Assessment of Impact of Dynamic Route Guidance through Variable Message Signs

by

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Abstract

Integration of Intelligent Transportation Systems (ITS) technologies with traffic surveillance has the potential of reducing the delays and costs incurred due to non-recurrent congestion through the dissemination of dynamic route guidance to drivers. Variable Message Signs (VMS), installed on freeways, are used for incident management and provide information about the incidents and diversion routes. VMS can prove to be a significant tool used by the Traffic Management Center (TMC) to improve the efficiency of the network by providing dynamic route guidance. Dynamic Traffic Assignment (DTA) tools can be used to generate predictive guidance, and the TMC can disseminate it through VMS to the drivers. However, on-line evaluation of such systems is very costly and there is a need to simulate the real traffic conditions to evaluate the DTA tools before their implementation in the field.

The current state of the art is to provide measured travel time information to drivers. The objective of this study will be to evaluate the network performance with the dissemination of *predictive* route guidance in case of severe incidents through the Variable Message Signs. Evaluation is done by developing a tool using the 'closed loop' integration between MITSIMLab, a microscopic traffic simulator as a proxy for the real traffic conditions, and DynaMIT, a DTA tool that is capable of generating predictive and consistent guidance. Using Genetic Algorithms with the 'closed loop' setup, a methodology is developed to identify VMS locations that result in the best consistent guidance to drivers. A case study is presented showing the benefits of using VMS by simulating incidents of major severity in Lower Westchester County, NY. Application of optimal location methodology and associated advantages in solving the problem is demonstrated with the help of a case study on a synthetic network. Results illustrate the potential and significant benefits obtained through Variable Message Signs. Using the optimal location methodology can improve these benefits even further.

Thesis Supervisor: Moshe E. Ben-Akiva
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Contents

List of Figures

List of Tables

Chapter 1 Introduction

Automobile traffic has been growing at a very rapid pace within the past two decades leading to ever increasing levels of congestion. Since the rate of increase of traffic is often higher than that for the addition in road capacity, better traffic management strategies are gaining the utmost importance in the field of transportation. Transportation forms the backbone of the economies of most of the countries, specially the developed ones. Any kind of disruption in the capacity is likely to have a very huge impact. These kind of disruptions can be natural (e.g. due to natural calamities) or man-made (accidents, terrorist attacks etc.). Although such incidents are difficult to avoid, it is possible to minimize the losses by a better traffic management system.

There is thus a need to develop better incident management strategies. To this end, we have seen a tremendous growth in the Intelligent Transportation Systems (ITS) Technologies. Traffic Management Centers (TMC) can make use of these technologies to help them manage traffic in cases of non-recurrent congestion and minimize the losses. Examples of ITS sub-systems are Advance Traffic Management Systems (ATMS) and Advance Traffic Information Systems (ATIS) which are gaining popularity as effective tools in managing various traffic issues. ATIS in a broad sense means providing information to travelers. Various tools of information dissemination such as Highway Advisory Radio (HAR), in-vehicle devices etc. are examples of ATIS.

Information dissemination can provide significant benefits in terms of reduction in travel times, distribution of traffic over the whole network etc. But in order to do it efficiently, it is very important to estimate and predict the traffic conditions, accounting for driver's reaction to the provided information. Dynamic Traffic Assignment (DTA) tools have been developed to address these issues. DynaMIT (Ben-Akiva, 2002) is a DTA tool that is designed to provide dynamic route guidance based on predicted network conditions after accounting for drivers' reaction to the information. It is designed to operate in a TMC and to support ATMS and ATIS operation. To test various incident management strategies, a representation of real traffic conditions is required in an offline mode. MITSIMLab (Yang, 1999), developed as a part of the Intelligent Transportation Systems Program at the Massachusetts Institute of Technology, is a microscopic simulator that mimics the real network conditions in an offline mode. Thus, strategies involving dynamic route guidance from DynaMIT can be tested using MITSIMLab. The 'closed loop' framework has been developed to enable this framework (Florian, 2004).

1.1 Motivation and Thesis Objectives

NYSDOT (New York State Department of Transportation) is in the process of deploying state-of-the-art ITS technologies in the Lower Westchester County (LWC) Network. LWC is located north of Manhattan and commuters use it for southbound traffic in the morning and the northbound traffic in the evening. At peak periods, the congestion levels are quite high. Moreover, severe incidents such as complete blockage of a link, are a common feature and they deteriorate the traffic conditions significantly causing huge congestion and long queues. Incident management is of utmost importance in LWC, and VMS, proven with the help of behavioral modeling and surveys to be an effective tool to that end, holds lot of potential in reducing the congestion and delays in LWC.

The basic concept of a VMS is information dissemination to drivers, specially when there is an incident in the network. The traffic dynamics with information through VMS are complicated and DTA tools (such as DynaMIT) are required for analysis. Also, in order to manage the diversion strategies efficiently, it should be ensured that the information given is reliable. The information needs to consist of predicted travel times so that the drivers know what they will experience when they reach the diversion route. This is called consistent guidance which means that the predicted network state matches the actual experience of the drivers in the network. The information provided by DynaMIT is unbiased and consistent (Ben-Akiva, 2002). Thus, by implementing the VMS in 'closed loop', predictive guidance generated by DynaMIT can be used for dynamic route guidance to drivers. To test such strategies, we need MITSIMLab as a proxy for the real world. VMS implementation in the 'closed loop' can thus help us assess the impacts and benefits of VMS. While there have been studies on the effects of VMS, the specific benefits that accrue from such a service is sensitive to the area of deployment as well as the nature of the information. Also, very few of the studies use DTA tools, and none of them have been applied to a network of this scale.

Knowing that VMS are an effective tool for incident management, one should try to maximize these benefits. Since we are talking about dynamic route guidance, the question becomes who should receive the guidance or rather, where should the guidance be available? We are trying to solve the problem from the system's perspective by giving the drivers a chance to maximize their own travel time benefits. Also, real networks are huge in size, thereby increasing the potential sites for incidents. A VMS or a set of VMS that are very beneficial in one case, might not be useful at all in another since the incidents that occur are random. Thus, it becomes a motivation to identify the locations of Variable Message Signs that would bring about these benefits in the most optimum way, and the system's performance averaged over many such incidents is improved.

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

- Implementation of Variable Message Sign functionality in MITSIMLab and DynaMIT (and hence, the 'closed loop').
- Assess the impact of VMS in improving the overall network performance of the Lower Westchester County Network, NY in case of a severe incident
- Development of a methodology to optimize locations of VMS that result in the overall best network performance averaged over the frequent incident scenarios and to test it in a synthetic network.

1.2 Summary of Results

The VMS evaluation framework developed as a part of this thesis is applied to the Lower Westchester County Network, NY. Two major incidents were simulated and the performance of Variable Message Signs was compared to the Base Case and the No-VMS case using the 'closed loop' framework. Results from the case study confirm many results in the literature. VMS help the drivers to make better informed route choice decisions thereby proving to be effective and powerful tools for incident management.

The methodology using Genetic Algorithm (GA) for finding the optimal location of VMS was successfully applied on a synthetic network with constraints of maximum 2 and 3 VMS respectively. Results show that GA can not only find the most effective VMS locations, but it also produces other near optimal solutions which might be important when practical implications are taken into account at the decision making level. The optimal solutions of GA were shown to improve the network performance significantly. Based on the successful implementation, we suggest direction for future work on the application of the algorithm to real sized networks.

1.3 Thesis Outline

The thesis proceeds as follows. Chapter 2 includes a review of the studies that have been done to show the effectiveness of dynamic route guidance and in particular, Variable Message Signs. It is followed by a summary of existing approaches to solve the problem of optimal location of Variable Message Signs. Chapter 3 presents the implementation of Variable Message Signs in the 'closed loop' framework that integrates DynaMIT and MITSIMLab. A methodology to assess the impact of Variable Message Signs is described. It is followed by a description of a methodology using the 'closed loop' and Genetic Algorithms to optimize the VMS locations. Chapter 4 discusses 'closed loop' evaluation of Variable Message Signs in the Lower Westchester County, NY. Chapter 5 presents an application of the Genetic Algorithm methodology to optimize the VMS locations on a synthetic network. Chapter 6 summarizes the research work and presents direction for future work in this area.

Chapter 2 Literature Review

This chapter covers the literature review on the prior evaluations of usage of Variable Message Signs and their effectiveness. VMS effectiveness can be maximized by choosing their optimal locations. There have been some studies in this section and they are presented later in the chapter.

2.1 Dynamic Route Guidance: Variable Message Signs

With the advancement in the development of real time Dynamic Traffic Assignment (DTA) tools, it is now possible to study the effects of providing various kinds of information to the drivers. Various media of disseminating information have been gaining popularity as they have the potential to provide traffic information and travel recommendations thus guiding the drivers to help them make better travel decisions, be it before they start their trip or on their way to their destination. Some examples of such media are variable message signs (VMS), radio, in-vehicle devices, cell-phones, World Wide Web etc. These systems are descriptive in nature that means the drivers are not mandated to follow the recommendations of the system. Prescriptive media impose restrictions and constraints on the traffic flow through control devices such as lane use signs, traffic signal, ramp metering etc. This introduces the concept of compatibility. Prescribed media have to be complied to. Descriptive media, in comparison, is designed to affect transportation demand by influencing travel decisions of drivers and drivers are free to comply to it or not.

Dynamic Route Guidance is a specific kind of information which is based on the current and future traffic conditions. Generation of dynamic route guidance has always provided new challenges to the transportation community. Previously, traffic simulators used to rely on static traffic assignment where the equilibrium models of steady state traffic govern the current network conditions. Clearly, this is not optimal. Every time one can expect something to happen that will deviate the conditions away from the state. These models no longer generate the optimum network state. Besides, we have seen the rise of real time route guidance applications, and with it the importance of dynamic route guidance comes into picture. Thus, it becomes critical that dynamic effects of traffic over time be captured in order to deliver detailed real time information about the traffic conditions.

It has been pretty well established in the literature that under recurrent congestion, the benefits of route guidance are minimal because habitual drivers have sufficient knowledge based on their everyday routine to make their route choice. It is more likely that provision of information is effective primarily under non-recurrent congestion conditions such as incidents, lane closures etc. There have been numerous studies that have established the usefulness of such systems that provide dynamic route guidance.

Carden, et al. (1998) presented their evaluation of the UK Midlands Driver Information System and estimated that huge reduction in vehicle delay is obtained in most cases where the Variable Message Sign displayed information about incidents. However, when the severity of the incidents was low, or the alternate diversion routes were already congested, some increase in travel times were observed.

A discrete probit choice model has been estimated by Levinson et al. (2002) that estimates the proportion of vehicles that are diverted to alternate routes based on the content of the variable message sign. He shows that VMS can be very effective in giving route guidance to travelers, and increase the rate of diversion of drivers significantly. He concludes that there is no obvious effect on reduction of travel time. However, as expected, information dissemination through variable message signs can significantly reduce the total delays faced in wake of non-recurrent congestion.

Al-Deek, et al. (1993) modeled the usefulness of information in traffic corridors and reported that travel time savings obtained are of the order of 30 percent based on a simulation study in a network with two routes. Simulation results in the Santa Monica Freeway corridor in Los Angeles (Gardes, et al., 1993), showed that in the presence of an accident, information provision can bring about 6.2 percent reduction in travel times. The vast difference between the benefits becomes a motivation to find optimal tools to disseminate real time guidance to the travelers. Variable Message Signs are one such tool that can prove very effective in non-recurrent congestion conditions.

As discussed above, the impact of Variable Message Signs typically depends on driver responses to these messages and the resulting traffic conditions. Response behavior of drivers in the presence of a VMS have been addressed by the use of logit models based on SP (Stated Preference) surveys (Bonsall, et al., 1997). The main disadvantage of these surveys is the well known problem with SP surveys (i.e. travelers do not usually respond in an actual situation in a manner concurrent with their survey responses).

The study conducted by Chatterjee, et al. (2002) is an example of this. It is reported that only one-fifth of the drivers diverted as compared to results based on SP surveys in London but SP results were consistent with observed diversion rates in another location. They also talk about the effect of type of messages that the current type of messages might be making the travelers lose confidence in the system, and thus, they ignore the VMS messages. It is advised to use the VMS frequently, so that people believe what they see. This again emphasizes the role of dynamic route guidance.

There have been numerous studies on VMS information that are based on SP surveys (Wardman, et al. (1997), Bonsall, et al. (1997) and Peeta, et al. (2000)). All these studies emphasize that relative journey times, delay on the current route, age, sex and previous network knowledge as being important factors that govern travelers' route choice decisions. Mc Arthur (1995), on the other hand, employed behavioral rules 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. Peeta, et al. (2006) tried three different Stated Preference survey methods: an on-site survey, a mail-back survey and an Internet based survey and concluded that there is a high correlation between VMS message type and driver response. Other examples of such studies are Hato, et al. (1996), Uchida, et al. (1994) and Zhao, et al. (1996), and Pedic, et al. (1999). All these studies underline the fact that travelers do respond well to the messages and overall results are the better traffic conditions.

Chatterjee, et al. (2004) have investigated the benefits and impacts of disseminating dynamic information via variable message signs in urban areas. Results show that up to 31% and in some cases 50% diversion rates are achieved. For messages related to incident, the important factors were the severity of the incident, location of Variable Message Signs, and presence of diversion routes to which the traffic can be diverted. Under normal conditions, if the message simply relays dynamic route guidance about the traffic situation on a major route, it tends to increase the use of that major route and reduce the usage of the alternate diversion routes if no traffic problems are reported on the major route.

From all these studies, it is clear that dynamic route guidance via Variable Message Signs is capable of improving the traffic conditions significantly. However, it is apparent that although the severity of the incident and content of the messages are important factors in influencing the level of diversions, specific locations of Variable Message Signs and the availability of viable alternate diversion routes can significantly alter the observed benefits. This provides a motivation to maximize these benefits by identifying the optimal location of Variable Message Signs. Following section provides a review of the existing work that has been done to optimize the location of Variable Message Signs.

2.2 Existing work on Optimal Location of Variable Message Signs

In the previous section, we saw the usefulness of Variable Message Signs in the wake of non-recurrent congestion, and that the optimally locating VMS can fetch even more benefits. Also, these studies focused on specific incident situations. However, the location of Variable Message Signs become critical because the location as well as the severity of the incidents is stochastic. A VMS that provides huge benefits in the case of an incident, might not be useful at all when an incident occurs in another location the next day. The usefulness as we have seen is more affected by the number of people that see the messages, and the number and viability of the available routes to which the traffic can be diverted. This becomes a motivation to look for methods to choose the optimal location of variable message signs to fully realize their benefits in most of the cases.

Not much work has been done in this direction. Notable among the ones is the study by Abbas, et al., (1999) who made use of Genetic Algorithms for to optimize VMS locations. Figure 2-1 shows the methodology that was used. A detailed description of Genetic Algorithms can be found later in this chapter. The methodology in this study was used to analyze the installation of VMS in the Omaha metropolitan area. The study concluded that the maximum number of Variable Message Signs to be installed is 14 based on the incremental cost-benefit ratio. It was shown that the benefits can be up to 75,226 vehicle-hours.

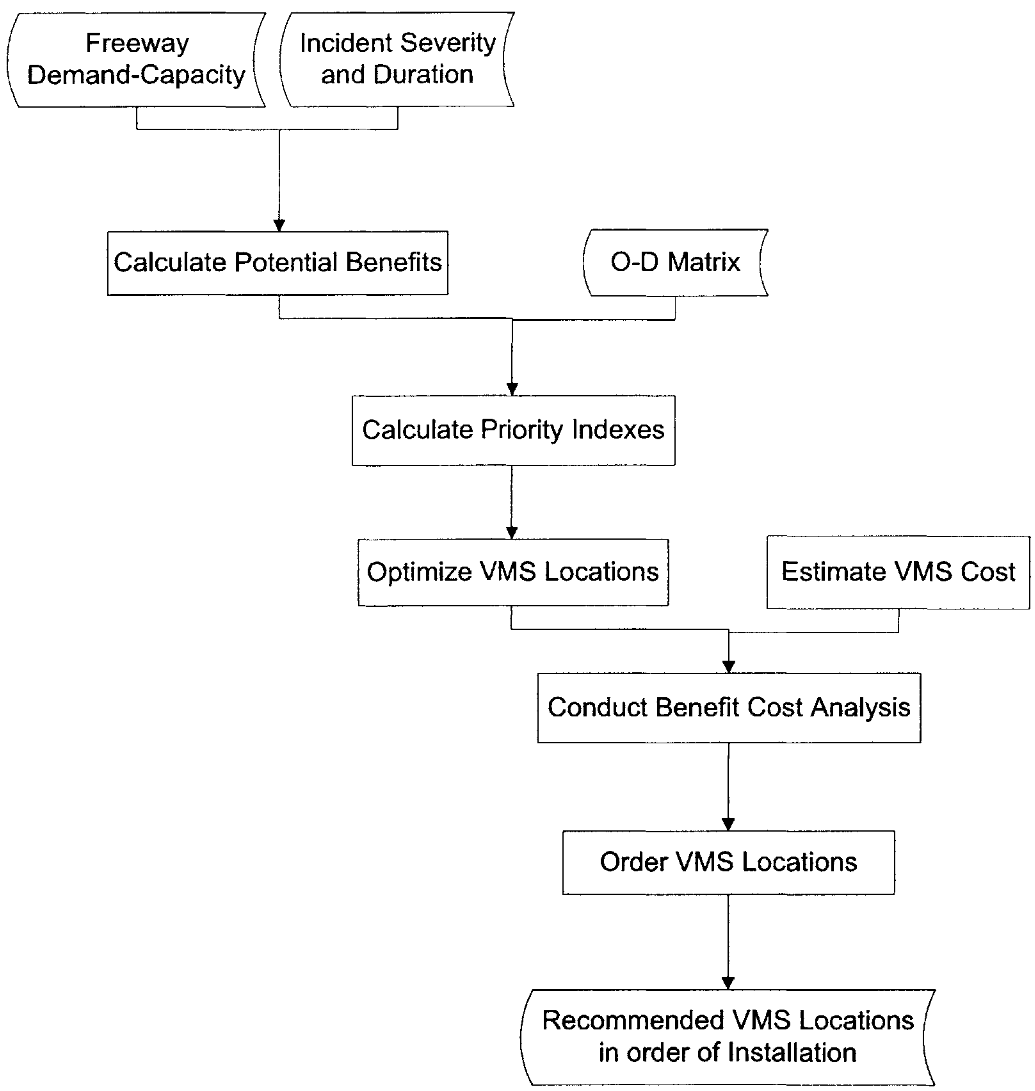

Figure 2-1 Methodology Flowchart (Abbas et al., 1999)

Chiu, et al. (2001) have developed a framework to seek solutions that are optimal with respect to minimization of the long term expectation of the system costs. The optimization is done at two levels. The upper level employs tabu search algorithm to generate feasible solutions. Based on the minimization of the total user travel time averaged over the space of stochastic incidents, the next candidate solutions are generated. These solutions are evaluated at the lower level in a simulation based Dynamic Traffic Assignment. This solution algorithm was applied to the Fort Worth network, and evaluated for cases with minimum 1 and up to 4 Variable Message Signs.

Another study was done by Huynh, et al. (2002) to find the near – optimal location of portable Variable Message Signs in Fort-Worth network. A solution procedure was developed to find such locations in the context of real time traffic management, and to do so in a relatively short time. The procedure consists of *greedy* heuristics and *drop* heuristics. The methodology applied is shown in Figure 2-2.

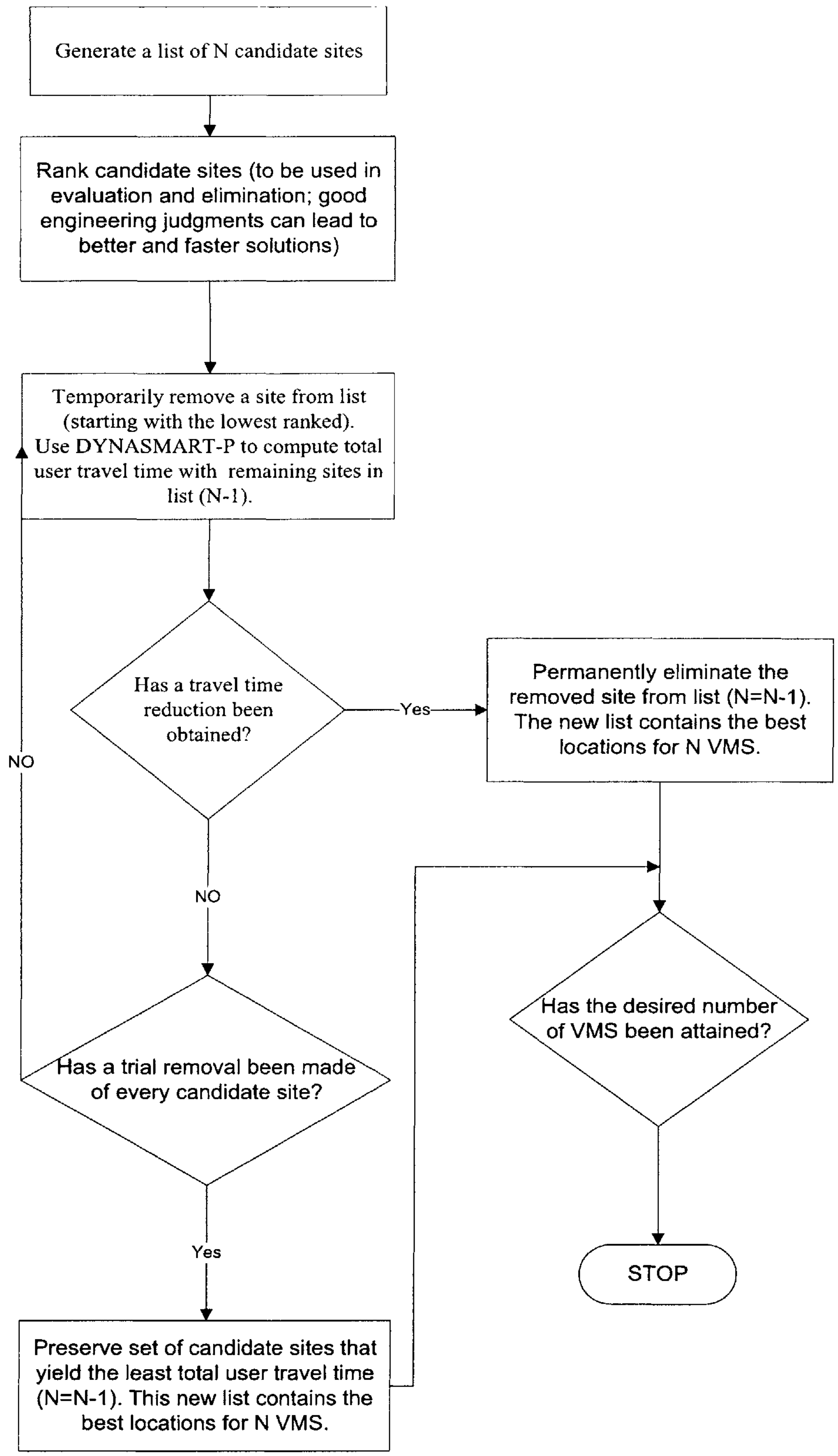

Figure 2-2 Solution Procedure for Solving the Real-Time VMS Location Problem (Huynh et al., 2002)

2.3 Summary

In this chapter, a literature review of the studies that evaluate the impact of Variable Message Signs was done. Studies show that Variable Message Signs can be a powerful tool in improving the traffic conditions in wake of non-recurrent congestion. We have also seen that optimizing their locations can significantly change the magnitude of benefits derived from diversion of vehicles. Thus, a tool is required to assess the impact of VMS when dynamic and predictive route guidance is given to travelers. Such a tool is developed and presented in the next chapter. The next chapter also develops a methodology to optimize the VMS locations.

Chapter 3 Assessment Methodology

The last chapter emphasized the importance of Variable Message Signs in incident management. This chapter discusses the development of a tool to assess the impact of Variable Message Signs using DynaMIT (a DTA tool) and MITSIMLab (a microscopic traffic simulator), both developed by the Intelligent Transportation Systems (ITS) Program at the Massachusetts Institute of technology. It is followed by the development of a framework to maximize these benefits from VMS by optimizing the VMS locations.

3.1 Implementation of VMS in the 'Closed Loop' integration of MITSIMLab and DynaMIT

In times of non-recurrent congestion, information is disseminated through the Variable Message Signs by the Traffic Management Center to divert the travelers to alternate available routes, thus using the capacity of the system to reduce delays. However, the state of the art is to deliver the current information about the incident and the diversion routes to the travelers, i.e. the current measured travel times on the incident affected and the diversion routes. When the driver sees this information, it is useful to him/her only if the diversion routes are near. If information is displayed about a road that is 30 minutes away from his/her present location, a habitual driver won't react to such information as he/she knows that things will be different when he/she reaches that road. Thus, disseminating the current information is hence not optimal, as most of it won't be used by the drivers anyway.

If a driver is however told the travel times that will be actually experienced by him/her, there is a higher chance that he/she will believe in the information and thus make a better informed decision. Thus, an ability to *predict* future traffic is desired. Lack of knowledge of future traffic conditions will make the information outdated or unusable. Dynamic Traffic Assignment (DTA) is a critical component of such traffic prediction systems.

However, it is not enough to extrapolate the current conditions to future and disseminate it to drivers. Drivers react to such information but when they reach those links, they don't experience what was being told by the VMS. The credibility of such systems therefore relies in their ability to generate and disseminate *consistent* route guidance. By consistency it is meant that the actual experienced travel times by the travelers are same as the ones that were predicted by the DTA system.

A tool is thus required that is capable of disseminating *predictive* and *consistent* route guidance through Variable Message Signs. A description of the tool that is used for the assessment of VMS is provided in the sections below.

For details about the functionality of MITSIMLab, DynaMIT and their 'closed loop' integration, the reader is advised to refer to the Appendices. Here is a brief description of the framework followed by the implementation of VMS in this framework.

3.1.1 Overview of the 'Closed Loop' Framework

To evaluate the effects of dynamic route guidance generated from the DynaMIT dynamic traffic management system we require either:

a. DynaMIT field deployment at a TMC or private transportation ISP for real-time information provision to drivers, or
b. DynaMIT integration with a 'real-world' simulator that can reproduce the effects of VMS during simulation.

In the present setup, to evaluate the effectiveness of ATIS, MITSIMLab is used here as a proxy for the real world. The overall framework integrating MITSIMLab and DynaMIT in a 'closed loop' is presented in Figure 3-1. During real-time operation of the 'closed loop' framework, MITSIMLab provides DynaMIT with surveillance reports (ie. sensor counts) of simulated 'real world' traffic flows. As in the real-world scenario, DynaMIT uses the surveillance report to perform consistent demand estimations and to generate unbiased guidance predictions. These guidance forecasts are relayed to MITSIMLab for dissemination to simulated drivers. The results of the MITSIMLab simulation are representative of what would occur in reality, and any relevant measures of effectiveness available in the MITSIMLab reporting capabilities can be used as a basis for an evaluation of the effectiveness of ATIS. For our present study, we need to implement the VMS logic in a similar manner as the ATIS.

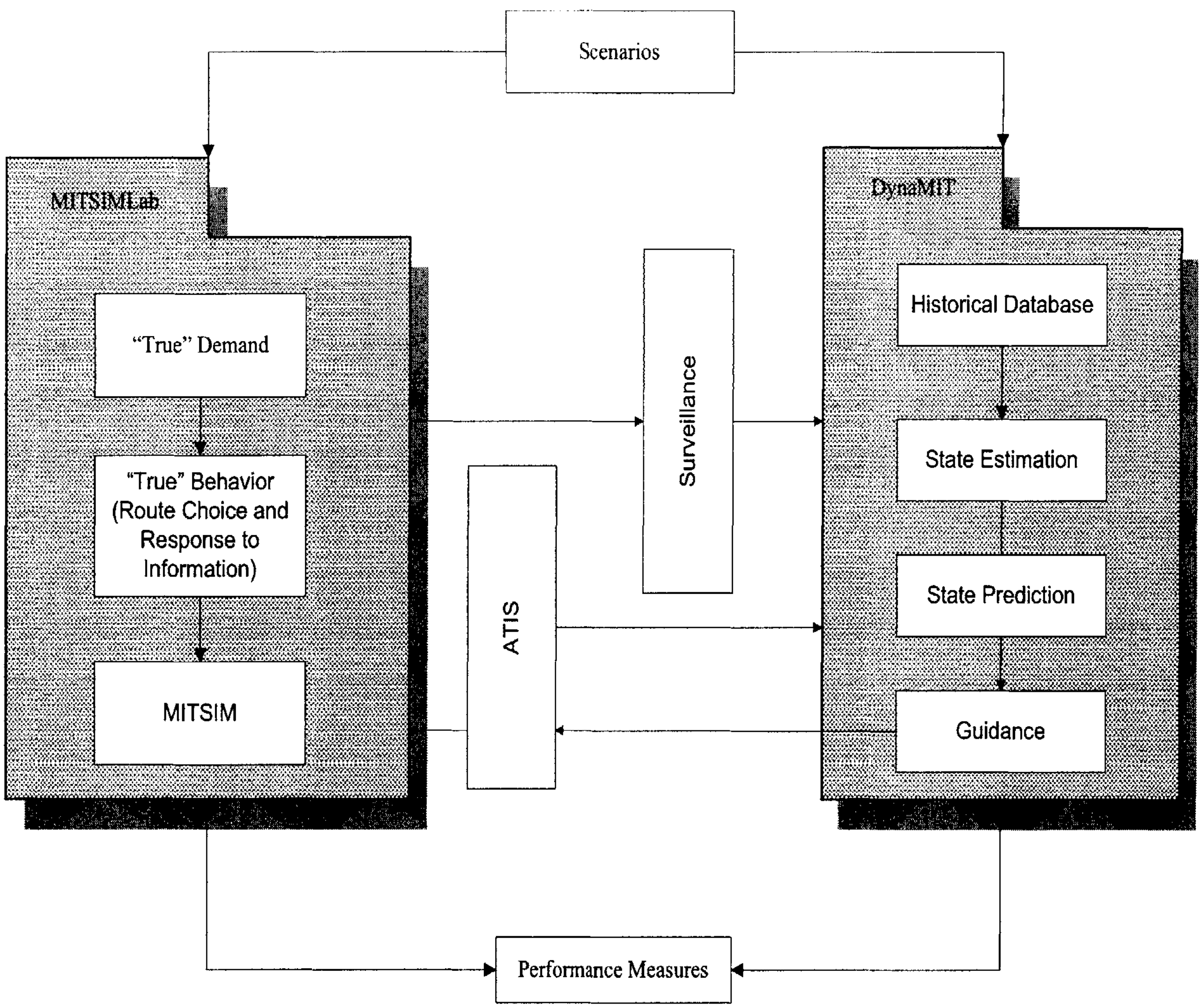

Figure 3-1 MITSIMLab - DynaMIT Interactions: 'closed loop' evaluation (Balakrishna, et al, 2005)

3.1.2 Implementation of VMS functionality in MITSIMLab

In the 'closed loop' integration, MITSIMLab was previously using a single network-wide information source which was disseminated to drivers having access to in-vehicle devices providing traffic information and guidance. Whenever guidance became available from DynaMIT (after each 'OD interval'), all the 'guided' drivers in the network were made to re-evaluate their route choice, in lieu of the availability of predictive information made available by DynaMIT. Also, the 'guided' drivers got access to updated travel time information about the whole network, including the predictive information. The drivers would then recalculate utilities for different paths leading to their destination, and switch the route with some probability. However, the functionality of VMS is different, and hence, its logic had to be implemented in MITSIMLab and DynaMIT separately.

MITSIMLab has the capability of modeling control devices within a segment. A segment can contain multiple control devices (e.g. a traffic signal). These control devices can be segment-based, or lane-based. VMS was modeled as a link-based control device. The user can define one VMS per segment.

All the VMS in the network have to be defined in the "network" file of MITSIMLab. Each VMS is associated with certain characteristics, and provides predictive information about certain links. These links will typically the links that are affected by the incident and the links to which traffic has to be diverted to. All this information is written in the network file under the section for "Control Devices".

The VMS functionality in MITSIMLab has the following features:

- As mentioned above, each segment can have one VMS.
- The VMS provides descriptive information which means that the VMS will provide the latest and predicted information about alternate diversion routes. This should be differentiated from prescriptive information, which is mandatory for the drivers to comply to.
- Each VMS is associated with its own visibility distance. A driver is able to see and hence respond to a VMS as soon as it comes within the visibility distance of a VMS. MITSIMLab models "familiarity" as one of the driver attributes. These drivers are

familiar with the network, and hence are assumed to know the locations of the VMS. Thus, these drivers will be able to respond to see the VMS earlier than the drivers who are not familiar with the network. This is captured by the "familiarity factor" which is multiplied to the visibility distance of a VMS. Although the visibility distance does not affect the route choice, it is important for the lane changing decisions of a driver, who would want to move to a different lane to maneuver to the newly chosen path at the downstream link.

- Each VMS can be assigned an attribute to denote the type of drivers (i.e. guided or unguided) that will respond to the VMS. For example, if the guided drivers have access to superior information then they might not rely on VMS and will ignore it. In that case, only the unguided drivers will respond to the VMS. However, for the purpose of this study, we want to evaluate the exclusive benefits of VMS. Hence, all the drivers have been assumed to be unguided.
- A VMS has a compliance factor associated with it. This is given from 0 to 100% in steps of 10, and denotes the percentage of drivers that will respond to the VMS. By response it is meant that for those 'compliant' drivers, the utilities for all the paths leading to his destination will be calculated again and a path will be chosen with certain probability, while no action will be taken for other drivers.
- Whenever a driver comes within the visibility distance of a VMS, he is made to re-evaluate the route choice based on the factors described above. Since the time-step in MITSIMLab is 0.1 second, a vehicle sees the VMS multiple times. However, the response takes place only the first time the vehicle is seen.
- Even though the application in this study considers only unguided drivers, the implementation is capable of providing information both through the in-vehicle devices (as in the 'closed loop' with guided drivers) and through en-route devices such as VMS.
- A Variable Message Sign provides descriptive information about certain links/paths in the network, that act as the diversion routes in case of an incident. In the network file of MITSIMLab, each VMS carries a list of links for which it provides guidance. Paths can be included as a set of links. When a driver recalculates the utilities of the paths in his/her choice set, he/she has access to the predictive information (made available from

DynaMIT) for these particular links, while for other links, the knowledge is based on the habitual travel times. Currently, we do not model prescriptive information.

- MITSIMLab can model multiple Variable Message Signs. The response to one Variable Message Sign is independent of the response to other. If a driver sees a second VMS after the first, the whole procedure of response to the VMS and re-evaluation of the route choice is executed again based on the latest available information, and his travel decision is updated.

3.1.3 Implementation of VMS functionality in DynaMIT

DynaMIT-P, the planning version of DynaMIT models VMS as a source of information dissemination. 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. Detailed description of DynaMIT-P can be found in Sundaram (2002).

Sundaram (2002) has shown that the Predictive VMS, that provides consistent guidance about the future network conditions to the travelers, 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, where the drivers are presented just the current travel times, might cause travelers to experience longer travel times 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 was extended to the real time version of DynaMIT.

Modifications were made in DynaMIT's C++ objects to extend the implementation of predictive VMS in DynaMIT-P to DynaMIT (which is the real time version). The equilibrium travel times, which in DynaMIT-P are the travel times based on day-to-day behavior, were set to be obtained from the historical travel times, which as stated before, are for the calibrated DynaMIT. DynaMIT-P generates a guidance table, and the codes were modified for it to be written in a format compatible to the 'closed loop' framework.

The features of VMS in DynaMIT are similar to those available in MITSIMLab. For an application of VMS in DynaMIT-P, readers are advised to read Chauhan (2003).

3.2 Assessment of Impact of VMS using 'Closed Loop'

The following methodology will be used to evaluate the effectiveness of Variable Message Signs Figure 3-2.

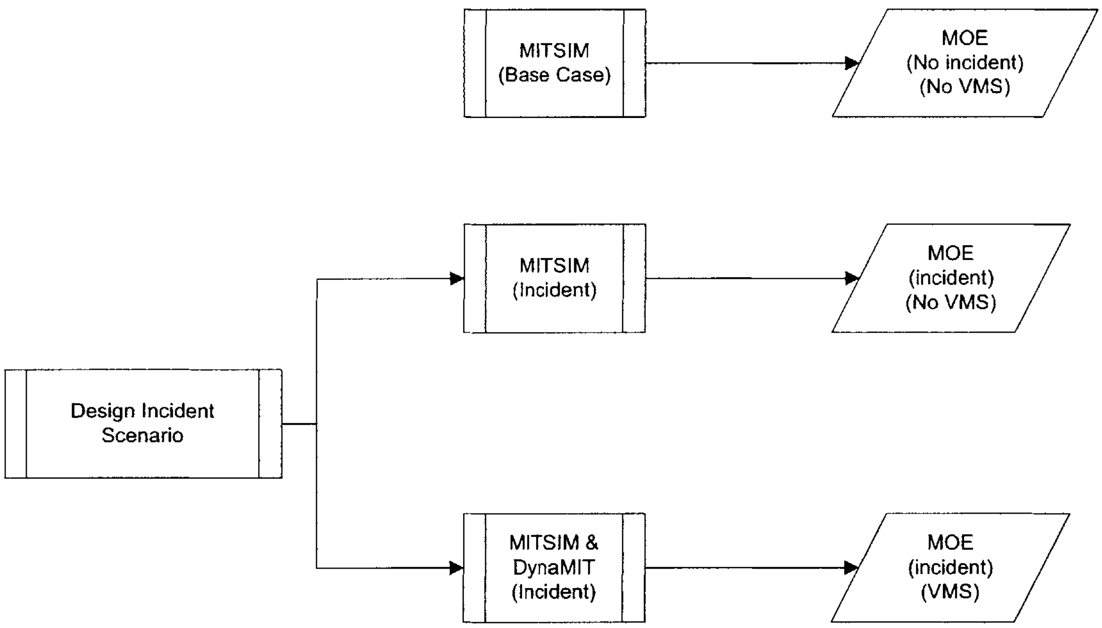

Figure 3-2 VMS Evaluation Methodology

This evaluation methodology makes use of the calibrated MITSIMLab model for the Lower Westchester County network (Antoniou, et al., 2006a), including all demand and supply characteristics. The DynaMIT model that is used is calibrated against the MITSIMLab model (Antoniou, et al., 2006b) including DynaMIT network supply characteristics, route choice parameters, and historical O-D representations.

First, the performance of MITSIMLab is evaluated in the base case, i.e. a normal day is simulated and no information is provided. Drivers make pre-trip decisions for their paths and do not change them. The 'closed loop' is not required in this case as no information is being provided. For evaluation, relevant MITSIMLab 'measures of effectiveness' (MOE) typically include total and mean travel times and distributional travel times across guided and unguided driver populations. It is also possible to examine these metrics according to driver departure and arrival time and route-choice decisions.

Since the effect of VMS is most promising under the conditions of non-recurrent congestion (e.g. an incident on a link causing the lanes to be blocked), we are typically interested in some perturbation of the baseline network conditions that modifies network supply or demand in some systematic way. Of course, VMS will impact network performance even without such a change to network conditions, but if the MITSIMLab historical travel time database (conventional driver wisdom) is already a very good representation of what drivers will experience, we won't expect significant benefits from VMS - users are already making the best decisions they can.

As illustrated in Figure 3-2, an incident is a good example of such an unforeseen impact to network supply. The same methodology can be used even if the network demand or supply gets modified in another way (e.g. spike/decline in specific demand, road closure, new alternate route, etc.). The next step in the methodology, then, is to capture the effects of the incident (or other change) in MITSIMLab without the presence of VMS. This again, will be simulated without the presence of DynaMIT.

Finally, DynaMIT predictive guidance is used to disseminate information to drivers in MITSIMLab through the Variable Message Signs, and the resulting benefits can be compared against the baseline results. This framework for the assessment of impact of VMS is applied to a case study in Chapter 4.

3. 3 Optimal Location of Variable Message Signs

After developing a framework to evaluate the Variable Message Signs, a methodology was devised to choose the VMS locations that maximize the benefits from VMS by making use of the 'closed loop' and genetic algorithms. This section presents a description of the methodology.

In chapter 2, we saw that the choosing the best locations for the Variable Message Signs can significantly increase the benefits. However, existing guidelines for the location of Variable Message Signs merely state that VMS should be located upstream of bottlenecks, high accident locations, and major diversion points. They also suggest that VMS should not be located within interchanges, and the minimum spacing should be at least ¾ miles. However, these guidelines do not provide any means to determine their optimal location.

Existing work that has been done in this direction is interesting. But there are limitations when their application is considered. The work of Chiu, et al. (2001) and Huynh, et al. (2002) have been applied to the Fort-Worth network that consists of just one freeway and the diversion routes are pretty clear and direct. Abbas, et al. (1999) apply their methodology to a very small network. In both cases, it is not clear how would the methodologies react in the presence of other main line routes in the network, where the network interactions are much more complex and difficult to predict. The methodologies need to be tested on such network for their robustness although they provide a good starting point.

3.3.1 Framework

The framework of the methodology for optimal location of VMS is shown in Figure 3-3.

A randomly generated initial set of solutions is selected. The number of solutions is based on the size of the solution space. Each solution is a set of Variable Message Sign locations in the given network.

Once the initial population of solutions has been generated, each particle's objective function is evaluated using the 'closed loop' integration between MITSIMLab and DynaMIT (Florian, 2004). It involves the microscopic simulation of drivers in the network with the dissemination of *predictive* and *consistent* route guidance through the Variable Message Signs in the network. The details of the 'closed loop' are presented at the beginning of this chapter. A set of incidents are chosen a priori based on the knowledge of the network conditions. These incidents should be indicative of the events that happen on a rather frequent basis. The reason for choosing multiple incidents is that the problem we are trying to solve is a better transportation network performance in wake of incidents. Since the location of incidents is random, we must try to obtain a solution that generates the best performance on an average. It might perform worse in a particular scenario, but simulating multiple incidents will ensure that on an average, this solution is the best among all.

The incidents are implemented one by one, and the 'closed loop' is simulated in each case. The average travel time for all the drivers for a period (based on the length of the simulation time and duration of the incident) is calculated in each simulation and averaged over all the cases of incidents. This is chosen as the objective function of the solution set.

Once all the solutions in a population are evaluated, a new population is generated and each solution is again evaluated using the 'closed loop'. The process of evaluation of each particle is then applied to the new generation. The process is repeated till the required number of generations are evaluated, or a stopping criterion is attained.

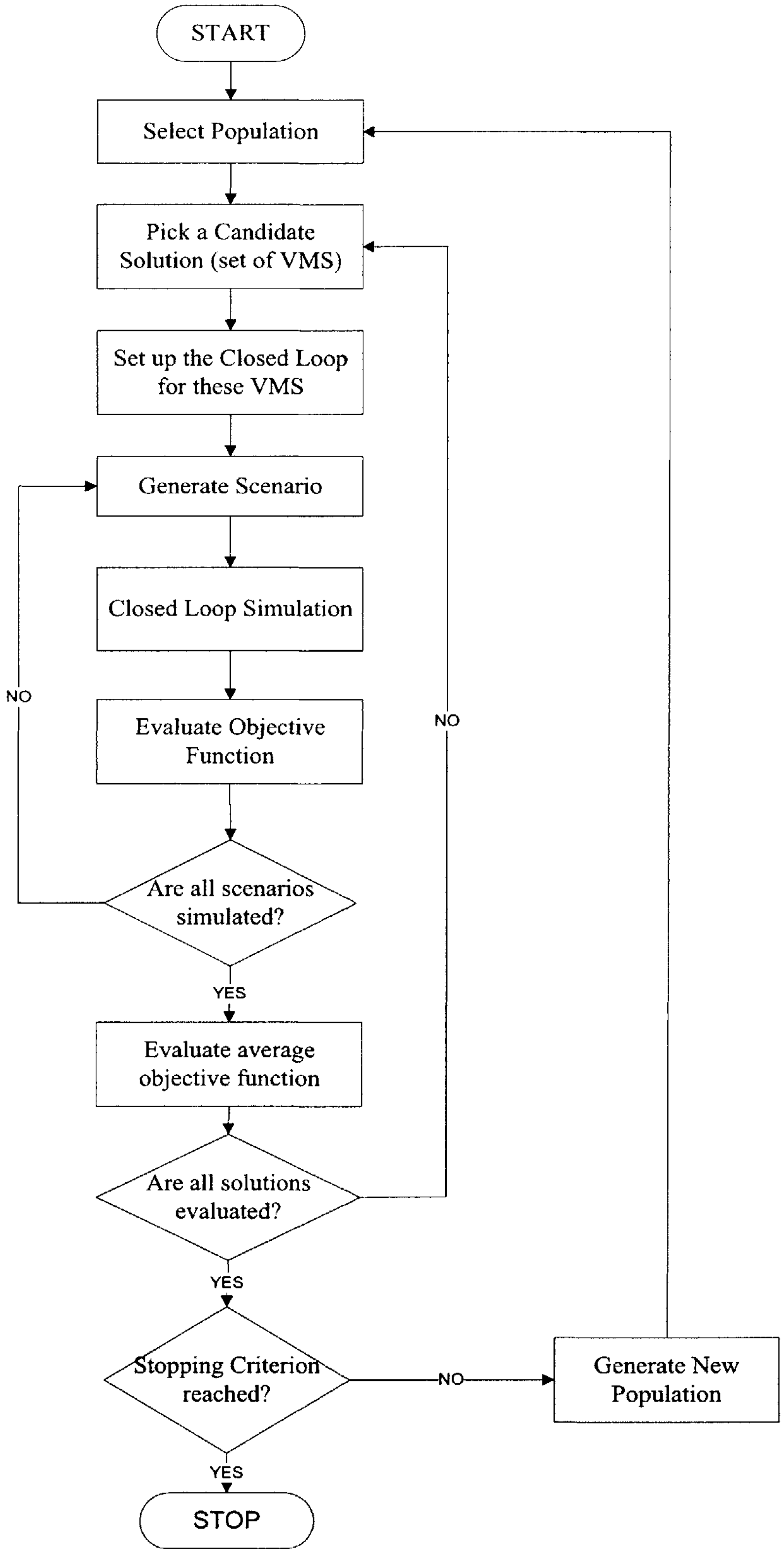

Figure 3-3 Methodology Flowchart for Optimal VMS Locations

3.3.1 Optimization Algorithm

In the framework for optimizing the VMS locations, we need an algorithm to obtain the next set of solutions from a previous set. There are several optimization methods that are available in literature. A brief discussion is provided for these methods, followed by a detailed description of Genetic Algorithm which is used as the optimization algorithm for this problem.

The problem at hand is a discrete binary optimization problem where every variable is a binary variable, with 1 representing a VMS installation, and 0 representing no VMS. The very nature of the problem makes the relaxation to continuous variables useless because non-integer values don't make sense in the scope of this problem.

Common optimization methods rely on the availability of an explicitly defined objective function. However, since we are making use of a stochastic simulation model, such an objective function is rendered intractable. Thus most of the optimization literature becomes irrelevant for optimization based on stochastic simulation. The relevant methods can be broadly classified into path search, pattern search and random search methods.

Path search methods start at an initial solution and move in a certain direction with the aim of improving the objective function value. Often, the gradient of the function is used to determine the direction. Response surface methodology and Stochastic approximation are two examples of path search methods. However, the gradient calculation for the decision variables in this case cannot be done since they are binary integers.

Pattern search methods are also called direct search methods as they do not require the calculation of a gradient. Instead, function values are compared to determine the direction of movement from the current solution. Again, the step size in our problem is one (going from 0 to 1 or vice versa). Thus, movement based on such methods is not relevant in our case. Hooke and Jeeves method, Nelder-Mead (Simplex) method, Box-Complex method are some examples of pattern search methods.

Random search methods adopt probabilistic mechanisms to randomly select updated parameter vectors with the hope of improving towards an optimum. They are gradient-free, free, yet are characterized by a large set of tuning parameters that must be selected (often on a case-by-case basis). They are more suited to the context of discrete variable optimization over small search spaces. Simulated annealing, Tabu search and Genetic algorithms are two examples of such methods.

Genetic algorithms are best suited for the binary optimization problems when the solution space is small. This is also a gradient-free method. Genetic algorithms generate a set of good solutions along with the best one. This is very important in the application of this study, since some of the good solutions might be economically more feasible than the best one. Thus, the simplicity of the implementation of genetic algorithm, and the ease of their implementation is a motivation for optimizing the Variable Message Sign locations in this study. Using Dynamic Traffic Assignment tools (MITSIMLab and DynaMIT) gives us a chance to study the benefits of Variable Message Signs in the presence of predictive route guidance information in complex network conditions, besides determining their optimal locations. A description of Genetic Algorithm is included in the following section. Descriptions of other algorithms mentioned above are easily available in literature and have not been included here.

Genetic Algorithms (GA)

Genetic algorithms belong to a class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. A population of abstract representations (called chromosomes or the genotype or the genome) of candidate solutions to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

As mentioned, the chromosomes in a GA population typically take the form of bit strings i.e. sequences of 0 and 1. Each chromosome can be thought of as a point in the search space of candidate solutions. The GA processes populations of chromosomes, successively replacing one such population with another. The GA uses the objective function of the optimization problem as the fitness function that assigns a score (fitness) to each chromosome in the current population. The fitness of a chromosome depends on how well that chromosome solves the problem at hand.

GA Operators

The simplest form of genetic algorithm involves three types of operators: selection, crossover, and mutation.

- Selection: During each successive generation, a proportion of the existing population is selected to breed a new generation. This operator selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce. Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection.
- Crossover: This operator randomly chooses two chromosomes and exchanges the subsequences of bit strings between two chromosomes to create two offspring. For example, the strings 10000100 and 11111111 could be crossed over after the third bit in each to produce the two offspring 10011111 and 11100100. The crossover operator roughly mimics biological recombination between two single-chromosome organisms. There are several crossover techniques that are used for different applications. Apart from the one-point crossover technique indicated by the above example, there are other popular techniques including two-point crossover and "cut and splice" crossover. Two-point crossover calls for two points to be selected on the parent organism strings. Everything between the two points is swapped between the parent organisms, rendering two child organisms. The "cut and splice" approach, results in a change in length of the children strings. The reason for this difference is that each parent string has a separate choice of crossover point.
- Mutation: This operator randomly flips some of the bits in a chromosome. For example, the string 00000100 might be mutated in its second position to yield 01000100. Mutation can occur at each bit position in a string with some probability, usually very small (e.g.,

0.001). The purpose of mutation in GAs is to allow the algorithm to avoid local minima by preventing the population of chromosomes from becoming too similar to each other, thus slowing or even stopping evolution.

Apart from these three operators, there exist some other operators such as inversion which are not common in practice. For detailed exposition of various types of genetic algorithm methods, implementation details and convergence issues, the reader is referred to Mitchell (1996).

Roulette Wheel Sampling

Genetic algorithms follow the concept of survival of the fittest. It means that higher the fitness of the particle, higher is the probability of it being selected in the subsequent population. It is implemented by the use of stochastic sampling with replacement, also called the roulette wheel sampling. It operates on the concept that the proportionate fitness of each particle should be reflected in that particle's incidence in the mating pool. Thus, each chromosome in the population has a probability of selection for crossover based on its relative fitness. This technique provides the greatest probability of selection to the most fit members of the population. To evaluate the expected occurrence of a particle in the mating pool, the fitness of a particle is divided by the fitness of all particles in the population. This is the probability of selection of the particle. If there are n repetitions of the same particle in the pool, the expected occurrence will be n times this probability.

The name 'roulette wheel' has been given to this technique (stochastic sampling with replacement) because the process of selection can be likened to spinning a roulette wheel. Each member of the population is allocated the amount of space on the wheel that reflects its relative fitness. The fitter the individual, the greater the area on the roulette wheel that is occupied by the individual. Each time a parent is needed for reproduction, the selection is based on a 'spin' of the wheel. Reader is advised to refer to Mitchell (1996) for further details.

The main strength of genetic algorithms is that they can easily avoid getting stuck in a local optimum. They are naturally suitable for integer optimization, especially when there are a large number of variables with small range of possible values for each. Previous studies involving the usage of genetic algorithms for solving small transportation problems. Kim, et al. (2004) and Henderson, et al. (2004) indicate that genetic algorithms do not perform as well as the path and pattern search methods which are better tailored for continuous optimization. A major difficulty arises from the requirement of coding the continuous variables into discrete strings. However, the definition of our problem poses no difficulty in this regard. Each Variable Message Sign location can be coded as a binary digit, with it becoming 1 when the VMS is to be installed at that location, else 0.

Scalability is another important issue especially when function evaluations are expensive. Henderson, et al. (2004) reviewed an application of GA for maximum likelihood estimation and explored the effect of population size and the number of generations indicating that the two quantities varied greatly depending on the search space and the nature of the objective function, and that large populations are necessary if high levels of accuracy are desired.

Another difficulty is the choice of suitable parameters for the genetic operators such as selection, crossover and mutation. De Jong (1975) performed an early systematic study of how varying parameters affected the GA's performance. De Jong's experiments indicated that the best population size was 50–100 individuals, the best single-point crossover rate was ~0.6 per pair of parents, and the best mutation rate was 0.001 per bit.

Application of GA in the framework

To use GA to solve the problem, each solution set is defined as a particle and contains as many number of digits as the number of feasible VMS locations. Each digit is binary, with one denoting a VMS installation and 0, otherwise. The fitness of a particle is defined as the inverse of the objective function defined earlier since we want a maximization function for the fitness.

Once all the particles in a population are evaluated, a new population is generated by mating the particles from the previous population based on "roulette-wheel sampling", described in the previous section on genetic algorithms. The particles are then mated (crossover and mutation) to generate the new population. The starting values of probabilities of crossover and mutation were chosen from the literature and iterated to get the best suited values, 0.7 and 0.002 respectively.

3.4 Summary

This chapter developed two frameworks. The first framework (Figure 3-2) will be used to assess the impact of Variable Message Signs using DTA tools (MITSIMLab and DynaMIT). The second framework (Figure 3-3) will be used to optimize the VMS locations in a network using Genetic Algorithm.

The next chapter presents a comparison of the benefits accrued due to the use of VMS in the Lower Westchester County Network of New York in the case of non-recurrent congestion using the framework in Figure 3-2.

Chapter 4 Case Study I: Evaluation of Variable Message Signs in Lower Westchester County, NY using the 'Closed Loop'

The objective of this chapter is to implement the framework described in Chapter 3 for evaluation of Variable Message Signs under incident scenarios and diversion strategies, using traffic surveillance data obtained from NYSDOT for the Lower Westchester County (LWC) network. A brief description of the study network is given first. It is followed by the baseline performance of the network on a normal day when there is no incident. Also, no information is being provided in the base case. The impact of an incident on I-95 freeway is then presented. It is followed by the performance of the network with information dissemination via the Variable Message Signs. Results are shown with varying number of iterations for prediction in DynaMIT. The evaluation is continued with the simulation of another incident on the SprainBrook Parkway and then using the 'closed loop' to disseminate information via the Variable Message Signs. The results are compared both for the overall network, and some selected O-Ds that are hypothesized to be affected the most due to the incident.

4.1 Incident on I-95

4.1.1 Network Description

The LWC network is just north of Manhattan, New York. The network is extremely congested, and has heavy traffic on both 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. Most of the freeways and parkways, except Cross County Parkway and I-287, run north/south. The general extent of the project network is shown in Figure 4-1.

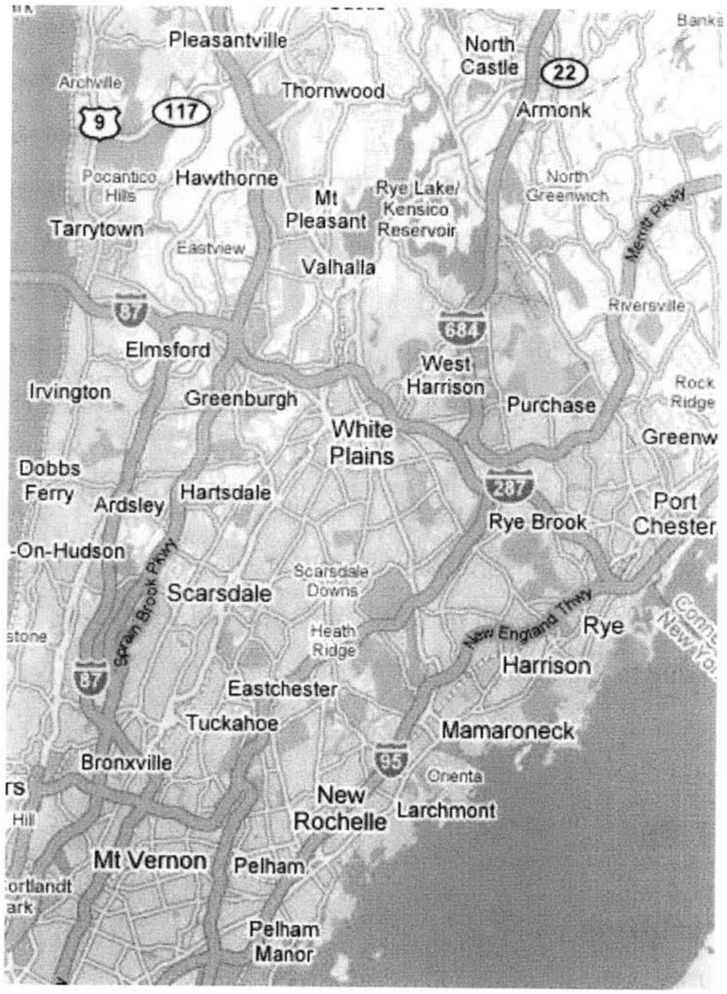

Figure 4-1 Lower Westchester County, NY (Source : http://www.maps.google.com)

The network is represented as a set of 482 O-D pairs connected by 1769 directed links. These links represent the physical links on the network, and are further subdivided into 2564 segments to model changing link characteristics.

The simulation interval is from 4 am to 4 pm. Beginning from 4:15 am, MITSIMLab sends the sensor counts to DynaMIT every 15 minutes. DynaMIT reciprocates by producing the 'closed loop' guidance every 15 minutes. The guidance provided is predictive, and is for the next 30 minutes. The details of the operation of the 'closed loop' are given in Chapter 3.

Sensor data from the field was provided by the NYSDOT and both MITSIMLab and DynaMIT were calibrated using the data. The details of the data and the calibration results can be found in these two reports: Antoniou, et al. (2006b) and Antoniou, et al. (2006a).

4.1.2 Incident Description and VMS Locations

Based on the major diversion routes and the most frequent incident locations provided by the NYSDOT, an incident on I-95 during the morning peak hour was selected to evaluate the Variable Message Signs (Figure 4-2). The incident lasts from one hour between 7 am to 8 am, and consists of blockage of all lanes during the one hour in the southbound direction. 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.

Except one, the VMS used for these simulations are the ones that are actually located in the field. The VMS on I-95 was created although it is not deployed on the field, because the incident is on I-95. The five VMS are shown using the blue triangles in Figure 4-2.

For the analysis a set of O-Ds was selected, which is expected to have the maximum effect of the Variable Message Signs. These were chosen based on the location of the VMS. The selected O-Ds are shown in Figure 4-3. The green rectangles are the selected origins, and the red diamonds are the selected destinations. It should be noted that analysis is presented for the whole network as well.

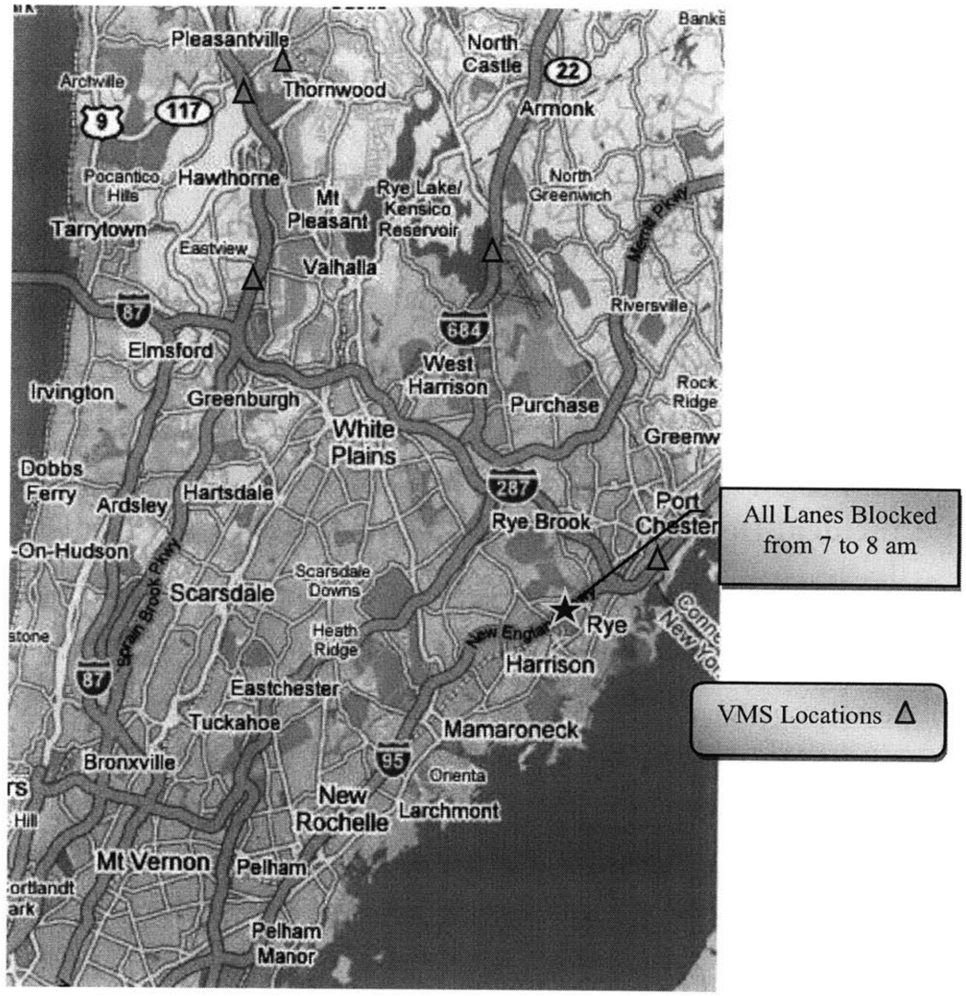

Figure 4-2 Incident and VMS Locations (Source : http://www.maps.google.com)

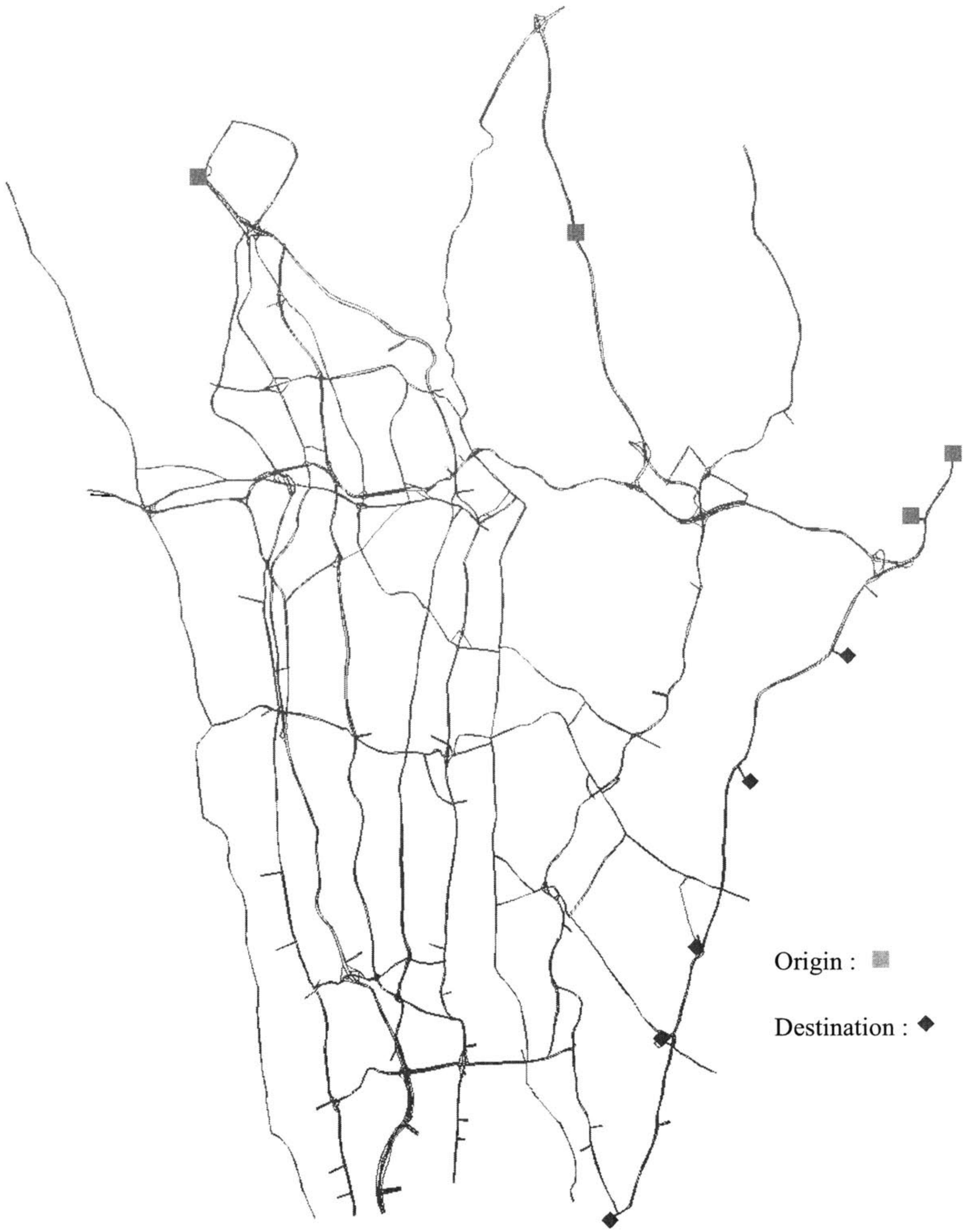

Figure 4-3 O-Ds selected for analysis of I-95 incident

4.2 Baseline Performance

The first simulation was done without any incident, nor VMS in the network. Please note that we thus, do not require DynaMIT, since the drivers are not being updated with any type of route guidance. Thus, MITSIMLab was used in the stand alone mode for this simulation. The results for the whole network are presented in Figure 4-4 and Figure 4-5, while results for the selected O-D pairs are in Figure 4-6 and Figure 4-7.

Results show that for the whole network, the average travel times experienced during the peak period by most of the travelers varies between 950 and 1050 seconds. Around 8:45 am it starts decreasing, and then remains around 875 seconds. Figure 4-5 shows that very few drivers experience high travel times. Similar observations can be made for the selected O-Ds. However, we see that the travel times are larger indicating that these routes are highly congested.

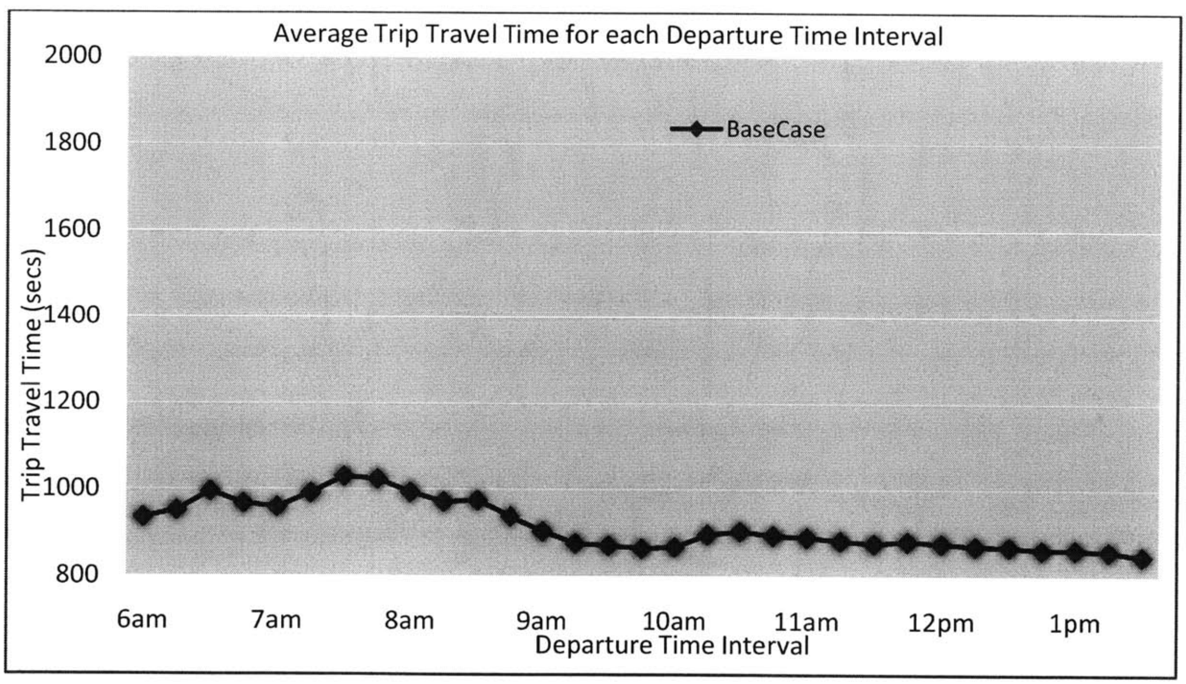

Figure 4-4 Avg. Travel Times by Departure Time Interval for all O-Ds (Base Case)

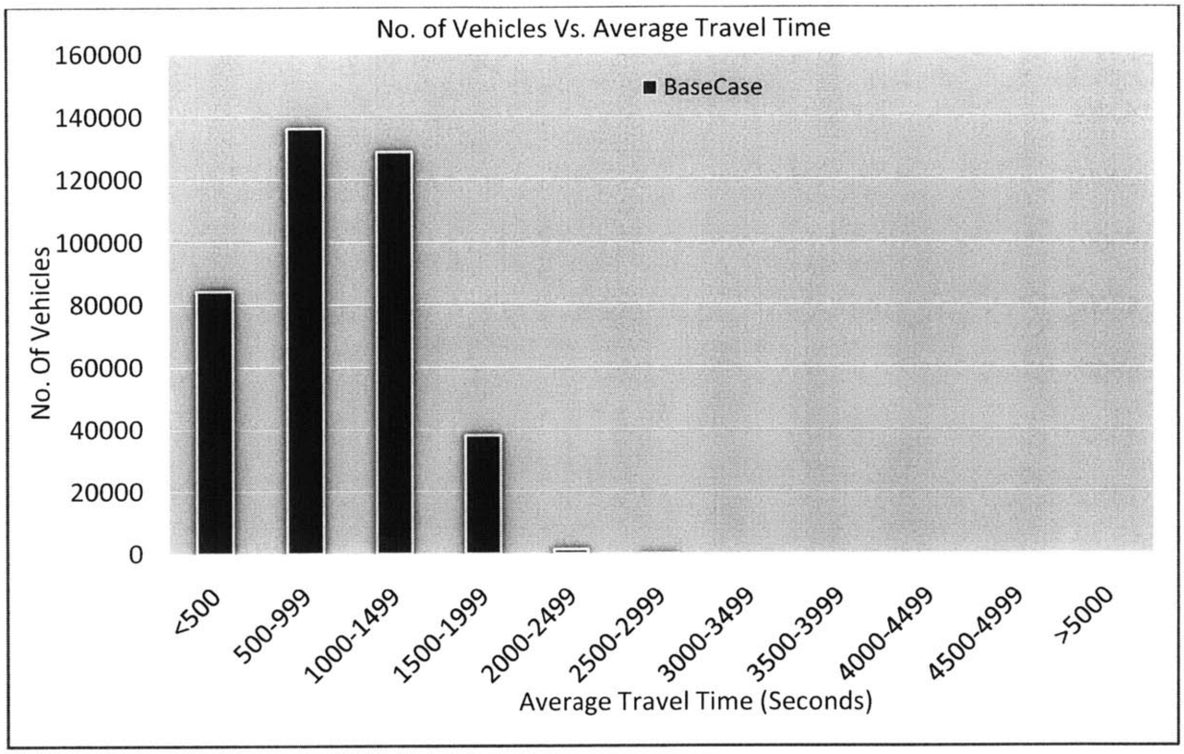

Figure 4-5 Frequency of Experienced Travel Times for all O-Ds (Base Case)

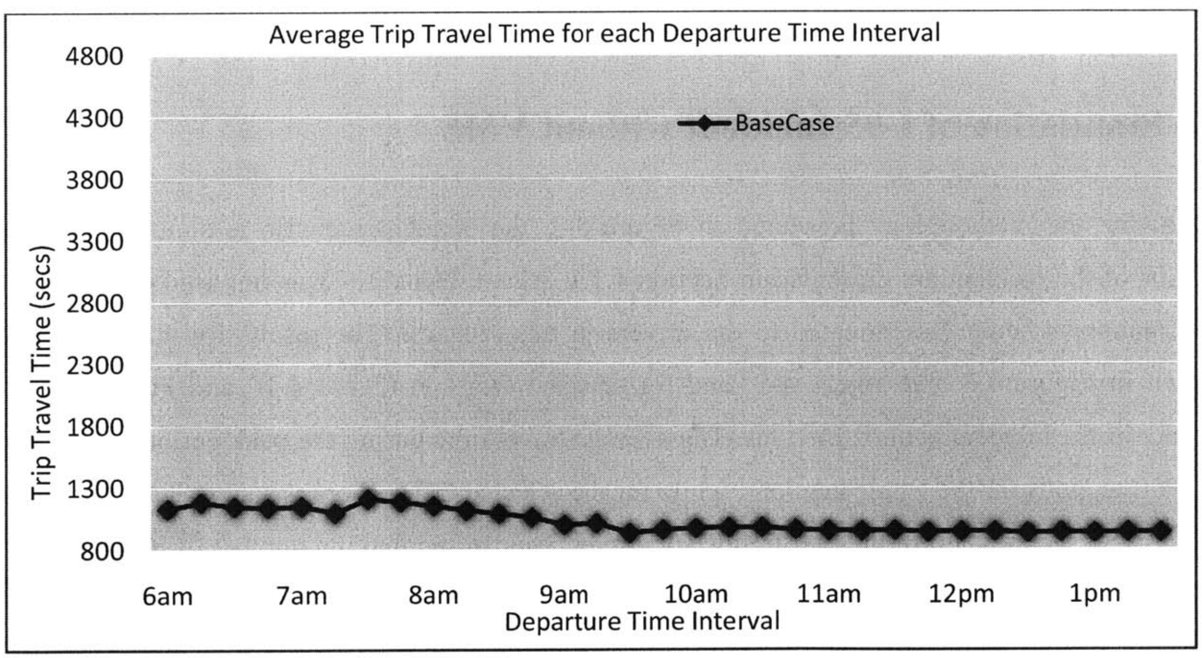

Figure 4-6 Avg. Travel Times by Departure Time Interval for selected O-Ds (Base Case)

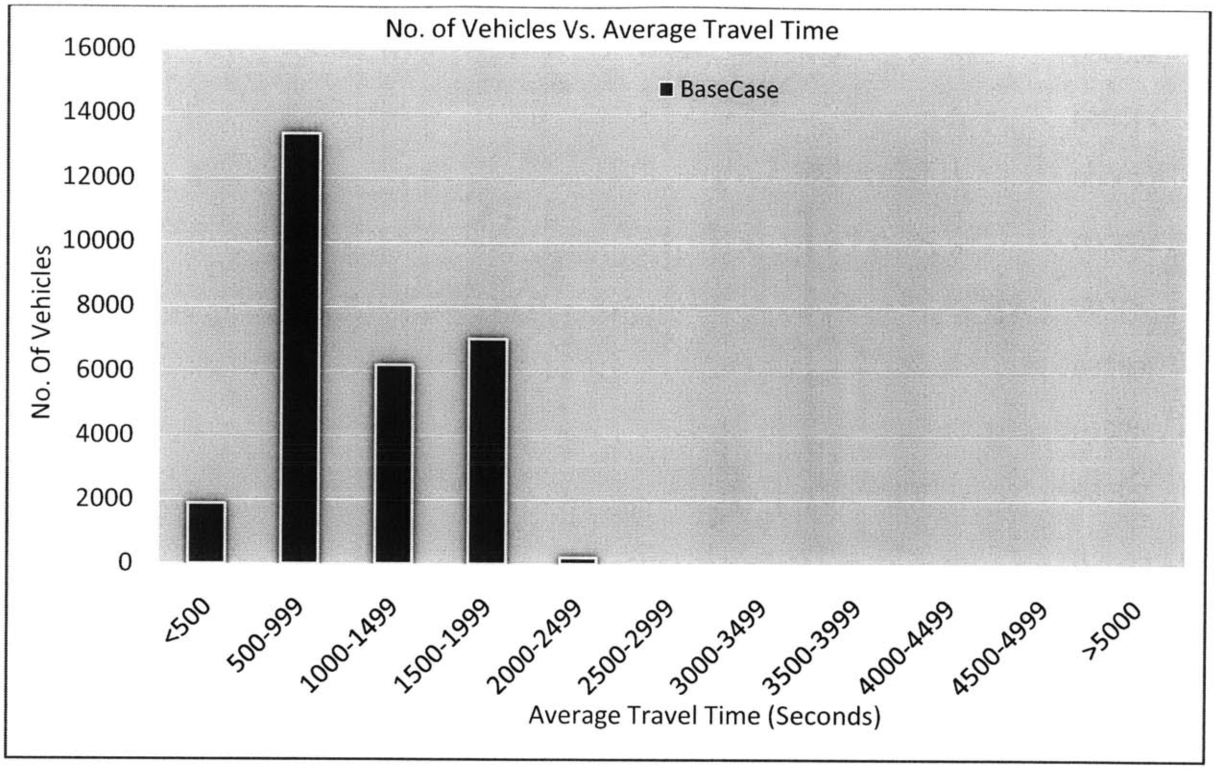

Figure 4-7 Frequency of Experienced Travel Times for selected O-Ds (Base Case)

4.3 Simulation of I-95 Incident without VMS

Following the methodology presented in Figure 3-2, the incident scenario is simulated next. Details of the incident are presented in Section 4.1.1. Again, DynaMIT was not used because no information is being disseminated to the drivers in this scenario. The results for all O-Ds are shown in Figure 4-8 and Figure 4-9; and for selected O-Ds in Figure 4-10 and Figure 4-11. Impact of the incident is quite obvious. The average travel time during the peak period increases to 1900 seconds for the whole network, while for the selected O-Ds, there is a significant jump to about 4450 seconds. From the two frequency curves, we can see that the number of people with larger travel times have increased dramatically in comparison to the base case. Due to the incident, people who depart around 6:45 am start facing huge delays because of the queue buildups.

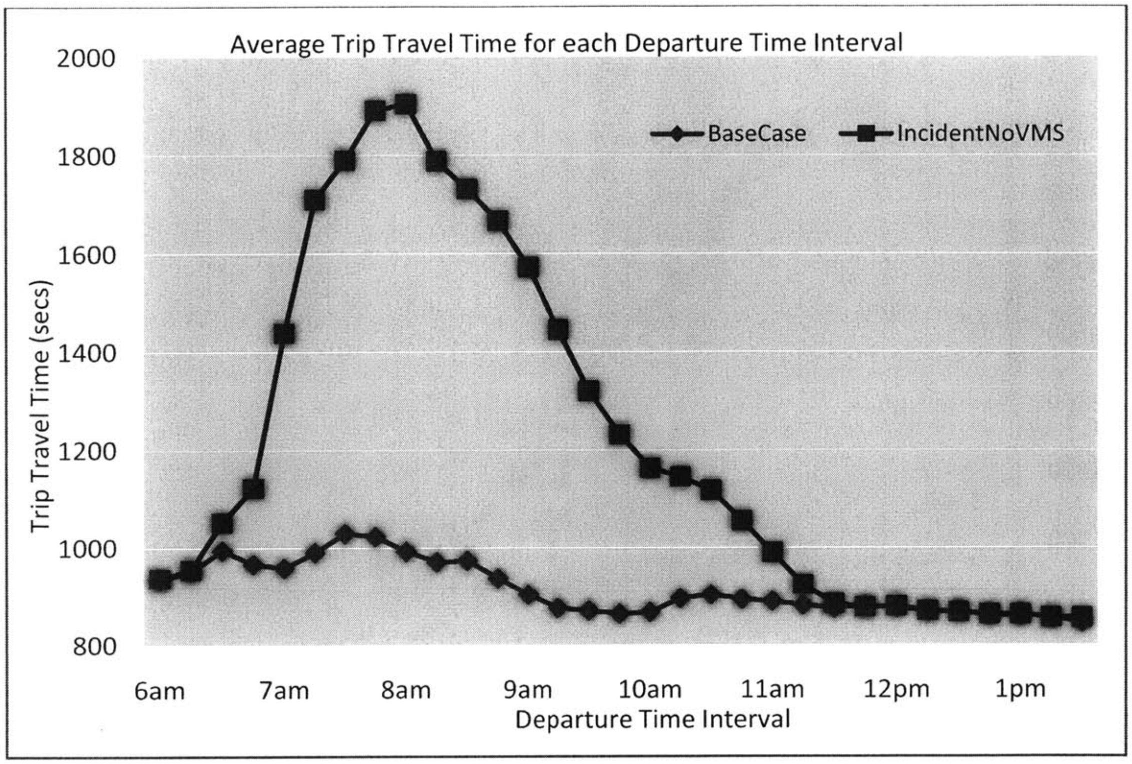

Figure 4-8 Avg. Travel Times by Departure Time Interval for all O-Ds (Incident on I-95)

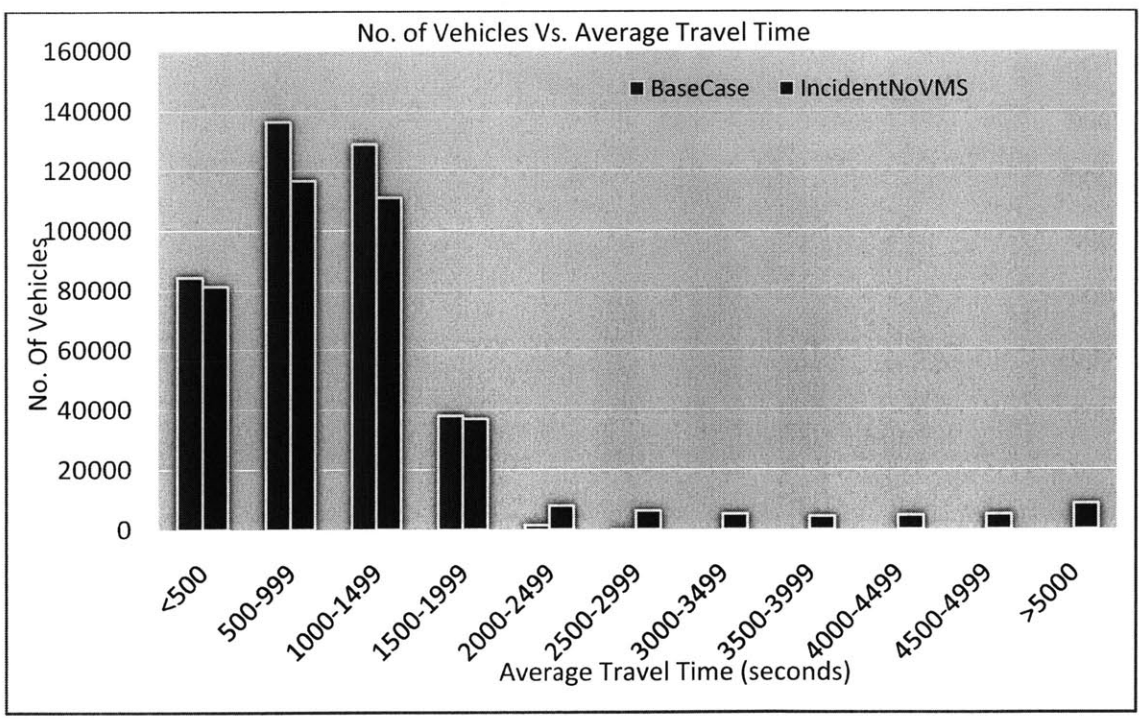

Figure 4-9 Frequency of Experienced Travel Times for all O-Ds (Incident on I-95)

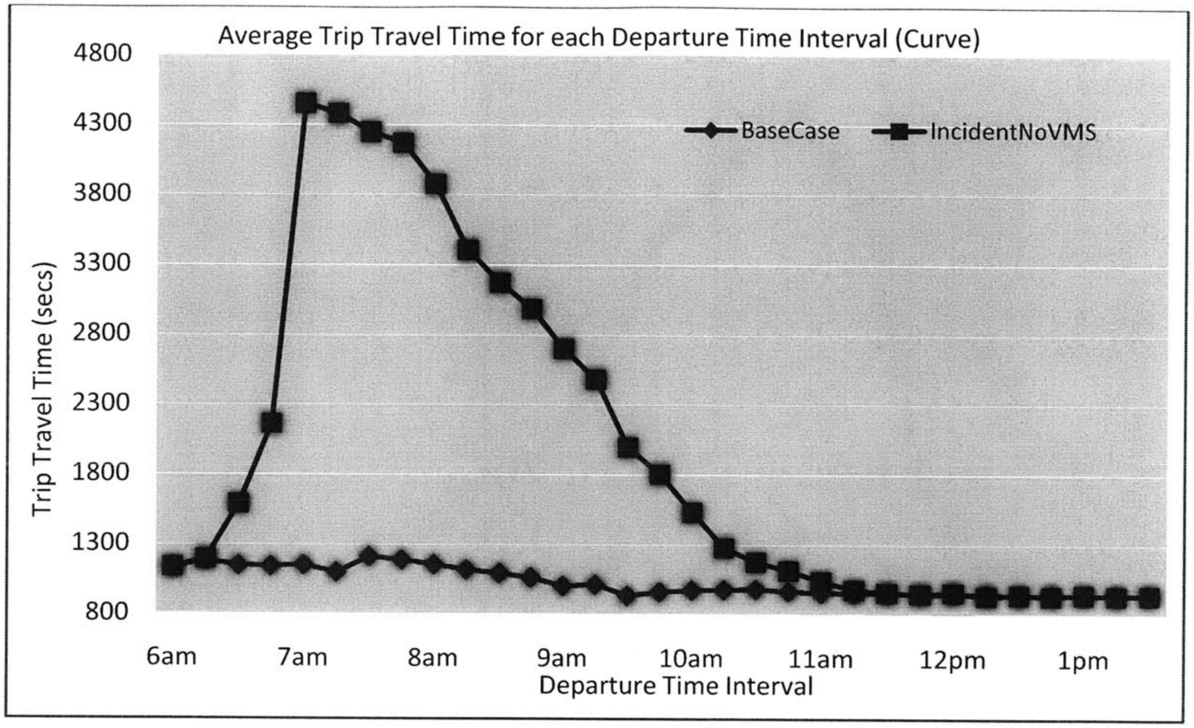

Figure 4-10 Avg. Travel Times by Departure Time Interval for selected O-Ds (Incident on I-95)

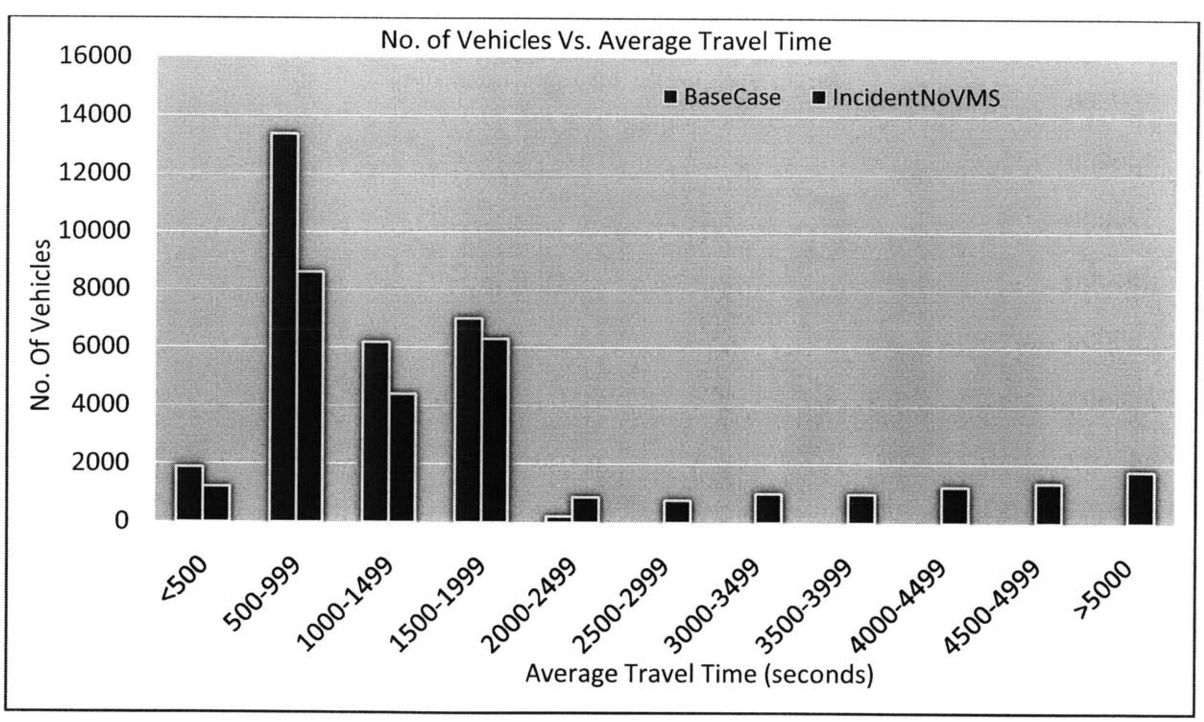

Figure 4-11 Frequency of Experienced Travel Times for selected O-Ds (Incident on I-95)

4.4 Simulation of I-95 Incident with VMS using 'Closed Loop'

To evaluate the impact of Variable Message Signs, they were installed in the network and simulation was done using the 'closed loop'. Their locations are shown in Figure 4-2. VMS strategies result in best overall network performance only when the predictive guidance given is consistent. To achieve consistency, DynaMIT has to do multiple iterations for generating predictive guidance (Balakrishna, 2002). If the guidance is not consistent, it may lead to overreaction and result in longer travel times (Sundaram, 2002). To evaluate the impact of the Variable Message Signs, the number of prediction iterations was varied to identify the optimum number of iterations for prediction that results in the best network performance. It will be seen that using three prediction iterations give the maximum benefit. It should be noted that the base case and the incident case do not change, since guidance was not being provided in the two cases. Also, everything except the number of iterations for prediction is same in the following five cases.

4.4.1 VMS in 'Closed Loop' with one Prediction Iteration

'Closed loop' simulation was done with VMS on the five locations (Figure 4-2). These VMS are link-VMS and provide information about the links that are affected by the incident, as well as the alternate diversion routes. These diversion routes were based on the information about the major diversion routes provided by the NYSDOT. The results for the whole network are shown in Figure 4-12 and Figure 4-13; for the selected O-Ds in Figure 4-14 and Figure 4-15.

The benefits of VMS are clearly visible. Although the travel times are greater than the base case, there is significant improvement compared to the incident case. This is expected since the incident is bound to deteriorate the network performance even in the presence of VMS. For the whole network, the maximum average travel time comes down to 1515 seconds from 1905 seconds, an improvement of about 21%. For the selected O-Ds, an improvement is seen from 4450 seconds to 3648 seconds (18% reduction). From the results, we can see that overall delay faced by the vehicles has come down significantly, as the average travel times for the incident period decreases during the whole duration. Vehicles that depart at 6:45 am do not benefit much because when the guidance is available, they have already passed the diversion nodes.

With the help of VMS, number of people who experience large travel times also comes down by a significant number as seen in Figure 4-13 and Figure 4-15.

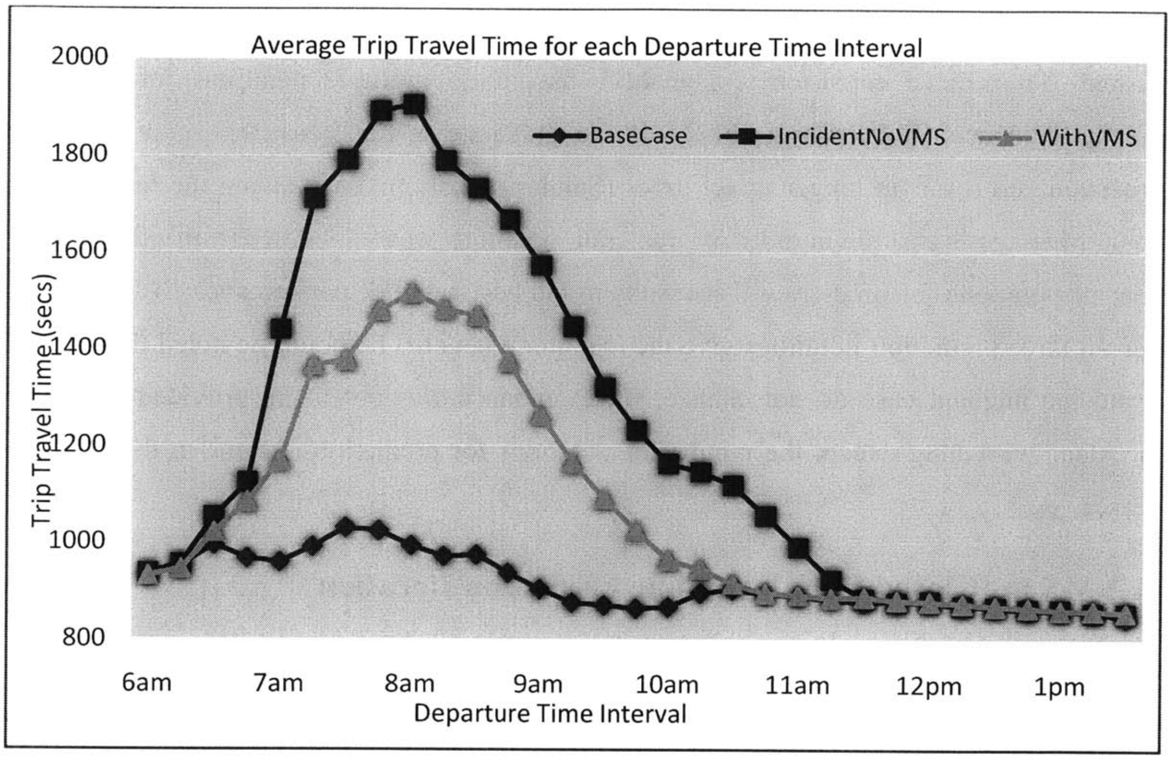

Figure 4-12 Avg. Travel Times by Departure Time Interval for all O-Ds (VMS for I-95, 1 iter)

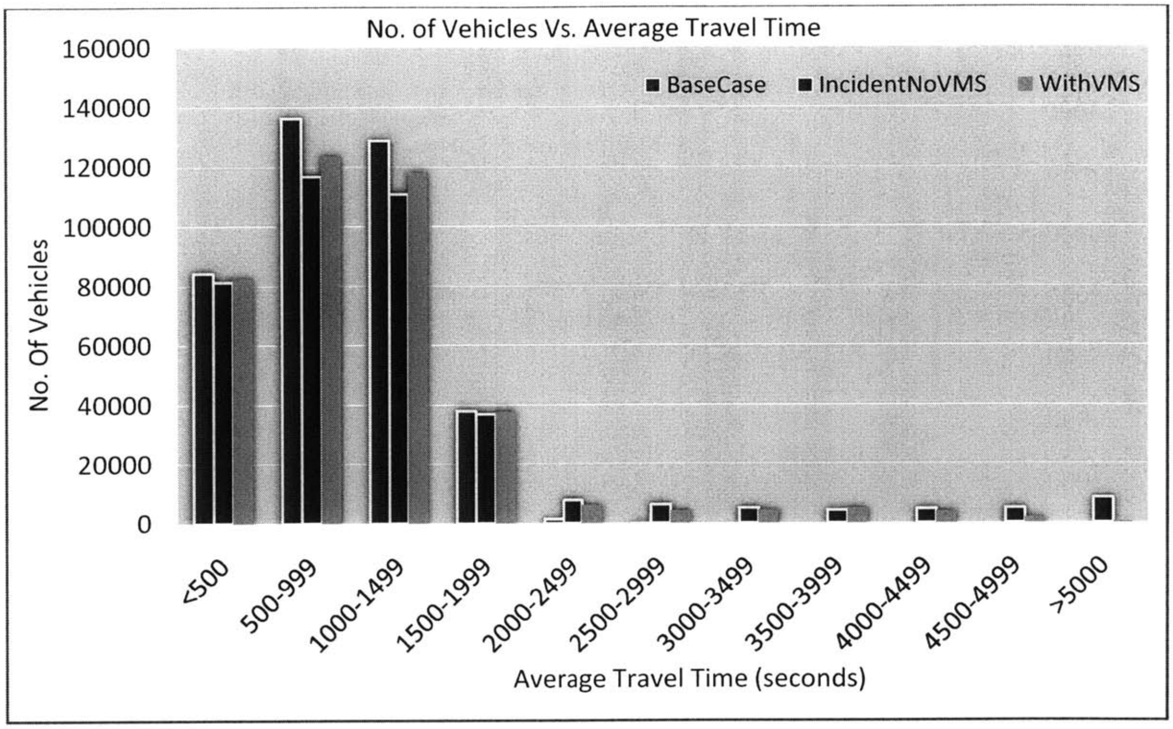

Figure 4-13 Frequency of Experienced Travel Times for all O-Ds (VMS for I-95, 1 iter)

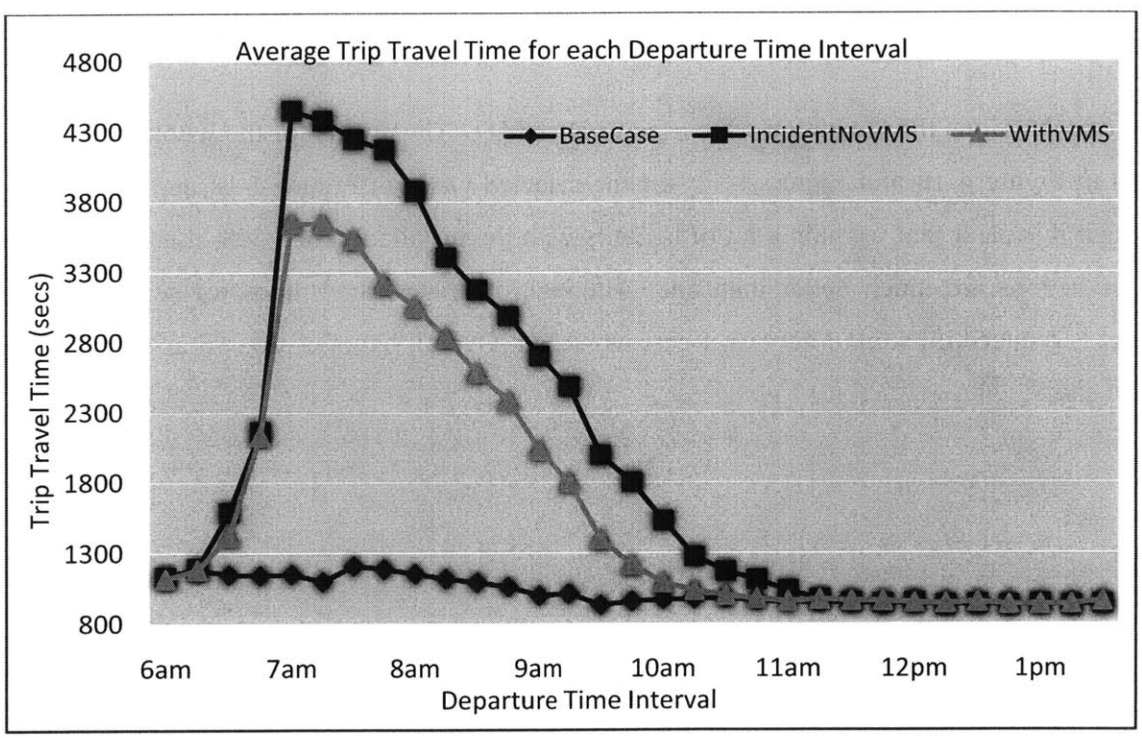

Figure 4-14 Avg. Travel Times by Departure Time Interval for selected O-Ds (VMS for I-95, 1 iter)

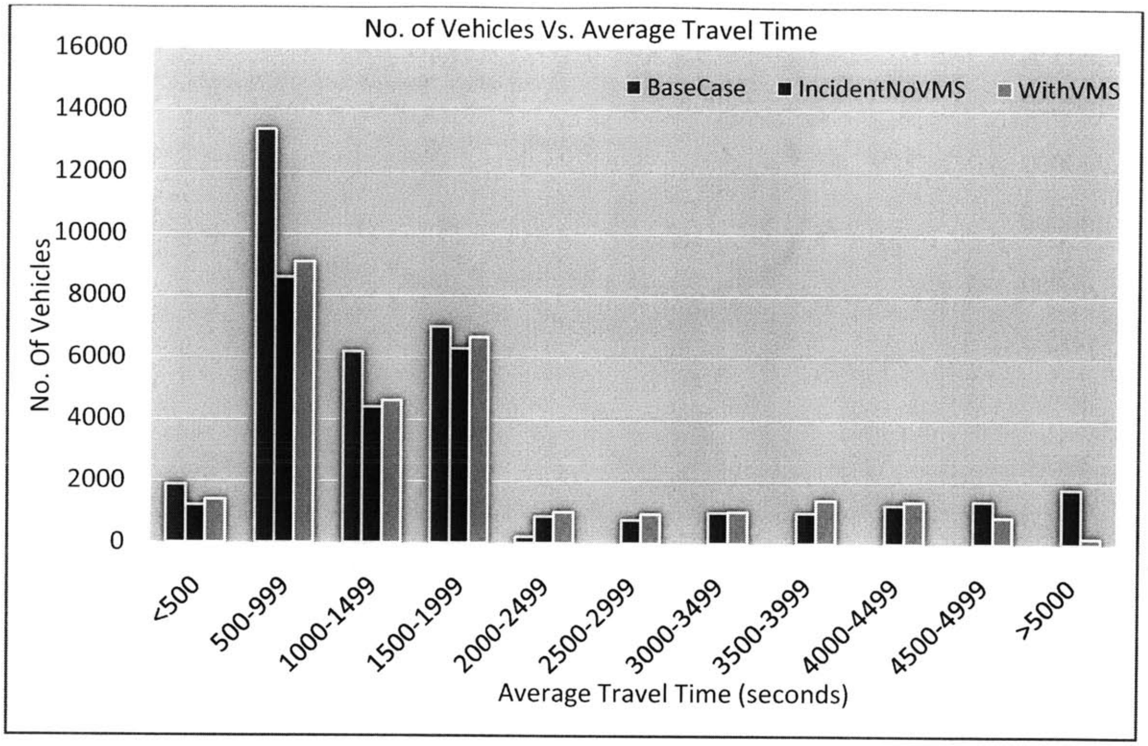

Figure 4-15 Frequency of Experienced Travel Times for selected O-Ds (VMS for I-95, 1 iter)

4.4.2 VMS in 'Closed Loop' with two Prediction Iterations

Next, two iterations for prediction were used in DynaMIT. The results for the whole network are shown in Figure 4-16 and Figure 4-17; for the selected O-Ds in Figure 4-18 and Figure 4-19. Although it is clear that we gain a lot of benefits with the installation of VMS, it is not clear that two predictions are much better than one. Although, average travel times for some departure interval is reduced, in some intervals it gets worsened. Overall benefits are still as significant as the last case.

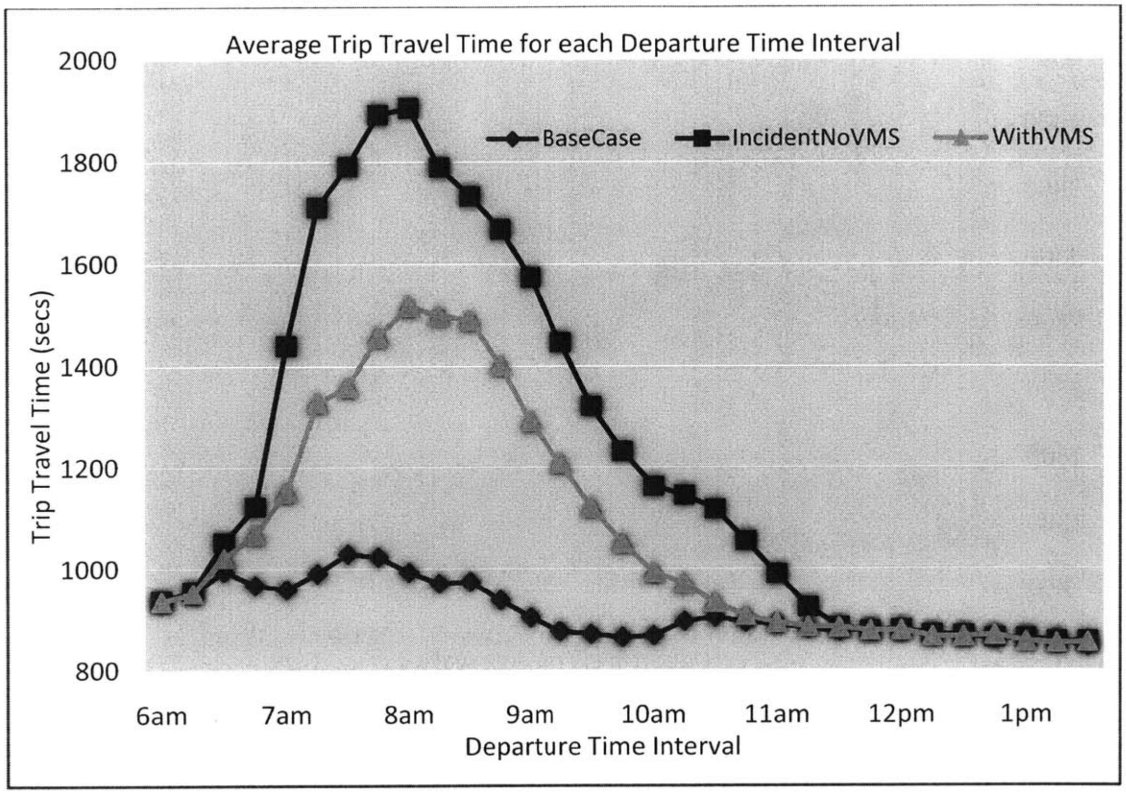

Figure 4-16 Avg. Travel Times by Departure Time Interval for all O-Ds (VMS for I-95, 2 iter)

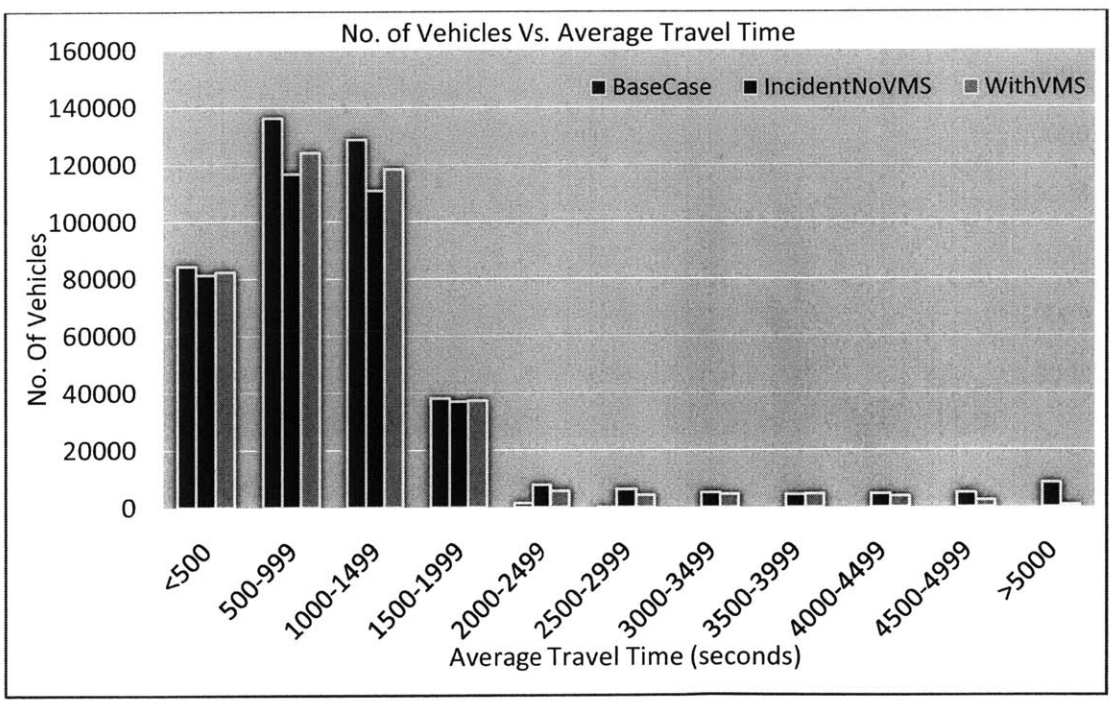

Figure 4-17 Frequency of Experienced Travel Times for all O-Ds (VMS for I-95, 2 iter)

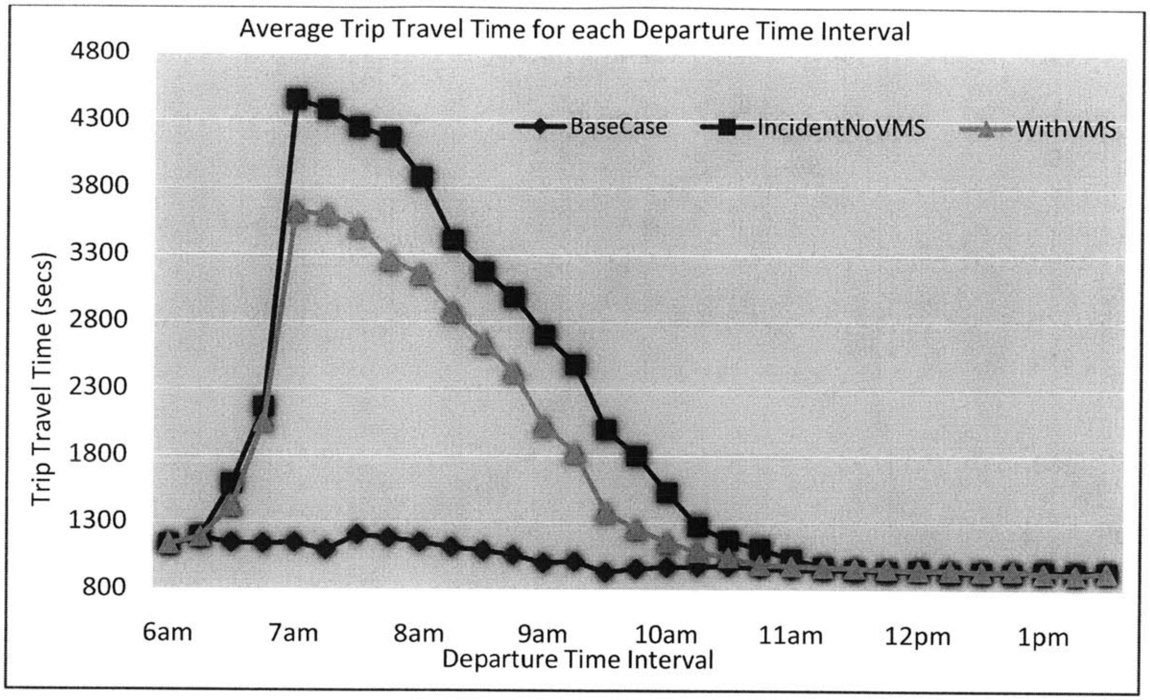

Figure 4-18 Avg. Travel Times by Departure Time Interval for selected O-Ds (VMS for I-95, 2 iter)

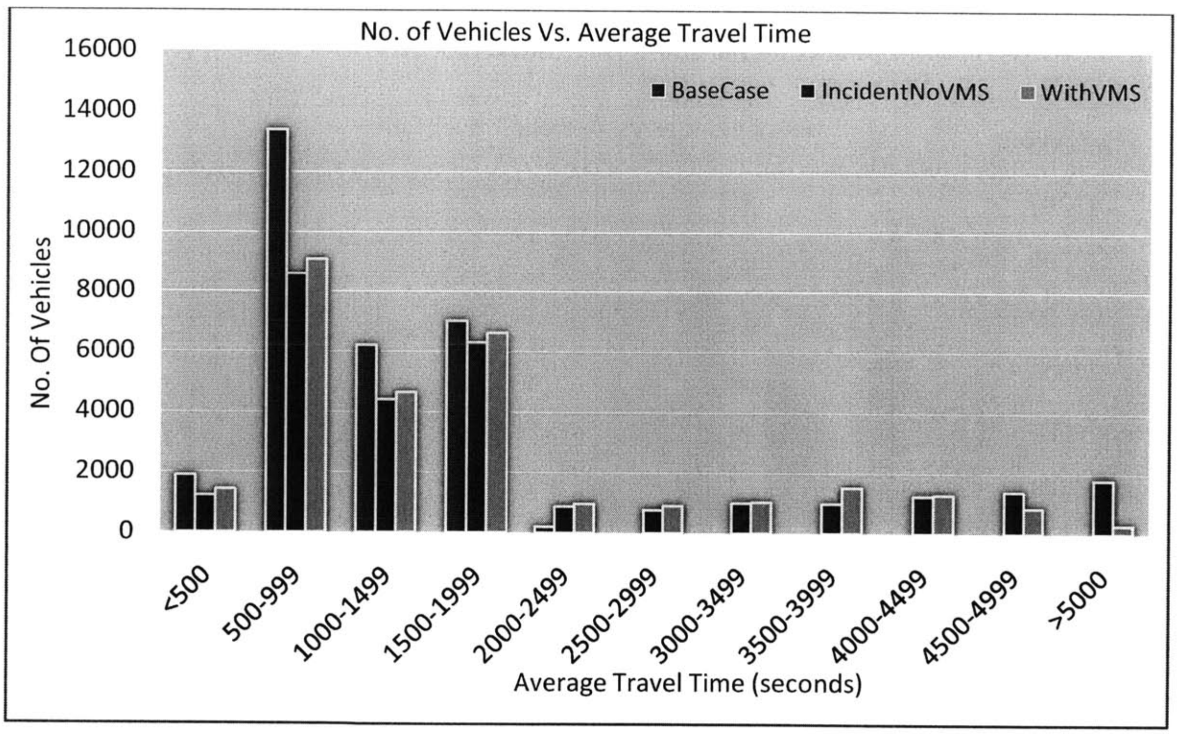

Figure 4-19 Frequency of Experienced Travel Times for selected O-Ds (VMS for I-95, 2 iter)

4.4.3 VMS in 'Closed Loop' with three Prediction Iterations

Using three prediction iterations clearly pulls the average travel times curve down (Figure 4-21 and Figure 4-23). The maximum average travel time in a departure interval is now 1481 seconds as compared to 1516 seconds in the case with two prediction iterations. In the whole period affected by the incident, the average travel times are lower in this case. The overall benefits of using VMS are still significant as in the previous two cases.

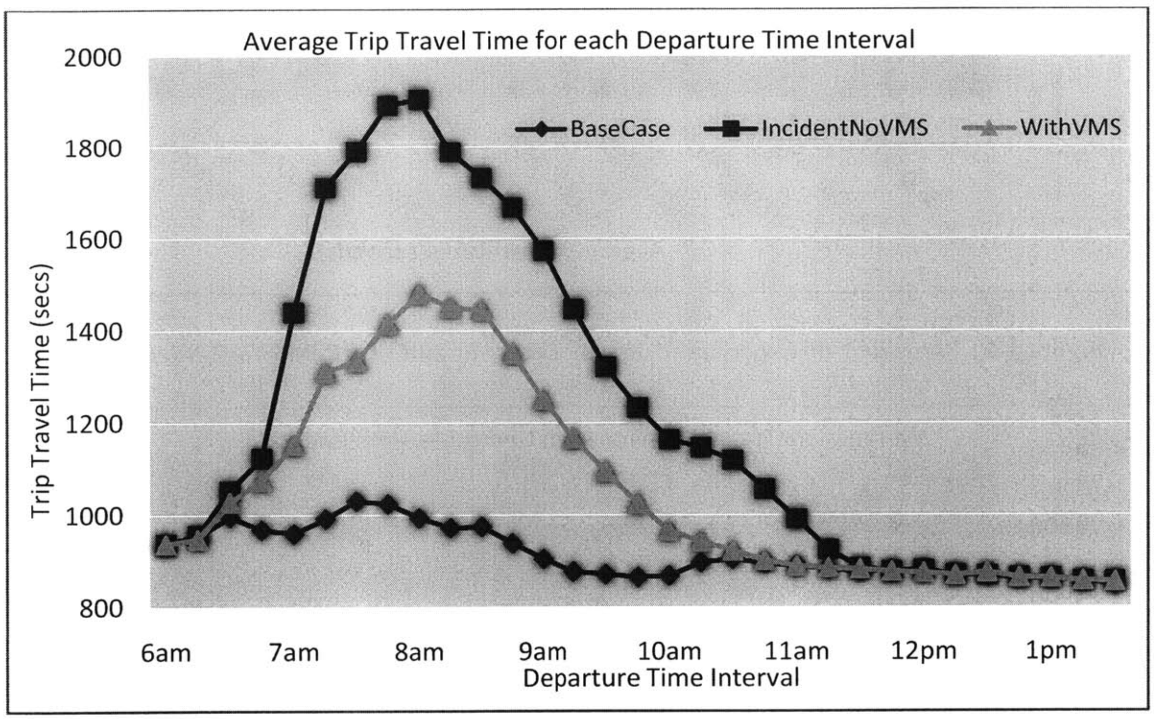

Figure 4-20 Avg. Travel Times by Departure Time Interval for all O-Ds (VMS for I-95, 3 iter)

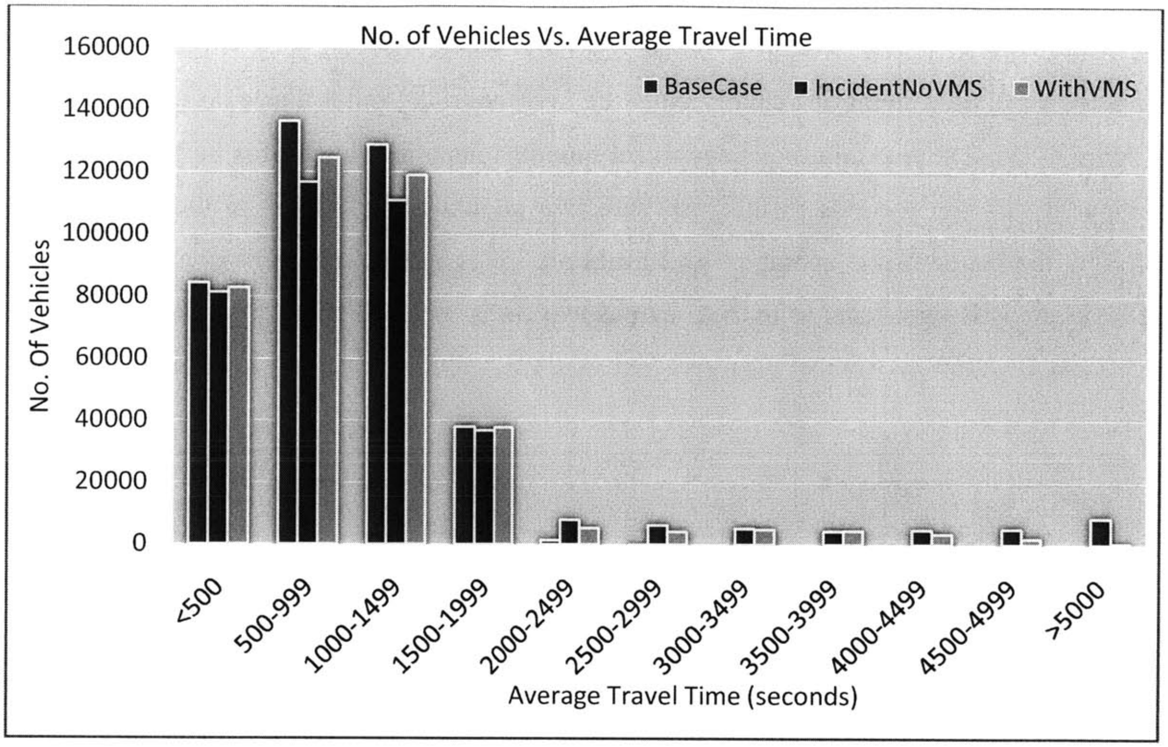

Figure 4-21 Frequency of Experienced Travel Times for all O-Ds (VMS for I-95, 3 iter)

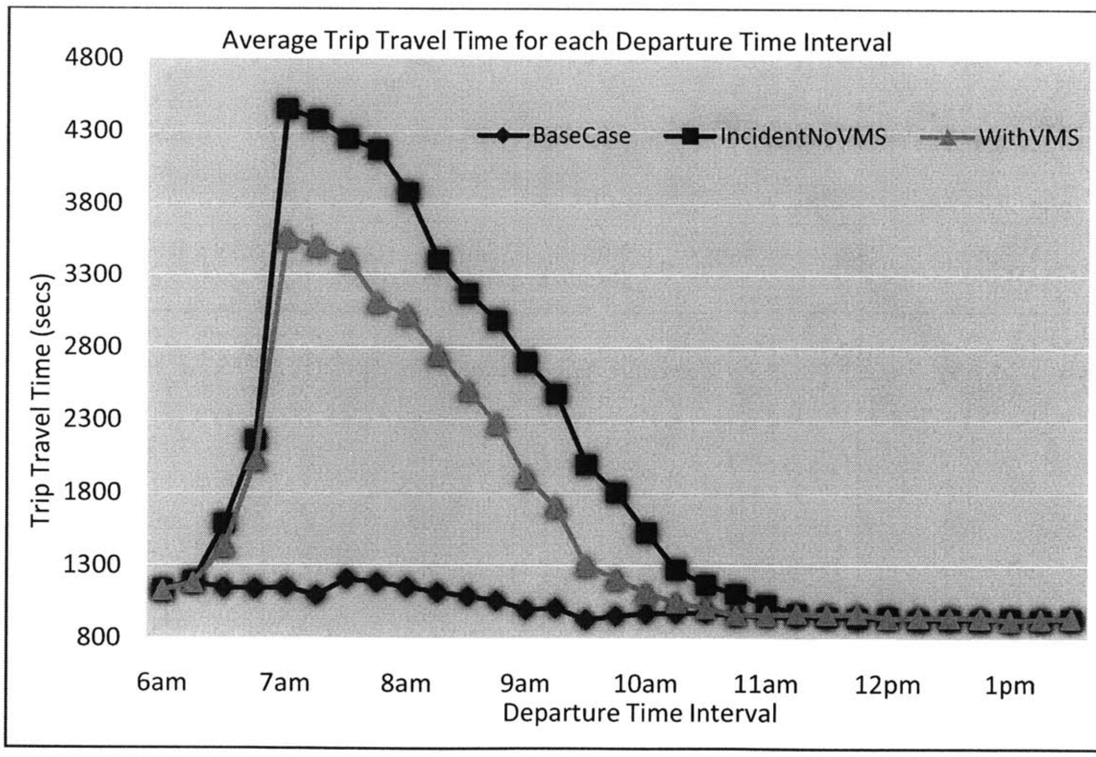

Figure 4-22 Avg. Travel Times by Departure Time Interval for selected O-Ds (VMS for I-95, 3 iter)

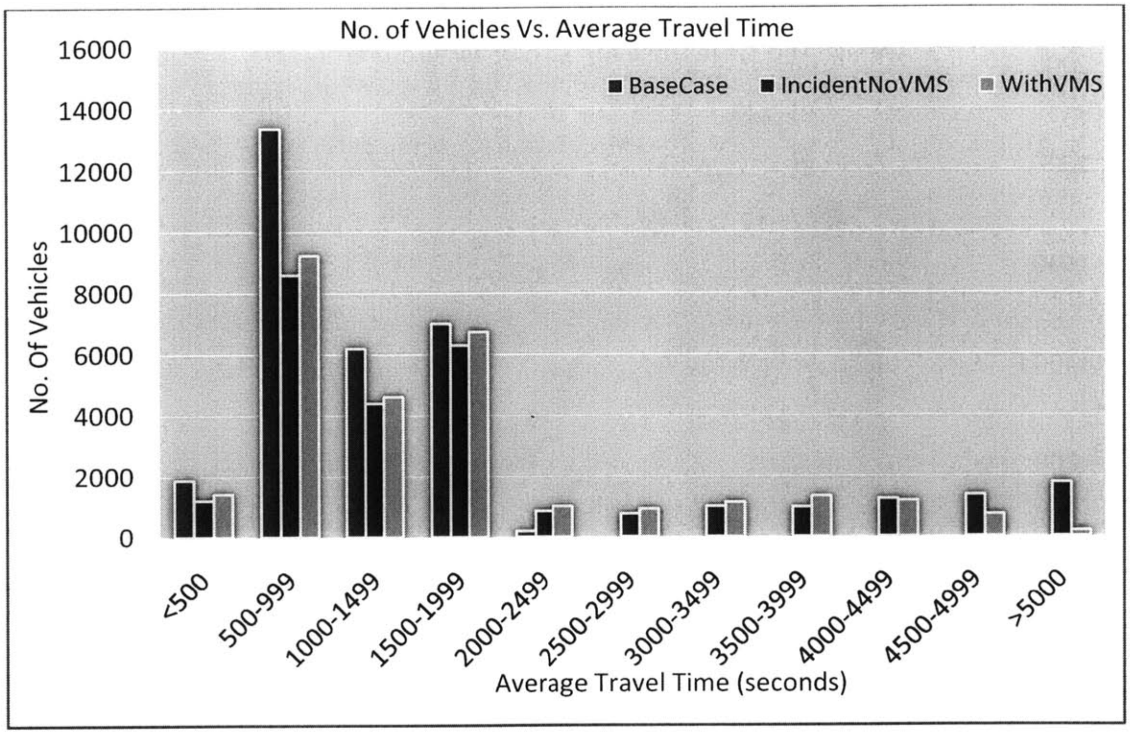

Figure 4-23 Frequency of Experienced Travel Times for selected O-Ds (VMS for I-95, 3 iter)

4.4.4 VMS in 'Closed Loop' with four Prediction Iiterations

The results for the whole network with four prediction iterations are shown in Figure 4-24 and Figure 4-25; and those for selected O-Ds in Figure 4-26 and Figure 4-27. We see that these results are not better than the case for three iterations. In fact, the average travel times in each interval gets worsened slightly, though they are still better than two iterations.

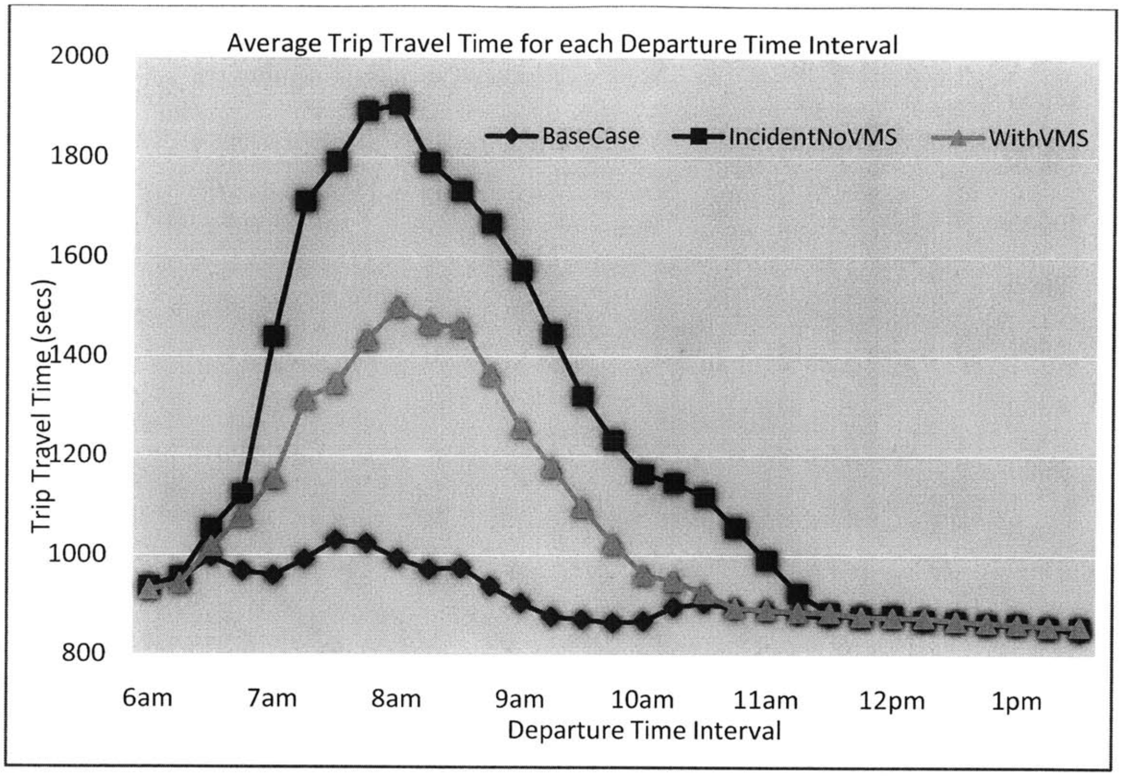

Figure 4-24 Avg. Travel Times by Departure Time Interval for all O-Ds (VMS for I-95, 4 iter)

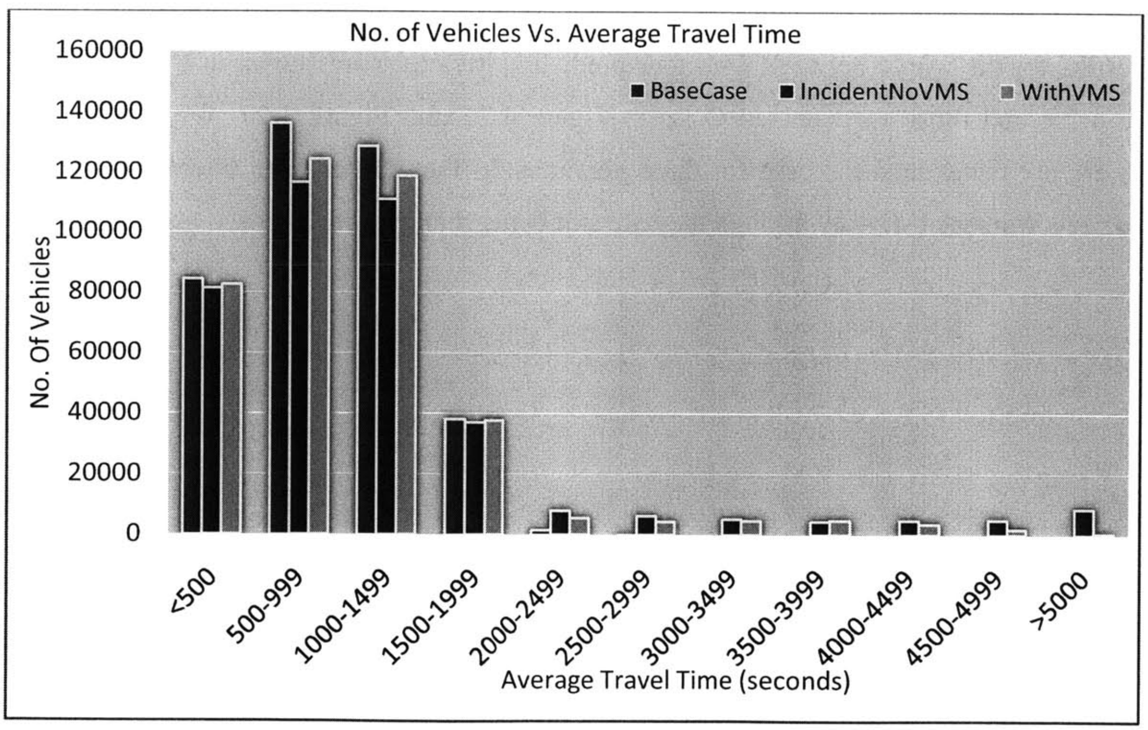

Figure 4-25 Frequency of Experienced Travel Times for all O-Ds (VMS for I-95, 4 iter)

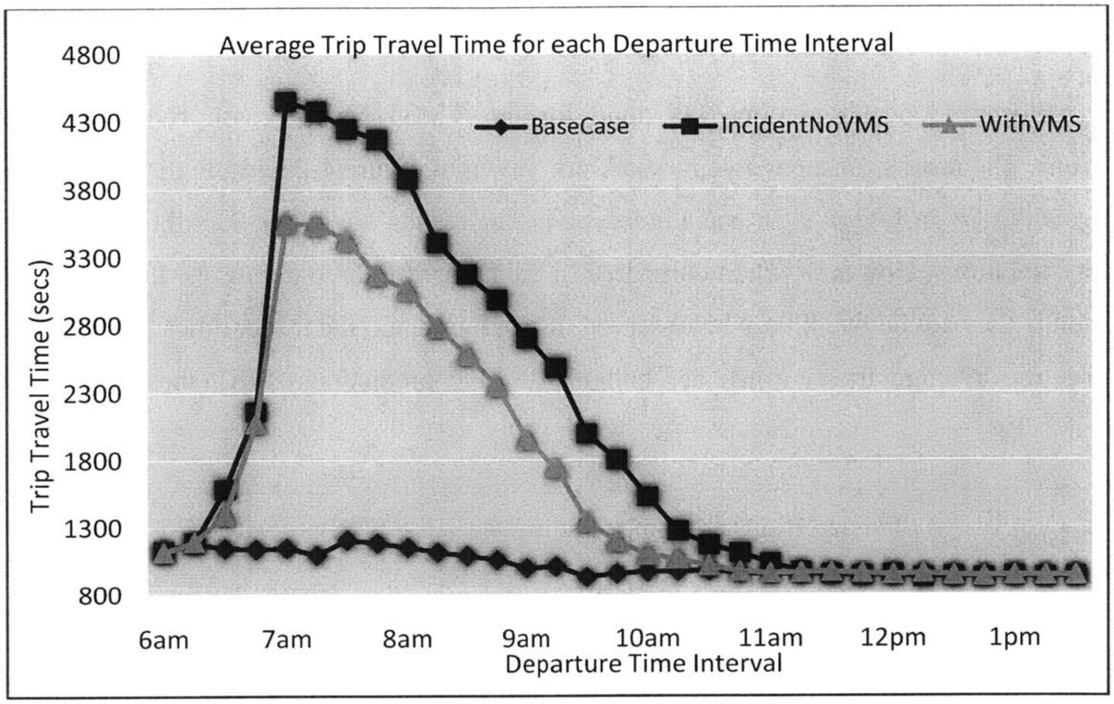

Figure 4-26 Avg. Travel Times by Departure Time Interval for selected O-Ds (VMS for I-95, 4 iter)

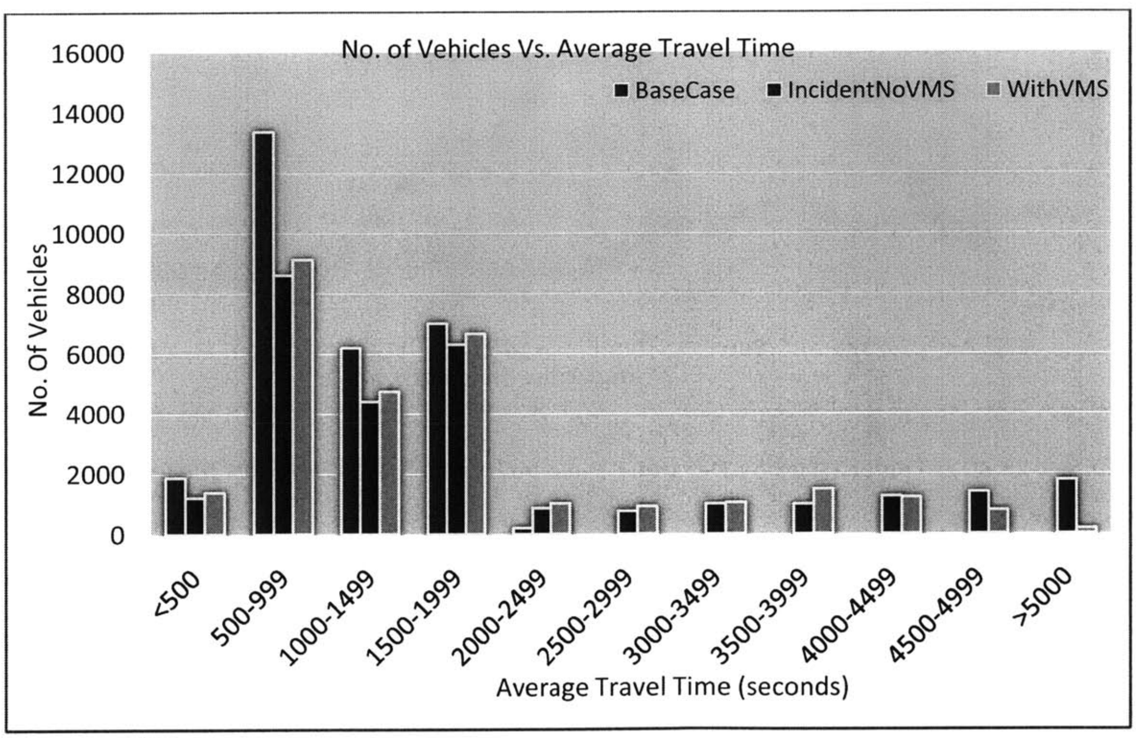

Figure 4-27 Frequency of Experienced Travel Times for selected O-Ds (VMS for I-95, 4 iter)

4.4.4 VMS in 'Closed Loop' with five Prediction Iterations

Finally, 'closed loop' simulation was done for the VMS scenario with five iterations of predictions. The results for the whole network are shown in Figure 4-28 and Figure 4-29; and for the selected O-Ds in Figure 4-30 and Figure 4-31. The results are better than the previous case with four iterations. However, when compared to the case with three iterations, there is no clear indication if they are better. It may be observed that before 8 am, the travel times gets worse, but after that the average travel times are better with five predictions. Still, these benefits are marginal.

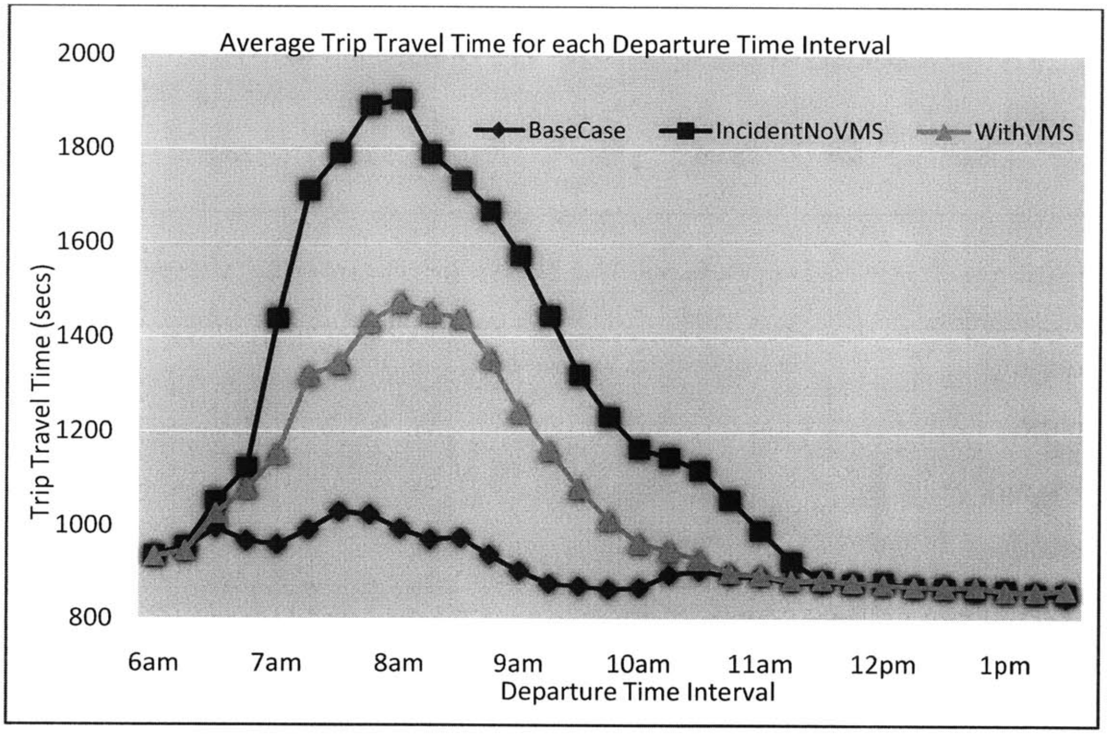

Figure 4-28 Avg. Travel Times by Departure Time Interval for all O-Ds (VMS for I-95, 5 iter)

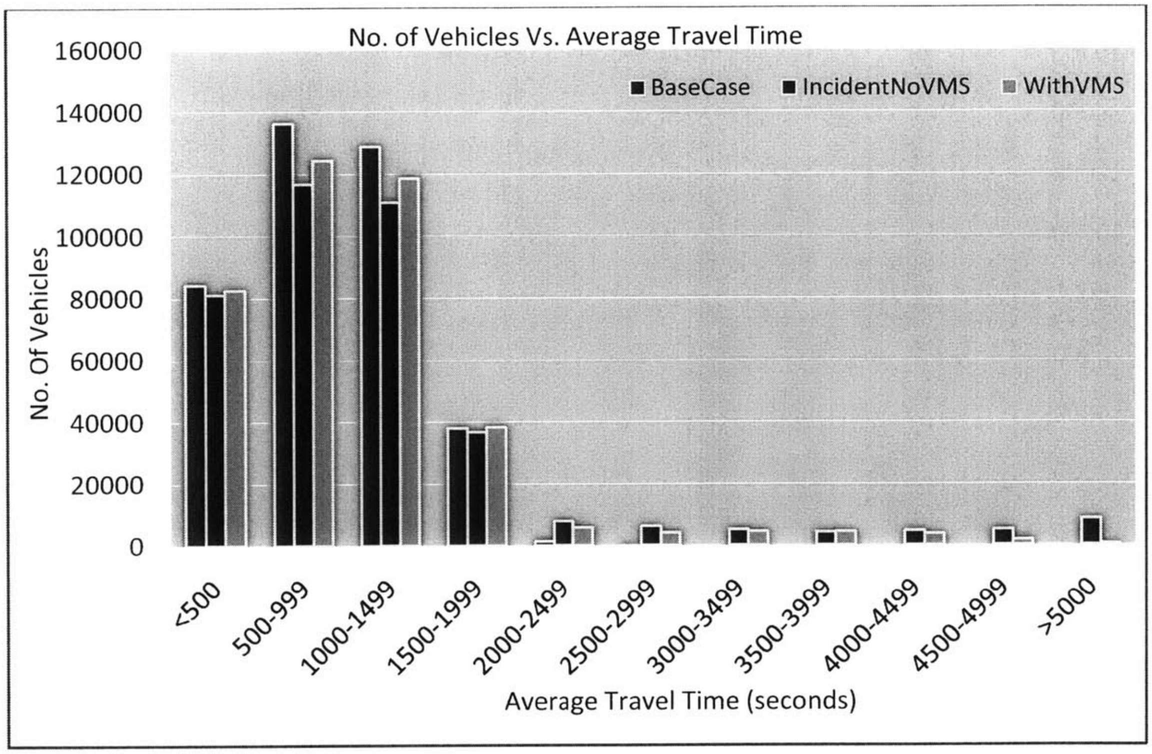

Figure 4-29 Frequency of Experienced Travel Times for all O-Ds (VMS for I-95, 5 iter)

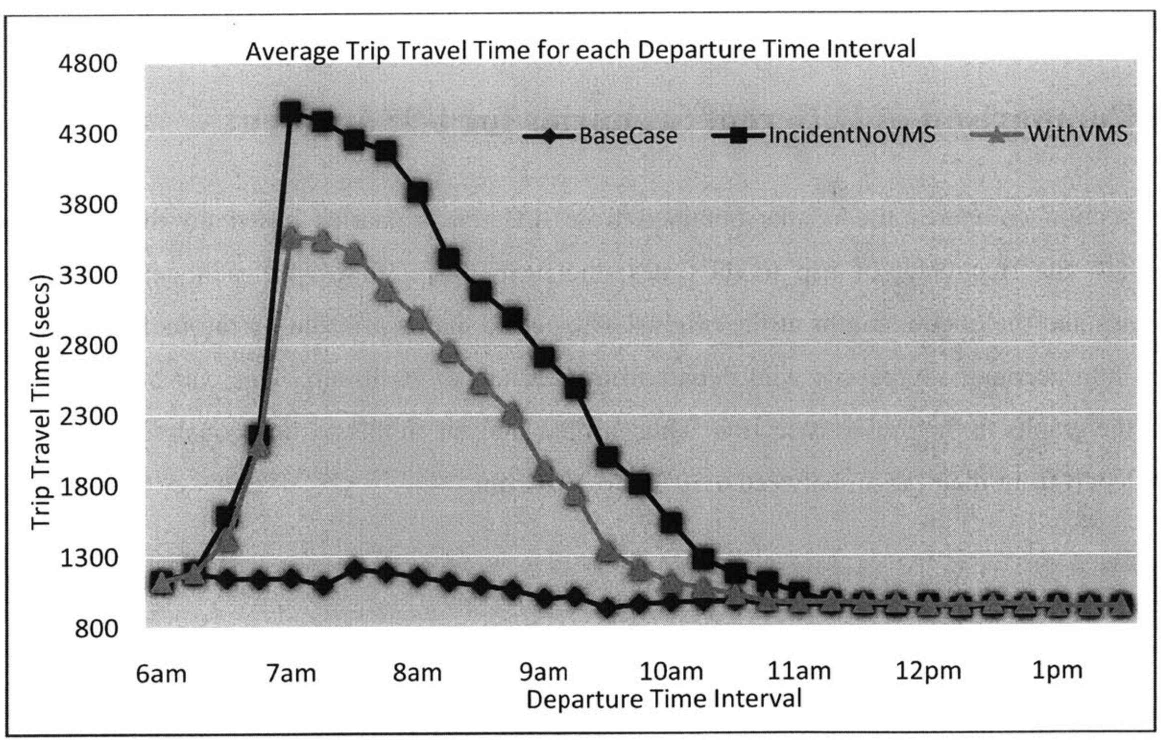

Figure 4-30 Avg. Travel Times by Departure Time Interval for selected O-Ds (VMS for I-95, 5 iter)

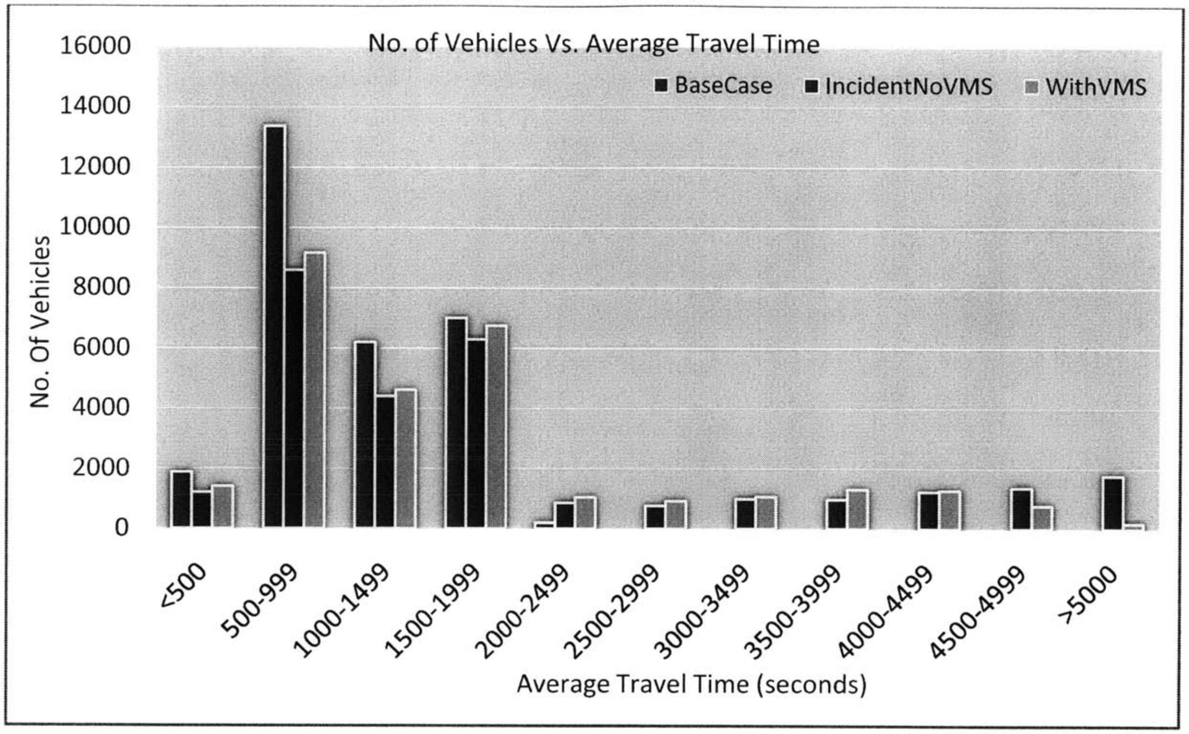

Figure 4-31 Frequency of Experienced Travel Times for selected O-Ds (VMS for I-95, 5 iter)

4.5 Comparison of Different Scenarios for I-95 Incident

This section compares the results obtained from different scenarios based on the aggregate statistics, the frequency of trip travel times; the mean travel times for each departure time intervals and the queue lengths at the origins. The period that is affected by the incident is only taken into account, i.e. people who depart from 6:30 am to 10:30 am. This can be confirmed from the graphs in the previous section. Thus, all the analysis in this section consist for travelers who depart from their origin between 6:30 am to 10:30 am.

4.5.1 Comparison Based on Aggregate Statistics

Table 4-1 summarizes the average travel times and the total vehicle hours for the various scenarios. As can be observed from these results, using a VMS can significantly improve the average travel times. Vehicle hours spent during the incident are 85852, which is 60% more than the base case. It may be observed that using a VMS can save about 15,000 vehicle hours out of these. The incident occurrence increases the mean travel times by 60% as well. Again, VMS usage can bring this down by about 20%.

Also, the results confirm our findings in the previous section that using three iterations for predictions is optimal. This case results in the minimum average travel time amongst the VMS scenarios. Thus, further results and analysis will now be done only for the three prediction iteration case.

	Avg Travel Time (sec)	Veh Hours	Veh Hours Saved
Base Case	956.4	53533	-
Incident	1532.6	85852	-
VMS - 1 Pred Iter	1261.8	70673	15179
VMS - 2 Pred Iter	1266.2	70920	14932
VMS - 3 Pred Iter	1239.4	69419	16433
VMS - 4 Pred Iter	1246.9	69841	16011
VMS - 5 Pred Iter	1239.9	69451	16401

Table 4-1 Comparison based on Aggregate Statistics (I-95 case)

4.5.2 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 O-D pairs is summarized below in Table 4-2. Similar comparison for the selected O-Ds is shown in Table 4-3.

The comparison reveals that as a result of the incident, a significant number of vehicles with lower travel times (500 – 1500 seconds) have shifted to higher travel times (> 2500 seconds). The impact of the VMS is obvious from the fact that there is a significant reduction in the number of people with travel times greater than 4500 seconds. Similar inferences can be drawn for the selected O-Ds. Due to VMS, there are very few people with travel times greater than 4500 seconds. Thus, the VMS has been largely beneficial in this regard.

TT	BaseCase	Incident NoVMS	WithVMS
<500	84307	81297	82810
500-999	136259	116673	124579
1000-1499	128745	110864	118955
1500-1999	37999	36851	37657
2000-2499	1401	7890	5233
2500-2999	20	6207	4116
3000-3499	0	5129	4830
3500-3999	0	4364	4417
4000-4499	0	4742	3479
4500-4999	0	5012	1905
>5000	0	8472	365

Table 4-2 Comparison based on the Frequency of Trip Travel Times for all O-Ds (I-95 case)

TT	BaseCase	Incident NoVMS	WithVMS
<500	1883	1213	1426
500-999	13370	8601	9241
1000-1499	6196	4401	4625
1500-1999	7007	6301	6745
2000-2499	201	865	1011
2500-2999	0	765	927
3000-3499	0	1000	1143
3500-3999	0	982	1335
4000-4499	0	1243	1182
4500-4999	0	1380	738
>5000	0	1779	189

Table 4-3 Comparison based on the Frequency of Trip Travel Times for selected O-Ds (I-95 case)

4.5.3 Comparison Based on Departure Travel Times

Table 4-4 compares the average travel times for all O-D pairs under each of the scenarios, as a function of the departure-time interval. Table 4-5 does the same for the selected O-Ds.

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 6:30 AM to 10:30 AM (time interval that is affected because of the incident) have increased by more than 80 % in some cases. After using VMS messages, the average travel times for these departure time intervals have come down significantly. The increase in the average travel times after using VMS is about half when compared to the incident case.

Dep Time	BaseCase	Incident NoVMS	WithVMS
6am	935	937	937
6:15-6:30	952	956	947
6:30-6:45	996	1053	1028
6:45-7:00	968	1123	1074
7am	959	1439	1152
7:15-7:30	991	1711	1310
7:30-7:45	1030	1791	1334
7:45-8:00	1024	1892	1414
8am	993	1905	1481
8:15-8:30	971	1789	1451
8:30-8:45	974	1732	1445
8:45-9:00	938	1667	1350
9am	904	1573	1249
9:15-9:30	876	1446	1166
9:30-9:45	871	1321	1094
9:45-10:00	864	1232	1024
10am	868	1164	965
10:15-10:30	896	1146	942
10:30-10:45	904	1119	922
10:45-11:00	894	1056	901
11am	890	991	889
11:15-11:30	882	924	885
11:30-11:45	876	885	882
11:45-12:00	881	878	877
12pm	876	880	874
12:15-12:30	870	870	869
12:30-12:45	868	868	875
12:45-13:00	861	864	864
1pm	862	863	863
13:15-13:30	858	856	857
13:30-13:45	846	856	856

Table 4-4 Comparison based on Departure Time Interval for all O-Ds (I-95 case)

Dep Time	BaseCase	Incident NoVMS	WithVMS
6am	1129	1133	1129
6:15-6:30	1183	1193	1182
6:30-6:45	1148	1588	1427
6:45-7:00	1141	2162	2023
7am	1149	4450	3557
7:15-7:30	1097	4379	3499
7:30-7:45	1209	4248	3413
7:45-8:00	1186	4171	3110
8am	1153	3877	3022
8:15-8:30	1117	3407	2748
8:30-8:45	1091	3174	2504
8:45-9:00	1060	2987	2275
9am	999	2701	1907
9:15-9:30	1011	2482	1703
9:30-9:45	931	1995	1303
9:45-10:00	958	1803	1211
10am	971	1529	1113
10:15-10:30	975	1274	1050
10:30-10:45	978	1171	1010
10:45-11:00	962	1111	965
11am	953	1035	962
11:15-11:30	949	975	974
11:30-11:45	953	953	968
11:45-12:00	940	944	974
12pm	944	953	943
12:15-12:30	944	930	948
12:30-12:45	933	939	948
12:45-13:00	940	929	946
1pm	934	940	929
13:15-13:30	940	931	938
13:30-13:45	936	938	944

Table 4-5 Comparison based on Departure Time Interval for selected O-Ds (I-95 case)

4.5.4 Comparison Based on Queue Lengths at Origins

Figure 4-32 shows a comparison of queue lengths at the origins for the incident without VMS case and the VMS case. The VMS have been successful in diverting the drivers, hence the lower queues at the origins. The queues are shortened by as much as 30%. Another interesting observation to be made is that the dissipation of the queues takes place 20 minutes earlier as compared to the incident without VMS case.

The queue building starts around 7:30 am. This is as expected since the data is only for the queues that are formed at the origins and not within a lane. For the first 30 minutes, the vehicles start queuing within the freeway and the arterials. As the queue propagates, travelers are not able to depart from the origin. Such travelers are a part of this queue. It should be noted that all origins are considered and not the ones for the selected O-Ds.

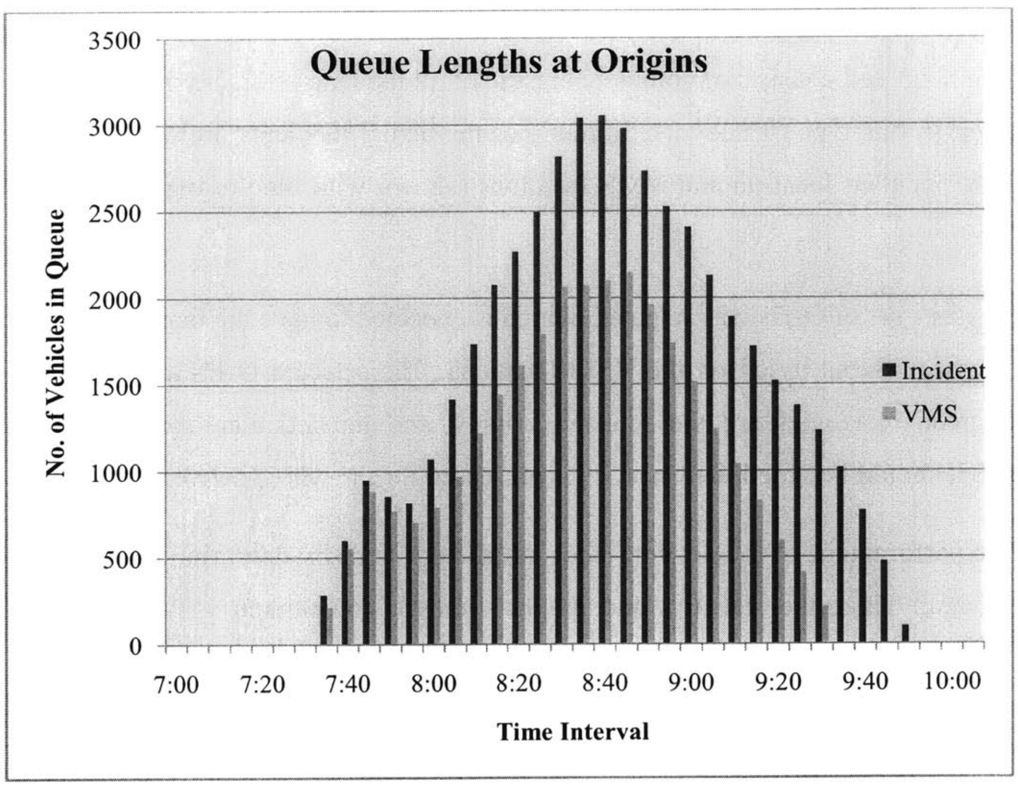

Figure 4-32 Queue Lengths at Origins (I-95 case)

The next section provides a similar analysis for an incident of same severity on the SprainBrook Parkway.

4.6 Incident on SprainBrook Parkway

4.6.1 Network Description

The network used for this incident is the same for the first part. Calibrated MITSIMLab and DynaMIT have been used for the simulations. Please refer to Section 4.1 for the details of the network and the data.

4.6.2 Incident Description and VMS Locations

For the assessment of VMS in this section, an incident is simulated on the SprainBrook Parkway from 7 am to 8 am and consists of complete closure of all the lanes. Again this kind of incident is very common in this type of network. Sometimes the actual incidents are even more severe in intensity. The incident location and VMS locations (shown with blue triangles) are depicted in Figure 4-33.

For the analysis a set of O-Ds was selected, which is expected to have the maximum effect of the Variable Message Signs based on the VMS locations. The selected O-Ds are shown in Figure 4-34. The green rectangles are the selected origins, and the red diamonds are the selected destinations. It should be noted that analysis is presented for the whole network as well.

The baseline performance of the network does not change since by definition there is no incident in the base case. Thus, the statistics and graphs used for comparison will be the same as in Section 4.2.

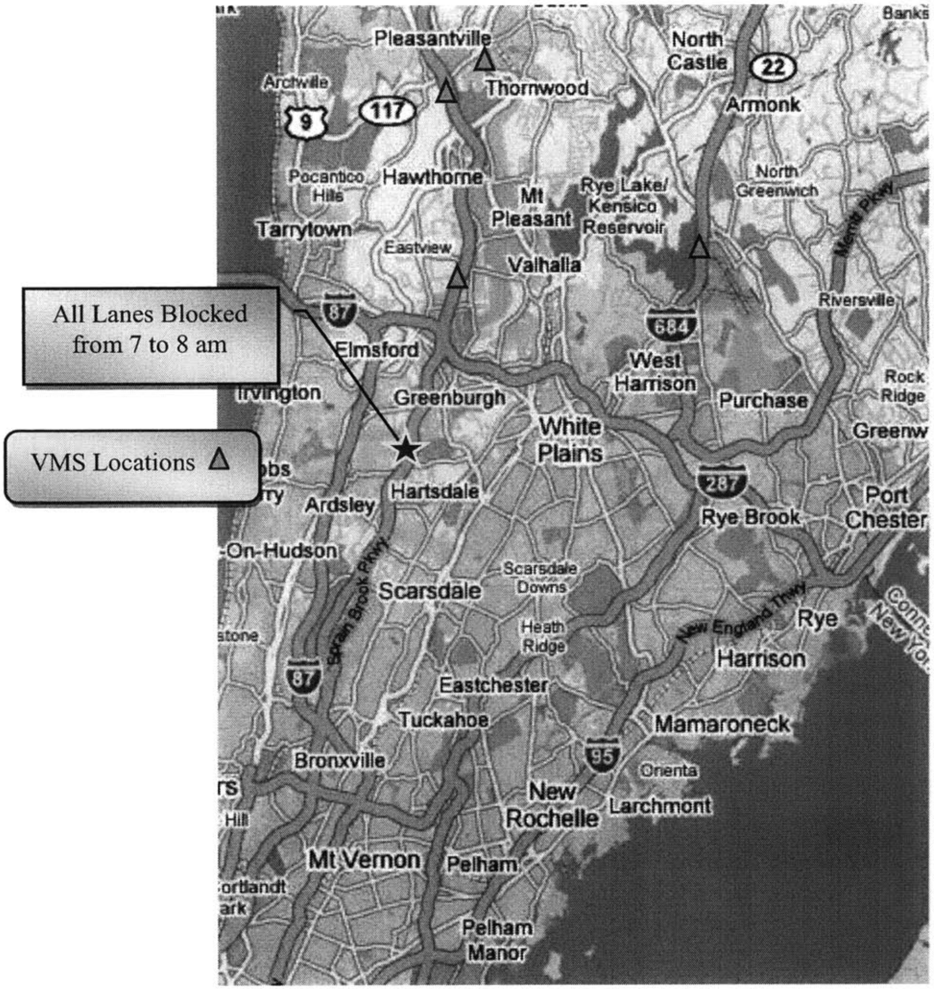

Figure 4-33 Incident on SprainBrook and VMS Locations (Source : http://www.maps.google.com)

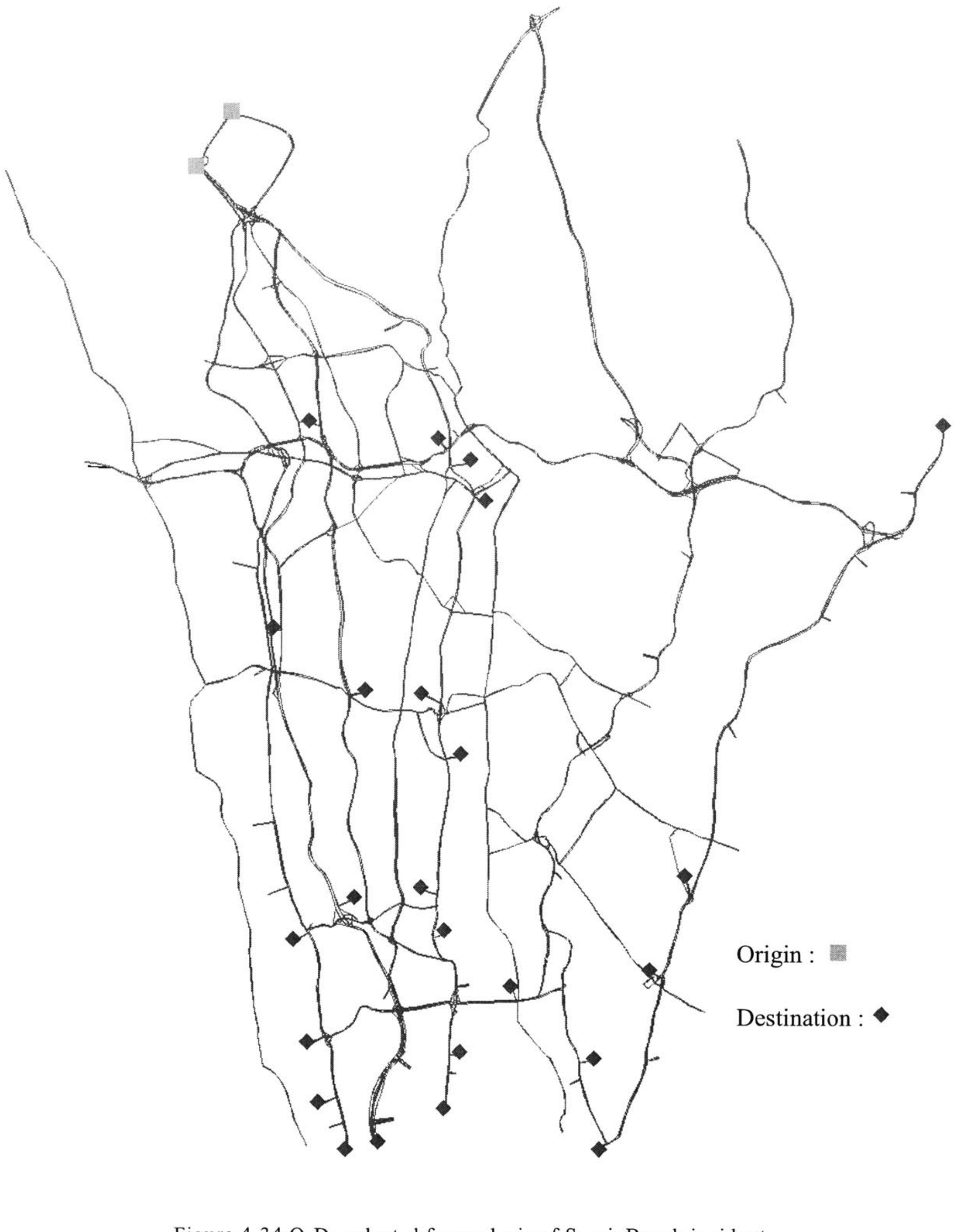

Figure 4-34 O-Ds selected for analysis of SprainBrook incident

4.7 Simulation of SprainBrook Incident without VMS

The simulation of incident was done using MITSIMLab for the incident described above. The results for all O-Ds are shown in Figure 4-35 and Figure 4-36; and for the selected O-Ds in Figure 4-37 and Figure 4-38. Again, impact of the incident is quite evident, but no as large as the I-95 incident. The average travel times experienced by the travelers increase upto almost 1500 seconds during the peak hour for the whole network. For the selected O-Ds, the jump is to about 3400 seconds. From the histograms, it can be seen that due to the incident, there are a significant number of people with higher travel times. Also, it can be seen that people who depart at 6:45 am also face increased travel times as the incident would have started by the time they are near the affected links.

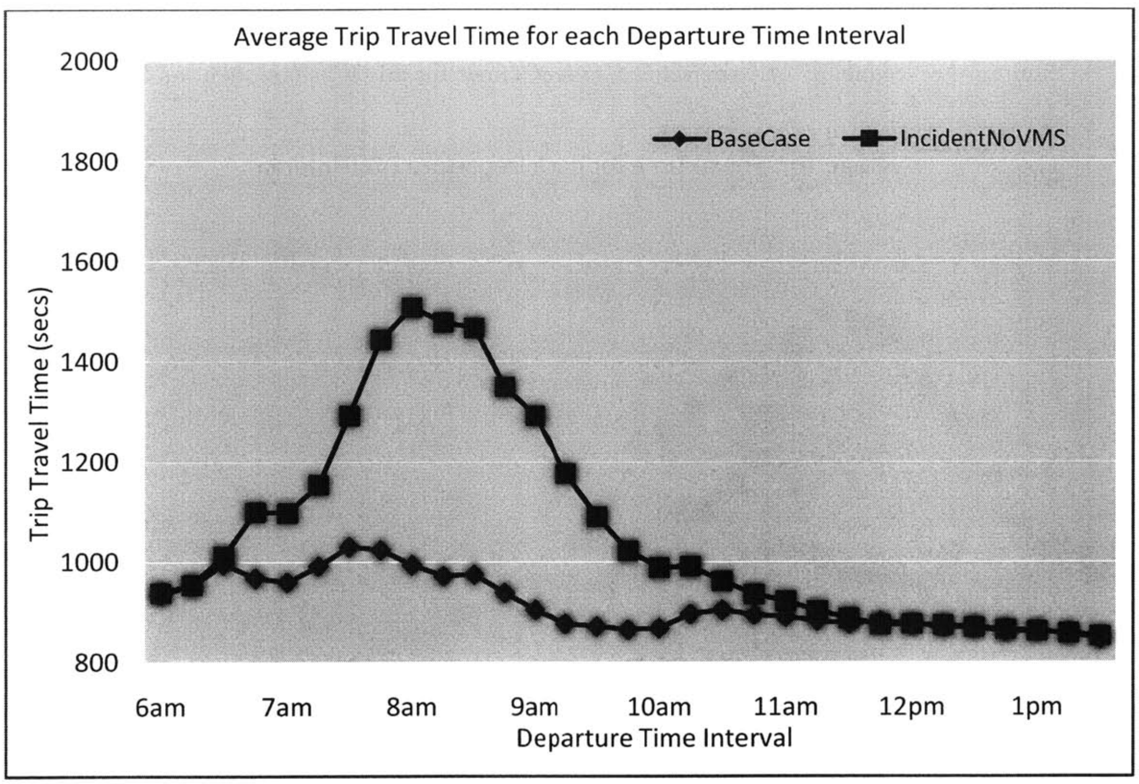

Figure 4-35 Avg. Travel Times by Departure Time Interval for all O-Ds (Incident on SB)

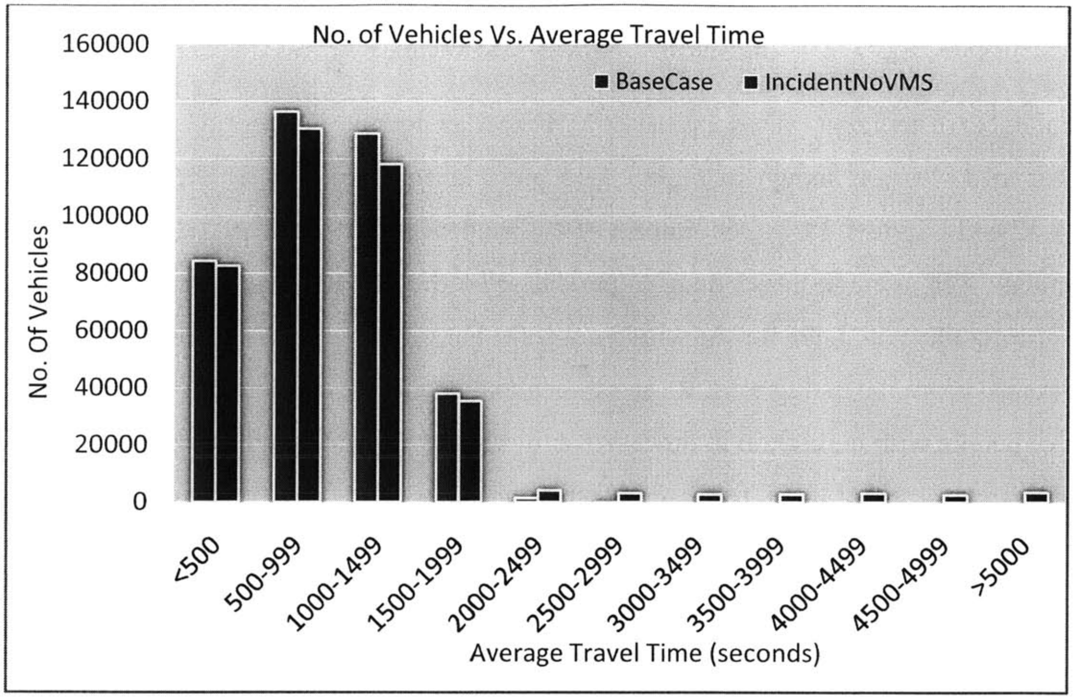

Figure 4-36 Frequency of Experienced Travel Times for all O-Ds (Incident on SB)

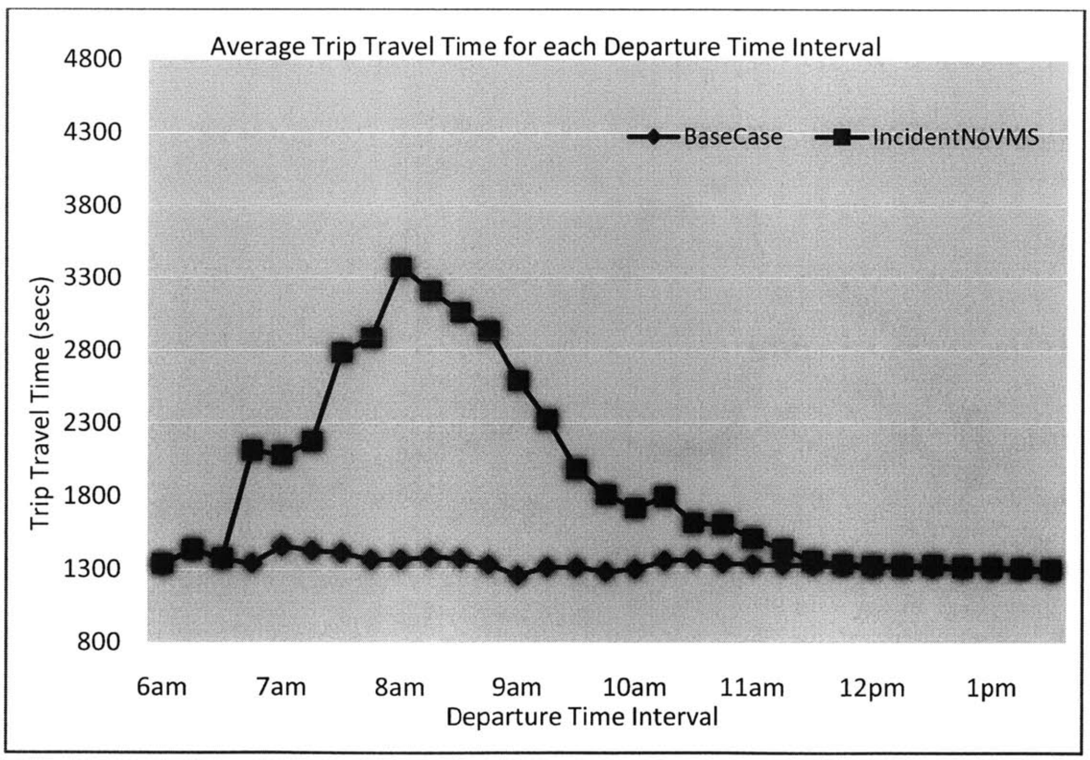

Figure 4-37 Avg. Travel Times by Departure Time Interval for selected O-Ds (Incident on SB)

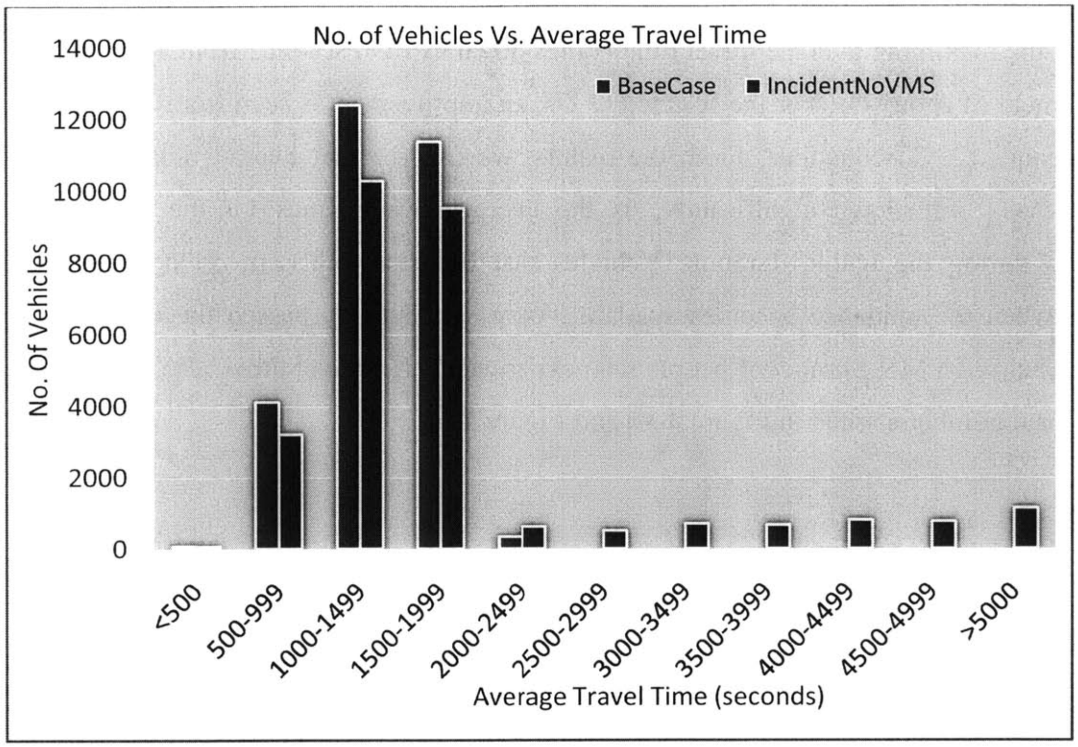

Figure 4-38 Frequency of Experienced Travel Times for selected O-Ds (Incident on SB)

4.8 Simulation of SprainBrook Incident with VMS using 'Closed Loop'

As in Section 4.4, to assess the impact of VMS, we use the framework developed in Chapter 3. Four VMS were used in this evaluation, and these four are the ones actually deployed in the field. Again these VMS are link-VMS and provide information about the links that are affected by the incident, as well as the alternate diversion routes. From the earlier part of this chapter, we concluded that using three iterations for prediction results in the best network state. Thus, in this section the results are shown using three iterations.

The results for the whole network are shown in Figure 4-39 and Figure 4-40; and for the selected O-Ds in Figure 4-41 and Figure 4-42. VMS is beneficial in this case as well as is evident from the graphs. As expected the average travel times are greater than that of base case since the network is still in worse conditions than the base case even with the VMS. For the whole network, the maximum average travel time comes down to 1390 seconds from 1500 seconds, an improvement of about 7%. For the selected O-Ds, an improvement is seen from 3374 seconds to 2615 seconds (23% reduction). From the results, we can see that overall delay faced by the vehicles has come down significantly, as the average travel times for the incident period decreases during the whole duration. Vehicles that depart at 6:45 am do not benefit much because when the guidance becomes available, they have already passed the diversion nodes. With the help of VMS, number of people who experience large travel times also comes down by a significant number as seen in Figure 4-40 and Figure 4-42.

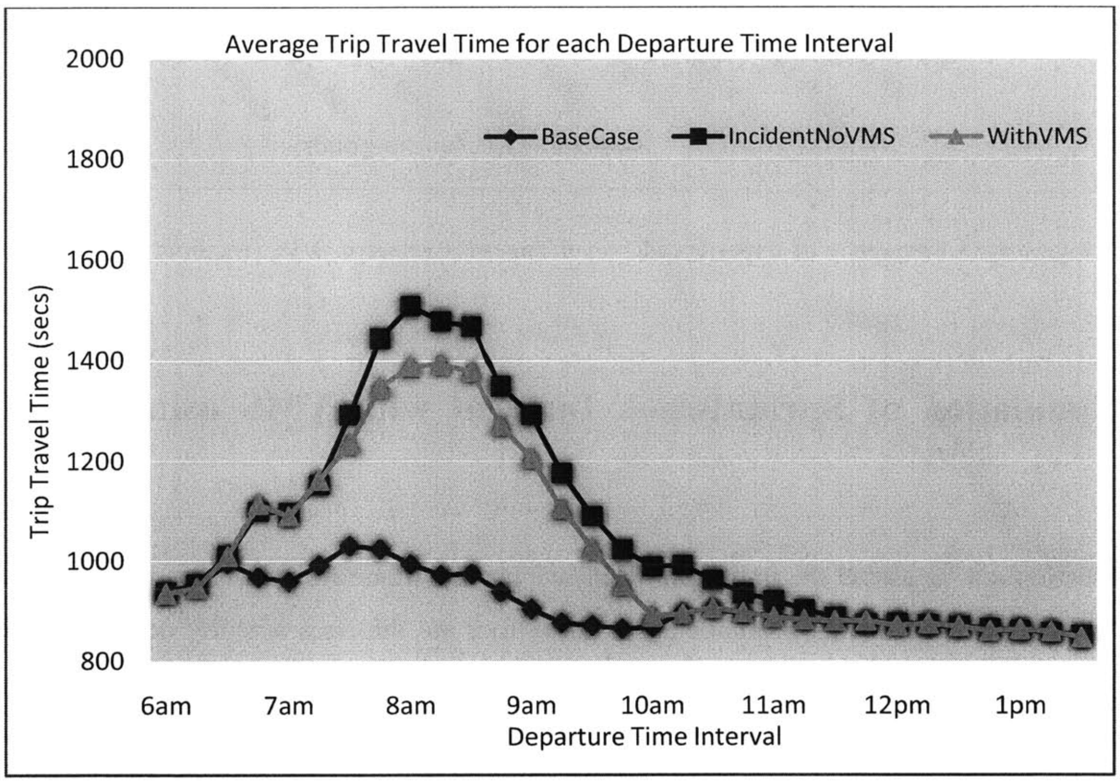

Figure 4-39 Avg. Travel Times by Departure Time Interval for all O-Ds (VMS for SB)

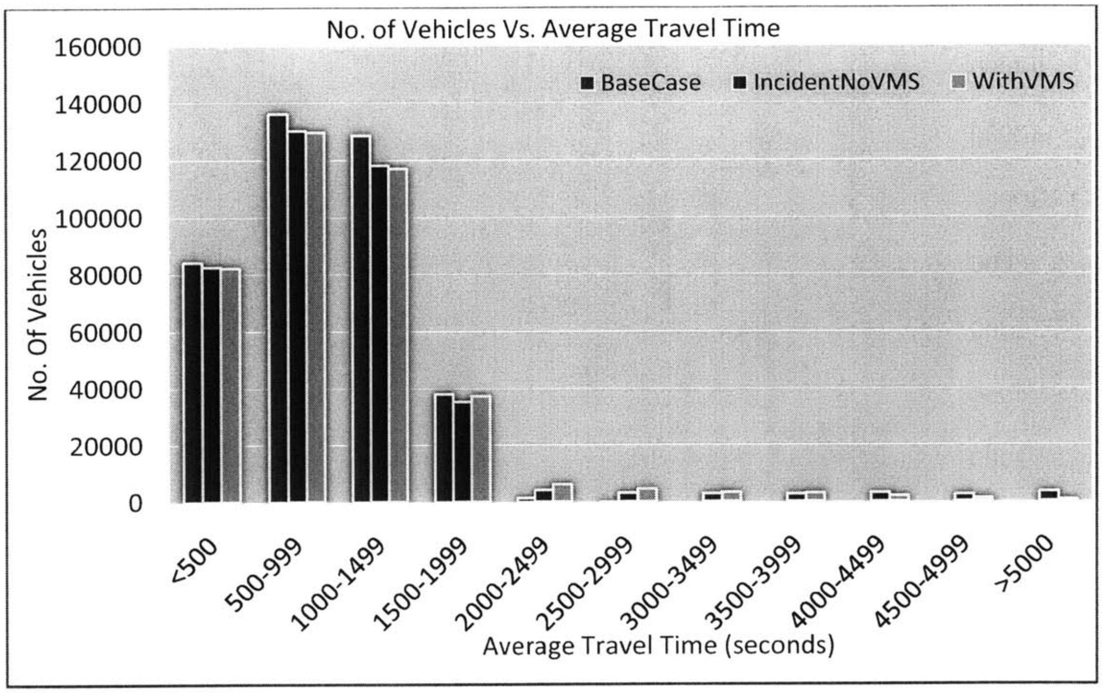

Figure 4-40 Frequency of Experienced Travel Times for all O-Ds (VMS for SB)

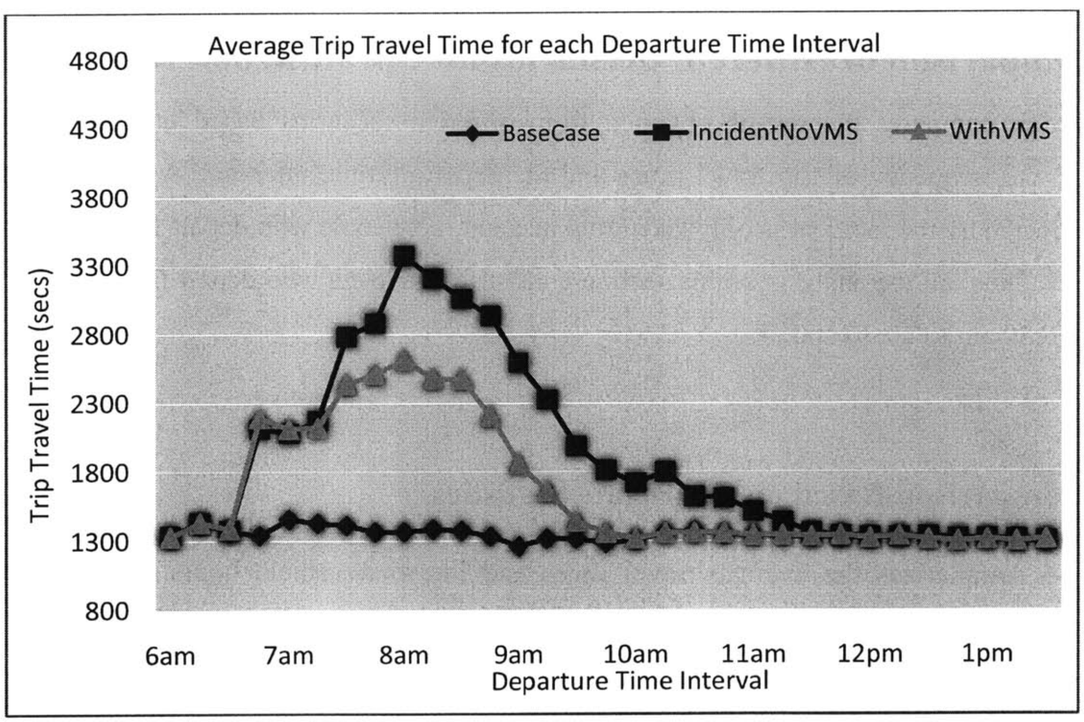

Figure 4-41 Avg. Travel Times by Departure Time Interval for selected O-Ds (VMS for SB)

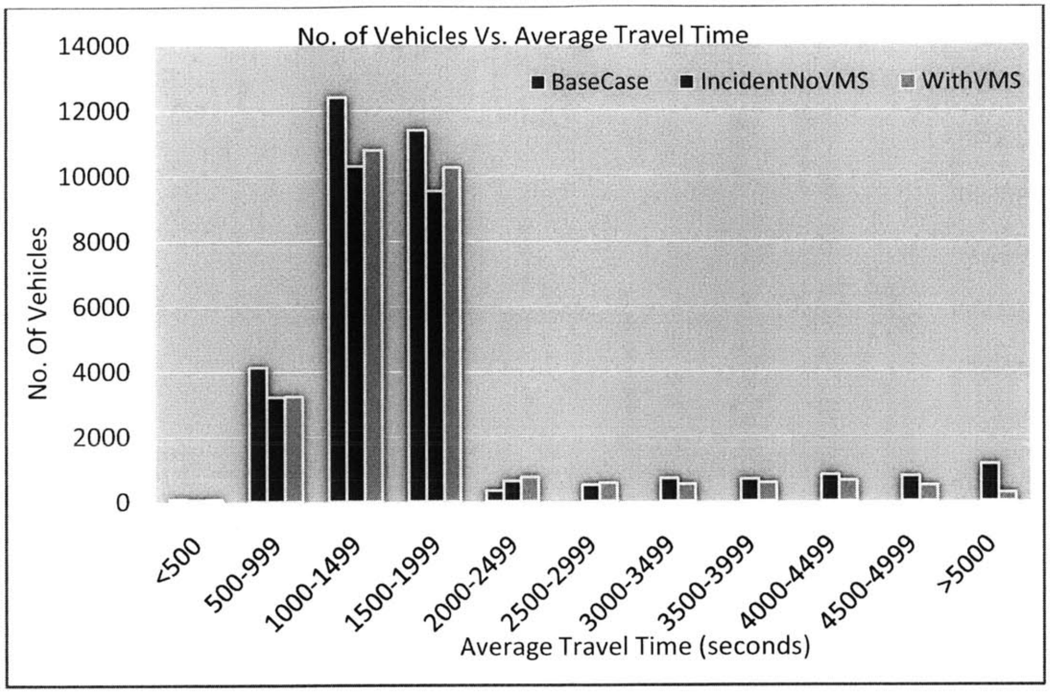

Figure 4-42 Frequency of Experienced Travel Times for selected O-Ds (VMS for SB)

4.9 Comparison of Different Scenarios for SprainBrook Incident

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. Again, the period that is affected by the incident is only taken into account, i.e. people who depart from 6:30 am to 10:30 am. Thus, all the analysis in this section consist for travelers who depart from their origin between 6:30 am to 10:30 am.

4.9.1 Comparison Based on Aggregate Statistics

Table 4-6 summarizes the average travel times and the total vehicle hours for the various scenarios. As can be observed from these results, using a VMS can significantly improve the average travel times. Vehicle hours spent during the incident are 69165, which is 30% more than the base case. Using a VMS can save about 3,400 vehicle hours out of these. The incident occurrence increases the mean travel times by 32%. VMS usage can bring this down by about 5%.

	Avg Travel Time	Veh Hours	Veh Hours Saved
Base Case	956.4	53533	0
Incident	1235.1	69165	0
VMS	1174.9	65763	3402

Table 4-6 Comparison based on Aggregate Statistics (SB Case)

4.9.2 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 O-D pairs is summarized below in Table 4-7. Similar comparison for the selected O-Ds is shown in Table 4-8.

The comparison reveals that as a result of the incident, a significant number of vehicles with lower travel times (< 2000 seconds) have shifted to higher travel times (> 2000 seconds). The impact of the VMS is obvious from the fact that there is a significant reduction in the number of people with travel times greater than 4000 seconds. Similar inferences can be drawn for the selected O-Ds. Due to VMS, there are now fewer people with travel times greater than 3000 seconds. Thus in this scenario the VMS has been very beneficial as well.

TT	BaseCase	Incident NoVMS	WithVMS
<500	84307	82635	82265
500-999	136259	130363	129774
1000-1499	128745	118138	117017
1500-1999	37999	35392	37240
2000-2499	1401	4134	6214
2500-2999	20	3179	4436
3000-3499	0	2846	3326
3500-3999	0	2783	3074
4000-4499	0	3129	2115
4500-4999	0	2485	1171
>5000	0	3455	597

Table 4-7 Comparison based on the Frequency of Trip Travel Times for all O-Ds (SB case)

TT	BaseCase	Incident NoVMS	WithVMS
<500	81	65	71
500-999	4127	3212	3229
1000-1499	12394	10288	10786
1500-1999	11388	9527	10260
2000-2499	339	623	746
2500-2999	0	514	567
3000-3499	0	710	531
3500-3999	0	679	573
4000-4499	0	816	633
4500-4999	0	774	490
>5000	0	1147	270

Table 4-8 Comparison based on the Frequency of Trip Travel Times for selected O-Ds (SB case)

4.9.3 Comparison Based on Departure Travel Times

Table 4-9 compares the average travel times for all O-D pairs under each of the scenarios, as a function of the departure-time interval. Table 4-10 presents same analysis for the selected O-Ds.

Analysis of the average travel times based on departure time interval also demonstrate potential of the use of VMS in this situation. As a result of the incident, average travel times for the travelers departing between 6:30 AM to 10:30 AM (time interval that is affected because of the incident) have increased by as large as 60% in some cases. After using VMS messages, the average travel times for these departure time intervals have come down significantly.

Dep Time	BaseCase	IncidentNoVMS	WithVMS
6am	935	938	935
6:15-6:30	952	954	947
6:30-6:45	996	1011	1010
6:45-7:00	968	1100	1115
7am	959	1098	1090
7:15-7:30	991	1154	1163
7:30-7:45	1030	1292	1235
7:45-8:00	1024	1444	1347
8am	993	1508	1388
8:15-8:30	971	1478	1393
8:30-8:45	974	1467	1378
8:45-9:00	938	1349	1271
9am	904	1292	1206
9:15-9:30	876	1176	1104
9:30-9:45	871	1090	1024
9:45-10:00	864	1022	951
10am	868	988	889
10:15-10:30	896	991	895
10:30-10:45	904	962	906
10:45-11:00	894	935	897
11am	890	921	887
11:15-11:30	882	902	882
11:30-11:45	876	888	880
11:45-12:00	881	874	880
12pm	876	876	871
12:15-12:30	870	873	875
12:30-12:45	868	870	869
12:45-13:00	861	865	861
1pm	862	862	864
13:15-13:30	858	857	859
13:30-13:45	846	852	848

Table 4-9 Comparison based on Departure Time Interval for all O-Ds (SB case)

Dep Time	BaseCase	IncidentNoVMS	WithVMS
6am	1328	1339	1331
6:15-6:30	1436	1435	1433
6:30-6:45	1366	1378	1386
6:45-7:00	1341	2112	2191
7am	1457	2082	2113
7:15-7:30	1428	2174	2124
7:30-7:45	1412	2785	2436
7:45-8:00	1364	2884	2510
8am	1366	3374	2615
8:15-8:30	1384	3208	2477
8:30-8:45	1374	3061	2473
8:45-9:00	1332	2935	2204
9am	1259	2593	1859
9:15-9:30	1314	2325	1660
9:30-9:45	1315	1985	1437
9:45-10:00	1283	1811	1358
10am	1302	1719	1315
10:15-10:30	1358	1798	1359
10:30-10:45	1369	1620	1360
10:45-11:00	1344	1609	1360
11am	1336	1514	1342
11:15-11:30	1332	1440	1342
11:30-11:45	1327	1361	1332
11:45-12:00	1323	1339	1341
12pm	1312	1329	1320
12:15-12:30	1326	1326	1337
12:30-12:45	1310	1332	1312
12:45-13:00	1307	1317	1297
1pm	1305	1316	1311
13:15-13:30	1297	1310	1296
13:30-13:45	1287	1301	1312

Table 4-10 Comparison based on Departure Time Interval for selected O-Ds (SB case)

4.9.4 Comparison Based on Queue Lengths at Origins

Figure 4-43 shows a comparison of queue lengths at the origins for the incident without VMS case and the VMS case. As in the previous case, the VMS have been successful in diverting the drivers. The queues are shortened by as much as 25 to 30%. In this case, the dissipation of the queues takes place almost 30 minutes earlier when guidance is provided through VMS. However, one strange observation is that the large queues start building again around 8:20 am. This phenomenon is probably attributable to the large demand originating from and around this origin (in this case, it is only one origin two links upstream of SprainBrook incident where the queues are being formed) that is not accommodated because the links are already queued up with vehicles. Overall, VMS does lower the queue lengths at origins. From this observation, we can conclude that the queue lengths in the network are lowered as well.

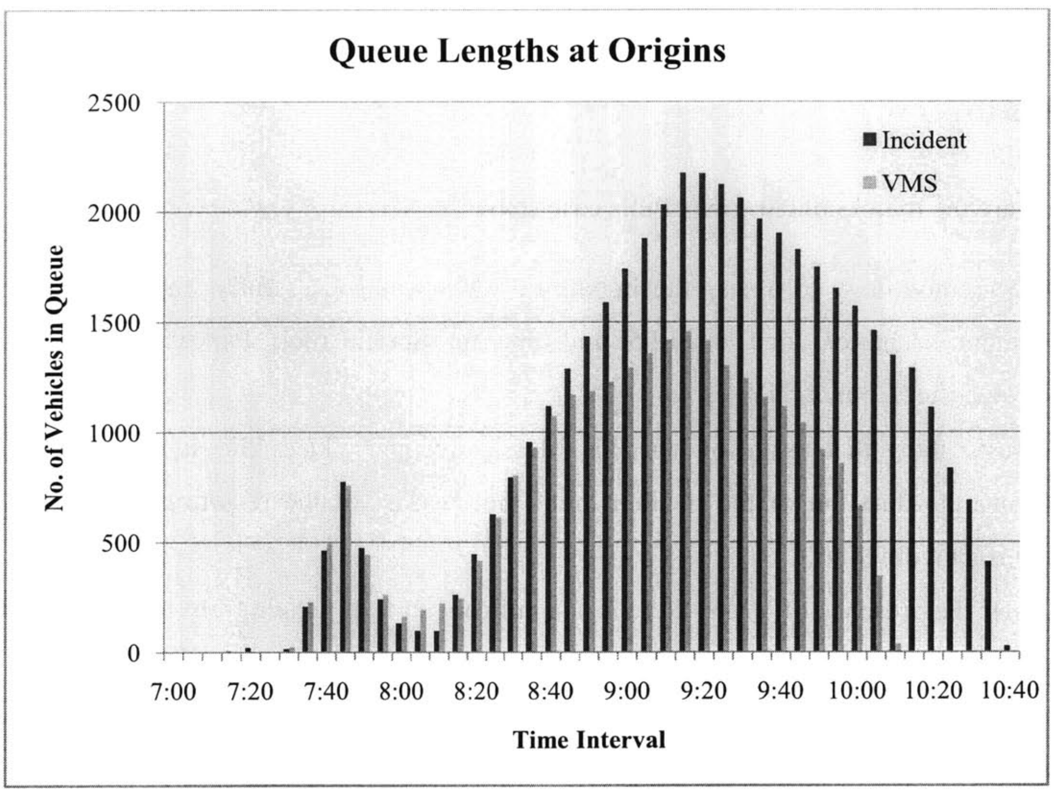

Figure 4-43 Queue Lengths at Origins (SB case)

From the above analysis, it can be concluded that VMS are indeed effective in mitigating the impact of an incident. The significant reduction in travel times and the number of hours saved is a testimony to this claim. However, these benefits are not as large as the ones obtained in the I-95 case. One of the possible reasons might be that the drivers who are actually taking the affected route are not the ones who are being informed by VMS. This is a problem of the location of VMS that they are accessible to people who are using less congested routes anyway. Very few of these drivers will change path on seeing a VMS. It should be noted that the 4 VMS in the I-95 case (i.e. except the one on I-95) are placed quite far away from the affected links, whereas in the SprainBrook case, at least three VMS are directly upstream of the affected links. Thus, one can possibly conclude that the benefits are influenced by the locations. This points to the need for a methodology to select the optimal locations of VMS. In this case study, we are constrained by the physical location of the VMS. The next chapter presents an application of such a methodology that was developed in Chapter 3.

4.10 Summary

Following are the major conclusions of this case study.

- The methodology to assess the impact of VMS was successfully implemented to two incident scenarios, one on I-95 and one on SprainBrook Parkway in the Lower Westchester County, NY.
- Results show that usage of Variable Message Signs reduces the average travel times during the duration of the incident until the clearing of the resulting congestion by a significant amount.
- Under the presence of VMS, there is a significant shift of people from higher travel times (>4500 seconds) in case of incident to lower travel times.
- Usage of VMS in this case can result into savings of approximately 15000 vehicle hours when an incident occurs on I-95 and 3400 vehicle hours when incident occurs on the SprainBrook parkway. The savings are significant.
- The average travel times come down to 1240 seconds from 1530 seconds in case of an incident on I-95; and from 1510 seconds to 1390 seconds in SprainBrook case.

- The optimal number of iterations for consistent guidance in DynaMIT to reap the maximal benefits is three.
- The queue lengths at the origins are reduced significantly due to the use of VMS. From this observation, we can conclude that the queues within the freeways and arterials are reduced as well.

Thus, with the help of this case study it can be successfully concluded that Variable Message Signs providing *predictive* route guidance can be a very useful tool in improving the overall traffic conditions in case of non-recurrent congestion. It is important that information is provided about the incident as well as about the alternative diversion routes. The predictive information that is consistent results in the best overall network performance.

One possible extension of this case study can be to include a comparison with a case where only instantaneous or current measured travel times are disseminated via the Variable Message Signs. Thus, no predictive guidance is provided. The 'closed loop' setup presently does not have this feature. Sundaram (2002) implemented the instantaneous VMS in the planning version of DynaMIT. Further work can be done to extend this feature to the 'closed loop' framework. This would be a representation of the state-of-the-art incident management by the TMC where they do not have tools to provide predictive guidance. However, the behavior of drivers under such conditions will be different and requires some research before developing this tool.

The next chapter presents the application of the methodology developed in chapter 3 in a synthetic network to choose the optimal location of Variable Message Signs.

Chapter 5 Case Study II: Application of GA to Optimize VMS Locations

The objective of this chapter is to demonstrate the applicability of the methodology to optimize locations of Variable Message Signs described in Chapter 3. The implementation is done on a synthetic network with the constraints of having maximum 2 and 3 VMS in the network respectively. First a description of the network performance in the base case and with an incident is presented. Next, the methodology is applied to the synthetic network and the results are compared with the incident scenario. The results from this case study demonstrate the applicability of the methodology in solving the problem at hand. The results show that optimal locations can improve the benefits from VMS significantly. A discussion about the large scale applications of the methodology is presented at the end.

5.1 Network Description

For the purpose of this study, a test network was created which is shown in Figure 5-1. The network consists of 21 links, with 3 Origins and 1 Destination. The network design has been chosen for two purposes. There is no trivial solution to the VMS location problem, specially when the maximum number of VMS is increased to 4. This ensures that a proper evaluation of Genetic Algorithm is done and that GA "evolves" to the solution. Secondly, this network is much smaller as compared to the real networks, yet it contains the complexities of making a route choice decision. Thus, we can validate the proper functioning of Genetic Algorithms and identify the factors that will influence the scalability to real sized networks.

There are 57 paths in the network. Each link consist of one segment and each segment has two lanes. The capacities of all the links are same. However, as can be seen from the figure, the link lengths are not the same. Different paths will thus have different travel times. It should be noted that links 14 and 15 together represent a two-way road. 16 and 17 together form a two-way as well. Network performance is evaluated for a one-hour period. We arbitrarily call this period 6:00 am to 7:00 am. The scenario with VMS is simulated with 'closed loop' as explained in Chapter 3. Every 15 minutes, MITSIMLab sends the sensor counts from the network to DynaMIT, and DynaMIT reciprocates with updated link travel times of the network.

The demand was varied for the three origins to further reduce the effects of symmetry in the network. Every hour 400 vehicles enter the network through O1, 200 vehicles from O2 and 300 vehicles from O3. All the vehicles exit the network at D1.

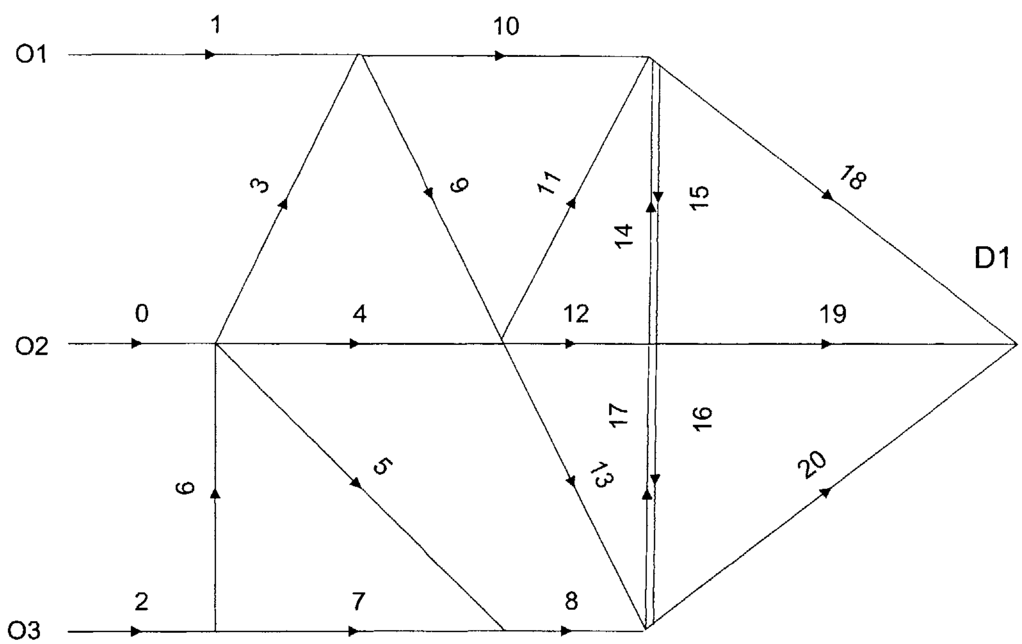

Figure 5-1 Synthetic Network

Incident Description

Two incidents were simulated in the network. The first incident occurs on link 19 and lasts for 20 minutes from 6:25 am to 6:45 am. It consists of complete closure of both the lanes for the 20 minutes. The location of the incident is between the midpoint of the link and the downstream end of the link. Information about the links 14, 15 , 16, 17, 18, 19 and 20 was disseminated through the VMS. These links together represent the incident affected links as well as the diversion routes. The second incident occurs on link 20 and lasts from 6:25 am to 6:45 am, and again consists of complete blockage of both lanes. The location of the incident is also between the midpoint of the link and the downstream end of the link. Information is provided for links numbered 8, 13, 16, 17, 18, 19 and 20.

5.2 Methodology

The methodology for the application of Genetic Algorithms in solving the problem of optimal location of VMS was described in Chapter 3. The flowchart is again presented in Figure 5-2 for convenience.

All links except 14, 16, 18, 19 and 20 were considered for possible VMS locations. Thus the length of a particle is 16, where each bit, when turned on, represents that a VMS is installed on that link. The links that have been left are because there is no use of giving information to the driver once he/she has reached either of this link. The reason is that if a driver is on either of these links, he/she has no choice of switching the route. This is by design of the network.

Each population consists of 30 particles. The algorithm was evaluated two times, with the maximum number of VMS to be installed being 2 and 3 respectively. The initial population was selected randomly. However, it was made sure that all feasible link locations have been selected at least once in the population. A particle, representing a set of VMS was then picked up and installed in the network. The 'closed loop' was simulated for the two scenarios with one incident in each. The average of the mean travel times in the runs with the two scenarios was taken and the average travel time in the base case was subtracted for scaling. The inverse of this value was defined as the fitness of a particle. It should be noted that the 'closed loop' was simulated three times for each scenario to account for the stochasticity. After all the particles of the population were evaluated, the next population was generated using Roulette Wheel Selection. Selected particles were then mated (cross-over) and mutated. The probability of crossover was chosen as 0.7 and the probability of mutation of each bit was chosen as 0.002. Each particle of the new generation was then evaluated in a similar manner as for the initial population. The algorithm stops when convergence is reached. Convergence can be defined as when the change in the average fitness of a population from the previous one is less than a threshold value.

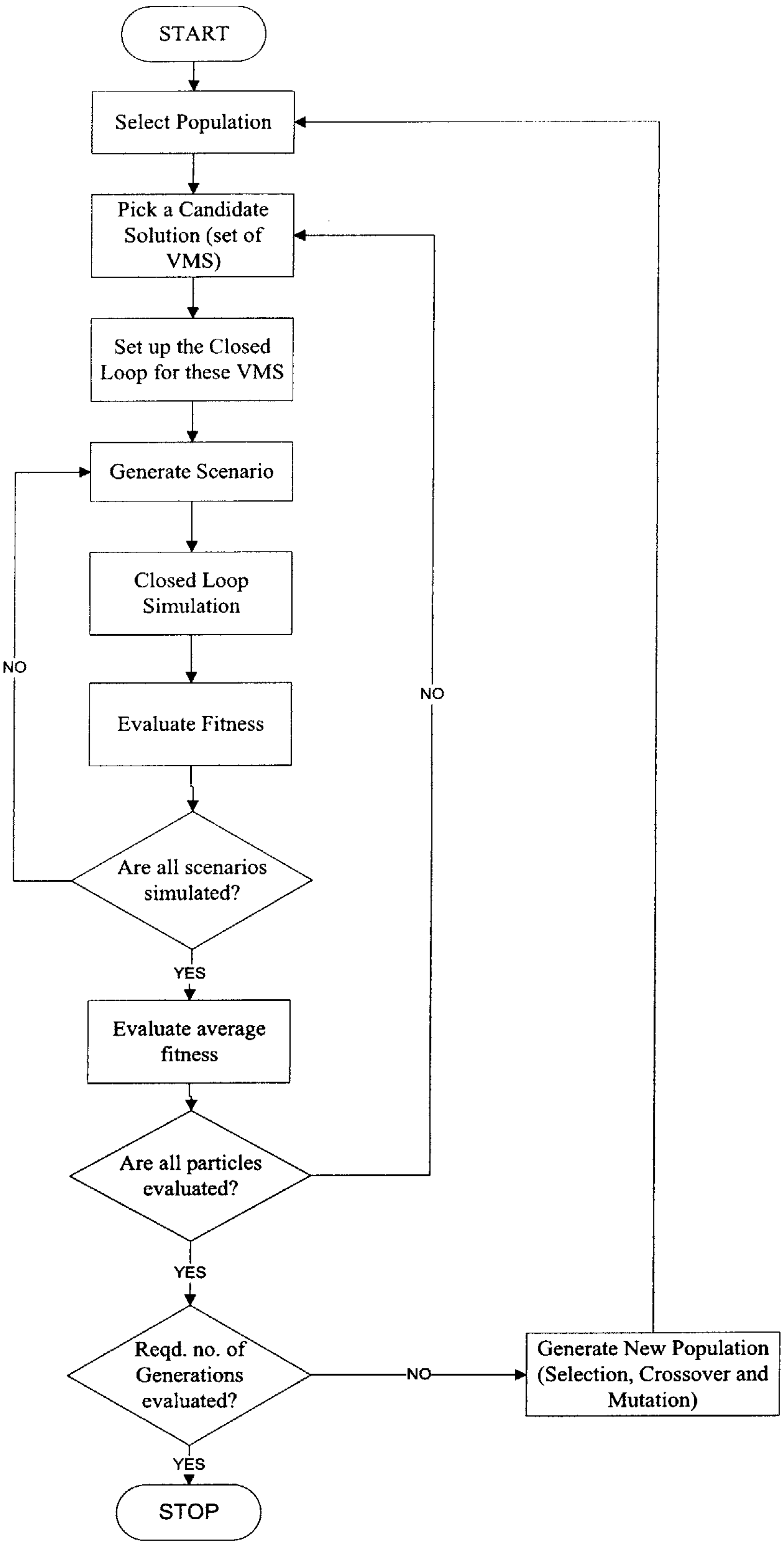

Figure 5-2 Methodology Flowchart

5.3 Baseline Performance

To evaluate the baseline performance of the network, it was first simulated without any incidents and Variable Message Signs in the network. Also, we need this analysis to compare with the results obtained in the VMS case. As before, when no information is being disseminated, DynaMIT is not required. Thus, MITSIMLab was used in the stand alone mode for this simulation.

Figure 5-3 shows the experienced travel times for drivers in each departure time interval. It can be observed that the travel times don't vary a lot and most of them are between 15 to 35 seconds. The mean travel time is 22.19 seconds. The standard deviation is 5.48 seconds. The total vehicle-minutes in this case is 328.4.

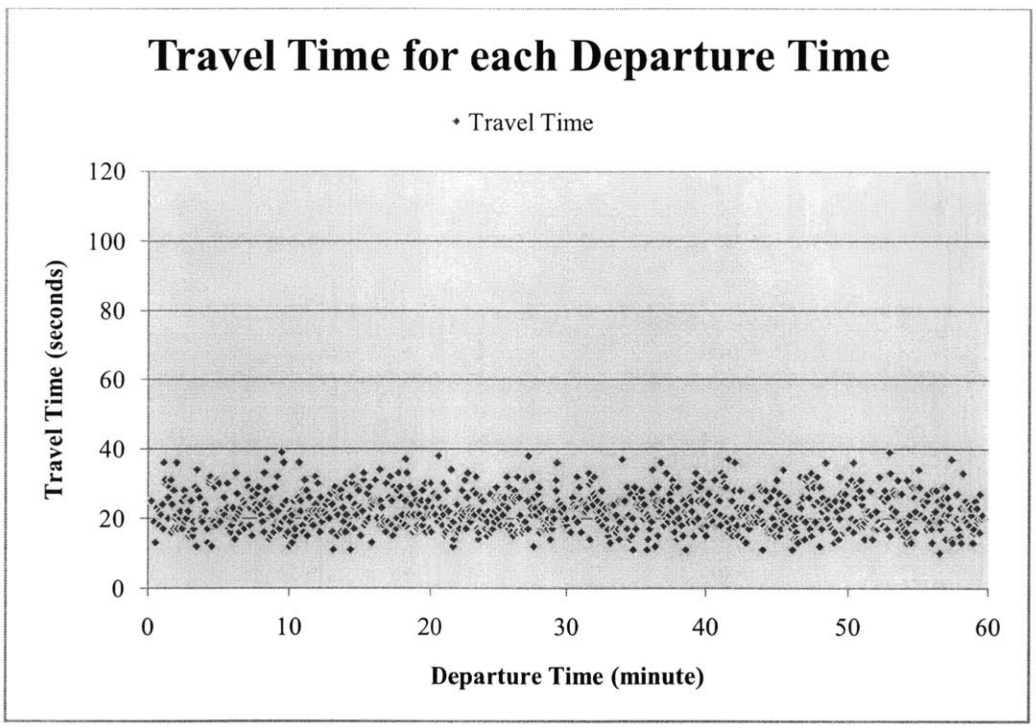

Figure 5-3 Travel Time for each minute of Departure time (Base Case)

5.4 Incident Scenario

Two incidents were simulated as per the above discussion. Again, MITSIMLab in the stand alone mode was used for the simulation. The observations for each incident are summarized below.

5.4.1 Incident 1: Link 19

This incident lasts for 20 minutes from 6:25 am to 6:45 am. Figure 5-4 shows the experienced travel times for drivers in each departure time interval. The impact of incident is quite clear. We see a huge jump in the travel times faced by the drivers. An interesting observation is that the effect lasts only for the duration of the incident. But it should be noted that these drivers left the origin between 6:25 am and 6:45 am and would have taken some time to reach the affected links. Also, the low demand is another reason for the quick dissipation of the delays.

The maximum travel time has jumped to 1203 seconds as compared to 39 seconds in the base case. Also from Figure 5-4, it can be seen that a lot of drivers have shifted to the high travel time range. The mean travel time is now 114.68 seconds. This is more than 4 times increase. The standard deviation is 236.18 seconds. The total vehicle-minutes in this case is 1697.2, again an increase of 400%.

If we consider the period from 6:20 am to 6:50 am (period affected by incident taking into account the boundary effects), the condition is much worse. The mean travel time is 205.24 seconds, and the standard deviation of travel time is 306.25 seconds.

Thus, we have observed that the incident has severely affected the network performance. Drivers who enter the network during 6:20 am and 6:45 am face huge delays, and very high travel times.

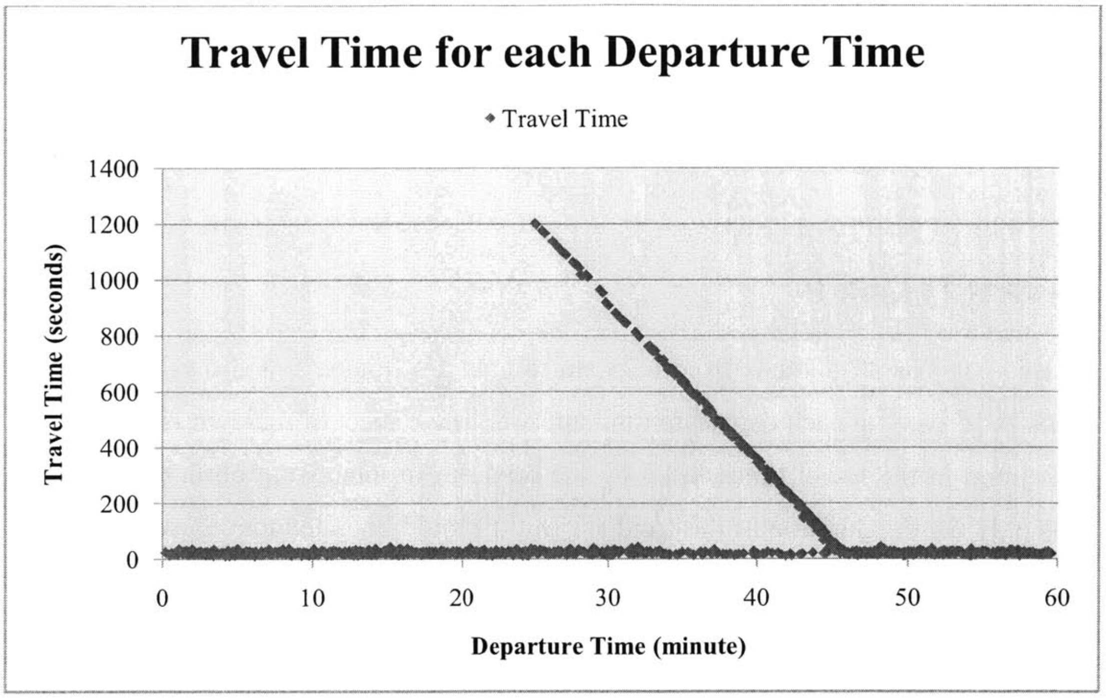

Figure 5-4 Travel Time for each minute of Departure time (Incident 1)

5.4.2 Incident 2: Link 20

This incident lasts for 20 minutes from 6:25 am to 6:45 am as well. Figure 5-5 shows the experienced travel times for drivers in each departure time interval. A similar impact is observed in this case as well. Experienced travel times for a lot of drivers are much higher. Again, dissipation of the queues is very quick owing to the small size of the network.

The maximum travel time has jumped to 1219 seconds. Also from Figure 5-5, it can be seen that a lot of drivers have shifted to the high travel time range. The mean travel time is 104.08 seconds. This also is a 400% increase as compared to that of the base case. The standard deviation is 235.48 seconds. The total vehicle-minutes in this case is 1540.3, again a significant increase than the base case.

For the period from 6:20 am to 6:50 am, the mean travel time is 184.18 seconds, and the standard deviation of travel time is 311.04 seconds.

Thus, we have observed that this incident affects the network performance severely as well. However, observing the mean travel times, this incident is slightly less severe than the first one.

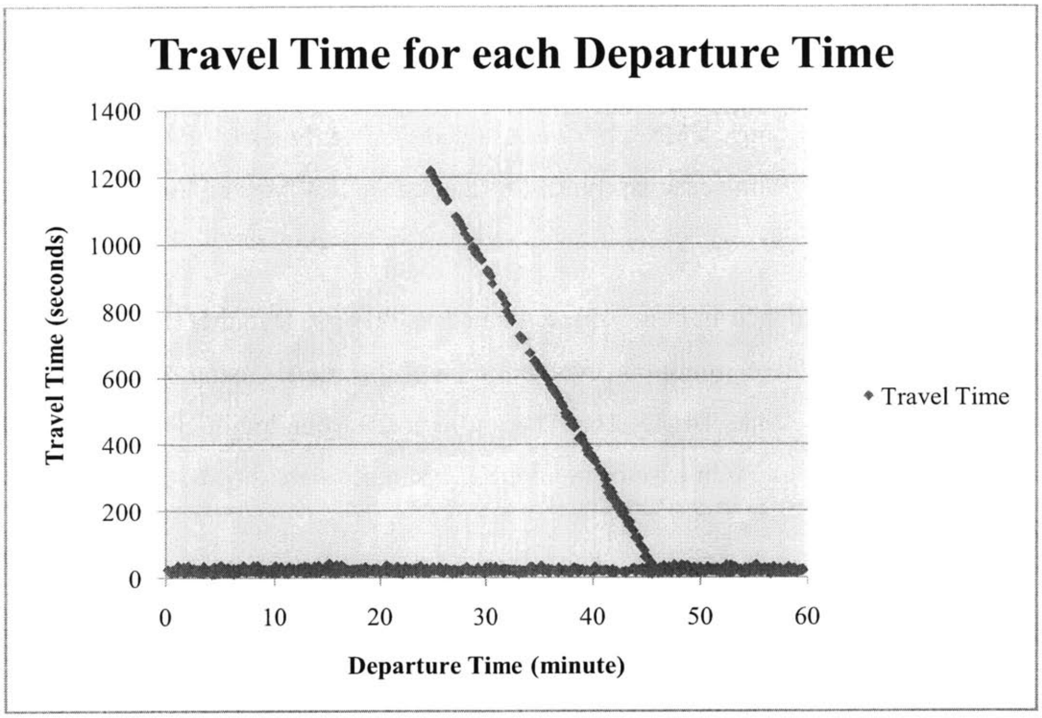

Figure 5-5 Travel Time for each minute of Departure time (Incident 2)

Here is a summary comparison of the statistics:

	Base Case	Incident 1	Incident2
Total Travel Time (veh-mins)	328.4	1697.2	1540.3
Mean TT (seconds)	22.19	114.68	104.08
Std Dev TT (seconds)	5.48	236.18	235.48
Max TT (seconds)	39	1203	1219

Table 5-1 Summary Comparison of Network Performance

Clearly, the incidents have had a severe impact on the network performance. From the table we can see that the travel times are highly volatile for the incident scenarios. If this occurs, then it becomes difficult for the drivers to effectively budget their travel time. Wunderlich (2001) gives a discussion of trip reliability under the impact of ATIS. The incidents greatly increase the standard deviation of the travel times from 5 to 235 seconds, reducing the trip reliability.

5.5 Results of application of Genetic Algorithm

To optimize the location of Variable Message Signs, Genetic Algorithm was applied with the constraint of maximum VMS to be installed to be 2 and 3 respectively. These constraints can be interpreted as budget constraints. VMS can't be installed on each link and these will be governed by the budget allotment. For this case study, the budget constraint has been arbitrarily chosen to be 2 and 3.

Since predictive route guidance is being disseminated to drivers, DynaMIT is required for the simulation and the objective function evaluation will be done using the 'closed loop'. Information is given for the links 14, 15, 16, 17, 18, 19 and 20 when incident 1 occurs, and about links 8, 13, 16, 17, 18, 19 and 20 in case of incident 2. The results are discussed below.

5.5.1 GA : Optimal VMS Locations with Constraint of Maximum 2 VMS

The first evaluation was done with the constraint that the maximum VMS to be installed in the network is 2. GA found the optimal location of the two VMS to be link 6 and link 10 as shown in Figure 5-6. Link 10 is clearly important as people might be approaching this link from all three origins. Information can thus be disseminated to lot of people. With link 6, the location is not that intuitive at the first thought. However, on close inspection, this VMS can be very important in advising people coming from Origin 3 and heading to link 19 (location of first incident) to use link 5 so that they can reach the destination by using link 20. Similar reasoning is valid when the incident is on link 20, these drivers can take link 4 and continue straight to D1.

Figure 5-7 depicts the travel times experienced by the travelers in the first case with 2 VMS. Although, we can see that the density in the upper part of the chart has decreased, we cannot say for sure. We thus confirm our hypothesis with aggregate statistics. Figure 5-8 shows the experienced travel times when the second incident occurs and information is disseminated through the two VMS. Again, we present the aggregate statistics to confirm that there is indeed improvement in the network (Table 5-2).

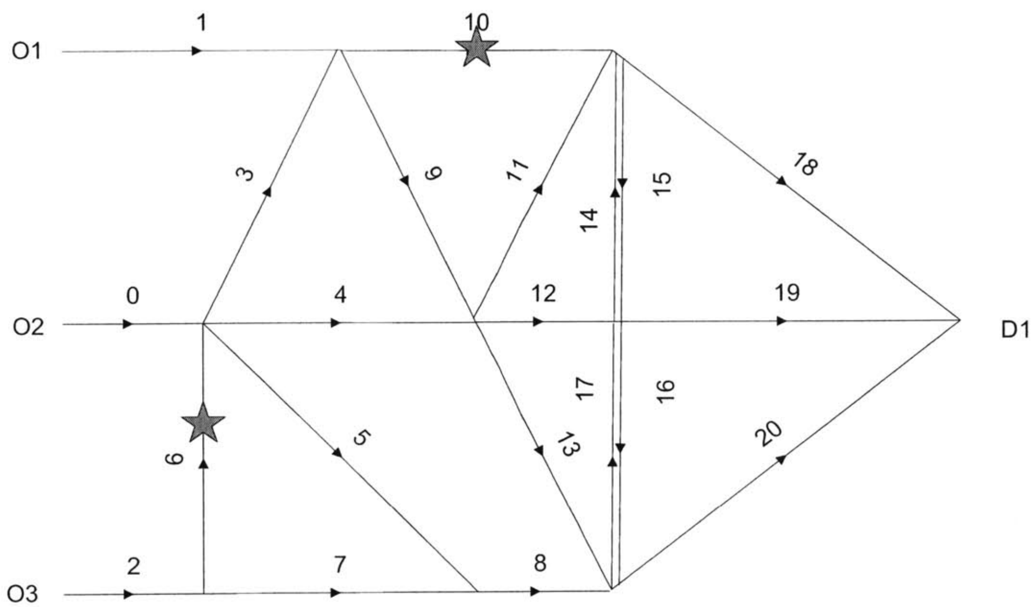

Figure 5-6 Optimal VMS locations with constraint of 2 VMS

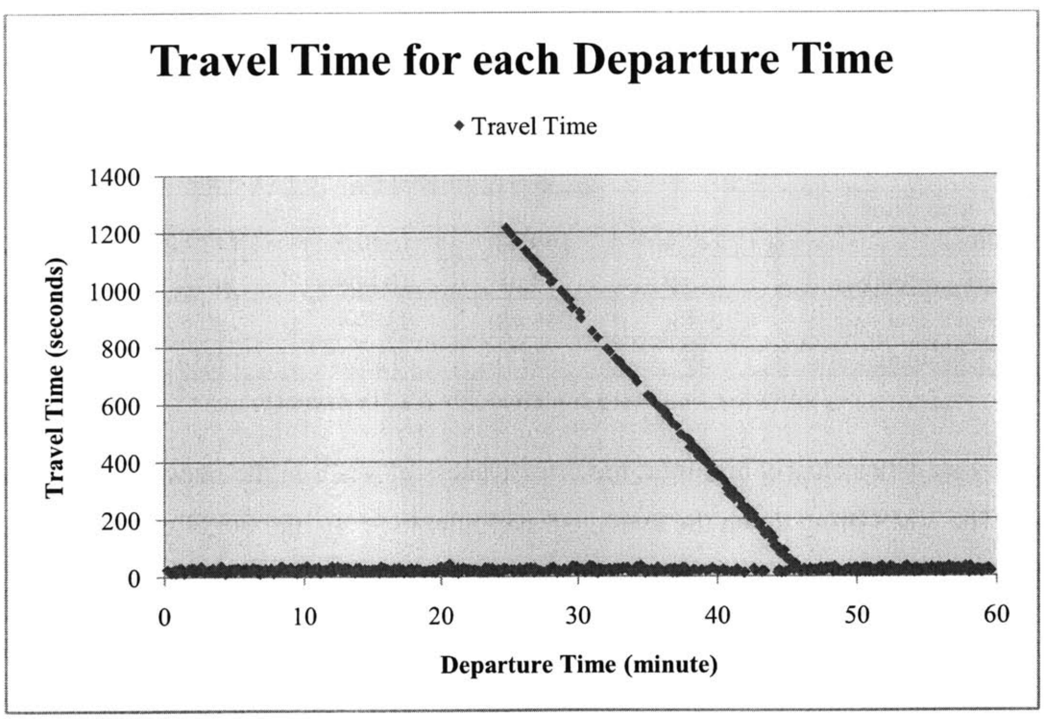

Figure 5-7 Travel Time for each minute of Departure time with 2 VMS (Incident 1)

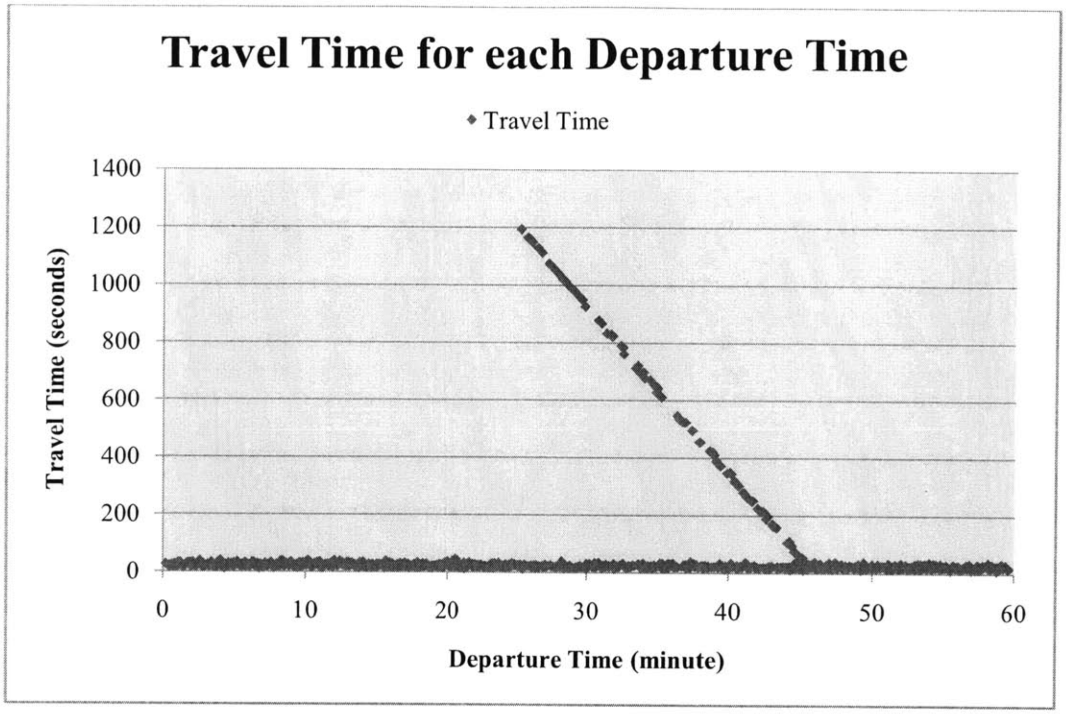

Figure 5-8 Travel Time for each minute of Departure time with 2 VMS (Incident 2)

		Incident		VMS	
	Base Case	Incident 1	Incident 2	Incident 1	Incident 2
Total Travel Time (veh-mins)	328.4	1697.2	1540.3	1429.2	1187.7
Mean TT (seconds)	22.19	114.68	104.08	96.46	80.34
Std Dev TT (seconds)	5.48	236.18	235.48	220.57	203.58
Max TT (seconds)	39	1203	1219	1216	1193

Table 5-2 Summary Statistics for 2 VMS scenario

The summary statistics clearly highlight the effectiveness of VMS in the network under incident conditions. The VMS bring down the average travel time to 96.46 and 80.34 seconds, which is a huge improvement. The total travel time spent by the drivers in the network is 1429.2 minutes in first incident case and 1187.7 minutes in second incident case. The trip reliability as denoted by the standard deviation of the experienced travel times has improved as well, though it is still quite high. The maximum travel time is still quite high in the VMS case. However, we need to analyze the number of people in each travel time bin. A comparison is shown in Table 5-3.

	Incident		VMS	
Travel Times	Incident 1	Incident2	Incident 1	Incident2
0-50	721	724	754	796
50-200	31	36	28	14
200-400	37	36	36	19
400-600	38	33	27	13
600-800	28	22	15	17
800-1000	13	17	9	13
>1000	20	20	20	15

Table 5-3 No. of people in each Travel Time bin

It can be observed that with the help of VMS, a lot more people are now experiencing lower travel times. 754 people in first incident scenario with VMS, and 796 people in the second scenario experience travel times less than 50 seconds. We can see that there is only slight improvement in people facing higher travel times. We can thus conclude that benefits have come from people facing travel times of 200-1000 seconds in the incident scenarios.

One of the advantages of using Genetic Algorithms is that it provides us with a number of good solutions besides the best one. If for every generation the fitness of each particle is stored, it can be compared with that of the fittest particle, and other solutions that look promising can be analyzed as well. This capability of GA helps a lot in problems that have some kind of constraints on some element of a particle. In our case, for example, we might not want to install VMS on two successive even though it results in the best fitness. The reason is that it might reduce the driver's trust in the system if information is changed very quickly. In that case, it might be better to look at the solution with the next best fitness, and see if it is practically more feasible to accept.

For the case, top three particles were selected and a comparison is presented in Table 5-4.

	VMS (links 6 &10)		VMS (links 4 & 10)		VMS (links 5 & 10)	
	Incident 1	Incident2	Incident 1	Incident2	Incident 1	Incident2
Total Travel Time (veh-mins)	1429.2	1187.7	1578.2	1134.8	1472.6	1275.7
Mean TT (seconds)	96.46	80.34	106.75	76.67	99.39	86.29
Std Dev TT (seconds)	220.57	203.58	229.5	203.29	211.7	221.05
Max TT (seconds)	1216	1193	1210	1216	1191	1221

Table 5-4 Comparison of three best solutions (with constraint of 2 VMS)

First thing to observe is that all cases are individually are better than the incident cases. This again confirms our claim about the effectiveness of VMS. An interesting observation that can be made is that the second best particle delivers the best performance in the case of second incident. However, this set of VMS does not perform that well for the first incident case. In fact the it performs the worst when the total travel times are compared. However, as discussed before we are looking for solutions that give us a better network performance. Based on this criterion, the best solution (VMS on links 6 and 10) is clearly the winner among the three.

The analysis thus shows the applicability of GA in solving the problem of VMS locations. The best solution (link 6 and 10) improves the network performance significantly. The next two best solutions reduce the travel times as well, and might prove to be a better practical solution.

The next section presents the results with the budget constraint being relaxed to 3.

5.5.2 GA : Optimal VMS Locations with Constraint of Maximum 3 VMS

The next evaluation was done with the constraint that the maximum VMS to be installed in the network is 3. GA found the optimal location of the two VMS to be link 0, 3 and link 9 as shown in Figure 5-9. VMS on Link 0 can be explained by the fact that this origin has the highest demand. Similarly Links 3 and 9 are heavily used ones, because they are in the paths of people that enter at any origin. The three VMS together can cover a lot of diversion routes when observed closely.

Figure 5-10 depicts the travel times experienced by the travelers in the case of first incident with VMS. Figure 5-11 shows the experienced travel times when the second incident occurs and information is disseminated through 3 VMS. The aggregate statistics are shown in Table 5-5.

		Incident		VMS	
	Base Case	Incident 1	Incident2	Incident 1	Incident2
Total Travel Time (veh-mins)	328.4	1697.2	1540.3	1351.8	1341.3
Mean TT (seconds)	22.19	114.68	104.08	91.23	90.43
Std Dev TT (seconds)	5.48	236.18	235.48	215.57	219.41
Max TT (seconds)	39	1203	1219	1191	1217

Table 5-5 Summary Statistics for 3 VMS scenario

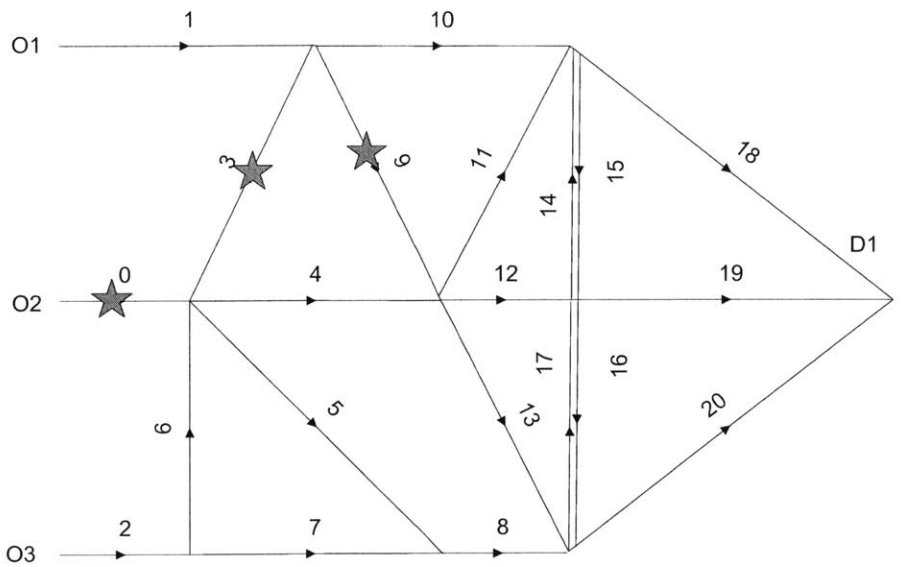

Figure 5-9 Optimal VMS locations with constraint of 3 VMS

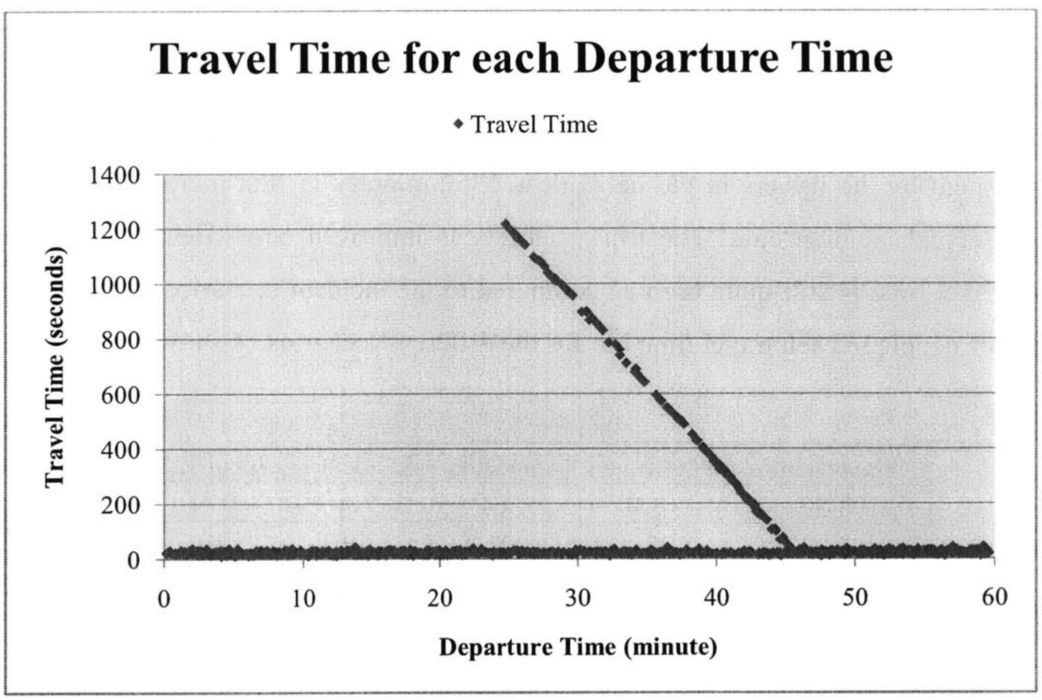

Figure 5-10 Travel Time for each minute of Departure time with 3 VMS (Incident 1)

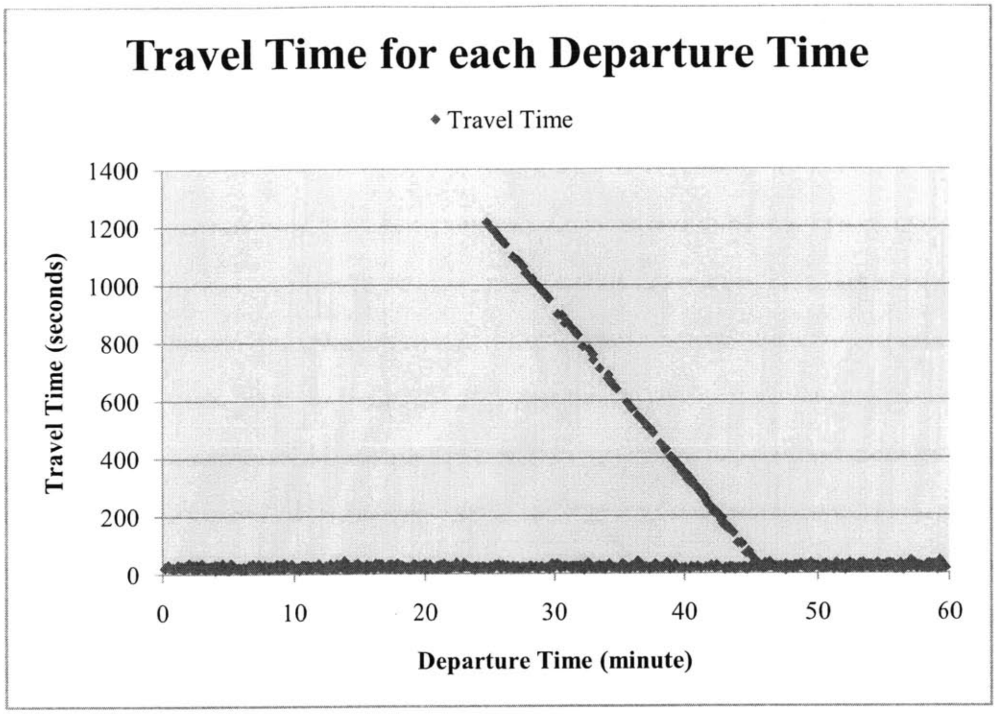

Figure 5-11 Travel Time for each minute of Departure time with 3 VMS (Incident 2)

The summary statistics demonstrate the effectiveness of VMS in the network as in the previous case. The average travel times with VMS are about 90 seconds in each incident case. The total travel time spent by the drivers in the network is 1350 minutes in first incident case and 1340 minutes in second incident case. The trip reliability is improved only slightly as before. The maximum travel time is still quite high as compared to the incident scenarios. A comparison of the number of people in each travel time bin for the different scenarios is shown in Table 5-6.

	Incident		VMS	
Travel Times	Incident 1	Incident2	Incident 1	Incident2
0-50	721	754	771	779
50-200	31	21	19	19
200-400	37	31	32	31
400-600	38	28	16	15
600-800	28	17	20	12
800-1000	13	17	13	15
>1000	20	20	18	19

Table 5-6 No. of people in each Travel Time bin

The conclusions are similar as in the previous case. A large number of people have been shifted to lower travel times. The shift is greater than that with only 2 VMS. Again, people with higher travel times shift only a little. Thus, major contribution comes from people facing travel times of 50 – 800 seconds.

GA provides us with multiple good solutions in this case as well. Three best particles were chosen based on their fitness and the comparison is presented in Table 5-7.

	VMS (links 0, 3 & 9)		VMS (links 7, 8 & 12)		VMS (links 1, 4 & 15)	
	Incident 1	Incident2	Incident 1	Incident2	Incident 1	Incident2
Total Travel Time (veh-mins)	1351.8	1341.3	1436.3	1257.5	1476.8	1297.4
Mean TT (seconds)	91.23	90.43	96.93	85.16	99.78	87.66
Std Dev TT (seconds)	215.57	219.41	220.04	206.93	219.71	210.82
Max TT (seconds)	1191	1217	1217	1181	1203	1217

Table 5-7 Comparison of three best solutions (with constraint of 3 VMS)

Again the effectiveness of VMS is strongly highlighted. Drivers experience much lower average travel times. The total benefits in terms of total travel time goes as high as 16% as compared to the incident case. Again one can observe that in case of incident 2, the other two particles perform a lot better as compared to our best solution. However, those two particles don't prove to be as effective in case of the first incident. However, the best solution (links 0, 3 and 9) performs well in both cases, even though not the best in one. Thus, it can be concluded that the application of GA has been successful in solving the problem.

This analysis demonstrates the applicability of GA in solving the problem at hand. The best solution identified by GA was installing VMS on links 0, 3 and 9 which also makes intuitive sense. Aggregate statistics confirm that the network performance has indeed improved. Other solutions that are marginally less than optimal also holds promise and might be preferred to be accepted under certain conditions.

5.5.3 Comparison of the best solutions

A comparison of the two best solutions is presented in Table 5-8. It can be observed that the solution with 2 VMS dominates the one with 3 VMS when one looks at the fitness function (the last row in the table). Although the first solution performs worse in the first incident case, it is a better solution to our problem based on our definition of fitness function. Its performance in the second case is much better than the solution with 3 VMS. Hence, on an average overall network conditions will be better with the 2 VMS than the other solution. However, if it is known that the incident 1 occurs much more frequently than the second incident, then installing 3 VMS might prove to be better. This is also a highlight of the approach to the problem. The more frequent and the major incidents should be chosen for evaluation and the fitness should be based on performance in each case.

It is interesting to see that we can have a better network state using only 2 VMS than using 3 VMS. In a larger network (e.g. the Lower Westchester County network used in Chapter 4 case study) we should not expect this to happen. The network state should not deteriorate with the better information because we are providing *consistent* route guidance. However, there might be a couple of reasons why we see this phenomenon here. As discussed in Chapter 3, the O-D interval in the 'closed loop' is 15 minutes, i.e. MITSIMLab sends its sensor counts to DynaMIT every 15 minutes, and DynaMIT sends predictive information to MITSIMLab, again every 15 minutes. As we have seen, the size of the network is very small. In fact, the mean travel time in the base case is just 22 seconds. Thus, an O-D interval of 15 minutes is probably too large for such a small network, thus reducing the 'quality' of the information. It should be noted that the 'O-D interval' can be set to a different interval with some modifications. However, since the main objective of the case study was to see the applicability of the methodology, the 'closed loop' setup was kept as such. Another implication of the network being so small is that may be 3 VMS are too many for this network. The drivers are being asked to reevaluate the paths too soon, thus leading to over-reaction, and higher experienced travel times.

	2-VMS		3-VMS	
	Incident 1	Incident 2	Incident 1	Incident 2
Total Travel Time (veh-mins)	1429.2	1187.7	1351.8	1341.3
Mean TT (seconds)	96.46	80.34	91.23	90.43
Std Dev TT (seconds)	220.57	203.58	215.57	219.41
Max TT (seconds)	1216	1193	1191	1217
Overall Mean TT (seconds)	88.4		90.83	

Table 5-8 A comparison of the best solutions

5.6 Summary

Following are the major findings of the case study.

- Optimal VMS location methodology was successfully applied in a simple network with constraints of maximum 2 and 3 VMS respectively.
- The best solutions found using GA make intuitive sense. With the optimal solutions in both cases, significant reduction in travel times is obtained. The total travel time spent by the drivers in the network is reduced as well.
- Effectiveness of VMS was again highlighted by the improvement obtained in the network performance.
- Besides giving the optimal solutions, the methodology provides other good solutions which might be preferred under certain constraints.
- The solution that works well under all incident scenarios was denoted to be the best by GA. GA thus gives an average optimal which is our main objective in solving the problem.
- It was found that installing 2 VMS gives more benefits than installing 3. However, proper analysis should be done before accepting that network state with 2 VMS is better than 3. Possible reasons for this unexpected behavior are the large 'O-D interval' in the 'closed loop' setup, and that 3 VMS are too many for this small network.

We can thus conclude that the methodology using Genetic Algorithm is a simple yet powerful tool in solving the optimal VMS locations problem.

The future step will be to extend the application of this approach to a real sized network such as the one used in Case Study I. GA being very simple and straightforward promises a successful implementation in larger networks as well. However, the scalability might have some issues:

- Using Dynamic Traffic Assignment in real networks can be very computationally intensive. It can create a bottleneck in terms of the time it takes to execute the algorithm.
- Complexity increases with an increase in size. Lots of feasible locations will increase the solution space greatly. Although the simplicity of GA can accommodate it, the population size has to be increased. Also, the convergence will not be as fast.
- In a large sized network, there might be the possibility of even more incidents. Thus, more incidents needs to be simulated for the evaluation. This again will increase the computation time towards convergence.
- The storage might become an issue due to large number of particles and iterations (generations). This can be overcome however by storing the particles at each generation so that the particles can be identified at the end. After selecting the best few particles (based on the fitness, for example), these particles can be simulated again in isolation and analyzed. It thus becomes a compromise between computation time and storage space.

The next chapter summarizes the contributions made in this thesis, and provides directions for future work.

Chapter 6 Conclusion

Incidents can hamper the traffic conditions specially if they occur on a major freeway. Although incidents, caused due to natural calamities or by human involvement, are difficult to avoid, better incident management can bring down the losses that occur due to the resulting congestion. In case of incidents, drivers obtaining dynamic route guidance through Variable Message Signs can improve their trip reliability and reduce the time spent in the network by making better decisions about their route choice. Variable Message Signs may prove to be powerful tools in diverting traffic to alternate routes, thus benefitting the system as a whole. The drivers get the benefit of making an informed route choice decision.

However, these benefits are significant only when the drivers are given predictive information about the network state. The state of the art is to inform the drivers about the present travel times on the affected and the diversion routes. When a driver sees such an information, it is useful to him/her if the links in question are nearby, else this information will be ignored thus rendering the presence of VMS to be useless. By the time, the driver reaches that route, the conditions would have changed completely. The thesis develops a tool that disseminates predictive route guidance to the travelers via the Variable Message Signs. The predictive guidance is generated using DynaMIT, a DTA system. The predictive guidance is both unbiased and consistent. This tool is evaluated using MITSIMLab, acting as a proxy for the real traffic networks.

Knowing the significant benefits that can be obtained by using the VMS, efforts should be made to maximize these benefits. One of the possible areas of optimizing this is to install the VMS at the locations where they are most effective. This requires both an optimization algorithm that can move towards the optimum solution; and an evaluation tool to evaluate the quality of a solution. The tool described above is capable of evaluating the VMS. Various algorithms are available for optimization, however, Genetic Algorithms are best suited to solve problems of this nature. The methodology presented in this thesis can be a basis to solve this problem for large scale networks.

6.1 Thesis Contributions

The thesis used the 'closed loop' framework integrating MITSIMLab and DynaMIT to assess the impact of dynamic route guidance through Variable Message Signs in case of severe incidents. A methodology was developed and applied to optimize the location of Variable Message Signs in a simple network.

As a part of the thesis, the functionality of Variable Message Signs was successfully implemented in both MITSIMLab and DynaMIT (and hence the 'closed loop') for evaluation. This implementation helps to study the effectiveness of VMS in diverting traffic in case of an incident. This functionality is able to use multiple VMS in the system. The dynamic route guidance to be disseminated to the drivers is obtained from DynaMIT which acts as the Traffic Management Center, as MITSIMLab does for the real world. DynaMIT is capable of generating predictive and consistent route guidance. The content of information provided through the VMS is very important. Current model provides descriptive information about the incident affected links and the alternate diversion routes. Drivers can thus make informed decisions about their route choice when they receive information through a VMS.

The impact of dynamic route guidance was evaluated with the help of a case study in the Lower Westchester County network of New York. Two one hour-long incidents with full blockage were simulated on I-95 and SprainBrook Parkway for the southbound traffic. These incidents are representative of the frequent closures and bottlenecks that occur on the freeway, both in terms of severity and location. For the simulation of the network conditions, MITSIMLab and DynaMIT calibrated for this network, were used. Simulation was done for seven cases for the I-95 incident: the Base Case representing a normal day; the incident scenario without any information being provided in the network; and the five VMS scenarios with varying iterations of prediction for consistent guidance. For the SprainBrook incident, simulation was done two times: the incident scenario without any source of information; and the VMS scenario with 3 prediction iterations. Results and comparison show the significant improvement in the network. The results underline both the successful implementation of VMS in the 'closed loop' as well as the effectiveness of dynamic route guidance produced by DynaMIT.

With the conclusion that the Variable Message Signs are an effective tool for incident management, an attempt was made to maximize these benefits by optimizing their locations in the network such that in case of random incidents (but at few and known locations) on an average the network performs significantly better than the case when there is no information. A methodology using Genetic Algorithms was developed and applied to a synthetic network. Two incidents were simulated and the optimal location of VMS was identified with the constraints of maximum 2 and 3 VMS. Results show that the methodology is a powerful tool in optimizing VMS locations, and that due to this optimization there is a significant improvement in the network performance under incident scenarios.

6.2 Future Research Directions

While the implementation of the Variable Message Signs in the 'closed loop' framework is general, there were several simplifying assumptions in the case studies in order to demonstrate the primary contributions of the methodologies. Relaxing these assumptions could yield potential research extensions to this work, some of which are outlined below.

- The case study on Lower Westchester County, NY was done with the VMS as the only source of dynamic route guidance. In reality information can be disseminated through in-vehicle devices and other means as well. A possible extension will be to assess the impact of dynamic route guidance in the presence of all available sources of information including the VMS.
- Compliance can be an important factor in response to VMS. Since here the information is only descriptive, by compliance it is meant whether the driver would re-evaluate the route choice or not. The case study was done using 100% compliance which makes sense since in the case of complete blockage everyone needs to be diverted (This parameter was tested before being set to 100%). Thus, evaluations can be done using less severe incidents and varying levels of compliance (as defined here) for drivers.
- The state of the art is to disseminate information about the incidents that is the current measured travel times on the affected links and the diversion routes. The instantaneous VMS framework developed by Sundaram (2002) for the planning version of DynaMIT

can be extended to the 'closed loop'. Evaluations done for this scenario would be representative of the state of the art, and comparisons can be made with the benefits obtained by using DynaMIT as a source of predictive guidance.

- In the literature, the content of information has been shown to be very important in the working of VMS. The present implementation uses descriptive information. The effects of prescriptive information can be explored.
- Genetic Algorithm was successfully implemented in a small network. Realizing the strength of the methodology, it should be tested and implemented for real sized networks. The various factors and bottlenecks for the scalability to large networks are discussed in Chapter 5.
- The methodology for optimal location of VMS can be extended to take into account the installation and operation costs in the objective function. Thus, it can be combined to optimize the number and location of Variable Message Signs.

Appendix A Overview of MITSIMLab

MITSIMLab framework (Yang, 1999) consists of a traffic flow simulator (MITSIM) and a traffic management system (TMS). MITSIMLab models traffic flows in the network at the vehicle level, including driver behavior, while TMS added functionality to disseminate traveler information to drivers loaded on a MITSIMLab network. In this new 'closed loop' framework, however, the TMS has been replaced with DynaMIT, a much more sophisticated guidance generation package. MITSIMLab is able to simulate the real world through its realistic models for network representation (topology, incidents), route choice, and vehicle advancement (acceleration models, lane changing models). Toledo (2003) provides a thorough treatment of MITSIMLab traffic models.

Figure A-1, from Yang (1999) shows the overall operation of the MITSIMLab clock-based simulation. A detailed description of the simulator can be found in Yang (1999).

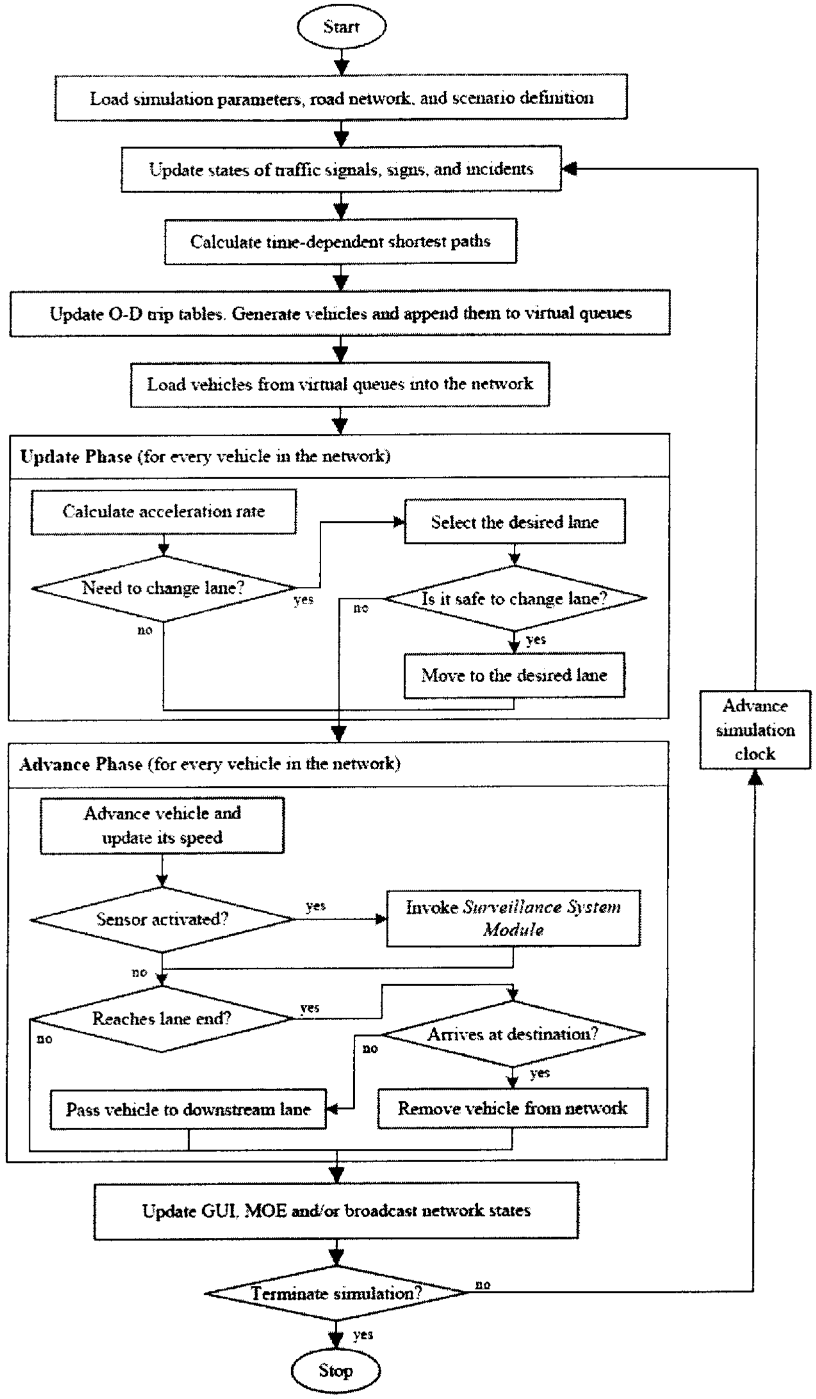

Figure A-1 MITSIMLab CLock-based Operation

A.1 MITSIMLab Network Representation

In MITSIMLab, a road network is represented with nodes, links, segments and lanes allowing one to monitor performance at an extremely fine level of resolution. The MITSIMLab network representation allows for the placement of sensors within lanes in the network. Incidents can be placed on any lane within the network, and can be placed and/or cleared at any time. Since providing information is especially useful in cases of non-recurrent congestion (e. g. incidents), MITSIMLab's ability to model the visibility, number of lanes affected, location, severity and duration of an incident is extremely powerful as we shall see in the later chapters. Because the incident may begin before it is reported, this allows for the evaluation of various incident detection schemes.

A.2 MITSIMLab Travel Demand

Demand is represented as *time dependent* OD tables in MITSIMLab, that loads vehicles onto the network according to a Poisson distribution based on parameters specified in the OD descriptions. MITSIMLab specified vehicle performance characteristics (e.g. maximum acceleration, speed) are specified deterministically, while driver behavior parameters are assigned randomly according to specified distributions which again, go as an input to the simulator. With specific regards to route choice decisions in response to traffic information, MITSIMLab assumes two distinct driver groups: *uninformed* drivers have access only to the historical travel time tables - this represents a 'conventional wisdom' of travel times – while *informed* drivers have access to travel time tables that, in this 'closed loop' evaluation framework, are updated according to newly received predictive guidance from DynaMIT. However, in this study, since we want to evaluate the effect of VMS, we will ignore any other sources of information in the network. All drivers will be considered unguided, and would receive the DynaMIT guidance only when they come within the visibility distance of a VMS.

In the 'closed loop' framework, MITSIMLab is a proxy for the real world, and hence its demand should represent the real demand so that it can perform its role effectively. For this purpose, calibrated MITSIMLab has been used for this study (Antoniou, et al., 2006a). Also, by experimental design this will be different from the historical OD representation used in DynaMIT since real-world demand will always be slightly different from historical estimates.

A.3 Route Choice and Route-Choice Models

Routes for MITSIMLab vehicles are calculated at each intersection using a *route-choice model* (Figure A-1):

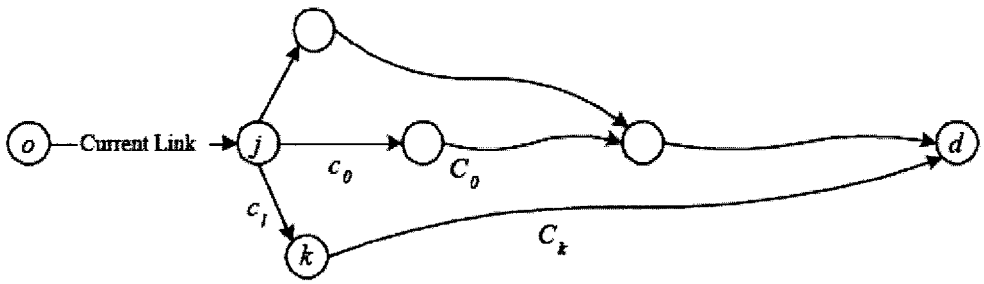

Figure A-1 Route choice example for MITSIMLab model

The model follows a multinomial logit structure ((Ben-Akiva, et al., 1985):

$$p(l \mid j,t) = \frac{\exp(V_l(t))}{\sum_{m \in L_j} \exp(V_m(t))}$$

Equation A-1 MITSIMLab path choice logit model

where:

$p(l|j,t)$ = probability to choose link l for a vehicle that expects to arrive at node j at time t;

L_j = set of outgoing links at node j;

$V_l(t)$ = systematic utility of choosing a route with link l as the next link.

In the default model, the utility is a function of:

$c_l(t)$ = perceived travel time on link l at time t;

$C_k(t)$ = perceived travel time on the *shortest path* from node k (the downstream node of link l) to the destination if the vehicle arrives at node k at time t; and

z_l = penalty that captures freeway bias.

The perceived travel times $c_l(t)$ and $C_k(t)$ are time dependent, and are calculated from either historical travel-times or guided travel-times. Thus, $p(l|j,t)$, the route choice probability, will differ among *informed* and *uninformed* vehicles, even for vehicles expecting to arrive at the same node j at the same time t.

A.4 MITSIMLab Route Switching and ATIS

Even though vehicles in MITSIMLab may be configured with pre-assigned paths so that they do not choose paths at each intersection, the provision of new ATIS in MITSIMLab triggers a route-switching model for drivers who receive some sort of information. This model specification is similar to the route-choice model.

$$p(l \mid j,t) = \frac{\exp(V_l(t))}{\sum_{m \in L_j} \exp(V_m(t))}$$

Equation A-2 MITSIMLab path switch logit model

where:

$p(s|r,t)$ = probability to choose path s for a vehicle that expects to arrive at the decision

node at time t using path r;

Sr = set of available paths from node j to the driver's destination;

$Vi(t)$ = systematic utility of choosing path i which is a function of:

$Cl(t)$ = expected time on path i at time t; and,

$Zi(t)$ = diversion penalty if path i is different from the driver's current path r

A.5 Other MITSIMLab Behavioral Models

MITSIMLab also incorporates detailed acceleration models (i.e. car-following models, free-flowing and emergency regimes, merging rules, and incident-response behavior) as well as lane-changing models (i.e. gap acceptance, nosing models) to accurately simulate driver behavior. These models are not discussed here because the provision of traffic information does not directly affect these behaviors. Toledo (2003) presents a thorough treatment of MITSIMLab traffic models.

Appendix B Overview of DynaMIT

DynaMIT is a simulation-based real-time system designed to estimate the current state of a transportation network, predict future traffic conditions, and provide consistent and unbiased information to travelers. DynaMIT combines real-time data from a surveillance system with historical travel time data in order to predict future traffic conditions and provide travel information and guidance to drivers. Although model errors within DynaMIT mean that it is not a perfect reflection of reality, the information that DynaMIT generates is:

- Unbiased – The information provided to any traveler is based on the best knowledge of future network conditions that is available.
- Consistent – The network conditions experienced by travelers coincide with the predicted conditions on which the information was based.

Therefore, a travel choice inferred from DynaMIT information will not be inferior to other network conditions as they develop.

The overall structure of DynaMIT is shown in Figure B-1. For a detailed discussion of DynaMIT, please see Balakrishna (2002). 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 capability to do real-time O-D estimation, taking into account user behavior for route, departure time and mode. It also models the impact of information by maintaining two separate travel time tables for guided and unguided drivers. The O-D model then uses the real-time sensor counts, updated O-D flows, and 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 (as a result of incidents etc.), traffic dynamic parameters, and generation of traffic information. Response of users to information dissemination is captured through the pre-trip and en-route driver behavior models.

The Prediction-based Guidance Generation module generates predictive guidance. An iterative framework is used to obtain *consistent* guidance, which means that route choice decisions inferred from this guidance will result in optimal path decisions for each driver. Each iteration consists of a trial strategy and network state prediction (both demand and supply prediction) under the strategy and an evaluation of the predicted state for consistency.

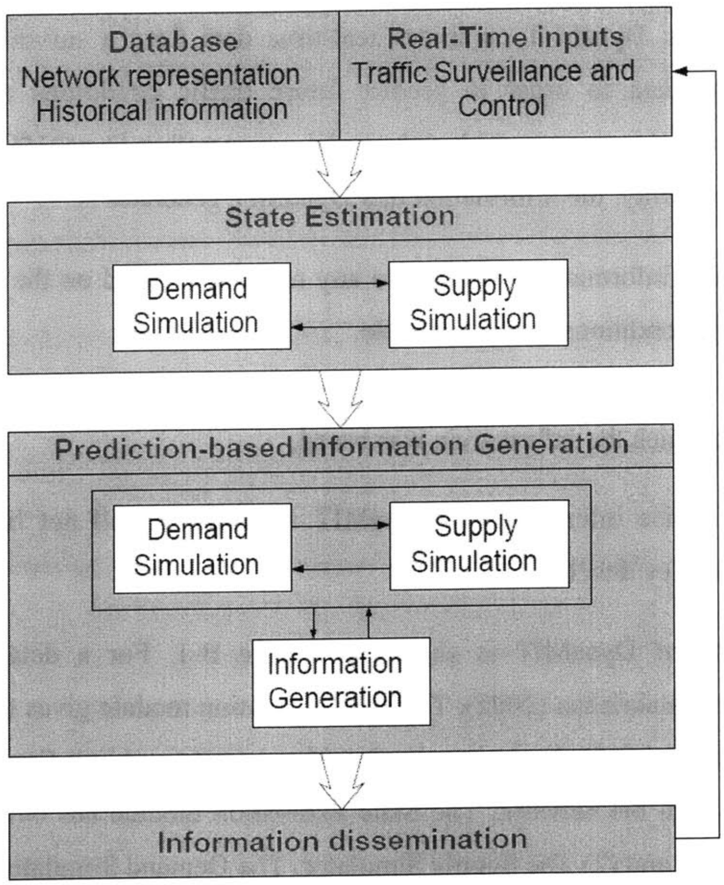

Figure B-1 DynaMIT framework (Balakrishna, 2002)

B.1 DynaMIT Network Representation

Like MITSIMLab, DynaMIT represents road networks with nodes, links, segments and lanes, and allows the analyst to place sensors within segments in the network. However, there are two key differences between the DynaMIT and MITSIMLab network representations:

1. DynaMIT maintains network supply characteristics separately from the network topology, whereas MITSIMLab models supply from the physical specifications of the network.
2. DynaMIT incidents are placed on a segment of road (segments may contain multiple lanes) whereas MITSIMLab incidents are placed on one or more specific lanes within a segment.

These discrepancies are important considerations in the integration of DynaMIT with MITSIMLab, and will be discussed later. As with MITSIMLab, incidents can be placed on any segment within the network, and can be placed and/or cleared at any time.

B.2 DynaMIT Travel Demand

DynaMIT represents habitual travel demand as *time dependent* OD tables. However, while DynaMIT and MITSIMLab both represent travel demand by OD and departure time interval, an important distinction is that MITSIMLab travel demand represents actual vehicles that will be released into the network, while DynaMIT travel demand represents habitual demand based on prior off-line estimates. DynaMIT computes deviations from the habitual travel demand based on information gathered through surveillance during simulation.

DynaMIT also requires the description of socioeconomic characteristics for vehicles in the habitual demand representation. These socioeconomic characteristics determine information availability and response characteristics that are used to model route choice decisions. DynaMIT modifies habitual demand according to surveillance information that becomes available during simulation.

For this thesis, the demand used for DynaMIT has been calibrated against MITSIMLab, which was calibrated from the sensor data provided by the NYSDOT (Antoniou, et al., 2006b).

B.3 DynaMIT State Estimation

State estimation in DynaMIT is an iterative process between the demand and supply simulation Figure B-1. The demand simulation computes estimated demand. This demand is then loaded into DynaMIT's mesoscopic supply simulator to compute a new OD assignment matrix. This process iterates until convergence; that is, until the demand estimates are consistent with assignment matrix generated by the supply simulator. Provision for information enters into the DynaMIT models in both the supply and demand simulators.

B.4 DynaMIT Demand Simulation

DynaMIT uses surveillance information (sensor counts) to estimate current demand since we cannot a priori know actual travel demand for a given day. This process is referred to as OD Estimation. In the 'closed loop' framework, these sensor counts are provided by MITSIMLab as will be seen later. DynaMIT uses a Kalman Filtering framework (Ashok, et al., 1993), which uses the information contained in historical OD data as well as surveillance traffic count data to generate OD estimates in real-time. Instead of conventional time-series approaches to estimation, this approach is based on demand *deviations* from historical values; the differences in estimated current demand vs. historical demand over a time period is richer in information than the absolute values because the deviations capture information about latent factors that affect travel demand over the course of time.

In order to account for the effect of pre-trip information, DynaMIT uses behavioral models to perform a pre-trip update of historical demand *before* computing the deviations between (estimated) current and (actual) historical demand. This model allows for drivers to change:

1. previously assigned paths,

2. departure time, or
3. transportation mode (i.e. driving trip cancelled)

The pre-trip behavioral update model is formulated as a nested logit model Antoniou (1997) and can have a choice set as illustrated in Figure B-2. This particular pre-trip behavioral model is presented as an example only to illustrate exactly how the provision of information will affect the DynaMIT demand simulation. Please refer to Antoniou (1997) for a detailed discussion of the model specification. The systematic utility of the alternatives in this nested logit model depends on many variables including historical travel times, as well as the 'updated' travel times. Thus, the effect of dynamic information enters the pre-trip behavior models, and hence, modifies the probabilities that drivers will maintain their habitual path choice, mode choice or departure time choices. In a similar manner, the provision of information affects the driver decisions at the lower levels of the nest.

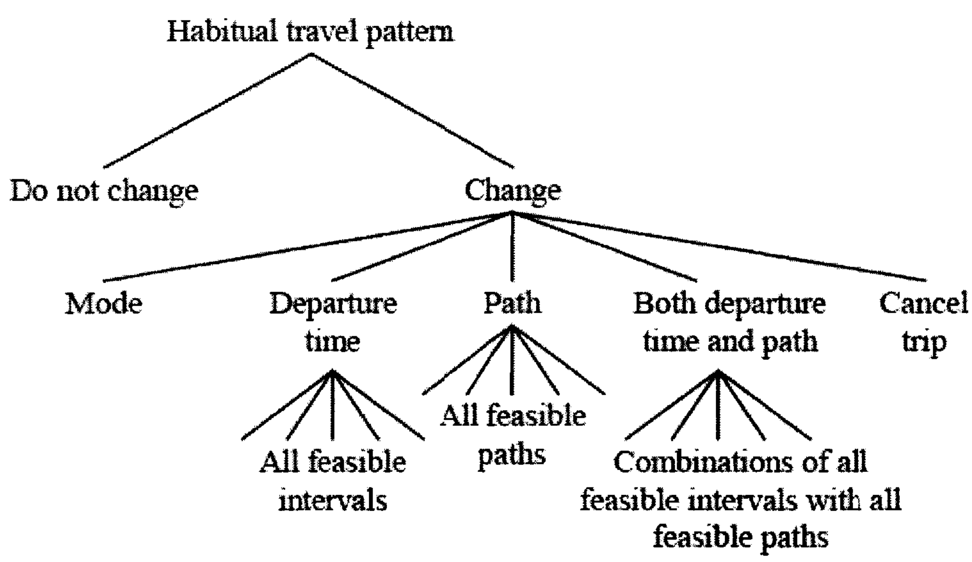

Figure B-2 DynaMIT pre-trip choice tree

B.5 DynaMIT Supply Simulation for Estimation

The DynaMIT supply simulator loads the simulated pre-trip demand into the supply network. DynaMIT uses en-route behavioral models for route choice during the supply simulation to capture the effects of en-route information on drivers already on the network. The impact of information enters the en-route models in the same way as discussed in the path choice component of the pre-trip model summarized above.

The result of the DynaMIT supply simulation results in a network state that is compared against the observed surveillance data. DynaMIT performs multiple iterations of pre-trip demand *and* supply simulation until the pre-trip demand is congruent with the supply simulation results.

B.6 DynaMIT Prediction

In order to generate predictive guidance, DynaMIT must also forecast OD estimates in real-time. DynaMIT uses an autoregressive process in a Kalman Filtering approach to do this. The autoregressive process models the temporal relationship among deviations in estimated OD flows, and thus implicitly accounts for unobserved factors that are correlated over time (Ashok, 1996). The OD prediction computes estimates of future OD flows from the OD estimates computed in state estimation (discussed above).

B.7 DynaMIT Supply Simulation for Prediction

The DynaMIT supply simulator then loads the forecasted demand into the supply network. DynaMIT uses en-route behavioral models for route choice during the supply simulation to capture the effects of en-route information on drivers already on the network, in exactly the same way as in the supply simulation step for estimation. The impact of information enters the en-route models in the same manner as previously discussed where the 'guided' drivers have access to ‘information’ as compared to the ‘unguided’ drivers who still have just the habitual travel time information.

The result of the DynaMIT supply simulation results in a network state that ensures that the driver behavior in response to information is consistent with the guidance.

Appendix C 'Closed Loop' Framework: Integration of MITSIMLab and DynaMIT

The previous two appendices have provided an overview of the processing steps in both the MITSIMLab and DynaMIT traffic simulators, and have also highlighted the steps where provision of information affects simulation behavior. This section discusses the framework that integrates these two software components as illustrated in Figure C-1.

The 'closed loop' framework consists of C++ objects that have been developed by Florian (2004). It is important to synchronize and interoperate MITSIMLab and DynaMIT, and this is controlled through the respective input files.

Figure C-1 represents the timeline of the 'closed loop' framework.

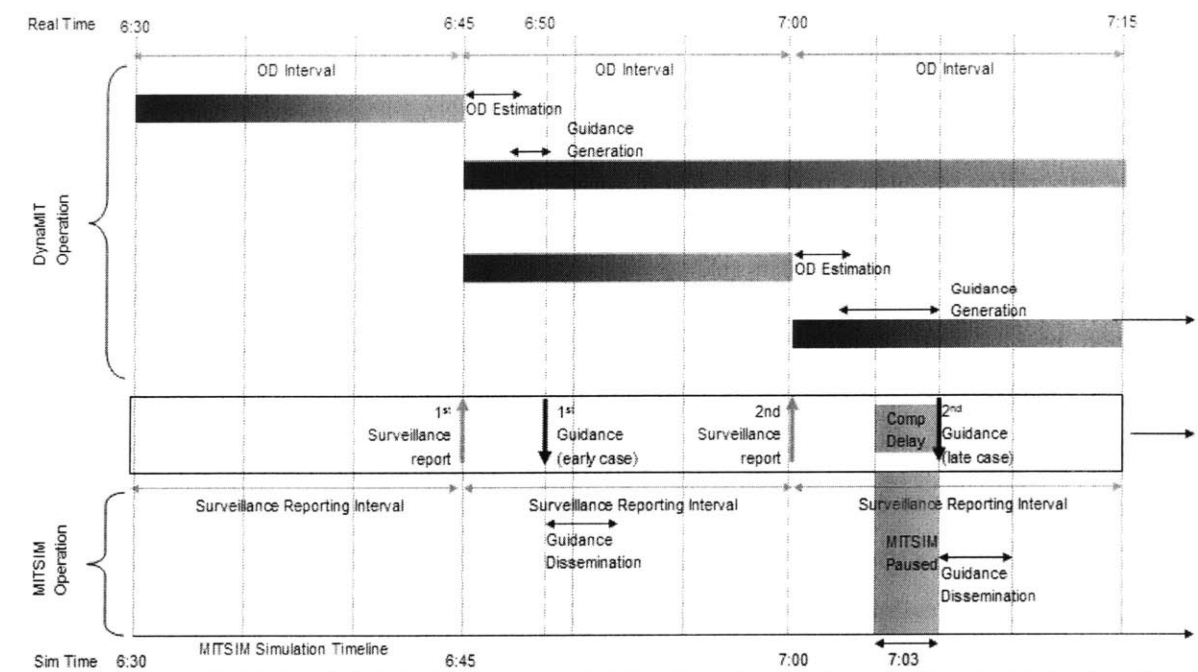

Figure C-1 'Closed loop' Evaluation with MITSIMLab and DynaMIT (Florian, 2004)

In this scenario, MITSIMLab and DynaMIT are started at the same 'simulation time' of 6:30 am. Until 6:45 am, the end of the first 'OD Interval'[1], both MITSIMLab and DynaMIT are operating concurrently; MITSIMLab is performing micro simulation while DynaMIT is running through initialization procedures. MITSIMLab must be configured to report surveillance to MITSIMLab at the end of each DynaMIT OD Interval. The MITSIMLab OD Interval has to be consistent with the DynaMIT OD Interval. In this example, DynaMIT's OD Interval is configured to be 15 minutes, so MITSIMLab's first surveillance report occurs at 6:45am. DynaMIT receives the surveillance information (designated by the orange 'up arrow' in the diagram) and begins a period of OD Estimation. Following the computational time required for OD Estimation, DynaMIT performs prediction and generates guidance. (The small horizontal arrows in the diagram illustrate the computational time required for the processing steps, while the thicker, shaded bars illustrate the data over which the computation is being performed. For instance, the first DynaMIT guidance generation in this example finishes at 6:50am, although the guidance contains predicted travel times through 7:15am.) At simulation time of 6:50am, DynaMIT transmits this information back to MITSIMLab, and the guidance is made available to the guided driver population in the micro simulation.

However, the computational requirements imposed in the DynaMIT state estimation and guidance generation processes may take much longer depending the number of vehicles and the extent of the network. But the benefits of predictive guidance are diminished if they are not broadcast in a timely manner (Balakrishna, 2004). Therefore it is critical for such systems to run faster than real – time. With the implementation of Sparse Matrices Algorithms for O-D estimation, DynaMIT is now capable of achieving this speed (Wen, et al., 2006). For the period, when DynaMIT is running, the simulation framework development includes a 'computational delay' mechanism that is capable of temporarily halting the MITSIMLab micro simulation till the guidance is ready. Figure C-1 illustrates this special case of 'computational delay' in the second period of state estimation and guidance generation; note the shaded box representing the temporary halt of MITSIMLab operation until the guidance generation process from DynaMIT is completed in 'simulation' time. In a similar manner, DynaMIT sleeps when MITSIMLab is simulating the traffic for its OD Interval and generating the sensor counts.

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[1] An Origin-Destination Interval (OD Interval) is a computational artifact in DynaMIT – it represents the time slice over which to perform OD Estimation and Prediction

The following flowchart describes the 'closed loop' framework without timing details.

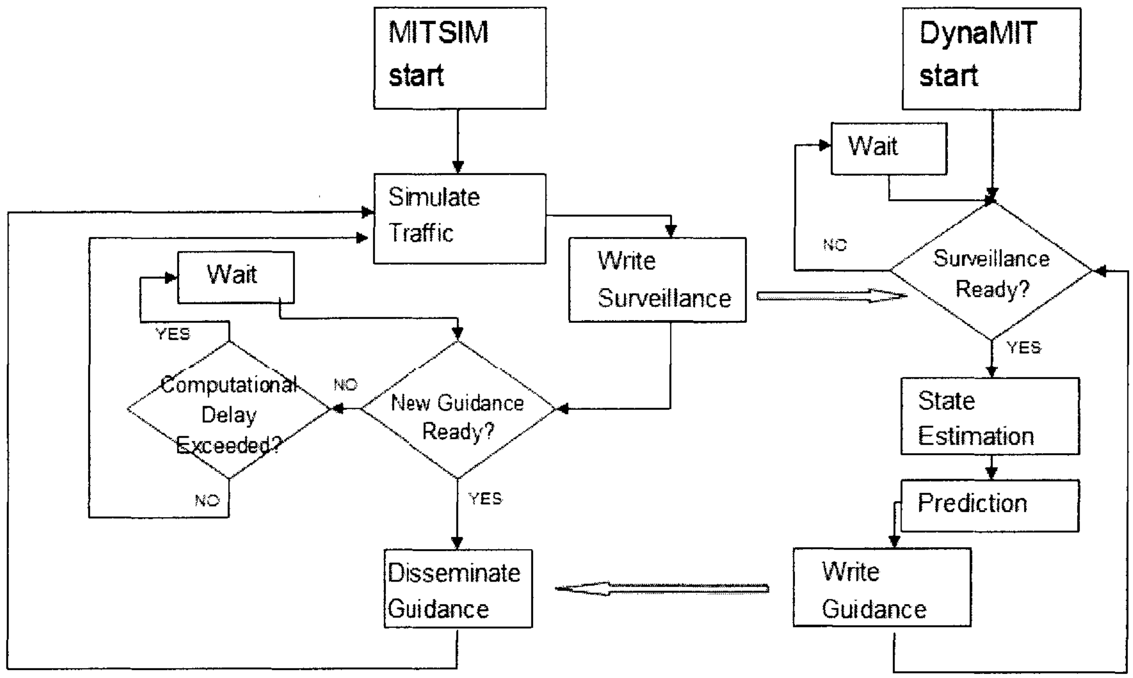

Figure C-2 'Closed loop' Flowchart

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