Development and Evaluation of Diversion Strategies under Incident Response using Dynamic Traffic Assignment System

by

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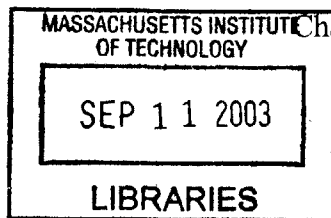MASSACHUSETTS INSTITUTE OF TECHNOLOGY

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Abstract

Integrating Intelligent Transportation Systems (ITS) technologies with traffic surveillance promises to reduce the cost incurred by non-recurrent traffic congestion by improving transportation agencies' ability to respond to and clear such incidents. Advance Traffic Management Systems (ATMS) and Advance Traffic Information Systems (ATIS) are examples of ITS sub-systems, which are increasingly becoming prevalent in the Traffic Management Center (TMC) of a city in order to address various traffic management issues. Dynamic Traffic Assignments (DTA) system can be used for dynamic traffic management purposes, like reducing delay on major highways, improving safety, efficiency and capacity of transportation network, and improving wide-area emergency responses through information sharing and coordination. DynaMIT-P is a DTA-based planning tool that operates in an offline mode, in which traffic managers investigate and prepare standard response strategies to different traffic and incident scenarios. The objective of this thesis is to apply DynaMIT's DTA capabilities to the Lower Westchester County (LWC) ITS subsystem and to use calibrated system to perform illustrative analyses of incident response strategies. First, DynaMIT-P has been calibrated in order to estimate traffic conditions in the LWC network with precision sufficient for ITS purposes. The results of two case studies, focusing on the evaluation of the diversion response strategy in case of an incident on the LWC network, illustrate the functionality and potential of the system.

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Chapter 1

Introduction

Transportation systems, especially those involving vehicular traffic, have been subjected to considerable increases in complexity and congestion during the past two decades. These conditions often produce traffic situations that jeopardize the safety of the people involved. Developed countries economies depend heavily on transportation systems and this dependence is likely to increase as "just-in-time" supply chain management is becoming more and more popular, that requires reducing the space and investment requirement for storage and rely on fast and reliable transportation network. Some transportation networks are more vulnerable to incidents ranging from natural disasters (like earthquakes, floods, storms, landslides and subsidence) or man-made disasters (like terrorist attacks, bridge or tunnel collapses and major accidents) at one end, to a variety of events (like congestion, road maintenance, badly-parked vehicles, and minor collisions). It is difficult to control the scale, frequency and predictability of these events but it is quite possible to design and manage the transportation system in such way that disruption caused by such events could be minimized.

It is thus needed to design a Transportation Management System that can handle a range of traffic conditions, emerging from the incidents mentioned above. In that direction, recent years have seen a tremendous growth in the field of Intelligent Transportation Systems (ITS) in parallel with the advancement in Information Technology (IT). Integrating ITS technologies with traffic surveillance promises to reduce the cost incurred by non-recurrent traffic congestion by improving transportation agencies' ability to predict and clear such incidents. Advance Traffic Management Systems (ATMS) and Advance Traffic Information Systems (ATIS) are examples of ITS sub-systems, which are increasingly becoming prevalent in the Traffic Management Center (TMC) of a city in order to address various traffic management issues. These tools

influence various factors associated with the transportation system like transportation demand (in reaction to information disseminated to drivers), network capacity (by using speed limit messages, Variable Message Signs (VMS)) and many other similar components. In order to make these sub-systems efficient it is very important to estimate and predict traffic condition as accurately as possible taking into account the impact of provided information to travelers, and thus provide better guidance to travelers.

Dynamic Traffic Assignments (DTA) systems ([36], [37], [38], [50]) are being developed to address these issues within Traffic Estimation and Prediction Systems (TrEPS). DynaMIT[1] ([37], [38]) is a DTA software system that provides travel guidance based on real-time traffic predictions and drivers reactions to provided guidance. It has been designed to operate in a Traffic Management Center (TMC) and to support ATIS and ATMS operations. DynaMIT-P is a planning tool that operates in an offline mode, in which traffic managers investigate and prepare standard response strategies to different traffic and incident scenarios.

1.1 Background

Traffic congestion in developed and developing countries is putting a lot of pressure on the economy of a country. Some recent surveys show that traffic congestion costs £15 billion per year to UK economy [26] and $72 billion per year to US economy [49]. These numbers itself reinforce the importance of good transportation networks that have minimal traffic congestion and efficient vehicular movement. A good transportation network not only helps in reducing traffic congestion but also plays a vital role in the development of a city, state and nation. Construction of new roads for solving the problem of traffic congestion is not only expensive and damaging to the environment but it also only provides a temporary solution to the existing problem. Construction of new roads will attract more traffic, which will nullify the projected benefits from its construction, making it a cyclic problem. Moreover, it is not always possible to build new roads due to many political, social and geographical constraints.

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[1] Dynamic Network Assignment for the Management of Information to Travelers

Above discussion leads us towards the need for better management of the existing road space with the help of emerging technological tools. Intelligent Transportation Systems (ITS) is one of the alternative approaches, which can be used to relieve traffic congestion by efficiently using the available road capacity. Adaptive traffic controls to minimize delays, Ramp Metering for smooth motorways traffic, Variable Message Signs (VMS) for incident management, speed control and parking guidance, Dynamic Route Guidance systems for guiding equipped vehicles to choose fastest path and to respond to incidents in real time, Electronic Toll Collection (ETC) for smooth revenue collection, are some of the examples which are already in practice to tackle different traffic scenarios.

A detailed analysis, including technical feasibility analysis and cost benefit analysis (environment impacts, safety and efficiency), is needed before implementing any one of the above traffic control alternatives. Most of the public or private agencies are also interested in evaluating different alternatives. Evaluation of different alternatives to quantify various performance factors could be quite challenging. One way would be to actually implement the alternative and then compare the data before and after the introduction of the new system. But this approach is not desirable because of the following two reasons:

- Implementation of a new system requires a large amount of investment. It might have severe political and social consequences if the new system is not successful.

- Many new systems are expected to have modest benefits, e.g. a new urban traffic control system may reduce travel times by less than 10%. Travel times however vary a lot from day to day anyway, so it can be hard to determine whether any measured changes are due to the new system or simply by chance. It is difficult to assess the benefits of a new system in place because many times it is hard to see if the measured changes are due to the new system or due to inherent variability in the network itself.

A more reliable and promising approach will be to use a traffic model to evaluate the system, in which the traffic modeler has complete control over the different components of the model. In this way pre and post conditions of a new system can be computed more reliably and with greater confidence in the results. Traditional traffic models, having simple speed-density-

flow relationships, are not able to assess the effectiveness of a new system which often requires more complicated models. Micro-simulation models, which capture the individual driver behavior using various car following, lane changing and gap acceptance rules, are becoming more and more prevalent for the analysis of an ITS system. These models take into account the response of individual drivers to a change in the network conditions and hence can be used as a proxy of the real world. Wide range of measures of effectiveness can be obtained as an output of the simulation in order to provide realistic results, prior to implementation of new system in the real world. MITSIM [30], PARAMICS [45], VISSIM [44] and CORSIM [21] are some of the examples of micro-simulation software system available for such kind of analysis.

One of the main problems with micro simulators is that they require a large amount of computational time for simulating a large transportation network and hence are not well suited for real-time use for such a network. This necessitates the development of a system that can be used for the operation of a transportation management system with precision enough for ITS purposes and is also real time. In this regard, development of a Dynamic Traffic Assignment (DTA) model has been a subject of major research for transportation experts for more than thirty years. With the ever-increasing deployment of ITS systems, it has become crucial to come up with a DTA system which can be used for dynamic traffic management purposes, like reducing delay on major highways, improving safety, efficiency and capacity of transportation network, and improving wide-area emergency responses through information sharing and coordination. With these goals in mind FHWA R&D started a DTA research project in 1994 to address complex traffic control and management issues in the information-based, dynamic ITS environment (http://www.dynamictrafficassignment.org). DynaMIT, developed at MIT Intelligent Transportation Systems Program, is a result of this project. It has features like real-time estimation and prediction of network conditions taking into account the drivers response to disseminated information, traffic information and route guidance to drivers for optimal decisions.

Since DynaMIT has reliable traffic estimation and prediction capabilities, it is well suited to assist transportation planners and policy makers while evaluating different diversion strategies in case of special events and emergency situations. Use of DynaMIT during such policymaking is justified by its *unbiased* and *consistency* features, which ensure that DynaMIT's prediction of

expected network state matches what drivers would experience on the network. DynaMIT-P, which is a planning version and meant to assist in offline planning decisions, focuses on short-term and within-day travel behavior, assuming that the long-term decisions are given.

1.2 Motivation and Thesis Objectives

NYSDOT (New York State Department of Transportation), in association with many public and private sector companies, is in the process of deploying state-of-the-art ITS installation in the Lower Hudson Valley (LHV) road network. Existing traffic surveillance and monitoring devices such as loop detectors and CCTV will be substantially augmented by the deployment of 24 TRANSMIT detectors on the LHV highways and bridges, many of which have high fraction of EZ-PASS users. With proper processing, the data should make it possible to obtain reliable real-time estimates of traffic flows and travel times by link, path and origin-destination (O-D) pair over much of the LHV network.

This information can form the basis for providing very effective travel guidance to network users. Lower Westchester County (LWC) ITS subsystem has considered installing VMS and Highway Advisory Radio (HAR) transmitter at key network locations. They are intended for routine guidance use as well as to assist with MPT activities. The combination of NYSDOT's ITS infrastructure with DynaMIT's guidance generation capabilities would lead to a very powerful system for improving traffic conditions in the LWC area, and is the motivation for this thesis.

In a nutshell, the purpose of the proposed thesis is to apply DynaMIT's DTA capabilities to the LWC ITS subsystem, to generate guidance for the LWC's ITS equipment in an offline mode, and to use calibrated system to perform illustrative analyses of incident response strategies. The efficiency of any traveler information and guidance system depends largely on the accuracy with which the system can estimate and predict network state and path travel times. In order to ensure that the system reacts and behaves in a realistic manner when used in TMC, it is critical to calibrate its model components against the field data observed from the network.

Based on the above discussion, the main objectives of the proposed thesis are:

i) to calibrate DynaMIT so that it can estimate and predict traffic conditions in the LWC network with precision sufficient for ITS purposes.

ii) to illustrate the use of calibrated DynaMIT system by applying it to investigate a limited number of incident scenarios and response strategies in the LWC test bed.

1.3 Thesis Outline

This thesis is organized as follows. Chapter 2 covers the literature available related to calibration of different components within a DTA system. A calibration methodology for DTA system is presented with particular emphasis on DynaMIT. It also covers a literature review on modeling of information dissemination devices. Chapter 3 presents a general framework for the development of incident scenarios and diversion strategies. It briefly covers components of DynaMIT-P, a planning version of DTA system, and then explains how it is been used for developing incident scenarios and corresponding response strategies. Chapter 4 implements the developed framework to generate several case studies for LWC network. It covers various issues with available data and assumptions made due to available data quality, with respect to the need of DTA system components. It presents different calibrated parameters of DynaMIT system for the LWC network. It finally describes the impact of different incidents and respective diversion strategies. Chapter 5 summarizes the research work and presents the direction for further work needed in this area.

Chapter 2

Literature Review: Calibration Methodology and Modeling of Information Dissemination

Traffic assignment models are used to simulate traffic flows on a transportation network, and various other variables like travel times, pollutant emission, congestion etc. Traditional planning methods like four-step process mainly consist of static and deterministic models. Currently agencies use static assignment models for many planning objectives, like improvement of traffic movement, traffic maintenance, air quality impact etc. However, these traditional tools are not able to capture the effect of traffic control, information dissemination, traffic dynamics and driver's response to any information, which make them unsuitable for certain applications, especially while evaluating evolving and existing ITS technologies. These drawbacks of traditional planning and assignment models are overcome by Dynamic Traffic Assignment (DTA) systems, which have evolved substantially in the last two decades and have reached a sufficient level of maturity to be used in many planning and operational applications. DTA systems capture traffic dynamics in realistic manner by modeling time dependent Origin-Demand (OD) demand, queues and spillbacks. Also, planning version of DTA system can be used in place of existing planning tools replacing static assignment models.

Despite the fact that uncertainty due to congestion, incidents or any special event should be accounted in good planning, it has rarely been used in the analysis and forecasting tools which provide quantitative design decision support for a transportation network. With the evolution of ITS and DTA systems, it is now possible to design such ATMS/ATIS strategies that will provide high level of network performance by providing guidance through VMS/HAR, in general measured in terms of travel times.

The Following sections will cover a detailed literature review of DTA systems, its components and calibration, and need for the development of a planning tool for short-term planning applications using a DTA system.

2.1 DTA systems

There are mainly two types of DTA systems: (i) Analytical, and (ii) Simulation-based. Analytical DTA models frame the problem as an optimization and use mathematical optimization techniques to solve this problem. There are two main disadvantages of analytical DTA system: (i) these models become very complex and intractable for large and realistic size networks, and (ii) these models can not capture the realities of network (like street, segment characteristics) due to the assumptions made to simplify the problem. Simulation-based DTA systems overcome these disadvantages but they also have several drawbacks like failure to reach convergence. While more research is needed towards further enhancements and applications of simulation-based DTA systems, they have several advantages:

(a) Simulation-based DTA systems capture some traffic issues which are difficult to capture in analytical approach, like complex vehicle interactions, traffic signals, realistic network representation, congestion, queues, spill-backs and congestion dissipation.

(b) Importance of simulation-based DTA systems increases in the context of modeling various ATMS, ATIS and ITS strategies.

(c) They can capture the time dependent interaction between different components of a DTA system (like supply and demand). Various travel choices, like mode, departure time and path, can be modeled easily by simulation-based DTA systems.

2.1.1 Simulation-based DTA systems

Examples of currently available simulation-based DTA systems for planning and decisions support are DynaMIT, DYNASMART and CONTRAM.

DynaMIT, developed at MIT's Intelligent Transportation Systems Program, is the state-of-the-art traffic estimation and prediction software system, which is designed to reside in a Traffic Management Center (TMC) for various real-time and planning applications, and to support ATIS and ATMS strategies. DynaMIT incorporates *unbiasedness* and *consistency* to achieve reliable prediction and credible guidance. Unbiasedness ensures that the information provided to travelers is based on the best available knowledge of current and anticipated network conditions. Consistency guarantees that DynaMIT's prediction of expected network conditions match what drivers would experience on the network. DynaMIT has the ability to trade off level of detail and computational practicability, without compromising the integrity of its output. Its important features and functionality include:

(a) Demand simulation using a micro-simulator, which generates individual travelers and simulates their choices regarding whether to travel or not, departure time, mode, and route (pre-trip and en-route) in response to information provided by the ATIS.

(b) Supply simulation using a mesoscopic traffic simulator that explicitly models the traffic dynamics of development and dissipation of queues, spillbacks, and congestion in general.

(c) Individually simulates each trip, to generate detailed vehicle trajectories, which is very useful to various ATIS requirements.

(d) Uses a rolling horizon to achieve efficient and accurate real-time estimations and predictions. It employs this predicted information to generate descriptive and prescriptive information that avoids overreaction to any incident.

(e) DynaMIT-P, planning version, is designed to assist the evaluations of infrastructural, operational, or informational changes to local and regional transportation networks, by efficiently modeling day-today and within-day patterns of traffic flows, travel demand and network conditions.

DYNASMART, developed at University of Texas at Austin, is an assignment-simulation-based framework that combines advance network algorithms and models trip-maker behavior in response to information, using real-time information, such as loop detectors, roadside sensors, and vehicle probes. *Consistency checking* and *updating* is an important function incorporated in

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DYNASMART to ensure consistency of the simulation-assignment model results with actual observations, and to update the estimated state of the system accordingly. Key Features of DYNASMART include:

(a) A simulation-based dynamic traffic assignment system with micro-simulation of individual user decisions in response to information and a mesoscopic traffic flow simulation approach.

(b) Recognizes multiple user classes in terms of (1) operational performance (e.g., trucks, buses, passenger cars), (2) information availability and type, and (3) user behavior rule and response to information.

(c) DYNASMART-P, planning version, can model several features, like ability to load individual trips and trip chains with several intervening stops of associated durations, evaluation of HOV/HOT pricing schemes, VMS and incident management.

CONTRAM (CONtinuous TRaffic Assignment Model), developed by Transportation Research Laboratory (TRL) and Mott Macdonald, UK, has the capability to model variety of situations from congested urban networks to regional inter-urban areas. It can model unexpected events such as incidents that reduce network capacity and the effects of driver information systems. Fuel consumption and pollutants emission can also be modeled by CONTRAM. By interfacing with TUBA (Transport User Benefit Appraisal) it can do the cost benefit analysis of new infrastructure changes and traffic control measure. Special vehicle lanes, like HOV/HOT, modeling or banning turning movements in certain situations can be handled by it. Dynamic modeling is done by CONTRAM by dividing the day into time slices to model peak and off-peak traffic conditions. Vehicles are assigned to minimum cost paths by taking into account the vehicle interactions and delays caused by these interactions. Some of the key modeling features are: dynamic matrix estimation, an unlimited number of time slices, up to 32 user definable vehicle classes, left or right hand drive. One of the major limitations of CONTRAM is that it cannot explicitly capture the individual driver behavior and decisions, which are very crucial for evaluating different ATIS/ATMS strategies.

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2.1.2 Model Components in DTA system

A general framework of the DTA system consists of three sub-models:

(1) Demand Model: simulates the effects of the transportation system state on the behavior of users.

(2) Supply Model: simulates the effects of user behavior on the transportation system. It captures the traffic dynamics (like congestion, queues, spill-backs, travel times, flows, speed densities) at all points on the network, and hence used to indicate network performance.

(3) Demand-Supply Interaction Model: simulates the interaction between the above two models (day-to-day and within-day models)

(1) The Demand Model

Demand model in DTA systems captures the driver behavior with respect to pre-trip or en-route information on departure time, mode and route choice, as well as day-to-day behavior modeling of these choices. These choices are represented as a function of different kinds of attributes like travel time, cost, comfort and other socio-economic factors like age, sex, income level etc. A key component of demand model is OD estimation, which involves adjustment in demand in order to match traffic sensor counts as closely as possible. A general framework for dynamic demand simulation is presented by Ben-Akiva et al. [11]. A detailed literature review about the different modules of the demand model is done by Sundaram, S. [48]. A brief discussion of these components and their importance with regard to DTA system is presented below:

(a) **The Route Choice Model**

The route choice model captures the important aspect of dynamic traffic assignments. It contains choice set of all the feasible routes for each driver. Most of the route choice models use Multinomial Logit Model (MNL) for calculating the choice probability for all feasible routes of each user. It then assigns the driver to the path with maximum probability and utility. The Independence from Irrelevant Alternatives (IIA) limitation of

MNL model is usually resolved by C-logit route choice model (Cascetta et al. [17]), which account for amount of overlapping among paths and hence give more realistic routes flow fractions. Path-size (PS) logit model by Ramming [46] uses the correction term for overlapping that takes into account behavior theory and uses discrete choice theory (Ben-Akiva and Lerman, [8]).

Route choice can be modeled at Pre-trip and En-route level based on the ATIS information. One of the major differences between these two kinds of models is the fact that shift in departure time is no longer available for en-route choice model because driver has already entered the network. Modeling of route choice in response to information, available through VMS or through some dedicated system, is usually done in two ways. One of them is to take into account the factors into discrete choice modeling, which are considered to influence en-route decisions. Other way is to model these choices by bounded rationality concept, which states that driver's decision depends on the satisfaction level (Simon [47], Mahmassani and Chang [35], Mahmassani et al. [36]). For example, driver will change the route only if the total saving in travel time is above some threshold value. An approach using fuzzy theory to model route-choice in the presence of information is also presented by Lotan and Koutsopoulos [33].

(b) The Departure Time Model

Departure time choice of driver is sensitive to information provided regarding incident, congestion, and some personal attributes like value-of-time and preferred time of arrival. Generally used models for departure time choice are Logit model, Generalized Extreme Value (GEV) model and Logit kernel probit etc. Similar to route choice model, these models suffer from IIA property especially when departure time choices are closer, in which case error term may be correlated. To overcome this problem, departure time switching models are employed where choices are either habitual departure time or, some earlier or later time slot.

(c) The Mode Choice Model

Most of the mode choice models are based on logit or nested logit models, which use random utility principle. To choose a mode like car, transit, bus or any other mode

depends on various explanatory variables like travel time, travel cost, comfort, number of changes, income level, age and many other socio-economic attributes.

(d) The O-D Estimation Module

The O-D estimation module estimates the OD flows by varying time interval so that simulated sensor counts and field counts match within desired limits. Generally used algorithms for OD estimation are either simultaneous or sequential. Some of these approaches are the Kalman Filter approach and Generalized Least Square (GLS) approach. Balakrishna [6], Ashok [4] and Brandriss [13] have described these two approaches in detail. Some of the very good and comprehensive work in this area is been presented by Ashok and Ben-Akiva [5], Cascetta [14] and Cascetta et al. [16].

(2) The Supply Model

The supply model of the DTA system captures the traffic dynamics of the network by simulating the movement of drivers. It does not capture the detailed drivers interactions, like lane changing, car following models in micro-simulation, but primarily captures queuing behavior of the traffic. It provides network performances in terms of flows, speeds, densities, travel times, and build-up and dissipation of lane-specific queues and spillbacks over all the points on the network.

Most of supply simulators are mesoscopic in nature based on two types of models: 1. a deterministic queuing model and, 2. a moving model. The queuing model simulates the spillbacks by using input and output capacity of the segment. Insufficient capacity or space on the current or downstream segments will cause vehicles to start queuing up. The moving model is based on macroscopic speed-density relationship. Further, capacities are also used to model incidents and signalized intersections. Detail literature on the supply simulation can be found in Ben-Akiva et al. [9] and Kunde [31].

(3) The Demand-supply Interaction Model

The Demand-supply interaction model captures the day-to-day learning experience of the users. This behavioral principle states that choices of the users depend on the expected pre-trip travel times. Expected value of the travel time is a result of experience, memory and learning. Cascetta and Canterella [15] have described day-to-day stochastic assignment models, which predict the driver's expected travel time based on his experienced and expected travel times in the past days. An equilibrium model, where travel choices are based on the weighted average of experienced travel times during the previous days, is proposed by Horowitz [25]. Ben-Akiva et al. [10] and Jha et al. [28] have presented models which incorporate information provided to drivers into the day-to-day learning models. Mahmassani and Chang [34] have proposed model which takes into account the late or early arrival of driver on the previous days.

2.2 Calibration Methodology for DTA systems

The efficiency of any traveler information and guidance system depends largely on the accuracy with which the system can estimate and predict network state and path travel times. This leads to level of detail and accuracy of the two simulation tools used by DTA systems: the demand simulator and the supply simulator. In order to ensure that the systems react and behave in a realistic manner when used in TMC, it is critical to calibrate its model components against the field data observed from the network.

2.2.1 Overall Calibration Approach

The generalized approach for the calibration of a DTA system can be summarized as shown in Figure 2-1. The process begins with the initial values of calibration parameters based on available data or on some reasonable assumptions. These initial parameters are fed into DTA system to generate model outputs. An objective function will then be computed based on model outputs and observed field data. The next set of parameters values will be determined by an optimization step, which will again be used in DTA system as new inputs. After the convergence, model outputs will be used for further analysis.

The Optimization problem mentioned in the above framework is usually very large and complex, and might therefore be solved sequentially. The calibration process can be seen as an iterative sequence of demand and supply model calibrations within the DTA system, with their interaction resulting into final model outputs in each iteration. The Following sections will present the approaches to calibrate the demand and supply models within DTA system.
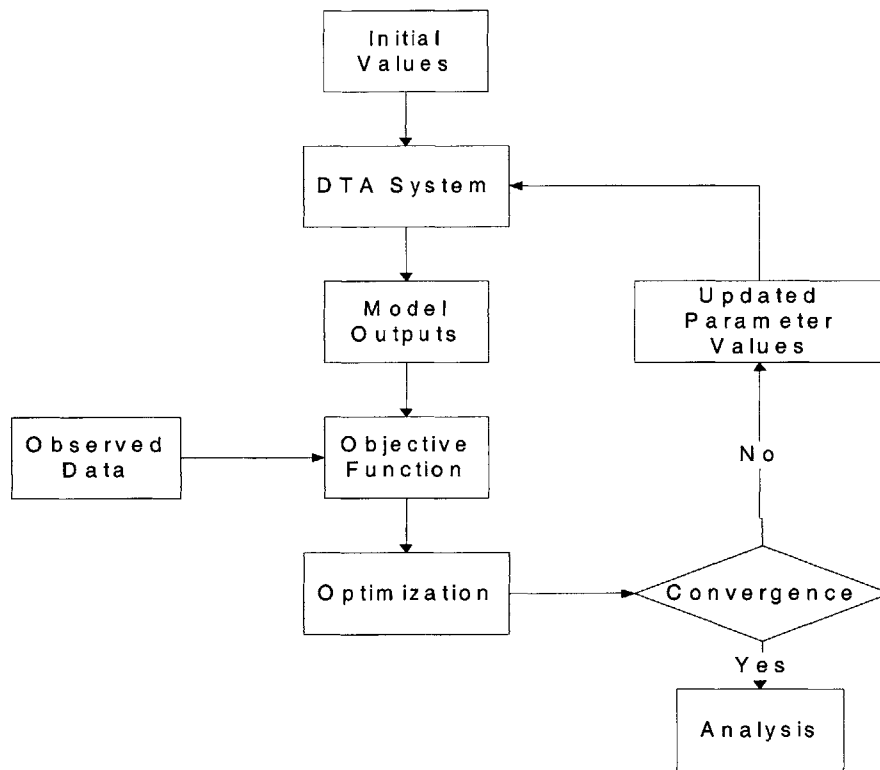
Figure 2-1: The Overall Framework

2.2.2 Demand Calibration

Demand Calibration Elements. Demand calibration methodology will integrate the route choice, departure time choice and O-D estimation modules into a single united frame. Input and output requirements of the demand calibration are shown in Figure 2-2. This process uses

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available estimates of O-D flows and several days of sensor counts and occupancies. The route choice parameters and O-D flows estimation models inputs are the outputs of this process.
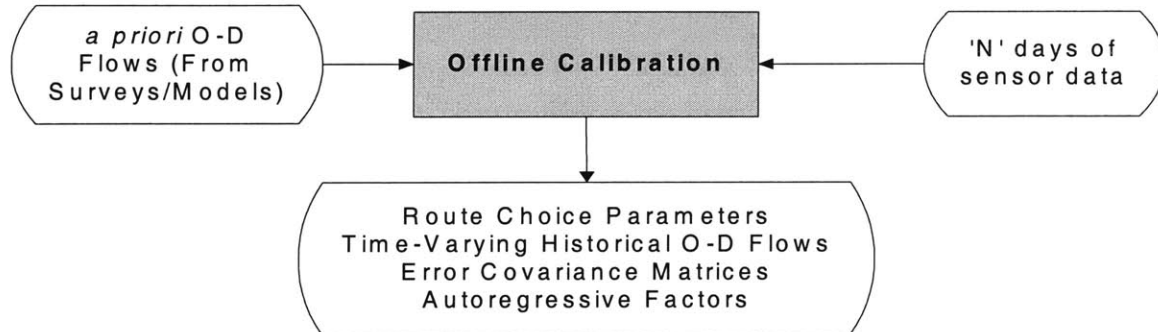
Figure 2-2: The Demand Calibration Problem

In summary, the demand simulator's parameters which need to be calibrated can be grouped as below:

Route Choice Parameters

i)   Parameters in the path choice set generation algorithm

ii)   Parameters in the path utility specification

iii)   Path-size exponent

O-D Estimation (and Prediction) Parameters:

i)   The historical database of O-D flows, X_h^H

ii)   The variance-covariance matrix V_h associated with indirect measurement errors

iii)   The variance-covariance matrix W_h associated with direct measurements errors

iv)   The matrices f_h^p of autoregressive factors

Balakrishna [6] has described that demand calibration problem becomes a fixed point problem between the route choice fractions, the assignments fractions and the O-D flows, and can be solved by iterative approach. The paper has described in detail an iterative approach (Figure 2-3) to demand calibration where route choice model has been used as the starting point in the iterative framework.

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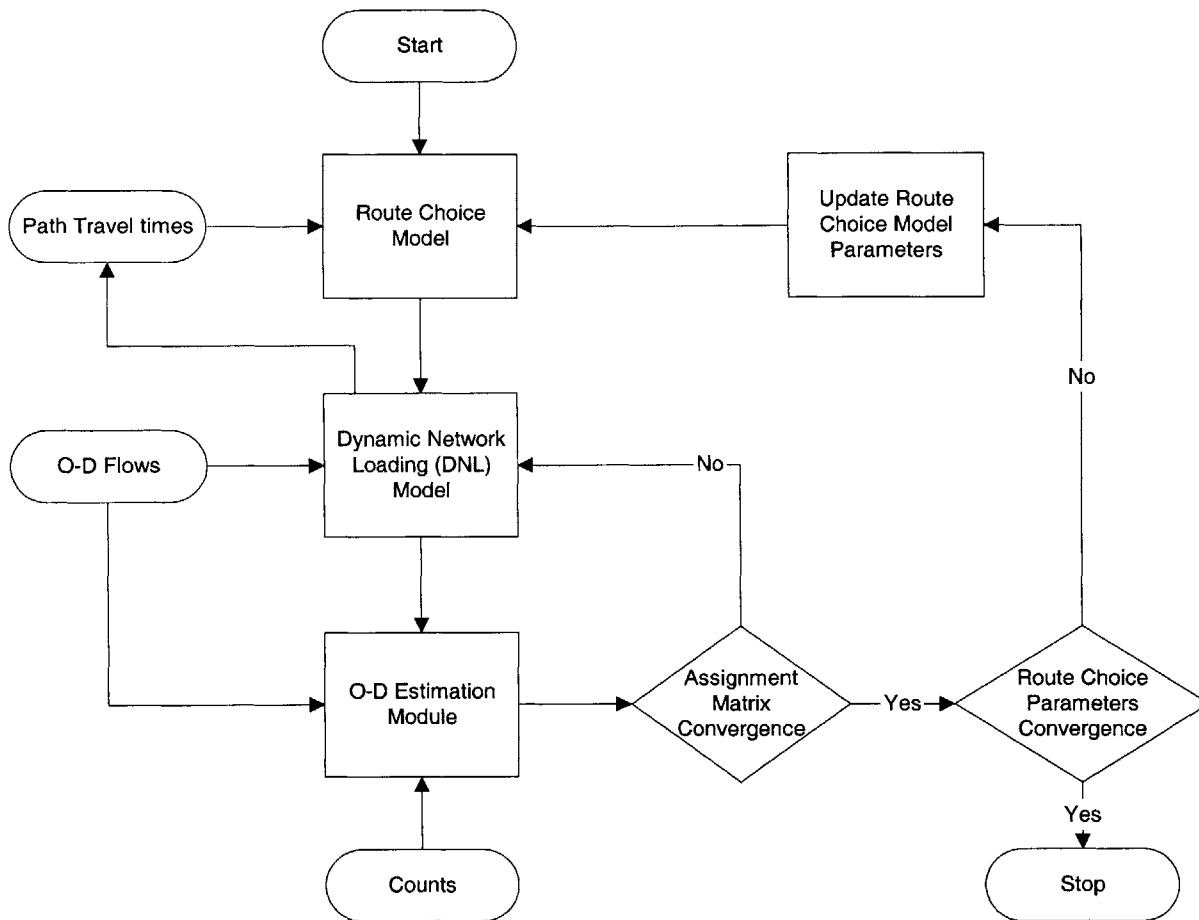
Figure 2-3: Iterative Demand Calibration Framework.

2.2.3 Supply Calibration

Supply Calibration Elements. The supply simulator in DTA system (in particular in DynaMIT) is a mesoscopic traffic simulator that simulates vehicular movements and provides matrices of network performances such as the temporal and spatial flows, speeds, queue lengths, and travel times at all points on the network. The supply simulator obtains the network description and the list of *packets* (vehicles) to be moved on the network through its interfaces with the network topology component and the list of packets component respectively. It then simulates the

movement of vehicles on the network for the given supply simulation time interval. Calibrated speed-density relationship parameters and lane group parameters (capacities) are the outputs of supply calibration module.

The list below shows the summary of parameters which are key to the calibration of supply simulator:

i)   Segment-specific speed-density parameters u_f, u_{min}, k_0, k_{jam}, α and β,

ii)   Lane group capacities on freeway and arterial segments, and

iii) Lane group capacities at the signalized intersections.

Kunde [31] has shown in detail the three-stage calibration methodology (Figure 2-4) for supply simulator parameters. The approach divides network into three different levels, (i) Disaggregate level (ii) Sub-network Level, and (iii) Entire Network level. Calibration of parameters is then done from microscopic level (disaggregate) to macroscopic level (entire network).

As mentioned before, since calibration of demand and supply parameters is a very large and complex problem calibration of these parameters is usually done iteratively between demand and supply models. While demand simulator needs specific supply model parameters (like link travel time) as an input, supply simulator moves the vehicles on the network assuming driver choices are known. Hence, calibration process can be seen as an iterative sequence of demand and supply model calibration, with their interaction resulting in the final model outputs in each iteration.
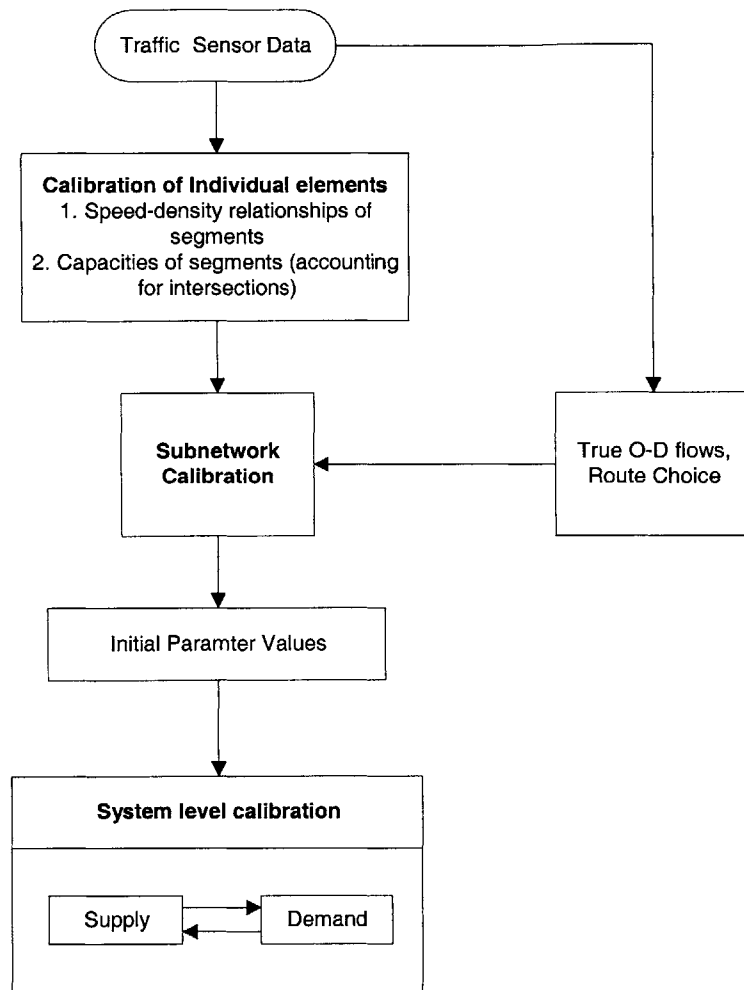
Figure 2-4: Three-stage Supply Calibration

2.3 DTA System for Short-Term Planning Applications

The main limitations of the static planning tools (like EMME2, TransCAD, TRANSIMS, TRANPLAN, etc.) for short-term planning applications, especially in the presence of ITS, are their inability to capture traffic dynamics, dynamic demand-supply interactions and characteristics of ATIS/ATMS. Furthermore, the network performance is due to the individual decision of the travelers and it is necessary to use disaggregate models to capture traveler behavior. Existing planning tools do not capture such a rich and explicit modeling of traveler

behavior. One of the main reasons for the need of a new planning tool is to address ITS in the planning context. Currently there are very few tools that are useful for analyzing ITS deployments. IDAS (Intelligent Deployment Analysis Software) is a recent tool developed by FHWA. However, existing planning tools (including IDAS), which are based on static techniques, are not very effective in evaluating ITS strategies.

A brief review of some of the studies for evaluating ITS and other strategies, and the limitations of the techniques used to evaluate them are summarized below. A more detailed treatment of the literature review on this topic can be found in Sundaram [48].

- **ATIS Strategies:**

It has been pretty well established in the literature that provision of information is effective primarily under non-recurrent congestion conditions. Al-Deek and Kanafani [2], modeled the benefits of information in traffic corridors and based on a simulation study reported that travel time savings are significant and can be in the order of 30 percent in a simple network with two routes. Simulation results in the Santa Monica Freeway corridor in Los Angeles (Gardes and May, [22]), showed that in the presence of an accident, information provision can bring about 6.2 percent reduction in travel times.

However, a few authors have questioned the significance of Advanced Traveler Information Systems (ATIS) benefits (e.g. Arnott et al. [3], Hall [23]). Arnott argues that ATIS may counter-productively lead travelers to congested alternative routes. Hall questions whether the problem of non-recurrent congestion is as significant as claimed. The general conclusion, however, from the available literature is that ATIS can be beneficial but this statement has to be verified, either by observing actual ATIS deployments or by conducting further studies. By modeling in-vehicle information, VMS and HAR devices, DynaMIT becomes a valuable tool for such studies.

Clearly, to analyze the impact of information either through in-vehicle guidance, VMS messages or other means, it is necessary to explicitly model both traveler behavior and traffic dynamics accurately. Existing simulation tools lack one or more of these critical features. Specifically regarding in-vehicle information, several authors have tried to analyze the impact of in-vehicle information with market penetration (e.g.

Jayakrishnan et al. [27], Walting and Van Vuren [51]). However, studies with respect to market penetration effects were based either on surveys or on queuing models and do not effectively capture traffic dynamics and traveler behavior in response to information.

Impact of VMS messages also typically depends on driver response to these messages and the resulting traffic conditions. Response behaviors of drivers in the presence of a VMS have been addressed by the use of logit models based on SP (Stated Preference) surveys (e.g. Bonsall and Merall, [12]). The main drawback of these surveys relates to the well-known problems with SP surveys (e.g. response bias, justification bias). An example of this issue is the study conducted by Chatterjee et al. [18]. As reported in that study, only one-fifth of the drivers indicated by SP surveys actually diverted in one area, while SP results were consistent with observed diversion rates in another location.

Under VMS information, studies based on SP surveys by Wardman et al. [52], Bonsall and Merall [12] and Peeta et al. [43] indicate that the following parameters are important factors that govern travelers' route choice decisions: relative journey times, delay on the current route, age, sex and previous network knowledge. McArthur [40] used behavioral rules employed in PARAMICS-CM and found that diversion is based on whether the savings that travelers perceive lie above a threshold, as well as on the travelers' patience and trust in the system.

• **Demand Management Strategies:**

Common example of demand management strategies is the use of HOV/HOT lanes. Several studies (Dahlgren [19], Johnston and Ceerla [29]) have tried to assess the impact of HOV/HOT lane strategies. However, these studies do not explicitly consider traffic dynamics and it is very difficult to analyze for example a strategy such as converting an already existing general-purpose lane into a HOV/HOT lane. Thus there is need to develop tools that would capture not only rich traveler choice models to estimate the mode shift associated with HOV lanes but that would capture traffic dynamics that will determine the network impacts of such strategies.

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Based on the preceding discussion, there is indeed a strong motivation to develop planning tools that will encapsulate traveler behavior, capture traffic dynamics and can be used for a variety of planning applications (including ITS strategies). The shortcomings of the traditional static planning tools are overcome by DTA systems, which capture traffic dynamics in a realistic manner by modeling time varying OD demands, queues and spill-backs. Sundaram [48] has further developed a framework for short-term planning applications using a DTA system. This framework is able to model day-to-day evolution of travel demand and network conditions and capture the within-day dynamics in the case of stochastic events. With current emphasis on ATIS/ATMS strategies and ITS investments to improve traffic conditions, the developed planning tool is capable of addressing these issues. This developed tool will be used, in the current thesis, for evaluating diversion strategy under incident response using VMS/HAR. The details of this planning tool are given in the next chapter.

2.4 Summary

In this chapter, first we have described different types of DTA systems, its main features and different kinds of models used within the DTA systems. The importance of calibration while implementing a DTA system and different calibration approaches for calibrating various supply and demand parameters were discussed next. Finally, this chapter focused on the modeling of information dissemination devices, which is very important and critical while supporting a decision system, especially in case of congestion and incident. It was emphasized that current DTA systems, like DynaMIT and DYNASMART, take into account the reaction of drivers to the information provided. Therefore these DTA systems, combined with ATMS/ATIS tools, can be used for better performance of network, especially in terms of reliability of travel times.

The next chapter presents a framework for the development and evaluation of diversion strategies in case of incidents using a state-of-the-art DTA system (DynaMIT).

Chapter 3

Development of Incident Scenario and Evaluation of Diversion Strategy using DynaMIT-P

This chapter presents the framework for developing incident scenarios and diversion strategies using the DTA system DynaMIT-P, a planning version of DynaMIT. A brief overview of its features and functionalities were given in Chapter 2. This chapter will provide a deeper understanding of its main components. A description of some of the modeling features that make DynaMIT-P suitable for this kind of planning applications are covered next, especially day-to-day and within-day driver behavior modeling. Finally, representation of incident scenarios and representation of VMS/HAR for response strategies in DynaMIT-P have been described.

3.1 DynaMIT: An Overview

The overall framework of DynaMIT showing its various components is shown in Figure 3-1. For detailed description of DynaMIT, reader is referred to Balakrishna [4]. It is designed to reside in a Traffic Management Center (TMC) for supporting various ATIS/ATMS operations. As clear from the figure, DynaMIT takes both real-time and off-line data for its operation. The off-line data consists of network description, time-dependent O-D matrices, link travel times and default parameters for different models. The real-time information consists of surveillance data, traffic control information and incident characteristics (like location, starting time, duration and severity).
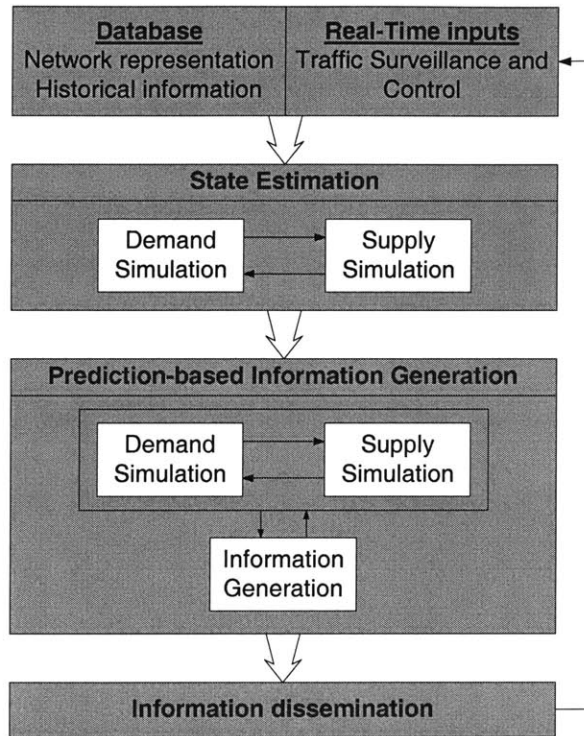
Figure 3-1: The DynaMIT Overview

The state estimation module gives the current estimate of the network in terms of O-D flows, speeds, densities, queues and link flows, using the inputs (sensor counts etc.) from the network. The State Estimation module has two main models: (1) The Demand Simulator, and (2) The Supply Simulator. The Demand Simulator has the capabilities to do real-time O-D estimation, taking into account the user behavior for route, departure time and mode. It also models the impact of information provided to user by modeling the reaction of each individual to the given information, and hence updates the historical O-D matrices. The O-D model then uses the real-time sensor counts, updated O-D flows, assignment matrices (fraction of OD flows to link flows) to estimate the current interval O-D flows. The Supply Simulator simulates the traffic conditions over the network using the estimated O-D flows from the Demand Simulator, updated capacities (due to incidents etc.), traffic dynamics parameters, traffic control strategies and traffic information and guidance disseminated (using VMS, HAR or any other dedicated guidance

system). Response of users to ATIS is captured through en-route driver behavior model. Demand-supply interaction is an important component of estimation module. The O-D estimation model uses assignment matrix that is an output of the Supply Simulator. But assignment matrix itself depends on route choice decisions made by drivers, which is a part of the Demand Simulator. Hence, it became necessary to iterate between the Demand Simulator and the Supply Simulator in order to achieve convergence.

The Prediction-based Information Generation module uses the predicted traffic conditions to generate information and guidance to users using various ATIS strategies. An iterative framework is used to obtain a guidance that should be the best under such conditions. This important property is called *consistency* that ensures that there would be no better path that the driver could have chosen. Each iteration consists of a trial strategy, network state prediction (both demand and supply prediction) under the strategy and evaluation of the predicted state for consistency. After the consistency is been achieved, information is disseminated to users in the network.

3.2 DynaMIT-P: Planning Version of DynaMIT

DynaMIT-P is the planning version of DynaMIT, which has the potential to substantially improve short-term transportation planning process, especially involving congested network. It is designed to assist the evaluations of proposed changes to local and regional transportation networks. Such changes could be infrastructural, operational or informational in nature. DynaMIT-P is the efficient adaptation of DynaMIT to achieve short-term planning process objectives.

DynaMIT-P models short-term (day-to-day) and within-day travel decisions. Short-term travel decisions include departure time, route, mode and destination choices. These short-term decisions are also affected by long-term decisions. For example, a long-term decision about residential location, auto ownership or changes in the network will affect the short-term decisions like departure time, route etc. With their daily travel choices and behavior, individuals develop habitual travel patterns that they follow regularly. Within-day decisions capture the

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deviation from the habitual travel pattern, in response to real-time information, weather conditions, special events or incidents. Since the objective of this thesis is to develop incident scenarios and diversion strategies for LWC network, DynaMIT-P is well suited for this purpose. Before we go into the framework for developing incident scenarios and diversion strategies, the main components of DynaMIT-P are described below.

3.2.1 Main Components of DynaMIT-P

The main components of DynaMIT-P are the demand simulator, the supply simulator and the learning models using demand-supply interactions.

3.2.1.1 Demand Simulator

The demand simulator in DynaMIT-P is a microscopic simulator, which captures driver behavior models and OD estimation models. The demand simulator consists of following main models:

    (a) O-D Estimation

    (b) Demand Disaggregation

    (c) Travel Choice Models

(a) O-D Estimation

The current version of DynaMIT-P uses a sequential GLS-based O-D estimation module that can be expressed by the following equation:

$$\hat{x}_h = \arg\min\left[\left(x_h - x_h^a\right)' W_h^{-1}\left(x_h - x_h^a\right) + \left(y_h - \sum_{p=h-p'}^{h-1} a_h^p \hat{x}_p - a_h^h x_h\right)' V_h^{-1}\left(y_h - \sum_{p=h-p'}^{h-1} a_h^p \hat{x}_p - a_h^h x_h\right)\right] \quad (3.1)$$

where,

$\hat{x}_h$ = Estimated flows for interval h,

x_h^a = Target OD flows,

W_h = Error covariance matrix associated with OD flow measurements,

y_h = Sensor counts for the time interval h,

a_h^p = Assignment matrix mapping OD flows to link flows from departure interval p to current interval h,

V_h = Error covariance matrix associated with the link counts and

p' = number of intervals needed for longest trip.

Under the constraint, all the OD flows should be non-negative.

As it is clear from the above equation, OD estimation tries to minimize the deviation of target OD flows and sensor counts from their estimated values. The key inputs to OD estimation module are sensor counts, time dependent historical OD flows and assignment matrix. While sensor counts and OD flows are provided externally, the assignment matrix is generated inside the supply simulator.

(b) Demand Disaggregation

Before the demand is loaded on the network, it is important to generate the population of drivers from the OD matrix, by assigning origin, destination, departure time and mode. The origin and destination is easily obtained from OD matrix, departure time is obtained from corresponding time interval and mode is assumed to be car by default. A number of socio-economic attributes (like informed/uninformed driver, value of time) and trip purpose (such as work) are also assigned to each driver.

(c) Travel Choice Models

Travel choice models within the DynaMIT-P can further be categorized as follows:

(1) Path Choice Set Generation

This is one of the crucial steps towards the route choice model and calibration, because in congested conditions drivers might be looking for routes other than shortest paths in uncongested conditions. This step generates a good set of feasible paths between each O-D pair. It consists of three steps. First step involves the generation of shortest paths between each OD pair. This will be the most probable path during uncogested conditions. Second step is the link elimination step,

which generates alternative paths from shortest paths. This is done by eliminating each link one by one and by regenerating shortest paths. Generation of alternative paths will also be crucial during incidents where driver needs to choose alternative path. Third step is the random perturbation step which perturbs the impedances of the links randomly to capture time varying link travel times, hence again creating the richer path set. Finally, all the paths are checked for uniqueness and unreasonably long paths are removed from the path set.

(2) Route Choice

After the path choice set has been generated, assignment of route choice to each driver is done by Path-Size Logit (PS-Logit) model (Ramming [46]) that can be defined mathematically as follows:

$$P_n(i) = \frac{e^{V_i + \ln PS_i}}{\sum_{j \in C_n} e^{V_j + \ln PS_j}} \tag{3.2}$$

where,

$P_n(i)$ = the probability of user n for choosing route i,

V_i = the utility of alternative i,

PS_i = the size of the path i,

C_n = the choice set for user n.

The utility V_i of each path is a function of many explanatory variables, like path travel times, travel costs and various socio-economic attributes of the users. The default utility function used in DynaMIT-P is given below:

$$V_i = \beta_1 tt_{Ai} + (\beta_2 \beta_1) tt_{Fi} \tag{3.3}$$

where tt_{Ai} and tt_{Fi} are the arterial and freeway travel time of the total travel time on route i. β_1 and β_2 are the coefficient of arterial travel time and freeway bias, respectively.

The Path-Size PS_{in} is defined as:

$$PS_{in} = \sum_{a \in \Gamma_i} \left(\frac{l_a}{L_i} \right) \frac{1}{\sum_{j \in C_n} \frac{L_i^\gamma}{L_j^\gamma} \delta_{aj}}$$ (3.4)

where l_a is the length of link a, L_i is the length of route i, δ_{aj} is either 1, if link a is part of route j, or 0 otherwise. The inner summation is over all the routes in the choice set C_n, while the outer summation is over all the links in the path Γ_i. γ is known as the path-size exponent.

(3) Departure Time Choice

The version of DynaMIT-P used for this thesis does not have a departure time choice model. Travelers are assigned a specific departure time based on the uniform distribution over a departure interval.

(4) Mode Choice

DynaMIT-P supports alternative modes such as HOV vehicles, but the default mode in the DynaMIT is assumed to be the car.

3.2.1.2 Supply Simulator

The supply simulator in DynaMIT-P is a mesoscopic simulator with the following key features:

- Movement of the vehicles in the uncongested uninterrupted part of the network is governed by a macroscopic speed-density relationship given by:

$$v = Max\left(v_{min}, \; v_{max} \left[1 - \left(\frac{\max(0, k - k_{min})}{k_{jam}} \right)^\beta \right]^\alpha \right)$$ (3.5)

where v is the speed of the vehicle (in mile per hour), v_{max} is the free-flow speed on the segment, k is the current segment density (in vehicles/mile/lane), k_{min} is the minimum density after which free-flow conditions begin to break down, k_{jam} is the jam density, and α and β are the segment specific coefficients. v_{min} is the minimum speed of the vehicle in the moving part which is determined by network and vehicle attributes.

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- The movement of vehicles from one segment to another is controlled by input and output capacities of the segments. Queuing will start building up if there is not required input/output capacity to process the vehicles. It employs deterministic queuing model to reflect the bottlenecks. Incidents and intersections controls are achieved through capacity controls. Further, the lanes within each segment are grouped into different lane-groups to capture the effect of turning-movement-specific capacities at diversion and merge points and at intersections.

- The simulation of traffic in the supply simulator is done in two phases: the update phase and the advance phase. The update phase computes the most time-consuming traffic performance measures like speeds, densities and flows. The advance phase moves the vehicles to their new positions. The durations of the update phase and the advance phase depend on the trade off between the accuracy of the result and the computational time.

3.2.1.3 The Learning Model

The learning model in the DynaMIT-P updates the drivers' perceptions of travel times based on the past experiences, according to the model given below:

$$\overline{T_k^t} = \lambda T_k^{t-1} + (1 - \lambda)\overline{T_k}^{t-1} \qquad (3.6)$$

where $\overline{T_k^t}$ is the time-dependent travel time along path k on day t, T_k^t is time-dependent travel time experienced along path k on day t, and λ captures the learning rate. The value of λ lies between 0 and 1, and is affected by the ATIS strategies.

3.3 DynaMIT-P for Short-term Planning Applications

In order to efficiently simulate the impact of an incident or a diversion strategy, a DTA system should have functionalities to model realistic day-to-day and within-day driver behavior. Day-to-day behavior tries to establish the network conditions resulting from traveler's habitual decisions. It generates the network conditions that would be representative of a normal day

without any accidents, special events etc. The within-day dynamics is the next stage of a planning tool that captures the network state in case of any unusual events. It disturbs the day-to-day equilibrium conditions and traffic control strategies. DynaMIT-P efficiently achieves day-to-day and within-day behavior modeling of a planning tool as shown in Figure 3.2. Hence, it is very suitable for the development of incident scenarios and diversion strategies. The outputs from this kind of planning tool are various measures of performance of the network such as travel delays, travel costs, fuel consumptions etc. DynaMIT-P's open system of demand models, detailed representation of network dynamics through supply simulator, learning models, and flexible structure make it a useful tool for many such planning applications.

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                    ┌─────────────────────────┐
                    │   Historical OD Matrix  │
                    └─────────────────────────┘
                                 │
                                 ▼
┌────────────────────────────────────────────────────────────────┐
│              ┌─────────────────────────────┐                    │        ┌──────────────┐
│              │      Day-to-Day Behavior    │                    │   ◄────│ Sensor       │
│              └─────────────────────────────┘                    │        │ Counts       │
│                                                                 │        └──────────────┘
│   ┌─────────────────────┐          ┌─────────────────────┐      │
│   │ Demand Simulator    │          │ Supply Simulator    │      │
│   │                     │─────────►│                     │      │
│   │ - Destination       │          │ - Control Strategies│      │
│   │ - Departure Time    │          │ - Segment Capacities│      │
│   │ - Mode / Route      │          │                     │      │
│   │ - Frequency / Purpose│         └─────────────────────┘      │
│   └─────────────────────┘                     │                 │
│             ▲                                  │                 │
│   ┌─────────────────────┐                      ▼                 │
│   │ Learning Models     │           ◇────────────────◇          │
│   │                     │◄── No ────│  Equilibrium ? │          │
│   │ - Travel Attributes │           ◇────────────────◇          │
│   │ - Information       │                    │                  │
│   └─────────────────────┘                    │                  │
│                                            Yes                   │
└────────────────────────────────────────────────────────────────┘
                                 │
                                 ▼
┌────────────────────────────────────────────────────────────────┐
│        Habitual Travel Patterns and Updated OD Flows            │
└────────────────────────────────────────────────────────────────┘
                                 │
                                 ▼
┌────────────────────────────────────────────────────────────────┐  ┌──────────────────┐
│              ┌─────────────────────────────┐                    │  │ Stochastic Factors│
│              │     Within-Day Behavior     │              ◄─────│──│                  │
│              └─────────────────────────────┘                    │  │ - Weather        │
│                                            ┌──────┐             │  │ - Incidents      │
│                                            │ ATMS │             │  │ - Special Events │
│                                            └──────┘             │  └──────────────────┘
│   ┌─────────────────────┐          ┌─────────────────────┐      │
│   │ Demand Simulator    │          │ Supply Simulator    │      │
│   │                     │─────────►│                     │      │
│   │ - Route Change      │          │ - Segment           │      │
│   │ - Mode Change       │          │ Capacities Changes  │      │
│   │ - Departure Time Change│       │                     │      │
│   │ - Add / Cancel Trip │          └─────────────────────┘      │
│   └─────────────────────┘                    │                  │
│             ▲                                 ▼                  │
│             │                        ┌────────────┐             │
│             │                        │ ATIS / VMS │             │
│             │                        └────────────┘             │
│             └──── Information ──────────────┘                    │
└────────────────────────────────────────────────────────────────┘
                                 │
                                 ▼
                    ┌─────────────────────────┐
                    │ Expected Resources      │
                    │                         │
                    │ - Level of Service      │
                    │ - Safety                │
                    │ - Energy Consumptions   │
                    └─────────────────────────┘
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Figure 3.2: System Framework of the Planning Tool using a DTA system

3.3.1 Modeling Day-to-Day Behavior in DynaMIT-P

We will now briefly review how DynaMIT-P models the day-to-day behavior. Sundaram [48] explained in detail the modeling of day-to-day and within-day behavior using DynaMIT-P. Figure 3.3 gives an overview of the implementation of day-to-day behavior modeling in DynaMIT-P. As shown in the figure, the inputs required for the day-to-day behavior modeling in DynaMIT-P are: time dependent historical OD matrices, time dependent historical link travel times, field sensor counts, socio-economic characteristics. The outputs from DynaMIT-P after establishing day-to-day behavior are: equilibrium travel times and planning OD matrices. The convergence criterion used in DynaMIT-P is given by:

$$\sqrt{\frac{\sum_{t=1}^{T}\sum_{s=1}^{S}\left(SC_s^t - FC_s^t\right)^2}{N_t N_s}} < \varepsilon \qquad (3.7)$$

where SC_s^t are the simulated counts reported by DynaMIT-P for sensor s in time interval t, FC_s^t are the corresponding field sensor counts, N_s is the number of sensor reporting counts, N_t is the number of time intervals and ε is the threshold parameter defined by the user.

Two of the most important modules used by this framework are "Equilibrium Travel Times Computation" and "OD Estimation". Readers are referred to Sundaram [48] for more details on these modules. The equilibrium travel times are established by an iterative procedure, until the traveler's expected travel times (i.e. the previous estimate of the equilibrium travel times) match their experienced travel times (generated by the supply simulator). The convergence criterion for "Equilibrium Travel Times Computation" tries to minimize the difference between the previous equilibrium travel times and the latest travel times obtained from the supply simulator, and is given by following equation:

$$\sqrt{\frac{\sum_{l=1}^{L}\sum_{t=1}^{T}\left(EQ_i^{l,t} - EQ_{i-1}^{l,t}\right)^2}{N_l N_t}} < \varepsilon \qquad (3.8)$$

where $EQ_i^{l,t}$ is the equilibrium travel time in the current iteration i, on link l, for a vehicle that enters the link in time interval t, $EQ_{i-1}^{l,t}$ is the corresponding travel time in the previous iteration

i-1, N_l is the number of links in the network, N_t is the number of time intervals with which the travel times are represented and ε is the threshold parameter defined by the user.

The "OD Estimation" module updates the planning OD to reflect the field sensor counts. As discussed in the chapter 2, problem of OD estimation is a fixed-point problem. The solution of OD estimation is obtained by an iterative process between the OD estimation algorithm and the supply simulator, linked by an assignment matrix. The assignment matrix consists of the fraction of each OD pair that has been counted on each sensor by the time period. The convergence criteria used for OD estimation is given by:

$$\sqrt{\frac{\sum_{n=1}^{N_{od}}\left(F_i^{o,d,p} - F_{i-1}^{o,d,p}\right)^2}{N_{od}}} < \varepsilon \tag{3.9}$$

where $F_i^{o,d,p}$ is the OD flow in the current iteration *i*, from origin *o* to destination *d* in time interval *p*, $F_{i-1}^{o,d,p}$ is the corresponding OD flow in the previous iteration *i-1*, N_{od} is the total number of OD pairs and ε is the threshold parameter defined by the user.

START

INPUT
Historical OD
Matrix

Initial OD Matrix =
Historical OD Matrix

INPUT
Historical
Travel-Times

Equilibrium Travel
Times = Historical
Travel Times

STEP 1: Compute Equilibrium Travel-
Times given the Initial OD Matrix

INPUT
Field Sensor
Counts

STEP 2: Estimate OD Matrix given the
historical OD as the seed, Equilibrium
Travel-Times and the Field Sensor
Counts.

Convergence ?

No

Update OD

Yes

OUTPUTS
Updated historical
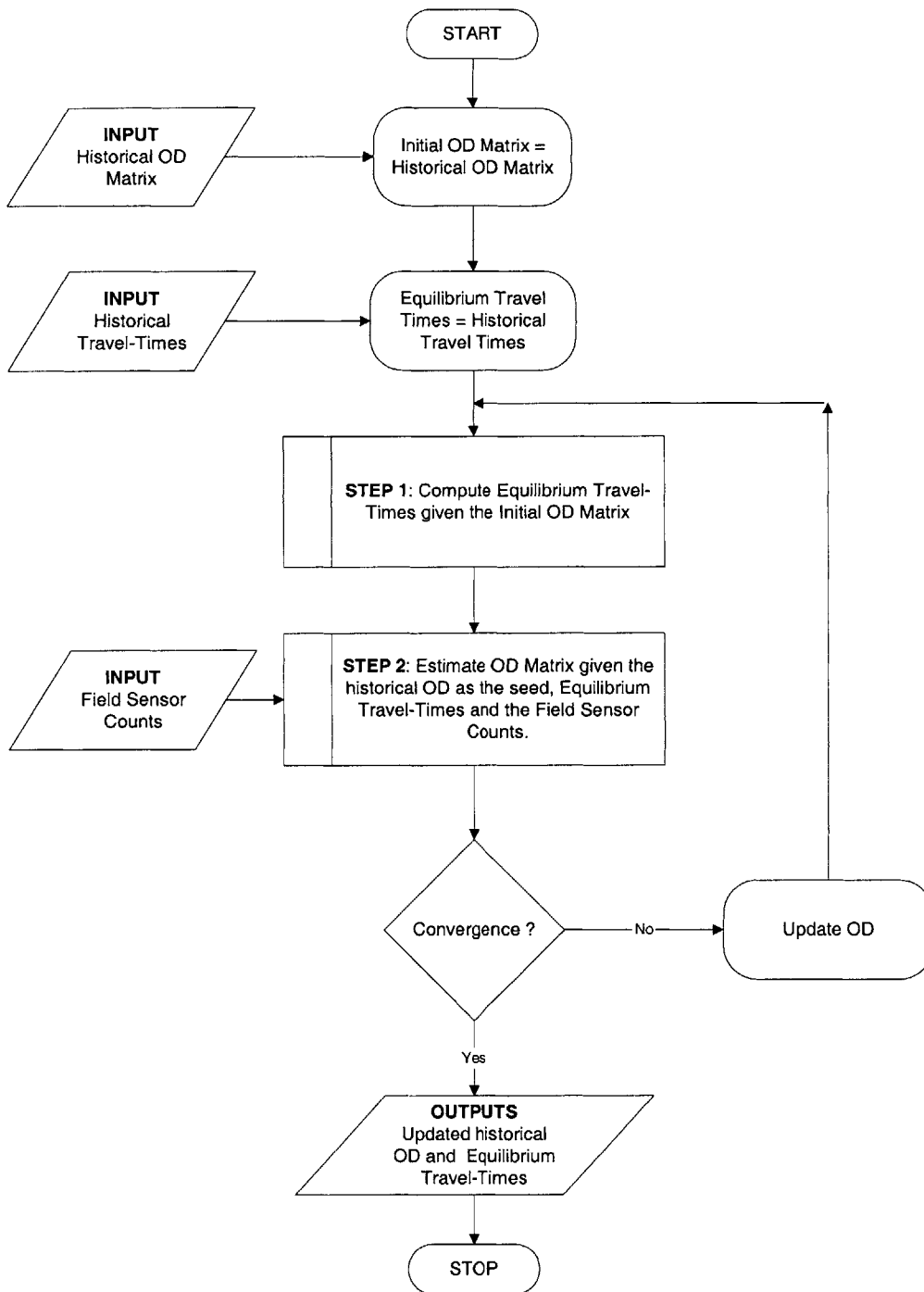OD and Equilibrium
Travel-Times

STOP

Figure 3.3: Modeling Day-to-Day Behavior in DynaMIT-P

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3.3.2 Modeling Within-Day Behavior in DynaMIT-P

Modeling the within-Day behavior becomes important especially in the case of special events, accidents or bad weather conditions. From the Figure 3.2, it is clear that within-day modeling takes equilibrium travel times and estimated planning OD matrix, from the day-to-day analysis, as inputs. Within-day behavior is obtained by simply doing iterations between the demand simulator and the supply simulator in response to stochastic events or ATMS/ATIS strategies. Implementation of within-day dynamics may require changes on both the supply and the demand sides. Most of the changes on the supply side of DynaMIT-P are captured through segment capacities and changes on the demand side are reflected through the planning OD matrix or through the travel choice models.

3.4 Representation of Incident Scenarios in DynaMIT-P

The day-to-day model captures incident scenarios. These scenarios are captured by modifying the relevant inputs on the supply or the demand side, and evaluating the network performances under modified inputs. Changes on the supply side are made primarily on the segment capacities. For example, lane closure due to an accident and its impacts for a temporary period are captured by reducing the capacity of the corresponding segment for required time interval. Other similar examples could be the case of work-zone management, severe weather conditions, etc. Any changes on the demand side are performed by updating the OD matrix. A typical example will be the increase in demand due to events like sports, concerts, special events etc. Once the inputs have been modified to suit particular scenario, the scenario is evaluated by disaggregating the appropriate OD matrix using the equilibrium travel times to evaluate users' choices. The supply simulator then yields the network conditions. Several iterations of the demand and supply may be required to account for the users' adjustment made in response to network conditions. The impact of the scenarios is analyzed by comparing the normal day network state with the obtained network state, through different outputs produced by DynaMIT-P.

3.5 Representation of ATIS/VMS Scenarios in DynaMIT-P

ATIS strategies (such as diversion strategies) are typically employed due to various stochastic events (such as incidents) and in order to evaluate them, handling information dissemination at various levels of sophistication. For example, a Variable Message Sign (VMS) may provide instantaneous information or it may provide predicted information. The approach that was modeled and implemented within DynaMIT to both generates instantaneous/predictive travel times and to evaluate the network performance is illustrated in the remainder of this section. DynaMIT was previously using a single network-wide information source to represent in-vehicle devices providing traffic information and guidance. This framework has been extended to allow for modeling of VMS devices. Furthermore, these devices have been implemented so that they may provide link-based or path-based travel time information, as well as either instantaneous, or predictive information. In this thesis, for development of diversion strategies during incidents, information to drivers will be disseminated through VMS. A more detailed presentation of this modeling work can be found in Sundaram (2002).

A brief description on in-vehicle information and VMS representation in DynaMIT-P is presented next.

In-vehicle Information:

Guided travelers who received in-vehicle information continuously update their paths using the en-route choice models in DynaMIT-P. The frequency with which drivers update their paths depends on the nature of information and the frequency with which the information is updated. Guided travelers use current guidance impedance tables to make en-route decisions. Currently, in DynaMIT-P in-vehicle drivers receive descriptive information.

VMS Information:

DynaMIT-P models Path-VMS and Link-VMS (see section 3.5.3). Both guided and unguided drivers may respond to the VMS messages and perform en-route decisions based on the VMS message. The implemented behavior is shown in Figure 3-4. Guided drivers respond to

the VMS signs with probability *p1* and ignore with probability *1- p1*. Similarly, unguided drivers respond with probability *p2* and ignore with probability *1 - p2*. The value of *p1* and *p2* are inputs to the model and can be determined through calibration.
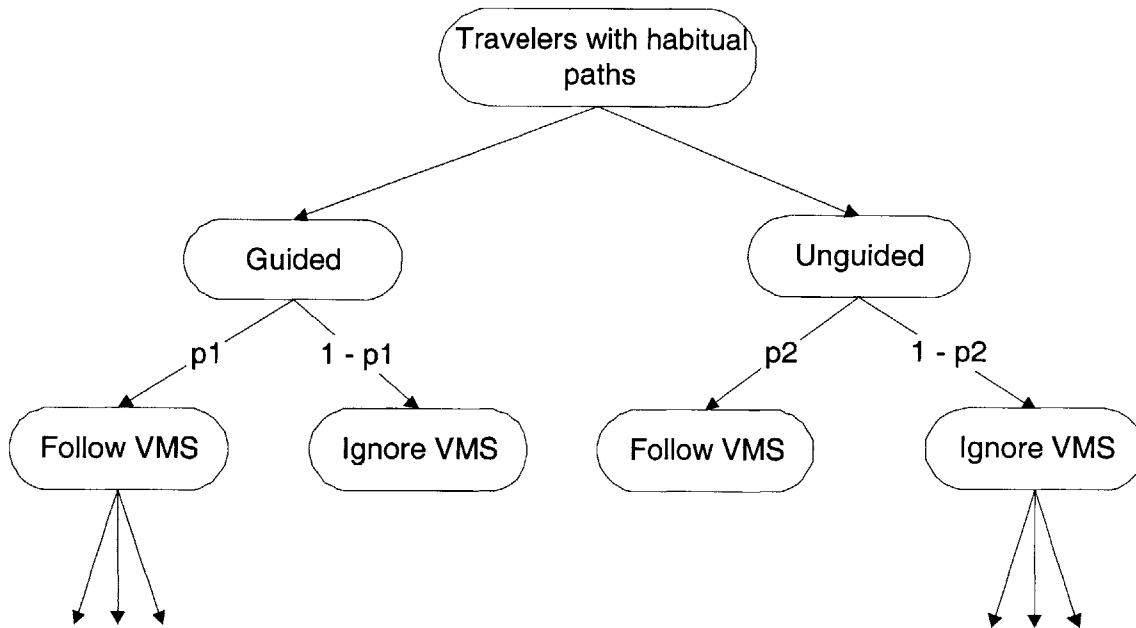
Figure 3-4: Travelers Response to VMS

3.5.1 Modeling ATIS/VMS with Instantaneous Information

The time-dependent OD matrix for a time interval is disaggregated to produce a list of travelers. Based on the information available about the percentage of unguided and guided travelers[2], the list of travelers is divided into two driver classes: informed and uninformed drivers. The habitual paths of both classes of drivers are obtained by the standard route choice model using the historical travel times. Uninformed travelers are loaded into the supply with the habitual

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[2] Guided drivers are the drivers that have access to in-vehicle information; unguided drivers are the drivers who do not have access to such information. In the application for the LWC network, all drivers will be assumed to be unguided.

paths and do not make en-route decisions unless they encounter a VMS message. Informed vehicles on the other hand may change their routes dynamically based on both in-vehicle and VMS information.

The instantaneous information is obtained by aggregating travel time information from the supply, after every information-update period. For example, if the frequency of the information updating is 5 minutes, every 5 minutes the travel times obtained from the supply simulator are broadcast to informed drivers. These informed drivers then make en-route choices depending on the travel times supplied to them, using appropriate compliance and en-route choice models. The travel times provided to drivers can be on certain links or on certain paths depending on the characteristics of the ATIS.

During the supply simulation, whenever any vehicle passes over a link which has a VMS, a driver may respond to the VMS with certain probabilities. In this case, traveler behavior models in the demand component are invoked to simulate en-route choice. The utilities for the en-route choice models are computed based on the travel times provided by the VMS (for the specific links or paths) and historical travel times for all the other links. For the instantaneous information VMS, the frequency of the update of the information that is provided by the VMS is a design parameter and an input to the system.

3.5.2 Modeling ATIS/VMS with Predictive Information

The important aspect of traffic prediction is the concept of consistency. Based on the guidance provided, travelers' response to the guidance will influence network conditions and hence the guidance strategy. Therefore, the problem of obtaining a consistent guidance is a fixed-point problem. Any ATIS based on predictive guidance has to iterate so that the outcome of the guidance strategy matches the network conditions after travelers' reactions to the guidance.

An initial set of predicted travel times is assumed (typically this is the historical travel times) and network conditions are simulated. Based on the simulated travel times, algorithms are used to obtain a new prediction of travel times, which are used for guidance generation. The new set of predicted travel times is provided either through in-vehicle or VMS information, and

travelers update their paths. If the resulting travel times do not match the predictive travel times provided to travelers, then consistency has not been achieved and more iteration are necessary. On convergence, a consistent guidance strategy is obtained.

3.5.3 Dissemination of VMS Information in DynaMIT-P

The information provided through the VMS may be path-based or link-based. Therefore, the following types of devices can be modeled:

- *Link-VMS:* VMS device that displays information on individual links

- *Path-VMS:* VMS device that displays information on specific paths or sub-paths

Both guided and unguided drivers may respond to the VMS messages and perform en-route decisions based on the provided information. The path travel times for travelers making en-route decisions in the presence of a VMS are computed based on the following rules.

In the case of a link-VMS, the latest travel times for the links served by the VMS are substituted for the historical travel times. These latest times are stored in the current guidance table. Thus, for the example in Figure 3-4, assuming that the VMS is located on link 4 and that it provides information about link 7, then for the path represented by a sequence of links 6-7-8, the travel time on link 7 is obtained from the current guidance table and the travel times of all other links are obtained from the historical travel time table.
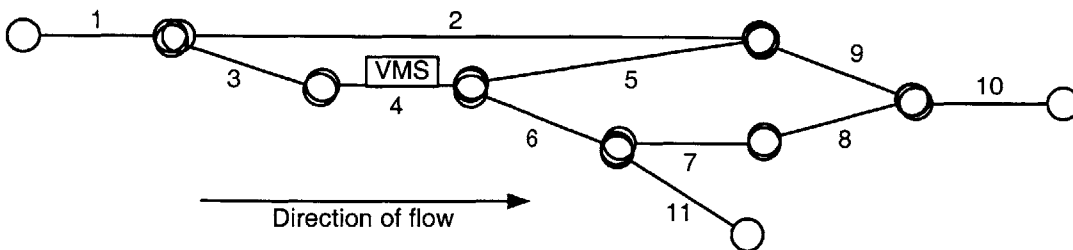

Figure 3-5: Example to illustrate link-VMS and path-VMS

In the case of a path-VMS, while computing path travel times for a particular path, it is checked whether sub-paths for which the VMS provides guidance is a subset of the current path. If this is the case, then for all the links in the sub-path the guidance provided by the VMS is employed to get the link travel times. Otherwise the historical travel times are used for the entire path. Thus, with reference to Figure 3-4, assuming that the VMS is again located on link 4, and gives path guidance for path 6-7, then for vehicles following the path 6-7-8 travel times from the current guidance table are used for links 6 and 7 and the historical travel times are used for all the other links. However, if for example a vehicle is using the path 4-6-11, then it uses historical travel times for all the links on this path, since path 4-6-11 does not contain the sub-path 6-7 in its entirety (even though it contains one of the links that belong in sub-path, i.e. link 6).

The structure of the VMS input file for DynaMIT is explained in Appendix B. The use of the input file is illustrated through examples.

3.6 Framework of the Planning Tool for the Lower Westchester County Case Study

The main objective of this thesis is to illustrate the use of a calibrated DynaMIT-P system for developing/evaluating incident response strategies. The framework described in the following sections will be used in the chapter 5 for analysis of incident scenarios and the diversion strategies.

3.6.1 Development of Incident Scenarios

Figure 3-6 describes the step-by-step process for the development of an incident scenario. First step is to identify and analyze those paths/links that are mostly used by travelers, since the impact of an incident affecting these paths/links will be more severe. This can be obtained from the historical data (sensor counts, O-D flows) or from the statistics of segments (densities and flows) on different paths/links in the Base-Case of DynaMIT-P, which is established during the calibration process under normal traffic conditions. Next step is to choose a path/link from the

set of high occupancy paths/links, for illustrating the impact of an incident. After choosing a high occupancy path/link, critical location(s) on this path/link will be identified that will have a major impact on traffic conditions as a result of an incident. These location(s) are found by analyzing the traffic flows, bottleneck points, number of options for diverting traffic incase of an incident and historical data about incidents. Incident descriptions will include information on the location, severity and duration of the incident. Incident details will be fed into the calibrated DynaMIT-P from the no-incident case, which will estimate the network traffic conditions at different points of time, assuming travelers follow their habitual routes. Estimated network state will show the impact of the incident in terms of total number of completed trips, average travel times for different departure intervals and total vehicle hours.
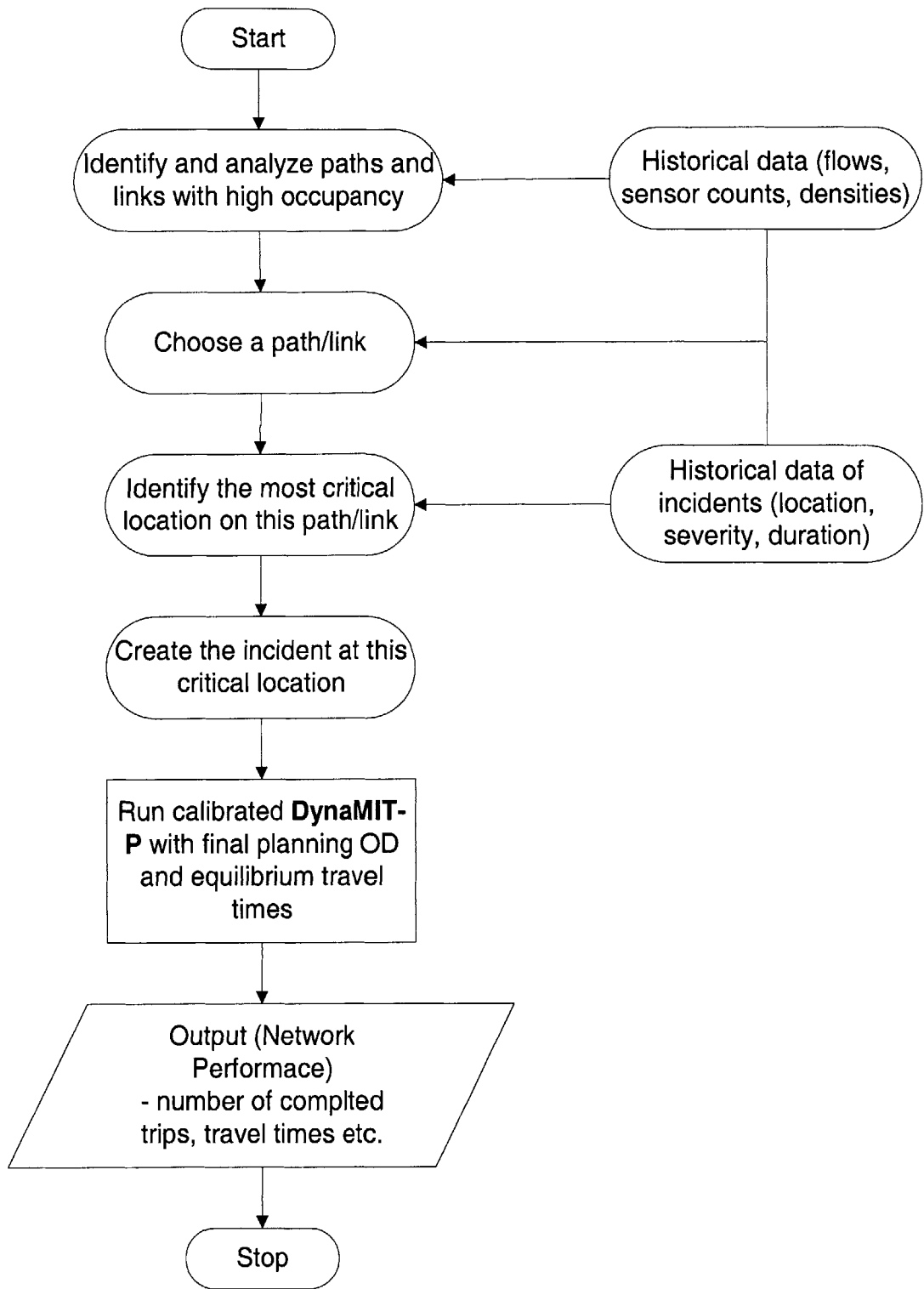
Figure 3-6: Development of Incident Scenario

3.6.2 Evaluation of Diversion Strategies

Sundaram [48] has concluded that the Predictive VMS strategy results in the best overall network performance, both in terms of the number of travelers who complete their trips and the average travel time. He further mentioned that the Instantaneous VMS strategy might cause travelers to experience longer travel times, since this strategy does not take into account future network conditions and may lead to overreaction. This effect may be avoided by using the predictive VMS scenario with a consistent guidance strategy. Therefore, only predictive VMS strategy will be applied for evaluating the diversion strategy on the LWC network.

Determining the location of the VMS is an important step in the response strategy. The VMS strategy in our analysis is constrained by the fact that the location of VMS on the network is fixed and only these fixed VMS can be used for the diversion of traffic flow. Appropriate VMS location from these fixed VMS locations will be chosen based on the incident location. In general, a response strategy designates a set of travel time messages for certain links or paths, together with the locations of VMS which are fixed over the LWC network. Various measures of effectiveness obtained during incident scenarios will provide benchmark performance measures that establish reference points for quantifying the benefits of alternative response strategies.

A framework for off-line generation and evaluation of diversion strategy with predictive ATIS is shown in Figure 3-7. The first in the process consists of loading the initial network state and disaggregating the planning OD to produce a list of travelers. An iterative approach is employed to achieve a consistent guidance. The list of travelers is then loaded into the supply simulator, which is used for the entire planning horizon to estimate the network conditions. During the supply simulation, if travelers encounter a VMS, they update their paths based on en-route choice models. Guided travelers on the other hand continually update their paths. These travelers perform route choice based on the current guidance table. Network performance is estimated after all routes are updated and subsequent updates to guidance are based on aggregated travel times from the supply simulator. A linear combination of the previous

current guidance and the latest travel time tables from the supply is used as the guidance generating algorithm.

Consistency is a key factor in the case of predictive ATIS strategy. Consistency takes into account the drivers' reaction to the provided information. Therefore, a consistency check is performed based on the following equation:

$$\sqrt{\frac{\sum_{l=1}^{L}\sum_{t=1}^{T}\left(TT_{i}^{l,t} - TT_{i-1}^{l,t}\right)^{2}}{N_{l}N_{t}}} < \varepsilon$$

where $TT_{i}^{l,t}$ is the link travel time from the guidance table in the current iteration i, on link l, for a vehicle with time of entry into the link t minutes after the start of the planning horizon, $TT_{i-1}^{l,t}$ is the corresponding link travel time from the guidance table in the previous iteration $i-1$, N_{l} is the number of links in the network, N_{t} is the number of time intervals corresponding to that of the impedance tables in DynaMIT-P and ε is the user defined threshold parameters. If the convergence criterion is not satisfied, then more iterations are done as indicated in Figure 3-7.

Performance of a response strategy will be evaluated in terms of total savings in travel times, frequency of travel times, number of completed trips, total vehicle hours etc.
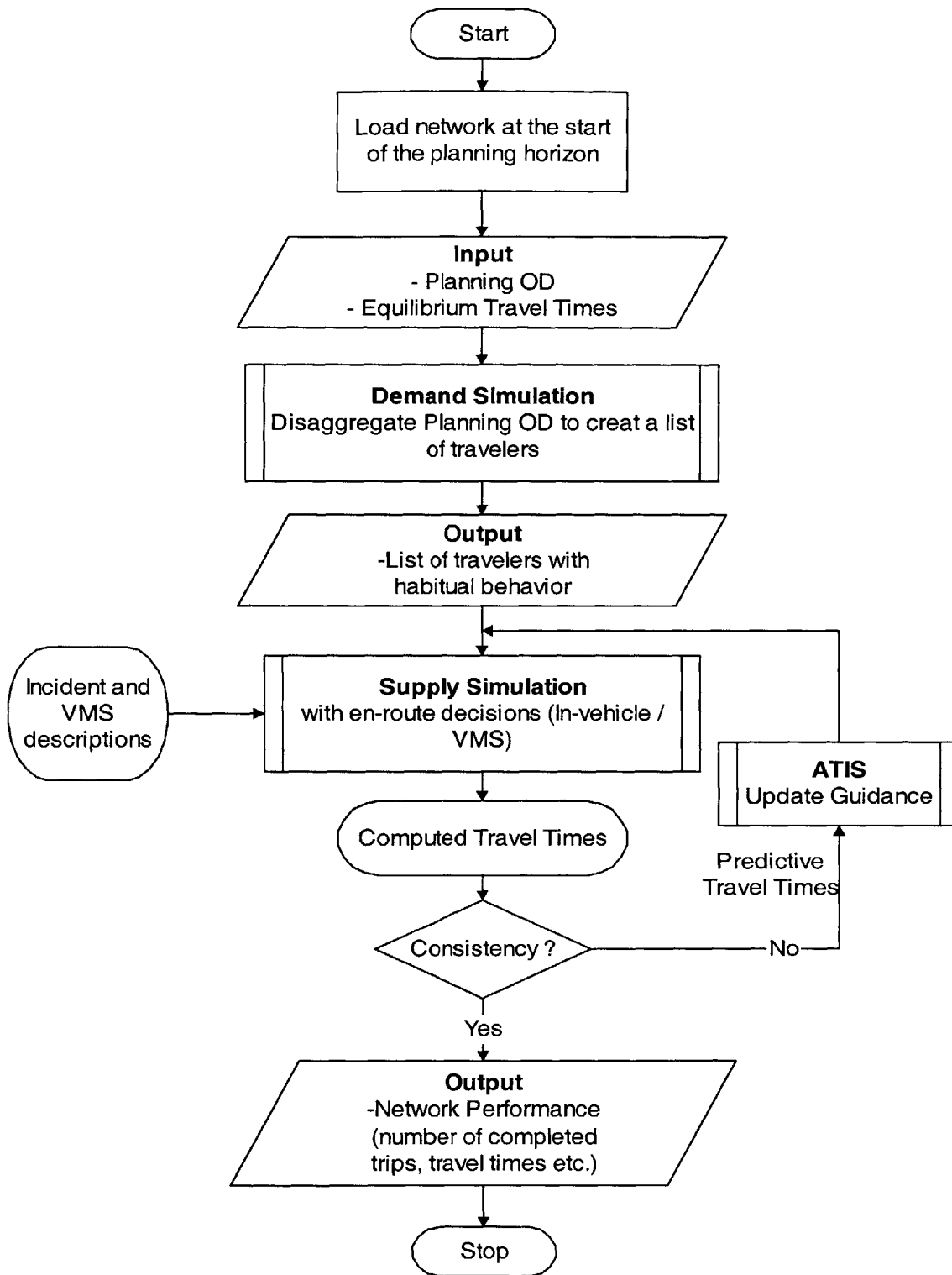
61

```
                         ┌─────────┐
                         │  Start  │
                         └────┬────┘
                              │
                              ▼
                   ┌──────────────────────┐
                   │ Load network at the start │
                   │  of the planning horizon  │
                   └──────────┬───────────┘
                              │
                              ▼
              ╱───────────────────────────╲
             ╱          Input                ╲
            ╱       - Planning OD             ╲
            ╲   - Equilibrium Travel Times    ╱
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              ┌─┬───────────────────────────┬─┐
              │ │     Demand Simulation      │ │
              │ │ Disaggregate Planning OD to creat a list │ │
              │ │        of travelers        │ │
              └─┴───────────────────────────┴─┘
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             ╱          Output               ╲
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            ╲         habitual behavior        ╱
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   ╭──────────╮    ┌─┬───────────────────────────┬─┐
   │ Incident and │───▶│ │     Supply Simulation      │ │
   │     VMS       │    │ │ with en-route decisions (In-vehicle / │ │
   │ descriptions  │    │ │          VMS)          │ │
   ╰──────────╯    └─┴───────────────────────────┴─┘
                              │
                              ▼
                    ╭──────────────────╮
                    │ Computed Travel Times │
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Figure 3-7: Evaluation of Diversion Strategy using Predictive ATIS Strategy in DynaMIT-P

3.7 Summary

This chapter gave a description of the use of DynaMIT-P for developing incident scenarios and diversion strategies. First a brief description of DynaMIT was given, followed by the detailed overview of DynaMIT-P and its main components. Suitability of DynaMIT-P for such planning purposes was described by its capabilities to do day-to-day and within-day behavior modeling. Finally, representation of incident scenarios and VMS scenarios in DynaMIT-P were covered which will be applied during some case studies over the LWC network in the next two chapters.

Chapter 4

Calibration of DynaMIT-P for the Lower Westchester County

The objective of this chapter is to calibrate the DynaMIT-P for the Lower Westchester County (LWC), using the methodology described in the chapter 2. Calibration of the DynaMIT-P will establish the no-incident case, which will be used for comparing incident scenarios and diversion strategies in the next chapter.

A brief description of the study network is given first. The data available from various sources and issues associated with data are discussed. Critical calibration results, which are to be obtained before the use of DynaMIT-P for incident scenario and diversion strategy, are presented next.

4.1 The Lower Westchester County (LWC) Dataset

The data used in this research was collected from LWC, New York, USA. Descriptions of the main features of the network, available data, issues and assumptions associated with the data are given in the following sections.

4.1.1 Network Description

The primary network of the project is the Lower Westchester County (LWC) freeways and parkways network. This network is just north of Manhattan, New York. It thus has heavy traffic on some of the freeways and parkways, resulting from a varied mix of commuters and travelers. Freeways and Parkways in the focus network include I-87 (the New York State Thruway), I-95

(the New England Thruway), I-287 (the Cross Westchester Expressway), I-684, the Cross County Parkway, the Hutchinson River Parkway, the Sprain Brook Parkway, the Saw Mill River Parkway, the Bronx River Parkway and the Taconic State Parkway. Four adjoining arterials (Tuchahoe Road, Ardsley Road, Hartsdale Road and Weaver Street) and Routes 9, 100 22, and 119 were also added to capture the effect of any diversion strategies in case of incident. Most of the freeways and parkways, except Cross County Parkway and I-287, run south- north, and vice versa, direction. The general extent of the project network is shown in Figure 4-1.
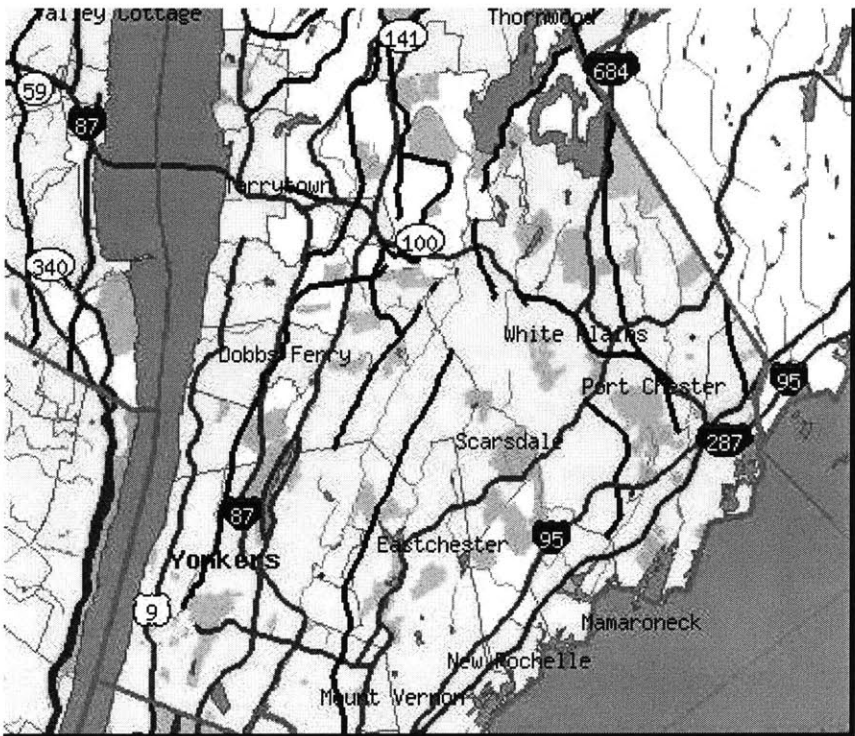

Figure 4-1: The Lower Westchester County Network

The network is represented as a set of 579 O-D pairs connected by 1659 directed links. These links represent the physical links on the network, and are further subdivided into 2421 segments to model changing link characteristics.

4.1.2 Data Description and Analysis

This section describes the available Origin-Destination data and traffic sensor data that are required for the calibration.

4.1.2.1 Origin – Destination Data

The New York Metropolitan Transportation Council (NYMTC) data included demand information in the form of very detailed origin-destination (OD) flows. Morning peak (6am-10am) data was used for the analysis.

The data was not suitable for the purposes of this application. In particular, many of the OD flows were not contributing to traffic in the study area. Furthermore, many origins and destinations corresponded to very small areas, thus leading into very small demand flows. Dealing with very small demands in demand estimation and prediction can be problematic.

NYMTC demand information was analyzed and the origins and destinations were aggregated to a manageable set of zones. The total number of OD pairs was thus reduced to 3344. Further analysis of this demand table indicated that most of the OD pairs had demand lower than 100 vehicles (for the entire peak period, i.e. less than 6 vehicles per 15 minute interval). In order to avoid numerical stability issues during the OD estimation and prediction, we decided to further aggregate OD flows. The resulting demand table consists of 579 OD pairs.

Figure 4-2 indicates the O-D pairs for LWC network. The thickness of the lines connecting the origin and destination is a measure of the magnitude of the O-D flow.
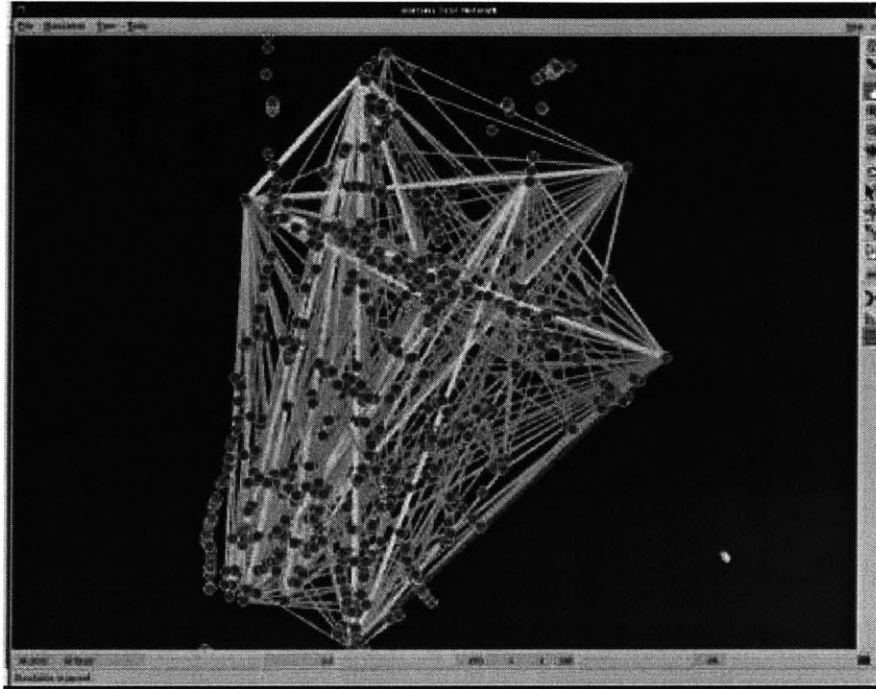
67

Figure 4-2: O-D Pairs for LWC Network

4.1.2.2 Surveillance Data

This section describes the available surveillance data and how it was processed for the purposes of this calibration effort.

Aggregate Archived Data

Aggregate data from 120 sensors were originally provided by NYSDOT. This was later supplemented by data from 12 more sensors, leading to a total of 132 sensors' data. The sensors were located on 4 freeways and 6 parkways in the LWC network. These freeways and parkways include I-87 (the New York State Thruway), I-95 (the New England Thruway), I-287 (the Cross Westchester Expressway), I-684, the Cross County Parkway, the Hutchinson River Parkway, the Bear Mountain Parkway, the Sprain Brook Parkway, the Saw Mill River Parkway and the Taconic State Parkway. No surveillance information was available for several road arteries in the

study network, namely the Bronx River Parkway, 4 adjoining arterials (Tuchahoe Road, Ardsley Road, Hartsdale Road and Weaver Street), Routes 9, 100 and 119. The original data was already aggregated in hourly intervals, and up to three (different) days of data were available for each sensor location.

Table 4-1 presents in detail the spatial distribution of the sensors in the network, as well as the period for which data is available from each sensor. 60 sensors are located on Parkways and the rest of the 72 sensors are located on the parkways. Out of a total of 132 sensors, data from 94 sensors (71%) were collected during 2000, data from 12 sensors (9%) were collected during 2001 and data from the remaining 26 sensors (20%) are from 2002.

Analysis of the available archived sensor data indicated that data from only 58 out of the 132 sensors could be used for the purposes of this study. The remaining detectors were either situated outside the study area, or provided inconsistent data. Table 4-1 shows the distribution of these finally selected sensors on freeways and parkways. 32 sensors are located on freeways while the remaining 26 sensors are located on parkways. Out of 58 usable sensors, 42 sensors' data (73%) were collected during 2000, 2 sensors' data (3%) were collected during 2001 and the remaining 14 sensors (24%) were collected during 2002. The location of sensors in the final network is shown in Figure 4-3. Furthermore, a detailed analysis of the traffic sensors' data is provided in Appendix C.

Time Horizon for All Sensors Data Collection

Freeway Sensors	Total Sensors	Jun-00	Jul-00	Aug-00	Sep-00	Oct-00	Nov-00	Dec-00	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01	Sep-01	Oct-01	Nov-01	Dec-01	Jan-02	Feb-02	Mar-02	Apr-02	May-02	Jun-02	Jul-02	Aug-02	Sep-02
I-87/NYS Thruway	14						4											2											8
I-95	18						12																						6
I-287/Cross Westchester Express	14						8												4										2
I-684	14					12										2													
Total Freeway sensors	60																												
Parkway Sensors																													
Saw Mill River Parkway	14			6		6											2												
Bear Mountain Parkway	4	2																						2					
Cross Country Parkway	2					2																							
Taconic State Parkway	18	18																											
Sprain Brook Parkway	12			6		4											2												
Hutchinson River Parkway	22	12				2																			8				
Total Parkway Sensors	72																												
Total Sensors	**132**																												

Time Horizon for All Sensors Data Collection

Freeway Sensors	Total Sensors	Jun-00	Jul-00	Aug-00	Sep-00	Oct-00	Nov-00	Dec-00	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01	Sep-01	Oct-01	Nov-01	Dec-01	Jan-02	Feb-02	Mar-02	Apr-02	May-02	Jun-02	Jul-02	Aug-02	Sep-02
I-87/NYS Thruway	11						4																						7
I-95	16						12																						4
I-287/Cross Westchester Express	4						3												1										
I-684	1					1																							
Total Freeway sensors	32																												
Parkway Sensors																													
Saw Mill River Parkway	7			4		2											1												
Bear Mountain Parkway	0																												
Cross Country Parkway	0																												
Taconic State Parkway	1	1																											
Sprain Brook Parkway	2			1		1																							
Hutchinson River Parkway	16	11				2																			3				
Total Parkway Sensors	26																												
Total Sensors	**58**																												

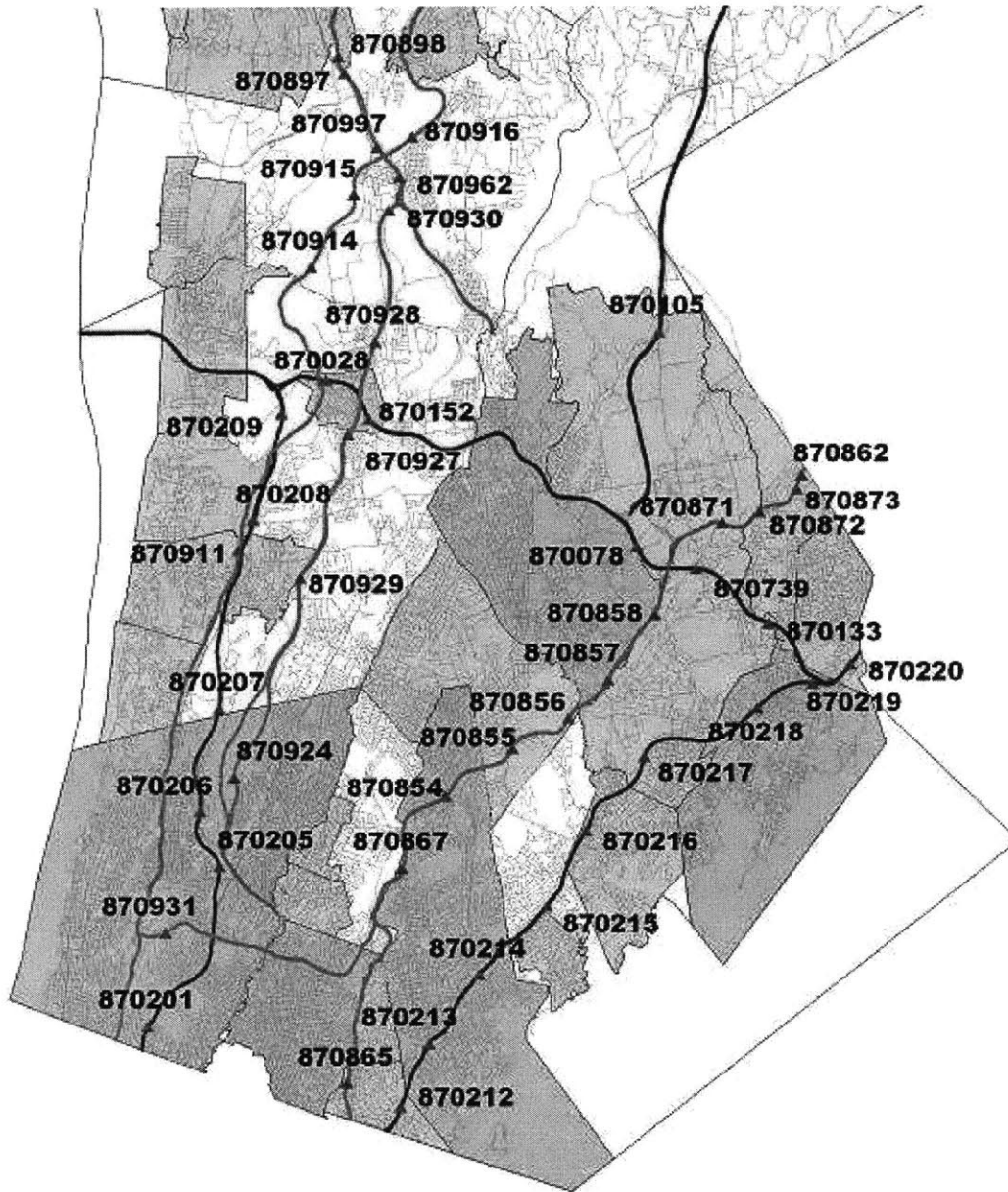Table 4-1: Total (top) and Usable (bottom) Sensors Received from NYSDOT

Figure 4-3: Location of Sensors on the LWC Network

Figures 4-4 and 4-5 show examples of freeway sensors count variability and Figure 4-6 shows parkway sensor count variability. Some of the conclusions about the traffic pattern can easily be drawn from these graphs. The maximum count reported by sensors, during peak hours, on most of the freeways is between 5000 to 6000 vehicles per hour. Maximum count reported by most of the parkways is between 3000 to 6000 vehicles per hour, depending on their location on the network. Most of the sensors report morning peak between 7 AM to 9 AM and evening peak between 4 PM to 6 PM. Figure 4-4 clearly indicates that morning peak sensor count on I-95 in North-bound direction is much higher than the South-bound direction count, and vice versa for evening peak hour. It is also observed that sensor counts never go below 1000 vehicles per hour at this section of I-95, making I-95 as a high traffic volume part of the network. Figure 4-5 shows the distribution of sensor counts in East-bound and West-bound direction, for a sensor on I-287. Unlike the I-95 sensor discussed above, there is not much of a difference in the morning and evening traffic volume at that section, in both the direction. Figure 4-6 shows a sensor count distribution on Saw Mill River Parkway, which shows that evening peak has more traffic in North-bound direction compared to morning and vice versa for South-bound direction traffic.
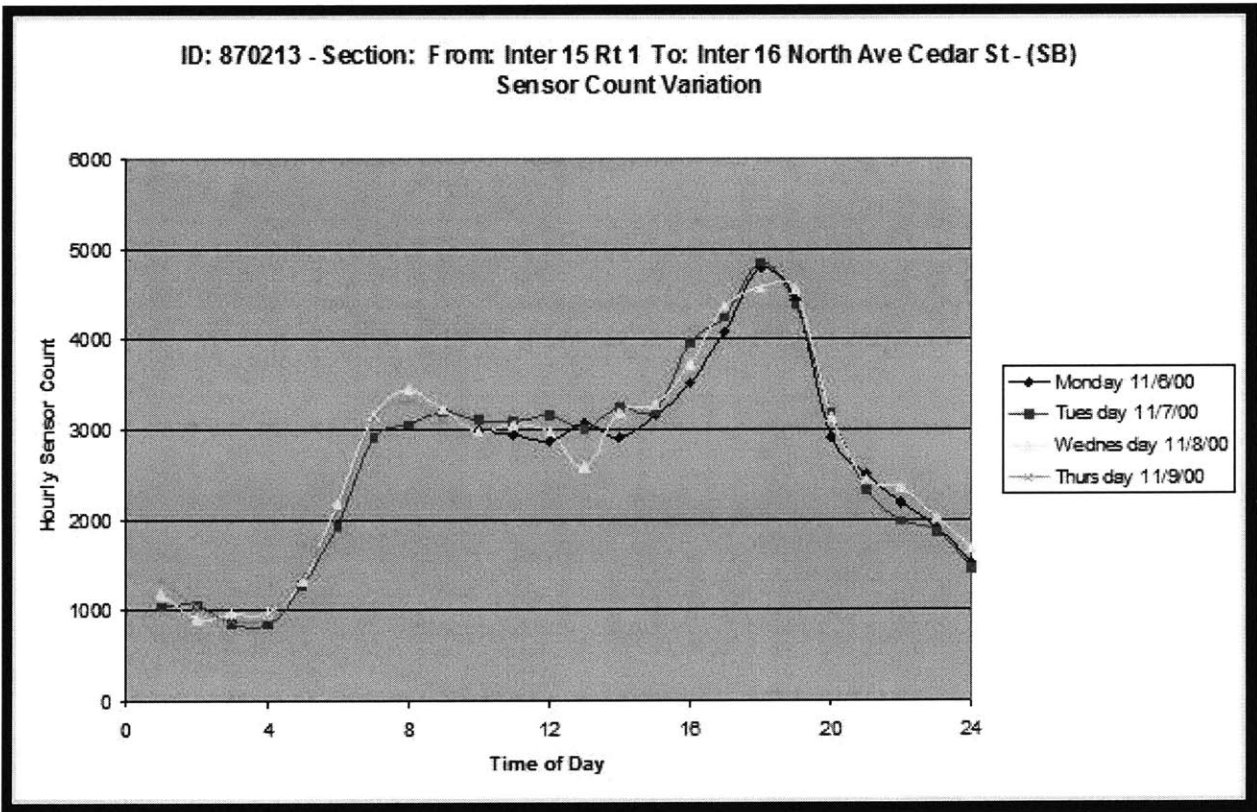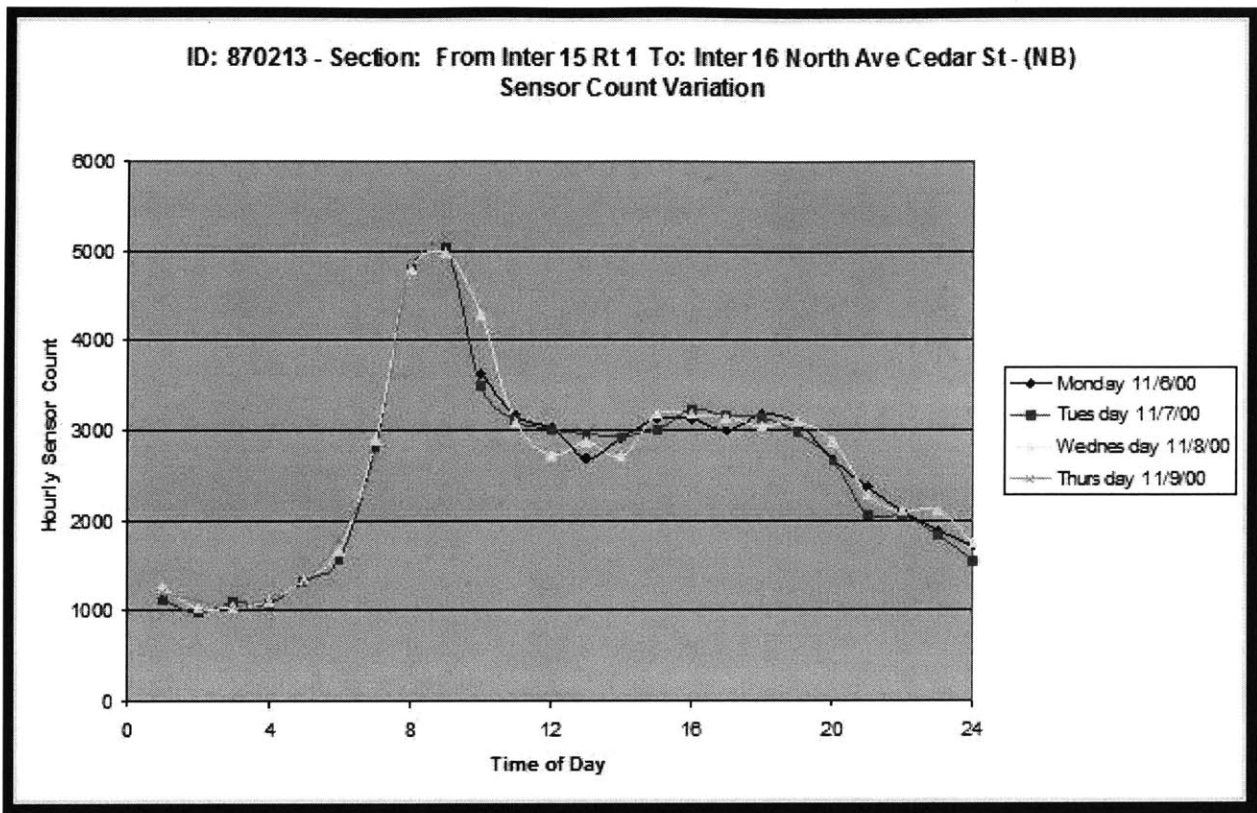
Figure 4-4: Sensor Count Variation for a Freeway (I-95, North and South Bound) Sensor

ID: 870739 - Section: From Acc Hutchison River Pkwy To: Acc Rt 120 - (EB)
Sensor Count Variation

ID: 870739 - Section: From: Acc Hutchison River Pkwy To: Acc Rt 120 - (WB)
Sensor Count Variation
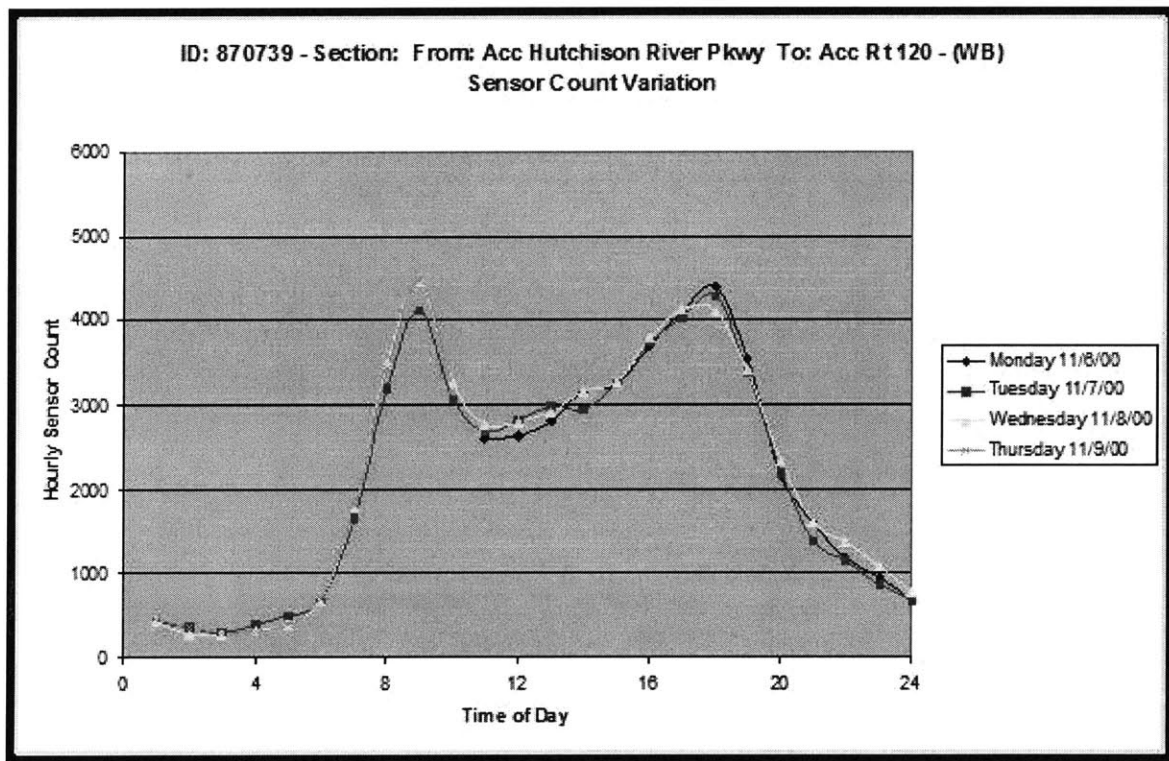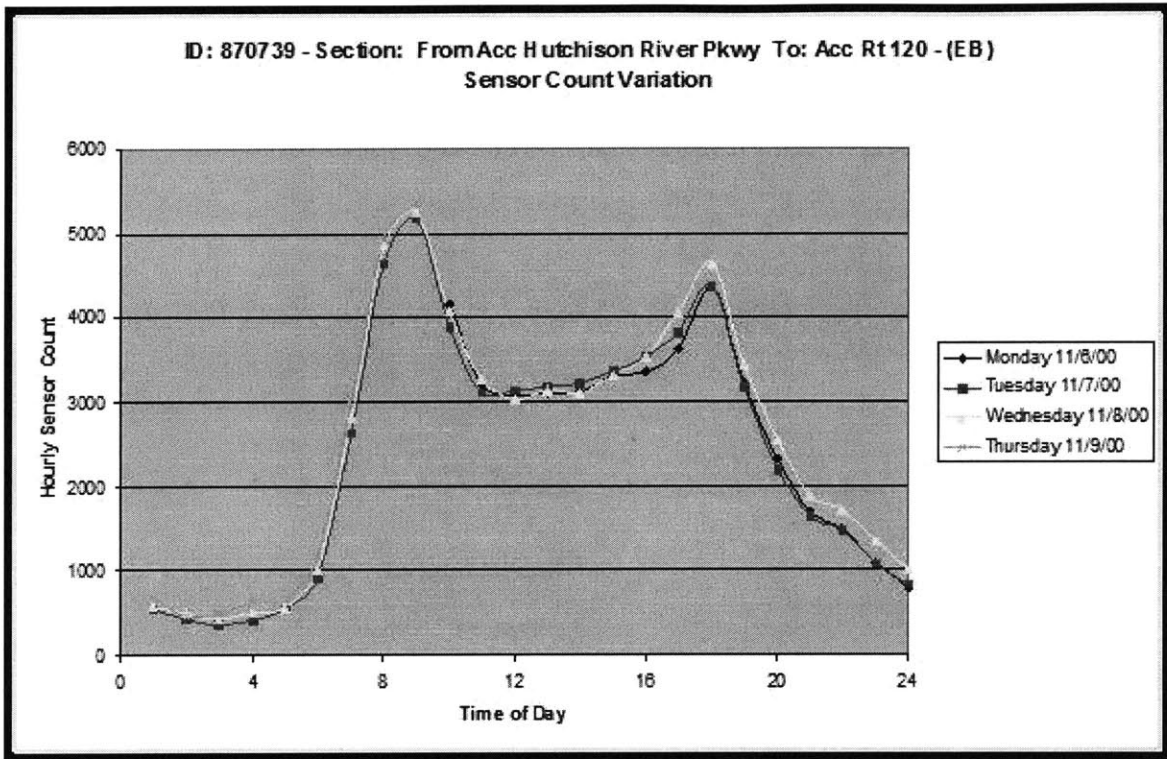
Figure 4-5: Sensor Count Variation for a Freeway (I-287, East and West Bound) Sensor
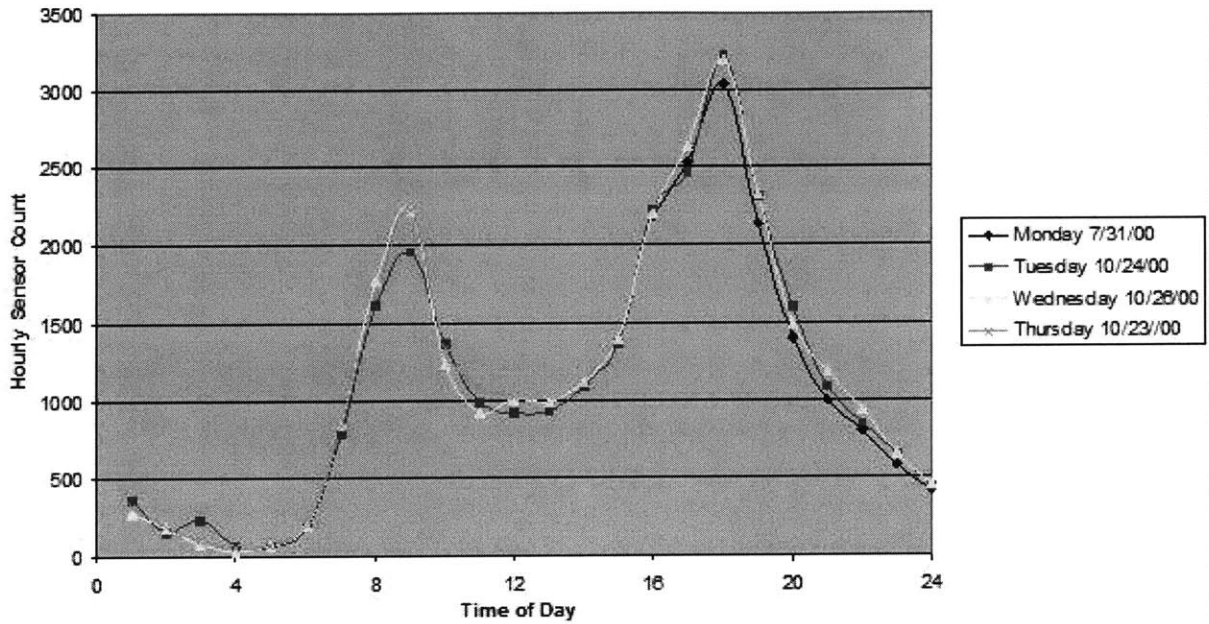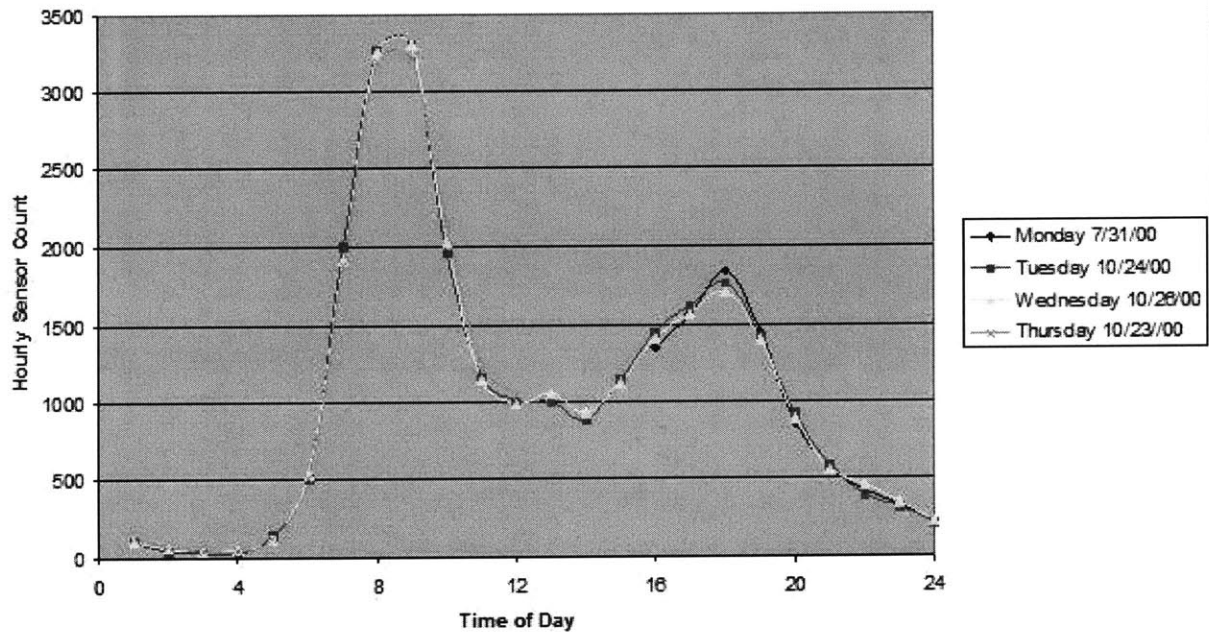
Figure 4-6: Sensor Count Variation for a Parkway (Saw Mill River Parkway, North and South Bound) Sensor

Issues and Assumptions Regarding Traffic Sensor Data

There were some important issues associated with traffic sensors data received from NYSDOT. Due to unavailability of TRANSMIT data from NYSDOT, loop detectors (sensor counts) data collected at different points over LWC network was provided by the NYSDOT, for the purpose of calibration and response strategies. All the sensor counts are from weekdays aggregated for a period of 1 hour. Most of the sensors have at most 3 days of data but sensor counts for different sensors have been recorded on different dates.

Therefore, there were two major challenges for incorporating these sensors counts into DynaMIT. First, DynaMIT needs sensor counts for finer interval for its estimation and prediction models. Unavailability of finer counts lead us to make required changes in DynaMIT so that it can take into account hourly sensor counts for its estimation and prediction.

Second, since sensor counts are from different dates and years (Table 4-1), this will again require a methodology for pooling the data. This was the bigger task, as for good calibration results we require traffic sensor data on similar time periods. As a result of this, a traffic sensor count variation was observed and studied at different locations over the network. It was important to see if there are traffic demand pattern changes over the three years (2000, 2001 and 2002), and how to account for these changes if they are present. As a result of this analysis it was found that Wednesday is the only common weekday where all the sensors have data, although for different years and dates as said above. We decided to look at sensors data on this day only as it will provide better comparisons for traffic demand pattern. Some of the sensors that were showing major differences in the sensor count value as well as variation were removed from the analysis, as it will be difficult to capture these differences over the years when we have only one weekday of data for calibration purposes. As said above, after these analysis only 58 sensors out of 132 sensors reported usable data. Although these 58 sensors were from different years, it was observed that traffic demand pattern is comparable for calibration purposes. As a result, it was decided to pool all the different Wednesday sensors data together and to consider it as a single day of sensor data. This is a very crude assumption but nothing else could be done, given the quality and availability of data. Moreover,

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changes in the traffic demand pattern were not very significant for 58 usable sensors. It reinforces our assumption of pooling different Wednesday data into a single day.

Acoustic Sensor Data

In order to estimate various supply simulator parameters (various speed-density relationship parameters like, jam density, parameter α and β, minimum speed, free flow speed), we need to have a detailed traffic sensor data that also have occupancy and speed measurements, other than just counts. Estimation of these supply parameters is very critical in order to replicate the field traffic conditions. Although we need detailed traffic sensors data at different locations over the network for estimating supply parameters for different segments, only one detailed traffic sensor data was provided by NYSDOT. This sensor is located near Exit 5 on I-287 Eastbound freeway and it uses acoustic relationships to calculate counts, occupancy and speed of the vehicle. Many days of data (including weekdays and weekends) from the month of August and November in year 2002 were provided by the NYSDOT. This acoustic sensor reports enormous amount of data at random intervals like 7, 11, 23 seconds etc.

Sensor data was processed and the graph for the day of November 8 (Friday), 2002 is shown in the Figure 4-7. There are 3 lanes at that section of the freeway. Flow is calculated by aggregating one-minute counts and scaling it to hourly value. Average speed for that minute is calculated by dividing the product of counts and speed by total number of vehicles reported during that minute. Classical flow-speed-density relationship (flow = density x speed) has been used to get an idea about the density variation. Figure 4-8 shows the aggregated hourly sensor counts variation with the time of the day. It is clear from the Figure 4-7 and 4-8 that values reported by the sensor are erroneous. As you can see from the Figure 4-8, hourly counts (10,000 – 12,000 per hour) reported at that location is much higher than the expected value for 3 lanes. Figure 4-7 shows the counterintuitive speed-density and speed-flow diagram. Problems with data quality were discussed with NYSDOT, who acknowledge that the data reported by the acoustic sensor is not correct.

Due to this problem the acoustic sensor data is not been used for estimating supply simulator parameters. Instead, some default widely accepted values of these

parameters were tried, and finally supply parameters value from Irvine, CA network were used. Irvine network is an urban network consisting of freeways and arterials, which is similar to LWC network.
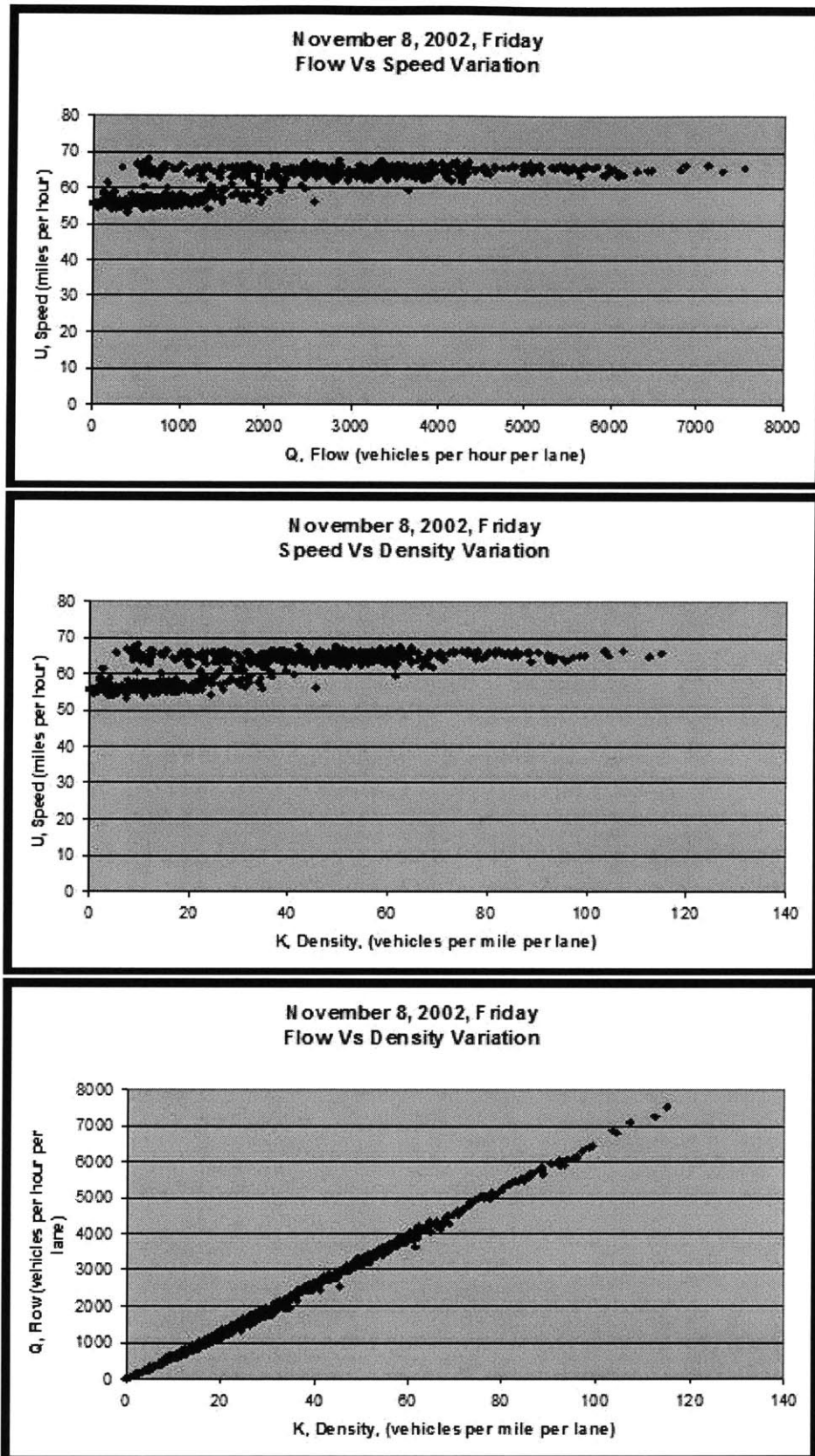
Figure 4-7: Speed-Density-Flow Variation from Acoustic Sensor Data, located near Exit-5 on I-287 Eastbound Freeway
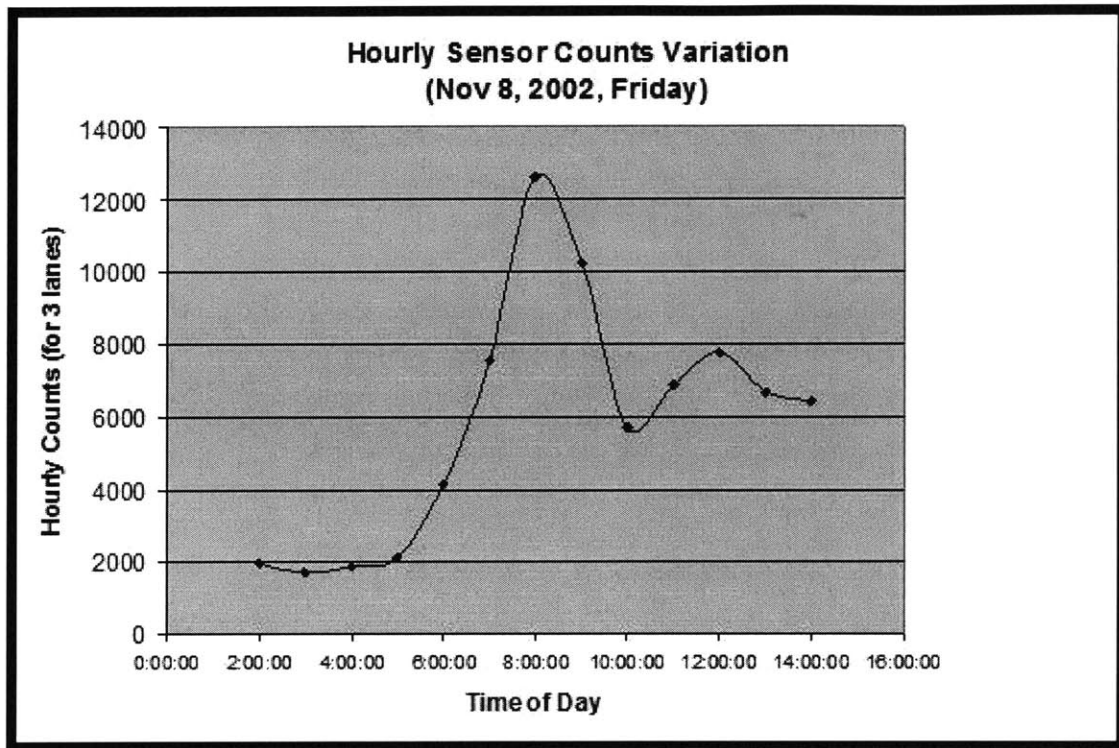
**Hourly Sensor Counts Variation
(Nov 8, 2002, Friday)**

Figure 4-8: Hourly Sensor Count Variation

4.1.3 Network Data and Network Preparation

This section focuses on the available data for network generation. The network representation of the study area was based on geographic information from New York Metropolitan Transportation Council (NYMTC), web-based resources, and additional information and feedback provided by NYSDOT. These data sources are described in the following subsections.

4.1.3.1 NYMTC Data

A large amount of data was provided to MIT in 2000. This data was not suitable for the purposes of ITS applications and substantial work was performed to process this data. The main issues were that the data covered many areas outside the scope of the current

project and also included irrelevant information. The data was processed and reduced to the appropriate scope and level of detail.

While the NYMTC data was complete, they were combined with U.S. Census TIGER files and geographic files provided with the TransCAD software. The additional data sources were helpful as references and mapping tools.
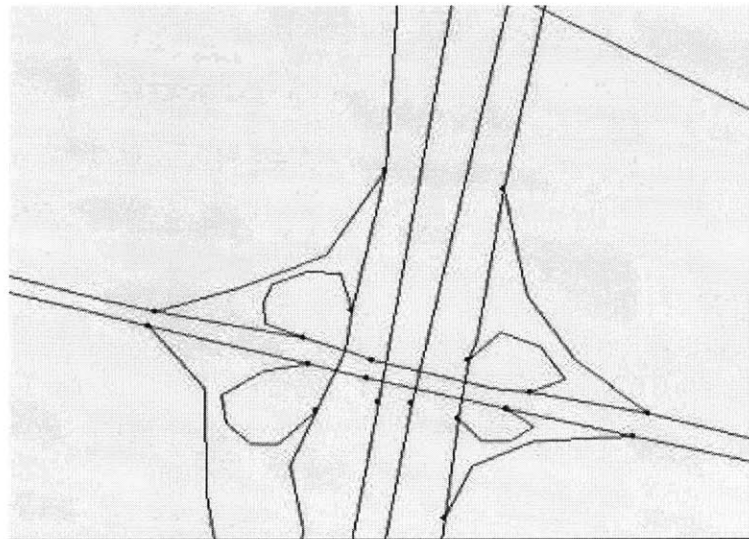

Figure 4-9: NYMTC Representation of Interchange of I-87 with Cross County Parkway

One major shortcoming of these data pertains to the detail with which the network is represented. In particular, since this data is usually used for planning applications, the network is represented as a collection of links and nodes. As shown above (Figure 4-10), however, the mesoscopic models within DynaMIT's supply simulator require a more detailed representation of the network topology. The next subsection describes additional sources of geographical data.

4.1.3.2 Additional Geographical Data

As mentioned above, the NYMTC data does not provide the necessary detail for the network representation in DynaMIT. Therefore, additional information sources were sought. From the publicly available sources, we selected the following two:

- New York State GIS Clearinghouse (http://www.nysgis.state.ny.us/)
- GlobeXplorer (http://www.globexplorer.com)

These two resources provide detailed ortho-photos that include the study area. This information was used to verify the topology of some complicated interchanges, as well as details not available in the NYMTC data (including lane connectivity, ramp topology, and curvature; see Figure 4-11).

Figure 4-10: Ortho-picture of Interchange of I-87 with Cross County Parkway from GlobeXplorer

4.1.3.3 Network Generation

One of the most important inputs to DynaMIT is the network representation of the study area. The available data sources have already been presented in Section 4.1.3.1 and

Section 4.1.3.2. Furthermore, a number of software tools have been used in the generation of the network representation:

- Caliper's TransCAD was used for viewing and manipulation of the original NYMTC GIS files. Information was exported from TransCAD in various formats for further processing in other tools.

- Microsoft Excel was used for the analysis of geographic data exported from TransCAD.

- RNE, the graphical network editor developed at MIT ITS Program, was used for the generation of the final network file in DynaMIT format.

The first step was the generation of a skeleton network file in TransCAD. Starting from the raw NYMTC data set, all links that were outside of the study area were removed. Furthermore, local streets that are not being modeled were also removed. The resulting network captured most of the traffic network of the study area but was still not complete and lacked the level of detail required by DynaMIT.

The data was exported in a suitable format and then imported to Excel for further processing. Links in the original NYMTC data were coded as bi-directional links. DynaMIT, however, requires that each bi-directional link is substituted by two single-directional links. Furthermore, some information on some of the links was missing.

Using detailed information from the GIS resources available from the web (see Section 4.3.1.1), the missing information was completed. The skeleton network representation was then converted to the DynaMIT network file format using a software utility that was developed for this task.

The final stage of the network coding was performed using the graphical road network editor. Additional details of the network representation were added to the network. In particular, interchange representation was considerably improved, lane connections were generated, and segment curvatures were introduced (Figure 4-12). (All this information was not present in the NYMTC data). The completed network was presented to NYSDOT and feedback was obtained. As a result, an additional number of arteries were added. Furthermore, the first simulation using this network indicated that there was a lack of horizontal arteries. In cooperation with NYSDOT a number of such arteries were identified and added.

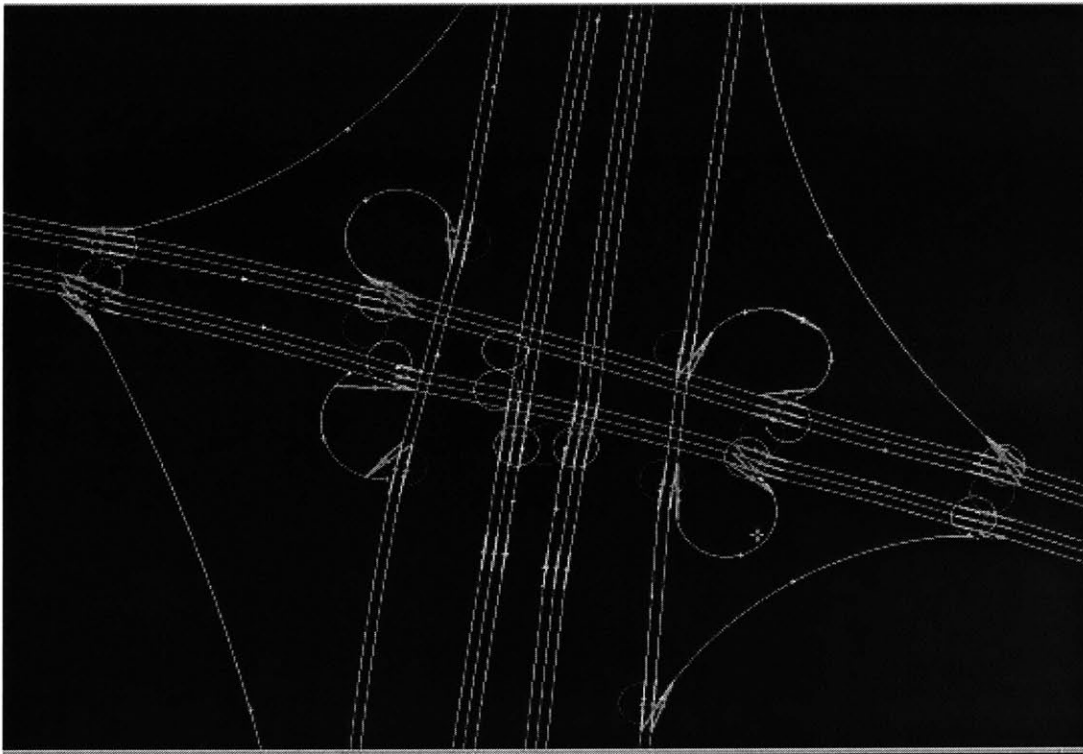Final network details used for calibration of DynaMIT are:

- Number of Links = 1659
- Number of Segments = 2421
- Number of lanes = 5242
- Number of OD Pairs = 579
- Number of Sensors = 58
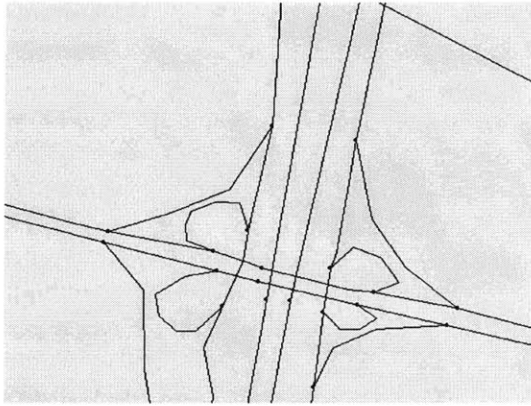
TransCAD Image of Interchange of I-87 with Cross County Parkway

GlobeXplorer Image of Interchange of I-87 with Cross County Parkway

Screen-shot of the same Interchange in Graphical Road Network Editor
(RNE)

Figure 4-11: Example of using TransCAD and GlobeXplorer Image to Construct Detailed Interchange required for the purpose of Traffic Modeling in DynaMIT.

4.2 Calibration Results

Before DynaMIT-P is employed, a critical task is the calibration of the system. The Following section covers the calibration results. The input files required for DynaMIT-P run and calibration are described in Appendix A.

4.2.1 Supply Simulator Parameters

As mentioned above, the supply parameters that need to be calibrated are the:

- capacities of the network segments, and
- parameters of the speed-density relationships.

The values for the capacities of the network segments have been computed based on the Highway Capacity Manual (Reference [11]). In particular, the resulting values for the freeways are 2200 vphpl (vehicles per hour per lane), while for the arterials (Tuchahoe Road, Ardsley Road, Hartsdale Road and Weaver Street) and routes 9, 22, and 100, was set to 1900 vphpl. Ramp capacities were set to 1600 vphpl or 1800 vphpl depending on the location and geometry of the ramp.

Detailed speed and occupancy data are required for the calibration of speed-density relationship parameters. From the available data, only the acoustic sensor data was conceptually appropriate for this purpose. However, analysis of this data provided counterintuitive results, thus indicating that the data is not very reliable. In particular, the measurements obtained from these sensors violated the fundamental traffic principles. These issues have been demonstrated in Section 4.1.2.2.

As a result, it was necessary to transfer values from other applications. This is admittedly a difficult exercise and should always be performed with extreme caution. Based on previous calibration experience from similar networks (e.g. the Irvine, CA, network, which is also a very congested, suburban network composed of freeway and arterial routes) appropriate values were selected for the model parameters. Extensive tests were performed to ensure that the parameters adequately capture prevailing traffic conditions.

The speed-density relationship parameters are shown in the following table. Different sets of parameters were selected for freeways, arterials and ramps.

	Free Flow Speed u_f (mph)	Minimum Speed u_{min} (mph)	Jam Density k_{jam} (vpmpl)	Minimum Density k_{min} (vpmpl)	Parameter α	Parameter β
Freeways	65	20	0.125	0.015625	2.0	0.5
Arterials	50	20	0.0625	0.00625	1.5	0.32
Ramps	45	20	0.125	0.0125	1.5	0.3

Table 4-2: Speed Density Relationship Parameters per Road Type.

where,

mph = miles per hour,

vpmpl = vehicles per meter per lane

4.2.2 Demand Simulator Parameters

4.2.2.1 Defining the Period of Study and Generating Seed O-D Flows

The period of study was defined as the AM peak, from 6:00 AM to 10:00 AM[3]. However, it had to be ensured that the first interval we estimated should not start with empty network. As a result few runs of DynaMIT were made for 4 AM[4] to 6 AM interval in order to have a starting network state, loaded with vehicles at 6 AM when we start doing our calibration. The study interval was divided into equal subintervals of duration of 60 minutes. This discretization was based on the fact that we have only 60 minutes sensor counts data, and finer sensor data was unavailable. A reasonable starting estimate of the O-D flows was constructed manually to start the O-D estimation process. The planning matrix of static O-D flows of 4 hours duration (this static O-D flows from 6 AM to 10 AM was based on the NYMTC data) was distributed across the time intervals within the study period. The fraction of flow assigned to a particular interval was proportional to a factor that was computed for each sensor as the ratio of the counts measured in the current interval to that measured across the peak period (6 AM – 10 AM). This factor for each O-D flow was approximated by considering an average of the primary sensors that measured the O-D flow under study.

4.2.2.2 Parameters for Path Choice Set Generation

An important step in the calibration process was the generation of a good set of paths for each O-D pair of interest. Optimum parameters for the path generation algorithm were identified so as to capture most of the feasible paths for every O-D pair. A suitable path set was obtained using 40 random draws to complement the set of link-elimination-based shortest paths from every link to a destination node. Recognizing the need to replicate

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[3] Flows were found to drop beyond 10:00 AM.
[4] Sensors indicated that network was predominantly empty at 4:00 AM.

most of the freeway-based paths, an internal freeway "bias" of 0.6 was used to force the path generation algorithm into preferring paths with longer freeway sections. The random draws helped augmenting this set with arterial paths. Manual inspection confirmed that most of the practical alternatives had been selected in the path generation stage. The final set contained a total of 7541 paths between 579 origin-destination paths.

4.2.2.3 Simplifying Assumptions

Several assumptions were made in order to accommodate practical considerations while estimating the model parameters with the limited data available. The error covariance matrices V_h and W_h (section 3.2.1.1) were assumed to possess a diagonal structure, in order to ensure that we had enough observations to estimate the elements of these matrices from just one day of data. The structure of the error covariances was also assumed to remain constant across the peak period. The autoregressive factor was assumed to be of degree one, meaning that the deviation of flow between O-D pair r from their historical values does not depend on the prior interval flow deviations between the O-D pair r. The O-D flows themselves were further grouped into high and low categories, based on the magnitude of the OD flows that they represented.

4.2.2.4 Error Statistics

The following error statistics were used in analyzing the results:

1. Root Mean Square (RMS) Error = $\sqrt{\dfrac{\sum_i (y_i - \hat{y}_i)^2}{N}}$

2. Root Mean Square Normalized (RMSN) Error = $\sqrt{\dfrac{N \sum_i (y_i - \hat{y}_i)^2}{\sum_i y_i}}$

where,

N = number of observations,

y_i = observed value,

$\hat{y}_i$ = estimated value,

4.2.2.5 O-D Estimation and Route Choice Parameters Values

As mentioned during the surveillance data analysis (section 4.1.2.2), data collected during Wednesdays was used for the calibration. The seed O-D flows computed from the static planning matrix were used as the input for the O-D estimation module. In the absence of any initial error covariance estimates, a weighted least squares approach was adopted, with the sensor counts being assigned higher weights than the target O-D flows. This step was employed in order to extract all the O-D flows information from the sensor counts, while obtaining structural information about the overall demand distribution from the seed O-D flows. The weights used for the O-D flows were not kept constant across the O-D pairs. Low flows (as indicated by the planning matrix) were assigned higher weights in order to maintain them in an acceptable range, and capture the fact that such flows normally exhibit low variability. As pointed in section 3.2.1.1, flows for each time interval were estimated sequentially using the GLS formulation.

As discussed in the chapters 2 and 3 (Figure 2-3 and Figure 3-3), problem of OD estimation is a fixed-point problem. The solution of OD estimation is obtained by an iterative process between the OD estimation algorithm and the supply simulator, linked by an assignment matrix. The planning OD was updated based on the framework shown in Figure 3-3. Several iterations of OD estimation and equilibrium travel times computation were performed until the overall convergence criterion was satisfied. At the end of this procedure, we had a set of equilibrium travel times and the final estimated OD.

The computation of the equilibrium travel times and the results obtained are described with respect to some important OD pairs for the LWC network. Figure 4-13 illustrates these origin and destination nodes along with a sample of paths in the path choice set of the OD pair 4-6. Origin nodes are numbered as 1, 2, 3 and 4, and destination

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nodes are numbered as 5, 6, and 7. Origin nodes 1, 2, 3 and 4 are grouped together for the analysis; since these nodes have similar characteristics in terms of demand, travel times, number of paths, etc. Figure 4-14 shows the equilibrium travel times (after convergence) for these OD pairs, during the peak demand period from 7:00 AM to 10:00 AM.
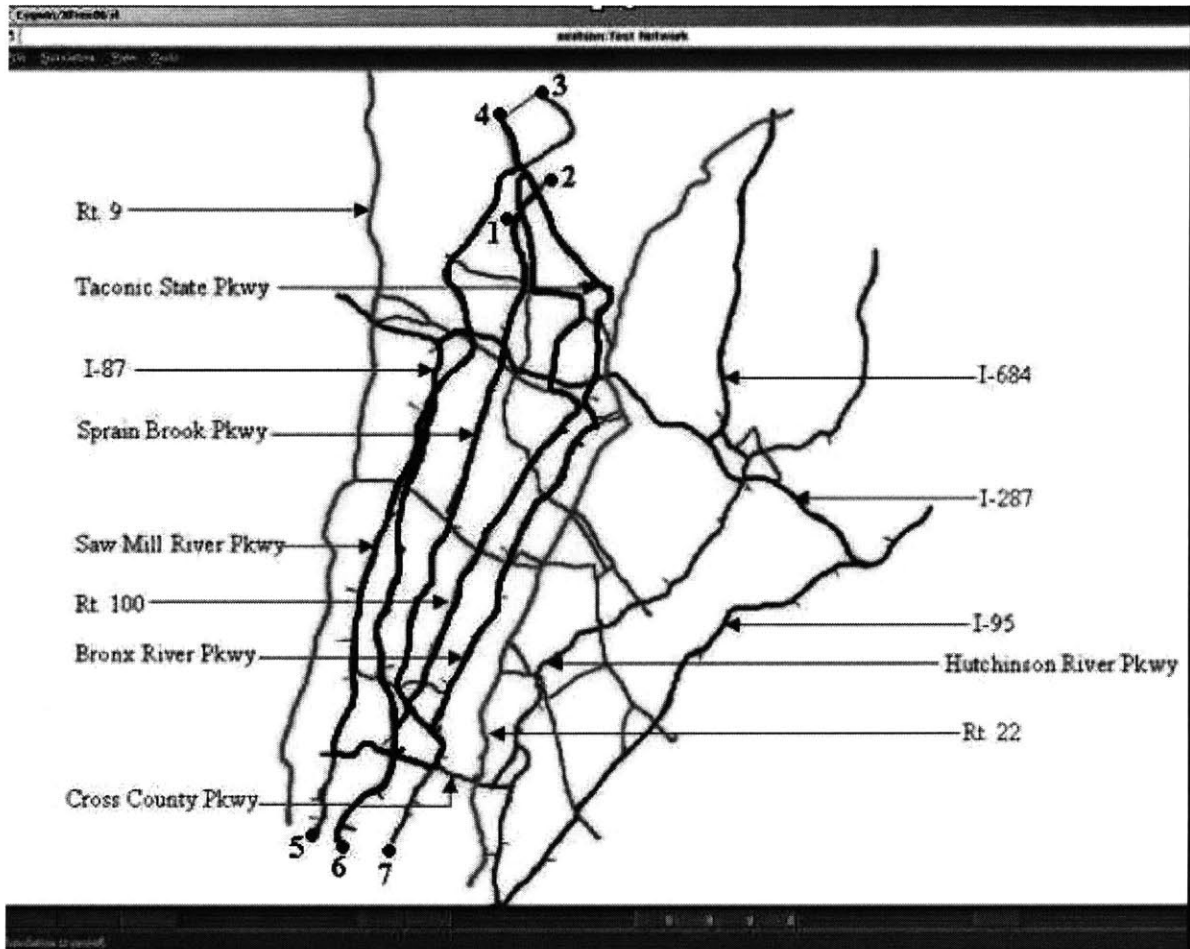

Figure 4-12: Network showing Origin Nodes (1,2,3,4) and Destination Nodes (5,6,7); Examples of Paths for the OD pair 4-6.
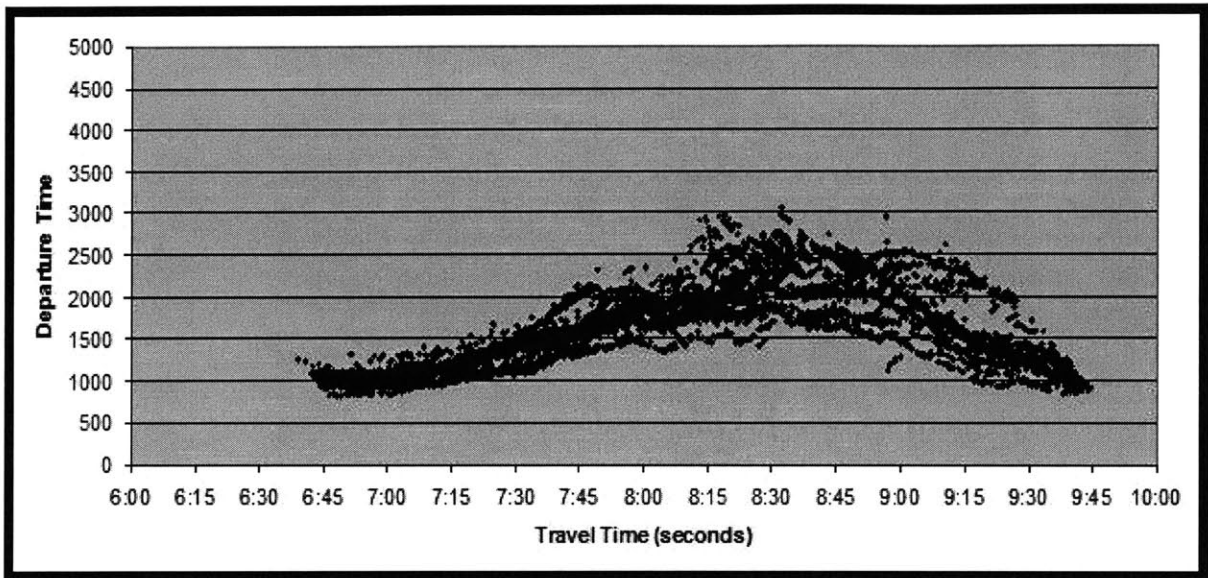
Figure 4-13: Travelers' Equilibrium Travel Times (after convergence) between all OD Pairs "1, 2, 3, 4 – 5, 6, 7".

Figure 4-15 shows another set of OD pairs ("1, 2, 3, 4, 8 – 9, 10, 11") that were considered for the equilibrium travel times computation analysis, along with the examples of paths between these OD pairs. Origin nodes are numbered as 1, 2, 3, 4 and 8, and destination nodes are numbered as 9, 10, and 11. Origin nodes 1, 2, 3, 4 and 8 are grouped together for the analysis purpose; since these nodes have similar characteristics in terms of demand, travel times, number of paths, etc. Figure 4-16 shows equilibrium travel times for east-bound travelers between these OD pairs, during the period of 7:00 AM to 9:00 AM.
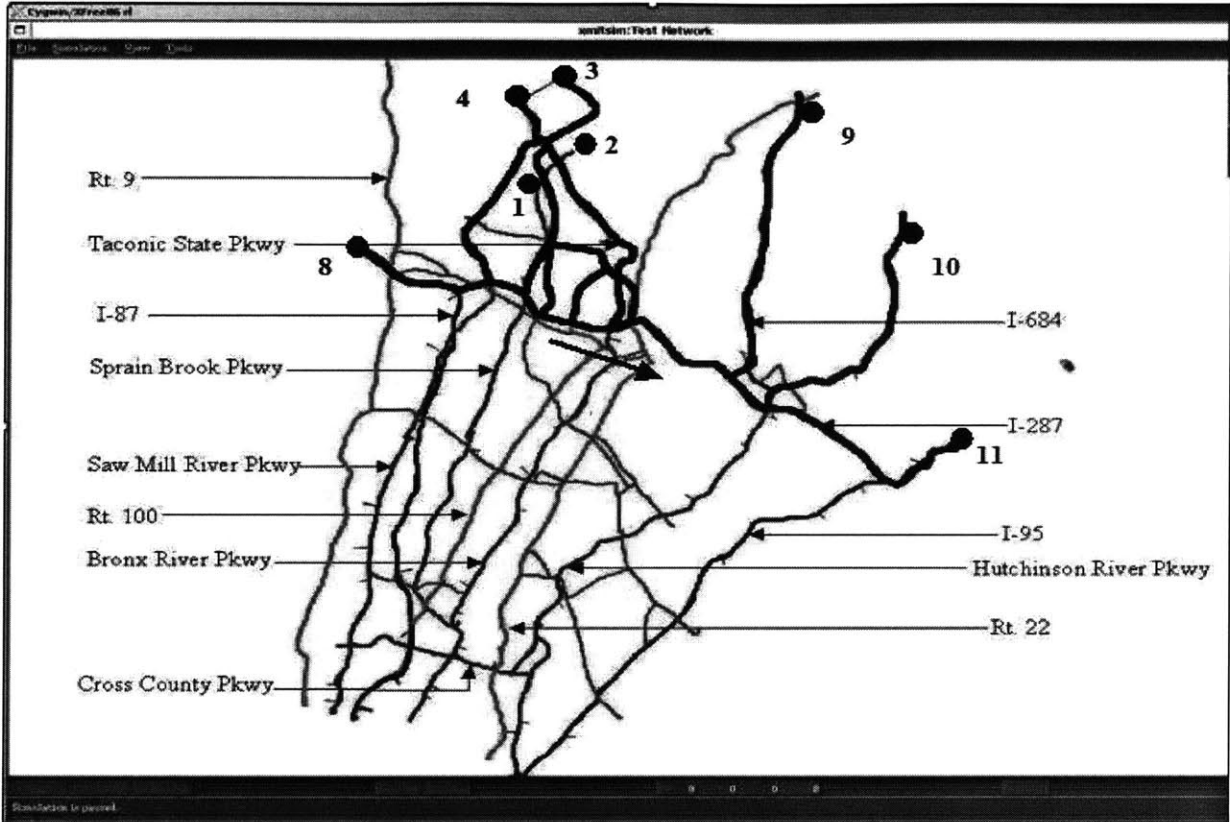
Figure 4-14: Network showing Origin Nodes (1,2,3,4,8) and Destination Nodes (9,10,11); Examples of Paths for the OD pairs is marked with dark color.
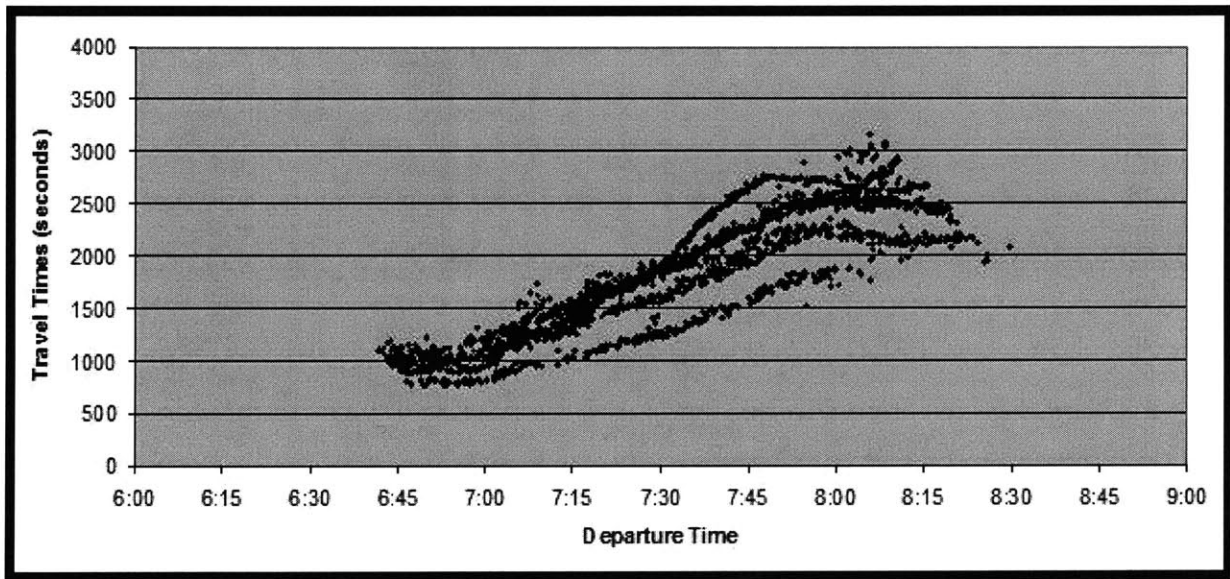

Figure 4-15: Travelers' Equilibrium Travel Times (after convergence) between all OD Pairs "1, 2, 3, 4, 8 – 9, 10, 11".

Several iterations were performed in conjunction with the O-D estimation step to determine an optimal set of parameters for the route choice model. Different combination of parameters β_1 and β_2 (see section 3.2.1.1 and equation (3.3) for details; β_1= coefficient of arterial travel time, β_2 = freeway bias[5]) were evaluated, covering a wide range of route choice situations. One would expect β_1 to have a negative sign and β_2 to be a positive number between 0 and 1. The optimal values for (β_1, β_2) were found to be (-0.025, 0.80).

4.2.2.6 Sensor Counts Comparisons

Figures 4-17 to 4-20 graphically depict the comparison of estimated (simulated) and observed (field) sensor counts during the different intervals in the peak period (6 AM – 10 AM). These graphs represent the final estimated counts when convergence has been achieved (after the final iteration of the calibration phase for each time interval). Counts in the graph represent the hourly counts per lane. In an ideal situation all points in these figures (representing individual sensor measurements) would fall on the "45 degree line", indicated by a thin line in the figures. This line would indicate perfect match between the observed and estimated counts. Furthermore, Table 4-3 shows the final Root Mean Square (RMS) and Root Mean Square Normalized (RMSN) error values after convergence, for each time interval.

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[5] Freeway bias attempts to capture the driver's preference for a freeway section over an arterial section.
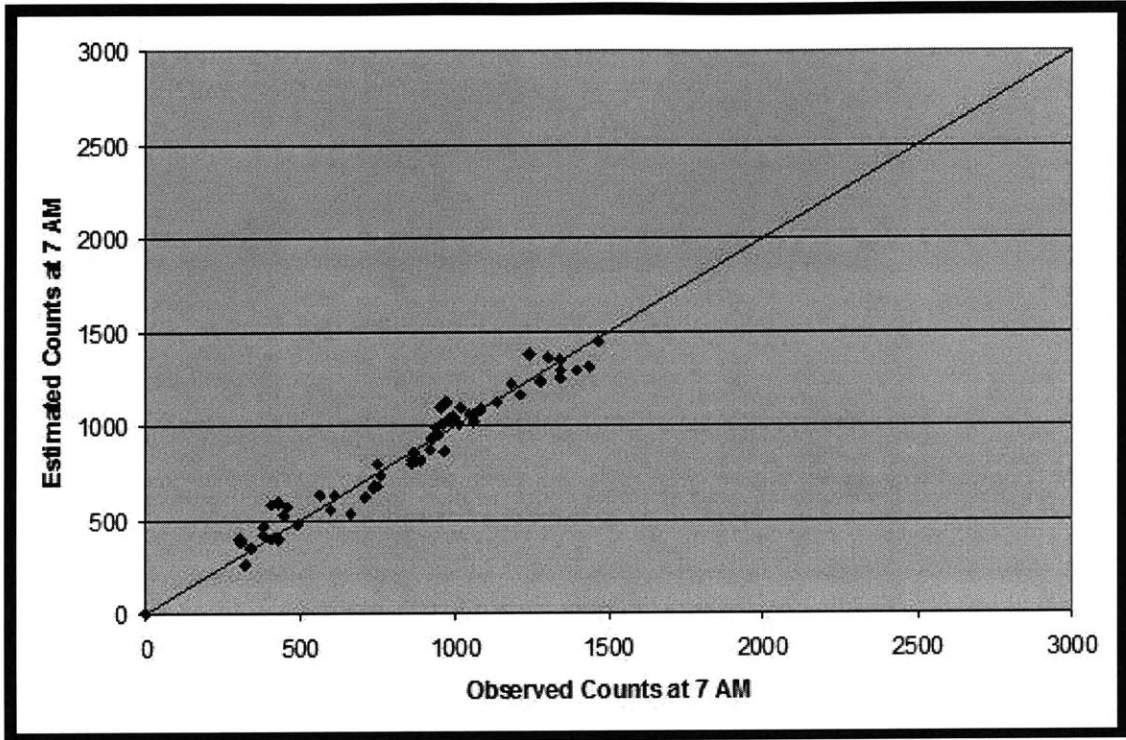
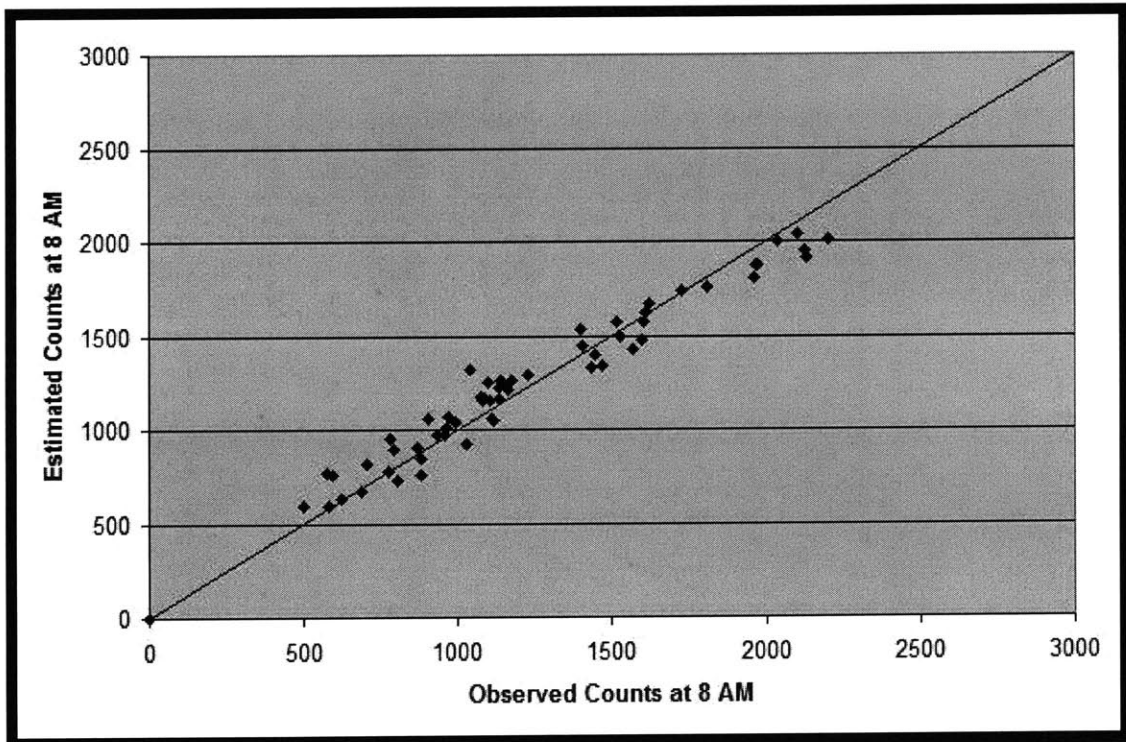Figure 4-16: Estimated vs. Observed Sensors Count from 6:00 AM to 7:00 AM

Figure 4-17: Estimated vs. Observed Sensors Count from 7:00 AM to 8:00 AM
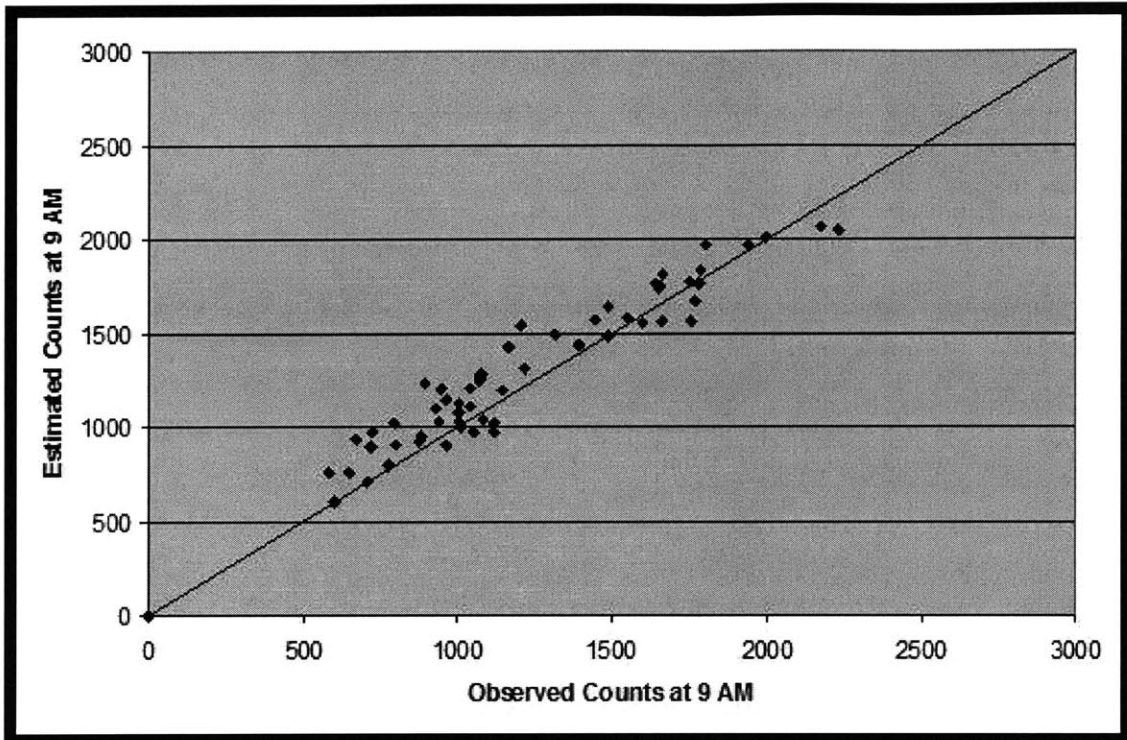
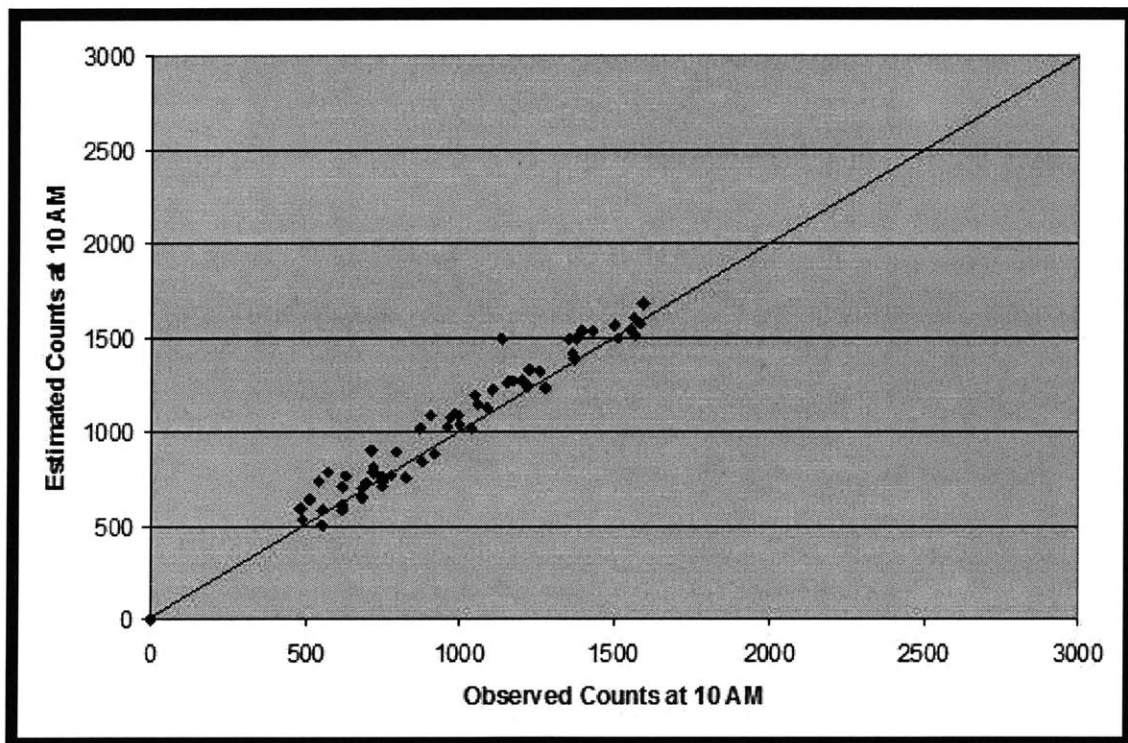Figure 4-18: Estimated vs. Observed Sensors Count from 8:00 AM to 9:00 AM

Figure 4-19: Estimated vs. Observed Sensors Count from 9:00 AM to 10:00 AM

Time Interval	RMS	RMSN
6:00 AM – 7:00 AM	73.2645	19.1538
7:00 AM – 8:00 AM	105.3485	22.7966
8:00 AM – 9:00 AM	145.2776	31.5403
9:00 AM – 10:00 AM	103.9146	25.1304

Table 4-3: Final RMS and RMSN Error for Each Time Interval

4.4 Summary

A brief description of the study network was given first. The data available from various sources and issues associated with data were discussed. Calibration results of the DynaMIT-P for the Lower Westchester County (LWC) were presented, using the methodology described in Chapter 2. Calibration of the DynaMIT-P established two no-incident cases, which will be used for comparing incident scenarios and diversion strategies in the next chapter.

Chapter 5

Case Study

The objective of this chapter is to implement the framework described in chapter 3 for incident scenarios and diversion strategies, using traffic surveillance data obtained from NYSDOT for the Lower Westchester County (LWC) network. The Incident and VMS scenarios are evaluated based on a hypothetical incident on the LWC network. Scenario 1 focuses on the south-bound direction traffic while Scenario 2 focuses on the east-bound direction traffic between major OD pairs. DynaMIT-P has been used to evaluate the predictive information through the VMS.

5.1 Scenario 1

A peak demand period between 7:00 AM and 10:00 AM was chosen for the scenario 1.

5.1.1 No Incident

The experienced travel times and the results obtained are described with respect to some important OD pairs for the LWC network. Figure 5-1 illustrates these origin and destination nodes along with a sample of paths in the path choice set between OD pair 4-6. Origin nodes are numbered as 1, 2, 3 and 4, and destination nodes are numbered as 5, 6, and 7. Origin nodes 1, 2, 3 and 4 are grouped together for the analysis, since these nodes have similar characteristics in terms of demand, travel times, number of paths, etc., and also because demand between a single OD pair is not significant enough to observe the impact of an incident and VMS messages. Figure 5-2 shows the experienced travel times for these OD pairs ("1, 2, 3, 4 – 5, 6, 7).
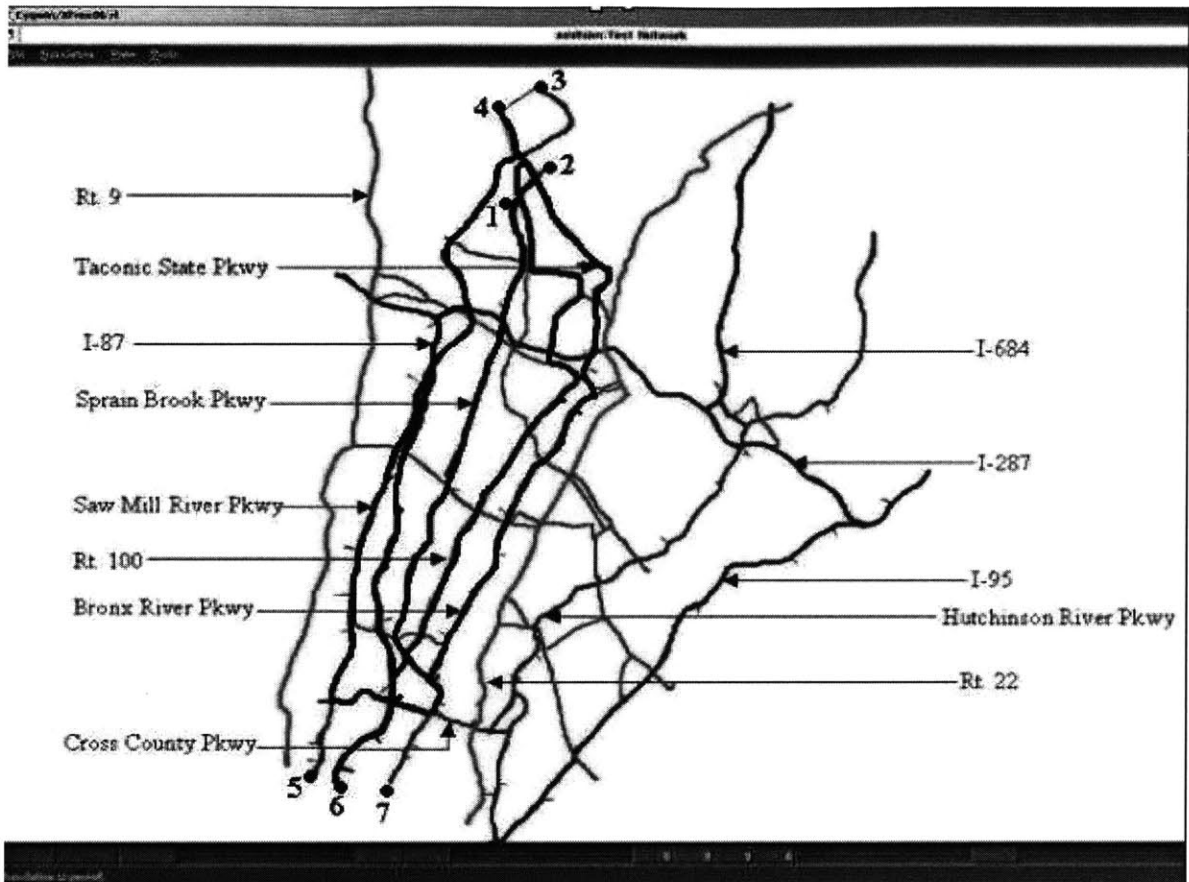
Figure 5-1: Network showing Origin Nodes (1,2,3,4) and Destination Nodes (5,6,7);
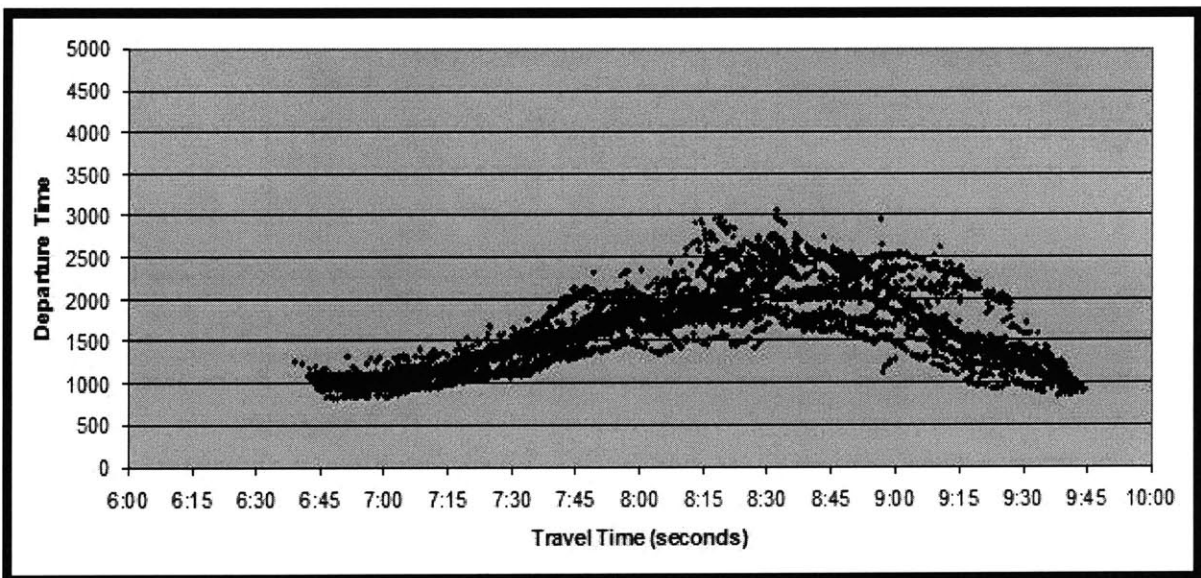Examples of Paths for the OD pair 4-6.

Figure 5-2: Travelers' Experienced Travel Times (after convergence) between all OD
Pairs "1, 2, 3, 4 – 5, 6, 7".

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Figure 5-3 shows that most of the travelers experienced travel times between 1000 and 2000 seconds. Only few travelers experienced low travel times (less than 1000 seconds) and high travel times (more than 2500 seconds). The average travel time experienced at different time intervals is shown in Figure 5-4. As can be seen from the figure, average travel time between OD pairs "1, 2, 3, 4 – 5, 6, 7" increases from 1000 – 1500 seconds (non-congestion time) to 2000 – 2500 seconds (congestion time). For these OD pairs average travel time starts decreasing after 8:45 AM.
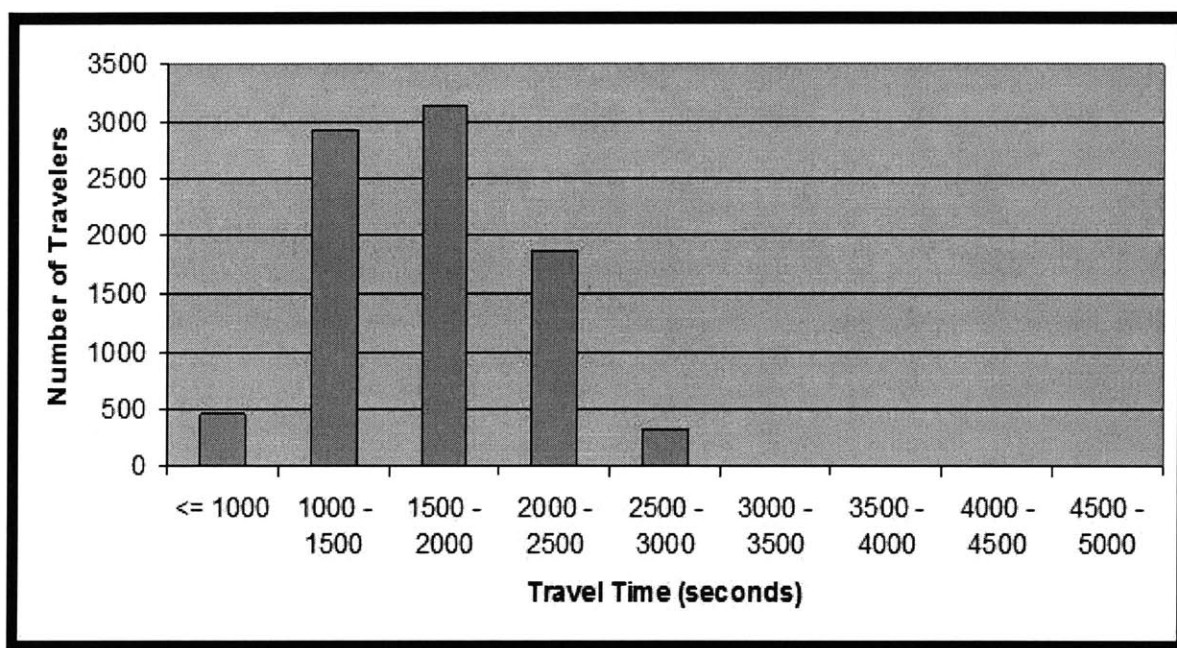

Figure 5-3: Frequency of Experienced Travel Times for all OD Pairs "1, 2, 3, 4 – 5, 6, 7".
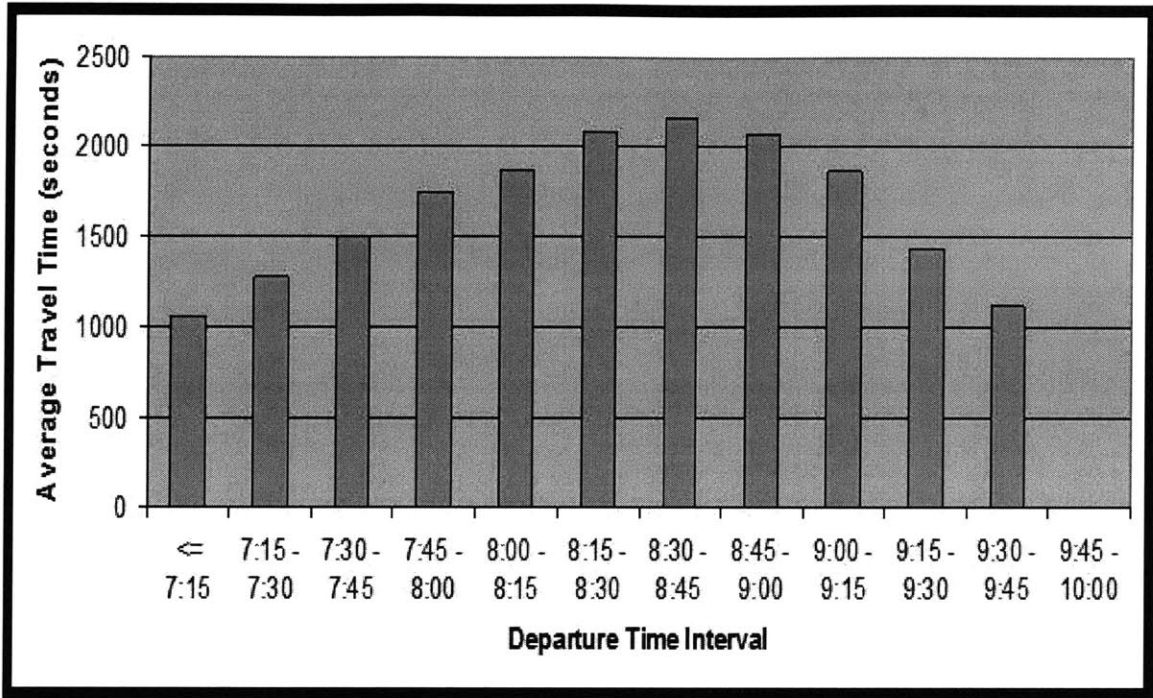
Figure 5-4: Average Travel Times between OD Pairs "1, 2, 3, 4 – 5, 6, 7".

5.1.2 Incident without VMS

This section presents the impact of an incident on the network. The planning OD and the equilibrium travel times obtained from the no-incident-case during the time period 7:00 AM to 10:00 AM were used as inputs for the scenario evaluation. The scenario that is discussed in this section is based on the impact of a hypothetical incident. An incident is introduced in the system at the location shown in Figure 5-5. This location is on Saw Mill River Parkway in south-bound direction. This Parkway along with Sprain Brook Parkway and Taconic State Parkway is highly used by the vehicles. The time of the incident is from 7:45 AM to 8:50 AM and twenty percent of the segment capacity is available during the incident. This kind of severity of incident is common in this network where a minor incident lasts for about half an hour to one hour. Major incidents may last for 3-4 hours where all the lanes are blocked for the traffic. The analysis focuses on OD pairs "1, 2, 3, 4 – 5, 6, 7", which are the primary OD pairs affected by the incident. Figure 5-5 also shows some examples of paths associated with OD pair 4-6 in dark color.
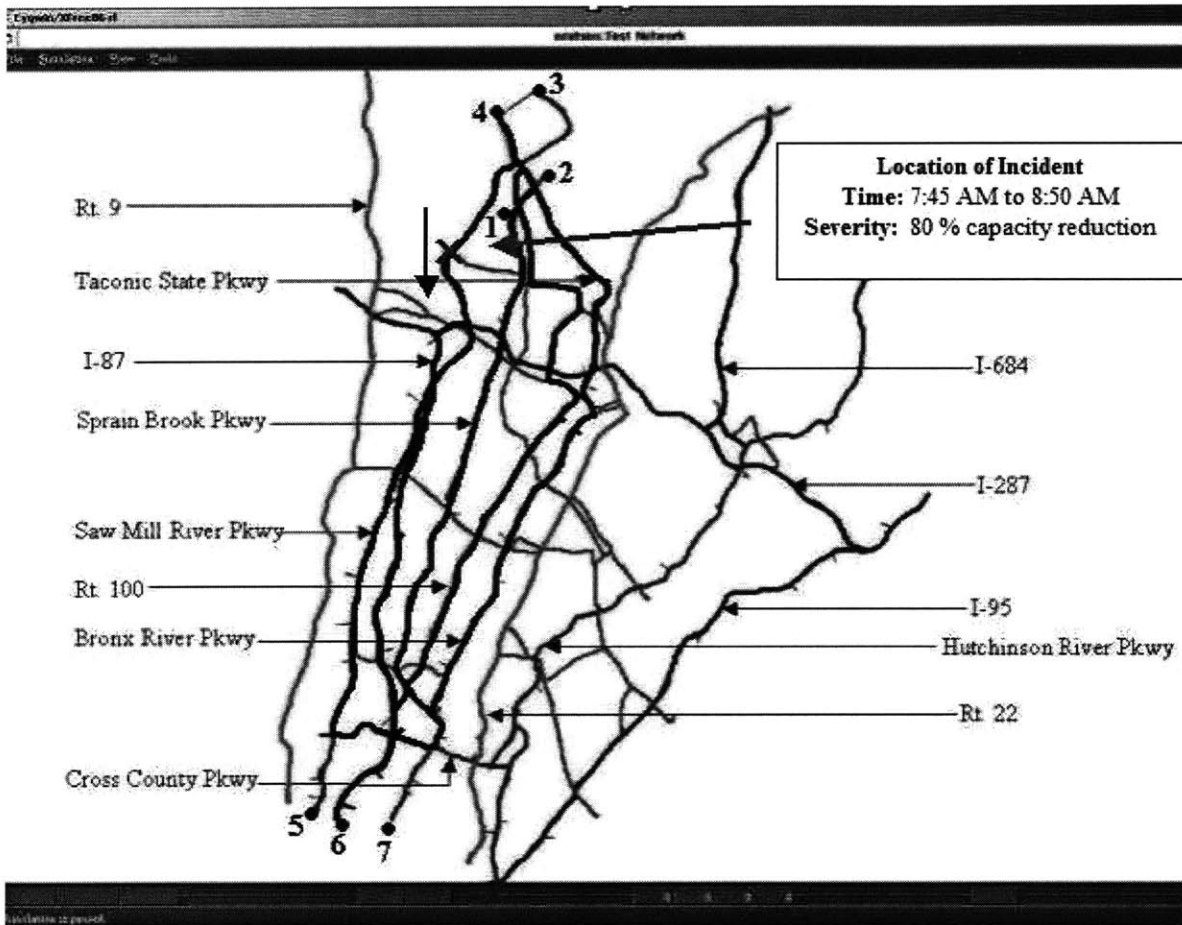
Figure 5-5: Location of the Incident 1 and Examples of Paths for the OD pair 4-6.

5.1.2.1 Impact of the Incident

To illustrate the impact of the incident alone, the incident was introduced in the system without VMS and the network performance was analyzed assuming that travelers follow their habitual routes (established by the equilibrium process). The resulting plot of the travel times experienced by the travelers based on their departure time is shown in Figure 5-6. Impact of incident is quite obvious as travel times during the peak period increase from 3000 seconds (no-incident case) to 4500 seconds, an increase of 150 percent.

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As pointed in the last chapter, origin and destination nodes are grouped together for the analysis, since these nodes have similar characteristics in terms of demand, travel times, number of paths, etc., and also because demand between a single OD pair is not significant enough to observe the impact of an incident and VMS messages. In order to illustrate the impact of the incident and as a reference for future comparisons, the frequency of experienced travel times is further analyzed based on the aggregated OD pairs, as done in the last chapter. Figures 5-7 shows the frequency of experienced travel times for aggregated OD pairs. Figure 5-7 clearly depicts that as a result of the incident, some of the travelers experienced high travel times of 3000 – 4500 seconds, which was not observed in the no-incident case. Number of travelers having travel times in the range 1000 – 2500 seconds has reduced significantly and those with travel times in the range 2500 – 3000 seconds have increased significantly.
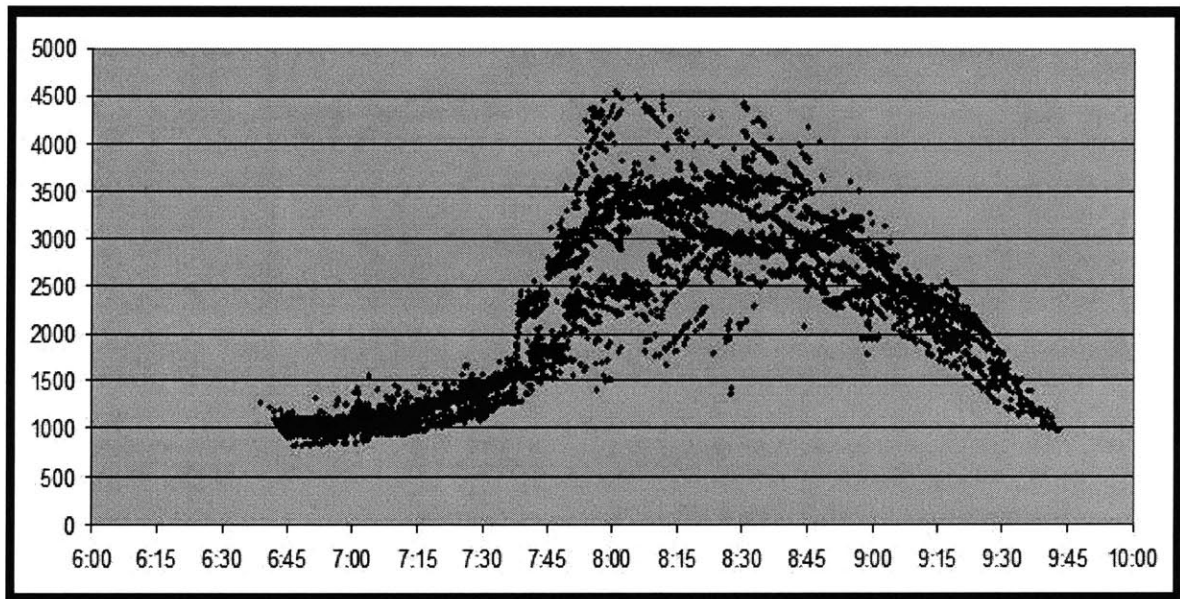

Figure 5-6: Impact of Incident 1. Travelers' Experienced Travel Times for all OD pairs.
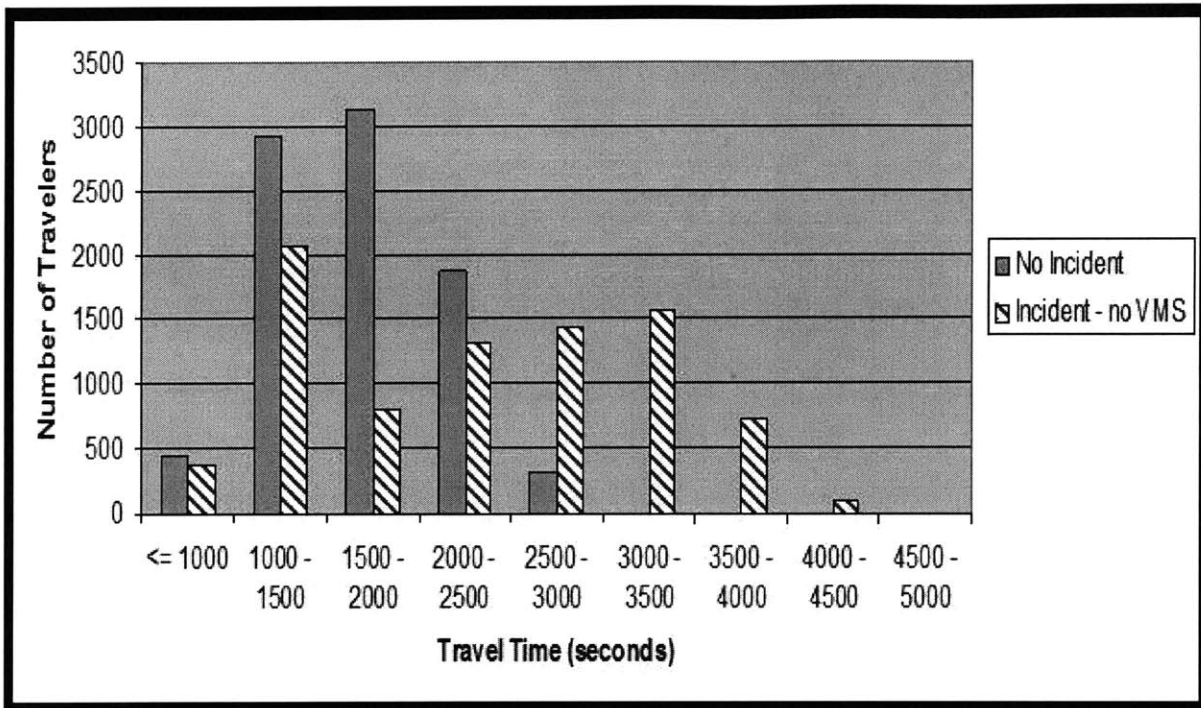
Figure 5-7: Impact of Incident. Frequency of Experienced Travel Times for all OD pairs "1, 2, 3, 4 – 5, 6, 7".

Some important statistics regarding all the OD pairs in the presence of the incident are:

- 8409 vehicles completed their trips as a result of the incident, while 8702 trips were completed during the no-incident case.

- The average travel times for travelers who finished their trips between 7:00 AM and 10:00 AM is 2313 seconds.

- The average travel times based on the departure time interval, aggregated for all OD pairs, is shown in Figure 5-7a. From this figure, it is clear that for all the OD pairs, travelers who departed after 7:45 AM experienced delay, as delay propagated until the end of the interval. The average travel time corresponding to the time interval 8:00 AM – 9:00 AM increased from 2000 seconds to 3000 seconds (approx.).
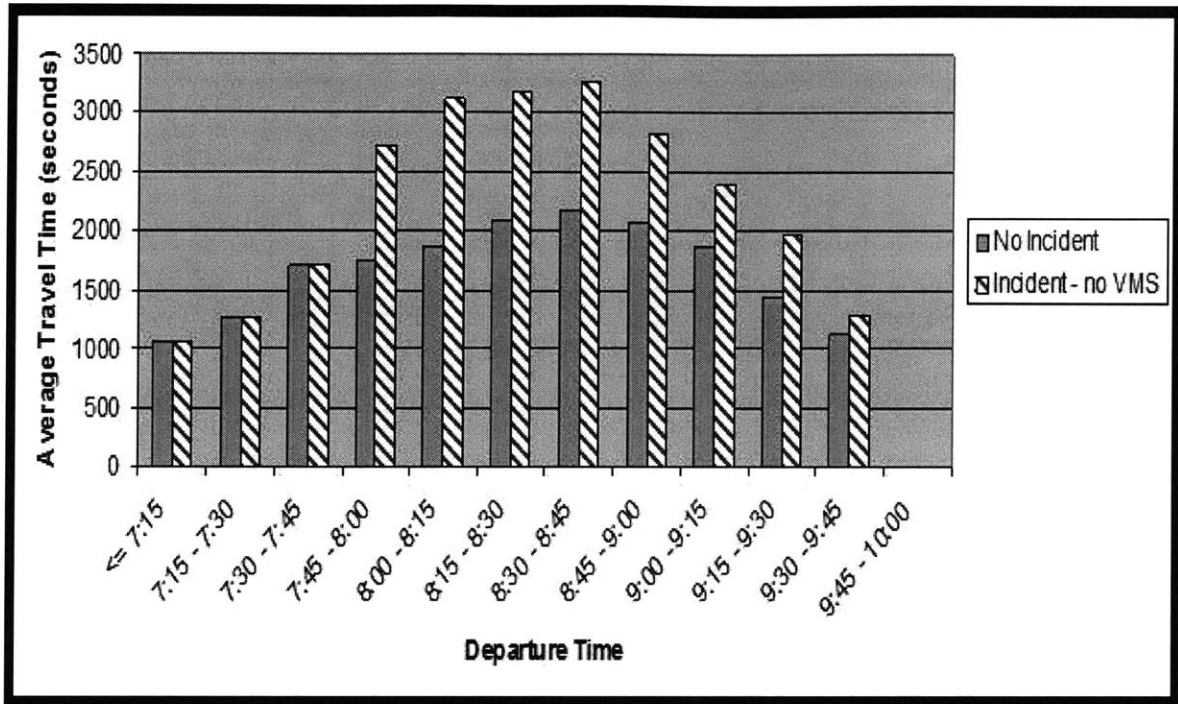
Figure 5-7a: Impact of Incident. Average Travel Time for all OD pairs "1, 2, 3, 4 – 5, 6, 7".

A comparison with the no-incident conditions presented in Section 5.1.1 yields the following conclusions:

- As a result of the incident, 293 fewer travelers completed their trips within the period of analysis.
- The average travel time for all the OD pairs in the analysis (1, 2, 3, 4 – 5, 6, 7) increased by 647 seconds, as evident from Figure 5-8.

5.1.3 Incident with VMS (Diversion Strategy)

Sundaram [48] has concluded that the predictive VMS strategies result in the best overall network performance, both in terms of the number of travelers who complete their trips and the average travel time. He further reports that instantaneous VMS strategies might cause travelers to experience longer travel times, since these strategies do not take into account future network conditions and may lead to overreaction. This effect may be

avoided by using the predictive VMS scenario with a consistent guidance strategy. Therefore, this section analyzes the impact due to a predictive VMS strategy only.
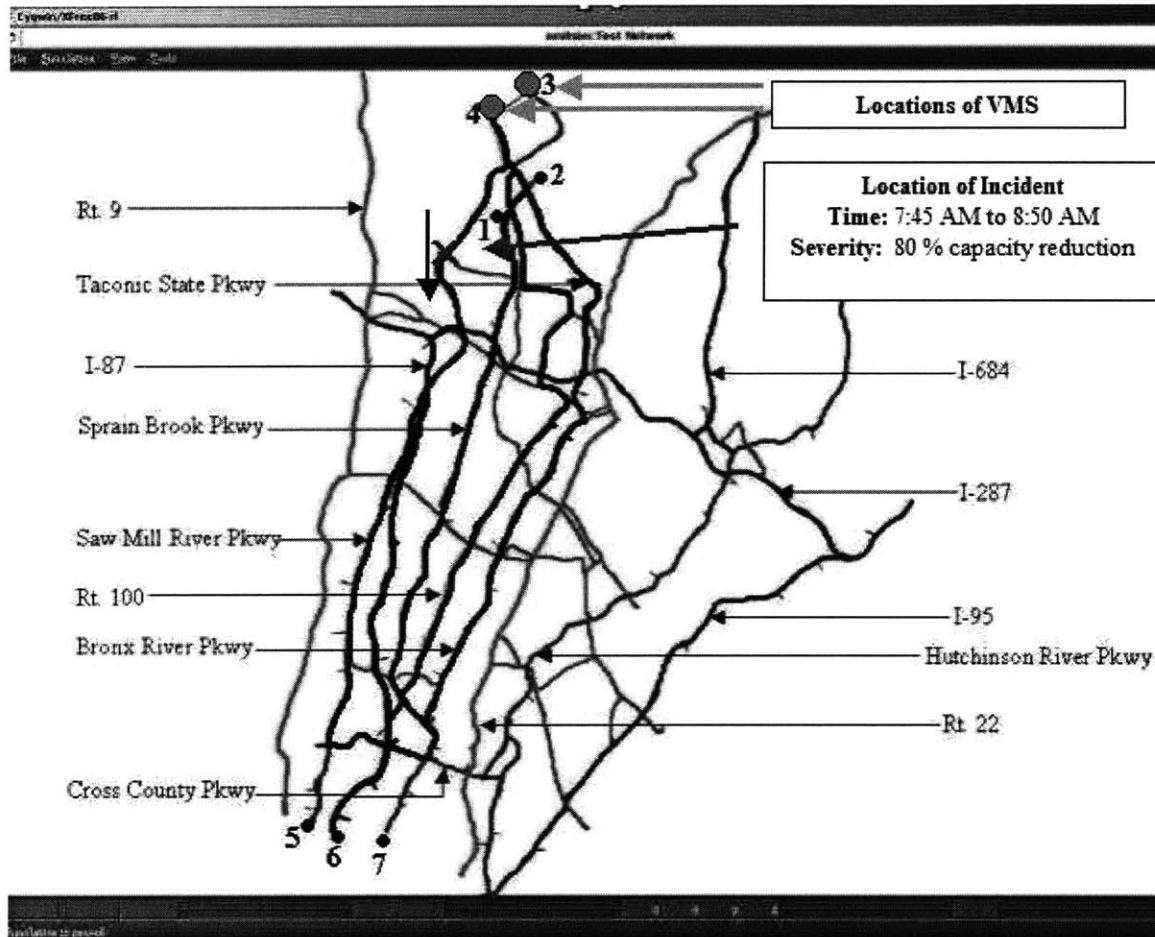

Figure 5-8: Location of VMS Message

The VMS strategy in our analysis is constrained by the fact that the location of VMS on the network is fixed and only these fixed VMS can be used for the diversion of traffic flow. For all OD pairs (1, 2, 3, 4 – 5, 6, 7) in the analysis, only two VMS, as shown in Figure 5-8, can be used for the diversion of traffic flow. As is clear from the locations of these VMS, no guidance can be provided to flow originating from nodes 1 and 2. Only flow for OD pairs "3, 4 – 5, 6, 7" can benefit from these VMS messages. Response of drivers from nodes 3 and 4 to the incident and VMS will primarily affect travel times for drivers originating from nodes 1 and 2. This was one more reason why

these nodes were aggregated for the incident and VMS analysis. The VMS chosen for this purpose are link-VMS, which provide information on the travel times of different links for alternative paths. Travelers update their route choice decision based on updated links travel times provided by the link-VMS. Link-VMS provide travel time information of all the links from the upstream of the incident location to the origin of travelers' trip, since only these links will have higher travel times due to increased congestion caused by the incident. In this case, link-VMS would be more appropriate since the incident location is close to the origin nodes and only a few links upstream of the incident location will be affected by the congestion due to the incident.

5.1.3.1 Impact of VMS Information Strategy

Several iterations were performed to achieve consistency in the prediction and the best guidance was chosen based on criteria such as the number of finished trips, the average travel time during the planning horizon and the distribution of the travel times experienced by travelers. The experienced travel times of travelers plotted as a function of their departure times is shown in Figure 5-9. Figure 5-9 shows that after using VMS maximum travel time has decreased from 4500 seconds (incident) to about 4000 seconds. Figure 5-10 shows the frequency of travel times for aggregated OD pairs (1, 2, 3, 4 – 5, 6, 7). Frequency analysis reveals that in the presence of VMS, many travelers have experienced reduced delay and many have shifted from higher travel times (3000 – 4500 seconds) to lower travel times.
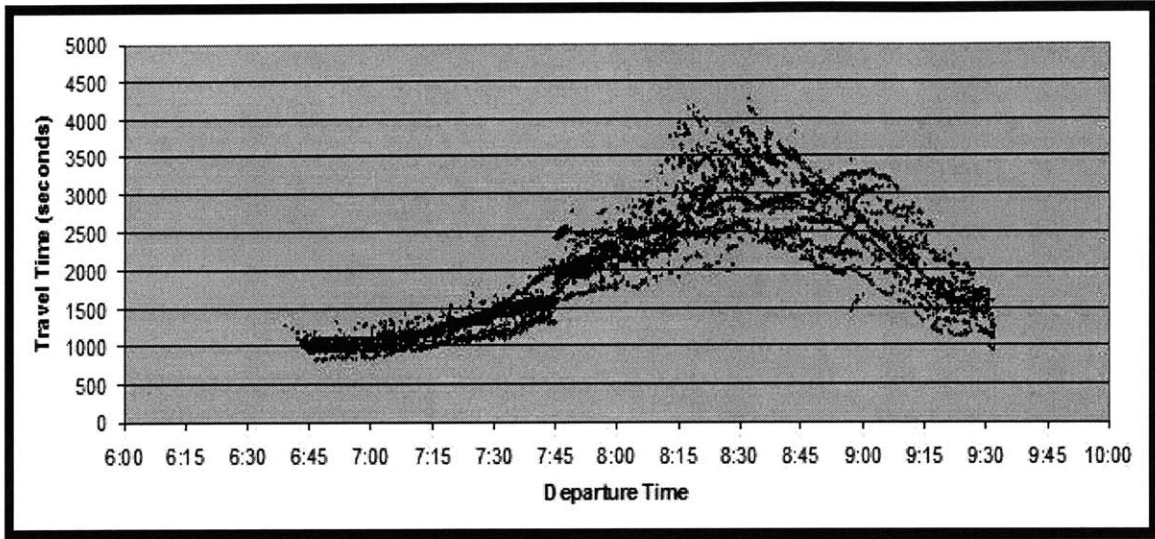
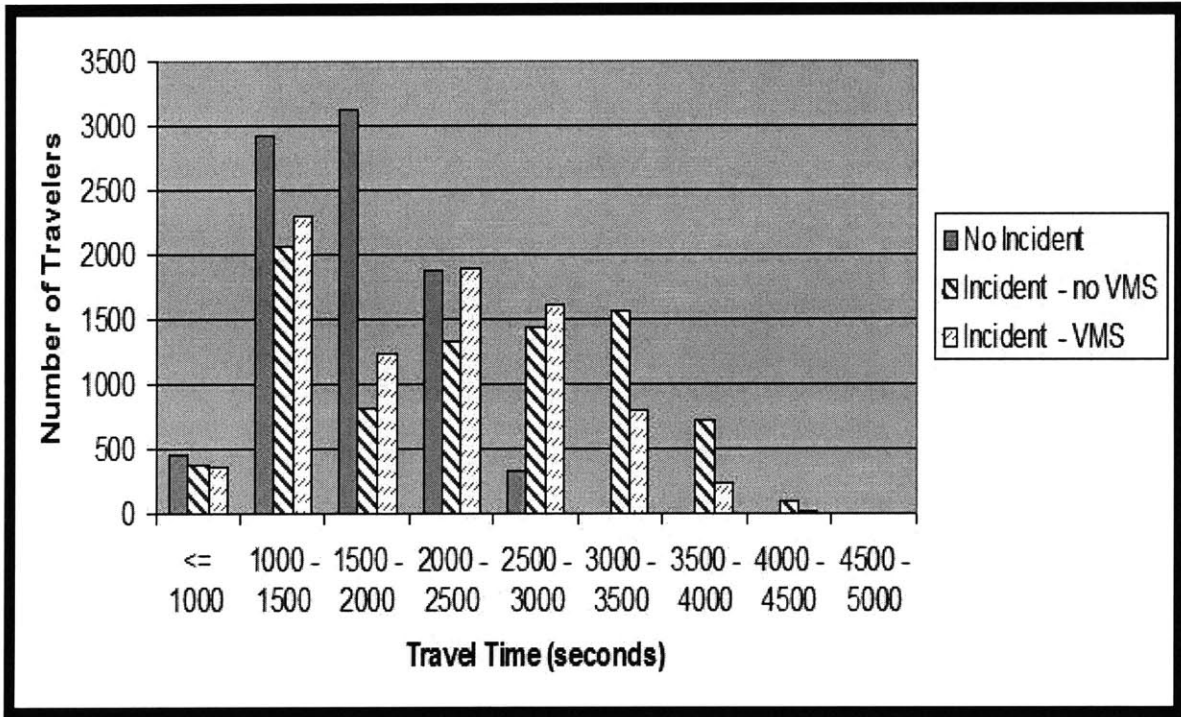Figure 5-9: Impact of VMS. Travelers Experienced Travel Times for all OD pairs.

Figure 5-10: Impact of VMS. Frequency of Experienced Travel Times for all OD pairs

"1, 2, 3, 4 – 5, 6, 7".

Again, some important statistics regarding all OD pairs under the VMS scenario are illustrated below:

- 8438 vehicles completed their trips, while 8702 vehicles completed their trips during the no-incident case and 8409 completed their trips during incident.

- The average travel time of travelers who finished their trips between 7:00 AM to 10:00 AM is 2084 seconds.

- The average travel times based on the departure time interval, aggregated for all OD pairs, is shown in Figure 5-11. Figure 5-11 clearly shows that average travel times in the VMS scenario decreased compared to the incident scenario. Major reduction in the delay can be seen during the incident interval (7:45 AM – 8:50 AM). During other intervals, savings in travel times are marginal.
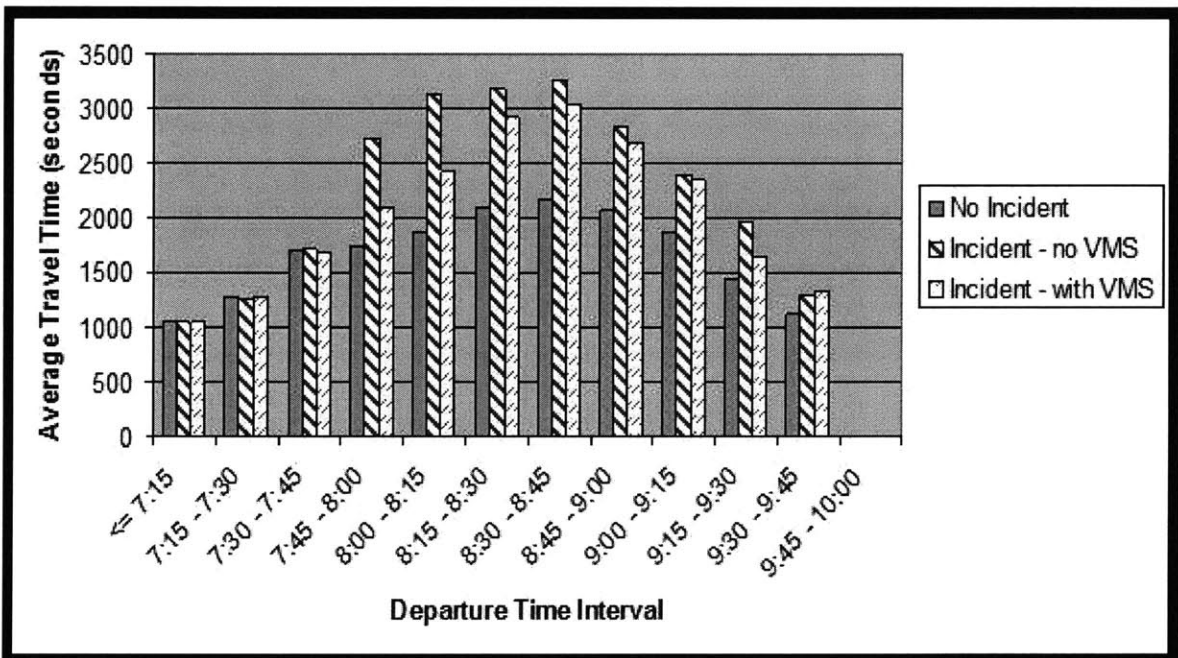

Figure 5-11: Impact of VMS. Average Travel Time for all OD pairs "1, 2, 3, 4 – 5, 6, 7".

5.1.4 Comparison of Different Cases: No Incident, Incident without VMS and Incident with VMS

This section compares the results obtained from different scenarios based on the aggregate statistics, the frequency of trip travel times and the departure time intervals.

5.1.4.1 Comparison Based on Aggregate Statistics

Table 5-1 summarizes the number of completed trips and the average travel times for different aggregated OD pairs. Further, the percentage change from the no-incident case is indicated in brackets.

As can be observed from Table 5-1, as a result of the incident, 293 fewer trips were completed for all OD pairs. Total number of completed trips in the presence or in the absence of VMS is almost the same. However, in the presence of VMS, there are savings in travel times. During the incident without VMS, the average travel time for all OD pairs increased by 37.2 %. In the presence of VMS during the incident, the increase in the average travel time of all OD pairs decreased from 37.2 % to 23.6 %. Thus, there is marginal savings in the average travel time using VMS. The main reason for no significant savings in travel times is that the incident is close to origins and travelers do not have more options to take alternative routes. In the presence of the VMS during this incident on Saw Mill River Parkway, drivers can take Sprain Brook Parkway or Taconic State Parkway. However, even these parkways have heavy traffic during peak hours. Therefore, diversion to these alternative paths will not result in significant savings.

	No Incident	Incident – no VMS	Incident – with VMS
Completed Trips (All OD pairs: "1, 2, 3, 4 – 5, 6, 7")	8702	8409	8438
Avg. Travel Time (sec) (All OD pairs: "1, 2, 3, 4 – 5, 6, 7")	1686	2313 (37.2%)	2084 (23.6 %)

Table 5-1: Comparison based on Aggregate Statistics

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The impact of VMS messages will be illustrated by a more rigorous analysis in the following sections.

5.1.4.2 Comparison Based on the Frequency of Trip Travel Times

The comparison based on the frequency of trips within various ranges of travel times for all OD pairs is summarized below in the Table 5-2.

	No Incident	Incident – no VMS	Incident – with VMS
Less than 1000 sec	454	388	376
1000 – 1500 sec	2923	2057	2293
1500 – 2000 sec	3131	807	1243
2000 – 2500 sec	1872	1326	1880
2500 – 3000 sec	321	1442	1610
3000 – 3500 sec	1	1569	793
3500 – 4000 sec	0	720	226
4000 – 4500 sec	0	96	17
4500 – 5000 sec	0	4	0

Table 5-2: Comparison based on the Frequency of Trip Travel Times. For All OD Pairs "1, 2, 3, 4 – 5, 6, 7".

The comparison reveals that as a result of the incident, a significant number of vehicles with lower travel times (1500 – 2000 seconds) have shifted to higher travel times (3000 – 5000 seconds). The impact of the VMS is also obvious from the fact that no vehicles have reported travel times between 4500 and 5000 seconds, and only very few vehicles have reported travel times in the range of 4000 – 4500 seconds. The number of vehicles that experienced travel times between 3000 and 4000 seconds also reduced significantly. The use of VMS has shifted these vehicles from high travel times to travel times between 1500 and 2500 seconds. Thus, the VMS has been largely beneficial in this regard.

5.1.4.3 Comparison Based on Departure Time Interval

The following Table 5-3 compares the average travel times for all OD pairs under each of the scenarios, as a function of the departure-time interval. The percentage change in the travel time is also indicated in brackets.

	No Incident Avg. TT (s)	Incident – no VMS Avg. TT (s)	Incident – with VMS Avg. TT (s)
<= 7:15	1057	1055 (-0.2%)	1057 (0.0%)
7:15 – 7:30	1271	1268 (-0.3%)	1272 (0.0%)
7:30 – 7:45	1700	1721 (1.2%)	1696 (-0.2%)
7:45 – 8:00	1750	2725 (55.8%)	2099 (20.0%)
8:00 – 8:15	1869	3132 (67.6%)	2426 (29.8%)
8:15 – 8:30	2088	3182 (52.4%)	2923 (40.0%)
8:30 – 8:45	2164	3256 (50.5%)	3027 (39.9%)
8:45 – 9:00	2075	2824 (36.1%)	2696 (29.9%)
9:00 – 9:15	1869	2394 (28.1%)	2350 (25.7%)
9:15 – 9:30	1442	1967 (36.4%)	1664 (15.4%)
9:30 – 9:45	1121	1293 (15.4%)	1334 (19.0%)
9:45 – 10:00	0	0	0

Table 5-3: Comparison based on Departure Time Interval. For All OD Pairs "1, 2, 3, 4 – 5, 6, 7".

Analysis of the average travel times based on departure time interval also hold promise for the use of VMS in this situation. As a result of the incident, average travel times for the travelers departing between 7:45 AM to 8:45 AM (incident duration) have increased by more than 50 %. After using VMS messages, the average travel times for these departure time intervals have come down by 30%. The increase in the average travel times after using VMS is only in the 20 to 30 % range. Vehicles departing between 7:45 AM to 8:15 AM have particularly experienced major savings.

Based on the above comparisons, the following conclusions are summarized below:

- The use of predictive VMS is recommended in this case as it has shifted significant number of vehicles from higher travel times to lower travel times. Similarly there are large savings in average travel times of vehicles departing during the incident duration.

- Overall savings in average travel time in the VMS scenario (2084 seconds, Table 5-1) is 13.6 % compared to the Incident scenario (2313 seconds, Table 5-1), which is also an achievement.

- After using VMS messages, the total number of completed trips is almost the same as the incident scenario, but number of travelers with lower travel times is higher.

- As a result of VMS messages, a large number vehicles that have experienced high travel times (3500 – 5000 seconds) have shifted to moderate travel times (1500 – 2500 seconds).

- The potential of VMS to mitigate network conditions during a particular incident depends to a large extent on the incident location, its severity and on the alternative paths that circumvent the incident location. During the incident at this location on the Saw Mill River Parkway, drivers do not have many alternative routes. This is also one of the main reasons for marginal savings in overall average travel times.

5.2 Scenario 2

This section presents the impact of a minor incident on the network. The planning OD and the equilibrium travel times obtained from the no-incident case during the time period 7:00 AM to 09:00 AM were used as inputs for the scenario evaluation. The scenario that is discussed in this section is based on the impact of another hypothetical incident. An incident is introduced in the system at the location shown in Figure 5-12. The incident is created in the east-bound direction of I-287 and flows from origins 1, 2, 3, 4, 8 to destinations 9, 10, 11 are aggregated for the purpose of incident and VMS

analysis. The time of the incident is from 7:45 AM to 8:15 AM and fifty percent of the segment capacity is available during the incident.

5.2.1 No Incident

As pointed before, the incident being considered for eastbound traffic is minor. Therefore for eastbound travelers, only the travel times during 7:00 AM to 9:00 AM will be considered for analysis. Figure 5-13 presents experienced travel times results for eastbound direction travelers between OD pairs "1, 2, 3, 4, 8 – 9, 10, 11", during the period of 7:00 AM to 9:00 AM. The average travel time for the travelers who completed their trips in the interval 7:00 AM to 9:00 AM is 1860 seconds and the number of completed trips in the interval is 2534. Figure 5-14 illustrates the frequency distribution of the travel times experienced. As can be seen from these figure, maximum number of travelers experienced travel times between 1000 – 2500 seconds. Also there are very few travelers who had travel times less than 1000 seconds or more than 3500 seconds. Figure 5-15 gives the average travel time experienced at different time intervals. It has increased from about 1100 seconds to 2500 seconds, which occurs at 8:45 AM.
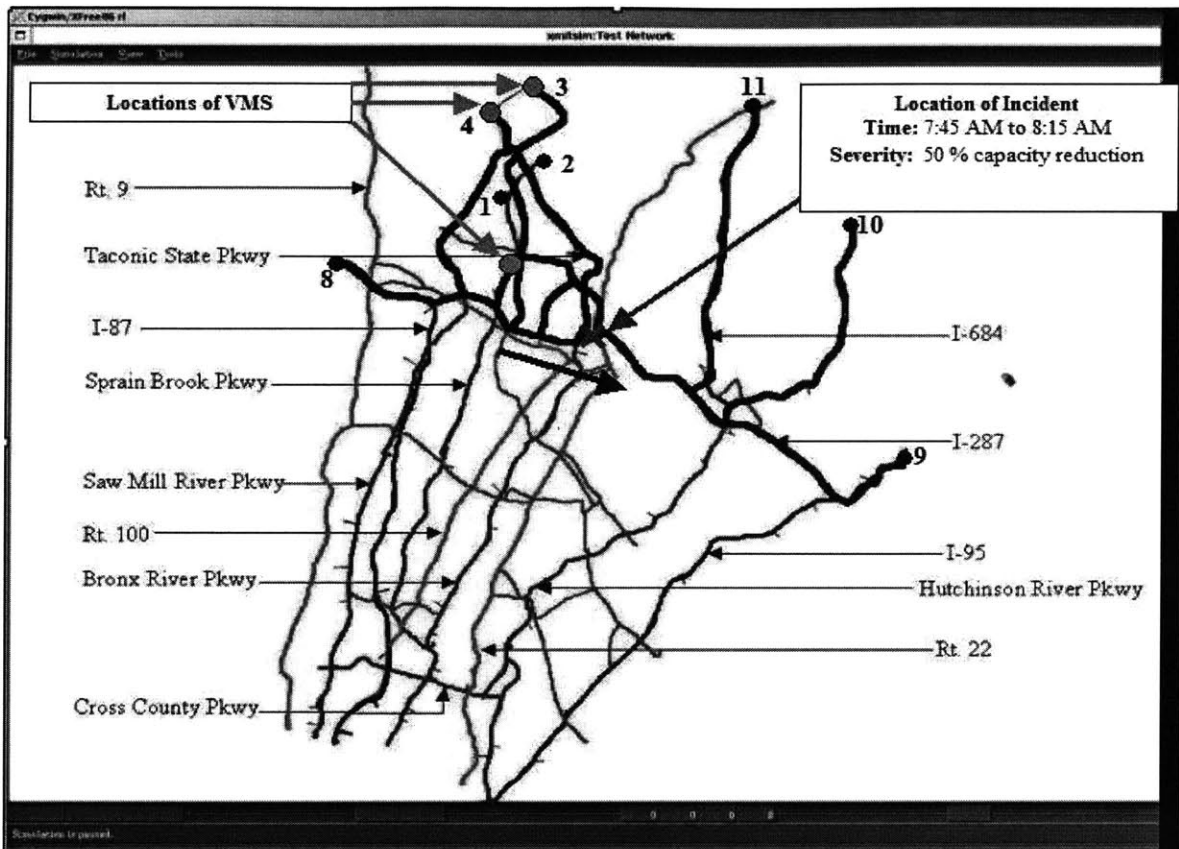
Figure 5-12: Network showing Origin Nodes (1,2,3,4,8) and Destination Nodes (9,10,11); Location of the Incident 2 and Examples of Paths for the OD pairs in dark color.
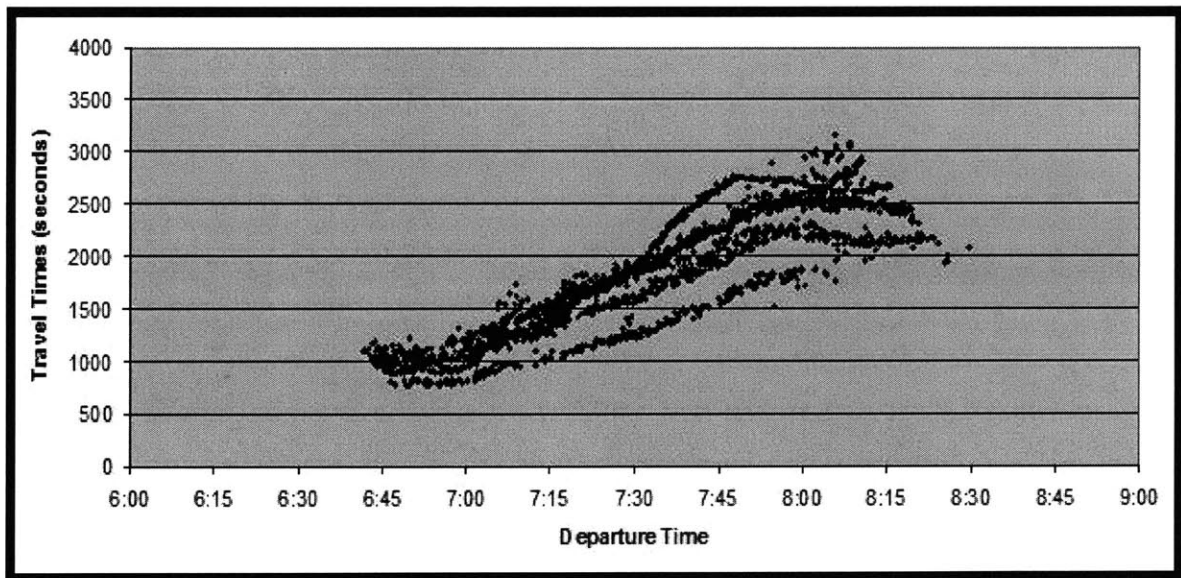

Figure 5-13: Travelers' Experienced Travel Times (after convergence) between all OD Pairs "1, 2, 3, 4, 8 – 9, 10, 11".
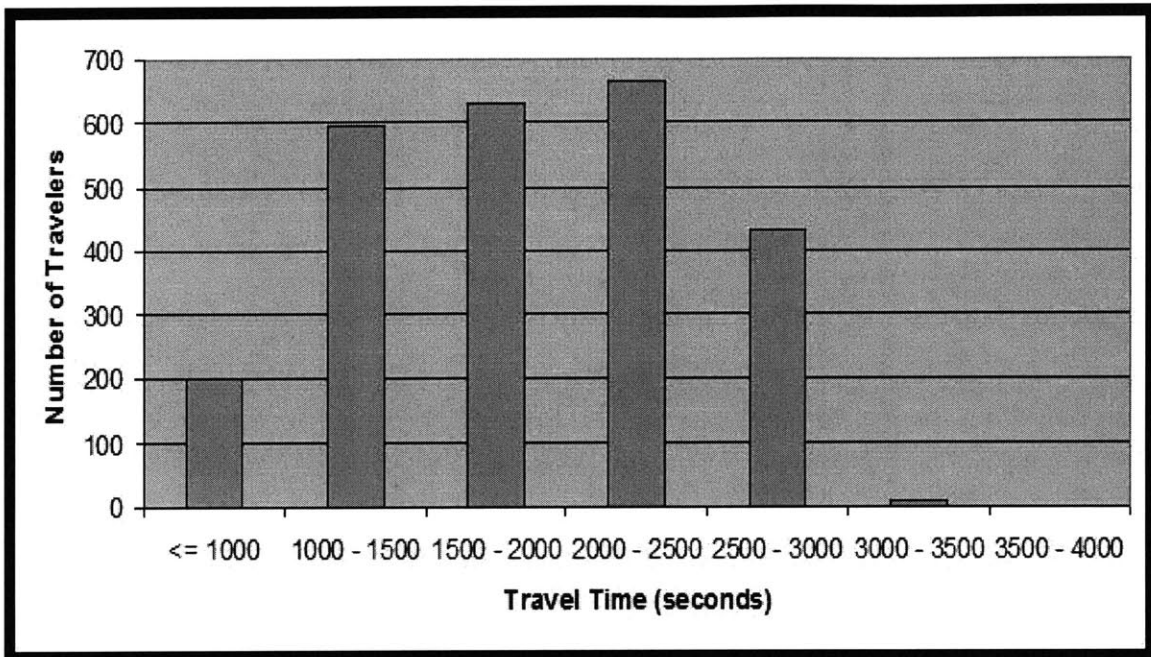
Figure 5- 14: Frequency of Experienced Travel Times for all OD Pairs "1, 2, 3, 4, 8 – 9, 10, 11".
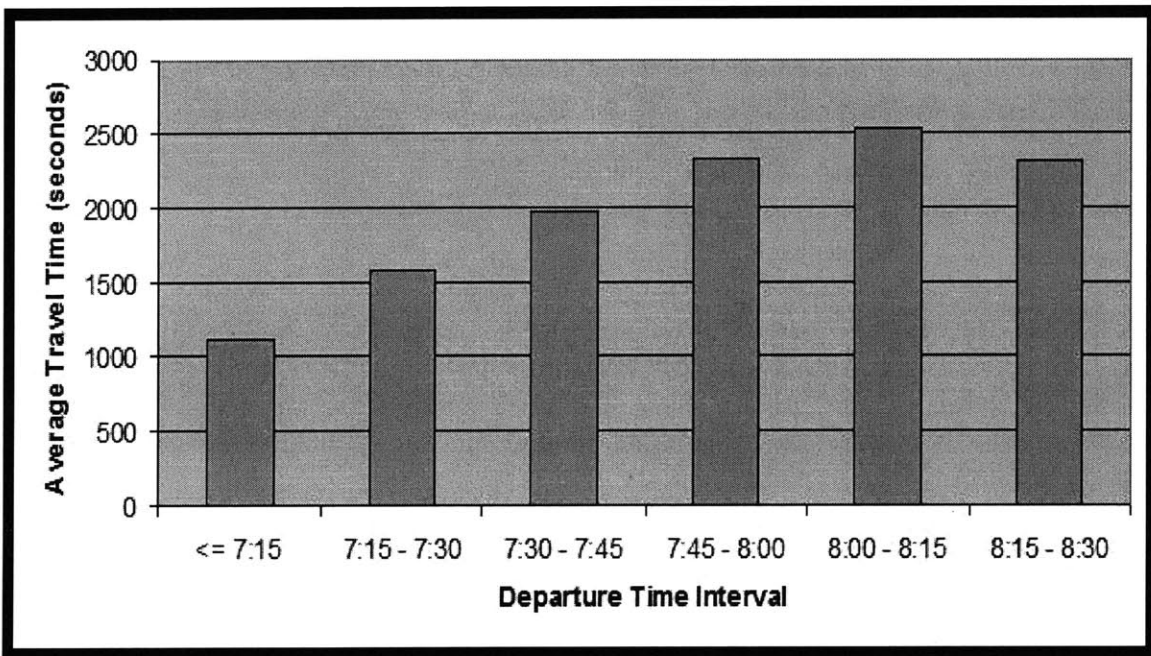

Figure 5-15: Average Travel Times between OD Pairs "1, 2, 3, 4, 8 – 9, 10, 11".

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5.2.2 Incident without VMS

To illustrate the impact of the incident alone, the incident (Figure 5-12) was introduced in the system without VMS and the network performance was analyzed assuming that travelers follow their habitual routes. The resulting plot of the travel times experienced by the travelers based on their departure times is shown in Figure 5-16. Since the incident is from 7:45 AM to 8:15 AM, only the impact between 7:00 AM to 9:00 AM has been analyzed. In order to illustrate the impact of the incident and as a reference for future comparisons, the frequency of the experienced travel times is further analyzed based on the aggregated OD pairs, as done in the previous section. As a result of the incident, the maximum travel time has increased from 3000 seconds to 3500 seconds, which is not a significant delay. Figures 5-17 shows the frequency of the travel times for aggregated OD pairs. Figure 5-17 clearly depicts that as a result of the incident, some of the travelers experienced high travel time of 3000 – 3500 seconds. Number of travelers having travel times in the range 1000 – 2500 seconds has reduced significantly and number of travelers with travel times 2500 – 3000 seconds has increased significantly.
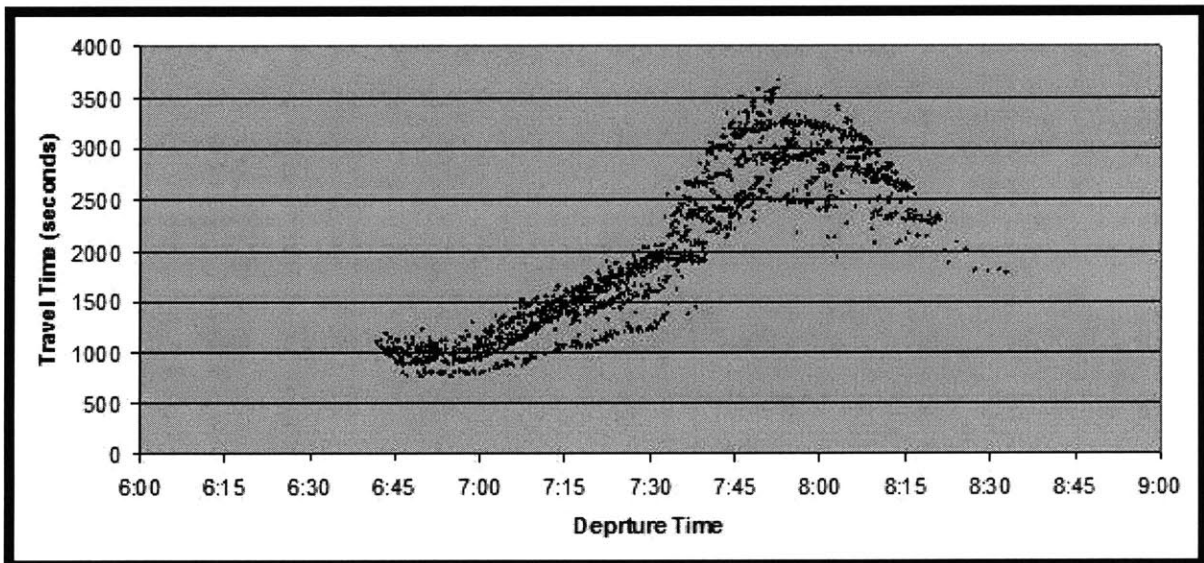
Figure 5-16: Impact of Incident. Travelers' Experienced Travel Times for all OD pairs.

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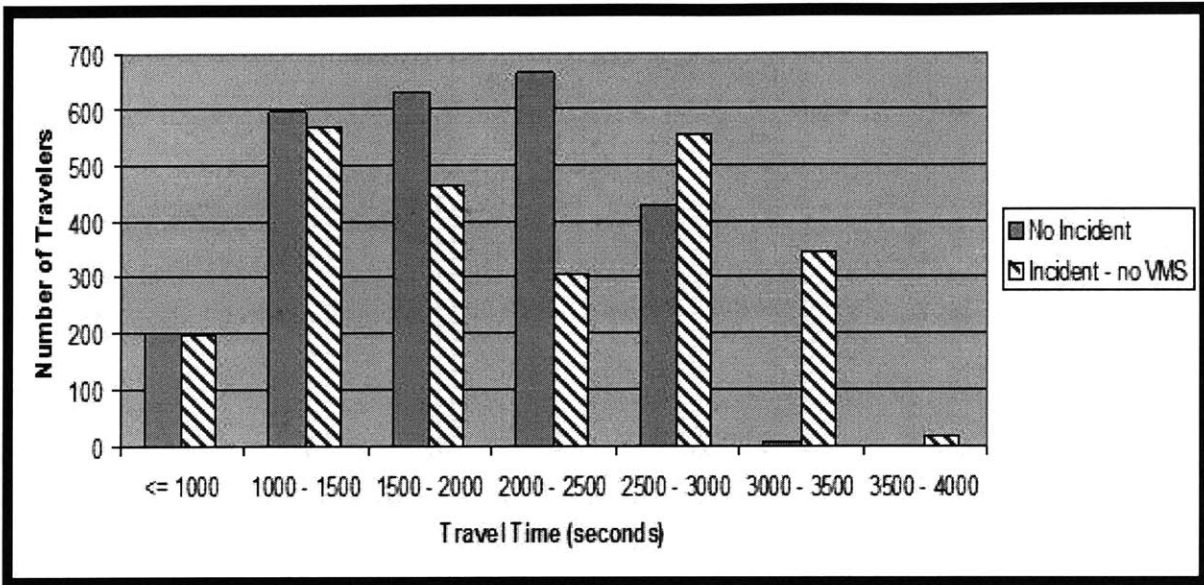
Figure 5-17: Impact of Incident. Frequency of Experienced Travel Times for all OD pairs "1, 2, 3, 4, 8 – 9, 10, 11".

Some important statistics regarding all the OD pairs in the presence of the incident are:

- 2457 vehicles completed their trips as a result of the incident, while 2534 trips were completed during the no-incident case.

- The average travel time of the travelers who finished their trips between 7:00 AM and 9:00 AM is 2070 seconds.

- The average travel times based on the departure time interval, aggregated for all OD pairs, is shown in Figure 5-18. From this figure, it is clear that for all the OD pairs, travelers that departed between 7:45 AM to 8:15 AM have experienced marginal delay.
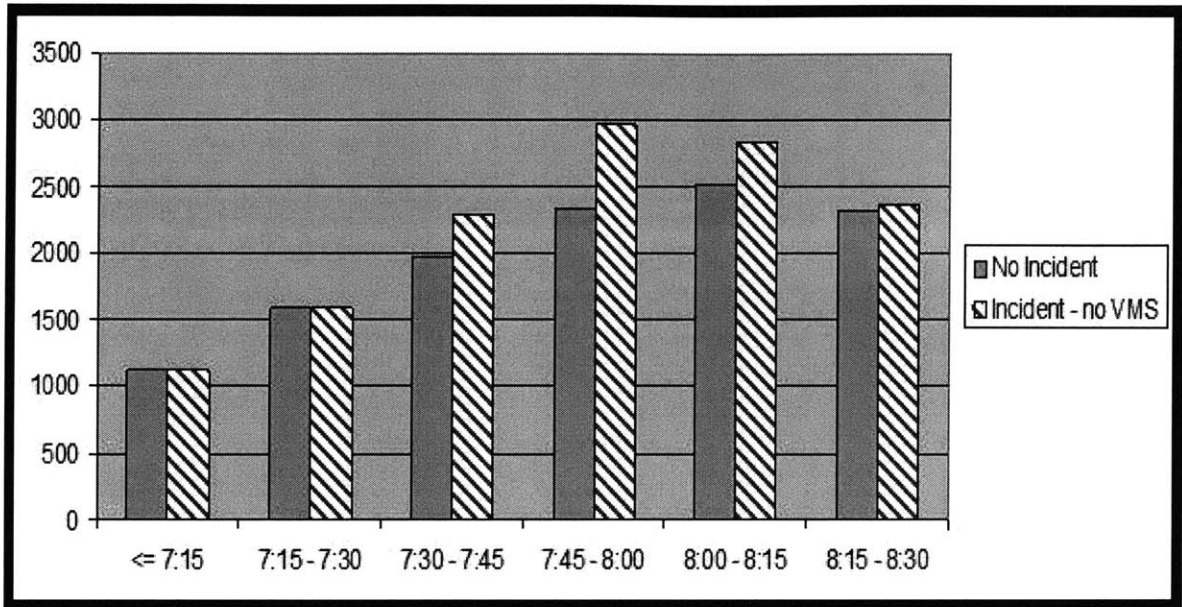
Figure 5-18: Impact of Incident. Average Travel Time for all OD pairs "1, 2, 3, 4, 8 – 9, 10, 11".

5.2.3 Incident with VMS (Diversion Strategy)

Again, the VMS strategy in our analysis is constrained by the fact that the location of VMS on the network is fixed and only these fixed VMS can be used for the diversion of traffic flow. For all OD pairs (1, 2, 3, 4, 8 – 9, 10, 11) in the analysis, only three VMS, as shown in Figure 5-12, can be used for the diversion of traffic flow. As is clear from the locations of these VMS, no guidance can be provided to flow originating from node 8. Only flow for OD pairs "1, 2, 3, 4 – 9, 10, 11" can benefit from these VMS messages. The VMS chosen for this purpose are link-VMS, which provide information on the travel times of different links for alternative paths.

5.2.3.1 Impact of VMS Information Strategy

Several iterations were performed to achieve consistency in the prediction and the best guidance was chosen based on criteria such as the number of finished trips, the average

travel time during the planning horizon and the distribution of the travel times experienced by travelers. The experienced travel times of travelers plotted as a function of their departure times is shown in Figure 5-19. It can be seen that the maximum travel time is again close to 3000 seconds, which is also no-incident case maximum travel time. Figure 5-20 shows the frequency of travel times for all OD pairs (1, 2, 3, 4, 8 – 9, 10, 11). It is clear from the Figure 5-20 that number of travelers with travel times more that 3000 seconds has reduced and with travel times of 2000 – 2500 seconds have doubled
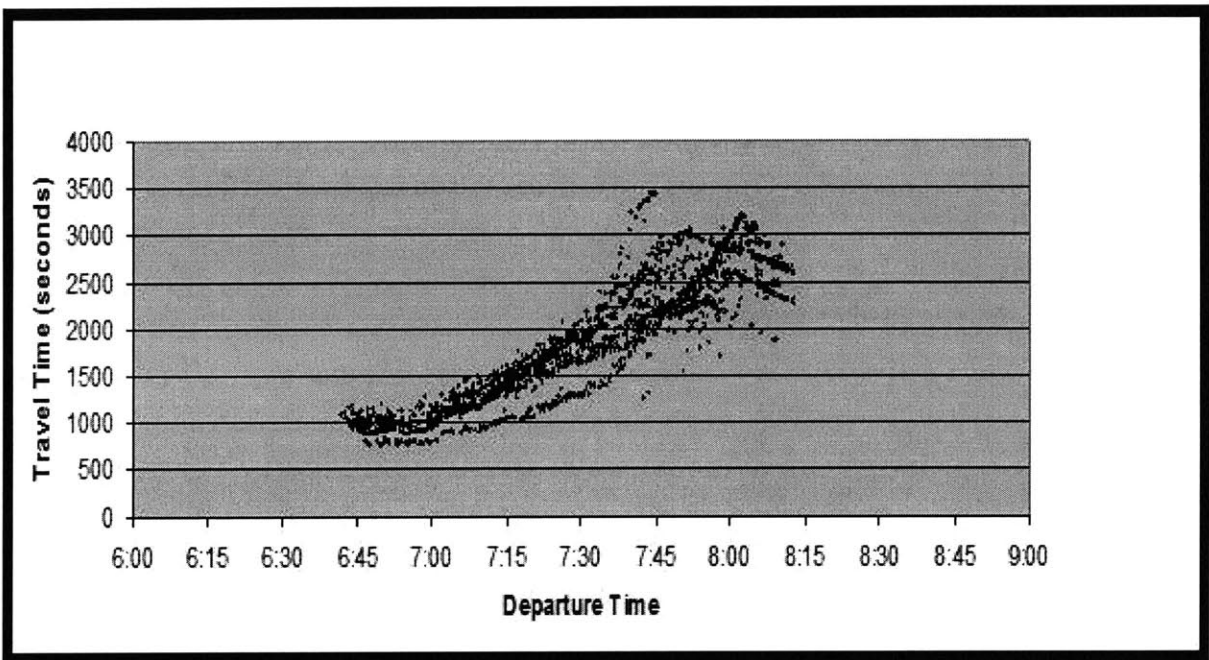
Figure 5-19: Impact of VMS. Travelers Experienced Travel Times for all OD pairs.
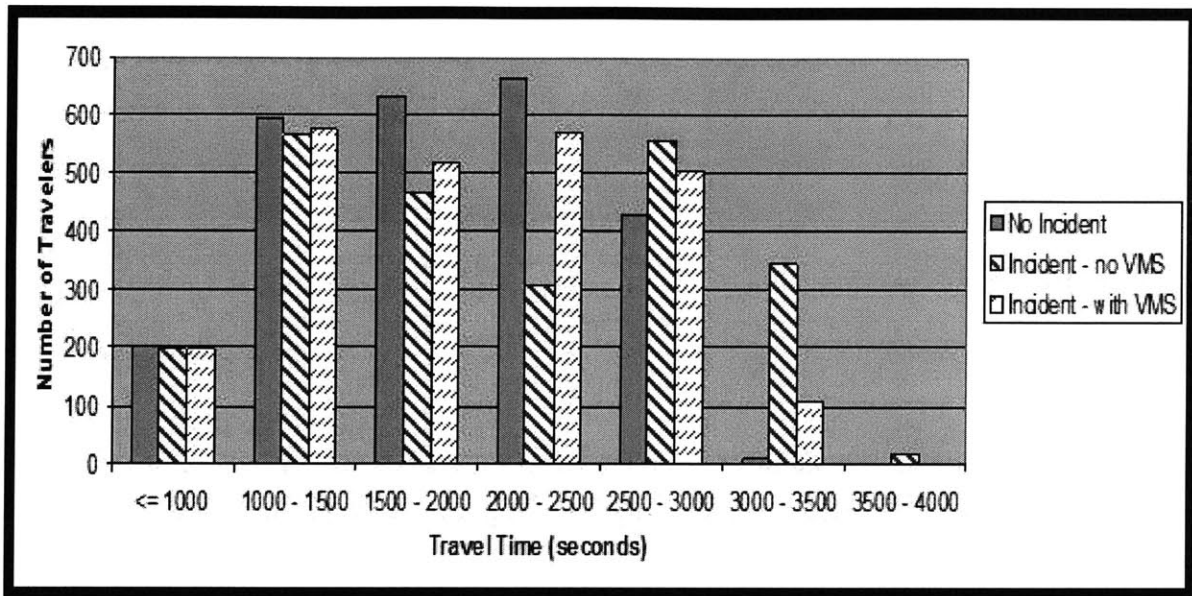
Figure 5-20: Impact of VMS. Frequency of Experienced Travel Times for all OD pairs "1, 2, 3, 4, 8 – 9, 10, 11".

Again, some of the important statistics regarding all OD pairs under the VMS scenario are illustrated below:

- 2477 vehicles completed their trips, while 2457 vehicles completed their trips during the incident and 2534 completed during the no-incident case.

- The average travel time for the travelers who finished their trips between 7:00 AM and 9:00 AM is 1942 seconds.

- The average travel times based on the departure time interval for aggregated OD pairs is shown in Figures 5-21. Figure 5-21 clearly shows that average travel time in the VMS scenario decreased compared to the incident scenario. In the presence of VMS information, average travel times are closer to the no-incident case average travel times. The effect of VMS is more pronounced between 7:45 and 8:00.
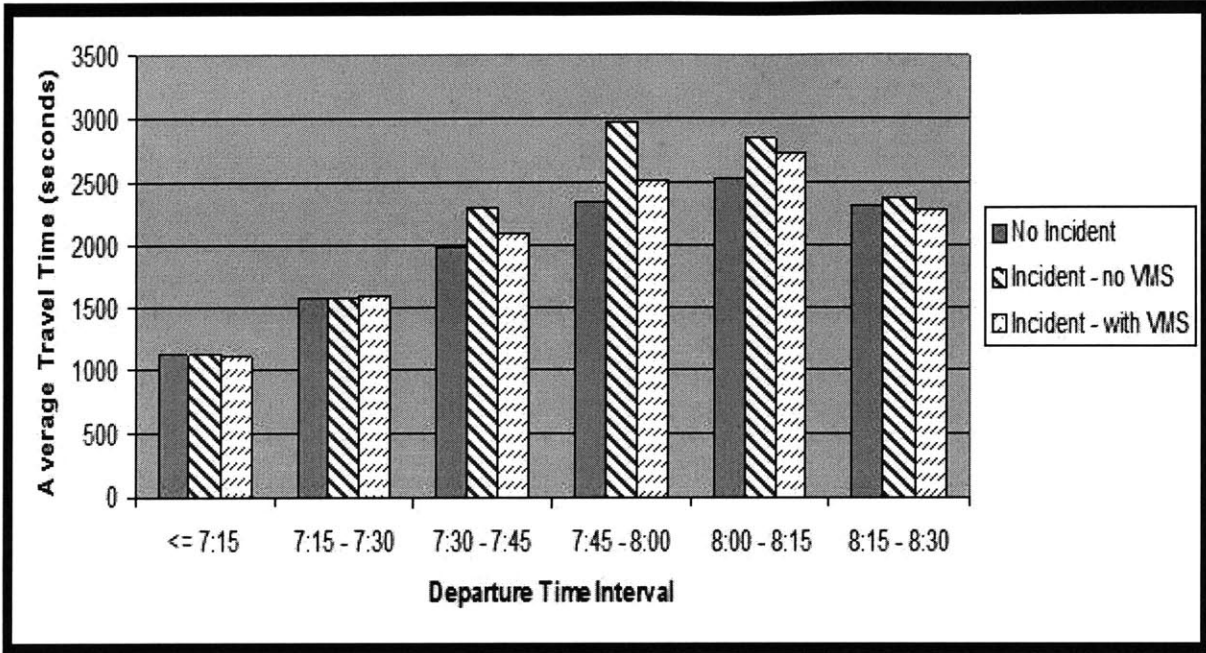
Figure 5-21: Impact of VMS. Average Travel Time for all OD pairs "1, 2, 3, 4, 8 – 9, 10, 11".

5.2.4 Comparison of Different Cases: No Incident, Incident without VMS and Incident with VMS

This section compares the results obtained from different scenarios, based on the aggregate statistics, the frequency of trip travel times and the departure time intervals.

5.2.4.1 Comparison Based on Aggregate Statistics

Table 5-4 summarizes the number of completed trips and the average travel time for different aggregated OD pairs. Further, the percentage change from the no-incident case is indicated in brackets.

As can be observed in Table 5-4, with the presence of VMS during the incident, the total number of completed trips is almost same as those during the incident. 77 fewer trips were completed for all OD pairs when VMS was not used in the presence of the incident. During the incident without VMS, the average travel time for all OD pairs

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increased by 11.3 %. However, in the presence of VMS during the incident, the increase in the average travel time for all OD pairs decreased from 11.3 % to 4.4 %. Thus, there are savings in the average travel time by using VMS. However, the average travel time after implementing the VMS (1942 seconds) is still larger than the average travel time without the incident (1860 seconds).

	No Incident	Incident – no VMS	Incident – with VMS
Completed Trips (All OD pairs: "1, 2, 3, 4, 8 – 9, 10, 11")	2534	2457	2477
Avg. Travel Time (sec) (All OD pairs: "1, 2, 3, 4, 8 – 9, 10, 11")	1860	2070 (11.3 %)	1942 (4.4 %)

Table 5-4: Comparison based on Aggregate Statistics

The impact of VMS messages will be illustrated by a more rigorous analysis in the following sections.

5.2.4.2 Comparison Based on the Frequency of Trip Travel Times

The comparison based on the frequency of trips within various ranges of travel times for all OD pairs is summarized below in Table 5-5.

	No Incident	Incident – no VMS	Incident – with VMS
Less than 1000 sec	202	200	202
1000 – 1500 sec	595	569	577
1500 – 2000 sec	632	471	516
2000 – 2500 sec	665	327	599
2500 – 3000 sec	430	570	426
3000 – 3500 sec	10	300	157
3500 – 4000 sec	0	20	0

Table 5-5: Comparison based on the Frequency of Trip Travel Times. For All OD Pairs "1, 2, 3, 4, 8 – 9, 10, 11".

The comparison reveals that as a result of the incident, a significant number of vehicles with travel times 1500 – 2500 seconds have shifted to higher travel times (2500 – 4000 seconds). The impact of the VMS is also obvious from the fact that no vehicles reported travel times between 3500 to 4000 seconds. The number of vehicles who experienced travel times between 2500 and 3500 seconds also reduced significantly. The use of VMS has shifted these vehicles from high travel times to travel times between 1500 and 2500 seconds. Thus, the VMS has been largely beneficial in this regard.

5.2.4.3 Comparison Based on Departure Time Interval

The following table compares the average travel times for all OD pairs under each of the scenarios, as a function of the departure-time interval. The percentage change in the travel time is also indicated in brackets.

	No Incident Avg. TT (s)	Incident – no VMS Avg. TT (s)	Incident – with VMS Avg. TT (s)
<= 7:15	1125	1122 (-0.3%)	1113 (-1.1%)
7:15 – 7:30	1584	1584 (0.0%)	1606 (1.4%)
7:30 – 7:45	1974	2284 (15.7%)	2093 (6.1%)
7:45 – 8:00	2333	2959 (26.9%)	2506 (7.4%)
8:00 – 8:15	2530	2825 (11.7%)	2774 (9.6%)
8:15 – 8:30	2311	2339 (1.2%)	2273 (-1.7%)
8:30 – 8:45	0	0	0

Table 5-6: Comparison based on Departure Time Interval. For All OD Pairs "1, 2, 3, 4, 8 – 9, 10, 11".

The average travel times in a departure time interval also hold promise for the use of VMS in this situation. As a result of the incident, average travel times of the travelers departing between 7:45 AM and 8:00 AM increased by more than 25 %. Although incident starts at 7:45 AM, vehicles departing between 7:30 AM and 7:45 AM have also

experienced an increase of 15 % in the average travel time. This increase is due to the fact that the incident had already begun by the time the vehicles departing between 7:30 AM and 7:45 AM reached the incident location. After using VMS messages, the average travel time for this departure time interval has almost halved. The increase in the average travel times after using VMS is only in the 5 to 10 % range. Vehicles departing between 7:30 AM to 8:15 AM have particularly experienced major savings.

Based on the above comparisons, some conclusions are summarized below:

- The use of predictive VMS is again recommended in this case as it has resulted in the shift of vehicles from higher travel times to lower travel times. Similarly, vehicles departing between 7:45 AM and 8:15 AM have significant savings in average travel times.

- After using VMS messages, the total number of completed trips is almost the same as those in the Incident scenario. However, average travel times have decreased after using VMS and number of vehicles with high travel times (3000 – 4000 seconds) during incident has shifted to lower travel times (1500 – 2500 seconds).

- The potential of VMS to mitigate network conditions during a particular incident depends to a large extent on the incident location, its severity and on the alternative paths that circumvent the incident location. In this case, vehicles have option to divert from I-287 to arterial roads at the upstream of the incident and they can later merge at I-287 at the downstream end of the incident. This might explain that average travel times after using VMS are close to no-incident case average travel times.

5.3 Summary

This chapter illustrated the potential of the planning tool (Sundaram [48]) in evaluating a VMS case study in the Lower Westchester County, New York. The Incident and VMS scenarios were evaluated based on hypothetical incidents on the LWC network. DynaMIT-P was used to evaluate predictive information through the VMS. The planning tool developed by Sundaram [48] was found to be extremely useful in analyzing various scenarios and capturing the relevant details. The case study was intended to give a sense of the potential of DynaMIT-P and illustrate the benefits of deploying such planning

tools. The next chapter focuses on areas where further research may be employed to improve the functionality of the planning tool.

Chapter 6

Conclusion

Dynamic Traffic Assignments (DTA) system can be used for dynamic traffic management purposes, like reducing delay on major highways, improving safety, efficiency and capacity of transportation network, and improving wide-area emergency responses through information sharing and coordination. DynaMIT-P is a DTA-based planning tool that operates in an offline mode, in which traffic managers investigate and prepare standard response strategies to different traffic and incident scenarios. The objective of this thesis was to apply DynaMIT's DTA capabilities to the Lower Westchester County (LWC) ITS subsystem and to use calibrated system to perform illustrative analyses of incident response strategies. First, DynaMIT-P has been calibrated in order to estimate traffic conditions in the LWC network with precision sufficient for ITS purposes. The results of a case study, focusing on the evaluation of the diversion response strategy in case of an incident on the LWC network, illustrate the functionality and potential of the system.

6.1 Thesis Contributions

This thesis used the simulation-based Dynamic Traffic Assignment (DTA) planning tool for short-term applications developed by Sundaram [48]. This tool overcomes the drawbacks of the traditional planning tools, which are static in nature and are not adequate to evaluate planning strategies that involve explicit modeling of traffic dynamics and traveler behavior. To evaluate the diversion strategies during incidents it is necessary to capture traffic dynamics and traveler behavior. Therefore, this planning tool was able to capture the different scenarios more accurately. Moreover, this tool also models day-to-day behavior, within-day behavior of travelers, and response of travelers to information.

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The planning tool was first calibrated from the limited data available for the network. Some assumptions regarding the sensor data were made, as sensor data from the same date was not available for calibration purpose. As a result, a thorough analysis of the traffic sensor data available was done and sensors that were not able to capture the traffic dynamics were removed from the analysis. The no-incident scenario was obtained first during the calibration process, which not only established the equilibrium travel time conditions in the network, but also provided an OD matrix that best reflected the observed sensor counts. The no-incident case captured the day-to-day behavior of travelers in the network.

The impact of two hypothetical incidents, in the absence of VMS messages, was analyzed by considering that travelers will follow their habitual paths. One incident was for 65 minutes on Saw Mill River Parkway and twenty percent of the segment capacity was available. The results show that the impact of the incident is severe as many vehicles reported travel times more than 4000 seconds, which was not observed during normal traffic conditions. The generation of the consistent predictive information was used for the VMS information systems. The result of the VMS scenario shows that predictive VMS is effective because it not only causes a large number of travelers to experience lower travel times, but average travel times experienced during different departure intervals also decrease. The use of VMS is recommended if the incident occurs at the same location since there is saving in travel times and more number of travelers is able to shift to lower travel times.

6.2 Scope of Future Research

This thesis applied the simulation-based DTA system for short-term planning applications. There are several issues that could be pursued in future.

The calibration of the DTA system was the most challenging part since demand calibration and supply calibration were done separately. A natural extension would be to focus on the integrated calibration of both the demand and supply simulator modules in the DTA system. During different steps of calibration process, it was clearly observed

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that better quality of field data is crucial for better estimates of demand and supply parameters.

It is very important to understand and model traveler behavior in response to information. Although many studies have been done in this direction, there is still significant scope for improvement to the existing models. Incorporation of traveler behavior models that closely mimic traveler response to information will enhance the importance of planning tools.

Appendix A

DynaMIT-P Input Files

Following are the brief details of the input files required by DynaMIT-P system:

(1) The *network file* contains the description of the network under study like nodes, links, segments, lanes and sensors. It also has the connectivity between different lanes in the network. Changing geometry within links is modeled by dividing the links into smaller segments.

(2) The *supply parameter file* contains the segment-specific details of parameters from the speed-density relationship, and segment capacities. These parameters are used by the supply simulator for simulating the movement of vehicles on the network.

(3) The *demand file* specifies the time-varying origin-destination flows for each OD pair.

(4) The *link travel times file* is used for the assignment of routes of vehicles.

(5) The *socio-economic file* has information regarding various socio-economic characteristics of drivers like trip purpose, value of time, access to ATIS etc. These characteristics are used while generating the population of drivers and are defined for each origin-destination pair in the demand file.

(6) The *behavior parameters file* has values of different coefficients in habitual, pre-trip and en-route route choice models.

(7) The *sensor count file* has the time-varying traffic sensor counts that are used during OD estimation process to map OD flows to sensor counts.

(8) In addition to the inputs discussed above, DynaMIT-P's demand simulator requires *error covariance and autoregressive matrices* that are used during OD estimation. These matrices result from a process of calibration.

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Appendix B

The vms.dat File

Information pertaining to the presence of VMS and HAR devices in the network is contained within the vms.dat file. As discussed earlier, DynaMIT has been enhanced to allow for two types of VMS: one that provides travel time guidance as it pertains to single links, and another that provides travel time guidance as applicable to paths (subpaths). Furthermore, HAR devices are implemented as groups of VMS that cover the area for which traffic information can be provided through the HAR devices. To illustrate this modeling convention we will once again use the same simple network (Figure B-1) as an example. A HAR whose range covers links 1, 3, and 4 can be modeled as three VMS (one located in each of the following links: 1, 3, and 4).
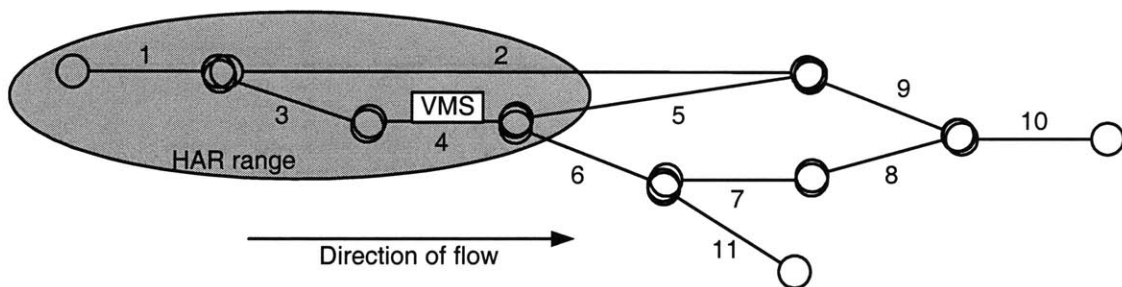
Figure B-1. Example to Illustrate link-VMS and path-VMS

In this section the structure of the input file that models VMS and HAR devices will be introduced. Furthermore, a sample file will illustrate the structure of the vms.dat file and its use in modeling realistic situations. The structure of the file is as follows. The first line contains two numbers. The first number provides the number of link-VMS and the second number provides the number of path-VMS devices (we assume that HAR devices have already been translated into equivalent VMS devices).

The syntax of the first line of the file then takes the following generic form:

```
#link_VMS #path_VMS
```

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The remainder of the file is composed by descriptions of each device, in the following order (assuming k link-VMS[6] and l path-VMS[7]):

```
Link VMS 1 description
...
Link VMS k description
Path VMS 1 description
...
Path VMS 1 description
```

The structure of each device description follows. A link VMS description has the following structure:

```
Link_on_which_the_VMS_is
#_of_links_the_VMS_provides_info_for   { ...
          list_of_links_for_which_info_is_provided }
```

For example, the following link-VMS definition:

```
1
2 { 2 3 }
```

implies that the particular VMS is located in link 1 (indicated in the first line) and provides information about 2 links (first number of second line). The links for which information is provided are links 2 and 3 (two numbers within brackets in second line).
A path VMS description has the following structure:

```
Link_on_which_the_VMS_is ...
          number_of_paths_for_which_information_is_provided
#_of_links_on_first_path_for_which_info_is_provided    { ...
```

---

[6] We assume that link-HAR have already been translated into equivalent link-VMS.
[7] We assume that path-HAR have already been translated into equivalent path-VMS.

```
                  links_that_make_up_path }
....

#_of_links_on_last_path_for_which_info_is_provided  {  …
                  links_that_make_up_path }
```

For example, the following path-VMS definition:

```
4  2
1 { 5 }
3 { 6 7 8 }
```

implies that the particular VMS is located in link 4 (indicated by the first number in the first line) and provides information about 2 paths (second number of first line). Each subsequent line provides information for each of the paths for which information is provided. The first path is composed of one link (first number of second line) and is composed of link 5 (number within brackets). Similarly, the second path is composed of three links (first number of last line) and these links are 6, 7 and 8 (the three numbers within the brackets at the remainder of the line).

The sample file below elucidates the structure of the file for a network with two VMS giving link (travel time) information and one VMS providing path (travel time information):

```
2  1
9
1 { 10 }
1
2 { 2 3 }
4  2
1 { 5 }
3 { 6 7 8 }
```

This entire file can be thought of as consisting of three sections, the first section having just a single line. The first line indicates that there are two VMS giving link (travel time) information and one VMS giving path (travel time) information. Figure B-2 shows the

file with explanatory information. This figure should be read in conjunction with the following paragraphs.

The next section that follows consists of (two times the number of link VMS) lines containing information about the link-guidance VMS. Thus, the second and third lines indicate that the first link VMS is on link 9 and that it provides information for 1 link— link number 10. Similarly, the fourth and fifth lines indicate that the second link VMS is on link 1 and provides information for 2 links—link 2 and link 3.

The third and last section contains information about the path-VMS. The first line in this section denotes the fact that the path guidance VMS is on link 4 and provides guidance for 2 paths. Each such line (one for every path-VMS) will be followed by as many lines as the number of paths for which guidance is being provided. The second line implies that the first of these two paths has just 1 link—link 5, and the third line implies that the second path has three links—links 6, 7 and 8 in that order.
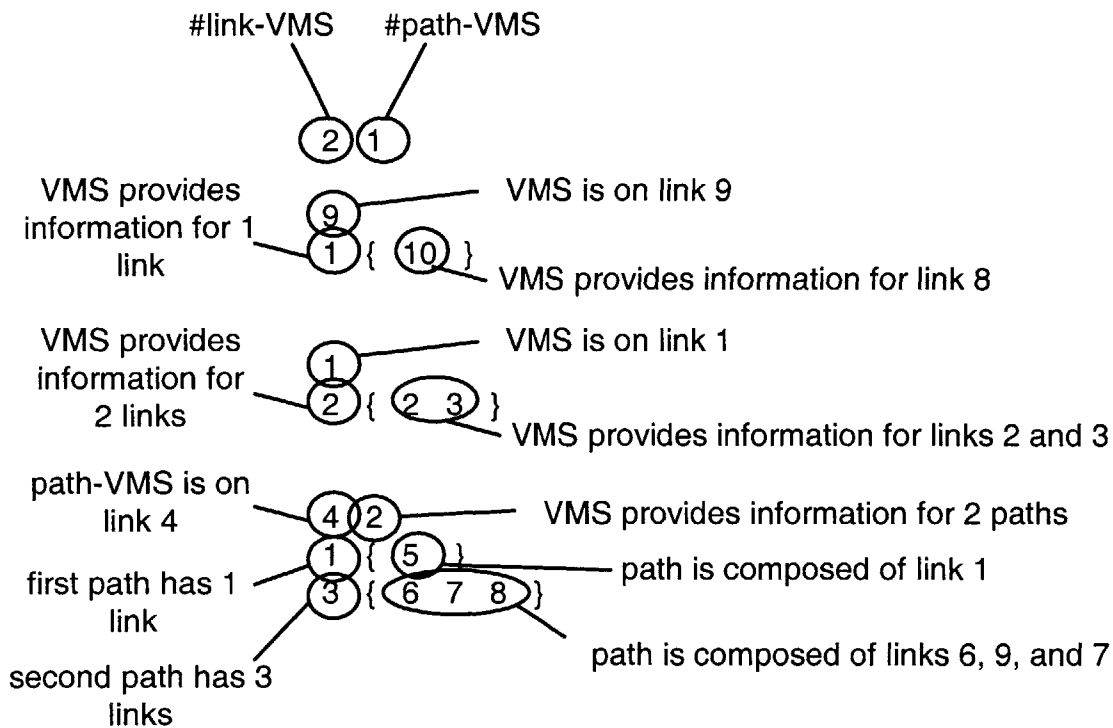

Figure B-2. Sample vms.dat File with Explanatory Information

Appendix C

Analysis of Sensor Data obtained from NYSDOT for LWC Network

Key Points:

- All sensors data obtained have HOURLY count.

- All sensors data are from WEEK DAYS.

- Most of the sensors data are for almost* 3 days.

- Each sensor means a pair of sensors in each direction (out of a pair of NB-SB or EB-WB) of traffic. Like, if there are 6 sensors data on I-87. It means there are actually 12 (6x2: 1 for North-Bound and 1 for South-Bound) sensors data.

All sensors in the LWC network are divided into 2 categories: (a) Freeway Sensors, and (b) Parkway Sensors

(a) Freeway Sensors

There are 4 freeways in the network. These are I-87, I-95, I-287 and I-684.

(i) I-87/NYS Thruway

7 sensor data are obtained for this freeway. 4 out of 7 sensors have data recorded in September 2002, 2 sensors have data from November 2000 and 1 sensor data is from November 2001.

---

3 out of 4 sensors data of 2002 have almost* 3 days of data starting from September 17, 2002. Remaining sensor also have almost 3 days data but starting from September 16, 2002.

2 sensors data from November 2000 have 3 days of data starting from November 6, 2000. 1 sensor data from November 2001 has almost 3 days of data starting from November 7, 2001.

(ii) I-95

I-95 has 9 sensors data. 3 out of 9 sensors have data from September 2002 and rest 6 have data from November 2000.

3 sensors data of 2002 have almost 3 days of data starting from September 17, 2002. 6 sensors data of 2000 have 3 days of data starting from November 6, 2000.

(iii) I-287/Cross Westchester Express

I-287 has 7 sensors data. 1 out of 7 sensors data is from September 2002, 4 sensors have data from November 2000 and rest 2 from November 2001.

1 sensor data of 2002 has almost 3 days of data starting from September 17, 2002. 4 sensors data of 2000 have 3 days of data starting from November 6, 2000. 2 sensors data from 2001 have almost 3 days of data starting from November 7, 2001.

(iv) I-684

---

* Word "almost" has been used deliberately to emphasis the fact that data for some sensors are less than 3 days but more than 2 day. Also for some sensors "starting time" and "ending time" for data are different even if they are for 3 days or for "almost" 3 days.

I-684 has 7 sensors data. 6 sensors data are for almost 3 days starting from October 16, 2000 and 1 sensor data from 2001 has almost 3 days of data starting from August 27, 2001.

(b) Parkway Sensors

There are 6 parkways in the network. These are: (i) Saw Mill River Parkway (ii) Bear Mountain Parkway (iii) Cross Country Parkway (iv) Taconic State Parkway (v) Sprain Brook Parkway, and (vi) Hutchinson River Parkway.

(i) Saw Mill River Parkway

This parkway has 7 sensors data. 3 out of 6 sensors have data from July-August 2000, 3 have data from October 2000 and 1 from September 2001.

3 sensors data of October 2000 have almost 3 days of data starting from October 23, 2000. 1 sensor data from 2001 has 3 days of data starting from September 10, 2001. 1 sensor data of July-August 2000 has 1 week of data (including Saturday and Sunday) starting from July 31. Rest 2 sensors of July-August 2000 have 3 days of data starting from July 31.

(ii) Bear Mountain Parkway

This parkway has 2 sensors data. 1 sensor has data from June 2000 and other has data from April-May 2002.

1 sensor data of April-May 2002 has almost 3 days of data starting from April 29, 2002. 1 sensor data of June 2000 has 3 days of data starting from June 12, 2000.

(iii) Cross Country Parkway

This parkway has one sensor data from October 2000. This sensor has almost 3 days of data starting from October 16, 2000.

(iv) Taconic State Parkway

This parkway has 9 sensors data from June 2000. All sensors have almost 3 days or 3 days of data starting from June 12, 2000 (except for 2 SB sensors out of total 18 (=9x2) sensors). These 2 SB sensors have almost 3 days of data for the same day of week but on different date (i.e. June 26, 2000).

(v) Sprain Brook Parkway

This parkway has 6 sensors data. 3 out of 6 sensors data are from July-August 2000, 2 sensors data are from October 2000 and rest 1 is from September 2001.

2 sensors data of October 2000 have almost 3 days of data starting from October 23, 2000. 3 sensors data of July-August 2000 have 3 days of data starting from July 31, 2000. 1 sensor data from September 2001 has 3 days of data starting from September 10, 2001.

(vi) Hutchinson River Parkway

This parkway has 11 sensor data. 4 out of 11 sensors data are from May 2002, 1 sensor data is from October 2000 and rest 6 have sensors data from June 2000.

4 sensors data of May 2002 have almost 3 days of data starting from May 14, 2002. 1 sensor data of October 2000 has almost 3 days of data starting from October 16, 2000. 6 sensors data of June 2000 have almost 3 days of data starting from June 12, 2000 (except for 1 NB and 1 SB sensors). This 1 NB sensor has data for almost 3 days but starting

from June 13, 2000 and 1 SB sensor has data for almost 3 days but taken 2 weeks later (i.e. June 26, 2000).

Summary: Initially, there were 120 sensors data received from NYSDOT. These include 52 sensors from freeways and 68 sensors from parkways. 36 of 52 freeway sensors were from year 2000 and rest 16 were from 2002. 58 of 68 parkway sensors were from 2000 and rest 10 from 2002.

After removing 32 sensors that were not in our network area, 88 sensors were left in the focused network. These included 42 sensors from freeways and 46 from parkways. 26 of 42 freeway sensors were from 2000 and rest 16 from 2002. 38 of 46 parkway sensors were from 2000 and rest 8 from 2002.

Later 88 sensors were supplemented by 12 more sensors from year 2001 to make it to total of 100 sensors. 8 of 12 sensors were from freeways and rest 4 from parkways.

After calibration results it was observed that 42 out of 100 sensors are not able to capture the real traffic conditions in the field, and as a result these 42 sensors were removed from the network making it to total of 58 sensors in the network. This removal of 42 sensors was done step by step as calibration process was progressing. 32 of 58 sensors are from freeways and 26 from parkways. 20 of 32 freeway sensors are from 2000, 1 from 2001 and 11 from 2002. 22 of 26 parkway sensors are from 2000, 1 from 2001 and 3 from 2002. In terms of year, 44 sensors are from 2000, 2 from 2001 and rest 14 from 2002.

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