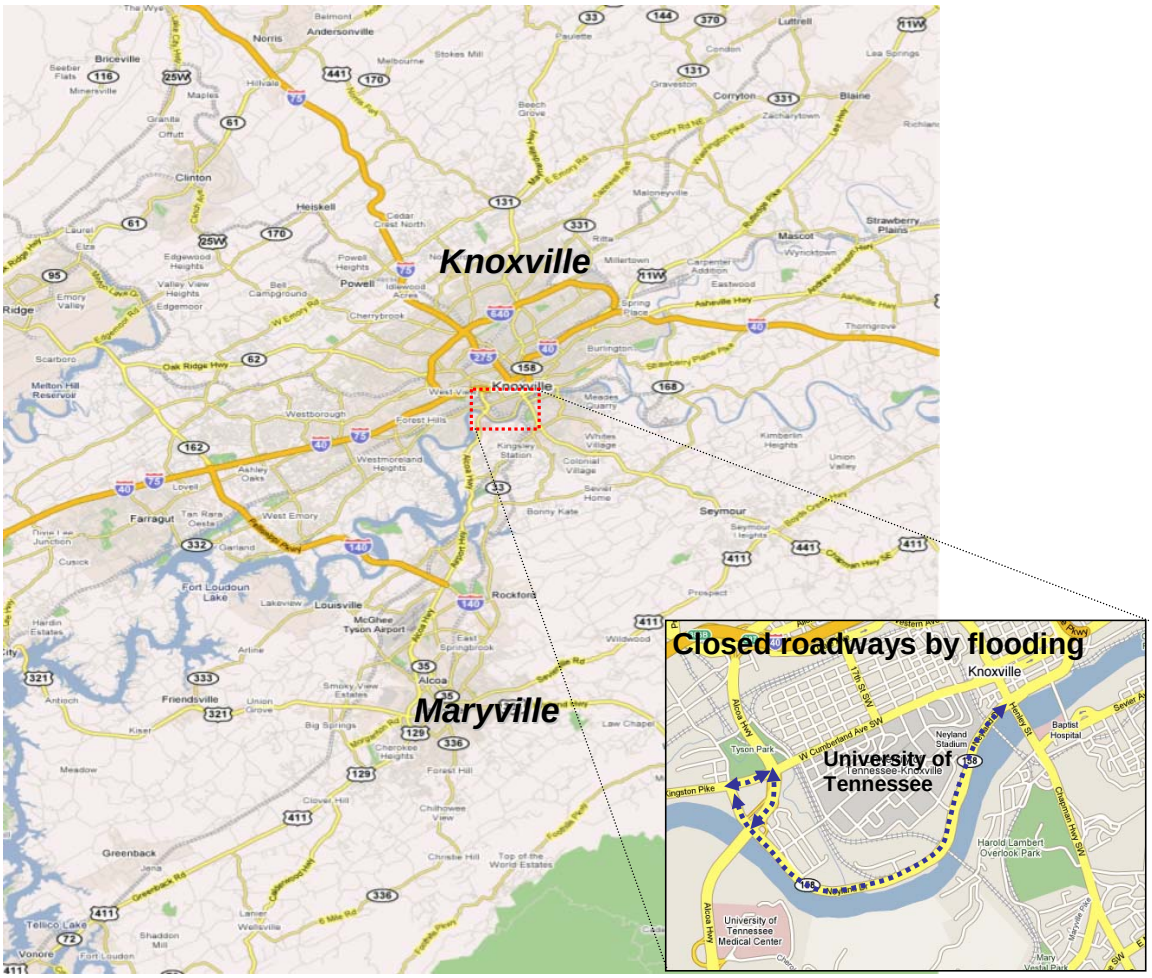
Scenario 4 and 5 (as well as 4 and 11) enable a comparison between conventional ITS and U-Transportation. Both Scenario 5 and 11 assume the same percentage of total information users as Scenario 4. Scenario 10 and 16 model the performance effect when all drivers use one of the two U-Transportation communication protocols (V2I or V2V).

In scenarios with less than full U-Transportation market penetration, a certain percentage of pre-trip info user class (Class 5) and no-information group (Class 1) was assumed. By increasing the U-Transportation users' market penetration, the remaining fraction of pre-trip info user class and no-information class is reduced.

UIS market penetration effects were not measured in the pilot studies. It was assumed that the infrastructure for U-Transportation is available network wide. However, this assumption is not realistic, since in the early period of development, UISs will be installed in parts of road network, probably on major corridors only. However, we simulated the effect of the reduced market penetration by assuming that not all vehicles in the network are able to communicate with the UTC. In effect our implicit assumption is that: the percentage of network links with full V2I capabilities is equivalent to the fraction of vehicles on the network with V2I capabilities.

8.4 Description of Network

Figure 8.2 shows the Knoxville, Tennessee network. This network includes two cities, Knoxville (a major metropolitan area) and Maryville (a bedroom community). The two are separated by the Tennessee River, with a riverside road on the northern bank (Neyland Drive) and two major bridges south of the University of Tennessee. The two bridges are major connectors between the two cities. The roads that are affected by a flooding scenario are shown on the right bottom of Figure 8.2.



Map source: Google map

Figure 8.2 Knoxville, Tennessee Topographical Map

Researchers from the University of Maryland had prepared the Knoxville DYNASMART-P network and calibrated the demand data and traffic flow models for this network in 2002. That network has not appreciably changed since that time. The Knoxville DYNASMART-P road network is shown in Figure 8.3. Basic network information for this network is as follows:

Network data

- Number of Nodes: 1347
- Number of Links: 3004
- Number of OD demand Zones: 356

Intersection control data (number of intersections)

- No Control: 992
- 4-Way Stop: 245
- 2-Way Stop: 72
- Signalized: 38

The locations of the flooding and road closures, as well as the VMSs are presented in Figure 8.3. The reason only Three VMSs were included in the simulation network was to estimate the effect of other information provision more clearly. The VMSs were located south of the flooding area and began to provide congestion warning after 15 minutes of start of the waterline rise. The locations of VMSs for emulating natural diversion behavior are presented in Figure 8.3.

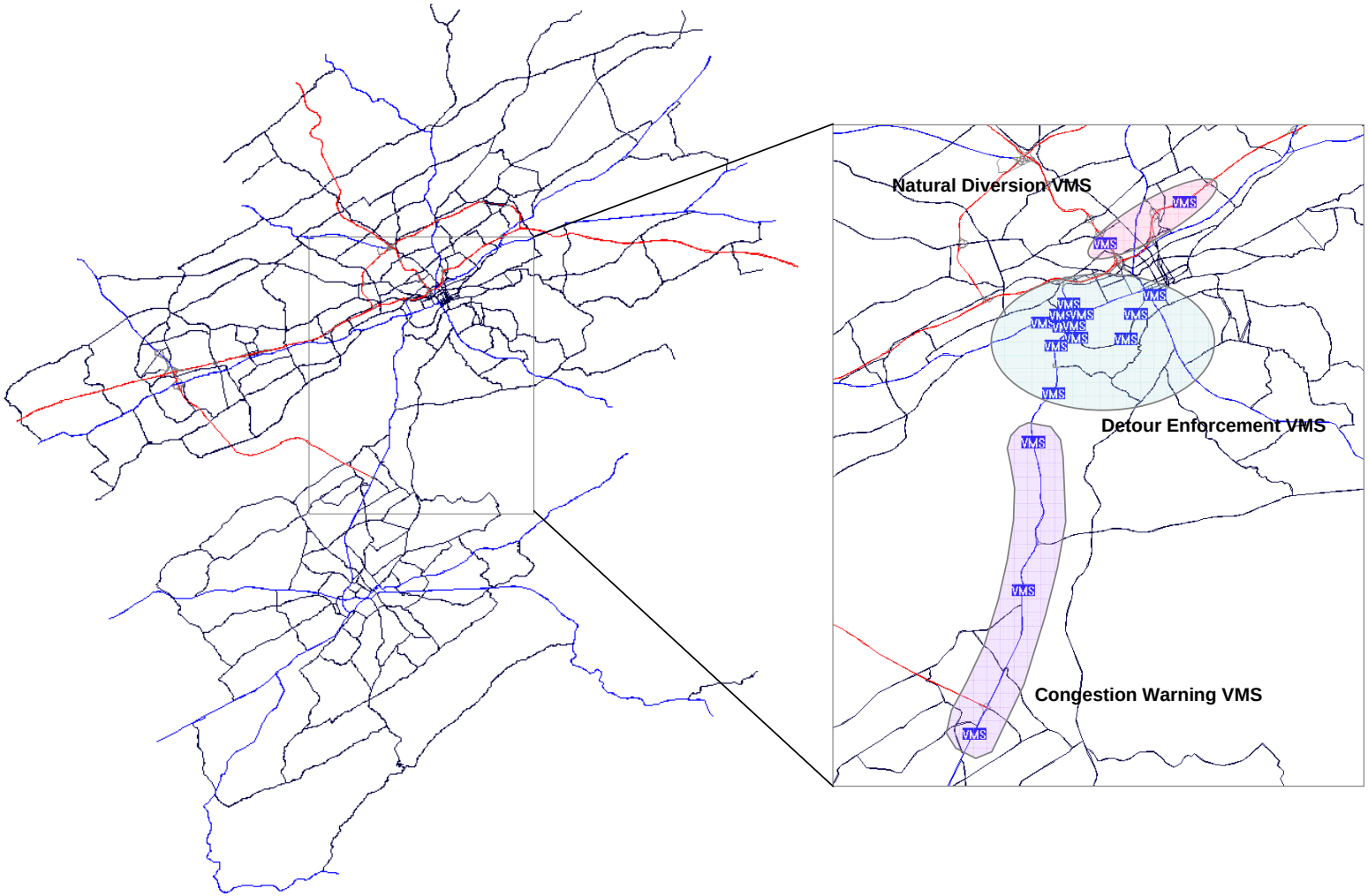


Figure 8.3 Knoxville Network and VMSs

The flooding scenario is intended to evaluate the U-Transportation effectiveness in flooding-prone areas. Table 8.2 presents the chronology of road capacity reduction and Mandatory detour VMSs operation. River and road names are shown in Figure 8.4. The locations of closed sections and Mandatory detour VMSs are shown in Figure 8.5, a Mandatory detour VMS is not a real VMS. It represents the control by enforcement officers near the flood area.

Table 8.2 Capacity Reduction and Mandatory Detour VMS

Time period		Available Capacity (% normal)		Mandatory detour VMS
1	7:00 ~ 7:20	None		None
2	7:20 ~ 7:35	The middle of Neyland dr. south of the U-Tennessee	50%	None
3	7:35 ~ 7:50	The middle of Neyland dr. south of the U-Tennessee	0%	See Figure 8.5
		The rest of Neyland dr. south of the U-Tennessee	50%	
4	7:50 ~ 8:05	The Middle of Neyland dr. south of the U-Tennessee	0%	See Figure 8.5
		The rest of Neyland dr. south of the U-Tennessee	0%	
		The Western portion of the U-Tennessee	50%	
5	8:05 ~ 9:00	The Middle of Neyland dr. south of the U-Tennessee	0%	See Figure 8.5
		The rest of Neyland dr. south of the U-Tennessee	0%	
		The Western portion of the U-Tennessee	0%	

Dotted arrow lines in Figure 8.5 represent the roads impacted by the flooding. We presumed that the middle portion of Neyland Drive south of the University of Tennessee is inundated starting at 7:20 AM. As the water level increases, Neyland Dr. south of the University of Tennessee and the Western portion of the University of Tennessee gradually begin to flood. Policemen are assumed to be deployed near the flooded area to assist travelers to detour and help evacuees. DYNASMART-P can model this behavior using Mandatory detour VMS

control which forces drivers who encounter this type of VMS to reroute to the pre-specified detour paths as input by the modeler.

The first time period doesn't involve any capacity reductions as shown in Figure 8.4. As indicated in Figure 8.5, in the second time period, roads abutting the river start to be inundated. Neyland Dr. south of the University of Tennessee and the Western portion of the University of Tennessee are inaccessible 45 minute later. Enforcement personnel are allocated and start their mission 15 minutes after the beginning of the first road capacity reduction. Therefore, the mandatory detour VMSs operation starts in third time period. Closures continue to occur in time period 4, and by period 5, these roads are completely closed. The pre-specified detour paths for this simulation study are depicted in Figure 8.5 for each time period.

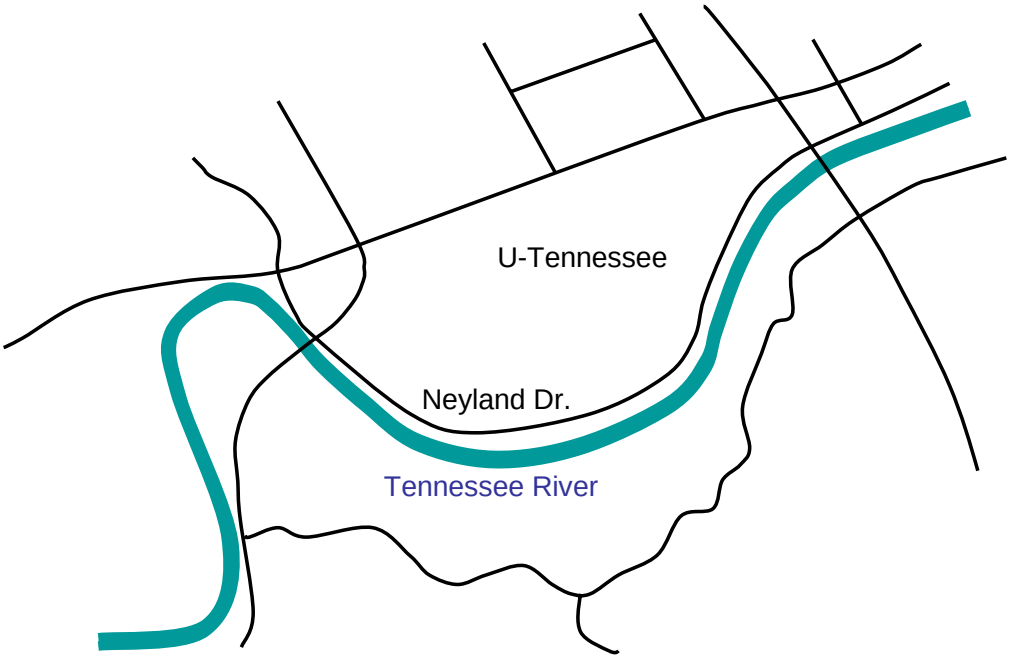


Figure 8.4 Capacity Reduction and Mandatory Detour VMS - Time Period 1

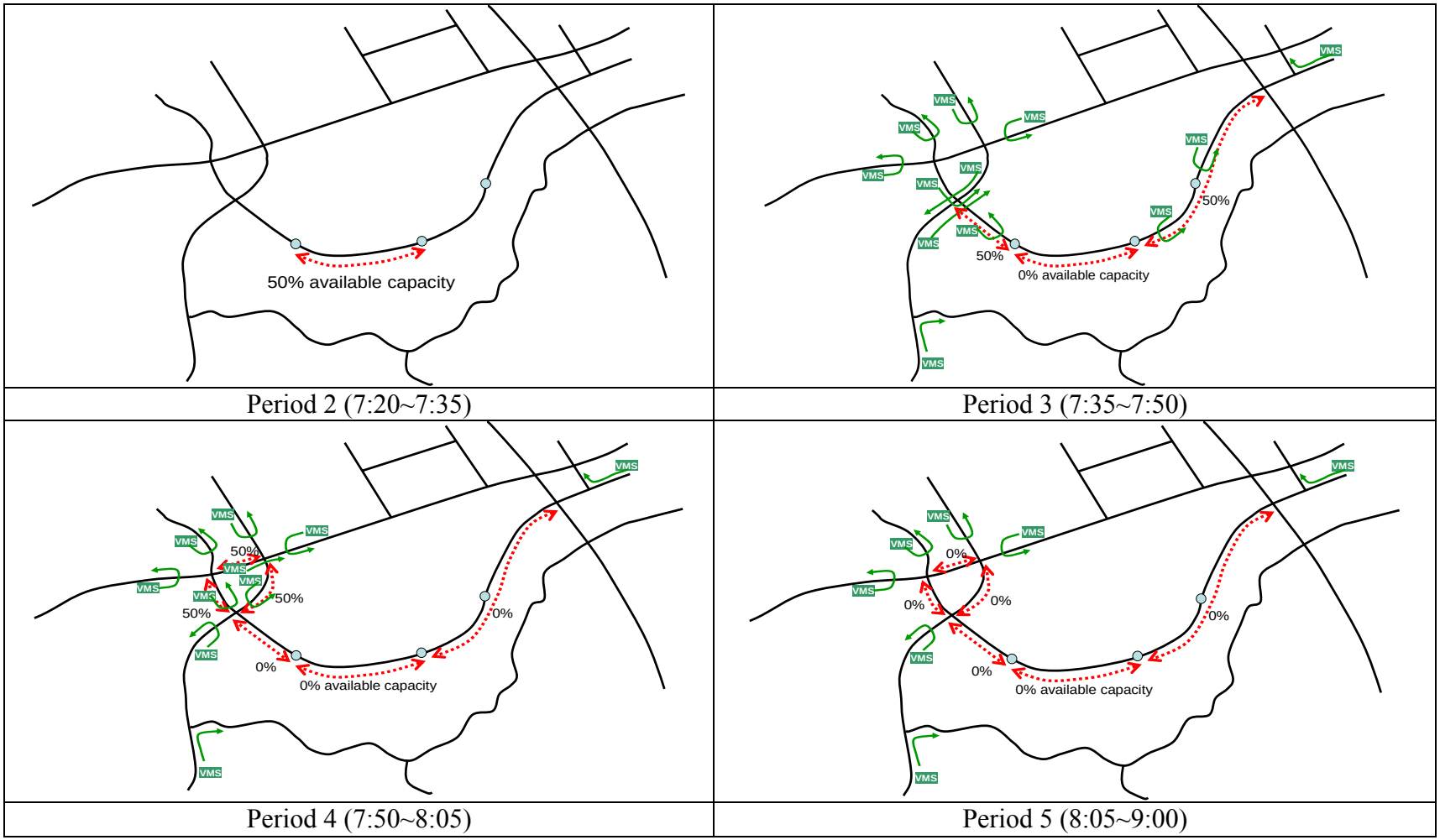


Figure 8.5 Capacity Reduction and Mandatory Detour VMSs- VMS - Time Period 2~5

Trends in traffic demand profiles were prepared as shown in Figure 8.6. This pattern is for the two hour AM peak (7:00~9:00). The demand level increases until simulation time 60 minutes, then decrease until 120 minutes. Figure 8.7 shows (a) the critical OD volumes, (b) link volumes, (c) densities and (d) speeds on the Knoxville network in the initial run, around minute 70. These figures indicate that the demand in Knoxville is, as expected, much higher than Maryville. The two bridges south of the University of Tennessee, Knoxville which are major connectors for the two cities service high volumes. However, no congestion was evident under normal conditions except small delays at a few intersections. In addition, Neyland Drive which abuts the river experiences very low volumes.

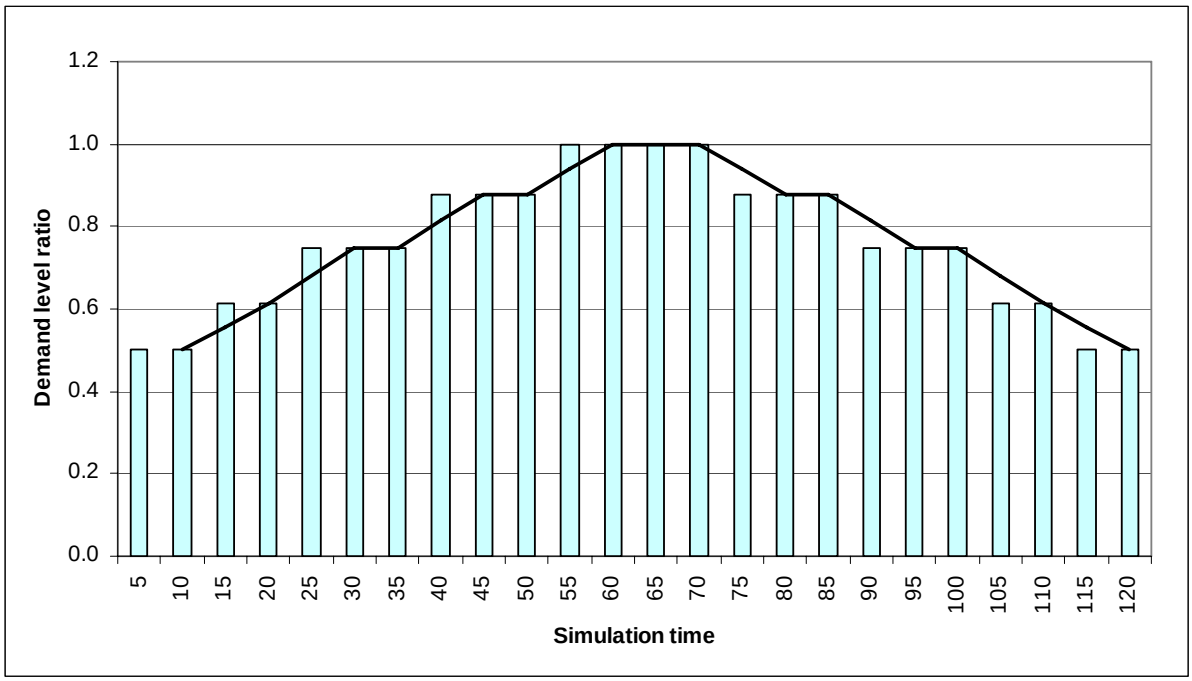
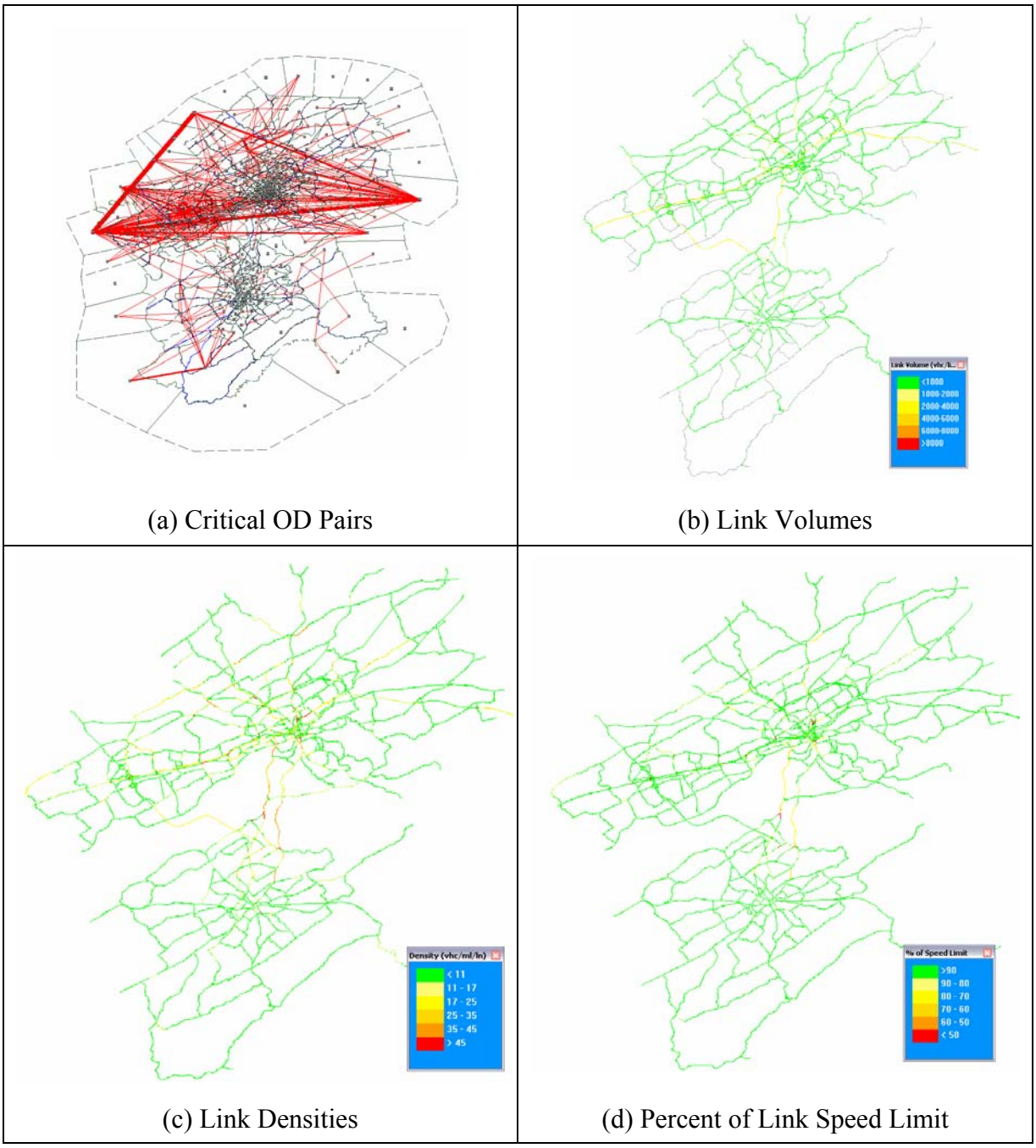


Figure 8.6 OD Demand Trend Profile – Knoxville Network



(a) Critical OD Pairs

(b) Link Volumes

(c) Link Densities

(d) Percent of Link Speed Limit

Figure 8.7 Characteristics of the Knoxville, Tennessee Network

8.5 Results from the Application Studies

In Table 8.3, the potential impacts and benefits of U-Transportation were defined. The performance measures and the tools for estimating the effectiveness of U-Transportation were proposed as well. Chapter 4 described the methodology for assessing U-Transportation technologies, including the use of DYNASMART-P which was selected for modeling the impacts at the strategic level. DYNASMART-P has the ability to model route choice processes and bottleneck and flooding avoidance. Further it can model route choice behavior due to different information sources, and market penetration effects. Various outputs provided by DYNASMART-P were given. Using those outputs, the impact of U-Transportation is analyzed in this chapter.

The results of DYNASMART-P simulation are reported with regards to three aspects:

(1) Behavior of the impacted vehicles and travel time savings for those vehicles,
(2) Overall network performance, and
(3) Overall network throughput.

It is essential to explain the behavior of and statistics associated with the impacted vehicles. These are the vehicles whose normal path will route them through any incident or impacted link. The normal paths are generated in the initial run. Some of the impacted vehicles with access to traveler information may change their normal path to a new optimal path. These diversions obviously affect network performance and the vehicles' travel times. Therefore, the resultant diversion rates and travel time savings for the impacted vehicles in every scenario are reported and compared.

Network wide performance was examined by comparing the average travel time per vehicle (min/veh), average stopped time (min/veh), and average travel distance (mile) in each scenario. The average travel time and the average stopped time can be used to examine the

mobility and efficiency performance of the network. Shorter travel distances represent efficiencies and energy savings on the network.

Capacity reduction on the road links increases network delays, and decreases the network throughput. Vehicle rerouting due to real-time information could increase the network throughput and capacity of the network to service traffic. It was measured by counting the number of vehicles which completed their trips during the analysis period. Throughput is also a good criterion for investigating the network evacuation capability in the flooding case.

Figure 8.8 depicts the classification of impacted vehicles. This figure is inserted to help interpret the DYNASMART-P simulation results, particularly those related to the impacted vehicle analysis. Generated vehicles are used in estimation of overall network performance. The impacted vehicle analysis tool in DYNASMART-P focuses only on the impacted vehicles and provides diversion rates and travel times for the diverted, non-diverted, and all impacted vehicles. Impacted vehicles are only those that pass through any impacted links, and only during the capacity reduction periods. Thus, non-impacted vehicles include those traveling on all other links or those traveling through the impacted links during non capacity reduction periods. An impacted vehicle is classified as 'non-diverted' if the vehicle's normal (initial) and new routes are identical, and as 'diverted' if the vehicle's normal (initial) and new routes are not identical. As mentioned in Section 8.3, using the archived vehicle information, the same stream of vehicles is used in simulating and evaluating every scenario to ensure accurate comparisons. The impacted vehicle analysis tool compares the normal path from the initial run and the new path from one of the evaluated scenarios for each subject vehicle and classifies each vehicle as 'diverted or 'non-diverted.

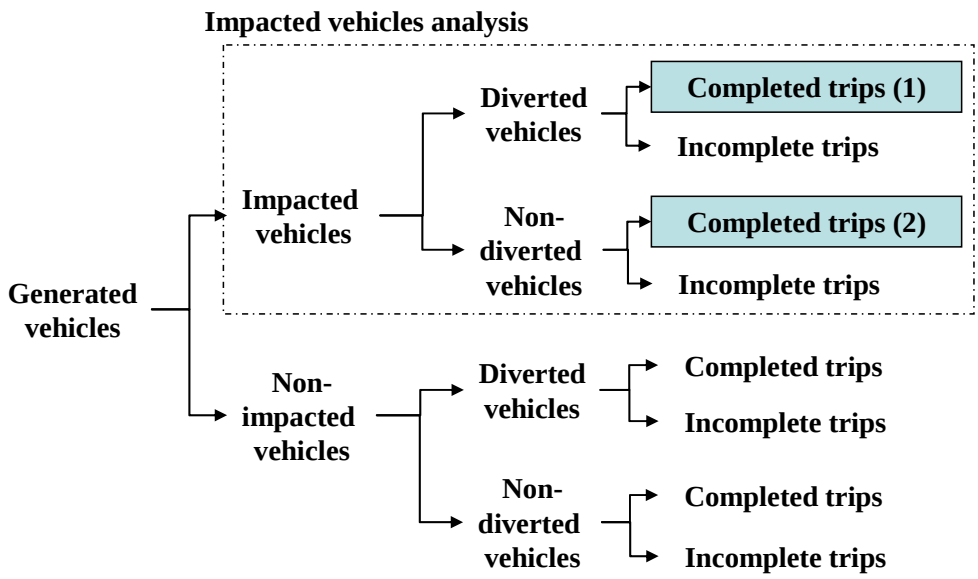


Figure 8.8 Classification of Impacted Vehicles

However, depending on the network congestion levels, some of the generated vehicles (mostly the impacted vehicles) may not complete their trip at the end of the simulation. Because every incomplete path is different from the normal full path, all vehicles that do not complete their trips are classified as diverted vehicles. To avoid this error, the impacted vehicle analysis considers only completed vehicle trips in the analysis.

If there are no incomplete trips like as in the Fort Worth case study, the diversion rate can be clearly defined as **Diversion rate = diverted vehicles / impacted vehicles.** However, in the event there are incomplete trips like as in the Knoxville case study diversion rate is redefined as **Diversion rate = completed trip (1) / {completed trip (1) + completed trip (2)}**, per Exhibit 4-1.

8.5.1 Impacted vehicle analysis

The simulation results from the Knoxville network are summarized in Table 8.3 . The simulation settings for each scenario were shown in Table 8.1. The left portion in Table 8.3 gives the results for the impacted vehicle analysis. The first column of the table refers to the scenario number, the second column shows the number of impacted vehicles which completed their trips, the third column shows the diversion rates and the fourth, fifth, and sixth columns give the average travel time for non-diverted vehicles, diverted vehicles, and all impacted vehicles, respectively.

However, there are three major factors that should be recognized to interpret these results. The first one is that natural diversion behavior was emulated in the flooding scenarios to realistically reflect the driver's response to the severe congestion. As shown in Table 8.3, Scenario 2-2 produced slightly better performance than Scenario 2-1 due to this factor. Therefore, Scenario 2-2 is the baseline for the comparison in measuring the effectiveness of traveler information technologies.

The second major factor is the existence of the mandatory detour VMSs around the flooded area, which is intended to simulate the presence of enforcement personnel attempting to evacuate the impacted area. Every vehicle encountering a mandatory detour VMS must follow it. While Mandatory detour VMSs are operating, diversion rate should be near 100%; there is virtually no chance that the mandatory route was the original route for any of the impacted vehicles.

The last important factor is that vehicles whose final destinations were the University of Tennessee cannot complete their trips because the roads around the university were closed. Figure 8.9 shows OD demands lines near the university (OD zone 32). In reality, such vehicles must change their final destination or cancel their trips, but current the DYNASMART-P algorithms do not allow destination change or trip cancellation. Those vehicles blocked the network around the university and many of the impacted vehicles

remained in the network through the end of the simulation (180 minutes) under low level of information scenarios. As a result, the average travel times of the impacted vehicles were underestimated and the diversion rates were also distorted as the vehicles which didn't complete their trips were not counted in the estimations.

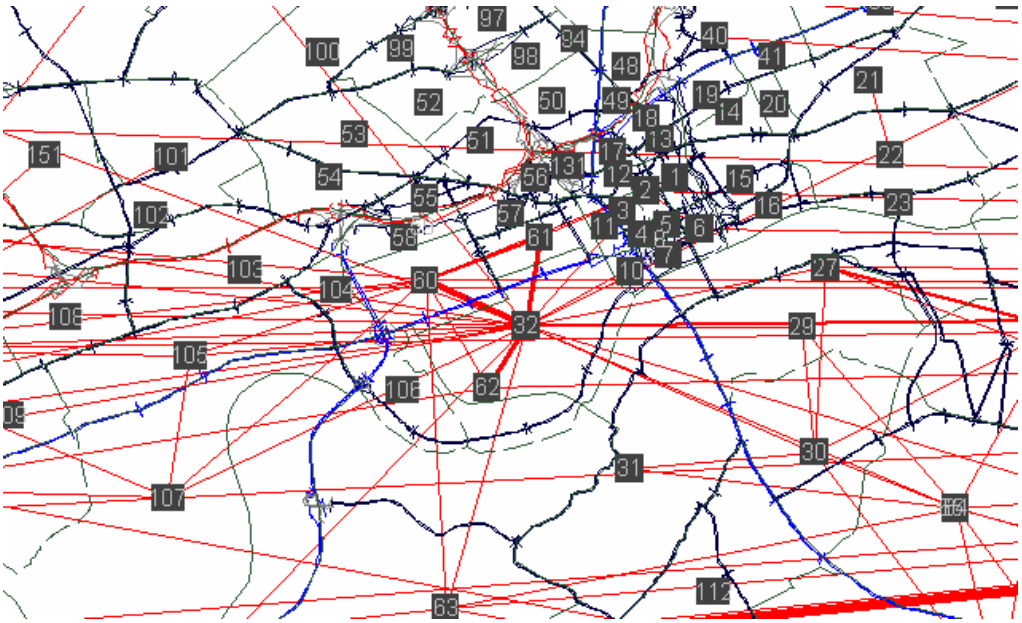


Figure 8.9 Critical Origin-Destination Volumes

Table 8.3 DYNASMART-P Simulation Results– Knoxville

Scenarios	Impacted Vehicles Statistics					Network Wide Statistics					
	Completed Vehicle Trips (veh)	Diversion Rate (%)	Average Travel Time for (min)			Completed Vehicle Trips (veh)	Incomplete Vehicle Trips		Average Travel Time (min)	Average Stop Time (min)	Average Travel Distance (mile)
			Non-Diverted Vehicles	Diverted Vehicles	All Impacted Vehicles		(veh)	(%)			
1	14,171	-			23.06	195,603	1	0.0%	10.75	0.80	8.04
2-1	5,441	18.4%	17.46	53.11	34.55	177,842	17,762	9.1%	16.66	5.86	7.60
2-2	**5,476**	**18.7%**	**17.46**	**51.15**	**33.72**	**177,885**	**17,719**	**9.1%**	**16.65**	**5.87**	**7.61**
3	6,593	26.5%	17.47	52.11	37.22	180,438	15,166	7.8%	15.79	5.07	7.85
4	7,034	29.8%	17.63	51.93	38.23	182,133	13,471	6.9%	15.31	4.55	7.87
5	8,523	40.2%	17.81	54.42	42.26	185,524	10,080	5.2%	15.31	4.16	8.02
6	9,605	47.4%	17.88	52.65	42.39	188,521	7,083	3.6%	14.23	3.14	8.13
7	10,959	57.8%	17.73	44.12	37.45	191,641	3,963	2.0%	12.63	2.05	8.15
8	11,643	62.6%	18.17	39.89	34.71	192,781	2,823	1.4%	12.18	1.73	8.16
9	12,303	70.2%	18.44	40.44	35.52	193,647	1,957	1.0%	12.28	1.57	8.19
10	12,234	68.2%	17.95	50.65	43.77	193,501	2,103	1.1%	13.66	2.05	8.40
11	8,423	38.7%	18.17	45.33	35.86	185,674	9,930	5.1%	14.22	3.64	7.99
12	9,700	47.6%	17.97	45.59	37.19	189,301	6,303	3.2%	13.14	2.70	8.08
13	11,181	57.3%	18.42	37.72	32.43	192,175	3,429	1.8%	11.99	1.85	8.07
14	11,856	61.1%	19.21	33.2	29.43	193,069	2,535	1.3%	11.54	1.54	8.03
15	12,643	64.5%	19.76	30.37	27.43	193,961	1,643	0.8%	11.08	1.24	7.99
16	12,998	64.8%	20.44	27.98	25.76	194,362	1,242	0.6%	10.85	1.14	7.94

Table 8.4 shows the travel behaviors of the impacted vehicles as influenced by the above two factors. The graph and table include the number of diverted, non-diverted, and total impacted vehicles in every scenario. By introducing a very small level of capacity reduction on the roads affected by flooding, about 14,171 vehicles were counted to pass the impacted links under the initial run. This is done to keep track of those same vehicles in the remaining scenarios. Most of the non-diverted vehicles in Table 8.4 are those that passed the flooding area 15 minutes **before** the beginning of operations of any Mandatory detour VMSs and after capacity reduction has taken hold. Since the portions of the roads in the flooding area had slight capacity reduction and the vehicles could pass the area without delay, the numbers of non-diverted vehicles are fairly constant through all the scenarios.

It appeared that before the flooding effects became severe, the system recommended the normal, later-to-be-impacted routes. This is why the number of the non-diverted vehicles increased in Scenario 14 through 16.

In this table, it is apparent that the total number of impacted vehicles increases with higher market penetration of U-Transportation, as the number of diverted vehicles increased. Many of the vehicles diverted their routes using U-Transportation information could complete their trips because the Mandatory detour VMSs prevented access to the impacted links, and U-Transportation, particularly V2I information provided the best alternative route.

The diversion rate increases with market penetration rate of U-Transportation as the number of the completed vehicle trips among the impacted vehicles increases. The reported diversion rate is not the actual diversion rate because incomplete trips were not counted, as stated earlier. However, the increase in completed vehicle trips implies that the higher market penetration of U-Transportation has better capability of evacuating the network.

Scenarios 11 though 16 showed less diversion rates than Scenarios 5 though 10 did. This is because the number of diverted vehicles from those two groups was almost the same, while

the group of Scenarios 11 though 16 had more non-diverted vehicles than the group of Scenarios 5 through 10. V2I information guided more vehicles to complete their trips without diversion before the flooding effects became severe.

Table 8.4 The Number of Impacted Vehicles-Knoxville

Scenarios	The Number of Vehicles for (min)			Diversion Rate (%)
	All Impacted Vehicles	Non-Diverted Vehicles	Diverted Vehicles	
1	14,171	-	-	-
2-1	5,441	2,833	2,608	18.4%
2-2	5,476	2,833	2,643	18.7%
3	6,593	2,834	3,759	26.5%
4	7,034	2,808	4,226	29.8%
5	8,523	2,830	5,693	40.2%
6	9,605	2,833	6,722	47.4%
7	10,959	2,772	8,187	57.8%
8	11,643	2,777	8,866	62.6%
9	12,303	2,752	9,951	70.2%
10	12,234	2,572	9,662	68.2%
11	8,423	2,937	5,486	38.7%
12	9,700	2,952	6,748	47.6%
13	11,181	3,062	8,119	57.3%
14	11,856	3,196	8,660	61.1%
15	12,643	3,504	9,139	64.5%
16	12,998	3,815	9,183	64.8%

Table 8.3 shows the average travel time of the impacted vehicles under every scenario. By comparing travel times in Scenarios 1 and 2-2, vehicles passing through the flooded location experience about 10 minutes delays when there is no traveler information and no diversions.

However, as mentioned above, almost 9,000 vehicles remain in the flooded area. In Scenario 2-2 the modeled flooding produced more very severe congestion.

In Scenarios 11 -16 where users prefer to comply with V2I information, as the market penetration of U-Transportation increase, the travel times of diverted vehicles decrease, while those of non-diverted vehicles slightly increases. That is, as the market penetration of U-Transportation increase, more non-diverted vehicles were able to complete their trips with the system help (V2I), but those vehicles generally experienced higher delay because they were assigned to the impacted links having higher delay, which caused the average travel time to increase. However, these findings do not imply that diversion is always desirable. The travel times of the non-diverted vehicles which didn't complete their paths cannot be estimated. The diverted vehicles, on the other hand, successfully avoided the flooded area, which caused the average travel time of diverted vehicles to decrease.

8.5.2 Network wide analysis

The right shaded part of Table 8.3 shows the summary of the network wide statistics. The first column depicts the vehicles which completed their trips among all generated vehicles. In all 195,603 vehicles were generated during 2 hours. As shown in the table, the number of incomplete vehicle tips decreased as market penetration of U-Transportation increased. This phenomenon is related to network throughput and is discussed in section 8.5.3.

By comparing scenarios 1 and 2-2, the modeled flooding scenario produced severe congestion when there is no traveler information. Network wide average travel time increased by about 5.9 minutes. The network wide average travel times for Scenarios 3 and 4 are slightly less than that of Scenario 2-2. Unexpectedly, in view of the network throughput, the performance of Scenario 4 was worse than that of Scenario 3. In other words, the number of completed trip vehicles in Scenario 4 decreased in comparison with Scenario 3. One of the possible reasons is that the pre-trip information given to the vehicles upon departing the

origin could be invalid at the time this vehicle group arrives at the impacted area. That is, the time gap between the time when users receive the information and the time when users arrive at an impacted area could cause the provided information to be outdated. The travel distance and travel time of the users who arrive at the impacted area with the wrong shortest path information may be increased, or the trips may not be completed. The time gap can be much larger in larger network.

The results of Scenarios 5 through 10 and Scenarios 11 through 15 indicate that both the average travel time and stopped time in the network wide are reduced by increasing the market penetration of U-Transportation vehicles. The higher the market penetration of U-Transportation, the more effective it was in relieving congestion.

Scenarios 5 though 10 and 11 though 16 are intended to compare the U-Transportation user's information selection. In Scenarios 5 though 10, users prefer to comply with the V2V information. In Scenarios 11 though 16, users prefer to select the V2I information. The latter group gives better overall performance at the same level market penetration. The reason is V2I group selects the path provided by the system, which considering all options in close to a "System optimum" path assignment.

Figure 8.10 includes results of average travel time and average travel distance by scenario. The travel distance in Scenario 2-2 is much smaller than for all other scenarios. It is because 17,719 of vehicles could not finish their trip and therefore had shorter travel distances. By decreasing the number of incomplete trip vehicles, the average distance increased. Also, the selection of longer alternate routes increased average travel distance. The numbers of incomplete vehicle trips are similar in Scenarios 5 through 10 and Scenarios 11 through 15 at each market penetration level, but the travel distances in Scenarios 5 through 10 are longer than Scenarios 11 through 15. It indicates V2I was able to find the shorter divert routes than V2V information by iteration.

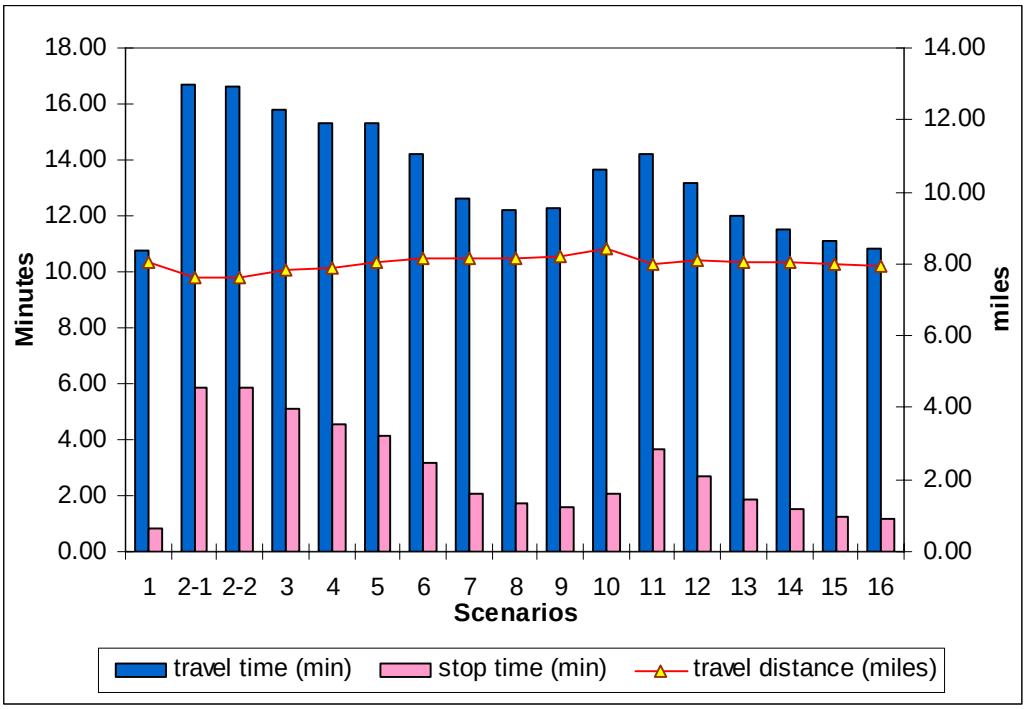


Figure 8.10 Overall Network Measure of Effectiveness-Knoxville

Figure 8.11 through Figure 8.13 are the visualized queues in the network around simulation time 130 minutes, when the impacted area by the incident has the longest queues. These graphs help judge the congestion relief capability of each information scenario. Figure 8.11 includes Scenarios 1 through 4, with red lines representing queues. Scenario 2 shows the worst case. Scenario 3 and 4 cannot decrease the congestion level effectively. Figure 8.12 and Figure 8.13 include the effect of U-Transportation market penetrations of 20%, 50%, 75%, and 100%, respectively.

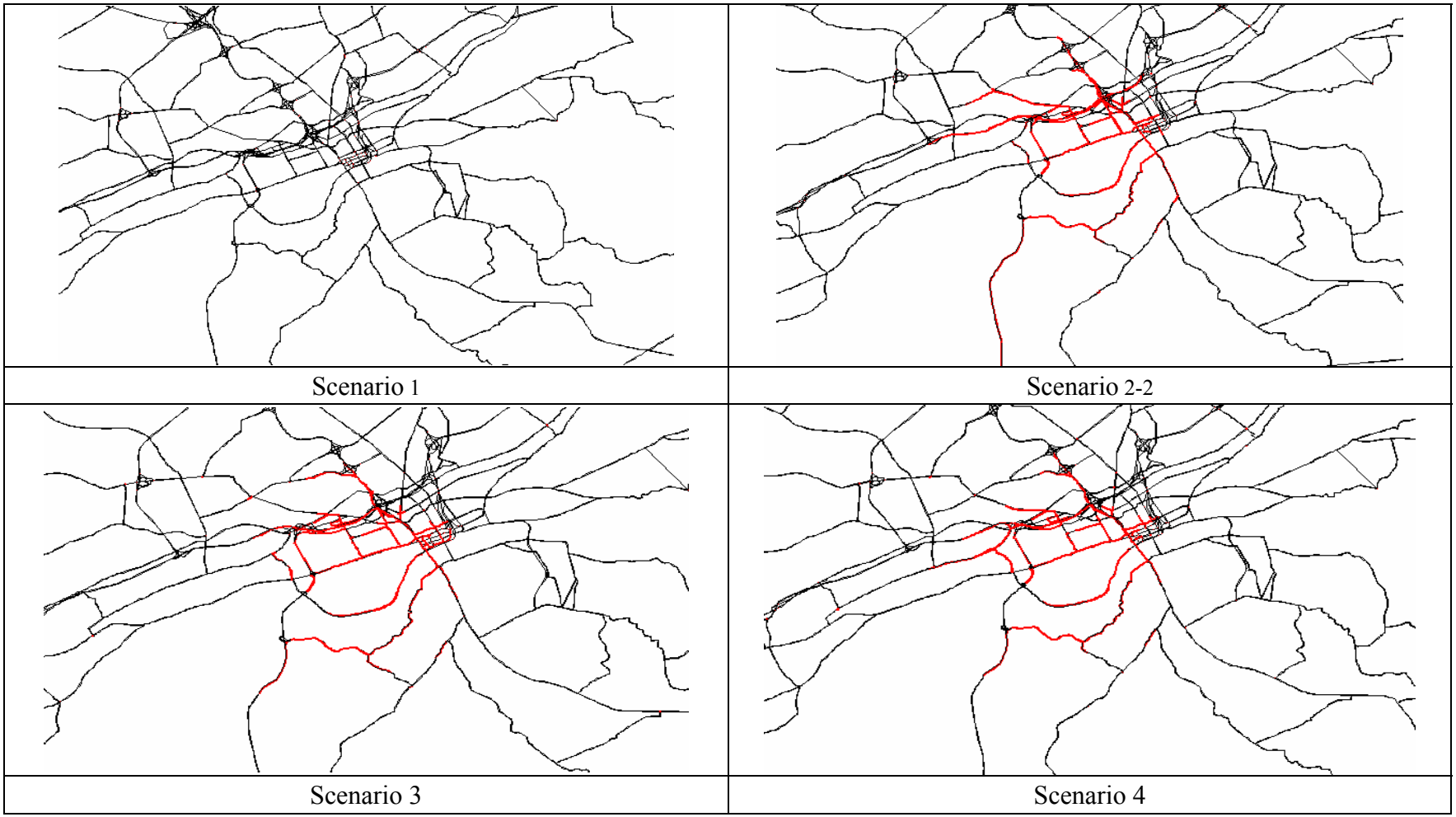


Figure 8.11 Vehicle Queue (a)–Knoxville

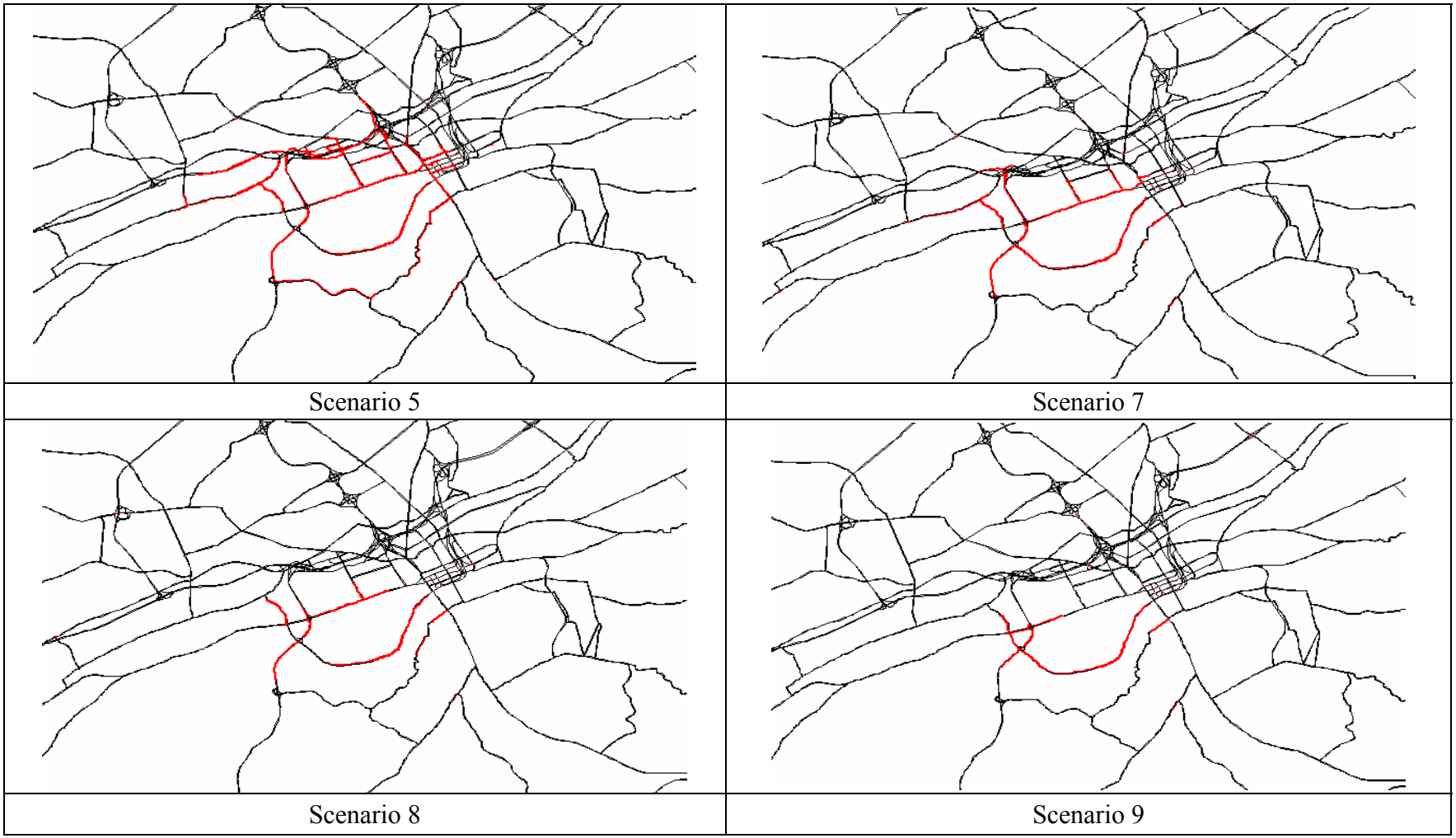
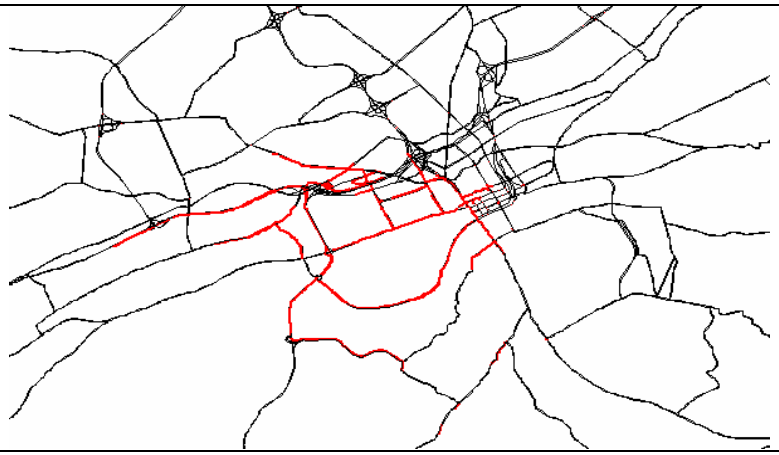
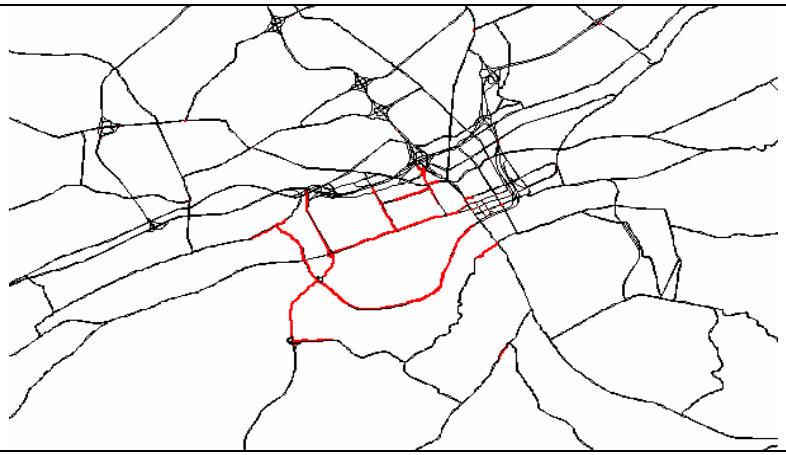


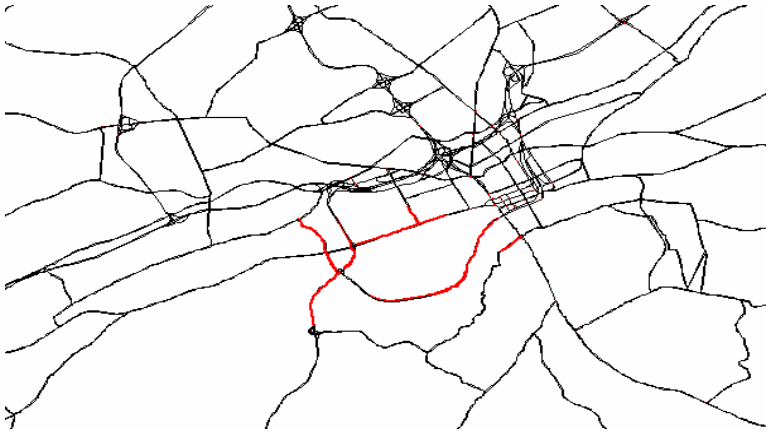
Figure 8.12 Vehicle Queue (b)–Knoxville



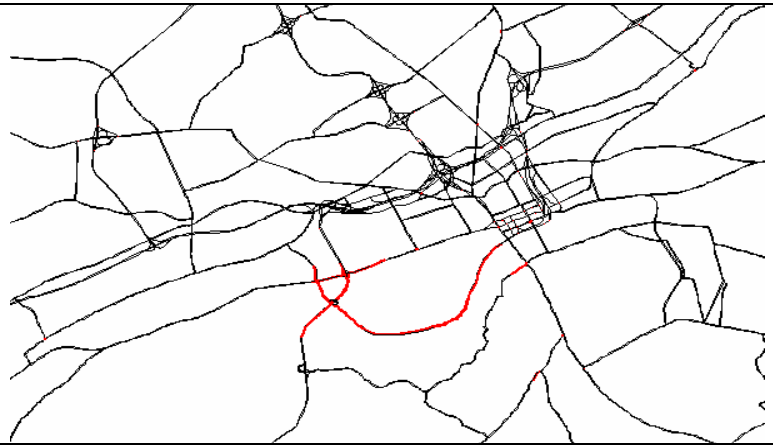
Scenario 11



Scenario 13



Scenario 14



Scenario 15

Figure 8.13 Vehicle Queue (c)–Knoxville

8.5.3 Network throughput

Figure 8.14 compares the network throughput for all scenarios. It depicts the number of incomplete vehicle trips at simulation time 180 minutes, 60 minutes after vehicle generation ends. In the initial run, most of the generated vehicles reach their final destination. The secondary Y axis represents the percentage of the incomplete vehicle trips from the total generated vehicles. Smaller value imply higher network throughput. It is evident that ITS information has some effectiveness in congestion relief. But it is not as effective as U-Transportation when, for example, we compare Scenario 4 with Scenario 5 or Scenario 11.

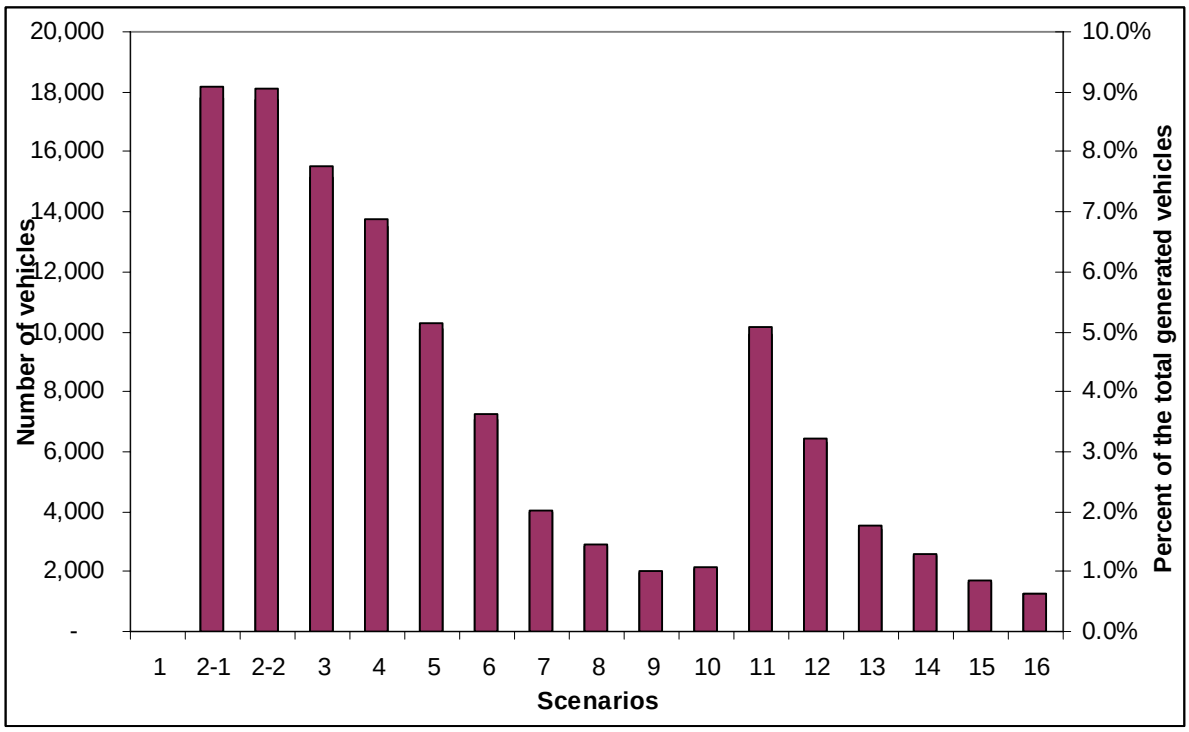


Figure 8.14 Incomplete Trips at Simulation Time of 180 Minutes

Figure 8.15 through Figure 8.17 show the cumulative arrival and departure curves for the indicated scenario numbers. The numbers in the label box indicate the scenario numbers shown in Table 8.1. These graphs indicate that network throughput increases as u-Transportation market penetration increases.

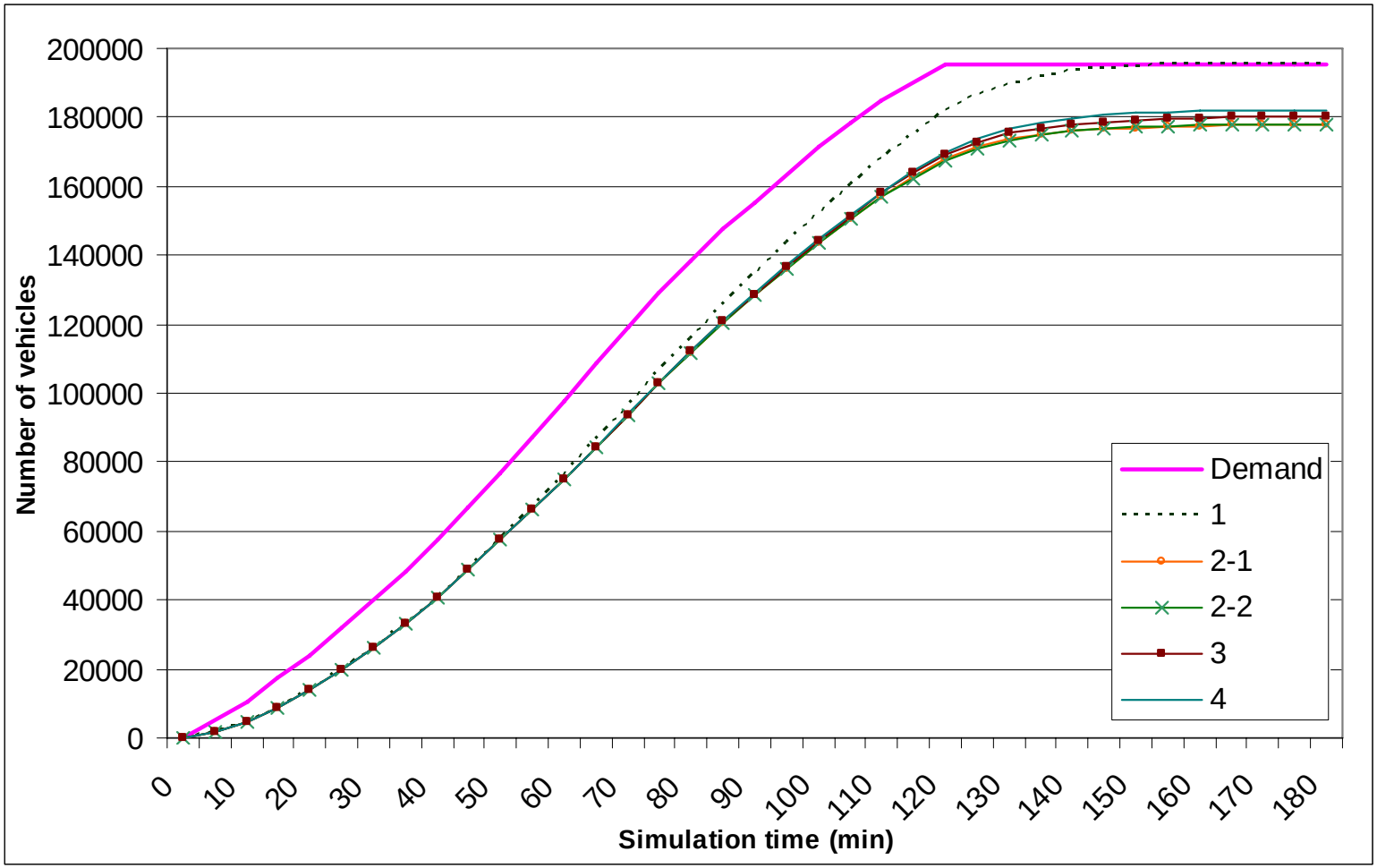


Figure 8.15 Cumulative Demand and Departure Curves - 0% Market Penetration

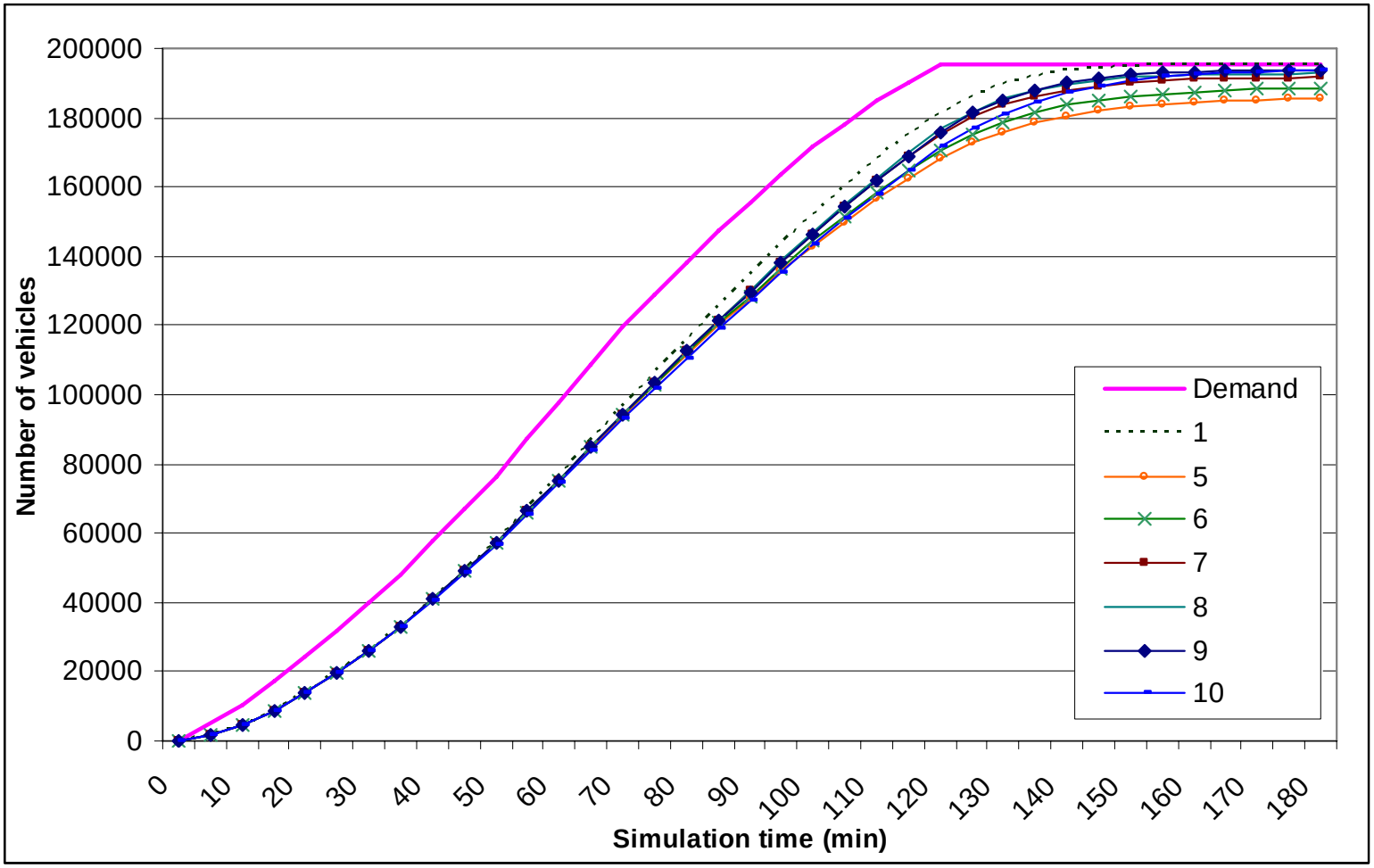


Figure 8.16 Cumulative Demand and Departure Curves – Higher V2V Market Penetration

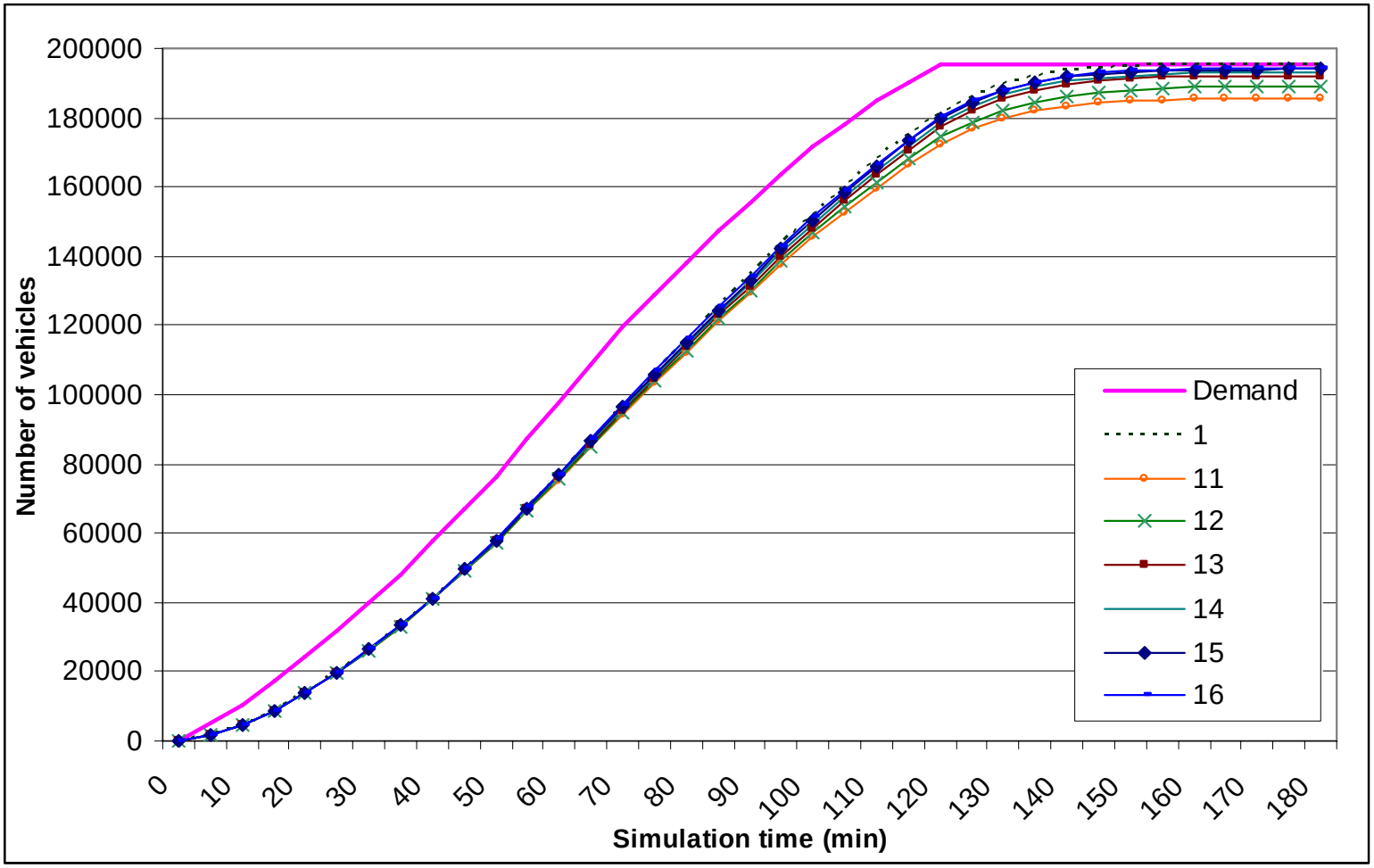


Figure 8.17 Cumulative Demand and Departure Curves – Higher V2I Market Penetration

8.6 Discussion

The occurrence of a substantial number of incomplete trips for the impacted vehicles in the Knoxville case study made the interpretation of the results much difficult. However this results of the case study still clearly showed the ability of DYNASMART-P to model the impact of flooding and drivers' behaviors to the information sources such as Mandatory detour VMS (enforcement personnel), traditional ITS installations (Congestion warning VMS and pre-trip information), and the real time V2V and V2I information.

Natural diversion behavior was modeled in the flooding scenarios to realistically reflect the driver's response to the severe congestion. This provides a valid baseline (Scenario 2-2) for the comparison in measuring the effectiveness of traveler information technologies.

Disasters monitoring and evacuation assistance will be included in the U-Transportation applications. It was possible to evaluate the evacuation capability of U-Transportation on the basis of the market penetration rates, using the results from this case study. However, since the current DYNASMART-P cannot model the altering of the final destination or trip cancellation, the evacuation capability might be underestimated in this case study.

The application of monitoring disasters using U-Transportation technologies will therefore make it possible to detect disaster like flooding earlier, so policemen could help evacuee earlier under the U-Transportation network information scenario. This was effectively modeled in this case study. Thus, in U-Transportation information scenarios, Mandatory detour VMSs should have operated earlier than in Scenarios 2-2 or 3.

Mandatory detour VMSs didn't suggest the best alternative path; they just prevented vehicles to pass through the impacted links. So, these drivers attempted to individually find an alternative path. Some vehicles even traveled the same route several times around the impacted area. In reality, this unusual route selection happens rarely.

For the sake of system efficiency, the system assigned some of the V2I users to the impacted links before roads were completely closed. These users could have taken shorter detours but they were advised to pass the roads near the flooded area. However, in order to provide better route guidance in an evacuation case, the system requires considering the additional goals of representing users' safety as well as efficiency.

CHAPTER 9. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

9.1 Summary

The motivation for this research stemmed from a pilot study sponsored by the North Carolina Department of Transportation (NCDOT) which was conducted in order to recommend a method for assessing the network impacts, especially the network performance benefits of candidate ATIS investments. The pilot study revealed several shortcomings in ATIS evaluation tools that needed to be addressed. Three of those issues were thought to be most pressing and served as the basis for carrying out this research. Therefore, the main objective of this research was to improve the functionality of ATIS evaluation tools in assessing ATIS through the implementation of three key enhancements:

- Enhancement A: modifying the traffic network simulator of the selected tool, DYNASMART-P, in order to incorporate a more realistic queue propagation algorithm,
- Enhancement B: modeling the "natural" diversion behavior of drivers who do not have access to real time traveler information but may be familiar with the network's alternate routes, and
- Enhancement C: understanding and modeling the relationship between drivers' socio-economic characteristics and their responses to traveler information.

In Enhancement A, this study examined the mesoscopic traffic simulator DYNASMART-P. The author identified three major unrealistic queue propagation phenomena in the modeling of link capacity reduction that results from events such as bottlenecks, incidents, and work zones. First, in the original simulation tool, the queue appears to form backward from the downstream end of a bottleneck link with no traffic congestion factor other than capacity

reduction. Theoretically, however, a queue builds backward from the upstream point of a bottleneck link, and the bottleneck link itself does not experience a queue in it. Second, it was shown in DYNASAMRT-P that the flow rate on the upstream links of a bottleneck link could be greater than the maximum flow rate of the bottleneck link. This is not theoretically defensible. Lastly, the model produced valid queue propagation only when the network has short links, which were similar in length to links in the cell based models by Daganzo (1994). Thus, queue propagation modeling results appears to be very sensitive to the link length in the network, even though the model is a link-based model. This third characteristic of the original model was the starting point to improve the queue propagation logic. The enhanced model prompted the addition of two more constraints. One is the link 'transfer flow capacity' constraint. When this constraint is added, the queue begins at the theoretically correct point and the flow rate cannot exceed the maximum link flow rate. The other constraint is a new 'backward gated flow' constraint to limit transfer flow rate when the downstream link is in the over-saturation regime. The new backward gated flow rate was estimated from the simplified flow density curve on oversaturated region. The enhanced model with the additional two constraints was implemented and tested on a very simple network containing a bottleneck link. The simulation results showed that the enhanced model provided much more realistic results.

Natural diversion behavior was modeled in Enhancement B. For the enhanced model it was proposed that natural diversion behavior could occur when downstream link density is greater than a critical density for detour decision. For the critical density, the minimum of the two density thresholds was suggested to be used; one of the density thresholds is the mid value of the optimal density and jam density, and the other threshold is the downstream link queue density estimated from the initial run. In order to calibrate the value for the 'natural diversion willingness rate (%) a relationship between this variable and the 'Maximum natural diversion willingness rate (%)', which is the fraction of drivers that can consider (but not necessarily undertake) a diversion' as well as an indicator of congestion severity' was proposed.. The congestion severity index is taken as the value of the downstream link

density divided by the maximum downstream link density. The enhancement was implemented and tested in a very simple network containing a main route and a diversion route. The main route had sufficient capacity under normal conditions and the diversion route was relatively longer than the main route. Thus, all drivers would typically select the main route under normal conditions and no capacity reduction would occur. In the original model, even though the main route has congestion because of an incident, no drivers use the alternate route if they have no access to real time traveler information. In the enhanced model, some of vehicles in the queue could divert based on a defined algorithm representing a natural diversion behavior.

In Enhancement C, this research developed models for predicting user profiles using the relationship between the driver's socio-economic characteristics and the responses to traveler information such as frequency of use, preferred information source, and travel decision change behavior based on the data from 'the 2006 greater Triangle Household Travel Survey'. The survey was conducted for the purpose of developing and updating a regional travel demand model. In conjunction with the NCDOT pilot study a set of specially designed ATIS-related questions were added to the survey. The survey responses were simplified into three choice levels: information access, information source, and travel decision for each information source selection. A total of five models were developed for the three response levels. One binary logit model for the level one, three multinomial logit models for the level two, and three binary logit models for the level three were developed. The models were useful for investigating which socio-economic factors were more related to a response. However, based on the validity test of the models, the prediction results are not close to the real response rate. Especially, models for the levels one and two showed poor prediction results. Only 58% and 51% of the responses were correctly classified in the levels one and two, respectively.

The enhanced model included only Enhancements A and B because Enhancement C simply did not provide good prediction results. The model was applied to two case studies for the following two purposes:

- Verifying the capabilities of the enhanced model which adopts the improved algorithms developed above using a regular bottleneck section on I-40 corridor in Triangle region, North Carolina, and
- Demonstrating the capabilities of the enhanced model under an advanced technology, U-Transportation which has been under development in Korea (similar system with Vehicle Infrastructure Integration (VII) program in USA) as a next generation ITS.

The enhanced model was calibrated for the PM peak traffic hour on a 20 mile-long segment of I-40 between Chapel Hill and Raleigh, North Carolina. The original model, the model with Enhancement A, and the model with Enhancements A and B were used for running the simulation network to test the proposed queue propagation algorithm and the natural diversion behavior model. Travel time on the corridor and exit ramp volumes were selected as comparison criteria in verifying the model. GPS equipment was installed in a probe vehicle to measure field travel time. Travel times and exit ramp volumes from the DYNASMART-P simulation were compared with the field travel times measured by the GPS and the field traffic counts. Comparison results presented that the recurring bottleneck of the network could be properly modeled through Enhancement A and the natural diversion behavior in the network was appropriately examined by Enhancement B.

The enhanced model was also applied for the evaluation of U-Transportation (similar system with Vehicle Infrastructure Integration (VII) program in USA) which can be viewed as the next generation ITS. U-Transportation systems have been studied in South Korea since 2005 (Kang et al., 2005). In U-Transportation systems, vehicles can communicate with the infrastructure and with other vehicles using short-range-communications sensors. The effectiveness of U-Transportation in the case of a natural disaster was evaluated. A roadway

system closure due to a flooding was simulated in a network in Knoxville, Tennessee. In the application, the enhanced model was able to provide a more valid assessment of the effect of U-Transportation on network performance and could pave the way for a similar benefit cost method for these investments.

9.2 Conclusions

The model verification results showed that the model with Enhancement A provided more accurate network performance results than the original model. The comparison between the results from the model with Enhancement A only and the model with Enhancements A and B revealed the existence of the effect of modeled natural diversion behavior. The following findings from the comparison results support the above statements:

- Queue beginning point in the model with Enhancement A was much closer to the field data in comparison with the original model.
- The Mean % Absolute Deviation (MPAD) in travel counts and travel times of the model with Enhancement A decreased from 28% to 1.4% and from 24% to 17%, respectively in comparison with the original model.
- There was no difference in the results between the scenarios with maximum willingness diversion rates of 25%, 5%, 3%, and even 1%. This indicates that the actual diversion rate under (known or anticipated) recurring congestion is very low.
- With natural diversions, the mainline traffic counts at upstream of the bottleneck decreased in comparison with the scenario without natural diversions. Also, the downstream hidden bottleneck became an active bottleneck and made severe congestion. Therefore, the MPAD in travel times increased from 17% to 30%.
- The results from model with Enhancement A only were closer to the field travel time data in comparison with the results from model with Enhancements A and B. It implies the actual diversion rate might be near 0% under recurring congestion in the

study network. However, the natural diversion rate could be higher under non-recurring congestion such as work zones or highway incidents.

In the NCDOT pilot study, DYNASMART-P was applied to the evaluation of case study scenarios including the cases of planned work zones occurring during non-peak traffic conditions and the cases of unplanned incidents occurring during peak commuting traffic conditions in the Triangle region in North Carolina. As a result of the pilot study, the benefit of ATIS and the high value of ATIS were revealed through an example benefit cost analysis. The following findings were acquired from the scenario case of planned work zones occurring during non-peak traffic conditions:

- A total of 7, 447 vehicles use a path where the planned reconstruction work took place (impacted vehicles). When there is no capacity reduction, the average travel time of those vehicles is 20.7 minutes. However, when lanes were partly closed and traveler information was not provided, their travel time increased to 71minutes, a 50 minute (or 233%) increase. As ATIS usage increased through the various scenarios, the diversion rates increased. Furthermore, as drivers began to use alternate routes, the impacted vehicles' travel time on the original route began to reduce dramatically until 36.36 min in the alternative with most intensive ATIS deployment.
- The impacted vehicles' detour behavior is primary cause of the difference in the network performance. Because the number of total vehicles in the network is extremely large, the difference in average travel time and stop time is relatively small. However, the network performance measures show that the ATIS alternatives did produce lower average travel and stop times. As ATIS usage % increase, 14% additional average travel time decreased to 3% and 79% additional average stop time decreased to 16%.
- The prototype benefit cost analysis results shows that for the two ATIS deployment plans, Planned ATIS I and II, the 0.28 million dollars of investment produced 5 or 9.5

million dollars of benefits in one year of the I-40 resurfacing work. The benefit/cost ratios were about 18.0 and 33.9 for Planned ATIS I and II, respectively.

The results from the application case study for evaluating U-Transportation revealed that DYNASMART-P with Enhancements A and B could model the progressive impact of flooded links and drivers' behavior to mandatory detour VMS (emulating enforcement personnel), traditional ITS installations (congestion warning VMS and pre-trip information), and real time vehicle to vehicle V2V, and vehicle to infrastructure V2I information. The effect of U-Transportation market penetration was modeled and the evacuation capability of U-Transportation by the market penetration rates was evaluated. The case study resulted in the following findings:

- It was shown that traveler information was instrumental in reducing congestion caused by the flooding. It was also shown having access to pre-trip information might not always be beneficial. For example, in a large network like in Knoxville the time gap between departing at the origin and arriving at an impacted location could make the pre-trip information about the path obsolete. It was evident that the network performance was enhanced as U-Transportation market penetration increased.
- The V2I protocol system performance optimization from a mobility perspective comes at the price of very high travel time differentials between diverted and non-diverted vehicles. It is recommended in the future that the system optimization algorithm for U-Transportation systems be able to consider multi-objectives including system efficiency and near equity in travel time between OD pairs.
- Because many links are inaccessible, and the network topology in this case rely on two bridge crossings (one of which is closed), there is every expectation that (a) higher diversion rates are necessary, and mandatory, and (b) large differentials in travel time are expected between those vehicles which completed their travel prior to the flooded area shutdown, and others that had to make significant detours. In this

case, the fraction of incomplete trips and the overall travel time are probably the most suitable performance measures to assess U-Transportation network effectiveness. Scenario 4, with fully ITS capabilities deployed has associated with it a 6.9% rate of incomplete trips, and an average system trip time of 15.3 min. By comparison, a fully deployed U-Transportation system, exemplified by Scenario 9, with 25% V2I capabilities, and 75% V2V capabilities has an incomplete trip rate of only 1.0%, and a system trip time of 12.3 min, a 20% reduction in travel time. More importantly, only 50% of the impacted vehicles complete their trip in Scenario 4, compared to 87% under scenario 9.

- The results indicate that while benefits accrue as a result of U-Transportation implementation, there is no 'magic' market penetration rate that is applicable across all networks. Considerations of travel time equity, availability of alternative routes, and the possibility of total link or area shutdown are important in designing and implementing such systems. It is clear, however, that as the scope of the event becomes more severe, as evident from the Knoxville case study, that higher U-Transportation market penetration rates will be needed.

9.3 Recommendations for Future Research

Enhancements A and B were only applied to the freeway links. Algorithms for arterial and local streets should also be improved in future research. The queue propagation logic and natural diversion behavior on arterial and local streets may be more complex to implement than on freeways, but the improvements will be essential in producing more realistic results.

The network data preparation effort was time consuming. To reduce the time required, future modeling efforts should be able to borrow a data set from other planning models such as TransCAD. After transferring, many hours were required for editing signal information, link geometry, etc. The problem is that those tasks need to be done again when the network boundary is changed. To alleviate this problem, a sub-network analysis tool was developed

in the original model. This tool saves time when the analyst needs to run part of the developed network. However, when the network boundary is expanded, all of the network building steps should be reconstructed from the beginning. If the Metropolitan Planning Organization (MPO) in a region is planning to evaluate various traffic management policies in cases using tools like DYNASMART-P, it would be better to have a more powerful database in their own planning model which includes signal control, lane configurations, and other such details. This will save much time and will prevent getting invalid simulation results due to a lack of data.

During the three case studies, some areas were found to be in need of improvement in DYNASMAR-P. First, freeway ramp merging and diverging behavior should be modeled correctly. Those were treated as an unsignalized intersection on surface streets in the original model. Freeway mainline priority, ramp area impact, auxiliary lane characteristics need to be considered. Second, in the Knoxville network case study, there are several important characteristics of system and users' behaviors which were not reflected in the evaluation process because of the limitation of original DYNASMART-P. For example, service delays in pre-trip information under conventional ITS could not be modeled. Also, what would be considered "normal" user behavior such as altering the trip time or destination, or trip cancellation in response to the flooding could not be considered. The impact of U-Transportation could be evaluated more accurately if functions for modeling these system and users characteristics were added. Third, the actual location of a queue end cannot be estimated because DYNASMART-P has a vertical queuing system. The number of vehicles in a queue can be estimated and the location of the queue end could be calculated using the predetermined average vehicle space. However, this may not be accurate because the average vehicle space can vary according to the queue density.

REFERENCES

Abdel-Aty, M. “Design and Development of a Computer Simulation Experiment to Support Mode/Route Choice Modeling in the Presence of ATIS”, Transportation Research, Part B 37, 2003, pp. 793–814.

Abdel-Aty, M. and M. F. Abdalla. “Modeling Repeated Multinomial Route Choices Under Advanced Traveler Information System: Generalized Estimating Equations With Polytomous Logit Function”, Transportation Research Records 1882, 2004.

Agresti, A. “Categorical data analysis” second edition, Chapter 5 and chapter 7, 2002.

Ajay, K. R. and Oak Ridge National Laboratory. “Models For Assessing The Impacts and the Potential Benefits of Intelligent Transportation System”. Prepared for IVHS Research Division Joint Program Office, August 15, 1995.

Ben-Akiva and Moshe. “Dynamit, a Simulation-Based System for Traffic Prediction and Guidance Generation”. Prepared for Massachusetts Institute of Technology. Intelligent Transportation Systems Program, 1998.

Bogers, E., F. Viti, and S. Hoogendoorn. “Joint Modeling Of ATIS, Habit, And Learning Impacts On Route Choice By Laboratory Simulator Experiments”, Transportation Research Records TBD, 2005.

Cambridge Systematics. “IDAS, Intelligent Transportation Systems Deployment Analysis System”, prepared for FHWA, 2000.

Chang, G. L., H. S. Mahmassani, and R. Herman. “A Macroparticle Traffic simulation Model to Investigate Peak-Period Commuter Decision Dynamics,” Transportation Research Record 1005, 1985, pp. 107~120.

Chen, Y., X. Qin, D. A. Noyce, and C. Lee. “A Hybrid Process of Micro-Simulation and Logistic Regression for Short-Term Work Zone Traffic Diversion”, 87th Annual Meeting of the Transportation Research Board, Washington, D.C., 2008

Chiu, Y. and L. Zhou. “An Anisotropic Mesoscopic Traffic Simulation Model: Basic Properties and Numerical Analysis”, 85th Annual Meeting of the Transportation Research Board, Washington, D.C., 2006.

Daganzo, C. F. “The Cell Transmission Model: a Simple Dynamic Representation of Highway traffic”, Transportation. Research B. 28. 1994, pp. 269-287.

Fellendorf, M. and R. Hoyer. “Parametrization of Microscopic Traffic Flow Models through Image Processing”, 8th IFAC Symposium on Transport, Crete, June 1997.

FHWA, “Vehicle Infrastructure Integration (VII) – VII Architecture and Functional Requirement”, 2005.

Florian, D. G. “Simulation-Based Evaluation of Advanced Traveler Information Services (ATIS)”, Master thesis at the Massachusetts Institute of Technology, 2004

Fox, J. E., and D. A. Boehm-Davis. “Effects of Age and Congestion Information Accuracy of Advanced Traveler Information Systems on User Trust and Compliance”, Transportation Research Records 1621, 1998.

Gel, Y. E., H. M. Zhang, and W. H. K. Lam. “Network Reserve Capacity under Influence of Traveler Information”, Journal Of Transportation Engineering vol. 129-3, June 2003.

Harder, K. A., J. R. Bloomfield, D. M. Levinson, and L. Zhang. “Route Preferences and the Value of Travel-Time Information for Motorists Driving Real-World Routes”, prepared for Minnesota Department of Transportation, May 2005.

Image sensing system, Inc. “Autoscope rackvision Terra “http://autoscope.com/products/rackvision_terra_eu.htm: Accessed Nov, 2008.

ITS joint program office, USDOT. Cost database and benefit database. Benefits: http://www.itsbenefits.its.dot.gov/its/benecost.nsf/ByLink/BenefitsHome, Costs: http://www.itsbenefits.its.dot.gov/its/benecost.nsf/ByLink/CostHome, Accessed July, 2005.

Jayakrishnan, R and H. S. Mahmassani. “In-Vehicle Information Systems for Network Traffic Control: A Simulation Framework to Study Alternative Guidance Strategies”, Texas University, Austin Transportation Center, 1992.

Jeannotte, K. “Evaluation of the Advanced Regional Traffic Interactive Management and Information System (ARTIMIS)”. Presented at the 11th Annual ITS America Meeting, Miami, Florida, 2001.

Jensen, M., C. Cluett, K. Wunderlich, A. Deblasio, and R. Sanchez. “Metropolitan Model Deployment Initiative Seattle Evaluation Report: Final Draft”. Prepared for the USDOT by SAIC, FHWA-OP-00-020, 2000.

Jung, S., J. Larkin, V. Shah, A. Toppen, M. Vasudevan, and K. Wunderlich. “On-Time Reliability Impacts of Advanced Traveler Information Services (ATIS), Volume II Extensions and Applications of the Simulated Yoked Study Concept”, Prepared for Federal Highway Administration, March 2002.

Jung, S., J. Larkin, V. Shah, A. Toppen, M. Vasudevan, and K. Wunderlich. “On-Time Reliability Impacts of ATIS, Volume III Implications for ATIS Investment Strategies”, prepared for Federal Highway Administration, May 2003.

Kang, Youn-soo, C. Oh, and B. Kim. “Transportation Systems under Ubiquitous Computing ”, the Korea Research Institute, 2005.

Khattak, A. J., H. M. Al-Deek, and R. W. Hall. “Concept of an Advanced Traveler Information System Tested for the Bay Area: Research Issues”, Journal: IVHS JOURNAL, Vol. 2 No. 1, 1994.

Khattak, A. J. and N. Rouphail. “Incident Management Assistance Patrols: Assessment of Investment Benefits and Costs”. Prepared for NCDOT. Report No.: FHWA/NC/2005-02, 2005.

Levinson, D. “The value of advanced traveler information systems for route choice”, Transportation Research Part C vol. 11, 2003, pp. 75–87.

Levinson, D., D. Gillen, and E. Chang. “Assessing the Benefits and Costs of Intelligent Transportation Systems: The Value of Advanced Traveler Information systems”, California PATH Research Report, July 1999.

Lighthill, M. J. and G. B. Witham. “On Kinematic Waves. I: Flood Movement in Long Rivers, II: A Theory of Traffic Flow on Long Crowded Roads”, Proc. Royal Society A, 229, 1955, pp. 281-345.

Liu, Y-H. and H. S. Mahmassani. “Dynamic Aspects of Commuter Decisions under Advanced Traveler Information Systems: Modeling Framework and Experimental Results”, Transportation Research Records 1645, 1998.

Lo, H. K. and W.Y. Szeto. “Modeling Advanced Traveler Information Services Static versus Dynamic Paradigms”, Transportation Research Part B vol. 38, 2004, pp. 495–515.

London Transport. “Survey Finds London Transit Info Changes Behavior, Creates Revenue”. Inside ITS, 1998, pp. 8.

Mahmassani, H. S., J. C. Williams, and R. Herman. “Investigation of Network-Level Traffic Flow Relationships: Some Simulation Results, Transportation Research Record No. 971, 1984.

Mahmassani, H. S. and R. Jayakrishnan. “System Performance and User Response Under Real-Time Information in a Congested Traffic Corridor”, Transportation Research. Part A: Policy and Practice, Vol. 25A No. 5, 1991

Mahmassani, H. S. and S. Peeta. “Network Performance under System Optimal And User Equilibrium Dynamic Assignments: Implications For Advanced Traveler Information Systems”, Transportation Research Record No. 1408, 1993.

Michalopoulos, P. G. “Dynamic Freeway Simulation Program for Personal Computers”, Transportation Research Record No. 971, 1984.

NuStats. “Greater Triangle Travel Study: Household Travel Survey Final Report”. 2006.

Pierce, S. and J. Lappin. “Evolving Awareness, Use, and Opinions of Seattle Region Commuters Concerning Traveler Information: Finding from the Puget Sound Transportation Panel Survey, 1997 and 2000”, Volpe National Transportation Systems Center, U.S. Department of Transportation. Washington DC, November 2002.

PTV, VISSIM. http://www.ptvamerica.com/vissim.html

Schiesel, R., and M. J. Demetsky. “Evaluation of Traveler Diversion Due to En-Route Information”, Department of Transportation, University Transportation Centers Program, May 2000.

Shah, V., K. Wunderlich, A. Toppen, and J. Larkin. “Potential of advanced traveler information system to reduce travel disutility”, Transportation Research Record: Journal of the Transportation Research Board, No. 1826, 2003.

Srinivasan, K. K. and Z. Guo. “Day-To-Day Evolution of Network Flows under Route Choice Dynamics in Commuter Decisions”, TRB annual meeting, 2004.

Sundaram, S. “Development of a Dynamic Traffic Assignment System for Short-Term Planning Applications”, Master thesis at the Massachusetts Institute of Technology, June 2002.

Tech Environmental, Inc. “Air Quality Benefit Study of the SmarTraveler Advanced Traveler Information Service”, Tech Environmental, Inc., 1993.

Toppen, A., K. Wunderlich, J. Lappin, M. Petrella, and S. Peirce. “Corroborating Qualitative Benefits of Online ATIS with Modeling: Los Angeles Case Study”, Prepared for Volpe National Transportation Systems Center; Federal Highway Administration, 2003.

Toppen, A., S. Jung, V. Shah, and K. Wunderlich, “Toward a Strategy for Cost-Effective Deployment of Advanced Traveler Information Systems”, Transportation Research Records 1899, 2004.

Transportation Research Board. “Highway Capacity Manual - HCM 2000 (U.S. Customary Units)”, 2000.

Ullman, G. L. “Queuing and Natural Diversion at Short-Term Freeway Work Zone Lane Closures”, Transportation Research Record 1529, 1996, pp. 19–26.

Ullman, G. L. and C. L. Dudeck. “Theoretical Approach to Predicting Traffic Queues at Short-Term Work Zones on High-Volume Roadways in Urban Areas”, Transportation Research Record 1824, 2003, pp. 29–36.

Van Aerde, M. “Modeling of Traffic Flows, Assignment and Queuing in Integrated Freeway/Traffic Signal Networks”. PhD. Thesis, Department of Civil Engineering, University of Waterloo, Waterloo, Canada, 1985.

Van Aerde, M. and H. Rakha. “TravTek Evaluation Modeling Study”, FHWA-RD-95-090, 1995.

Van Aerde, M. and S. Yagar. “Dynamic Integrated Freeway/Traffic Signal Networks: A Routing-Based Modeling Approach”, Transportation Research A, Volume 22A, Number 6, 1988a, pp.445-453.

Van Aerde, M. and S. Yagar. “Dynamic Integrated Freeway/Traffic Signal Networks:Problems and Proposed Solutions”, Transportation Research A, Volume 22A, Number 6, 1988b, pp.435-443.

Vasudevan, M., K. Wunderlich, A. Toppen, and J. Larkin. “Making the Most of Limited Data in the Evaluation of Advanced Traveler Information Services (ATIS) Through Experimental Resampling”, 83rd Annual Meeting of the Transportation Research Board, Washington, D.C., 2004.

Vickrey, W. “Congestion theory and transport investment”, American Economic Review 59, 1969, pp251~261.

Williams, B. M, H. Hu, N. M. Rouphail, A. J. Khattak, and X. Pan. Effectiveness of Traveler Information Tool. Publication NCDOT 2006-13, 2007. PDF copies of the report can be downloaded from http://www.ncdot.org/doh/preconstruct/tpb/research/download/2006-13FinalReport.pdf

Yang, Q., H. N. Koutsopoulos, and M. E. Ben-Akiva. “Simulation Laboratory for Evaluating Dynamic Traffic Management Systems”, Transportation Research Records 1710, 2000.

Yim, Y. and H. Yang. “Simultaneous Determination of the Equilibrium Market Penetration and Compliance Rate of Advanced Traveler Information Systems”, Transportation Research Part A vol. 37, 2003, pp. 165–181.

Yim, Y. and J-L. Ygnace. “Link Flow Evaluation Using Loop Detector Data: Traveler Response to Variable-Message Signs”, Transportation Research Records 1550, 1996.

Yim, Y. and M. Miller. “Evaluation of TravInfo Field Operational Test”, University of California at Berkeley. Institute of Transportation Studies, California PATH Program, 2000.

Zhang, H. M. and Y. Nie. “Modeling network flow with and without link interaction: properties and implications”, Presented at the 84th annual meeting of the Transportation Research Board, Washington D.C., 2006 .

Ziliaskopoulos, A. K. and S. Lee. “A Cell Transmission Based Assignment-Simulation Model for Integrated Freeway/Surface Street Systems”, Transportation Research Record, No. 1701, 1997, pp. 12-23.

Ziliaskopoulos, A. K., and S. T. Waller. “An Internet-Based Geographic Information System that Integrates Data, Models and Users for Transportation Applications”, Transportation Research Part C, vol.8, 2000, pp. 427-444.

Zimmerman, C., J. Marks, J. Jenq, C. Cluett, A. DeBlasio, J. Lappin, H. Rakha, and K. Wunderlich. “Phoenix Metropolitan Model Deployment Initiative Evaluation Report”, Prepared by Battelle for the USDOT FHWA, FHWA OP-00-015, 2000.

APPENDICES

Appendix A. Benefits of ATIS by Measures

Table A.1 Benefits of ATIS by Measures

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in Capacity/Throughput							
Hardy et al, 2000	Advanced Traveler Information System	Seattle, Washington	Freeway and Arterial	Simulated (no field data)	Number of Stops: -6.39%, Travel Time -0.74%	Moderately positive	Vehicle Kilometers of Travel increased by 0.15 percent
Wunderlich & Larkin, 2000	Advanced Traveler Information System	Seattle, Washington	Freeway and arterial	Simulated (no field data)	0.1% increase in throughput	Mixed	Reduction in delay and number of stops
Van Aerde & Rakha, 1996	Dynamic route guidance	Orlando, Florida,	Urban transportation network	Predicted	10% increase	Highly positive	Market penetration rate of 30% and constant average trip duration
Shah & Wunderlich, 2001	Internet-based pre-trip ATIS, highway advisory radio, ramp metering, variable message signs	Detroit, Michigan	Freeway	Simulated (without field data)	Beneficial to corridor capacity		Speed:+5.4 mph Trip time:-4.6 mins Delay: -22%
Jensen et al., 2000	Advanced Traveler Information System	Seattle, Washington	Freeway	Simulated (no field data)	Slight increase in vehicle throughput	Mixed	Delay: -1.8%; Stops: -5.6% Emissions: -2%
Look and Abdulhai, 2001	Dynamic Route Guidance Systems	Toronto, Canada	Urban transportation networks	Simulated (no field data)	Reduced travel times, and increased network throughput	Mixed	A maximum 15.5 % increase in accidents was observed at a market penetration of 60%

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in Capacity/Throughput							
Wunderlich et al., 1999	Integrated ATIS and ATMS	Seattle, Washington	Freeway and arterial	Simulated (with field data)	Higher vehicle throughput	Mixed benefit	More sub-area travel, fewer stops resulted in mixed bag of energy and emissions impacts
Benefits in Cost/Saving							
London Transport, 1998	Travel enquiry system	London, United Kingdom	Public Transit	Behavioral survey & measured	13% increase in ridership generates benefits: Operators: 3.5 million Societal benefits: 11 million	Highly positive	Benefit units: pounds sterling Route changes: 38%
Kato, 2000	Vehicle-guidance system designed for heavy fog	Kanetsu, Oita, Japan	Inter-Urban Expressways	Predicted	B/C: 1.7 to 2.1 (Kanetsu Expressway); 1.8 to 2.2 (Oita Expressway)		Benefits: measured by estimating 75% drop in costs generated by road closures.
Cambridge Systematics, and Science Applications International Corp., 2000	Carrier Operations & Fleet Management, Traveler Information	General USA Data	Freeway	Measured (Survey)	Motor carrier operational efficiencies not significantly impacted as far as on-time delivery, estimated arrival times, delivery penalties, fuel consumption, etc	Mixed	
Shah et al., 2003	Personalized pre-trip notification service	Wash. D.C., Maryland, Virginia	Urban transportation networks	Simulated (with field data)	40% of all ATIS users achieved individual net positive benefit ≥$60/year		Significant benefit: reduced frequency of early and late arrivals (56% and 52% ,resp)

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in customer satisfaction							
Wetherby, 1997	Incident information delivery via alphanumeric pagers	Minneapolis, Minnesota	Urban transportation networks	Measured-field operational test	Only 2% dropped out of project due to dissatisfaction with the service	Highly positive	65% Genesis users reported using the service daily; 88% once or more per week
Yim & Miller, 2000	TravInfo regional traveler information system	San Francisco, California	Urban transportation networks	Measured (Survey)	Only 9 percent of households were aware of TravInfo	Mixed	TravInfo effective in changing behavior, but insignificantly impacted transport system
Cordis Transport Sector, 2000	Traveler information	Europe	Urban transportation networks	Measured (Survey)	79-95% of users finding the systems easy to use	Highly positive	1/3 third users reported changing mode, 1/2 changed route.
Reed, 2000	Commercial radio traffic information	Detroit, Michigan	Freeway	Measured (field test & survey)	89% drivers use commercial radio for traffic info; 62% rate route-specific traffic reports "extremely useful"	Highly positive	Commercial radio information was perceived as "more reliable" than television or CMS information
Clemons et al., 1999	Advanced Regional Traffic Interactive Management and Information System	Kentucky, Ohio	Urban transportation networks	Measured (survey)	> 99% respondents avoided traffic, saved time, reduced frustration, arrived on time; 81% recommended the service to others	Highly positive	Users rated service very high in accuracy, ease of use; 65% willing to pay for service (free during survey); most common suggestion: expand service
Perez & Wetherby, 1995	Advanced Traveler Information System	Seattle, Washington	Urban transportation networks	Measured (survey)	Generally users found infor-mation useful for making travel decisions reduction in stress and travel time	Slightly positive	This system includes a wristwatch, an in-vehicle navigation system, and a PC based system.

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in customer satisfaction							
Baum, 1999	Traveler information services	Cologne, Germany	Urban transportation networks	Measured (customer questionnaires)	Average Willingness-to-Pay: 7.17 to 12.90 Euro/month		
Giuliano & Golub, 1995	Smart Traveler Information Kiosks	Los Angeles, California	Urban transportation networks	Measured	The number of daily accesses ranges from 20 to 100 in a 20-hour day.		Most frequent request (83% users): freeway map
Jensen et al., 2000	Transit information dissemination	Seattle, Washington	Public Transit	Measured (focus group, questionnaire)	High rate but low usage	Mixed	
Inman et al., 1996	Navigational information	Orlando, Florida	Urban transportation networks	Measured	38% of rental car users and 63% of local drivers found the device helpful	Slightly positive	Navigational information may reduce travel stress for drivers in unfamiliar areas.
Soolman & Radin, 2000	Public and private internet web sites with traffic and transit information	General USA Data	Urban transportation networks	Measured (Survey)	The most sought-after traffic information is not available in most metro areas of the country.	Mixed	Private web sites have more features related to traffic; public sites have more features related to transit
Ygnace, 1998	Telephone Assisted Traveler Information System	San Francisco, California	Urban transportation networks	Measured (Survey)	Average scores: Convenience: 4.2 out of 5; Ease of comprehension: 4.3 out of 5	Highly positive	Better than television or radio traffic information reports, but users were not willing to pay much for the information.
ERTICO News, 1998	Vehicle Information and Communication System (VICS)	Tokyo, Aichi, Osaka, Kyoto	Urban transportation networks	Measured (Survey)	▪ VICS advice = less stress ▪ valuable information on traffic jams ▪ want expanded service area	Highly positive	The system provides drivers with upcoming road conditions and alternative routes to avoid congestion.

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in customer satisfaction							
Zimmerman et al., 2000	Traveler Information Service	Phoenix, Arizona	Urban transportation networks	Measured (Survey)	77% respondents rate service "useful" for radio broadcasts, 60% for finding congestion first-hand	Highly positive	pre-trip information in general may be less useful than en-route information
Orban et al., 2000	Traveler and Tourist Information System (TTIS)	Arizona, Missouri	Urban transportation networks	Measured (Survey)	>50% of tourists inter-viewed in Arizona agreed or strongly agreed that the info saved them time.	Moderately positive	78% aware of at least one deployed ATIS component, and 45% of travelers surveyed used the system.
Remer et al., 1995	Transit route and schedule information	Minneapolis Minnesota	Public transit	Measured (Survey)	33% of visitors accessing the system requested bus schedule adherence; 31% sought bus schedules	Moderately positive	Averaged slightly more than one access per participant per week.
Englisher et al., 2002	Real-time traffic information	Houston, Texas	Urban transportation networks	Measured (user surveys, diaries, participant use statistics)	▪ rated the handheld portable computer system good or very good ▪ 40% willing to pay for travel information.	Moderately positive	▪ preferred radio, internet, or television over handheld portable computers or phones ▪ preferred traffic over mode-choice info
Fekpe, & Collins, 2002	Web-based traveler information services	Pittsburgh & Philadelphia, Pennsyl-vania	Urban transportation networks	Measured (website surveys)	18% of internet respondents in Pittsburgh and 47% in Philadelphia: Traffic.com shortened commute	Slightly positive	68% of users in Pittsburgh and 86% of users in Philadelphia changed their original route

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in customer satisfaction							
Daigle & Zimmerman, 2003	Traveler information systems	Bar Harbor, Mount Desert Island, Maine	Urban transportation networks	Measured (mail-back questionnaire)	Useful technologies: visitors who used real-time transit departure (90%), automated on-board next-stop announcements (84%), real-time parking info (74%)	Highly positive	Most visitors who experienced ITS at Acadia indicated the information they received was accurate, clearly understandable, and easy to use.
Sanchez et al., 2003	The Greater Yellowstone Weather and Traveler Information System	Montana	Urban transportation networks	Measured (Survey)	Overall customer satisfaction increased from 71% to 81% after the new 511 service was deployed	Moderately positive	Caution: The before survey measured respondents' *perception* of system; after survey measured *satisfaction*
Swan et al., 2004	Virginia's 511 phone and website service	Virginia	Urban transportation networks	Measured (focus group, phone and web surveys)	The majority of those who utilized Virginia 511 were satisfied to very satisfied with the service	Moderately positive	Awareness of the Virginia 511 service was higher than the national average of 511awareness
Hallinan et al., 2003	Travel information services	Philadelphia Pennsyl-vania	Urban transportation networks	Measured (Mail survey)	Commercial radio rated most useful travel info sources; TV and variable message sign also useful	Moderately positive	The response rate was 31.3% (a total of 1,124 responses).
Glazer et al., 2003	CommuterLink Website (CLW) 511 Telephone Service (511) Variable Message Signs (VMS) Highway Advisory Radio (HAR)	Salt lake city, Utah	Freeway	Survey	Visitors and residents answered the ATIS systems worked well.	Highly positive	

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in customer satisfaction							
Cutler et al, 2001	Telephone based service and web site	Minnesota	Freeway	Survey (before/after)	between 45 and 48 percent of respondents said that the quality of the service was improved		
PSRC, 2004	HAR, TV, telephone, and internet	Seattle, Washington	Freeway and arterial	Survey	75% of respondents use Radio for traffic information Telephone: 12% of respondents use telephone for traffic information		
Cluett, 2004	HAR, Web and telephone	Spokane, Washington	-	Survey	56% of CVO respondents use HAR, 46% of post-deployment operators for CVOs use the internet Respondents answered HAR and Web information is useful.		
McCoy and Pesti, 2000	VMS	Greenwood, Nebraska	-	Field observations and survey	57% of passing vehicles saw the sign		4% increased in traffic diversion
Pierce and Lappin, 2002	Web, Radio, and TV	Seattle, Washington	-	Survey	3.2% of respondents consult traveler information Radio 56%, pre-trip radio 22%, TV news 13%, traffic website 6%, transit website 6%		37% change in travel behavior (1.1% of total trips)-13% change departure time, 11% make small route change, 9% took whole different route, 2% added, delayed, or cancelled trip, 1% change mode
ITERIS, 2004	Web	East bay smart corridors, Alameda county	-	Survey	43.8% of respondents visit website		

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in delay/time							
Wunderlich & Larkin, 2000	Web-Based Urban Freeway ATIS	Seattle, Washington	Freeway and arterial	Simulated (without field data)	▪ Vehicle-Hours of Delay: -3.4% ▪ Total Number of Stops: -5.5%	Moderately positive	Vehicle Throughput: +0.1%
Atsush et al., 1998	Traffic control system equipped with Dynamic Message Signs	Osaka-Kobe, Japan	Freeway	Predicted	▪ Saved 9.8 min/vehicle in periods of congestion ▪ Saved up to 38 min/vehicle during incident congestion		The average divergence rate increased 3.7% during periods of congestion.
Ajisawa, 1998	Pre-trip Information	Tokyo, Japan	Urban transportation networks	Simulated (no field data)	40%-80% decrease in time loss	Highly positive	
Wunderlich et al., 2001	Advanced Traveler Information Services (ATIS)	Washington DC	Urban transportation networks	Simulated (with field data)	ATIS users' on-time reliability (97%) more than Conservative Non-User 92%	Slightly positive	ATIS users demonstrated better performance than conservative non-users
Jeannotte, 2001	Advanced Regional Traffic Interactive Management and Information System	Cincinnati, Ohio	Freeway	Simulated (without field data)	Travel time delay reduced by 12,000 hours per A.M. peak period and 6,940 hours of unexpected delay per P.M. peak period		
Hardy et al., 2000	Web-based Traffic Information and Weather Events	Seattle, Washington	Urban transportation networks	Simulated (without field data)	▪ # stops decreased by 6.39% ▪ Adjusted Travel Time decreased by 0.74 % ▪ VKT increase by 0.15%	Slightly positive	VKT: Vehicle Kilometers Treveled

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in delay/time							
Shah et al., 2003	Pre-trip Advanced Traveler Information Service	Washington DC	Urban transportation networks	Simulated (with field data)	Reducing the frequency of early and late arrivals by 56% and 52% respectively	Highly positive	ATIS users were early 12% and late 2% of all trips, and ATIS non-users were early 28% and late 4% of all trips.
Toppen et al., 2002	ATIS	Washington DC	Urban transportation networks	Simulated (with field data)	Significantly reduced the amount of time spent on early arrivals		Using ATIS, unfamiliar drivers arrived at destination within 15 minutes of target arrival time 79% of time. Without ATIS--42% of time.
Carter et al, 2000	Variable Message Signs, Kiosk, Internet-based ATIS, In-Vehicle Device	San Antonio, Texas	Freeway and arterial	Simulated (with field data)	VMS: 5.7% decrease in delay Web: 5.4% reduction in delay In-Vehicle device: 8.1% reduction in delay		Kiosk had a function problem.
Glassco, R., et al.,1997	Advanced Traveler Information System ATMS, CVO	Detroit CBD	Urban transportation networks	Simulated (without field data)	25%~ 41% under non-incident conditions		
Noonan and Shearer, 1998	Various pre-trip and en-route information systems technologies	Several region	-	Field operation test	TravTek: 12% reduction in travel time and 32% reduction in vehicle stops ADVANCE: 4 % reduction in travel time		The impact are generally positive with a few exceptions

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in delay/time							
Prevedouros, 1999	HAR, VMS	Honolulu, Hawaii	-	Simulation	40% reduction in delay		Traffic diversion increased by 25%
Trombley and Wetherby, 1998	In-vehicle system	Seattle, Washington	-	Survey			With traveler information: 80% changed route, 50% changed departure time, 10% change mode With route guidance: 63% changed route, 12% changed departure time
Inman et al., 1995	In-vehicle system	Orlando, Florida	-	Field observation	80% time savings in trip planning		No observed benefit for real time traffic information
Benefits in Energy & Environment							
Tech Environmental, Inc., 1993	SmarTraveler Advanced Traveler Information Service	Boston, Mass.; Seattle, Washington	Urban transportation networks	Simulated (without field data)	▪ Reduced VOC by 498 kilograms (25%) per day, ▪ Reduced NOx by 25 kilograms (1.5%) per day ▪ Reduced CO by 5,032 kilograms (33%) per day	Moderately positive	50% of travelers changed their travel route and 45% changed their departure time as a result of better traveler information
Jensen et al., 2000	Advanced Traveler Information System	Seattle, Washington	Freeway	Simulated (without field data)	2% reduction in vehicle emissions	Slightly positive	• 1.8% reduction in delay • 5.6% reduction in the number of stops

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in Energy & Environment							
Jeannotte, 2001	Advanced Regional Traffic Interactive Management and Information System	Cincinnati, Ohio	Freeway	Simulated (without field data)	▪ Hydrocarbon: -3.6% - 3.8%. ▪ CO: -3.6% -3.8%. ▪ NOx: -4.5% -4.7%.	Moderately positive	
Zimmerman et al., 2000	Advanced Traveler Information Systems (ATIS)	Phoenix, Arizona	Urban transportation system	Simulated (with field data)	▪ 1.6% reduction in fuel consumption ▪ 1.2% increase in CO ▪ no significant change in HC or NOx emissions	Mixed	▪ 6.2% increase in vehicle speeds ▪ a reduction in the crash risk along the mainline of 6.7%
Noonan and Shearer, 1998	Various pre-trip and en-route information systems technologies	Several region	-	Field operation test	TravTek: 11% reduction in fuel consumption and 6% reduction in emission		The impact are generally positive with a few exceptions
Carter et al, 2000	Variable Message Signs, Kiosk, Internet-based ATIS, In-Vehicle Device	San Antonio, Texas	Freeway and arterial	Simulated (with field data)	VMS: 1.2% decrease in fuel consumption Web: 1.8% reduction in fuel consumption In-Vehicle device:3% reduction in fuel consumption		
Benefits in safety							
Jeannotte, 2001	Advanced Regional Traffic Interactive Management and Information System	Cincinnati Ohio	Freeway	Simulated (without field data)	Fatalities were reduced by 3.2 %		Travel time delay reduced by 12,000 hours per AM peak period; 6,940 h unexpected delay per PM peak

Table A.1 Continued

Source	ITS category	Location	Study subject	Methodology	Benefits	Benefit *	Comments
Benefits in safety							
Carter et al, 2000	Variable Message Signs, Kiosk, Internet-based ATIS, In-Vehicle Device	San Antonio, Texas	Freeway and arterial	Simulated (with field data)	VMS: 2.8% decrease in crashes Web: : 0.5% reduction in crashes In-Vehicle device: 4.6% reduction in crashes		

Note: * "mixed" <1% improvement; "slightly positive" 1% to 5% improvement; "moderately positive" 6%-10%; and "highly positive" >10%.

Source: NCDOT research project, titled “Effectiveness of Traveler Information Tools”, 2007

Appendix B. SAS Results Example of Model Development (Level 1)

Collinearity Test

The CORR Procedure

7 Variables: GENDER AGE INCOM EDUCA workstatus LIVED USETR

Covariance Matrix, DF = 2572

		GENDER	AGE	INCOM	EDUCA
GENDER	GENDER	0.2429488	-0.0134006	0.1286929	0.0708406
AGE	AGE	-0.0134006	222.3610408	-1.3440115	-3.1570990
INCOM	INCOM	0.1286929	-1.3440115	3.2443028	1.0065885
EDUCA	EDUCA	0.0708406	-3.1570990	1.0065885	2.0504117
workstatus		0.0154040	-2.1167622	0.2180982	0.1470977
LIVED	LIVED	-0.0101338	8.1896120	0.2700001	-0.0932331
USETR	USETR	0.0000852	-0.6093470	-0.0905541	-0.0322171

Covariance Matrix, DF = 2572

		workstatus	LIVED	USETR
GENDER	GENDER	0.0154040	-0.0101338	0.0000852
AGE	AGE	-2.1167622	8.1896120	-0.6093470
INCOM	INCOM	0.2180982	0.2700001	-0.0905541
EDUCA	EDUCA	0.1470977	-0.0932331	-0.0322171
workstatus		0.1780501	-0.0302072	0.0010058
LIVED	LIVED	-0.0302072	1.7245456	-0.0543820
USETR	USETR	0.0010058	-0.0543820	0.1095269

Main Effects Examination for Level 1 (Gender)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3557.469
SC	3563.941	3569.174
-2 Log L	3556.089	3553.469

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2.6201	1	0.1055
Score	2.6209	1	0.1055
Wald	2.6216	1	0.1054

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.1839	0.0518	12.6119	0.0004
GENDER	1	-0.1298	0.0802	2.6216	0.1054

Main Effects Examination for Level 1 (Age)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3535.453
SC	3563.941	3547.159
-2 Log L	3556.089	3531.453

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	24.6357	1	<.0001
Score	24.5672	1	<.0001
Wald	24.3743	1	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq

Intercept	1	0.7828	0.1382	32.0680	<.0001
AGE	1	-0.0132	0.00268	24.3743	<.0001

Main Effects Examination for Level 1(Income Level)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3517.556
SC	3563.941	3529.262
-2 Log L	3556.089	3513.556

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	42.5327	1	<.0001
Score	42.4011	1	<.0001
Wald	41.8067	1	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.6007	0.1198	25.1398	<.0001
INCOM	1	0.1440	0.0223	41.8067	<.0001

Main Effects Examination for Level 1 (Education Level)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates

AIC	3558.089	3559.240
SC	3563.941	3570.946
-2 Log L	3556.089	3555.240

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	0.8487	1	0.3569
Score	0.8479	1	0.3571
Wald	0.8454	1	0.3579

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.2477	0.1341	3.4119	0.0647
EDUCA	1	-0.0254	0.0276	0.8454	0.3579

Main Effects Examination for Level 1 (Work Status)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3527.104
SC	3563.941	3538.809
-2 Log L	3556.089	3523.104

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	32.9849	1	<.0001
Score	33.0058	1	<.0001
Wald	32.6367	1	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.2838	0.0827	11.7598	0.0006
workstatus	1	0.5391	0.0944	32.6367	<.0001

Main Effects Examination for Level 1 (Length Lived)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3558.105
SC	3563.941	3569.810
-2 Log L	3556.089	3554.105

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1.9841	1	0.1590
Score	1.9850	1	0.1589
Wald	1.9860	1	0.1588

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-0.0250	0.1167	0.0458	0.8306
LIVED	1	0.0424	0.0301	1.9860	0.1588

Main Effects Examination for Level 1 (Transit User)

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3559.044
SC	3563.941	3570.749
-2 Log L	3556.089	3555.044

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1.0450	1	0.3067
Score	1.0425	1	0.3072
Wald	1.0416	1	0.3074

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	0.1147	0.0422	7.3846	0.0066
USETR	1	0.1224	0.1199	1.0416	0.3074

Model Development for Level 1 (Forward selection)

The LOGISTIC Procedure

Model Information

Data Set	ATIS2.TRIANGLE
Response Variable	info_access
Number of Response Levels	2
Model	binary logit
Optimization Technique	Fisher's scoring

Number of Observations Read	2573
Number of Observations Used	2573

Response Profile

Ordered Value	info_access	Total Frequency

1	1	1370
2	2	1203

Probability modeled is info_access='1'.

Forward Selection Procedure

Step 0. Intercept entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

-2 Log L = 3556.089

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
70.8681	3	<.0001

Step 1. Effect INCOM entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3517.556
SC	3563.941	3529.262
-2 Log L	3556.089	3513.556

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	42.5327	1	<.0001
Score	42.4011	1	<.0001
Wald	41.8067	1	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
28.8541	2	<.0001

Step 2. Effect AGE entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3497.703
SC	3563.941	3515.261
-2 Log L	3556.089	3491.703

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	64.3861	2	<.0001
Score	63.8983	2	<.0001
Wald	62.2982	2	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq

7.1119	1	0.0077

Step 3. Effect workstatus entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3558.089	3492.618
SC	3563.941	3516.029
-2 Log L	3556.089	3484.618

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	71.4708	3	<.0001
Score	70.8681	3	<.0001
Wald	68.7714	3	<.0001

NOTE: All effects have been entered into the model.

Summary of Forward Selection

Step	Effect Entered	DF	Number In	Score Chi-Square	Pr > ChiSq	Variable Label
1	INCOM	1	1	42.4011	<.0001	INCOM
2	AGE	1	2	21.7923	<.0001	AGE
3	workstatus	1	3	7.1119	0.0077	

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq

Intercept	1	-0.2129	0.2050	1.0784	0.2990
INCOM	1	0.1229	0.0233	27.7635	<.0001
workstatus	1	0.2785	0.1046	7.0905	0.0077
AGE	1	-0.0100	0.00286	12.3123	0.0004

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
INCOM	1.131	1.080	1.184
workstatus	1.321	1.076	1.622
AGE	0.990	0.984	0.996

Association of Predicted Probabilities and Observed Responses

Percent Concordant	58.5	Somers' D	0.177
Percent Discordant	40.7	Gamma	0.179
Percent Tied	0.8	Tau-a	0.088
Pairs	1648110	c	0.589

Partition for the Hosmer and Lemeshow Test

		info_access = 1		info_access = 2	
Group	Total	Observed	Expected	Observed	Expected
1	256	89	91.22	167	164.78
2	257	109	112.19	148	144.81
3	256	130	124.37	126	131.63
4	259	142	133.83	117	125.17
5	256	145	138.61	111	117.39
6	256	133	143.97	123	112.03
7	251	138	145.52	113	105.48
8	257	154	152.96	103	104.04
9	263	168	160.92	95	102.08
10	262	162	166.41	100	95.59

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
6.3895	8	0.6037

Model Validation for Level 1

The FREQ Procedure

Table of F_info_access by I_info_access

F_info_access(From: info_access)
I_info_access(Into: info_access)

Frequency Percent	1	2	Total
1	267 41.52	87 13.53	354 55.05
2	181 28.15	108 16.80	289 44.95
Total	448 69.67	195 30.33	643 100.00

Appendix C. SAS Results for Linearity Test (GPS vs. SpeedInfo)

The REG Procedure
Model: MODEL1
Dependent Variable: GPS GPS

Number of Observations Read	304
Number of Observations Used	304

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	67845	67845	887.37	<.0001
Error	302	23090	76.45585		
Corrected Total	303	90934			

Root MSE	8.74390	R-Square	0.7461
Dependent Mean	58.84046	Adj R-Sq	0.7452
Coeff Var	14.86036		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	1.72091	1.98198	0.87	0.3859
SpeedInfo	SpeedInfo	1	1.00366	0.03369	29.79	<.0001

The REG Procedure
Model: MODEL1

Test 1 Results for Dependent Variable GPS

Source	DF	Mean Square	F Value	Pr > F
Numerator	1	0.90284	0.01	0.9135
Denominator	302	76.45585		