ESTIMATION OF NETWORK BASED INCIDENT DELAY IN A TRANSPORTATION NETWORK USING DYNAMIC TRAFFIC ASSIGNMENT

BY

CAMILLE KAMGA NGASSA

A dissertation submitted to the Graduate Faculty in Civil Engineering in partial fulfillment of the requirements for the degree of Doctor of Philosophy
The City University of New York
2006

UMI Number: 3231943

This manuscript has been read and accepted by the Graduate Faculty in Civil Engineering in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

__7/19/2006__________ ______________________________________

Date

Professor Robert E. Paaswell
Distinguished Professor of Civil Engineering
Chair of Examining Committee

_7/19/2006___________ ____

Date

Dean Mumtaz K. Kassir
Executive Officer

Supervisory Committee

Professor Cynthia Chen
Department of Civil Engineering
The City College of New York

Professor Claire E. McKnight
Department of Civil Engineering
The City College of New York

Dr. Kyriacos C. Mouskos
Research Professor
CUNY Institute for Transportation Systems

Professor Neville A. Parker
Department of Civil Engineering
The City College of New York

THE CITY UNIVERSITY OF NEW YORK

ABSTRACT

ESTIMATION OF NETWORK BASED INCIDENT DELAY IN A TRANSPORTATION NETWORK USING DYNAMIC TRAFFIC ASSIGNMENT

by

Camille Kamga Ngassa

Adviser: Professor Robert E. Paaswell

The reduction of incident-induced delay is one of the main objectives of transportation management in many states. Many studies were performed in the past that developed models to estimate the delay resulting from an incident on the roadway. These methods are based on the impact of incidents on a single link that captures only the delay for travelers traversing a freeway segment upstream of the location of the incident. They do not take into account its spatial and temporal characteristics of the transportation system and the effect of information provided to travelers during an incident. This dissertation introduces a more comprehensive methodology to estimate the incident impacts on travel times at the network level. The method can be applied to more types of operational traffic conditions. The incident impact is estimated by calculating the incident delay as the difference of travel times on average between the travel times under normal and incident conditions. Using the VISTA computer transportation simulation DTA model, two transportation networks are simulated under a range of traffic demand levels, incident durations, lane blockages, and deployment of ATIS. Dynamic Traffic Assignment (DTA) can provide a more realistic representation of the traffic patterns on a network given the time-dependent demand. DTA produces the time-space trajectory of each individual vehicle from its origin to its destination. The estimates of travel times, vehicle flows, and corresponding statistics are obtained under varying incident schemes. The incident-induced delay is calculated using the proposed method to estimate the incident impacts on the roadway at the link, OD pair, and network levels. The results suggest that incidents have a different impact on different OD pairs. Incident delay depends mostly on the duration of the incident, the number of lanes blocked, and its location. When the network is operating near capacity conditions, the incident delay may be less than the corresponding delay if the network is operating on non-congested conditions. An effective traveler information system can alleviate the impacts of an incident to various travelers at varying degrees.

ACKNOWLEDGMENTS

I thank God for giving me the strength to complete this dissertation.

I would like to gratefully acknowledge some very special people for their help, encouragement, and assistance. I especially thank Professor Robert Paaswell, my advisor and committee chair, for his guidance, support, and thoughtful encouragement in helping me to complete this dissertation. Professor Paaswell has consistently been a great mentor and kindest friend throughout my professional career at the University Transportation Research Center. I would like to express my deepest appreciation and gratitude to Dr. Kyriacos Mouskos, who was unfailing in providing constant step-by-step technical guidance, for always being there whenever I needed his advice and support, and for providing constructive criticisms. I thank Professor Neville Parker for his invaluable contributions to my knowledge. I am grateful to Professor Claire McKnight and Mr. Herbert Levinson for their technical advice. I would like to thank Professor Cynthia Chen for reviewing this dissertation on a very short notice. I express my grateful thanks to Curtis Barrett for assisting in using the VISTA software. I also owe a debt of thanks to my colleagues, Robert Baker, Dr. Todd Goldman, and Alma Jefferson for their valuable and inspiring discussions. I would also like to acknowledge my special thanks to Dean Mumtaz Kassir for his assistance throughout my time in the Ph.D. program.

I thank my mother and my wife, Amina, for their infinite support and unwavering faith in my ability to succeed. I thank my toddler son, Wassim, and my infant daughter, Zara Simone, for sacrificing their playtime to allow me to complete this dissertation.

TABLE OF CONTENTS

LIST OF TABLES

LISTS OF FIGURES

CHAPTER 1 INTRODUCTION

A traffic incident represents a planned or unplanned event creating a temporary reduction in roadway capacity that, in turn, impedes the normal flow of traffic. Incidents vary widely in severity, from vehicles stranded on the roadway shoulder with a flat tire to car crashes or overturned trucks coupled with hazardous materials spills closing an entire highway section. The reduction of Non-Recurring Delay (NRD) or incident-induced delay is one of the main objectives of traffic management systems (TMS) in every state. One of the methodologies used to alleviate the impact of NRD is the provision of relative information to the travelers through various means such as variable message signs (VMS), radio, Internet, television, etc.

The estimation of incident delay is one of the indicators used to assess the performance of a traffic incident management program. The estimation and prediction of incident delay is even more important for emergency services and traffic operators. Emergency agencies need to optimize their fleet of vehicles to respond to various incidents that are occurring throughout the day. Traffic operators could utilize these measures of effectiveness (MOE) to optimize the performance of the transport system through route diversions, signal optimization, ramp metering, and demand management. Information regarding delay can be used for real time transportation operations and transportation planning including assessment of traffic improvement projects. Therefore, it becomes an essential component in the successful implementation of traffic incident management. The occurrence of traffic incidents, whether they are major or minor incidents, is a main cause of variability in travel time. It is also important to provide drivers with projected to the near future information of incident related traffic conditions ahead rather than simply “current” roadway performance. Predictive traffic information could provide a more reliable MOE and would give travelers a better basis for decision-making including diversion decisions, departure time and mode choice. It would allow them to adjust their expectations and reduce their travel time uncertainty.

Current incident delay estimation models are based on the impact of incidents on a single link that captures only the delay for travelers traversing a freeway segment upstream of the location of the incident. The impact of an incident on a freeway in an urban area may have a network-wide effect depending on its location, severity, duration and the prevailing traffic conditions throughout the duration of the incident. A more comprehensive approach in estimating incident-induced delay is to estimate the impact of incidents by taking into consideration the spatial and temporal characteristics of the transportation system and the effect of information provided to user groups (e.g., emergency vehicles, commercial vehicles, passenger vehicles) during an incident.

The objective of this dissertation is to develop a methodology that will produce estimates of network delay, origin-destination (OD) delay, user group delay and further explore the impacts of incident severity, incident duration and demand on the incident-induced delay. A simulation based on the Dynamic Traffic Assignment (DTA) model is selected to analyze the impact of incidents on delay. DTA models produce the spatio-temporal trajectories of all vehicles from their origin to their destination under a simulated environment. The proposed empirical incident impact estimation methodology will calculate the incident delay by taking the difference of average travel times under normal conditions and incident conditions. The incident delay is the relative difference between the travel time spent by a user group or individual traveler under incident conditions and the corresponding travel time that would have been spent under non-incident conditions.

1.1 Background

Congestion delays constitute one of the most significant challenges to the world's urban highways (Balke *et al.*, 2002). The cost of delay is a function of occupant time, vehicle operating expenses, and air pollution. Delays also add to the cost of doing business, both in terms of freight logistics and higher wages paid to employees in compensation for long commutes. Non-recurring delay reduces productivity by having significant impact on travel time and reliability. In most metropolitan areas, incident related traffic delay was estimated to be between 50 and 60 percent of total congestion delay (Lindley, 1987). This incident-related congestion problem is expected to worsen in the future. Robinson (1990) predicted that in 2005, the impacts of incidents in terms of hours delay, wasted fuel consumption, and excess road user costs were expected to increase five fold over levels experienced just 10 years ago.

Law enforcement organizations, emergency service providers, transportation agencies, and transportation information service providers are working to reduce the impacts of incidents. There has been increasing interest in the past few years into integrating public safety, emergency responses, and traffic management communications through incident management programs. Departments of Transportation (DOTs) at the local, regional, state and federal levels in the United States are recognizing the potential to improve the management of their transportation systems through the use of Intelligent Transportation Systems (ITS) technologies. Traffic Incident Management (TIM) is one of the main functions of the overall Traffic Management (TM) of most transportation agencies. The main functions of TIM are: incident detection, incident identification, incident response, incident clearance, incident information to other agencies, communication media and travelers, route diversion, coordination and synergism with emergency agencies (police, fire department, emergency medical services (EMS), towing services, hazardous materials (HAZMAT) services, and security agencies. Around the nation, metropolitan regions, localities, and cities, are implementing Traffic Incident Management programs to limit the negative effects of non-recurring events and improve handling of such events.

A TIM program cannot succeed without good estimation and prediction of prevailing traffic conditions. The estimation of non-recurring incident delay becomes an essential component in the successful implementation of TIM. Non-recurring incident delay models found in the literature are either difficult to implement due to the non-availability of data and parameters used in the model or present difficulties to overcome in the finding of a comprehensible solution to the formulation of the problem. Current incident delay estimates are based on the impact of a single link that captures only the delay for travelers traversing a freeway segment upstream of the location of the incident.

The impact of an incident on a freeway in an urban area may have a network-wide effect. This impact can be observed statewide, regionally, or just locally. The existing methodologies that estimate the impact of incidents ignore the spatial and temporal characteristics of the transportation system. Furthermore, the traditional model for estimating delay ignores the changes in demand due to information provided to different user groups (e.g., emergency vehicles, passenger vehicles, etc.) during the incident that may result in rerouting, destination change, postponement of departure time, or total cancellation of the trip. This dissertation challenges the estimates of incident delay that were reported in the literature since they were not based on the totality of the trip.

The development of dynamic traffic assignment (DTA) models substantially enlarges the scope of transportation related studies and bridges the differences between traffic operations and transportation planning studies. DTA models can estimate and predict time-dependent network conditions by capturing the temporal and spatial variations in dynamic traffic networks (Peeta and Ziliaskopoulos, 2001.) DTA models produce the time-space trajectory of each individual vehicle from its origin to its destination. Each vehicle trajectory includes the departure time from the origin, the arrival time at the destination, the vehicle’s chosen path and the location of the vehicle at any time along this path. DTA models are used to estimate time-varying network conditions by capturing traffic flow and route choice behavior.

1.2 Problem Addressed

Despite the increasing investment in incident management programs by most state highway agencies, rigorous and comprehensive studies for estimating network-based incident delay in a traffic network taking cumulatively into account the traffic flow upstream and downstream of the incident location, as well as the technologies and the strategies used by incident management (IM) programs, are not found in the transportation literature. The majority of the models in the literature consider only one component of non-recurring delay, the delay temporary experienced by travelers upstream of the location of the incident. They typically ignore the network wide impacts of an incident, which may result in either an underestimation or overestimation of the actual delay.

Incident delay is defined as the difference in travel time between the actual travel times under incident conditions and the normal travel times under non-incident conditions. Given this definition, the following principal measures of performance (MOPs) of a TIM program that are used for NRD (List *et al.,* 2004) can be estimated more accurately.

- *Person-hours of delay (PHD):* This parameter is the most useful one for travelers in that it takes into account vehicle occupancies (it captures passenger car trips, transit trips and intermodal trips.)
- *Vehicle-hours of delay (VHD):* This parameter captures only vehicle related delays.

- *Truck-hours of delay (THD):* This parameter reflects the specific delays that affect the truck fleet.
- *Ton-hours of delay - for goods (TonHD):* This is a more specific parameter that captures the delays related to the goods movement that targets specifically the delay associated with the actual cargo in each truck.
- *The cost of passenger delays (given a value for the cost of time) (CPHD):* This is a parameter that is derived from the PHD. A rather controversial one since the value of time per passenger is a rather “subjective” measure – however, it is used widely throughout the transportation profession.
- *The cost of “goods” (freight)-related delays (CTonHD):* This parameter includes the primary impact of an increase in inventory carrying cost, from the additional time that goods spend in inventory and the indirect impacts of lost economic productivity due to the fact that goods are delayed in reaching the manufacturing plant, the point of potential sale, etc. This parameter is rather difficult to estimate due to the limitations in data availability from trucking companies.

This thesis proposes the development of a comprehensive methodology to estimate the incident impact by calculating the incident-induced delay at the network, origin-destination, and link levels per user group using a Dynamic Traffic Assignment Model. This method takes into account the spatial and temporal characteristics of the transportation systems and the change in demand and route that may result from the provision of delay information to motorists during incident conditions.

Most studies do not consider the effect of the incident on the travel patterns in the vicinity of the incident. During an incident, one can expect the travel times for nearby links to vary with time relative to the incident, and this may affect considerably incident response time, and also may affect considerably downstream travel time.

Most studies of incident delay extrapolate the incident delay estimates by using only the vehicles that are severely affected by the incident. This study will provide a methodology to estimate incident delay experienced by user groups of the traffic network by origin-destination pairs. The location, severity, and duration of an incident have different impacts on different user groups and origin-destination pairs.

Existing delay models ignore the spatial and temporal characteristics of incident delay, limiting their planning and operational capabilities. The traffic demand during any time period of the day is not constant but fluctuates and this characteristic should be captured in the delay model. Travelers entering the facility downstream of the location of the incident may experience less or more congested conditions due to the change in the traffic flow rate downstream from the location of the incident. Their travel time should be incorporated into a universal incident delay model.

Furthermore, the traditional model for estimating delay ignores the changes in demand due to information provided to different groups during the incident that may result in rerouting or destination change. Some travelers may decide to change their route and try to avoid passing through the location of the incident, some may decide to use public transportation such as train, and some may decide to cancel their trip or change their destination. It is therefore important to develop a more universal model that can capture the true impact of an incident on incident delay. Such a model will not be trivial and its success will depend on the availability of a sufficient traffic surveillance system throughout the transportation network, including the transit system.

1.3 Research Objectives

This research will provide a methodology to estimate incident-induced delay for a transportation network for real time transportation operations, and for transportation including the assessment of traffic improvement projects. This estimation of incident delay takes advantage of the recent development of the simulation-based DTA models. The objective is to provide a rigorous estimation of incident delay at the network level, at the sub-network level, for origin-destination (OD) pairs, and for separate user groups using a DTA model. The development of a methodology to estimate the above measures of effectiveness will be more useful for the evaluation of TIM programs, as well as short term and long term transportation planning. Emergencies Medical Services (EMS), Fire Department, Police, Towing Services, Homeland Security, Hazardous Materials (HAZMAT) have a perspective on the incident delay different from other user groups. Whereas for a passenger a 15-minute delay may be a nuisance, such a delay is critical to EMS. As the EMS fleet resources are limited, each vehicle must serve the incident in an efficient manner. The interest by EMS is the distribution of travel time to arrive at the location of an incident and the corresponding travel time distribution from the location of the incident to the hospital or to other locations. The above groups should be further classified per origin-destination pairs to capture the impact of incidents both for their group and for the specific OD pairs. In addition, each subgroup should be aggregated for each time period of the day, day of the week or any special day (e.g., holiday, day of a special event, etc.) Under this objective, the relationship of the impact of incident severity and duration on the abovementioned characteristics will be investigated.

This research will take into account the changes in traffic demand/route choices due to information provided to motorists through Advanced Traveler Information System (ATIS) during incident conditions. Traffic demand has significant effect on incident congestion. The traditional model for estimating delay ignores the changes in demand due to information provided to different groups during the incident that may result in re-routing and destination change. Some travelers may decide to change their route and try to avoid passing through the location of the incident, some may decide to use public transportation, and some may decide to cancel their trip or change their destination. In urban areas, the availability of alternative routes for each origin-destination pair may be substantial and they may cover a very wide area. It is therefore important to develop a more universal model that can capture the true impact of an incident on the traffic delay. The demand during any time period of the day is not constant but fluctuates. A more accurate delay model should provide a discretized representation of the demand upstream of the location of the incident (e.g. 5, 10, or 15 minute time intervals). Travelers entering the facility downstream of the location of the incident may experience less congested conditions due to the reduction in the traffic flow rate downstream from the location of the incident.

The methodology developed in this research will enable someone to evaluate the impact of the incident delay according to influencing factors such as the location of the incident, its duration, or its severity. Previous studies found that the delay that a vehicle will experience as a result of an incident depends on many factors including time of day, day of week, weather, vehicle fleet, geometric characteristics of the roadways, incident severity, incident duration, traffic volume, and the time when the vehicle arrives at the incident location (Qi, 2002). The model developed in this research will account for all of these factors.

1.4 Structure of the Dissertation

As stated above, this dissertation proposes a method to estimate incident-induced delay in a transportation network that takes into consideration the spatial and temporal characteristics of the transportation network. Previous studies related to this research, including those of factors influencing incident-induced delays such as incident duration and capacity reduction are reviewed in Chapter 2. Chapter 2 provides as well a literature review on incident management and incident delay models and a discussion of previous work. In Chapter 3, the proposed method of estimating incident-induced delay using DTA models is presented. Chapter 4 describes the empirical settings that will be simulated including the transportation networks, data, and scenarios used for the analysis.

Chapter 5 presents the details of the analyses of incident delay and the impacts of other factors related to the incident delay. In Chapter 6, the results, conclusions, and policy implications are presented.

CHAPTER 2 LITERATURE REVIEW

This dissertation is concerned with the problem of estimating the delay resulting from incidents occurring on the transportation network. A short discussion of existing methods to evaluate benefits of incident management program is presented. It is followed with a brief review of models currently used to estimate incident duration and capacity reduction, as factors that influence the incident delay. The final section reviews previous methods to estimate the delay caused by incidents. The emphasis is on describing the basic concepts and ideas that are involved in estimating non-recurrent delay and on the implemented models used by many departments of transportation.

2.1 Incident Management

There have been numerous efforts during the past two decades to evaluate the implementation and benefits of incident management programs and to analyze incident impacts on freeway traffic. The evaluation of incident management programs range from field observation and testing to simulation and analytical techniques.

The level of incident management varies considerably from location to location. Many locations in the U.S. use motorist assistance patrols or service patrols that roam the freeways looking for incidents and providing necessary assistance to clear stalled or disabled vehicles off the roadway. Other locations have built a complex traffic control system that uses video surveillance cameras and automatic incident detection systems to monitor the status of the freeway and detect potential problem situations.

Regardless of the size and complexity of the incident management system in operations, decision-makers and operators want to know how well the goals and objectives of their incident management systems are being met. There have been several previous studies that estimated the benefits and costs of incident management programs (Lindley, 1986, Skabardonis *et al.*, 1995, Raub, 1997, Skabardonis *et al.*, 1998, Taylor *et al.*, 1999, Nee *et al.*, 2001, Olmstead, 2001, El-Geneidy, *et al.*, 2003, and Bertini *et al.*, 2001), each with slightly varying methodologies. The majority of the evaluation studies have also emphasized the benefits resulting from the implementation of Advanced Traveler Information Systems (Al-Deek and Kanafani, 1993, Hall, 1993, Sengupta and Hongola, 1998, Al-Deek, Khattak, and Thananjeyan, 1998). Some studies focused on the performance of freeway incident detection techniques or algorithms in order to evaluate Incident Management (IM) programs (Stephanedes *et al.*, 1993, Cheu *et al.*, 1995, Wen *et al.*, 2001, Petty *et al.*, 2002, and Teng *et al.*, 2003). Other studies have evaluated the incident response strategies (Zografos, 1997, Sherali *et al.*, 1999, and Hall, 2000).

Zografos *et al.* (1997) reviewed a number of operational Incident Management Systems (IMS) in USA and Europe. They found that most of the incident response decisions are taken empirically, i.e. dispatching and routing of Response Units. The lack of coordination and communication between the various agencies needed for incident response and clearance is considered to be the major bottleneck that limits the performance of IMS. They identify communications and information exchange between the various stakeholders as the cornerstone for the successful operation of an incident management system.

These evaluation studies show that reducing response time to the incident location, verification of incident, incident duration and delay are all considered important for incident management programs. However, a consistent finding among most incident management program evaluations is that many of the benefits of these programs are difficult to quantify. For example, incident management programs provide valuable public relations functions, a heightened sense of safety and security for motorists, and also prevent secondary crashes. As stated by Bertini *et al.* (2005) assigning a value to the lost time of a commuter or shipment of goods due to delay caused by an incident is difficult and debatable. Each vehicle on the road has a different purpose and the cost of delay for each individual vehicle varies. Many studies use wage rates and fuel consumption averages of idling or slow moving vehicles to assign dollar values to incidents. These are really just approximations using the best available data. With the increasing availability of more detailed data these types of evaluations can become more accurate and become more valuable tools to planners and operators of IR programs.

In most studies, one of two indicators was used to estimate the benefits of the IM program: the costs saving resulting from reduction in delay (Carson *et al.*, 1999, Peng *et al.*, 2000, Presley *et al.*, no date) or the time saving from reduction in delay (Maas, 1998, Chang *et al.*, 2002, Nee *et al.*, 2001)

2.2 Incident Duration

It is useful to describe the basic steps frequently considered in determining the duration of incidents. The total duration caused by an incident is usually partitioned into four components, namely incident detection, incident verification, dispatch time and response vehicles travel time, and incident clearance time (Zografos *et al.*, 1993, and Chang *et al.*, 2002).

The first phase of incident management is detection. The true start time of an incident is not usually known. Incident detection is the process that brings an incident to the attention of the agency or agencies responsible for maintaining traffic flow and safe operations on the facility. Included in this phase is the verification of the incident as severe enough to warrant a response. Incident victims are most vulnerable from the time of the incident until the first responder arrives. Traffic is also likely to be most disrupted during these initial moments of the incident. The automated detection of freeway incidents is an important function of a freeway traffic management center. The capability of any incident management program to effectively respond to incidents depends heavily on an efficient and reliable incident detection technique.

Hall (2000) focuses on response and dispatch time and their contribution to congestion and delay. Dispatch time is the time from detection until the time that an emergency crew (or crews) is dispatched to the incident. Response time is the travel time for the emergency response crew to the scene of the incident. Last, service time is the time required to remove the incident and restore traffic once the emergency crew (or crews) has arrived at the scene. The total clearance time (T) is the sum of the incident detection time (I), waiting time from incident detection until clearance vehicle is dispatched (W), response time from dispatch until arrival (R), and Service time to clear the incident, subsequent to arrival of response vehicle (S).

$$T = I + W + R + S$$

Incident response time is modeled as a function of distance from the response vehicle to the incident, along with their relative direction of travel, the positioning of interchanges, and the presence of congestion that may slow incident response.

The incident duration generally reported in the literature is the so-called modified incident duration, i.e., the incident duration less the detection time. The influencing factors can be highly correlated. For example, response times can depend on the expected incident duration. That is, the response team(s) may be quicker to respond to major incidents than they are to minor ones. Given the institutional barriers associated with reporting and archiving the incident data by the emergency teams as well as the transportation management teams, it is difficult to retrieve the relevant data for the development of incident duration estimation models.

Generally, incident duration is affected by many factors including location, severity, and the managing procedures of the local emergency services. It has been observed that the total duration usually has a large variation. For example, Giuliano

(1989) reports that the mean duration is about 37 minutes with a standard deviation of 30 minutes while Cohen and Nouveliere (1997) indicate that the mean duration is 26 minutes with a standard deviation of 23 minutes based on the respective incident databases used.

As research on incident duration analysis has evolved, hazard-based models and standard regression approaches have emerged as the two primary competing methodological alternatives. Regression models were developed by various researchers to either forecast the incident duration (Garib *et al.*, 1997, Khattak *et al.*, 1995, Smith *et al.*, 2000), or predict the incident clearance times (Ozbay and Kachroo, 1999), or determine the incident duration distribution (Sullivan, 1997, Goolsby and Smith, 1971, Juge, Kennedy, and Wang, 1974, Giuliano, 1989, Golob *et al.*, 1987).

Hazard-based models are mostly used in the biometrics and industrial engineering fields to estimate incident duration. Hazard-based models use conditional probabilities to find the likelihood that an incident will end in the next short time period given its continuing duration. Hazard-based models are used because incidents can be assumed to have an increasing or decreasing hazard function (Jovanis and Chang, 1989; Jones et *al.*, 1991, Nam and Mannering, 2000).

The regression and hazard-based model estimates were largely similar in terms of their statistical properties. Standard regression approaches to incident duration analysis offer the advantage of being more easily understood and interpreted relative to hazard-based models. Hazard-based models have an advantage in that they allow the explicit study of duration effects (i.e. the relationship between how long an incident has lasted and the likelihood of it ending soon).

There has been much research in the past analyzing non-recurring highway incident duration and looking into predictive techniques applied to incident duration. The results from these studies have been mixed and comparisons between different methods are difficult due to data issues. Almost each study uses a different source of incident data with different descriptive variables and reporting techniques. The true start time of an incident is not usually known. The durations in the literatures are *modified* incident durations, i.e., the incident duration less the detection time. As will be discussed in incident delay models, one of the major pieces of information required for estimating incident delay is incident duration. Generally, the incident duration is a function of the incident managing capability of the local authority, the incident location, and the incident severity among other factors.

2.3 Capacity Reduction

An important factor in incident duration is the capacity that pertains during and after the incident. Incidents occurring within the traveled way create severe capacity restrictions, leading to excessive delays if not attended to and cleared as quickly as possible. The temporary obstruction of just one freeway travel lane reduces the available capacity of single-direction, two-lane and three-lane freeways by 65% and 51%, respectively (Gordon *et al.*, 1996).

McShane *et al.* (1990) present an example to illustrate the effect of capacity reduction on the volume-to-capacity ratio. They consider three different values for the volume-to-capacity ratios and then they simulate the losses in capacity due to an incident by changing these three values by different percentage. The authors conclude that decreasing capacity by 10% or more may change freeway operation from a functional system to an oversaturated system. They note that it also depends on the demand level at the capacity reduction time.

Goolsby and Smith (1971) study capacity reduction caused by incidents using detailed incident logs coupled with video surveillance along the Gulf Freeway in Houston, Texas. By comparing the volumes under normal conditions to the volumes under incident conditions, they were able to determine the capacity reduction along the three-lane Gulf Freeway due to incidents. With the objective to determine the accuracy of Goolsby's study, Smith *et al*. (2003) analyzed the capacity reduction due to incident by using a larger sample size. The incident data was collected using an incident database with loop detectors along the three-lane Hampton Roads region of Virginia. The flows during the incident conditions were compared to normal conditions in order to determine the reduction in capacity due to incidents. Smith et al. determine incidents cause a greater reduction in capacity than what Goolsby and Smith (1971) established.

It has also been observed that the lane-blocking incidents have more than a proportional impact on capacity. For example, Urbanek and Rogers (1978) indicate that the blockage of a single lane on a three-lane facility reduced freeway capacity by 40-50%, instead of 33% based on space reduction. Lindley (1986, 1987) developed a methodology to quantify urban freeway congestion using the highway performance monitoring system database. A reduction in section capacity, due to an incident, as a function of the total number of lanes and the number of blocked lanes was determined. He also found that the amount of capacity reduction is greater than the percentage of blocked lanes to the total number of lanes. For example, if the percentage of blocked lanes is 50%, the remaining capacity after blocking two out of four lanes is 25%.

2.4 Incident Delay Models

Many models have been proposed to estimate incident delay. These models can be classified into three types based on the methods adopted: (1) methods based on queuing analysis (Morales, 1987); (2) methods based on shock wave analysis (Messer *et al.*, 1973, Wirasinghe, 1978, and Chow, 1974) and (3) methods based on freeway traffic simulation (Wickes and Lieberman, 1980 and FRESIM, 1984). These models can also be categorized into two types based on the scales: (1) models that focus on total incident delay caused by incidents (Morales, 1987, Messer *et al.*, 1973, Wirasinghe, 1978, Chow, 1974, Wickes and Lieberman, 1980 and FRESIM, 1984); and (2) models that focus on individual vehicle incident delay (Fu *et al.*, 1997).

Among the difficulties that some of these models pose to the transportation agencies are:

- They require detailed traffic flow characteristics, roadway geometry and traffic control data for calibration.
- They lack ability to predict the travel behavior of the drivers once they are notified about the incident through Variable Message Signs, In-Vehicle Navigation Systems, Highway Advisory Radio (HAR), or Commercial Radio.
- Deterministic models ignore the spatial characteristics of incident delay and primarily concentrates on the delay incurred to drivers who are joining the incident queue.
- They have not been widely implemented so it is difficult to evaluate them.

2.4.1 Basic Concept of Incident Delay

It is useful to describe the basic concepts and ideas that are involved in predicting non-recurrent delay. When an incident occurs, there is an increase in the congestion on top of the recurrent delay. Figure 1 shows the queuing diagram approach that is typically used to describe the general ideas of estimating incident delay.

- *Incident detection time* is the interval from the occurrence to the detection of the incident.
- *Incident response time* is the time between detection to the time the first response unit arrives.

- *Clearance time* is the time it takes for the incident to be removed from the road.
- *Recovery time* or residual delay is the time for the queue formed due to the incident to dissipate and the demand flow rate is restored after the incident has been cleared from the road.

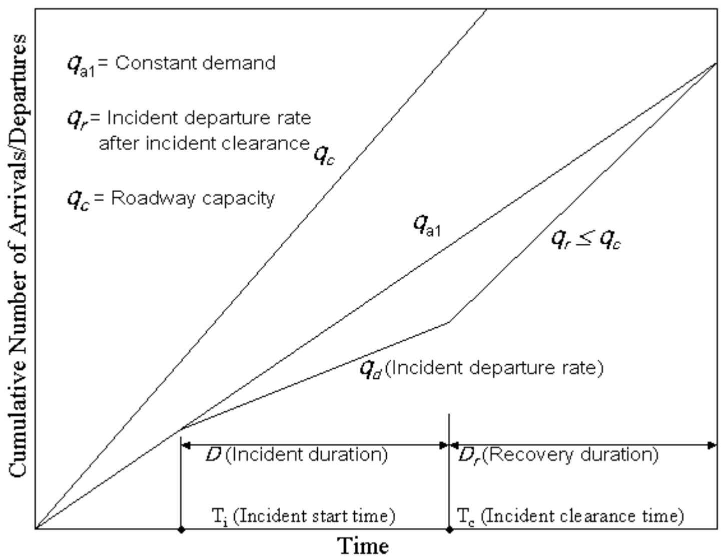

Figure 2.4.1 Incident Delay Diagram - Deterministic Model (one arrival rate)

Incident detection, response, and clearance times constitute the incident duration, which is denoted by *D*. Most incident duration models are concerned with these three components. The last component, residual delay or recovery time (D_r) assesses the efficiency of the traffic control strategies used to recover from the event, such as traffic diversion and early traveler information systems. Not every incident involves all four components.

The delay equation that expresses the total incident delay based on the simple deterministic model shown in Figure 2.4.1 is as follows:

$$Delay = \frac{D^2(q_r - q_d)(q_{a1} - q_d)}{2(q_r - q_{a1})} \tag{2.1}$$

where D is the incident duration, q_{a1} is the rate of traffic flow just before the incident occurs, q_c is the saturation flow rate (prevailing roadway capacity) of the road segment where the incident occurs, q_d is the departure flow rate while the incident is present, and q_r is the departure flow rate once the incident has been cleared.

As is always the case, q_c depends on the geometric design of the roadway, environmental conditions and the traffic flow characteristics such as the proportion of heavy vehicles and proportion of non-commuting driver population. The most widely used methodologies for determining q_c are found in the Highway Capacity Manual 2000 (TRB, 2000). However, if local estimates of q_c exist, they should be used instead. One source of q_c is freeway detectors. For a given analysis, the detectors that should be used should be upstream of the location of the incident, not downstream, because the queue forms upstream. It is up to the analyst to determine the detectors that are eligible to be considered for the estimation of demand at each specific time interval. This creates a specific problem for urban freeway systems where entrance and exits ramps may be affected by the incident queue that is generated as a result of the incident.

The specification of a reasonable value for q_d is also important as it represents the capacity that remains after the incident has occurred. It reflects the effect of lane blockages on one hand and the use of the shoulder, if possible, on the other.

Similar thoughts pertain to q_r, which is the departure flow rate that arises after the incident has been cleared. It is typically less than q_c because the highway does not exactly return to its before-incident condition. There may be debris left at the site or other evidence that the incident has occurred.

D_r is the duration of the incident recovery phase. It lasts from the time the incident is cleared until the queue disappears. This phase may be difficult to estimate especially under congested conditions as regular recurring congestion may mask the actual queue that is related only to the incident.

2.4.2 Incident-Induced Delay Models Derived from the Queuing Diagram

Variations of the model from Equation (2.1) have been proposed by researchers. Derr (1987) proposed a model that takes into consideration the potential reduction in demand that might occur due to the incident. With this model, the demand is divided into two components: The first one has the same magnitude as q_{a1}, which is the expected demand for that time period of the day and lasts for a certain time period D_1 and a second one, q_{a2} that is smaller in magnitude and lasts for a time period $(D – D_1)$. The latter represents a reduction in demand for that roadway facility and time period of the day due to information on the existence and nature of the incident and the availability of other alternative routes.

Morales (1987) presented a graphical method of calculating the delay by making a plot of time versus cumulative traffic volume. The demand flow and the flow reduction caused by an incident were plotted and the area enclosed by the two plots was the delay. Different types of incidents had different flow characteristics, which changed the appearance of the queue graph. This method assumed constant flows, which was an approximation to dynamic conditions.

Lindley (1987) performed a study on recurrent and incident induced delay using traffic counts from 37 cities across the United States to calculate V/C ratios and travel demand for the cities. The Highway Capacity Manual was used to determine average speeds and travel times based on the calculated V/C ratios. The incident delay was calculated by assuming a given amount of incidents based on facility type. The impact of the incident on the traffic was then used to calculate the delay caused by the incident.

Sullivan's (1997) method for determining incident-induced delay used queuing theory developed by Morales (1987), but used it in a way similar to Lindley's method. Sullivan generated an empirical model to estimate the number of freeway incidents and their associated delays. Sullivan computed incident durations as the weighted averages of the clearing times reported in many study data sets and added fixed time increments representing detection and response times determined from judgment based on data sets where total incident durations were documented. The model used the 20^{th}, 55^{th}, 80^{th}, and 95^{th} percentile duration corresponding to each accident situation to estimate the overall expected delay for the entire duration distribution. Sullivan’s delay sub-model used the percentage of incident type and the associated incident rate to determine a capacity reduction for each incident type. Each incident type was then matched to an incident duration to formulate weighted delay averages. Like in Lindley (1987), this method used delay estimates to compute the delay for a region.

The New York State Department of Transportation (NYSDOT) developed a Congestion Needs Analysis Model (CNAM) for solving congestion issues on major transportation facilities in the New York State (CNAM, 1999). The purpose of the incident model of CNAM is primary to estimate the magnitude and cost of incident delay on limited-access roads (i.e., freeways) and secondary to assess the effectiveness (on delay) of strategies implemented to reduce incidents. The CNAM delay model is a link-based incident delay model that utilizes a modified queue diagram to estimate delay for each type of incident for each hour of the day. The CNAM model calculates incident delay for each roadway segment independently. Its incident delay model is based on a queuing model that uses parameters such as incident occurrence time, demand (arrival rate), getaway rate, and type of incident. The variables used in CNAM are described below:

- *Incident Occurrence time:* An incident is predicted to occur at a specific hour of the day. The mid-point of the predicted hour is also the estimated time of occurrence of the incident.
- *Incident demand accumulation curve estimation (five hour demand curve):* For each incident type a demand (volume) accumulation function is developed based on the demand during and after the incident. CNAM produces estimates of hourly volumes for each hour of the day. These estimates are based on either traffic counts (if they exist) or on hourly estimates from factors based on the Annual Average Daily Traffic (AADT). The AADT is recorded in the Highway Sufficiency File. A five-hour demand profile is generated for each incident type and for each hour of the day, which is based on the incident occurrence type. Each of the estimated hourly traffic volumes is used as the demand arriving at the incident location within the segment. Then the model estimates when the queue due to the incident dissipates.
- *Accident classification:* Accidents are classified based on the number of lanes blocked (including shoulder). This designates each incident to its corresponding type within a file stored in CNAM. The CNAM accident classification is: (a) accidents on shoulder, (b) accidents blocking one lane, (c) accidents blocking two lanes, and (d) accidents blocking more than two lanes.
- *Incident factors:* Incident factors measure the proportion or frequency of occurrence for each incident type. Two types of incident factors are used: If a shoulder could be utilized during the incident (more than 6 feet) or not (less than 6 feet). The incident factors are classified based on the number of lanes,

incident type and location of the incident. CNAM has a table with default values of incident factors that are based on the above characteristics for each roadway segment. Users of CNAM have the ability to utilize their own incident factors if they have better data for their localities.

- *Incident duration:* CNAM utilizes a default table for each area type to provide estimates of incident duration. Six area types are identified, from rural to urban.
- *Incident type and available capacity:* Given the incident type for the specific roadway segment, the corresponding roadway capacity reduction is identified through the use of a look-up table.
- *Queue Dissipation Time:* The queue dissipation time is the time required for the queue that developed during the incident (from the time of occurrence up to the time that the incident is cleared) to dissipate. CNAM utilizes the following procedure to produce the queue dissipation time: The time period is divided into 15-minute (default) time intervals. The model allows the user to select a smaller time interval (e.g. 5, 10 minutes) if desired. The model compares the total volume serviced with the cumulative demand at each time interval. If the cumulative demand is larger than or equal to the total volume serviced then the specific 15-minute time interval is considered to be the queue dissipation time. The service accumulation curve is based on the capacity available during the incident as well as capacity of the road section under prevailing traffic and environmental conditions.

The incident delay is estimated based on the cumulative arrivals, the service volume during the incident, the service volume after the incident is cleared (also known as the getaway rate), the incident duration and the queue dissipation time. The total incident delay (annual incident delay per roadway segment and hour of the day) for each roadway segment is calculated based on the accident rates and the incident delay calculation per incident type and hour of the day.

2.4.3 Other Delay Model Approaches

Another approach to analyzing incidents was to determine the amount of delay caused by incidents. When an incident occurred, there was an increase in the congestion on top of the recurrent delay. Two studies were performed based on I-880 in San Francisco, one by Skabardonis *et al*. (1996) and one by Garib *et al*. (1997). Loop detectors were used to determine the speed of vehicles through the segment and the probe vehicles were used to detect the incidents. Skabardonis *et al.* (1996) use a formula for delay that calculates delay as a function of traffic volume, time of congestion, length of impacted freeway segment, average incident travel speed, and normal travel speed. Garib (1997) uses a regression analysis of the I-880 data to develop two models to predict incident induced delay. The first model uses four variables that included number of lanes involved, number of vehicles involved, incident duration, and traffic demand upstream of the incident. The second model only consists of three variables because it ignored the traffic demand upstream of the incident. The models cannot be applied directly to other segments or regions without calibration.

Fu *et al.* (1997) modeled incident delay by a random variable that represents the stochastic characteristics associated with the incident rather than using a deterministic value. Incident delay is estimated with a model that considers the randomness of incident duration. Many factors affect the delay a vehicle experiences as a result of an incident. These include incident severity, capacity reduction, incident duration, arrival pattern, traffic volume, and the specific time when the vehicle arrives at the incident location. It was found that a deterministic model might overestimate or underestimate the expected incident delay, depending on when the vehicle arrives at the incident location. The maximum estimation error is proportional to the standard deviation of the incident duration.

As a follow-up study, Fu (2004) presents a fuzzy queuing model that can be used to predict the possible delay that a vehicle will experience at an incident location based on real-time information and uncertainties involved in traffic demand, capacity, incident duration, current queuing conditions, future traffic arrivals, departure rate during incident, and lane closings. The rationale behind this approach is that information typically available under incident conditions is often in the form of linguistic descriptions characterized by imprecision and vagueness. The traffic arrival rate and the discharge rate during an incident are assumed constant over the time period of the incident. It is also assumed that there is no spillback to the upstream link.

By using video reidentification (ReID), Pierce *et al.* (2005) estimate incident delay by taking the difference between the actual travel times and the normal travel times. The normal travel times are estimated based on the conditions before or after the incident or from average conditions for the segment from non-incident days. ReID is time consuming and labor intensive because each individual vehicle is tracked from upstream to downstream. Due to the limited sample size, general conclusions could not be made concerning the accuracy of the delay computation methods.

Hall (2000) focuses on response and dispatch time and their contribution to congestion and delay. He finds that the amount of delay occurring during an incident depends on three primary factors: the nature of the incidents, roadway conditions, and execution of incident clearance. Delay also depends on how quickly the incident can be cleared and actions taken during the incident to ensure smooth traffic flow.

Li *et al.* (2006) present a model to estimate incident induced delay on freeway by introducing the incident duration model and the reduced capacity model into the traditional deterministic queuing model in order to take into account the stochastic characteristics of the network. Delays in terms of the mean delay, the variance of delay, and the total delay are estimated based on the proposed model.

In summary, the above models have some key weaknesses. The delay models do not capture the spatial characteristics of incident delay. The network characteristics of incident delay are ignored. They consider only the demand upstream of the incident location that arrives from the roadway’s mainline and many of them are applicable only for non-congested traffic flow conditions as it utilizes delay functions that are also based on volume to capacity ratios (v/c), which cannot exceed one. As observed by Skarbadonis (1996), another major limitation of the queuing diagram method, which is often overlooked, is that it estimates delays at a specific point. Several incidents, however, may occur simultaneously along a freeway section, and the traffic conditions at the incident of interest could be influenced by conditions upstream.

CHAPTER 3 METHODOLOGY

This chapter presents the methodology to estimate incident delay in a transportation network using simulation-based DTA models. Section 3.1 gives a background of the traffic flow theory models that are used as a basis to formulate the DTA models. Sections 3.2 and 3.3 describe the simulation-based DTA and time-dependent origin-destination matrix estimation recently developed. VISTA system's characteristics are described in detail in section 3.4 to expose the tools available to develop a methodology to estimate incident delay. Finally, in Section 3.4, the method for calculating incident-induced delay is presented.

3.1 Traffic Flow Theory

Traffic flow theory models are used as the basis to formulate the DTA models. Traffic flow theory aims to mathematically describe interactions between vehicles and their environment. Traffic flow theory and simulation models are typically classified as macroscopic, mesoscopic, and microcospic.

3.1.1 Macroscopic Models

Macroscopic models are based on the average movement of a group of vehicles, which improves their computational performance but reduces the detail of representation.

Macroscopic traffic models are derived from the fundamental relationships between traffic speed, traffic flow, and traffic density.

$$q = ku$$

where

q = traffic flow rate

k = traffic density

u = traffic average speed

The basic premise of traffic flow models is that the speed is a decreasing function of the density. As the density increases, the spacing between vehicles decreases and the speed is consequently reduced.

$$u = u_f \left(1 - \frac{k}{k_j}\right)$$

where

u = traffic average speed

u_f = traffic free-flow speed

k_j = jam density

A weakness of the macroscopic model is that because the model deals with aggregate variables instead of individual vehicles, all vehicles are assumed to travel at exactly the same speed for a specific condition on the flow-density relationship. For example, when vehicles are discharged from a bottleneck, the hydrodynamic model predicts that all the vehicles will move forward at the same speed; however, in reality the lead cars will move faster into the empty road ahead of them. Further, the hydrodynamic model is always stable, and cannot explain stop-and-go traffic behavior observed in real traffic.

3.1.2 Microscopic Models

Microscopic models attempt to explain traffic phenomena based on the behavior of individual vehicles. Those used in practice are typically derived from the fundamental car following models. These models describe both the space-time behavior of vehicles as well as their interactions at an individual level. Microscopic models are typically computationally intensive but accurate in representing traffic evolution. The general form of the car-following model is shown in the following Equation:

$$\ddot{x}_{n+1}(t+\Delta t)=\alpha[\dot{x}_n(t)-\dot{x}_{n+1}(t)]$$

where

$x_n(t)$ = position of vehicle n at time t

$\dot{x}_n(t)$ = speed of vehicle n at time t

$\ddot{x}_n(t)$ = acceleration of vehicle n at time t

Δt = time step

α = sensitivity

This equation suggests that the acceleration of the following vehicle is proportional to the difference between its own speed and that of the leading vehicle with a certain time delay.

Car-following models are often considered to be more realistic than macroscopic models. However, in practical terms they require calibration of behavioral parameters, which are difficult to validate because human behavior is difficult to observe and measure. Also, while car following models are more detailed than macroscopic and mesoscopic models, they are also more computationally intensive.

3.1.3 Mesoscopic Models

Mesoscopic models provide a level of detail between that provided by macroscopic and microscopic models. Typically, models that can propagate vehicles using macroscopic rules but capture microscopic details, such as individual vehicle location and queue evolution, are considered mesoscopic. Mesoscopic models lie between macroscopic and microscopic approaches and balance accuracy of representation and computational performance. The cell transmission model described below and the introduced enhancements can both be considered as a mesoscopic approach, because they move vehicles based on average conditions in a cell but the cell size can be sufficiently small to capture the state of individual vehicles.

3.2 Dynamic Traffic Assignment Models

3.2.1 Overview of DTA Models

Dynamic Traffic Assignment (DTA) models are used to estimate and predict time-varying network conditions by capturing traffic flow and route choice behavior. The development of dynamic traffic assignment (DTA) models substantially enlarges the scope of transportation related studies and bridges the differences between traffic operations and transportation planning studies. The main characteristic of DTA is that it produces the time-space trajectory of each individual vehicle from its origin to its destination. Each vehicle trajectory includes the departure time from the origin, the arrival time at the destination, the vehicle's chosen path and the location of the vehicle at any time of interest along this path. For a transit or intermodal traveler, the DTA model produces the corresponding time-space trajectory that may involve two or more modes of transportation.

Dynamic Traffic Assignment (DTA) has substantially evolved in the last two decades and has reached a sufficient level of maturity to be used in a number of planning and operational applications. In planning, off-line DTA models can be used to replace existing static models for many traditional applications. While DTA was originally developed to meet operational Intelligent Transportation Systems (ITS) needs, in principle, it can be used as a planning tool replacing static assignment models. In the past, the transportation planners utilized static traffic assignment (STA) models in predicting the route choices of the travelers due to limitations in the state of the art and computational power that was necessary to run large-scale transportation networks. STA models are proven to be inadequate to capture the dynamic nature of traffic. Static Traffic Assignment utilizes link travel cost functions that depend only on the flow of the link disregarding the impact of upstream, downstream, left/right turn links on the travel time on the link. In principle the DTA models produce the paths of all travelers from their origins to their destinations, including the time of departure and arrival. Given the traffic assignment, the analyst has the capability to derive any associated network wide, link specific, path-specific, sub-area, or user group statistics of interest.

DTA models are typically classified as analytical approaches, including mathematical programming, variational inequality and control theory approaches, or as simulation-based heuristic models. Extensive work has been performed for all of these approaches, and an overview of this literature can be found in Peeta and Ziliaskopoulos (2002). This section will concentrate on the simulation-based DTA models that offer the most promising future for implementation by the transportation planners and engineers. The following section briefly describes major developments in simulation-based DTA models.

3.2.2 Simulation-based DTA Models

The term “simulation-based” primarily connotes the solution methodology rather than the problem formulation (Peeta and Ziliaskopoulos, 2002). In the simulation-based DTA models, the constraints that describe the traffic flow propagation and the spatio-temporal interactions are addressed through simulation instead of an analytical formulation. Simulation offers the tools to address difficult modeling issues to circumvent limitations of analytical DTA models.

Over the past 14 years the United States Federal Highway Administration (FHWA) has sponsored the development of simulation-based DTA models that could be used for planning, given the inherent faults of the static traffic assignment, and for Intelligent Transportation Systems (ITS) applications such as the estimation and prediction of traffic conditions. As part of this research effort, the FHWA developed two mesoscopic DTA models: The DYNASMART (Mahmassani and Peeta, 1993, Jayakrishnan *et al.*, 1994) developed at The University of Texas at Austin, and the DYNAMIT (Ben-Akiva *et al.*, 1997) developed at the Massachusetts Institute of Technology. Parallel to this effort Ziliaskopoulos at Northwestern University, developed the RouteSim mesoscopic simulator and the Visual Interactive System for Transport Algorithms DTA - VISTA (Ziliaskopoulos and Waller, 2000).

A basic characteristic of these models is the utilization of a traffic simulator to emulate the traffic conditions, especially for signalized systems where it is very difficult to capture the dynamics of traffic through analytical techniques. In general, simulation-based DTA models iterate between a traffic simulation module, a time-dependent shortest path module, and a network-loading module. First, given a set of vehicles and their travel paths, the traffic simulation module replicates complex traffic flow dynamics as the vehicles are propagated through the network. The link travel times reported by the simulator are then used to calculate the time dependent shortest paths. Those shortest paths are then combined with all previous sets of shortest paths, and the vehicles are loaded onto the network on those paths. A new iteration then begins as the simulator propagates vehicles through the network along the new combination of paths. The process stops when some user-specified convergence criterion is met.

A DTA model could be used for either the evaluation of an incident management plan, a traffic signal timing plan, for the change in capacity of existing roadways or the addition of a new roadway into the network. In addition they could be used for the evaluation of travelers' path choices based on the traveler information provided, especially under incident conditions. A simulation-based DTA requires substantial traffic flow data to be calibrated and correct geometric data.

It is envisioned that in the future two types of models will be established: off-line models that will be based on historical traffic flow data and real-time models that will be integrated with a traffic surveillance and communication system. The off-line simulation based DTA models may replace the existing static-based traffic assignment models for short term and long term transportation planning, as well as for the evaluation of existing and new traffic control strategies, fleet management, emergency management, and traveler information. Off-line models could be used for training purposes such as incident management plans, evacuation plans, and homeland security plans. Real time simulation-based DTA models are expected to become the new traffic forecasting tools for traffic management, traffic operations, emergency management, fleet management, and traveler information. Next, a brief discussion of some of the main simulation-based DTA models that used mesoscopic simulators is presented.

3.2.2.1 DYNASMART

Mahmassani *et al.*, (1993) presented a simulation-based assignment model called Dynamic Network Assignment Simulation Model for Advanced Road Telematics

(DYNASMART). The model simulates the movement of individual vehicles (Mahmassani, 2001) using a macroscopic speed-density relationship that is a modified version of Greenshield's equation. Abdelghany and Mahmassani (2001) extended the simulator capability to capture bus movements. In addition, the routing algorithm in DYNASMART was enhanced to calculate inter-modal paths (auto, bus, train, auto plus bus, auto plus train, bus plus train). Abdelghany *et al.*, (2001) used the multi-modal model to evaluate bus preemption strategies at signalized intersections.

3.2.2.2 DYNAMIT

DYNAMIT is a simulation-based DTA model developed by Ben-Akiva *et al.*, (1994) at the Massachusetts Institute of Technology to estimate and predict in real-time, current and future traffic conditions. It consists of a demand and supply simulator that interact to generate user equilibrium (UE) route guidance under the rolling horizon framework. No underlying formulation is proposed. The demand simulator estimates and predicts OD demand using a Kalman Filtering methodology. It considers both historical information and the driver response to information. The supply simulator is used to determine the flow pattern based on the demand. It is a mesoscopic traffic simulator, where vehicles are moved in packets, and links are divided into segments that include a moving part and a queuing part to model traffic flow. The traffic simulator iterates between the update phase and the advance phase. During the update phase, queue lengths, link densities and speeds are updated, and in the advance phase, packets of vehicles are moved to their new positions.

3.2.2.3 VISTA

Ziliaskopoulos and Waller (2000) introduced the Visual Interactive System for Transportation Algorithms (VISTA) system. VISTA is an internet-based GIS system that integrates data and models into one framework. The principal characteristics of VISTA are: 1) The travelers behavior is modeled using a Dynamic Traffic Assignment (DTA) model; 2) it utilizes a universal database model that is based on a spatial Geographic Information System (GIS) that can be easily interfaced with other databases; and 3) it is Internet and/or Intranet based, providing access to the various stakeholders to run the various algorithms, view the results of the models, query the database, and change the database based on the authorization level of each. A thorough description of VISTA is presented in section 3.4.

3.3 Time Dependent Origin-Destination Matrix Estimation/Calibration

The problem of estimating dynamic travel demand has not been studied extensively and has been a major hurdle in applying DTA in real-world applications. The time-dependent OD matrix is a critical component of DTA models. The OD matrices are either estimated through surveys, traffic counts, travelers socioeconomic and land use characteristics, or an estimation procedure that may involve a combination of these methods. The OD estimation is also the most difficult step of the traffic assignment procedure. A most up-to-date time dependent OD matrix is critical to the success of advanced traffic management systems for solving complex transportation problems.

Therefore, one issue in using DTA is the need for a time-dependent OD demand. While a single OD matrix for the entire peak period suffices for static assignment, for DTA one needs to know how this demand changes during the peak period. An accurate time dependent OD matrix can produce accurate estimation and prediction of the traffic states within a transportation network, which makes it possible to generate efficient traffic management strategies and effective transportation network configurations. Therefore, the estimation and continuous calibration of time dependent OD matrices becomes a critical part in reaching the consistency of real time and off-line DTA models. However, many DTA routines approximate OD matrices by requiring an OD matrix for each of many small intervals, for instance, five or ten minutes in length, which unfortunately are not readily available. Thus, a problem of the time dependent OD estimation is how to create time-dependent demand at a much finer resolution from the aggregate data. This is known as the *demand profiling problem* (Kockelman *et al.*, 2006.)

Other difficulties of the time-dependent OD calibration problem are related to representing network dynamics, such as user behavior and equilibrium conditions. There are two broad categories of OD calibration models, DTA based and non-DTA based. Models that have a DTA component embedded in them can robustly address the various issues of network dynamics. The time-dependent OD calibration models try to replicate the observed traffic flows on the links per time period of the day. Their success is based on the network coverage of the traffic count detectors, the accuracy of the static OD matrix and the accuracy of the representation of the geometry and the traffic control system under consideration.

3.4 VISTA

VISTA (Visual Interactive System for Transport Algorithms) is a network-enabled software that can perform dynamic traffic assignment. VISTA integrates spatio-temporal data and models for a wide range of transport applications: planning, engineering, and operational (Ziliaskopoulos *et al.*, 2000.)

3.4.1 VISTA Simulator

The VISTA model's simulator, called RouteSim, uses cell transmission model (CTM) rules developed by Daganzo (1994) for traffic propagation. The CTM is a discrete version of the hydrodynamic traffic flow model. In other words, the movements of small groups of vehicles are simulated as they enter and leave sections of each link. RouteSim is a simulation-based model that tracks the number of vehicles in each cell through a series of discrete time steps on the order of five seconds. The network's links are divided into cells that are equal in length to the distance traveled in one time step by a vehicle moving at free flow speed. As such, if no congestion exists, all vehicles in a cell will move to the next cell forward in one time step; however, the number of vehicles that move forward is limited by the amount of space available in the next cell, and the maximum flow permitted across the cell boundary. Limits on the maximum number of vehicles in each cell and the maximum number of vehicles that can move from one cell to the next between iterations correspond to maximum densities and capacity for links in the network.

In the CTM, if the number of vehicles attempting to move forward exceeds the space or flow constraints, some vehicles will not be able to move forward, and a queue will develop. A key feature of the CTM is that flows are explicitly prohibited from exceeding capacity. This ability to model queues in a somewhat realistic manner is one of the prime attractions of the CTM. The simulator used in VISTA is an extension of the basic CTM. The main enhancements of the cell transmission model used in RouteSim over the basic cell transmission model are: (1) the concept of adjustable size cells that improves the flexibility, accuracy and computational requirements of the model, and (2) a modeling approach to represent signalized intersections. The basic cell transmission model along with the enhancements yields a model that can simulate integrated freeway/surface street networks with varying degree of details (Shi, 2004).

In the cell transmission model vehicle position is tracked only at a cell level, and vehicle speeds are estimated based on transmission time across cell boundaries. While this may be less detailed than other models, the cell length and time step can be reduced for a higher degree of detail. The RouteSim model does not require explicit calculation of speeds, and thus does not rely on the use of speed-density functions to propagate traffic; however, the principles of the cell transmission model are consistent with the hydrodynamic theory of traffic flow. Further, the model can capture many realities of the network, such as traffic signals, by using time-dependent cell capacities and saturation flow rates. The simulator has been enhanced to capture bus stopping behavior, and the roadway capacity reduction that results from a stopped bus.

3.4.2 Traffic Assignment

The DTA model assigns each vehicle to a path based on either the User Equilibrium or System Optimal rule. The traffic assignment models are usually based on Wardrop's (1952) principles. Wardrop's first principle characterizes an equilibrium flow distribution of traffic as the aggregate result of the user's individual decisions when a set of network parameters is specified. Under the User Equilibrium rule all vehicles for an OD pair are assigned to a set of paths that have equivalent travel time. This principle represents realistically the behavior of travelers. Wardrop's second principle is the System Optimal principle that states the used paths and the associated flows are such that the total travel cost of the network is minimized. The second principle assumes that travelers will obey some higher authority and follow paths such as to minimize the total network wide cost. This assignment is usually used as a guideline as what could be achieved if travelers were assigned optimally. Under this assignment some travelers of the same OD pair may experience lower costs and some will experience higher cost.

In addition, the VISTA-DTA model captures intermodal travelers and performs a person assignment that can be used to evaluate various transit related improvements such as bus/train schedules, transit stop locations, transit signal priority systems, location of park and ride facilities. The VISTA system can generate automated statistics per link, movement, an OD path as well as area wide statistics. Furthermore, the system is flexible enough to allow the user to conduct parametric analyses by allowing only a percentage of vehicles to change their original paths. This is particularly useful in incident cases where only a set of users may have information about the incident and any alternative routes.

3.4.3 VISTA Incident Management Output

VISTA Incident Management module (see appendix) can produce measures of effectiveness (MOE) for traffic management, traveler information, and infrastructure planning. The DTA models could further produce each individual OD-path parameters such as travel time, traffic volume, and distance traveled. These parameters could be based on the mode of transportation such as auto, bus, train, auto plus bus, auto plus train, bus plus train, truck, or truck plus train.

The main MOEs that could be produced by the VISTA system are:

- *Total travel time distribution* of the network or sub-area for all vehicles, autos, trucks, and buses, respectively. This may be further disaggregated for each OD pair or each link.
- *Total Vehicle-Miles Traveled (VMT)* for all vehicles, autos, trucks, and buses, respectively on the network - this may be further disaggregated for each OD pair or each link.
- *Path travel time distribution* per time period of the day for each OD pair; this may be disaggregated at an individual trip level such as auto only, transit only (bus or train), intermodal (auto plus bus, auto plus train, or bus plus train), truck only, train only, or truck plus train.
- *Shortest path travel time* distribution of EMS, police, fire department, towing services, from their current origins to the incident location and from the incident location to their next destination (EMS station, hospital, police station, or other incident scene, etc.). This information is extremely useful for emergency services

and they could be used for training purposes by examining the spatial distribution of their vehicles and their fleet assignment to multiple incidents occurring within the same geographical area and time period.

- *Link/Superlink travel time distribution* (mean and variance) per time period of the day (e.g. 5, 10, 15 minutes). A superlink is a combination of two or more consecutive links into one link. The aggregation of links to superlinks is recommended in cases where the analyst tries to avoid situations where an upstream or downstream link has a significant impact on the operation on its upstream or downstream link(s). Examples of superlink definitions for signalized intersections could be straight through - straight through movement, straight through - left turn movement, straight through - right turn movement, etc.
- *Link/superlink traffic volume per time period of the day* (e.g. 5, 10, 15, 30, or 60 minutes). The traffic volume per vehicle category or for all vehicles is used traditionally for capacity analyses, to estimate the impact of traffic volume on link/superlink travel time, ramp metering analysis, signal timing analysis, pavement deterioration, other. Under incident conditions this estimate could be used to optimize the ramp metering rates and/or the signal timing of various signalized intersections in the affected area.
- *Link/Superlink vehicle OD identification per time period of interest*. The analyst could further identify the specific OD paths that utilize each link per time period of interest. This result could aid the analyst to further study the impact of a roadway capacity reduction at a link of the network on the businesses within the

vicinity of the impacted link, the travelers that pass through and utilize this link or the travelers who arrive in the area to do their business.

- *Air quality MOEs* such as CO, NOx, HCs for the entire network, sub-area, link/superlink, OD pairs, for all vehicles, autos, trucks, buses, respectively.

3.5 Methodology for Calculating Incident-Induced Delay

In this study, a method to estimate incident impact through the calculation of the incident-induced delay is proposed. The incident delay is estimated at the network level, for origin-destination pairs, for a link segment, and per user group. This method of estimating incident delay can be used for transportation planning and for transportation operations. This approach builds on the knowledge derived from the capability of simulation-based DTA models. The estimation of the incident delay takes into account the spatial and temporal characteristics of the traffic network, the characteristics of the traffic demand (distribution, type of vehicles, users, etc.), the characteristics of the incident (duration, number of lanes affected, severity, incident location, etc.), and the incident management strategies (traveler information). The tools used for the estimation of incident delay are the simulation-based Dynamic Traffic Assignment (DTA) models. Traffic simulation is one of the most promising tools that the transportation agencies will have in the near future.

The concepts of estimating the incident-induced delay based on the difference in travel times between normal and incident conditions are by no means new (see, for example Epps *et al.*, 1994; Skabardonis *et al*., 1995; and Pierce *et al.*, 2005). Skabardonis *et al*. (1995) proposed a methodology to estimate incident delay based on the travel time difference under normal and incident conditions. However, they use data from loop detectors to estimate travel time. In their proposed model, no considerations are taken for the spatial and temporal distribution of the traffic and vehicles are not tracked to their final destinations. As mentioned earlier, in this study, travel times will be estimated through a simulation-based DTA that offers the capability to track each vehicle from their origin to their destination at each time step. Therefore, incident delay can be estimated for each vehicle in the system.

The approach proposed in this study to estimate incident delay is based on the travel time difference between normal and incident conditions using DTA simulation software. This procedure avoids some of the problems in using the queuing diagram and directly provides the delay perceived by the motorists. The general formula for the determination of the total non-recurring delay (NRD) could be defined as follows:

Total *NRD = Network wide total travel time under incident conditions* - *Network wide total travel time under normal conditions*

where,

Network wide total travel time under incident conditions is the expected total travel time of all the travelers (all OD pairs) from the occurrence time of an incident until its conclusion and until all travelers reach their destinations.

Network wide total travel time under normal conditions is the total travel time of all the travelers (all OD pairs) from the time that the incident presumably occurred until they reach their destinations under normal conditions.

The method to estimate incident delay is applied to a traffic network with a set of nodes N and a set of arcs (links) A connecting the nodes. Each OD pair r-s is connected by a set of paths (routes) K through the network. Let $\mathcal{F}=\{\tau_{ij}(t)\}$ represent the set of non-negative real valued travel times on the network arcs for every time t. Hence, $\tau_{ij}(t)$ is the time required to travel from node i to node j of a link (i,j), where t is the entry time at node i, defined for every $t \in \mathcal{S}$ in such a way that $t+\tau_{ij}(t) \in \mathcal{S}$, where $\mathcal{S}$ is the set of discrete time intervals.

Let $x_{ij}(t)$ and $y_{ij}(t)$ represent, respectively, the inflow on link (i,j) and the outflow on link (i,j) when departure time from node i is t. Let $X_k^{rs}(t)$ and $Y_k^{rs}(t)$ represent, respectively, the inflow on path k and the outflow on path k at time t. V represents the total number of vehicles entering and exiting the network. $c_k^{rs}(t)$ represents the travel time on path k at time t. The travel time on a particular path, at time t, is the sum of the travel times on the links comprising this path. Mathematically, this relationship can be expressed as follow:

$$c_k^{rs}(t) = \sum_{ij} \tau_{ij}(t)\delta_{ij,k}^{rs} \quad \forall k \in K_{rs},\ \forall r \in R,\ \forall s \in S$$

where R denotes the set of origin centroids and S denotes the set of destination centroids, and $\delta_{ij,k}^{rs} = 1$ if link (i,j) is a part of path k connecting OD pair r-s, and $\delta_{ij,k}^{rs} = 0$ otherwise.

Let $\tau_{ij,inc}(t)$ and $c_{k,inc}^{rs}(t)$ represent the travel time on link (i,j) and the travel time for a particular OD, respectively, at time t, under incident conditions.

$$c_{k,inc}^{rs}(t) = \sum_{ij} \tau_{ij,inc}(t)\delta_{ij,k}^{rs} \quad \forall k \in K_{rs}\,,\ \forall r \in R\,,\ \forall s \in S$$

The incident-induced delay resulting from the incident on link (i,j) at time t is defined as the difference between the time traveled driving under incident conditions and the time traveled under non-incident conditions or normal conditions.

$$d_{ij}(t) = \tau_{ij,inc}(t) - \tau_{ij}(t)$$

The standard deviation of the incident-induced delay on link (i,j) at time t is

$$\sigma_{ij,delay}(t) = \sigma_{ij,inc}(t) + \sigma_{ij}(t)$$

The incident-induced delay is given in time units (generally in minutes) and depicts the average travel time difference per vehicle for a set of vehicles departing their origins at time t.

The incident delay for an OD pair at time t, following a path k_1 during the incident, given that the initial path is k under normal conditions is calculated as

$$d_{k_1/k}^{rs}(t) = \sum_{ij} \tau_{ij,inc}(t)\delta_{ij,k_1}^{rs} - \sum_{ij} \tau_{ij}(t)\delta_{ij,k}^{rs}$$

If $k_1 = k$, there is no diversion from the initial path and the delay becomes

$$d_k^{\ rs}(t) = \sum_{ij} (\tau_{ij,inc}(t) - \tau_{ij}(t))\delta_{ij,k}^{rs}$$

The total delay is given in vehicle-hours (VH) or vehicle-minutes (VM). It quantifies the total delay experienced by a group of vehicles departing their origins at time *t*.

Link vehicle time delay estimation for time period: $D_{ij}(t)$ *(vehicle-hours)*

The vehicle time delay (vehicle-hours) for a particular link at time *t* is calculated as

$$D_{ij}(t) = (x_{ij}(t) - y_{ij}(t))\, d_{ij}(t)\text{ , or}$$

$$D_{ij}(t) = (x_{ij}(t) - y_{ij}(t))(\tau_{ij,inc}(t) - \tau_{ij}(t))\text{ ,}$$

and the standard deviation is $\sigma_{ij,delay}(t) = (x_{ij}(t) - y_{ij}(t))(\sigma_{ij,inc}(t) + \sigma_{ij}(t))$,

This formula holds only if there is no diversion during the incident. The number of vehicles traversing the link under no-incident conditions should be equal to the volume under incident conditions.

OD vehicle time delay estimation for time period: $D^{rs}(t)$ *(vehicle-hours)*

The vehicle time delay (vehicle-hours) for a particular OD at time *t* is the difference between vehicle-hours during the incident and vehicle-hours under normal conditions. It is observed that the vehicle hours for the OD include all sets of paths used by vehicles for the OD.

$$D^{rs}(t) = \sum_{k_1} \sum_{ij} (x_{ij}(t) - y_{ij}(t))\tau_{ij,inc}(t)\delta^{rs}_{ij,k_1} - \sum_{k} \sum_{ij} (x_{ij}(t) - y_{ij}(t))\tau_{ij}(t)\delta^{rs}_{ij,k}$$

The vehicle time delay for a particular OD is the difference between the sum of vehicle hours for all used paths (k_1) of the OD during incident conditions and the sum of vehicle hours for all used paths (k) of the OD under normal conditions.

Network vehicle time delay for time period: D (vehicle-hours)

The total vehicle time delay (vehicle-hour) for a transportation network during a time interval Δt is the sum of delays for all ODs in the network during the specific interval of time Δt

$$D = \sum D^{rs}(t)$$

The average travel time delay (in minutes) per vehicle for the overall network is the total vehicle time delay divided by the total number of vehicles entering and exiting the network during the time period interval in consideration.

$$d = \frac{D}{Q}$$

where Q is the vehicle demand on the network.

CHAPTER 4 ANALYSIS FRAMEWORK

For this study, the simulation is performed using VISTA dynamic traffic assignment and simulation software. During simulation, vehicles are propagated mesoscopically, according to Daganzo's cell transmission model, such that link conditions are simulated by evaluating flow at a finite number of intermediate points along each link. The principles of the cell transmission model are consistent with the hydrodynamic theory of traffic flow, but can also capture microscopic effects, such as queuing. The key feature of the cell transmission model used in VISTA is that flows are explicitly prohibited from exceeding capacity. In the cell transmission model, if demand for a cell exceeds the available capacity, queuing forms to maintain flows less than capacity. This ability to model queues in a somewhat realistic manner is one of the prime attractions of the model and it is of importance while simulating incidents in congested or non-congested traffic conditions. VISTA uses a mesoscopic simulator that computes the cell location of each vehicle at every time step. This information is less detailed than the output provided by microscopic simulation (exact vehicle position, speed and acceleration at each time step) but is much more computationally efficient. The computational efficiency of the mesoscopic model allows simulators such as VISTA's RouteSim to provide solutions for large networks. The sections in this chapter describe the transportation networks used in the simulation and the process used in VISTA to perform the simulation.

4.1 Transportation Networks for Case Studies

VISTA is used to analyze the effect of an incident on two transportation networks different in size and function. The first network is small in size and represents a segment of a freeway with four origins and one destination. Because of its very small size, it is possible to analyze the impact of an incident at the link level. This network is used to estimate the impact of the incident as a function of the available capacity of the network, the incident duration and the vehicle volumes on the transportation system.

The second case study network is an abstraction of the Chicago area network that comprises interstate highways I-94 and I-294 and surrounding arterial roads. This network contains 123 centroid nodes and 208 links, and a total of 194 OD pairs. The relatively medium size of this network allows one to quickly analyze the impact of the incident for most of the OD pairs traversing or not traversing the incident link. The size of the network makes it possible to simulate it in reasonable time that ensures arrival to destinations of all loaded vehicles.

4.2 Data Requirements and Descriptions

The simulation begins with the setup of the network and vehicle demand data to represent the transportation systems to be analyzed. The VISTA software package stores data in a PSQL database, which can be accessed through either a GIS client interface, or a web-reporting interface. The GIS interface provides data input and editing windows and is thus user-friendlier; however, the web interface is more convenient for querying and viewing many records at once. This section describes the data required for VISTA simulation through a discussion of VISTA's PSQL database tables.

For the evaluation of traffic incident management, the VISTA dynamic traffic assignment and simulation software requires the network definition data, the origin-destination demand definition data, and the closure definition data.

4.2.1 Network Definition Data

The network definition data includes zone, node, link and cell definitions. The zones, nodes and links are obtained from network data. The cell generation module is then used to split the links into cells, which form the basis of the cell transmission-based mesoscopic simulation.

4.2.1.1 Zones

Each network is divided into zones, which are geographic sub-regions that generate and attract OD demand. Each zone is assigned an identification number, and the physical shape of the zone is defined in the points column of the zone geometry table. Further, each zone contains two centroid nodes, one for vehicles entering the network from the given zone and one for vehicles exiting the network to the given zone. Centroids are considered to be imaginary nodes that represent the sources and destinations of all demands from and to the given zone, and they must be listed in the *nodes* table with node type=100. Each zone is also assigned a list of actual nodes that exist within the boundaries of the zone. The zone centroids are connected to these actual nodes by centroid connectors, which are links with link type=100. Connectors can be created to join the centroids to one or all of the actual nodes in the zone; however, addition of connectors increases the number of links in the network, and thus also the computational time required for assignment and simulation.

4.2.1.2 Nodes

Nodes are defined in the *nodes* table, and each node is assigned an identification number and an (x,y) coordinate location. Nodes are also defined in terms of their node type, with node type=1 for actual nodes, and node type=100 for centroid nodes. (x,y) coordinates are not important for centroid nodes and can be set to arbitrary values, such as (0,0), since centroids nodes are imaginary and do not exist in the physical world.

4.2.1.3 Links

Links are defined in the *links* and *linkdetails* table, where the data in the *links* table determines the appearance of each link in the VISTA GIS client, and the data in the *linkdetails* table is used to determine the vehicle path assignment. Each link is assigned an identification number and a link type, where type=1 for actual links, and type=100 for centroid connector links. The geometry of each link is defined by a series of (x,y) coordinates in the points column of the *links* table. The first point in the series must correspond to the coordinates of the source node, and the last point must correspond to the coordinates of the destination node listed in the *linkdetails* table. The street name, length and speed are also defined for each link. The capacity of the link can be defined by defining the capacity directly, or by defining the number of lanes in the *linkdetails* table (if no capacity value is explicitly defined, the cell generator assumes a capacity of 2,000 vehicles/hour/lane). All links in VISTA are uni-directional. To represent bi-directional streets, two links must be defined (e.g., a to b and b to a).

4.2.1.4 Cells

When the network's nodes and links have been fully defined, VISTA's cell generator module is run to create the cells, which are used in the cell transmission-based mesoscopic simulation. In other words, cell data is not entered based on acquired data sets, as with the zone, node and link data, but instead is generated automatically using the cell generator module based on the node and link definitions.

4.2.2 Demand Definition Data

The vehicle OD demand definition data includes static and dynamic demand definitions. The VISTA software requires exact vehicle departure times in order to assign and simulate vehicles; however, regional vehicle origin-destination (OD) trip data is typically only available for a 24-hour period. The daily demand must then be factored down to represent the demand for the simulation period in question, for example, morning peak hour from 7:00-9:00am. This demand for the simulation period is then referred to as the "static" demand, since exact vehicle departure times are not specified.

The VISTA software's demand profiler is then used to convert the "static" demand to "dynamic" demand, in which each vehicle is assigned a specific departure time within the simulation period.

4.2.2.1 Static Demand

Static vehicle OD demand is defined for each OD pair and vehicle type (cars, trucks, etc.), and each OD-vehicle type is assigned an id number and a demand quantity indicating the number of vehicles of the given type moving between the given OD pair during the whole simulation period.

4.2.2.2 Dynamic Demand

The values in the *static_od* table are then converted to dynamic demand using the VISTA demand profiler module. The demand profiler assigns exact departure times to each vehicle for dynamic traffic assignment and simulation. Dynamic demand is stored in the *demand* table, and each record in the *demand* table represents an OD pair, for a specific vehicle type and departure time. Each OD-vehicle type-departure time combination is assigned an id number, and a value representing the number of vehicles of the given type traveling between the given OD pair at given departure time. Using the demand profiler, different proportions of the static demand can be assigned to different intervals within the simulation period by assigning weights to each interval (weights must sum to 1.0). Thus, the assignment interval listed in the *demand* table refers to the interval defined by the demand profiler.

In this study, however, profiles are created using demand data used for static assignment. It is assumed that demand is distributed uniformly throughout the period of interest. For instance, if the demand for an OD pair in a three-hour peak period is 3,600 vehicles, and an OD matrix is needed for every fifteen minutes, the approach used is to simply assign a demand of 300 vehicles for each of those fifteen-minute intervals, for a total of 3,600 in the three hours. This is unlikely to be a realistic model of this demand profile, since one would expect a slight demand variation. The development of rigorous demand modeling approaches is beyond the scope of this dissertation.

4.2.3 Closure Definition Data

The VISTA software requires a closure definition data in order to simulate vehicles under incident conditions. In VISTA, an incident is simulated as a closure of lanes. The closure definition data includes the location of the closure, its duration and severity, and the number of lanes closed. The closure location is defined by its distance from the starting point of the affected link, the length of the link affected and the id of the affected link. The temporal definition of the incident is defined by the start and end time of the incident which defines the incident duration. The incident duration is exogenous in VISTA. The “severity” of the incident in terms of traffic impacts, is defined by the available capacity remaining during the closure. A severity of zero means that the available capacity is zero, while a severity of one means full capacity is available. The number of lanes closed determines the physical state of affected lanes. In this study, the severity is used in parallel with the number of lanes closed to characterize the physical capacity remaining. For instance, if 1 lane is fully closed on a 3 lanes roadway, therefore the severity (or capacity remaining) used is 0.67.

4.3 Simulation Scenarios

The power of VISTA is the implemented suite of routing (path computation) algorithms. The paths are generated using Dynamic Traffic Equilibrium with drivers departing at a fixed time. A modified method of successive average (MSA) is used to identify the paths for each OD using the Time-Dependent Shortest Path (TDSP) algorithm. After the paths for each OD are generated, a mesoscopic simulator (RouteSim) is used to propagate vehicles into these paths. In other words, the movements of small groups of vehicles are simulated as they enter and leave sections of each link. After, the first set of paths are generated using the TDSP algorithm, the DTA-Dynamic User Equilibrium (DTA-DUE) model is used to load vehicles into these paths in order to attain an equilibrium state. At equilibrium, no additional new paths for any OD pair are generated, while all used paths for each OD pair and departure time appear to have equal travel time. For each OD departure time, the demand on the existing path set is updated, such that the path costs for all existing paths approach equilibrium based on an approximation of the path cost. An iterative solution approach has been designed, where path demands are distributed and redistributed among paths until equilibrium is reached.

As the simulation iteratively progresses, it stores the link density, the link flows, the travel times, and the path sets. The flows and travel times are stored as typical vectors indexed over time. The calculation of travel time begins by recording the cumulative flow into and out of each link. Therefore, when a vehicle enters a link, its next desired link is examined; the vehicle is then recorded as an inflow for the link-movement combination it intends to perform. When a vehicle departs from a link, it is recorded as an outflow for the intersection movement performed. This effectively creates two vectors (inflow and outflow) for each link-movement combination indexed over time. These cumulative flows are examined to calculate the travel time for every link and movement performed. The path set is stored as a dynamic vector with a key containing the destination, assignment time and iteration. Each record consists of the optimal path calculated during the iteration for each origin to that destination, in the specified time period.

The average travel time, standard deviation of the travel time, density, inflow and outflow by time step Δt for specified links *(i,j)* and specified Origin-Destinations *(r,s)* are extracted from the simulation results. Using the above definitions, the impact of the incident is estimated and analyzed. The ODs are grouped by ODs traversing the incident location and ODs non-traversing it. Furthermore, the impacts of the incident are determined for upstream and downstream links of the incident location as well as for the overall network.

As mentioned earlier, two networks are simulated to estimate the impacts of incident-induced delay. A ten-hour assignment of vehicles is used in the simulation.

Various scenarios are simulated to extract MOE at the link, OD and network levels. A set of test runs were completed for different incident duration levels from 15 to 120 minutes, different vehicle volume levels and different number of lanes closed. Three cases are examined: (i) the base case under prevailing incident-free conditions, (ii) an incident scenario where no information is presented to drivers, where all drivers are expected to maintain their “no incident” paths, and (iii) a perfect information scenario, where it is assumed all drivers are aware of the incident and re-equilibrate their paths accordingly.

To simulate the base case conditions, VISTA path assignment model and dynamic user equilibrium model are used with no closure data. The base case, defined as the normal state of the transportation network under prevailing incident-free conditions, represents the state of the traffic during normal conditions. It is assumed that the traffic is therefore under equilibrium. Under normal traffic conditions, the DTA model assigns each vehicle to a path based on the user equilibrium. Under the user equilibrium rule, all vehicles for an OD pair are assigned to a set of paths that have equivalent travel time.

Two cases of incident scenarios are examined: the incident scenario with no information provided to drivers is simulated by assuming that all vehicles used the initial paths for each OD as determined in the base case. The VISTA’s RouteSim model is used to simulate this case with the closure data imported into the dataset. Vehicles are propagated to the assigned paths determined in the base case and no drivers will change their predetermined paths to avoid the incident location. No DTA is used, otherwise it may generate additional paths for some ODs or load vehicles to other paths. The second case of incident is simulated by reassigning vehicles to paths to attain a new user equilibrium state. This case assumes that all drivers are aware of the location, duration, and severity of the incident and the conditions of the transportation network. Therefore, each driver will use the path that will minimize his/her travel time to arrive at his/her destination. This is unrealistic and ideal behavior in response to travel information. This scenario is studied for demonstration purposes only, as in reality only a small fraction of travelers usually have information about the incident and its anticipated impact. VISTA path assignment model and dynamic user equilibrium model are used with the incident data in the dataset. New sets of paths are generated using DTA-path generator and DTA-DUE models. Drivers are reassigned to a set of paths that have equivalent travel time.

The following Chapter shows detailed data for each of the networks used to simulate the scenarios, results, and analysis of the impact of incident-induced delay.

CHAPTER 5 INCIDENT DELAY ANALYSIS

This chapter applies the delay calculation methods proposed in Chapter 3 are applied to two transportation networks. Network #1 is a section of a freeway comprised of 12 nodes and 11 links. The configuration of Network #1 permits to estimate the delay caused by an incident on a freeway with few controlled access. For this network, the incident delay is estimated for vehicles entering the freeway either upstream or downstream of the incident location and exiting it at a unique point downstream of the incident. Network #2 is a small extraction of the Chicago network. This network is used to estimate the incident-induced delay on a more realistic transportation network that includes a section of a freeway, access ramps, and arterial streets at the periphery of the freeway. The network is comprised of many origin and destination nodes. Thus, its configuration allows the diversion of vehicles away from the incident location. The existence of alternative routes for OD pairs allows evaluating the effect of the dissemination of incident information to travelers. VISTA software is used to simulate different variations of incident durations, lanes blockage, and vehicle demand for both transportation networks.

The incident-induced delay is estimated for the overall network, for OD pairs depending on their location vis-à-vis of the incident location, and for surrounding links of the incident link. The effect on incident delay of factors such as the available capacity of the network after an incident occurred, the duration of the incident, and the vehicles volume of the transportation system at the time of the incident is analyzed.

5.1 Incident Impact on Network #1

The first case study performed is to demonstrate the methodology of estimating the impacts of an incident on a section of a freeway as shown in Figure 5.1.1. The network comprises four origin nodes (nodes 2,12,14, and 15) and one destination node (node 10) that form a total of 4 OD pairs. The network characteristics are illustrated in Table 5.1.1 and Table 5.1.2 displays the weighted distribution of the demand during the simulation. Table 5.1.3 shows the OD demand matrix for a total demand of 51000 vehicles in the network.

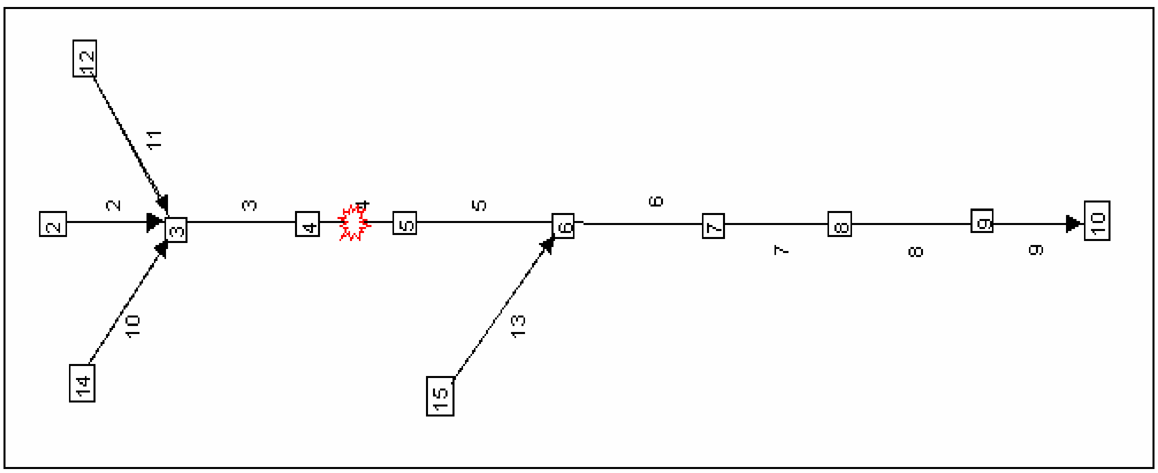

Figure 5.1.1 Network #1 with the incident on Link #4

Table 5.1.1 Characteristics of Network #1

Nodes	12	Maximum Capacity	2,000 vphpl
Links	11	Free Flow Speed	55 mph
OD Pairs	4	Simulation Duration	10 hours
# Lanes per Link	3	Demand Distribution	Uniform
Length for Link # 4	¼ mile	Length of Other Links (except Link #4)	5 miles

Table 5.1.2 Demand profile per assignment sequence

Assignment #	Weight	Start Time (second)	Duration (second)	Assignment #	Weight	Start Time (second)	Duration (second)
0	0.025	0	900	20	0.025	18,000	900
1	0.025	900	900	21	0.025	18,900	900
2	0.025	1,800	900	22	0.025	19,800	900
3	0.025	2,700	900	23	0.025	20,700	900
4	0.025	3,600	900	24	0.025	21,600	900
5	0.025	4,500	900	25	0.025	22,500	900
6	0.025	5,400	900	26	0.025	23,400	900
7	0.025	6,300	900	27	0.025	24,300	900
8	0.025	7,200	900	28	0.025	25,200	900
9	0.025	8,100	900	29	0.025	26,100	900
10	0.025	9,000	900	30	0.025	27,000	900
11	0.025	9,900	900	31	0.025	27,900	900
12	0.025	10,800	900	32	0.025	28,800	900
13	0.025	11,700	900	33	0.025	29,700	900
14	0.025	12,600	900	34	0.025	30,600	900
15	0.025	13,500	900	35	0.025	31,500	900
16	0.025	14,400	900	36	0.025	32,400	900
17	0.025	15,300	900	37	0.025	33,300	900
18	0.025	16,200	900	38	0.025	34,200	900
19	0.025	17,100	900	39	0.025	35,100	900

Table 5.1.3 OD Demand Matrix

Origin Node	Destination Node	Vehicle Type	Demand (vehicles)
2	10	Passenger	10,000
2	10	Commercial	4,500
12	10	Passenger	8,000
12	10	Commercial	3,000
14	10	Passenger	8,000
14	10	Commercial	3,000
15	10	Passenger	10,000
15	10	Commercial	4,500

As shown in the incident definition data table (Table 5.1.4), an incident consisting of full closure of all lanes of the three-lane roadway for 30 minutes along Link #4 is modeled for demonstration purposes. It is assumed that a closure of all lanes of a three-lane roadway will physically reduce the available capacity to zero. The base case and an incident case are simulated using VISTA software. For this section of freeway, there is only one path per origin-destination pair for all vehicles; therefore, all vehicles are using their base case paths before and after the incident. The average travel time and its standard deviation, the total volume of OD pairs, the inflow and outflow volume of links are extracted from the simulation results for each defined time step.

Table 5.1.4 Overview of incident closure data

Link ID	Length	Speed	Capacity	Start Time	End Time	Lanes Closed
4	0.25 mile	55 mph	2,000 vphpl	2:00:00	2:30:00	3

Table 5.1.5 shows the summary results of the overall network for the base case and for the 30 minutes incident duration with full closure of the incident link. It can be observed that the incident case performs worse as expected. The average travel time per vehicle in the network increases to 41.50 minutes under incident conditions from 34.86 minutes under prevailing free-incident conditions.

Table 5.1.5 DTA results for the base case and incident case on Network #1

CASE	Demand (vehicles)	Total System Travel Time (hour)	Average Travel Time (min/veh)	Standard Deviation (min/veh)
Base Case – VISTA DUE	51,000	29,633	34.86	5.03
Incident Case (30 min) – VISTA DUE	51,000	35,272	41.50	10.95

The impact of the incident is shown in Table 5.1.6. The average delay per vehicle and total vehicle delay are calculated as illustrated in chapter 3. Each vehicle experiences on average 6.64 minutes of delay caused by the incident to reach its destination. The total vehicle delay on the network is 5644 vehicle-hours.

Table 5.1.6 Incident delay on Network #1

Volume (vehicles)	Average Delay (min/veh)	Standard Deviation (min/veh)	Total Delay (vehicle-hour)
51,000	6.64	15.98	5,644

The average delay per vehicle or the total delay for the overall section of the freeway demonstrates neither the temporal distribution of delay nor its spatial distribution. The analyst should determine these distributions in order to estimate the true impacts of delay for the segment of freeway. The importance of using the DTA simulation software is in its capability to track the spatio-temporal characteristics of the traffic. The average travel time per vehicle departure time and the corresponding delay distribution for the overall freeway segment are illustrated in the following tables (Table 5.1.7 and Table 5.1.8).

Table 5.1.7 Temporal distribution of travel time on Network #1

Departure Time Interval	Demand (vehicle)	Base Case AVG TT (min/veh)	Base Case TT STD (min/veh)	Incident AVG TT (min/veh)	Incident STD (min/veh)
0:00:00 - 0:15:00	1402	34.86	5.05	34.86	5.05
1:30:00 - 1:45:00	1402	34.86	5.04	34.86	5.04
1:45:00 - 2:00:00	1402	34.87	5.05	50.31	18.42
2:00:00 - 2:15:00	**1403**	**34.86**	**5.04**	**55.06**	**17.80**
2:15:00 - 2:30:00	**1403**	**34.86**	**5.03**	**53.86**	**17.05**
2:30:00 - 2:45:00	1403	34.84	5.03	52.83	16.09
2:45:00 - 3:00:00	1403	34.86	5.04	52.15	15.05
3:00:00 - 3:15:00	1403	34.85	5.03	51.12	13.80
3:15:00 - 3:30:00	1403	34.84	5.03	50.30	12.70
3:30:00 - 3:45:00	1402	34.86	5.04	49.52	11.60
3:45:00 - 4:00:00	1402	34.86	5.03	49.05	10.74
4:00:00 - 4:15:00	1403	34.86	5.02	48.29	9.65
9:45:00 - 10:00:00	1403	34.82	5.01	34.82	5.01

Table 5.1.8 Temporal distribution of incident delay on Network #1

Departure Time Interval	Demand (vehicle)	AVG Delay (min/veh)	Delay STD (min/veh)	Total Delay (VH)	Delay STD (VH)
0:00:00 - 0:15:00	1402	0.00	10.01	0	236
1:30:00 - 1:45:00	1402	0.00	10.08	0	236
1:45:00 - 2:00:00	1402	15.44	23.47	361	548
2:00:00 - 2:15:00	**1403**	**20.20**	**22.84**	**472**	**534**
2:15:00 - 2:30:00	**1403**	**19.00**	**22.08**	**444**	**516**
2:30:00 - 2:45:00	1403	17.99	21.12	421	494
2:45:00 - 3:00:00	1403	17.29	20.09	404	470
3:00:00 - 3:15:00	1403	16.27	18.83	380	440
3:15:00 - 3:30:00	1403	15.46	17.73	362	415
3:30:00 - 3:45:00	1402	14.66	16.64	343	389
3:45:00 - 4:00:00	1402	14.19	15.77	332	368
4:00:00 - 4:15:00	1403	13.43	14.67	314	343
9:45:00 - 10:00:00	1403	10.84	10.02	253	234

These tables exemplify the fact that incident impacts may last beyond its duration and clearance time. Incidents impact vehicles that were already loaded in the freeway before it occurred as well as those that enter the freeway after it is cleared.

Incident delay is often reported only for the affected and upstream links. Therefore, it may produce misleading results as to the impacts of an incident and does not provide any meaningful measure of effectiveness that a transport professional could use. Figure 5.1.2 shows the average delay per 5 minutes of vehicle assignment for the incident link (#4) and for its immediate upstream (#3) and downstream (#5) links. The average delay on the affected link #4 increases to a maximum of 28 min/veh at the beginning of the incident (120 minutes after the start of the assignment) before decreasing to zero at its clearance time (150 minutes). This behavior is expected because no vehicles are traversing the incident link during its duration. All vehicles present at Link #4 at the occurrence time of the incident will wait until the end of the full 30 minutes incident duration before proceeding, resulting in a more severe impact on upstream links. The average delay caused by the incident increases to 30 minutes for vehicles in the link (#3) at the beginning of the incident and then dissipates after 105 minutes (or time step of 225 min). If one was to consider just the impact of the incident for upstream links and for the affected link, one will conclude that it does not last more than 105 minutes. Therefore, the recovery time will be estimated to last 75 minutes. However, it is observed that the incident has an impact on downstream links (#5) as well. There is no delay observed on vehicles at the downstream during the duration of the incident. But, after its clearance, downstream traffic disturbances are formed and vehicles experience a delay that may increase up to 26 minutes. As observed in Figure 5.1.3, the downstream traffic disturbances derive from the congestion that arises by the release of vehicles after the clearance of the incident. The number of vehicles at Link #5 increases from no vehicle during the incident to more than 2180 vehicles in the link one hour after the incident. During the incident (all lanes are closed on Link #4), no vehicles are entering the link (#5) while vehicles present in the link are exiting it.

These results strengthen the conclusion that an incident has a different impact on vehicles depending of their location during it occurrence and duration. As demonstrated in this section, the incident has a different impact on the upstream, affected, and downstream links. It may negatively or positively affect the vehicle travel time depending of their location when it occurred. Only taking into account the incident delay on the upstream and affected links may over or under estimate its impact. Therefore, the impact of the incident should be considered at the network-wide level.

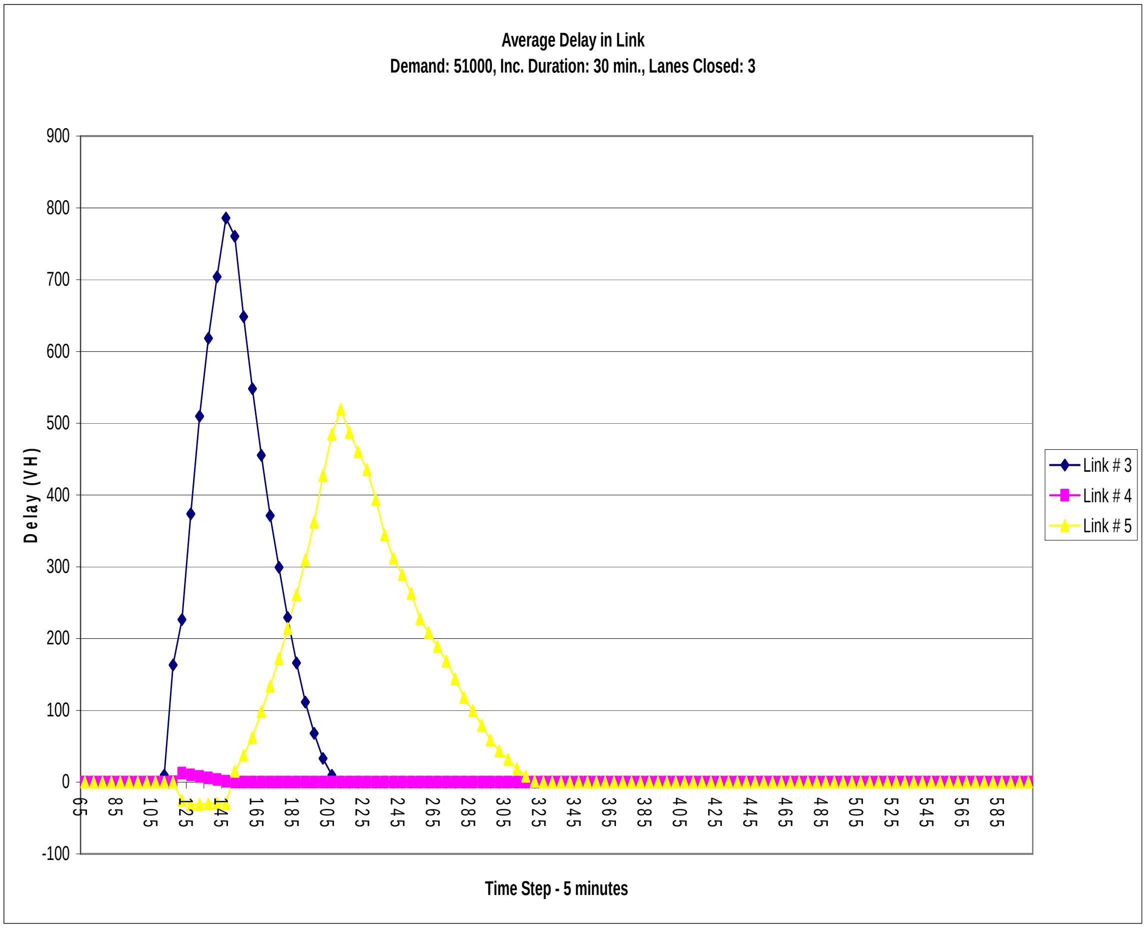

Figure 5.1.2 Average delay on incident link (#4), upstream link (#3) and downstream link (#5)

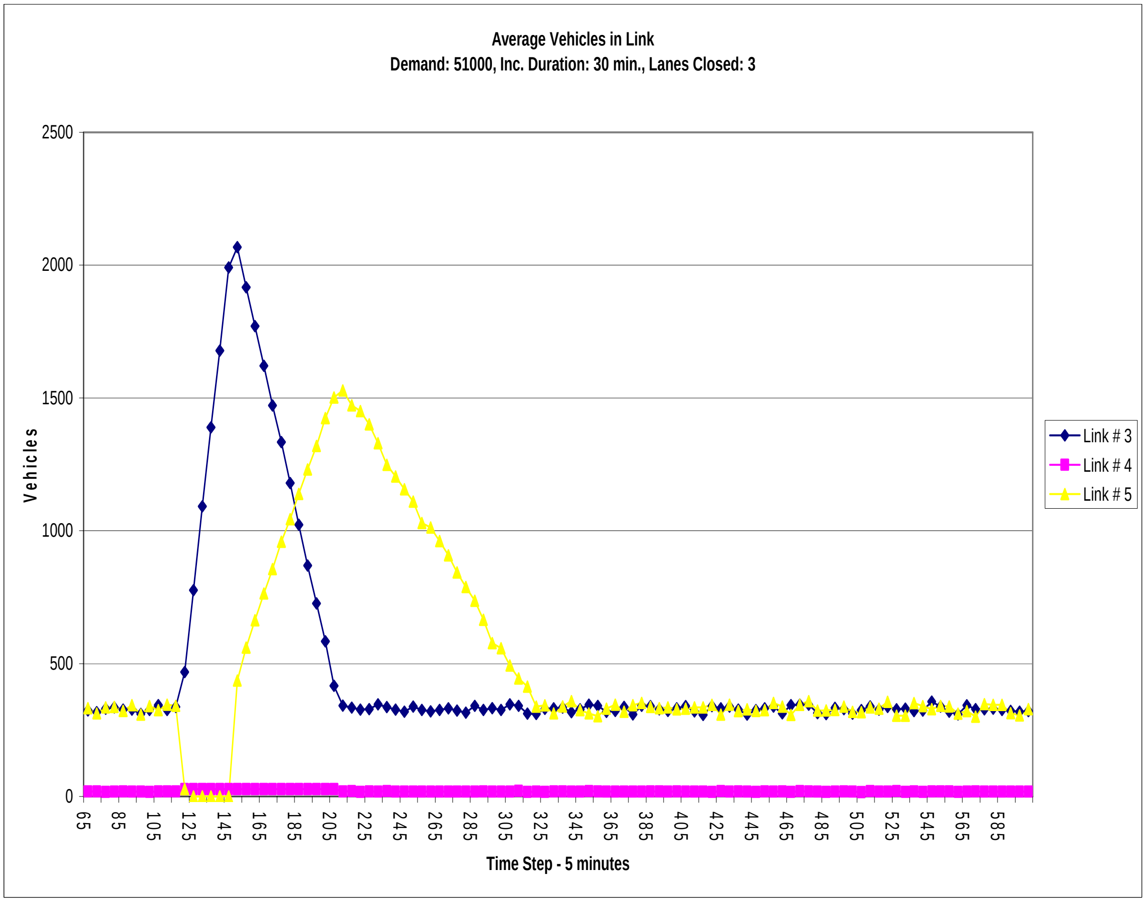

Figure 5.1.3 Demand on the incident link (#4), upstream link (#3) and downstream link (#5)

The spatial distribution of vehicles in the freeway is important for the analysis of the incident impacts. By considering the OD pair distribution, one can determine the impact of the incident on vehicles depending of their departure origin, travel path in the network, and arrival destination. Table 5.1.8 and Table 5.1.9 show the corresponding average travel time and delay for OD pairs originating either upstream or downstream of the incident location. For this specific network and traffic characteristics, the main observation from these results is that an incident has a different impact on different OD pairs – a rather obvious but often neglected and not reported set of statistics. It is observed (in Table 5.1.9) that some vehicles downstream of the incident location experience travel time savings under incident conditions compared to travel time under normal conditions.

Table 5.1.9 Travel time and delay for vehicles entering the freeway upstream of the incident link (OD 2-10)

Depart Time	Vehicles	Base Case AVG TT (min)	Base Case STD (min)	Incident AVG TT (min)	Incident STD (min)	Delay AVG (min)	Delay STD (min)	Delay (VH)	Delay STD (VH)
0:00	279	38.28	0.07	38.28	0.07	0.00	0.55	0	3
1:50	263	42.28	0.08	67.98	0.12	25.70	0.20	113	1
2:00	**279**	**42.63**	**0.15**	**68.32**	**0.15**	**25.68**	**0.30**	**119**	**1**
2:10	**260**	**42.83**	**0.22**	**68.43**	**0.08**	**25.60**	**0.30**	**111**	**1**
2:20	**259**	**43.52**	**0.13**	**68.62**	**0.15**	**25.10**	**0.28**	**108**	**1**
2:30	**260**	**43.63**	**0.20**	**68.62**	**0.17**	**24.98**	**0.37**	**108**	**2**
2:40	263	44.00	0.13	68.82	0.12	24.82	0.25	109	1
2:50	275	44.25	0.17	69.22	0.12	24.97	0.28	114	1
3:00	251	44.63	0.10	69.08	0.12	24.45	0.22	102	1
3:10	291	45.02	0.23	69.30	0.25	24.28	0.48	118	2
9:40	262	59.63	0.35	76.83	0.80	17.20	1.15	75	5
9:50	262	57.42	0.77	74.12	0.77	16.70	1.53	73	7

Table 5.1.10 Travel time and delay for vehicles entering the freeway downstream of the incident link for OD 15-10

Depart Time	Vehicles	Base Case AVG TT (min)	Base Case STD (min)	Incident AVG TT (min)	Incident STD (min)	Delay AVG (min)	Delay STD (min)	Delay (VH)	Delay STD (VH)
0:00	229	26.85	0.03	26.85	0.03	0.00	0.07	0	0.27
1:50	275	30.40	0.13	30.22	0.18	-0.18	0.32	-1	1.47
2:00	**272**	**30.92**	**0.13**	**27.85**	**1.25**	**-3.07**	**1.38**	**-14**	**6.26**
2:10	**246**	**31.30**	**0.13**	**26.85**	**0.03**	**-4.45**	**0.17**	**-18**	**0.70**
2:20	**278**	**31.53**	**0.12**	**26.87**	**0.03**	**-4.67**	**0.15**	**-22**	**0.70**
2:30	**270**	**32.07**	**0.18**	**27.18**	**0.20**	**-4.88**	**0.38**	**-22**	**1.71**
2:40	252	32.33	0.08	27.82	0.20	-4.52	0.28	-19	1.18
2:50	274	32.72	0.10	28.50	0.20	-4.22	0.30	-19	1.37
3:00	260	32.98	0.12	29.17	0.20	-3.82	0.32	-17	1.39
3:10	276	33.42	0.08	29.80	0.18	-3.62	0.27	-17	1.24
9:40	259	44.67	0.08	46.38	0.05	1.72	0.13	7	0.56
9:50	261	44.63	0.07	46.27	0.05	1.63	0.12	7	0.52

A temporal distribution of the travel time for some OD pairs of the freeway is plotted in Figures 5.1.4 and 5.1.5. Depending on the access point of vehicles to the freeway, an incident will have different impacts on them. The Figure 5.1.5 below clearly shows that vehicles entering the freeway downstream of the incident location are benefiting from its occurrence while Figure 5.1.4 shows vehicles entering upstream are negatively affected by it. On average, travel times under incident conditions for vehicles entering the freeway downstream of the incident are decreased beyond the incident duration while they increase for vehicles entering the freeway upstream of the incident.

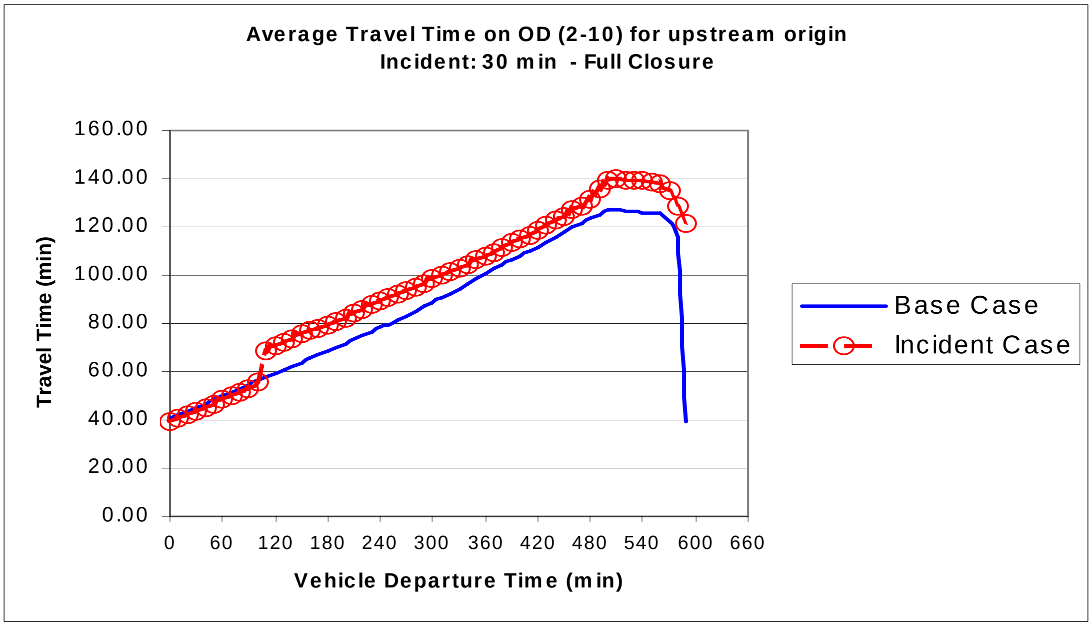

Figure 5.1.4 Average travel time on an OD originating upstream of the incident link and traversing the incident link

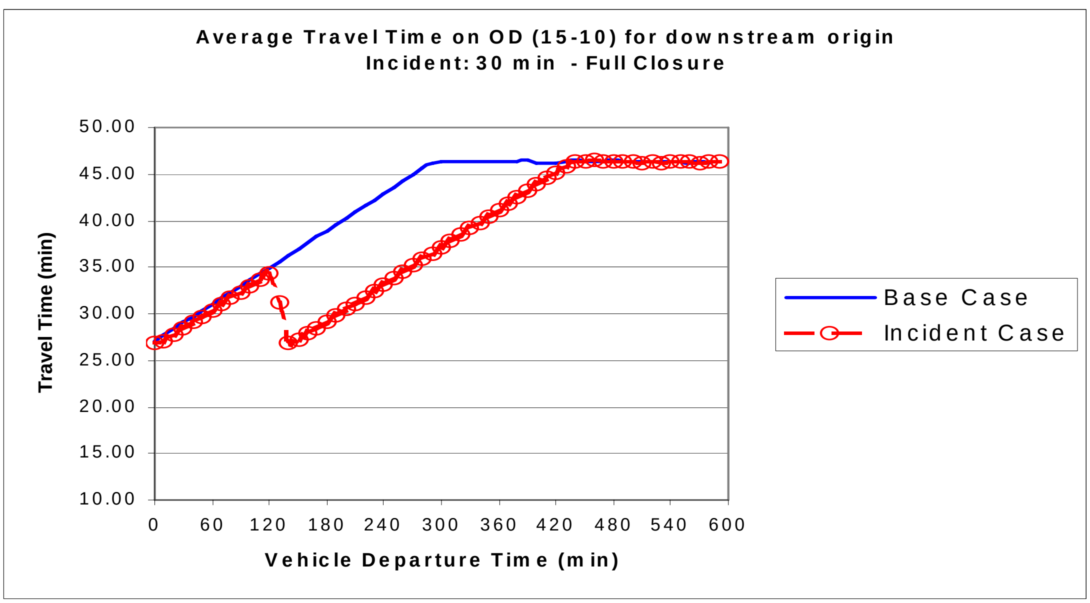

Figure 5.1.5 Average travel time on an OD originating downstream of the incident link and traversing the incident link

5.2 Incident and Traveler Information Impacts on Network #2

Network #2, shown in Figure 5.2.1, is a small abstraction of the Chicago network. Compared to Network #1, this network configuration comprises 123 nodes (some nodes are not displayed on the Figure) and 194 OD pairs, thus allows for alternative routes for OD pairs. This will permit to evaluate the impact of the dissemination of incident information to travelers under the incident conditions. The characteristics of the network are illustrated in Table 5.2.1 while Table 5.2.2 provides a summary of the incident data. Sets of simulation runs were completed for an incident duration of 45 minutes. The incident occurs 3 hours after the beginning of the simulation, lasts 45 minutes, and requires the closure of 2 lanes of the two-lane Link #13139. The total demand of the network during the 10 hours of simulation assignment is 190,259 vehicles. The demand is uniformly distributed for each of the 15 minutes time step of the assignment period. The analysis covers one direction of travel.

Table 5.2.1 Characteristics of Network #2

Nodes	Links	OD Pairs	Demand	Passenger Vehicles	Commercial Vehicles
123	208	194	190,259	187,417	2,842

Table 5.2.2 Incident closure overview (Network #2)

Link ID	Length	Speed	Capacity	Start Time	End Time	Lanes Closed
13139	2,400 ft	45 mph	1,800 vphpl	3:00:00	3:45:00	2 of 2

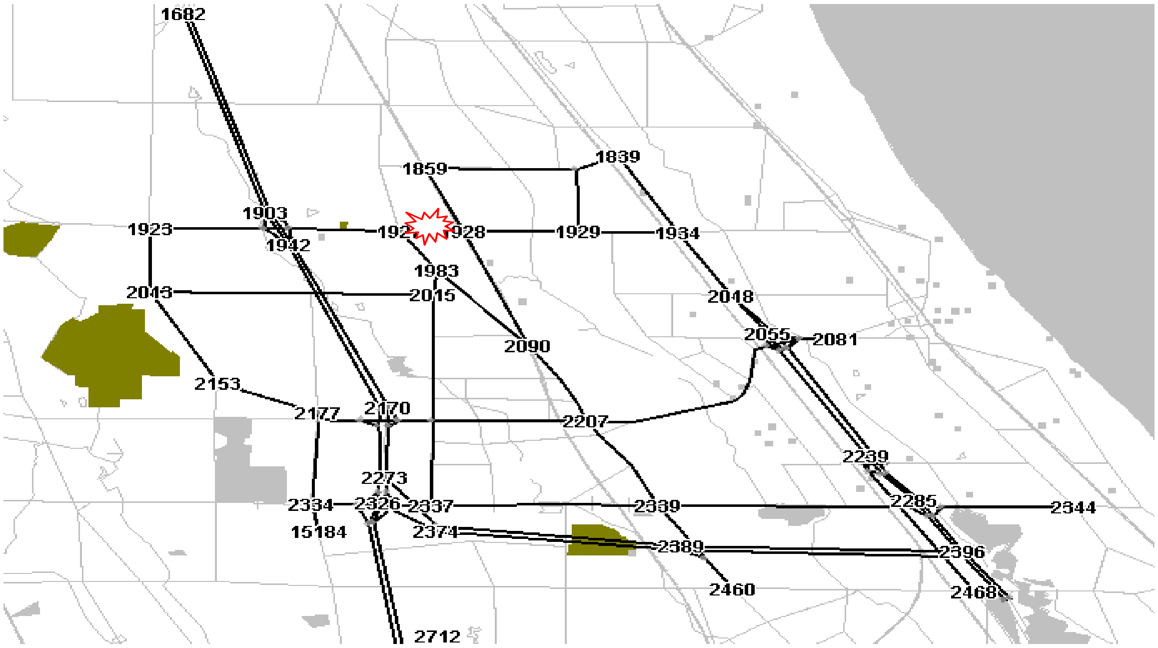

Figure 5.2.1 Network #2 (a small extraction of the Chicago network) with an incident on link #13139

5.2.1 Incident Impacts for the Overall Network #2

Table 5.2.3 displays the results for the base case (without an incident). It shows the number of vehicles loaded onto the network, including a differentiation among passenger cars and commercial vehicles. The corresponding total travel time for all vehicles is provided in hours while the average travel time and standard deviation per vehicle are reported in minutes. The table also shows the corresponding vehicle miles traveled in the network.

Table 5.2.3 Simulation results for the base case, Network #2

	Demand (vehicle)	Total TT (hour)	AVG TT (min/veh)	STD (min/veh)	VMT (miles)
All Type Vehicles	162,626	20,918	7.72	2.68	973,732
Passenger Cars	160,249	20,542	7.69	2.68	953,486
Commercial Vehicles	2,377	376	9.51	1.48	20,246

Table 5.2.4 shows the corresponding simulation results for the case under incident conditions with an assumption that all travelers are aware of the incident and are choosing paths that minimize their travel time in the network. This is a non-realistic case since only a small fraction of travelers usually have information about the incident and its anticipated impact. In VISTA, the evaluation of the implementation of an advanced traveler information system (ATIS) can be simulated by routing vehicles to pre-determined paths. The evaluation of the traveler information system is beyond the scope of this dissertation. However, results from scenarios of providing ATIS will be briefly examined to determine its potential impact on the transportation system under incident conditions.

Table 5.2.4 Incident with Dynamic User Equilibrium (incident information)

	Demand (vehicle)	Total TT (hr)	AVG TT (min/veh)	STD (min/veh)	VMT (miles)
All Type Vehicles	162,626	22,063	8.14	3.98	974,839
Passenger Cars	160,249	21,686	8.12	4.00	954,593
Commercial Vehicles	2,377	376	9.51	1.47	20,246

Table 5.2.5 depicts the travel times and vehicle miles traveled for the incident case when drivers have no information about the incident. In this case, it is assumed that all travelers are followed their initial (base case) routes. RouteSim, a mesoscopic traffic simulator, is executed to propagate vehicles on initial paths determined by the DTA model of the base case. No new paths are generated from the base case. As in the above case, this situation is also not realistic. It is expected that the occurrence of the incident may result in some vehicles changing their travel plan either by changing their initial route, or changing their departure time or destination, or canceling their trip. However, this has no major influence on the dissertation's objectives of estimating incident delay caused by an incident at the network level.

Table 5.2.5 Incident with RouteSim (no incident information)

	Demand (vehicle)	Total TT (hr)	AVG TT (min/veh)	STD (min/veh)	VMT (miles)
All Type Vehicles	162,626	27,671	10.21	9.69	973,732
Passenger Cars	160,249	27,157	10.17	9.69	953,486
Commercial Vehicles	2,377	513	12.96	9.69	20,246

The incident delay is calculated according to the methods shown in Chapter 3 and the results are illustrated in the following tables. Table 5.2.6 shows the substantial difference in incident delay between the case where all travelers are aware of the impact and location of the incident (full information) and the case where all drivers are following their initial base case paths (no information). Once again, these results show the importance of dissemination of traveler information system in helping to reduce the negative impact of an incident on traffic operations at the network level. However, in reality, it is expected that only a small fraction of travelers will likely have knowledge about the incident, its impact, and some alternative routes, such that they may avoid its undesirable impacts.

Table 5.2.7 and Table 5.2.8 show respectively the temporal distribution of travel time and incident delay for the base case and both cases of incident for all vehicles at the network level. Once again, it is observed that an effective traveler information system can alleviate the undesirable impacts of an incident to various travelers at varying degrees. The comparison of the results presented in Table 5.2.9 demonstrates substantial reductions in travel times and incident delays are achievable as a result of user awareness of the incident conditions and impacts. During the period of the incident (3:00-3:45), the delay reduction resulting for the provision of incident information to travelers declines up to 80%.

Table 5.2.6 Delay for the overall network

	Complete Incident Information				**No Incident Information**			
	Delay AVG (min/veh)	Delay STD (min/veh)	Total Delay (VH)	Delay STD (VH)	Delay AVG (min/veh)	Delay STD (min/veh)	Total Delay (VH)	Delay STD (VH)
All Type Vehicles	0.42	6.66	1,138	18,051	2.49	12.37	6,749	33,528
Passenger Vehicles	0.43	6.68	1,148	17,841	2.48	12.37	6,624	33,038
Comm. Vehicles	0.00	2.95	0	117	3.45	11.17	137	443

Table 5.2.7 Temporal distribution of travel time for the base case and both incident cases for the overall network

		Base Case		Incident Case with Information		Incident Case with no Information	
Departure Time Interval	Demand (vehicles)	AVG TT (min/veh)	STD (min/veh)	AVG TT (min/veh)	STD (min/veh)	AVG TT (min/veh)	STD (min/veh)
0:00 - 0:15	4,066	7.70	2.68	7.70	2.68	7.70	2.68
0:15 - 0:30	4,066	7.71	2.68	7.71	2.68	7.71	2.68
2:30 - 2:45	4,066	7.73	2.67	7.72	2.67	7.73	2.67
2:45 - 3:00	4,066	7.72	2.67	9.52	9.59	9.74	10.15
3:00 - 3:15	**4,066**	**7.71**	**2.68**	**10.18**	**9.38**	**16.78**	**19.10**
3:15 - 3:30	**4,066**	**7.71**	**2.67**	**10.84**	**8.59**	**19.89**	**21.27**
3:30 - 3:45	**4,066**	**7.70**	**2.68**	**10.43**	**6.60**	**21.27**	**21.83**
3:45 - 4:00	4,066	7.72	2.67	10.41	5.74	19.64	19.82
4:00 - 4:15	4,066	7.71	2.67	9.55	4.43	17.81	17.46
9:30 - 9:45	4,065	7.72	2.67	7.71	2.68	7.72	2.67
9:45 - 10:00	4,065	7.70	2.67	7.70	2.68	7.70	2.67

Table 5.2.8 Temporal distribution of delay for both incident cases at the network level

		Incident Case with Information		Incident Case with no Information	
Departure Time	Demand (vehicles)	Delay (VH)	STD (VH)	Delay (VH)	STD (VH)
0:00 - 0:15	4,066	0	363	0	363
0:15 - 0:30	4,066	0	363	0	363
2:30 - 2:45	4,066	0	362	0	362
2:45 - 3:00	4,066	122	831	136	869
3:00 - 3:15	**4,066**	**169**	**817**	**617**	**1,476**
3:15 - 3:30	**4,066**	**210**	**763**	**827**	**1,622**
3:30 - 3:45	**4,066**	**183**	**629**	**922**	**1,661**
3:45 - 4:00	4,066	183	570	806	1,524
4:00 - 4:15	4,066	122	481	684	1,364
9:30 - 9:45	4,065	0	363	0	362
9:45 - 10:00	4,065	0	363	0	362

Table 5.2.9 Distribution of delay (case with information vs. no information)

Departure Time	Demand (vehicles)	Delay (VH) (no information)	Delay (VH) (with information)
0:00 - 0:15	4,066	100%	100%
0:15 - 0:30	4,066	100%	100%
2:30 - 2:45	4,066	100%	100%
2:45 - 3:00	4,066	100%	90%
3:00 - 3:15	**4,066**	**100%**	**27%**
3:15 - 3:30	**4,066**	**100%**	**25%**
3:30 - 3:45	**4,066**	**100%**	**20%**
3:45 - 4:00	4,066	100%	23%
4:00 - 4:15	4,066	100%	18%
9:30 - 9:45	4,065	100%	100%
9:45 - 10:00	4,065	100%	100%

5.2.2 Incident Impact for OD Pairs

Disaggregate travel time and delay for each origin-destination pair that comprise the transportation network are helpful to understand the incident effects on vehicles upstream and downstream of the incident location. The spatial distribution of vehicles during and after the incident is an important “parameter” for analyzing the impacts of an incident. The average travel time distribution for some origin-destination pairs is extracted from the simulation results. The origin-destination pairs are classified in two groups: OD pairs with paths that include the incident location link and OD pairs with paths that do not. By grouping the OD pairs in these two categories, one can analyze the effect of an incident on vehicles as a direct response to the incident impact. The following tables show that the impacts of the incident are greater on vehicles with paths that include the incident link compared to those with paths that do not include the incident link. The former vehicles experience more delay, especially if there is no information provided that may help some of them to divert away from the incident. However, it is found that providing information upstream of the incident may not always be beneficial for vehicles with paths not traversing the incident link. A few of them experience slightly more delay resulting from the rerouting of affected vehicles that generates an increase vehicle volume in non-congested alternate routes.

Table 5.2.10 Travel time for OD pairs with paths that include the incident link (no provision of incident information)

OD Pairs	Demand (vehicles)	Base Case TT (min/veh)	Base Case STD (min/veh)	Incident Case TT (min/veh)	Incident Case STD (min/veh)
102717-201929	973	10.14	0.03	15.47	0.26
102090-202081	870	6.07	0.14	6.94	0.19
102015-202344	1,569	10.02	0.08	14.70	0.38
102015-202081	639	7.00	0.17	12.49	0.51
102013-202081	955	9.05	0.17	17.96	0.38
101983-202344	2,914	9.54	0.09	14.48	0.32
101983-202081	1,132	6.54	0.17	12.20	0.30
101923-202344	714	11.06	0.09	19.05	0.21
101923-202207	600	6.36	0.04	12.90	0.31
101923-202090	357	4.65	0.04	11.19	0.32
101923-202081	815	8.07	0.16	17.04	0.39
101861-202081	1,379	4.63	0.17	5.57	0.23
101682-202344	5,206	13.10	0.11	25.53	0.30
101682-202090	1,137	6.68	0.06	17.48	0.33
101682-202081	870	10.10	0.16	23.31	0.32
101682-201929	1,799	6.18	0.05	16.88	0.20

Table 5.2.11 Travel time for OD pairs with paths that include the incident link (with provision of incident information)

OD Pairs	Path 1 (vehicle)	Path 1 TT (min/veh)	Path 2 (vehicle)	Path 2 TT (min/veh)	Path 3 (vehicle)	Path 3 TT (min/veh)	Path 4 (vehicle)	Path 4 TT (VH)
102717-201929	900	11.00	73	12.17				
102090-202081	834	6.39	33	6.84				
102015-202344	1,452	10.57	107	13.29	10	11.05		
102015-202081	487	8.68	129	13.04	17	8.50	6	8.71
102013-202081	698	11.03	57	10.32	193	11.52	7	11.71
101983-202344	2,869	11.70	45	10.53				
101983-202081	811	7.50	96	7.95	225	7.99		
101923-202344	662	11.92	48	15.06	4	15.11		
101923-202207	555	7.13	17	23.08	28	6.97		
101923-202090	330	5.42	25	18.10	2	6.13		
101923-202081	536	10.51	241	10.48	38	11.20		
101861-202081	1,275	5.04	104	4.75				
101682-202344	4,816	14.32	390	17.21				
101682-202090	1,100	8.63	34	20.35	3	10.34		
101682-202081	465	12.96	383	13.67	12	35.32		
101682-201929	1,772	8.79	27	13.19				

Table 5.2.12 Delay for OD pairs with paths that include the incident link (no provision of incident information)

OD Pairs	% vehicles	Incident Delay (VH)	OD Pairs	% vehicles	Incident Delay (VH)
102717-201929	100%	86	101923-202207	100%	65
102090-202081	100%	13	101923-202090	100%	39
102015-202344	100%	122	101923-202081	100%	122
102015-202081	100%	58	101861-202081	100%	22
102013-202081	100%	142	101682-202344	100%	1,079
101983-202344	100%	240	101682-202090	100%	204
101983-202081	100%	107	101682-202081	100%	192
101923-202344	100%	95	101682-201929	100%	321

Table 5.2.13 Delay for OD pairs with paths that include the incident link (with provision of incident information)

OD Pairs	Path 1 % vehicles	Path 1 Incident Delay (VH)	Path 2 % vehicles	Path 2 Incident Delay (VH)	Path 3 % vehicles	Path 3 Incident Delay (VH)	Path 4 % vehicles	Path 4 Incident Delay (VH)
102717-201929	92.5%	12.8	7.5%	2.5		0.0		
102090-202081	95.9%	4.3	4.1%	0.4				
102015-202344	92.5%	13.0	6.8%	6.0	0.7%	0.0		
102015-202081	76.2%	13.6	20.2%	13.0	2.7%	0.4	0.9%	0.2
102013-202081	73.1%	23.0	6.0%	1.2	20.2%	7.9	0.7%	0.3
101983-202344	98.5%	103.3	1.5%	0.7				
101983-202081	71.6%	13.0	8.5%	2.3	19.9%	5.3		
101923-202344	92.7%	9.5	6.7%	3.2	0.6%	0.3		
101923-202207	92.5%	7.1	2.8%	4.7	4.7%	0.3		
101923-202090	92.4%	4.2	7.0%	5.6	0.6%	0.0		
101923-202081	65.8%	21.8	29.6%	9.7	4.7%	2.0		
101861-202081	92.5%	8.7	7.5%	0.2				
101682-202344	92.5%	97.9	7.5%	26.7				
101682-202090	96.7%	35.8	3.0%	7.7	0.3%	0.2		
101682-202081	53.4%	22.2	44.0%	22.8	1.6%	5.0		
101682-201929	98.5%	76.8	1.5%	3.2				

As shown in the above tables, some vehicles are diverted away from the incident location. For example, 71.6% of vehicles for OD pair 101983-202081 remain on their initial path (Path #1) while 8.5% and 19.9% of vehicles are rerouted to a second path (path 2) and/or a third path (path 3) respectively. The rerouting of vehicles for OD pair 101983-202081 reduces the average delay per vehicle from 107 Vehicle-Hours (all vehicles in path 1) to 13, 2.3, and 5.3 Vehicle-Hours for path 1, path 2, and path 3 respectively, after diversion. The diversion of vehicles helps reduce considerably the average travel time for most vehicles traversing the incident, therefore reducing the total delay in the network. There are some OD pairs with paths that do not traverse the incident link that are also affected. While most of these OD pairs are not impacted, Table 5.2.14 and Table 5.2.15 show that a few OD pairs are slightly negatively affected for both incident cases. Once again, the effect of the incident is network wide. The estimated of its impact should take into account the resulting comportment of all vehicles, including as well vehicles not necessarily traversing it. By comparing both states of the network, one can capture the true impact caused by the incident.

Table 5.2.14 Travel time for OD pairs with paths that do not include the incident link

	Base Case			Incident - no information			Incident - with information		
OD Pairs	Demand (veh)	TT (min/ veh)	STD (min/ veh)	Demand (veh)	TT (min/ veh)	STD (min/ veh)	Demand (veh)	TT (min/veh)	STD (min/veh)
115184-202344	2,985	8.36	0.04	2,985	8.44	0.12	2,985	8.76	0.13
102717-202344	2,264	10.83	0.06	2,264	10.91	0.11	2,264	11.22	0.12
102717-202339	1,414	6.24	0.02	1,414	6.24	0.03	1,414	6.36	0.05
102717-202207	870	7.45	0.04	870	7.45	0.04	870	7.45	0.04
102717-202090	828	9.45	0.05	828	9.45	0.04	828	9.45	0.04
102717-202081	917	11.79	0.23	917	12.66	0.20	917	12.07	0.15
102344-202207	955	6.24	0.02	955	6.24	0.03	955	6.24	0.03
102344-202090	955	8.24	0.03	955	8.24	0.03	955	8.24	0.03
102344-202081	1,362	4.68	0.03	1,362	4.68	0.06	1,362	4.70	0.08
102339-202081	825	6.07	0.12	825	6.96	0.18	825	6.35	0.14
102207-202344	5,220	6.96	0.02	5,220	7.03	0.11	5,220	7.12	0.11
102207-202081	1,026	4.38	0.08	1,026	5.24	0.20	1,026	4.66	0.15
102090-202344	4,046	8.65	0.03	4,046	8.73	0.11	4,046	8.82	0.11
102081-202344	3,083	5.07	0.01	3,083	5.12	0.06	3,083	5.14	0.06
102081-202207	1,343	4.15	0.01	1,343	4.15	0.04	1,343	4.15	0.04
102081-202090	1,220	5.95	0.02	1,220	5.95	0.04	1,220	5.95	0.04
102081-201929	1,963	3.25	0.01	1,963	3.25	0.04	1,963	3.25	0.04
102013-202344	1,378	11.76	0.11	1,378	11.84	0.11	1,378	12.15	0.14
102013-202339	2,228	7.15	0.01	2,228	7.15	0.03	2,228	7.26	0.05
102013-202207	600	5.95	0.03	600	5.95	0.03	600	5.95	0.03
102013-202090	789	5.14	0.02	789	5.85	0.08	789	5.14	0.03
101923-202339	639	8.14	0.05	639	8.14	0.03	639	8.27	0.05
101839-202081	1,609	4.01	0.05	1,609	4.92	0.21	1,609	4.41	0.22
101682-202339	1,804	9.95	0.02	1,804	15.08	0.25	1,804	10.06	0.05

Table 5.2.15 Delay for OD pairs with paths that do not include the incident link

	Incident - no information			Incident - with information		
OD Pairs	Vehicles	Delay (VH)	STD (VH)	Vehicles	Delay (VH)	STD (VH)
115184-202344	2,985	4.0	7.5	2,985	0.4	8.5
102717-202344	2,264	3.0	6.0	2,264	0.4	6.8
102717-202339	1,414	0.0	1.0	1,414	0.1	1.0
102717-202207	870	0.0	1.0	870	0.0	1.2
102717-202090	828	0.0	1.2	828	0.0	1.2
102717-202081	917	13.3	6.6	917	0.3	5.8
102344-202207	955	0.0	0.8	955	0.0	0.8
102344-202090	955	0.0	1.0	955	0.0	1.0
102344-202081	1,362	0.0	2.0	1,362	0.0	2.5
102339-202081	825	12.4	4.1	825	0.3	3.6
102207-202344	5,220	7.0	11.3	5,220	0.2	11.3
102207-202081	1,026	14.7	4.8	1,026	0.3	3.9
102090-202344	4,046	5.4	9.4	4,046	0.2	8.8
102081-202344	3,083	2.6	3.6	3,083	0.1	3.6
102081-202207	1,343	0.0	1.1	1,343	0.0	1.1
102081-202090	1,220	0.0	1.2	1,220	0.0	1.2
102081-201929	1,963	0.0	1.3	1,963	0.0	1.3
102013-202344	1,378	1.8	5.1	1,378	0.4	5.7
102013-202339	2,228	0.0	1.9	2,228	0.1	2.2
102013-202207	600	0.0	0.6	600	0.0	0.7
102013-202090	789	9.3	1.3	789	0.0	0.7
101923-202339	639	0.0	0.7	639	0.1	1.0
101839-202081	1,609	24.4	7.0	1,609	0.4	7.2
101682-202339	1,804	154.5	8.4	1,804	0.1	2.1

There is indication in the following figures (Figures 5.2.2, 5.2.3, 5.2.4, and 5.2.5) that incidents are not just affecting vehicles on links upstream of its location. Some vehicles originating downstream of the incident location may also experience minor delay or benefit from it depending of the prevailing level of demand on the roadway when it occurred. For both incident cases, the incident impacts on downstream vehicles are mixed. The vehicles originating upstream of the incident with paths including the affected link experience a longer recovery time if no traveler information is provided, compared to when it is provided. With the deployment of ATIS, the negative impacts of incidents may be reduced and shortened for upstream vehicles. However, vehicles originating downstream of the incident may not always benefit from the deployment of ATIS at the OD level. The improvement of travel conditions for vehicles originating upstream may at the same time have a negative effect on the downstream flow. Thus, the importance of considering the network wide impact is once again recommended.

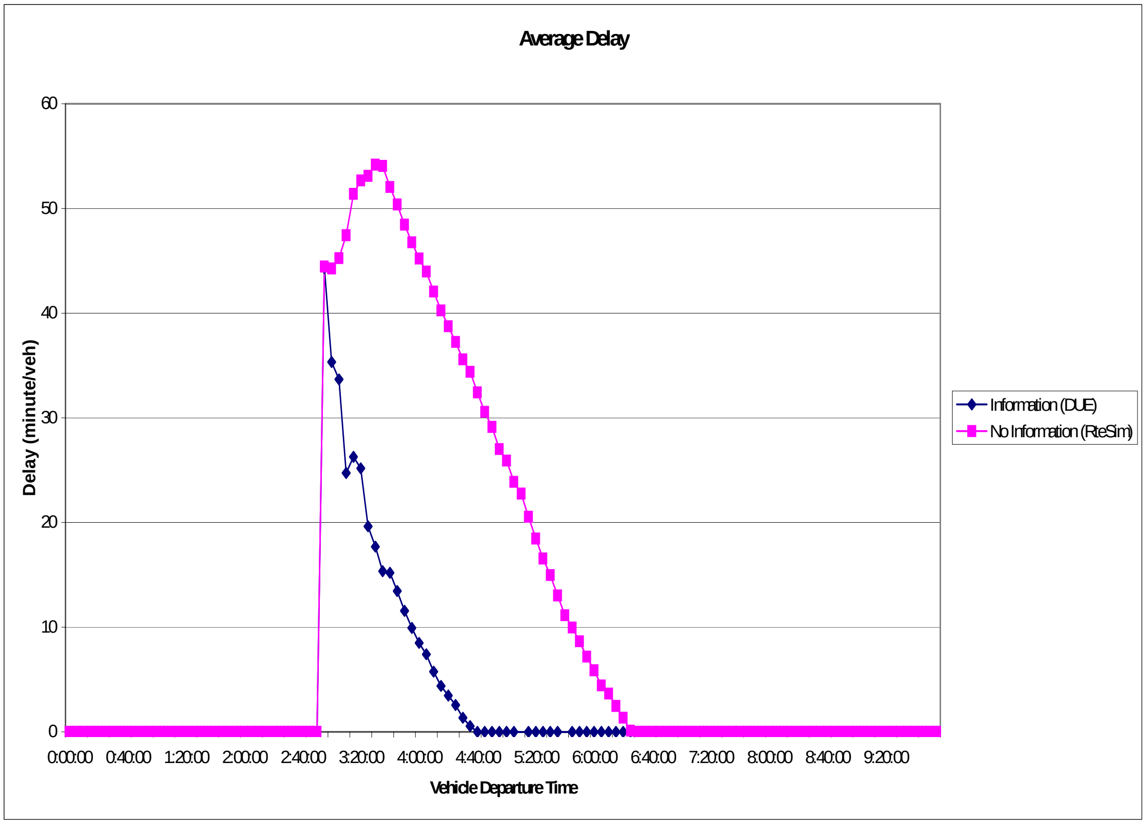

Figure 5.2.2 Temporal distribution of delay for an OD (101682-201929) traversing the incident link

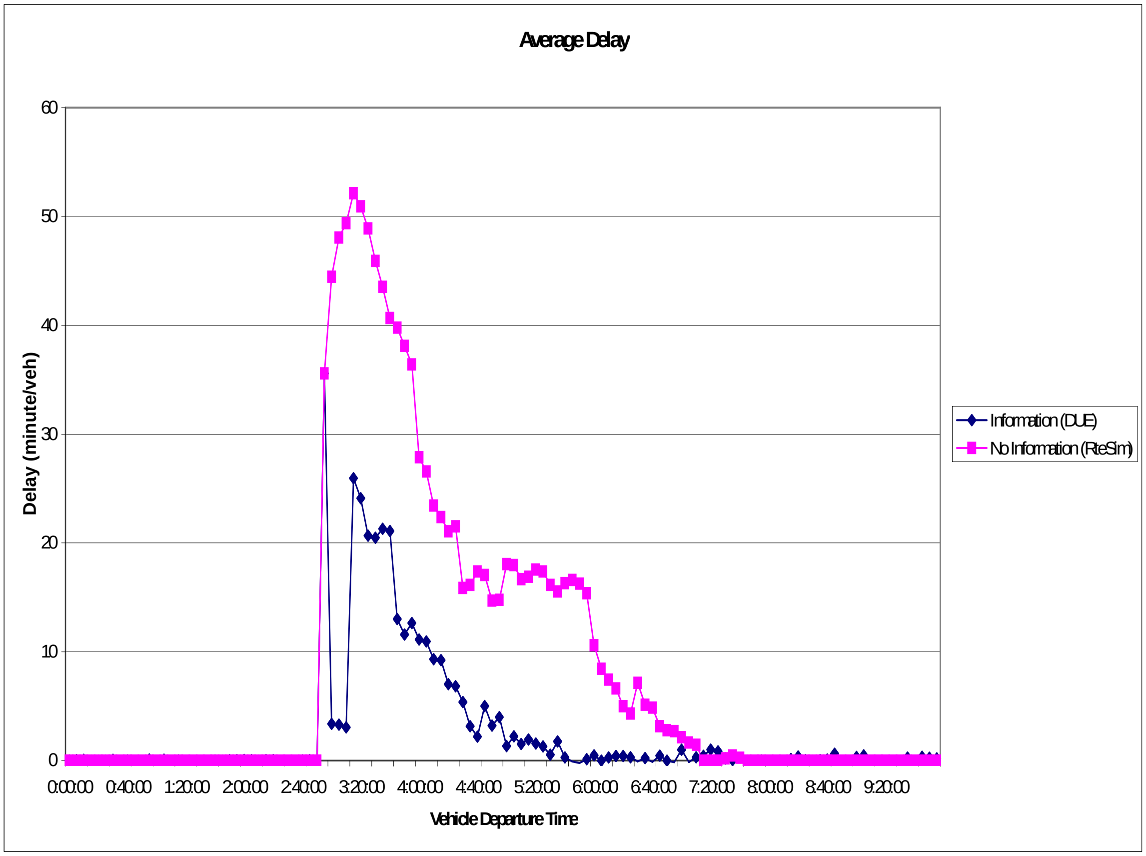

Figure 5.2.3 Temporal distribution of delay for an OD (101923-202081) traversing the incident link

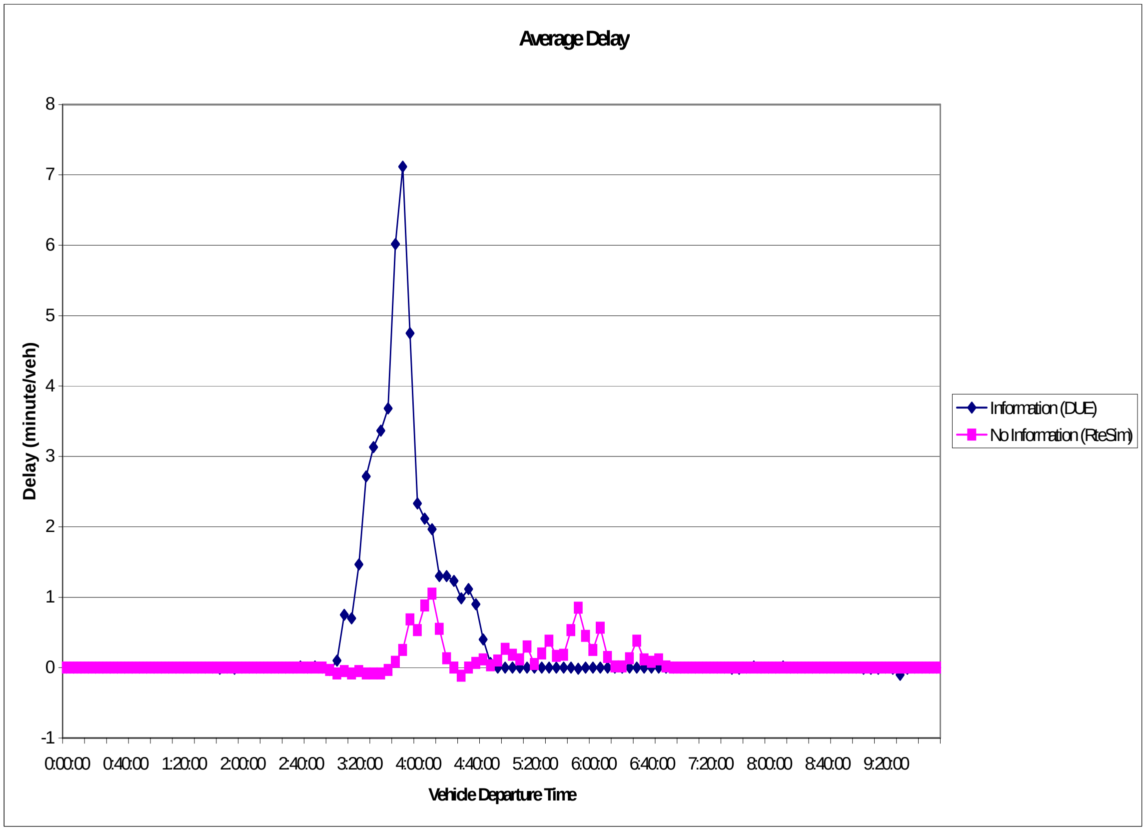

Figure 5.2.4 Temporal distribution of delay for OD (115184-202344) with origin located downstream of the incident with paths not including the incident link

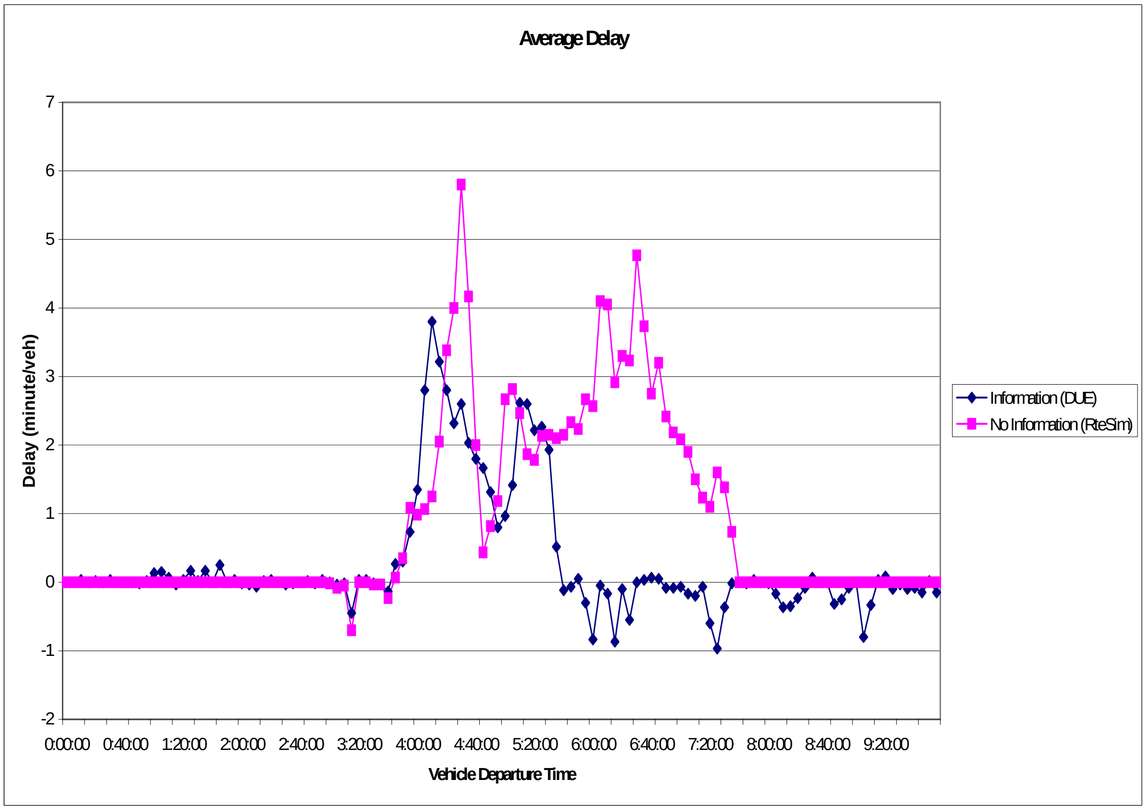

Figure 5.2.5 Temporal distribution of delay for OD (102339-202081) with origin located downstream of the incident with paths not including the incident link

The remainder section of the chapter analyzes the effect of influencing factors on the incident delay. Incident duration, lanes blockages, and vehicle demand when the incident occurred are identified in the literature as influencing factors of the incident delay.

5.3 Incident Duration Effects on Incident Delay

This section examines the impact of incident duration on travel time and incident delay is examined through the simulation of incidents for varying incident duration with and without the availability of incident-related traveler information systems. The section of freeway (Network #1) and the extraction of the Chicago network (Network #2) were used for the analysis. A set of simulation runs were completed for five different incident duration levels varying from 15 to 120 minutes. As stated in the literature, the incident duration is difficult to estimate. In this study, the incident duration is an exogenous variable. It is defined as the time period from the occurrence time of the incident to its clearance time. In VISTA, it is defined by its start time and end time in the incident definition data. The incident duration does not include the recovery time, which is the time for the queue formed due to the incident to dissipate and the demand flow rate to be restored after the incident has been cleared from the road.

5.3.1 Incident Duration Effects on Incident Delay for Network #1

The section of freeway with the following parameters, as shown in Table 5.3.1, is simulated for different incident durations. The incidents start at 2:00:00 and last 15, 30, 45, 60, and 120 minutes to be cleared for each scenario. The other variables for the simulation remain unchanged.

Table 5.3.1 Characteristics of Network #1 for the incident duration analysis

Nodes	12	Simulation Duration	10 hours
Links	11	Demand Distribution	Uniform
# Lanes per Link	3	Incident Link	#4
Free Flow Speed	55 mph	Incident Start Time	2:00:00
Max. Capacity	2,000 vphpl	Number of Lanes Closed	3
Total Demand	56,100	Severity	0

Table 5.3.2 presents the DTA simulation results for the base case and incident durations for the overall network. The average travel time per vehicle in the network is 45.57 minutes and the total travel time for all vehicles is 42609 hours under prevailing free-incident conditions. Under incident conditions, the average travel per vehicle is 50.57, 59, 67.46, 75.93, and 108.5 minutes for incident durations of 15, 30, 45, 60, and 120 minutes respectively. It is noted that the travel time variation (STD) increases with the average travel time. The main observation is that the average travel time per vehicle and the total travel time for all vehicles in the network during a period of time will increase with the duration of the incident. This observation is consistent with findings in the literature.

Table 5.3.2 Results for the base case and incident case for the overall network (#1)

Incident Duration (min)	Vehicle Type	Total Travel Time (hr)	AVG Travel Time (min)	STD (min)	VMT (miles)
Base Case	all	42,609	45.57	8.12	1,786,552
15	all	47,282	50.57	11.66	1,786,552
30	all	55,161	59	18.51	1,786,552
45	all	63,078	67.46	25.69	1,786,552
60	all	70,990	75.93	32.76	1,786,552
120	all	101,444	108.5	64.54	1,786,552

The corresponding results of calculated incident-delay are shown in Table 5.3.3 and illustrated in Figure 5.3.1. These results demonstrate that the incident duration has an effect on both the travel time and the incident-induced delay for the overall network. The total travel time and delay at the network level increase with the duration of the incident.

Table 5.3.3 Average delay per vehicle for the overall network (#1)

Incident Duration (min)	Type	Avg Delay (min/veh)	STD (min/veh)	Total Delay (VH)	STD (VH)
15	all	5.00	19.78	4,675	18,494
30	all	13.43	26.63	12,557	24,899
45	all	21.89	33.81	20,467	31,612
60	all	30.36	40.88	28,387	38,222
120	all	62.93	72.66	58,840	67,937

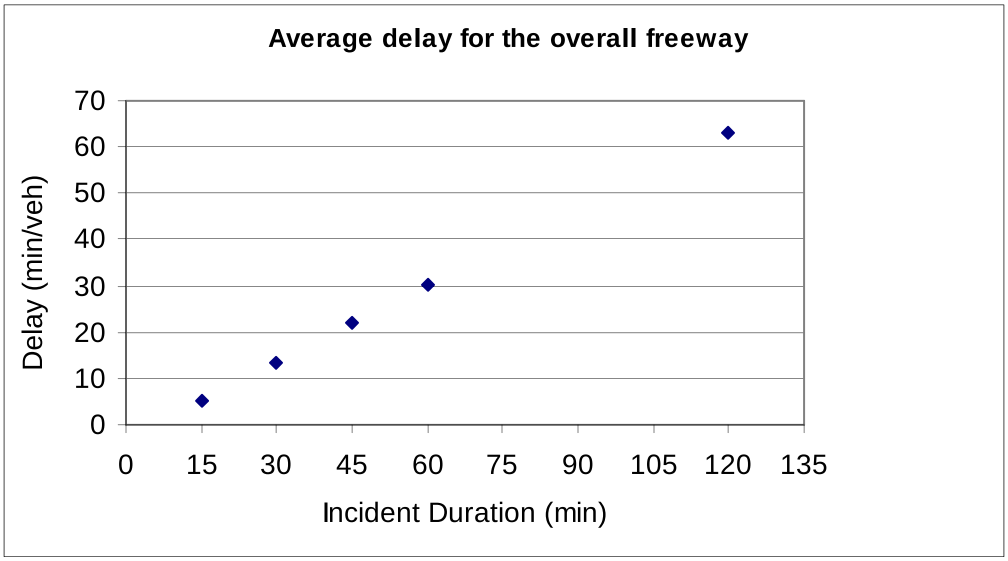

Figure 5.3.1 Average delay for the overall network (#1) per incident duration

For this specific case, with a full closure of all lanes of the three-lane freeway, a demand of 56100 vehicles (or a demand-to-capacity ratio of 0.94), and an incident on link# 4, there is a strong correlation between the incident duration and the average travel time at the network level. A strong correlation also exists between the incident duration and the average delay per vehicle. The quadratic regression models for Table 5.3.3 and Figure 5.3.1 are presented below:

$T = 44.530 + 0.4868X + 0.000396X^2$ (R-Sq = 0.998)

$D = -1.039 + 0.4868X - 0.000396X^2$ (R-Sq = 0.998) where,

T is the average travel time in the network (minute)

D is the average delay per vehicle in the network (minute/vehicle)

X is the incident duration (minute)

The last section of this chapter further explores the relationships between the incident duration and the delay for different vehicle demand levels and number of lanes closed. This method can help produce a model for estimating the travel time and the incident delay for a transportation network given the prevailing traffic conditions and the incident duration.

Figure 5.3.2 shows that incidents may have an impact on the network that lasts beyond the duration of the incident when the demand-to-capacity ratio is 0.94. For the case study scenario, the network does not recover to its normal conditions during the 10-hour simulation for all incident durations. Even though the acuteness of the delay increases with the duration of the incident, the effect on the recovery time, as shown in Figure 5.3.2, may not always be a function of the incident duration. It is observed that the recovery time does not increase nor decrease with the incident duration. For all simulated incident durations, the network recovery time remains approximately the same. However, for a lower demand level (as shown in Figure 5.3.3) with a demand-to-capacity ratio of 0.81, the recovery time after the incident is observed to vary with the duration of the incident. These observations suggest that the effect of the incident duration on the recovery time may depend on the demand level prevailing during the occurrence of the incident.

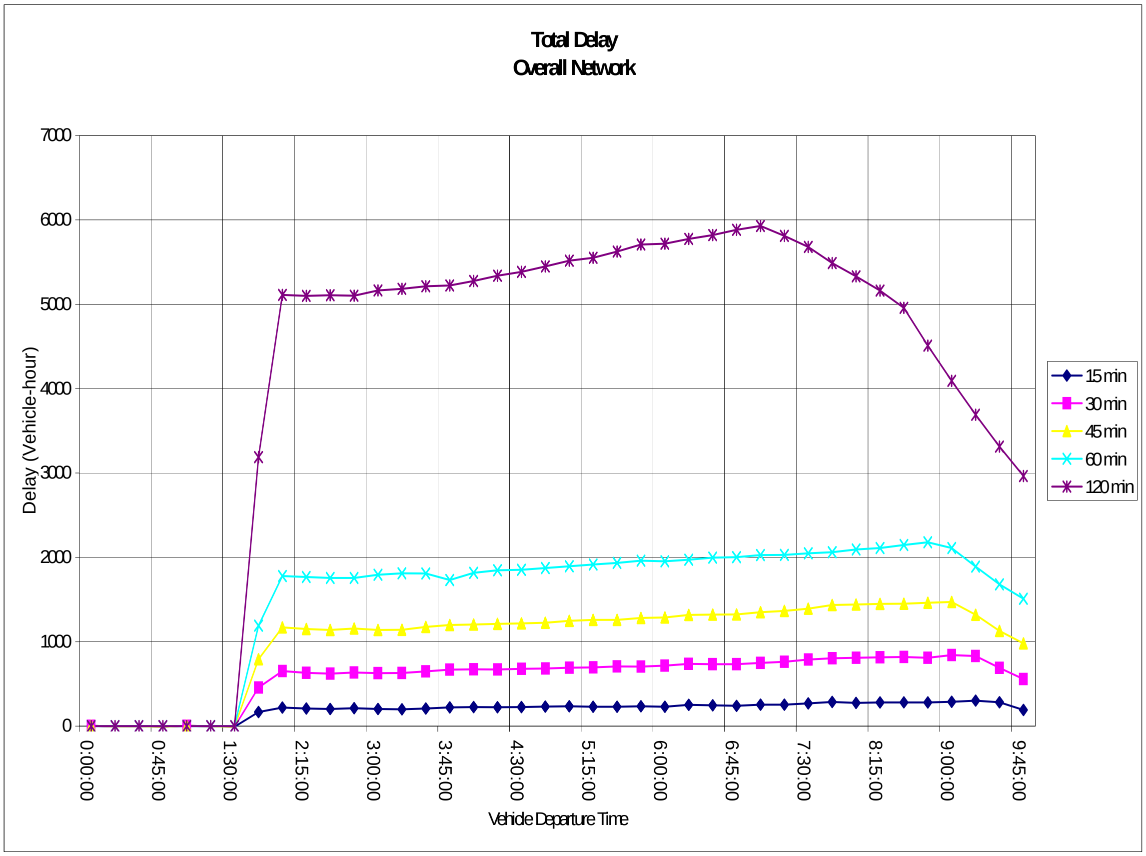

Figure 5.3.2 Temporal distribution of delay for the overall network (#1) per incident duration, demand: 56100 vehicles

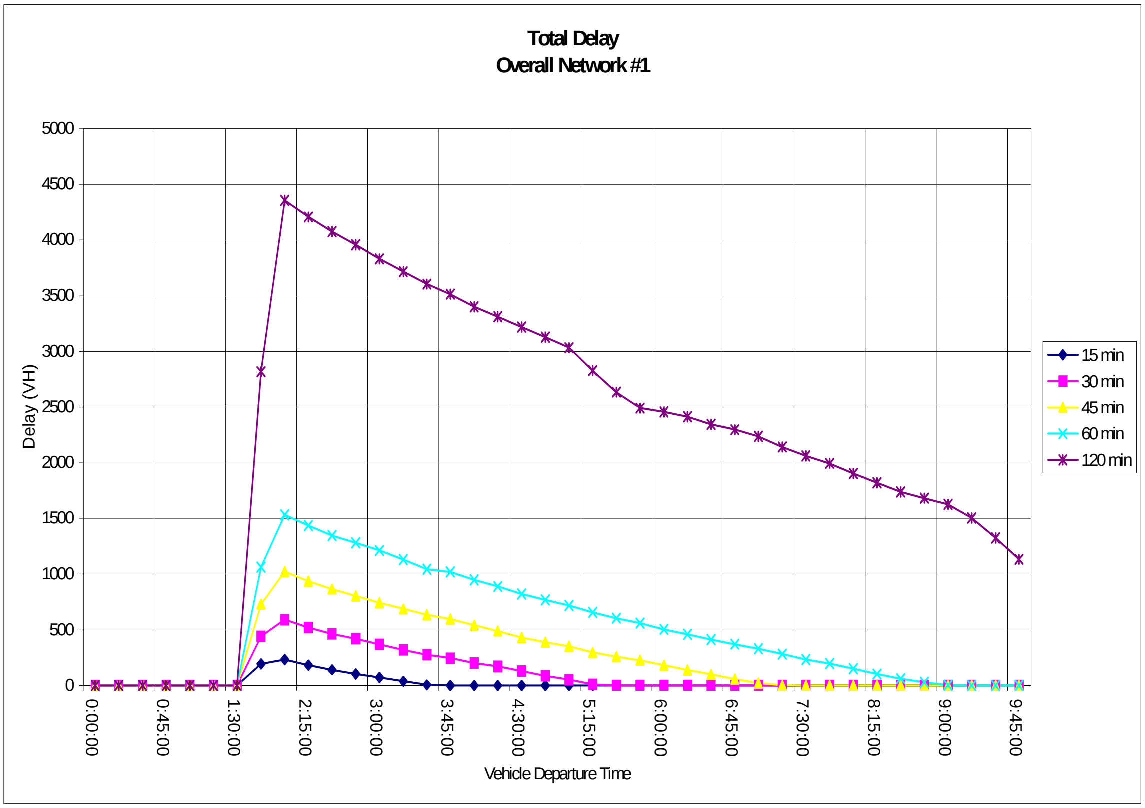

Figure 5.3.3 Temporal distribution of delay for the overall network (#1) per incident duration, demand: 48572 vehicles

The impact of incidents on the OD pairs for vehicles starting their trip upstream of the incident location increases with the duration of the incident. Upstream vehicles are severely affected and experience longer recovery time in comparison to the downstream vehicles (as shown in Figures 5.3.4 and 5.3.5). The temporal distributions of the travel time and delay for OD pairs entering the freeway downstream of the incident are displayed in Figures 5.3.6 and 5.3.7, respectively. For a time period after the occurrence of the incident, the average travel time per vehicle entering the freeway downstream of the incident location decreases with the increase of the incident duration. There is a time period after the occurrence of the incident that downstream vehicles traveling on the freeway under incident duration of 60 minutes experience on average less travel time to reach their destinations than if the incident has lasted 30 minutes. Some of these vehicles that enter the freeway downstream of the incident location are positively affected by the occurrence of the incident.

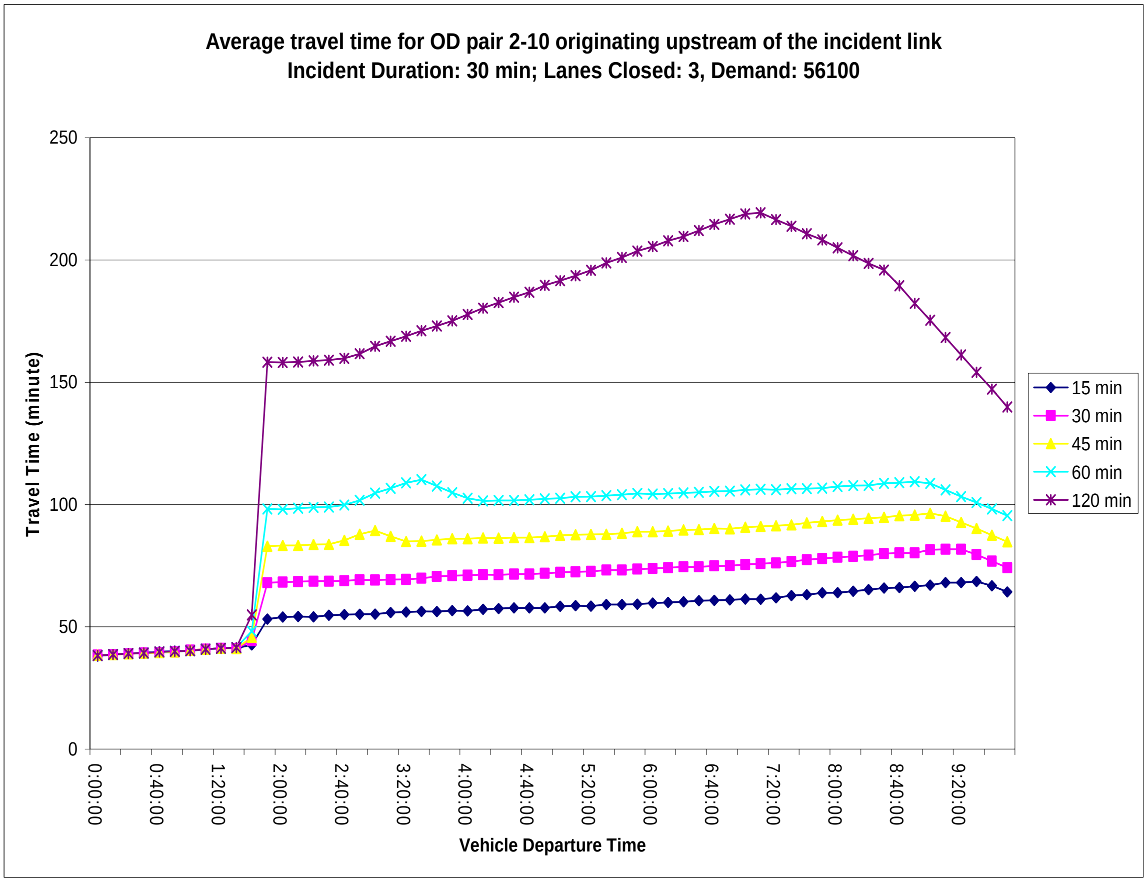

Figure 5.3.4 Temporal distribution of travel time for OD pair (2-10) per incident duration

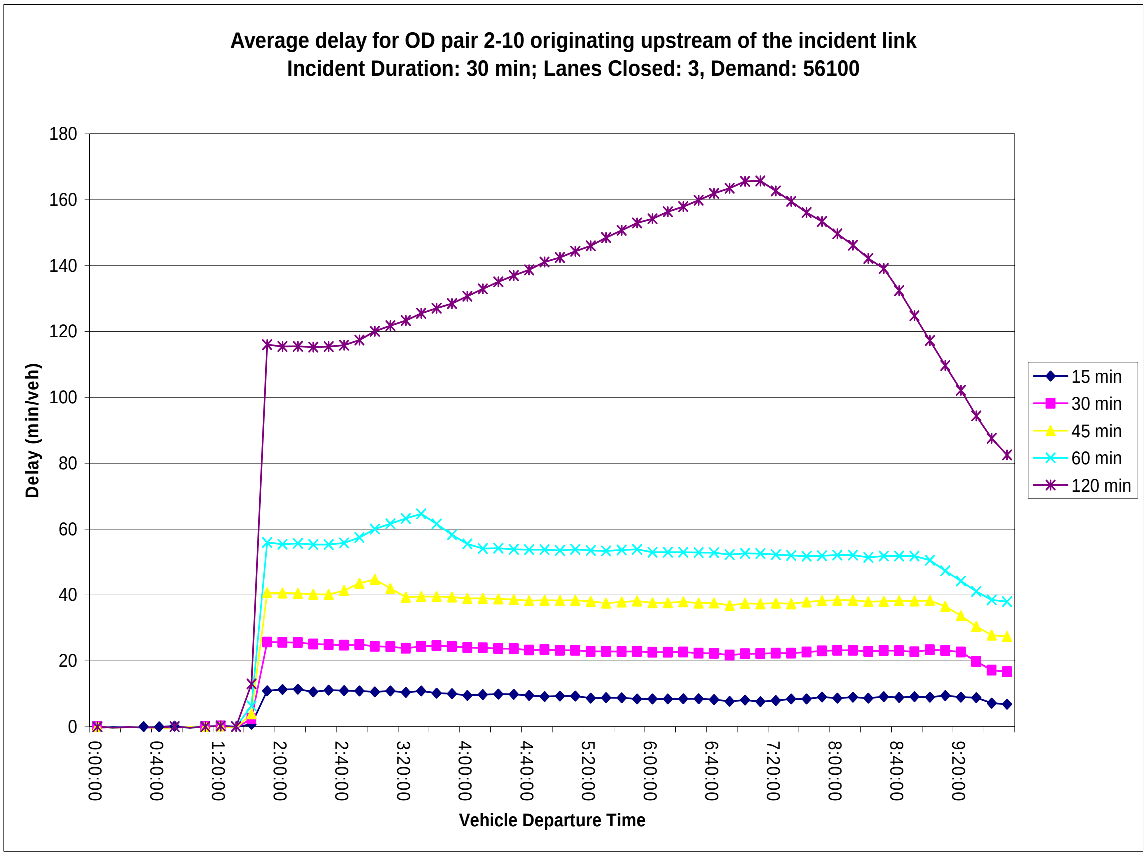

Figure 5.3.5 Temporal distribution of delay for OD pair (2-10) per incident duration

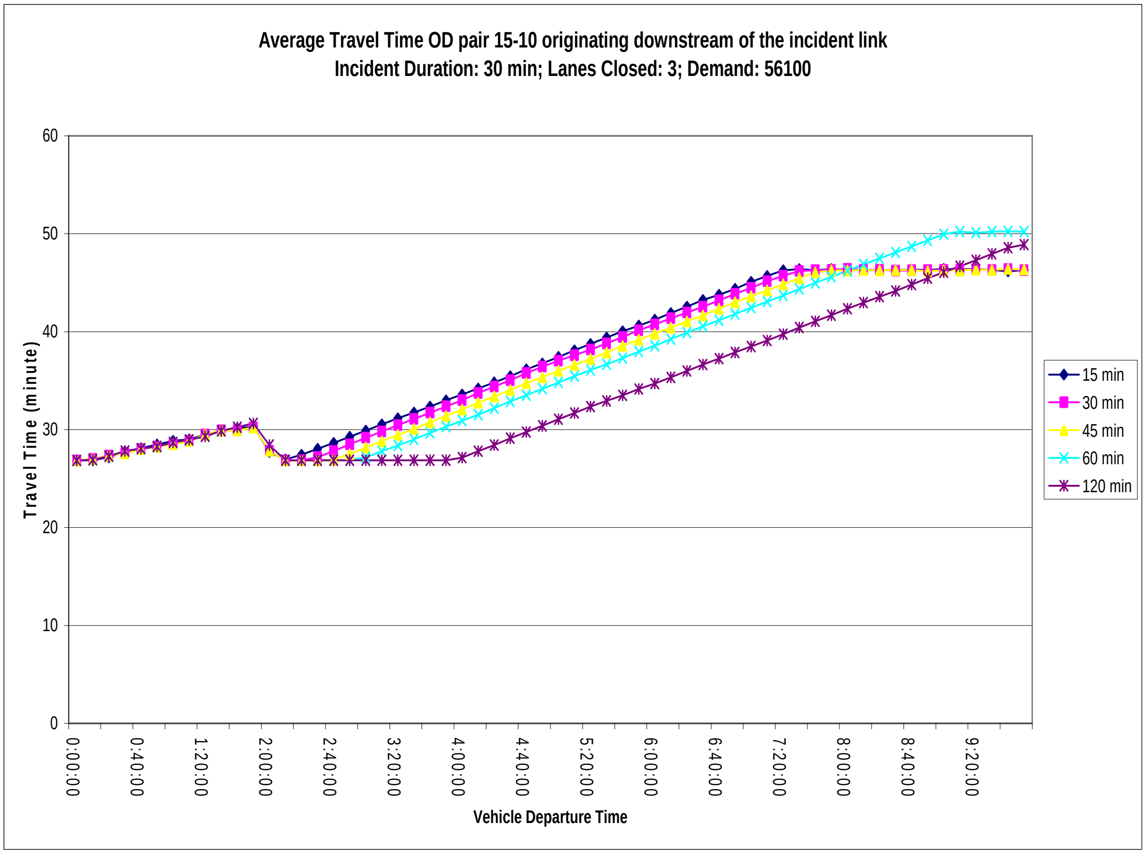

Figure 5.3.6 Temporal distribution of travel time for OD pair (15-10) per incident duration

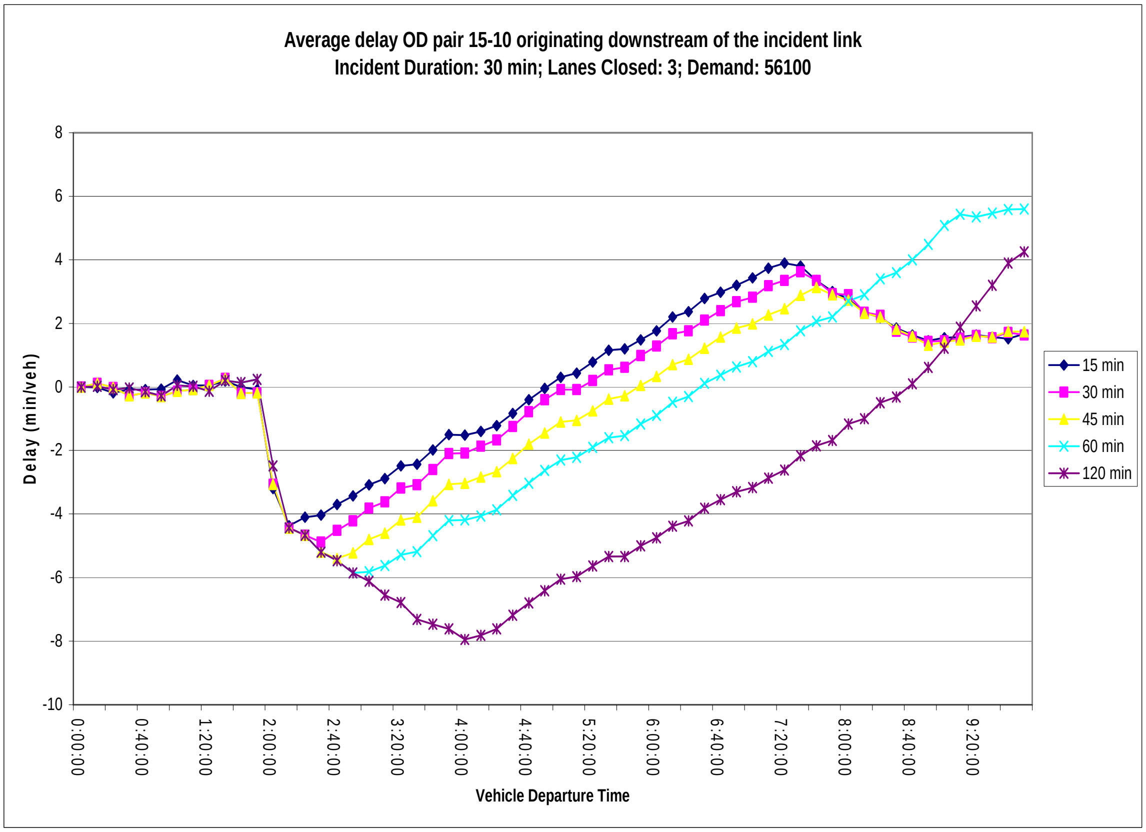

Figure 5.3.7 Temporal distribution of delay for OD pair (15-10) per incident duration

5.3.2 Incident Duration Effects on Incident Delay for Network #2

The small extraction of the Chicago network has been simulated with varying incident durations of 15 to 120 minutes. The closure definition data is presented in Table 5.3.4 and shown in Figure 5.3.7. The base case results depicting prevailing incident-free conditions are shown in Table 5.3.5

Table 5.3.4 Incident closure data for the incident duration analysis of Network #2

Link ID	Length	Speed	Capacity	Start Time	Lanes Closed
19691	4,160 ft	55 mph	1,800 vphpl	3:00:00	3

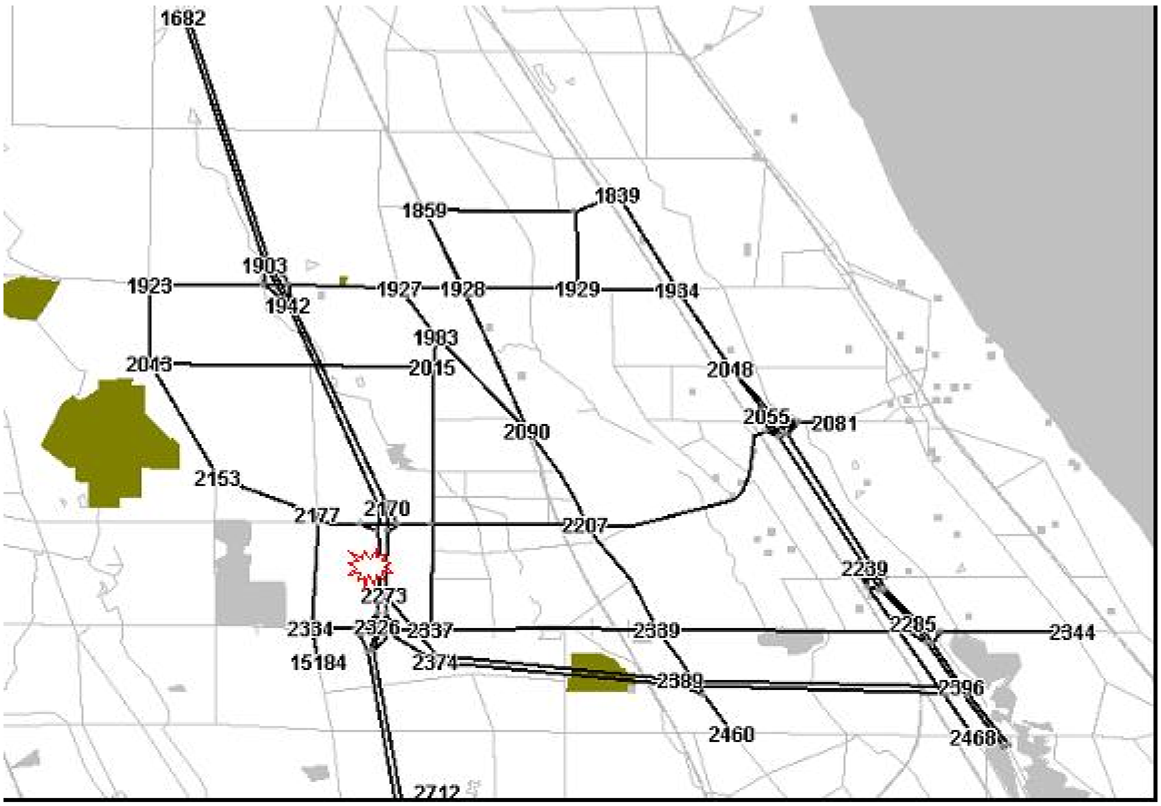

Figure 5.3.8 Network #2 with incident at link #19691

Table 5.3.5 Results for the base case, Network #2

Demand (vehicles)	Total TT (hr)	AVG TT (min/veh)	STD (min/veh)	VMT (Miles)
190,259	52,620	16.59	16.89	1,209,655

Tables 5.3.6 and 5.3.7 show that the impacts of the incident on the overall network increase with its duration as depicted by the total travel time, the average travel

time per vehicle, the vehicle miles traveled, and the average delay per vehicle on the network.

Table 5.3.6 Results for the incident case with no provision of incident information

Incident Duration (min)	Vehicle Type	Total Travel Time (hr)	AVG Travel Time (min/veh)	STD (min/veh)	VMT (miles)
15	all	53,221	16.78	17.00	1,209,655
30	all	55,041	17.37	17.60	1,209,655
45	all	58,453	18.44	19.18	1,209,655
60	all	67,740	21.37	23.98	1,209,655
120	all	130,522	41.18	55.97	1,209,655

Table 5.3.7 Results for the incident case with provision of incident information

Incident Duration (min)	Vehicle Type	Total Travel Time (hr)	AVG Travel Time (min/veh)	STD (min)	VMT (miles)
15	all	53,078	16.74	16.99	1,212,251
30	all	53,523	16.89	17.13	1,210,266
45	all	55,063	17.37	17.80	1,209,772
60	all	58,139	18.34	19.32	1,213,255
120	all	93,882	29.62	39.81	1,209,907

Table 5.3.8 and Figure 5.3.8 display the network wide average delay per vehicle as a function of the incident duration for both incident cases. Figure 5.3.9 displays the network total delay in vehicle-hour as a function of the incident duration. There is a non-linear relationship between the incident duration and the delay as demonstrated by the following models:

No information provided (RouteSim)

$D = 0.209 - 0.0516X + 0.00212X^2$ (R-Sq = 0.999)

$D = 0.0808 – 0.0263X + 0.0014X^2 + 0.00000388X^3$ (R-Sq = 0.999)

With information provided (DUE)

$D = 0.279 – 0.0459X - 0.00126X^2$ (R-Sq = 0.997)

$D = 0.01519 + 0.00605X - 0.0001029X^2 + 0.00000797X^3$ (R-Sq = 1.0)

where,
D is the average delay in minute per vehicle for the network

X is the incident duration in minute

Table 5.3.8 Delay on the overall network (#2) for both incident cases

		RouteSim (no information)			DUE (with information)		
Incident Duration (min)	Vehicle Type	AVG Delay (min/veh)	STD (min/veh)	Delay (VH)	AVG Delay (min/veh)	STD (min/veh)	Delay (VH)
15	all	0.19	33.89	602	0.15	33.88	476
30	all	0.78	34.49	2,473	0.30	34.02	951
45	all	1.85	36.07	5,866	0.78	34.69	2,473
60	all	4.78	40.87	15,157	1.75	36.21	5,549
120	all	24.59	72.86	77,974	13.03	56.7	41,318

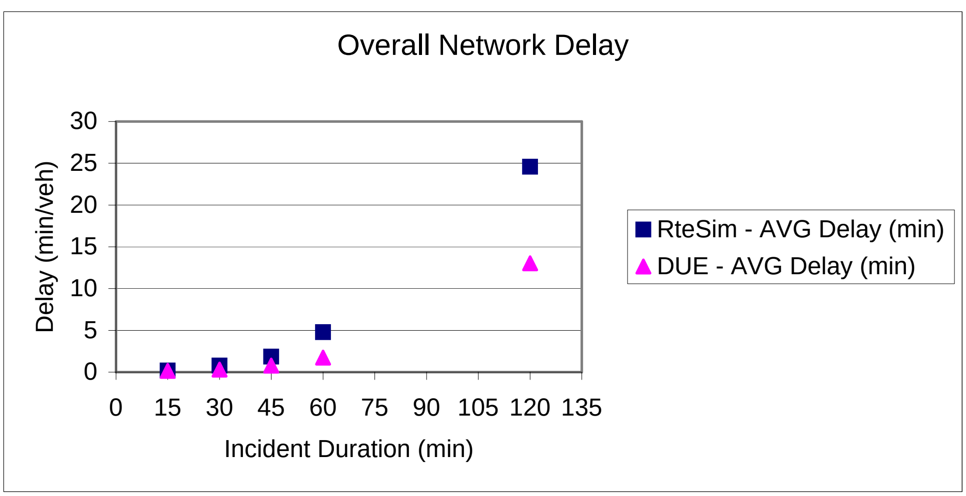

Figure 5.3.9 Average delay on the network (#2) for both incident cases

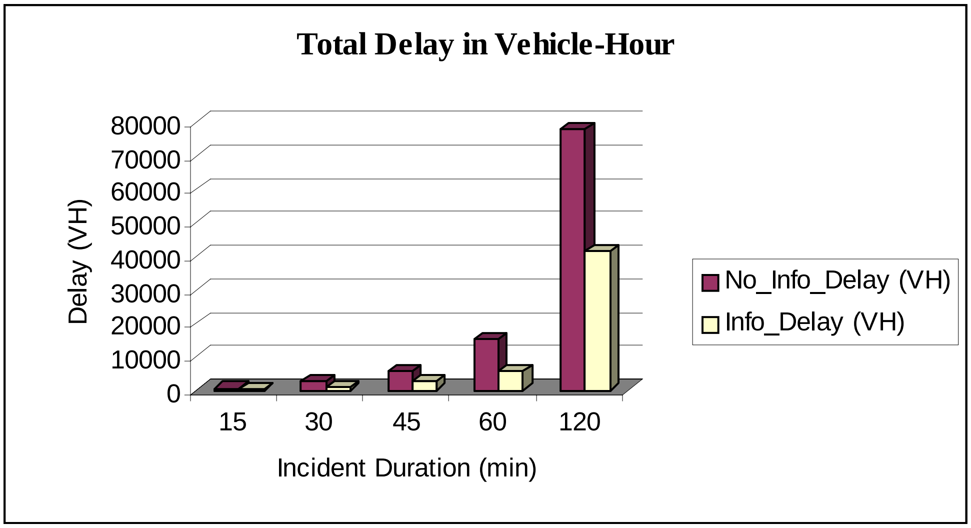

Figure 5.3.10 Total delay on the network (#2) for both incident cases

The tables (5.3.9 and 5.3.10) show the temporal distribution of the vehicles for OD pairs with demand more than 2000 vehicles and with paths that do not include the incident link. For incident durations of 15 and 30 minutes, none of these OD pairs experience any delay. For incident durations above 60 minutes, two OD pairs (101682-202204 and 102478-202204) experience a delay when no incident information is provided to travelers. With the provision of incident information to travelers, a single OD pair 101682-202204 experiences delays when the incident duration is120 minutes.

Table 5.3.9 Delay for some OD pairs with no provision of incident information

Simulation: RouteSim				Incident: 45min		Incident: 60min		Incident: 120min	
OD Pairs	Path (included links)	Length (mile)	Demand	Delay (min)	STD	Delay (min)	STD	Delay (min)	STD
101682-202204	{43870,19021,18983,25030,13133,34802,30200,13153,43902}	5.92	2,087	0.00	0.37	**7.85**	0.44	**60.02**	0.70
102460-202483	{43886,33319,28589,13188,34856,34864,19475,18923,19948,43909}	4.3	12,168	0.00	0.09	0.00	0.09	0.00	0.09
102334-202712	{43883,34850,20141,20032,43910}	3.39	12,174	0.00	0.07	0.00	0.07	0.00	0.07
101839-202468	{43871,13142,34808,18897,43858,19945,43861,19947,19419,13197,34866,43908}	5.96	4,375	0.00	0.08	0.00	0.08	0.03	0.08
102478-201839	{43888,18921,19946,20036,19195,43860,18898,19689,43859,13141,34809,43892}	5.96	2,999	0.00	0.07	0.00	0.07	0.00	0.07
102478-202204	{43888,18921,18919,20019,19024,19693,21620,7136,43902}	6.24	5,403	0.00	0.07	0.00	0.07	**4.92**	0.27
102478-202344	{43888,18921,19946,19418,8631,43906}	2.29	7,404	0.00	0.07	0.00	0.07	0.00	0.07
101923-202015	{43874,34951,13150,43899}	2.78	2,133	0.00	0.06	0.00	0.06	0.00	0.06
102334-202483	{43883,34850,31655,31654,28789,34856,34864,19475,18923,19948,43909}	5.63	3,655	0.00	0.08	0.00	0.08	0.00	0.08
102204-201683	{43881,28803,43867,21622,19019,19016,43891}	5.32	3,520	0.00	0.06	0.00	0.06	0.00	0.06

Table 5.3.10 Delay for some OD pairs with provision of incident information

Simulation: DUE				Incident: 45min		Incident: 60min		Incident: 120min	
OD Pairs	Path (included links)	Length (mile)	Demand	Delay (min)	STD	Delay (min)	STD	Delay (min)	STD
101682-202204	{43870,19021,18983,25030,13133,34802,30200,13153,43902}	5.92	2,087	-0.02	0.37	0.50	0.36	**33.09**	0.53
102460-202483	{43886,33319,28589,13188,34856,34864,19475,18923,19948,43909}	4.3	12,168	0.00	0.09	0.00	0.09	0.00	0.09
102334-202712	{43883,34850,20141,20032,43910}	3.39	12,174	0.00	0.07	0.00	0.07	0.00	0.07
101839-202468	{43871,13142,34808,18897,43858,19945,43861,19947,19419,13197,34866,43908}	5.96	4,375	0.00	0.08	0.00	0.08	0.03	0.08
102478-201839	{43888,18921,19946,20036,19195,43860,18898,19689,43859,13141,34809,43892}	5.96	2,999	0.00	0.07	0.00	0.07	0.00	0.07
102478-202204	{43888,18921,18919,20019,19024,19693,21620,7136,43902}	6.24	5,403	0.00	0.07	0.00	0.07	0.00	0.07
102478-202344	{43888,18921,19946,19418,8631,43906}	2.29	7,404	0.00	0.07	0.00	0.07	0.00	0.07
101923-202015	{43874,34951,13150,43899}	2.78	2,133	0.00	0.06	0.00	0.06	0.00	0.06
102334-202483	{43883,34850,31655,31654,28789,34856,34864,19475,18923,19948,43909}	5.63	3,655	0.00	0.08	0.00	0.08	0.00	0.08
102204-201683	{43881,28803,43867,21622,19019,19016,43891}	5.32	3,520	0.00	0.06	0.00	0.06	0.00	0.06

The vehicle demand distribution does not reveal any conclusive characteristic for OD pairs with paths that include the incident link. Generally, one can expect that more vehicles will be diverted away from the incident as its duration increases. As illustrated in Figure 5.3.10 less than 3% of vehicles are diverted away from the incident link and approximately 7% of vehicles are diverted from the incident link when the incident duration is 120 minutes.

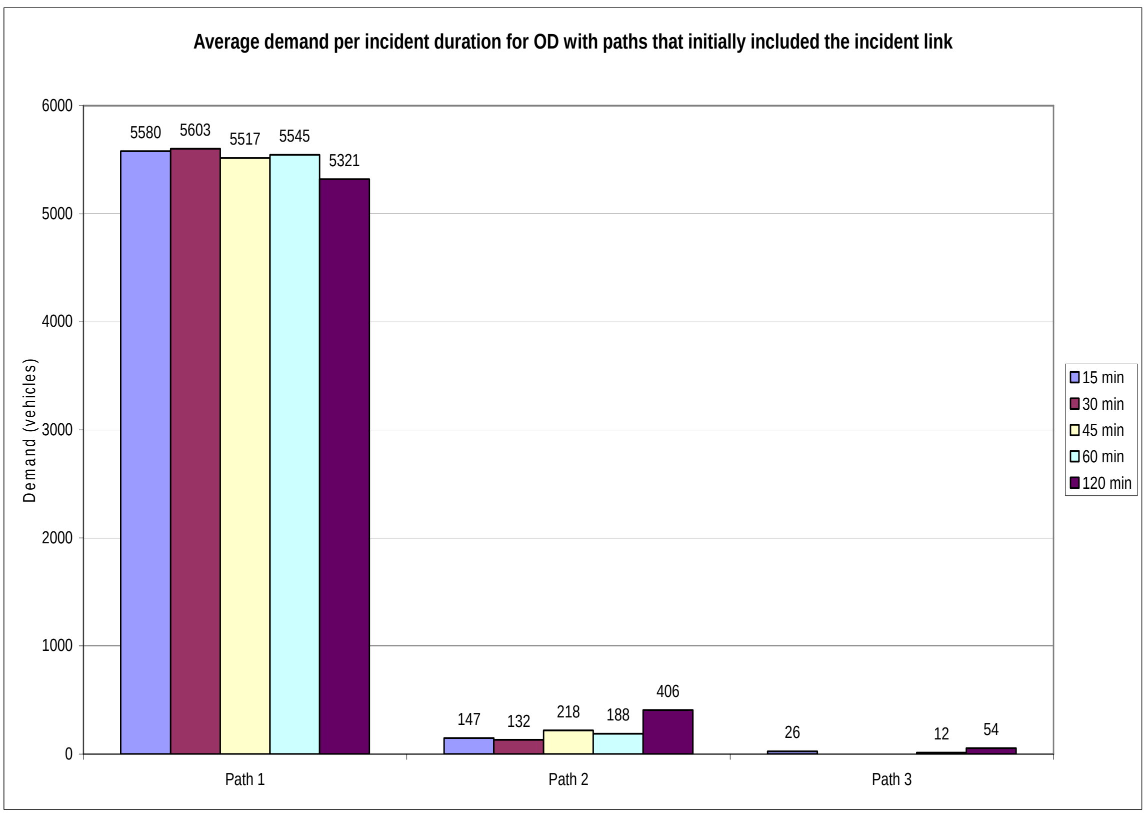

Figure 5.3.11 Demand per incident duration after rerouting

As illustrated in Figure 5.3.11, the average delay per vehicle is higher in the initial path of the base case compared to the delay for the alternative paths. Even though the chart (Figure 5.3.11) shows a high average delay for the 60 minutes duration on path

3, it is noted on Figure 5.3.12, that there are only 12 vehicles that experience this level of delay and therefore the total delay on this path is not significant as shown in Figure 5.3.12. Most vehicles on the second alternative path are improving their average travel time of the base case except when the incident duration is 120 minutes. Vehicles using the second alternative path are actually experiencing a positive impact caused by the presence of the incident.

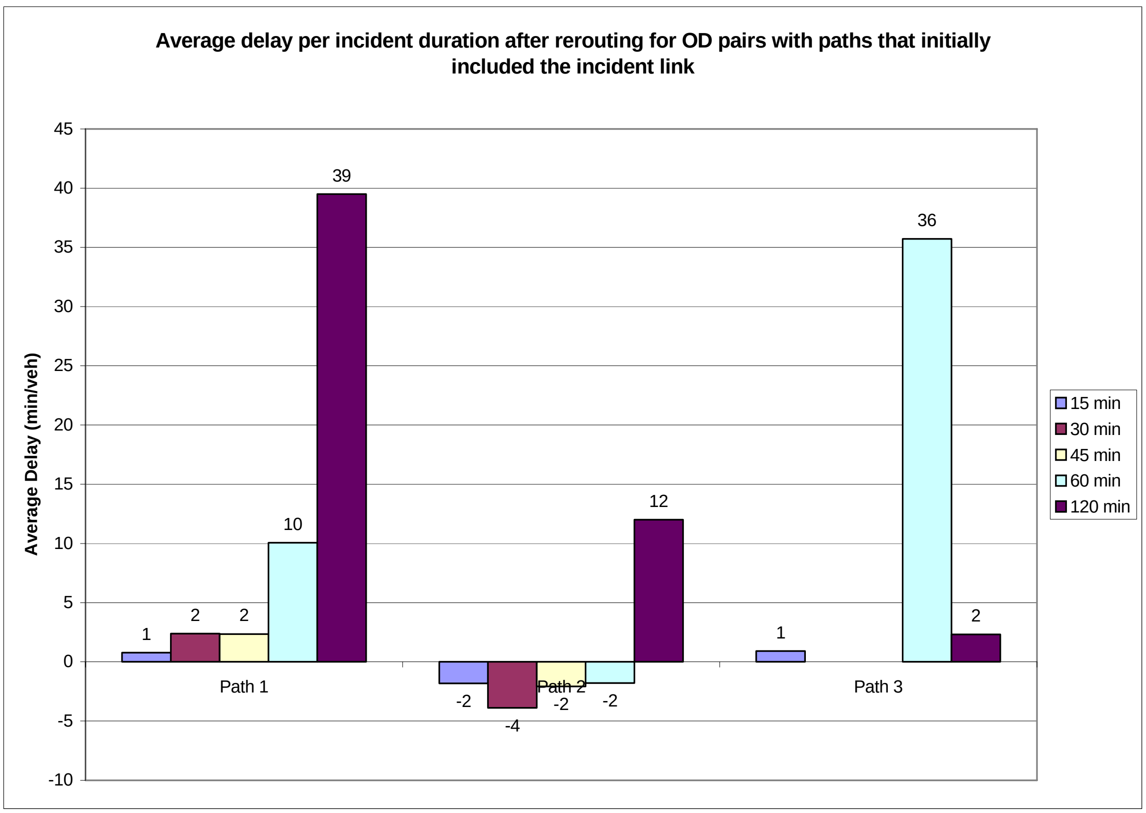

Figure 5.3.12 Average delay per incident duration after rerouting for OD pairs with paths that initially included the incident link

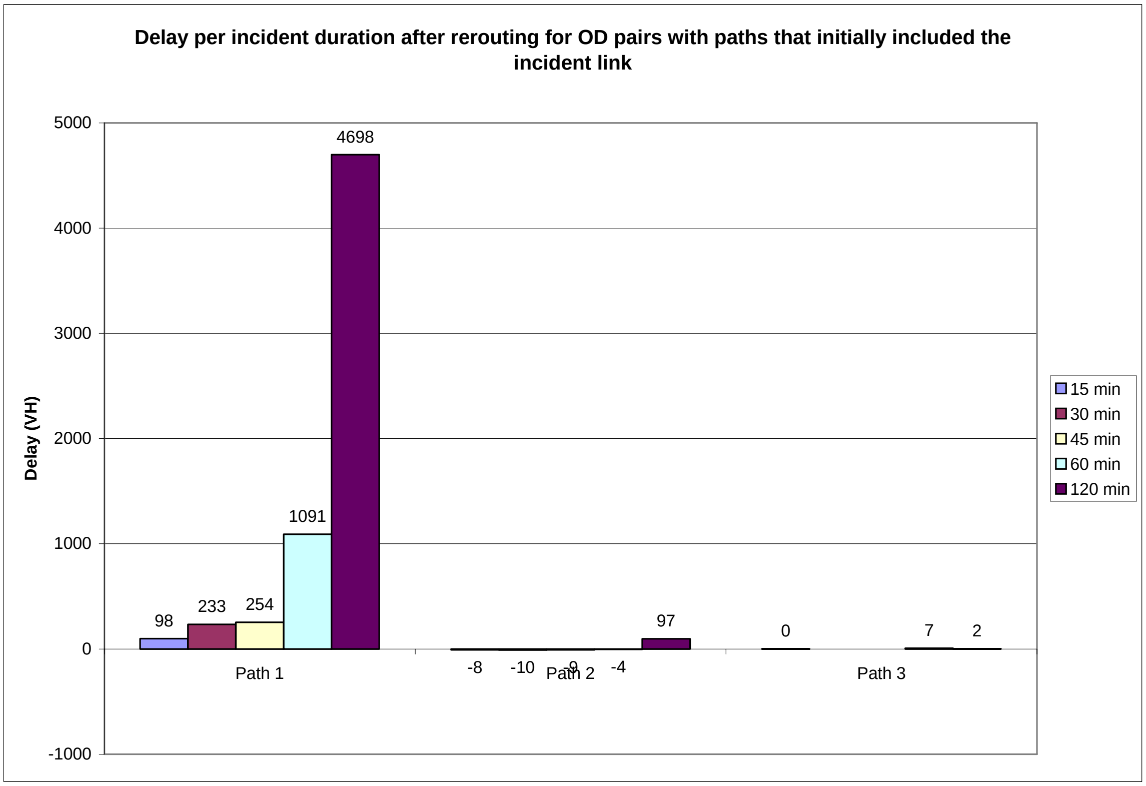

Figure 5.3.13 Delay per incident duration after rerouting for OD pairs with paths that initially included the incident link

An incident has an impact on the network that lasts longer than its duration. From the point of view of the overall network, the severity of impacts of incidents increases with its duration. These results are consistent with the general observation that delay caused by incidents depends on how quickly the incident can be cleared. Therefore incident management strategies should be guided toward responding quickly to an incident in order to reduce its clearance time. Detection, dispatching, and response to freeway and highway incidents should receive more attention from an operational perspective. It was observed that the recovery time from an incident might not always depend on its duration. Short incident duration may experience approximately the same recovery time as long-lasting incidents, however the intensity of the impact is less severe for shorter incidents and more acute for incidents that last longer. At the OD level, it was observed that some vehicles not traversing the incident link may be positively impacted by the incident if originating downstream of the affected link. It was found that the average incident-induced delay per vehicle at the network level exhibits both a cubic or quadratic relation with the incident duration with high coefficients of correlation.

5.4 Lane Blockage Effects on Incident Delay (Capacity Reduction)

Incidents reduce freeway capacity when they block traffic lanes. Many studies in the literature indicate that the capacity reduction (or remaining capacity) of lane blockages due to incidents is disproportionate to the physical lane blockage (Lindley, 1986, 1987; McShane, 1990; and Skabardonis, 1996). For example, Skabardonis (1996) finds that incidents blocking one lane reduce capacity by 51 percent on a six-lane freeway and by 42 percent on an eight-lane facility. In this section, VISTA software is used to analyze the impacts of lane blockage from incidents on delay.

The principal objective of this section is not to find the available capacity resulting from lane blockages, but rather to determine the impacts of lane blockage on travel time and delay. In VISTA, the lane closure variable may be used to depict the severity of the incident. Severe incidents cause more pronounced freeway blockage. A closure of two lanes of a three-lane freeway with a severity of one will not result in any reduction of the available capacity of the roadway. The severity is considered as the available physical capacity remaining after the closure of the lanes. VISTA will treat it as if the roadway is performing at full capacity. A closure of two lanes of a three-lane freeway with a severity of 0.33 will result to 2/3 reduction of the available capacity. The severity represents the remaining physical capacity resulting from a lane blockage.

As in the previous sections, Network #1 will be used for the case study. Incidents with one lane to full closure of the three-lane freeway are simulated. Table 5.4.1 exhibits the network characteristics and Table 5.4.2 shows the resulting travel times for each of the lane blockage scheme. The total travel time in the network increases with the number of lanes blocked.

Table 5.4.1 Parameters of the simulation for Network #1 for the lanes blockage analysis

Nodes	12	Simulation Duration	10 hours
Links	11	Demand Distribution	Uniform
# Lanes per link	3	Incident Link	#4
Free Flow Speed	55 mph	Incident Start Time	2:00:00
Max. Capacity	2,000 vphpl	Total Demand (2)	51,000 and 56,100

Table 5.4.2 Travel time for lanes blockage scenarios, overall network

	Demand: 51,000 vehicles Incident Duration: 30 minutes			Demand: 56,100 vehicles Incident Duration: 45 minutes		
	1 lane	2 lanes	3 lanes	1 lane	2 lanes	3 lanes
Total Travel Time (hr)	29,669	33,197	42,032	42,514	51,940	63,078
AVG TT (min/veh)	34.91	39.06	49.45	45.47	55.55	67.46
STD	5.06	8.95	15.88	8.28	16.06	25.69

(min/veh)						

Figures 5.4.1 and 5.4.2 display at the network level, the temporal impact of lane closure due to an incident for a demand of 51000 and 56100 vehicles and for incidents that start at 2:00:00 and last 30 and 45 minutes, respectively. It is observed that the incident impact increases with the number of lanes closed. As the number of lanes blocked increases, the intensity of the incident impact will increase accordingly. A closure of one lane does not exhibit any detectable impact on the three-lane freeway for this incident scenario. The closure of two or three lanes creates a delay in the network. The figures show a negative impact on travel time that lasts beyond the incident duration time. A 2-lane blockage exhibits a shorter recovery time than a 3-lane blockage at the network level.

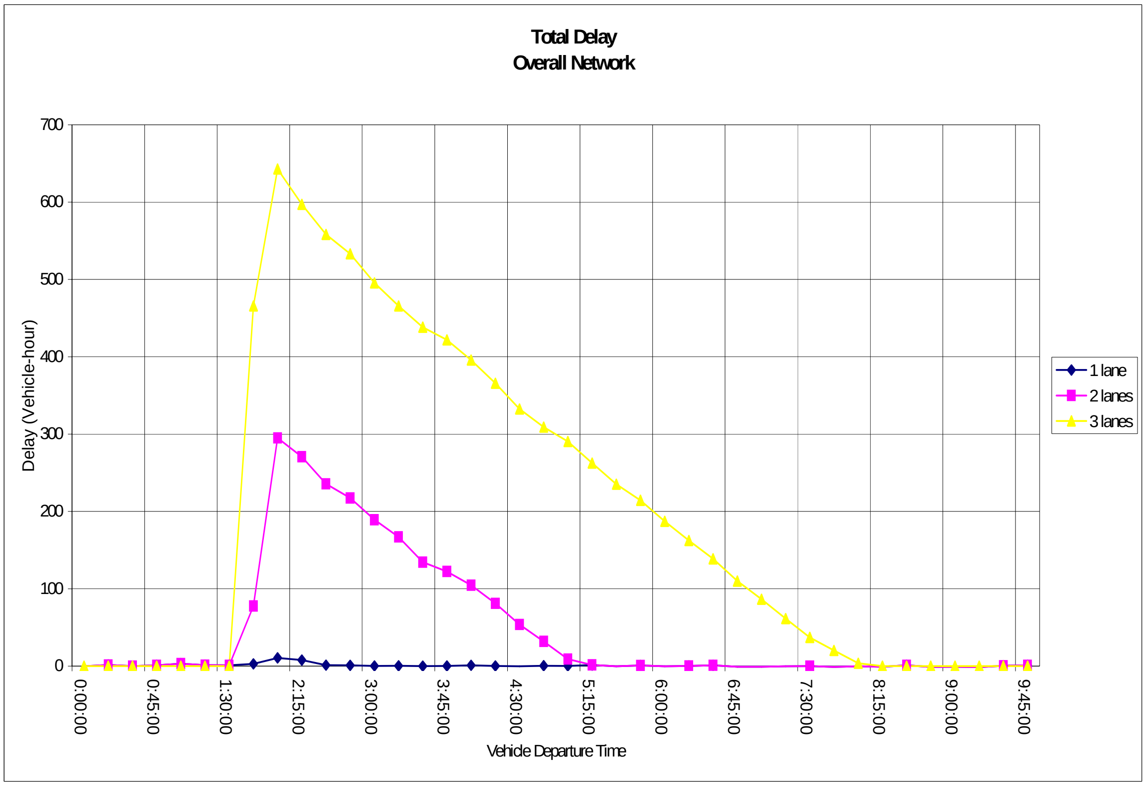

Figure 5.4.1 Temporal distribution of delay per lanes closed for the overall network (demand: 51,000)

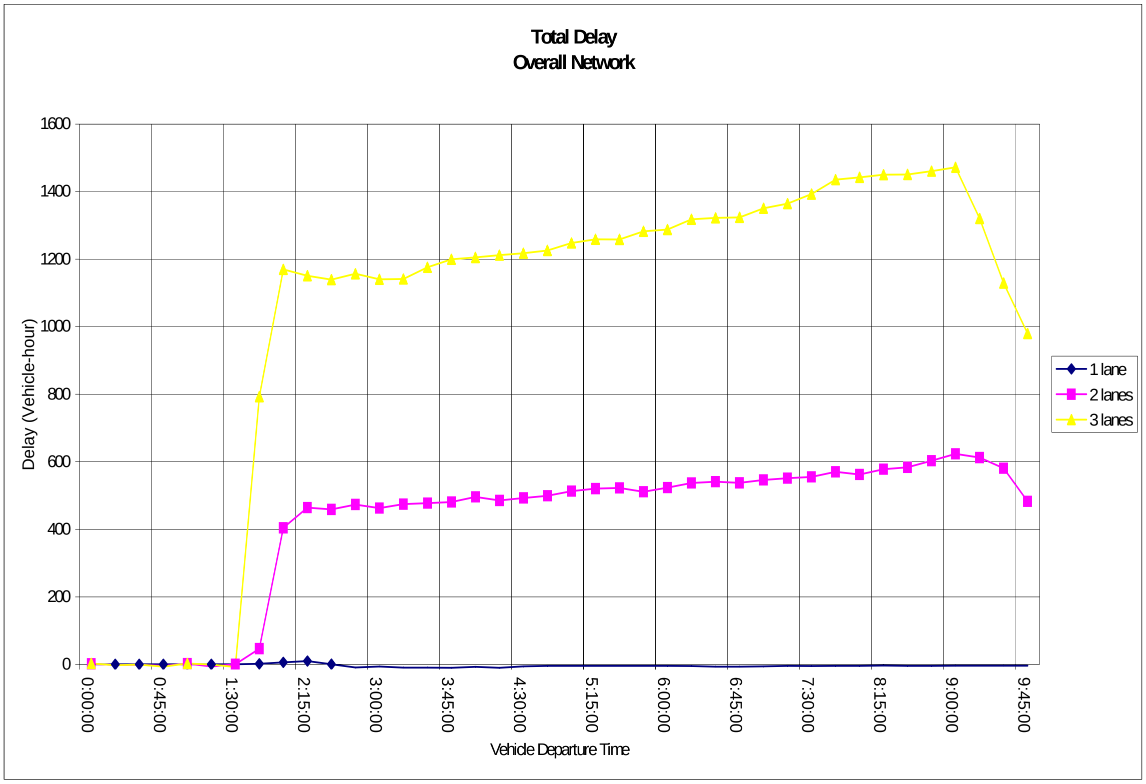

Figure 5.4.2 Temporal distribution of delay per lanes closed for the overall network (demand: 56,000)

Figure 5.4.3 shows that the extent of the reduction of the available capacity of the incident link has on the performance of the roadway. The impacts caused by the blockage of lanes increase with the duration of the incident. The figure shows that the gap between the delays among lanes closed increases with the incident duration. In addition, the average delay per vehicle increases with the number of lanes closed. From the point of view of the network-wide performance, one may conclude that sometimes, a brief incident with full closure may have a lesser impact on the freeway than a longer incident with few lanes closed. Therefore, incident management strategies would be more effective in closing more lanes as needed to quickly clear the incident than closing few lanes that may result in longer incident clearance and recovery time. These results strengthen the importance of incident management strategy of quickly responding and clearing incidents on freeways. Minimizing the duration of the incident plays an important role towards reducing the overall network delay than merely reducing the number of lanes closed. Therefore, minimizing the incident duration should be the most important element in the development of incident management strategies that seek to reduce traffic-related impacts of incidents.

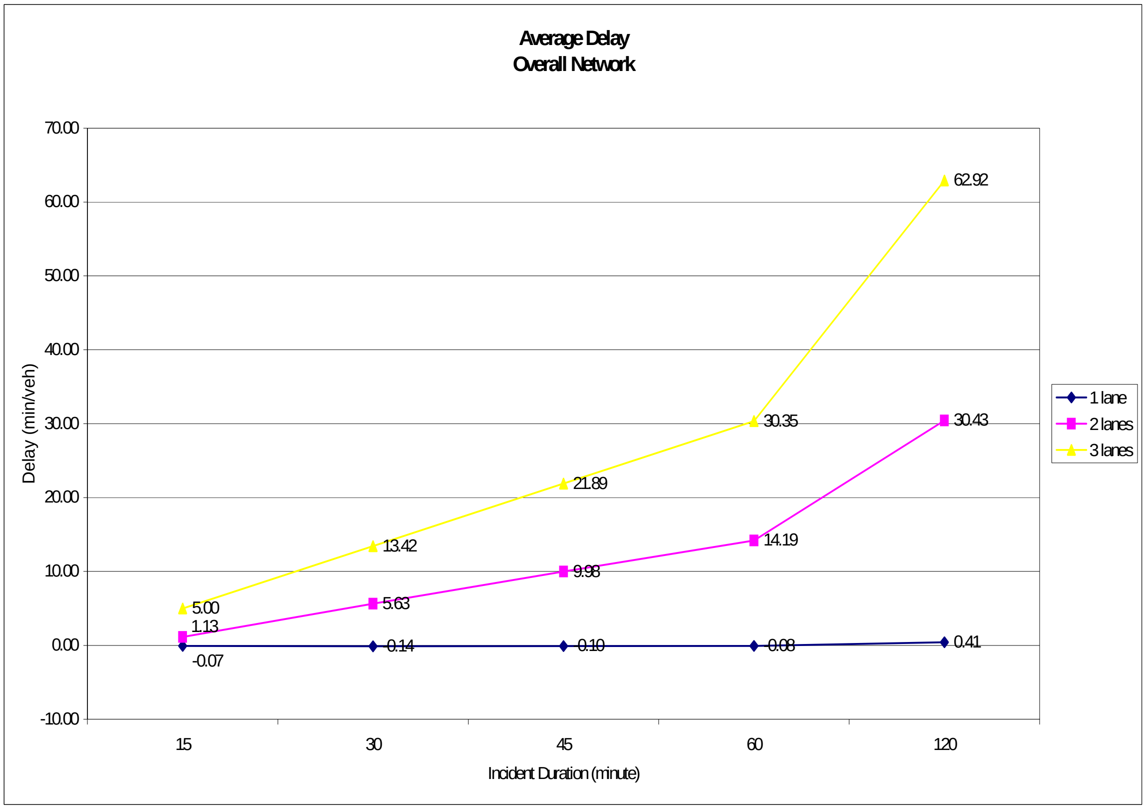

Figure 5.4.3 Average delay by incident duration and lane closures (demand: 56100)

Figures 5.4.4 through Figure 5.4.7 show the temporal distribution of the impact of incident per the number of lanes closed for an OD pair that originates downstream of the incident and for an OD pair with origin upstream of the incident. For the incident scenarios of two or three lanes closure, the vehicles originating downstream of the incident are negatively affected by the incident after the affected lanes are reopened. The downstream vehicles experience traffic disturbances resulting from an increase of flow upstream. The impacts of the incident start at its time of occurrence for upstream vehicles, while it starts at its end for downstream vehicles.

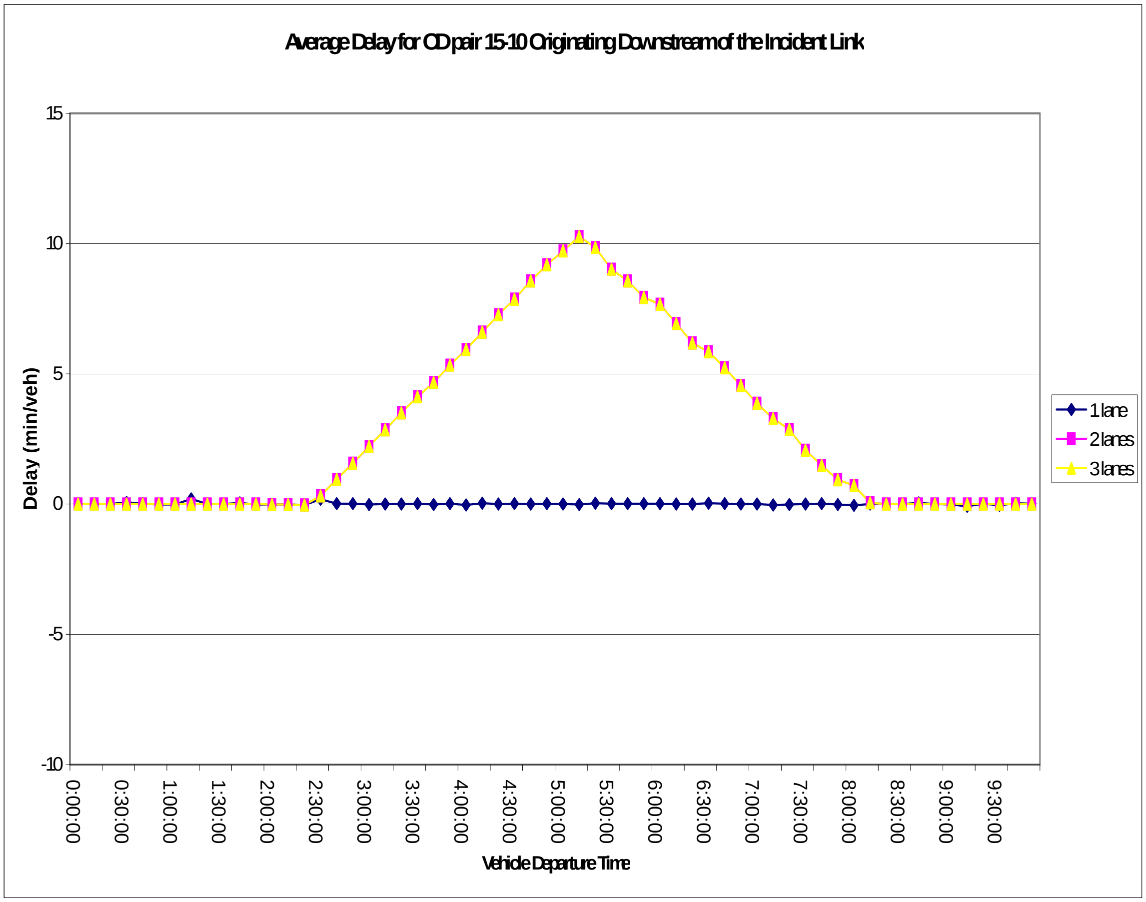

Figure 5.4.4 Temporal distribution of average delay per lane blocked for OD (15-10) with origin downstream of the incident link (demand: 51000)

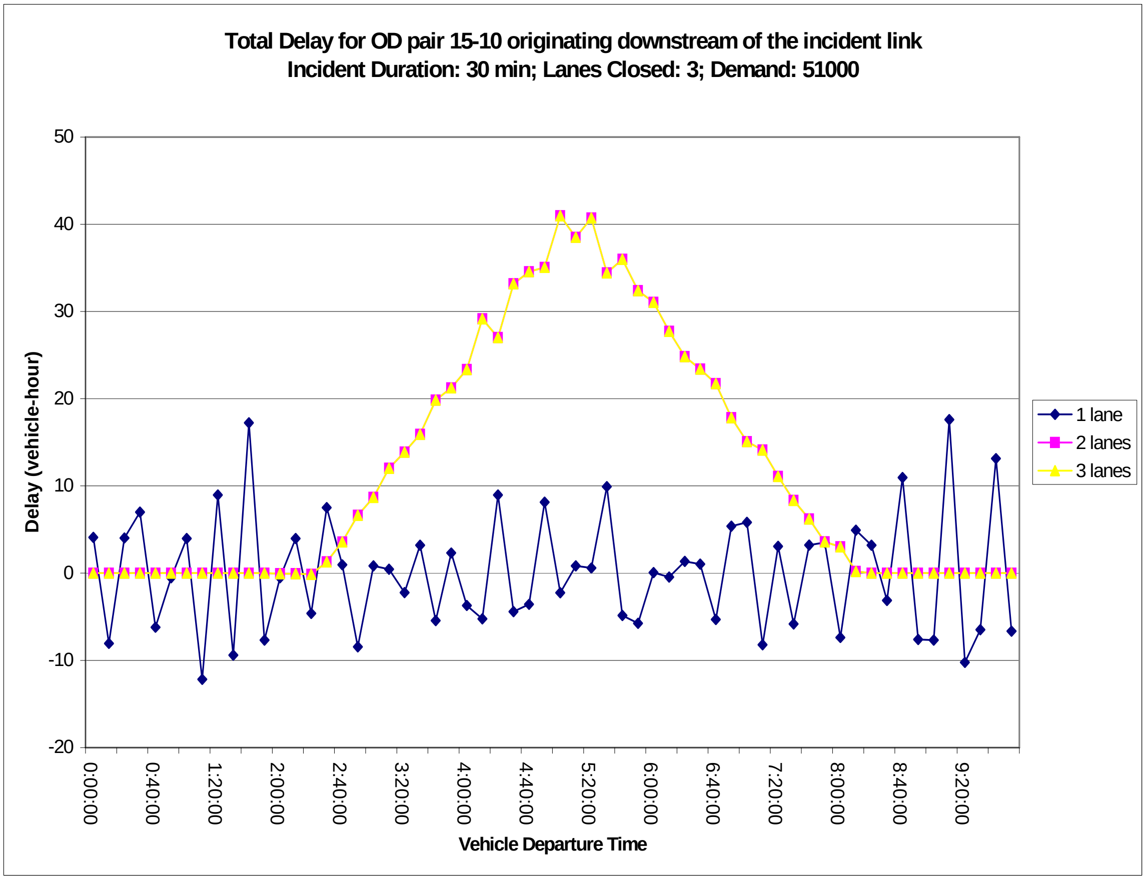

Figure 5.4.5 Temporal distribution of total delay per lane blocked for OD (15-10) with origin downstream of the incident link (demand: 51000)

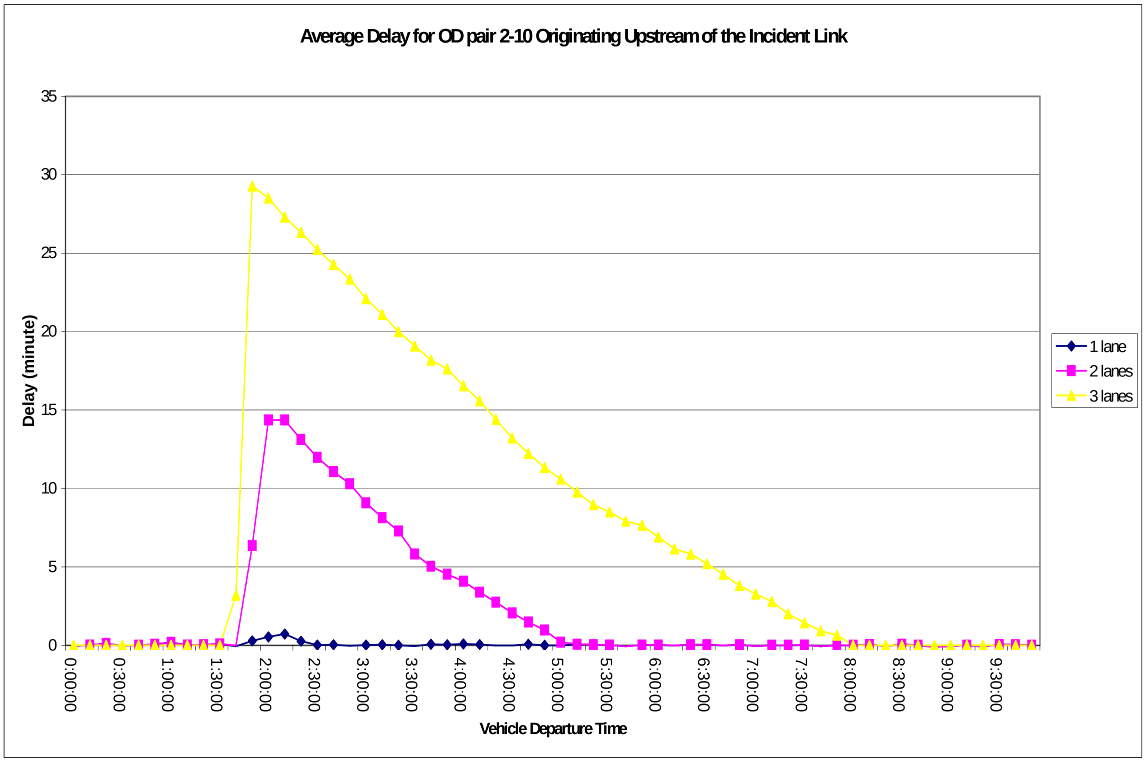

Figure 5.4.6 Temporal distribution of average delay per lane blocked for OD (2-10) with origin upstream of the incident link (demand: 51000)

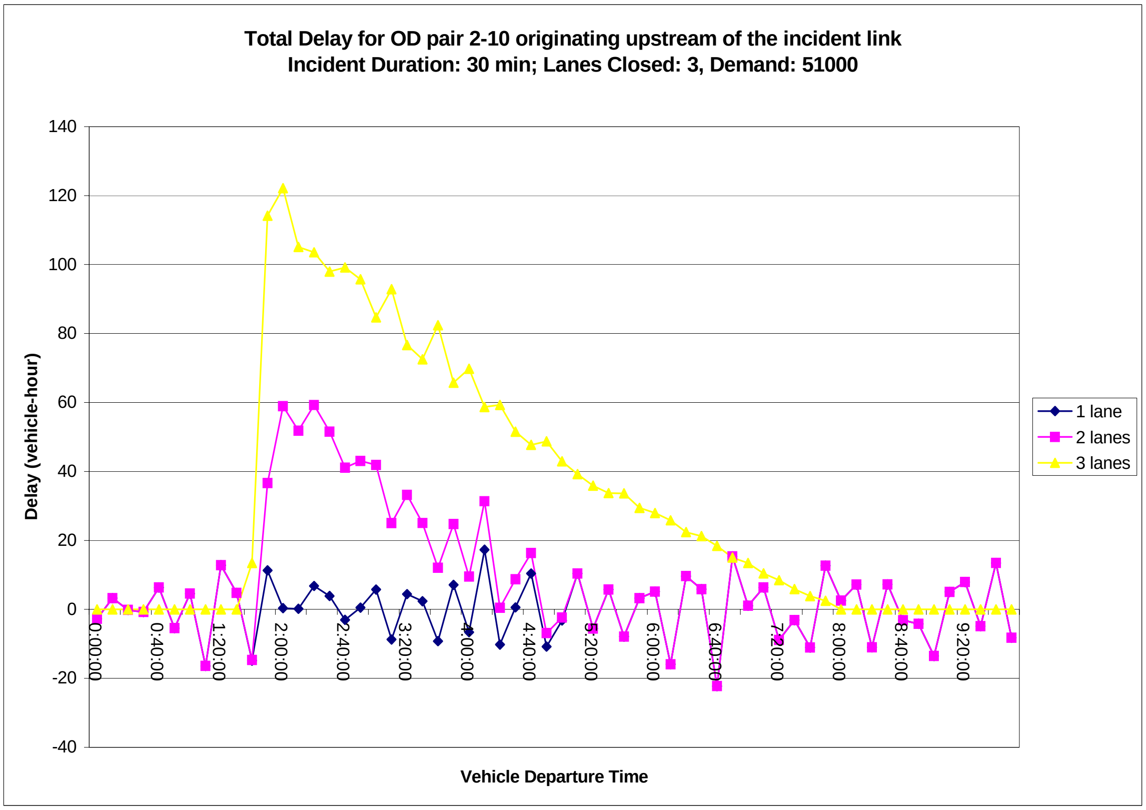

Figure 5.4.7 Temporal distribution of total delay per lane blocked for OD (2-10) with origin upstream of the incident link (demand: 51000)

5.5 Demand Effects on Incident Delay (congested vs non-congested)

This section deals with the impact caused by the vehicle demand on a roadway under incident conditions. Previous incident delay models are only applicable to non-congested conditions. With the DTA simulation software, more types of traffic conditions can be simulated. The proposed method of calculating incident-induced delay can be applied to congested or non-congested traffic conditions. Under congested conditions, the method will separate the true delay caused by the incident (sometimes misrepresented or non-perceived by motorists) from the recurrent delay that may already be present in the network.

The section of freeway (Network #1) is used for the analysis. The network is simulated for different demand levels under no-incident and incident conditions. The demand profile is kept constant during the 10-hour simulation time to facilitate the understanding of the analysis even though in reality, the travel demand changes by time of the day.

The travel time shown in Table 5.5.1 represents the average travel time of vehicles from their origins to their final destinations under non-incident conditions. It is observed that the total travel time in the network increases with the vehicle demand level. The total demand on the network is varying from a demand-to-capacity ratio of 0.81 to 1.02 as illustrated in the following charts and graphs. As shown in Figure 5.5.2, the network at demand levels of 48572, 51000, and 53428 are operating under non-congested conditions and at demand levels of 56100, 57218, and 61200 are operating close to capacity or congested conditions. As displayed in Figure 5.5.1, vehicles at the latter demand levels are experiencing a recurrent delay resulting from the high demand conditions. The recurrent delay is shown to increase with the network demand.

Table 5.5.1 Network #1 – DTA results for different level of demand (base case)

Total Demand (vehicles)	Average Travel Time (minutes)	Standard Deviation (minutes)	Total Travel Time (hours)
48,572	34.83	5.02	28,198
51,000	34.86	5.06	29,633

53,428	34.98	5.05	31,149
56,100	45.57	8.12	42,609
57,218	51.06	12.34	48,689
61,200	73.28	31.18	74,745

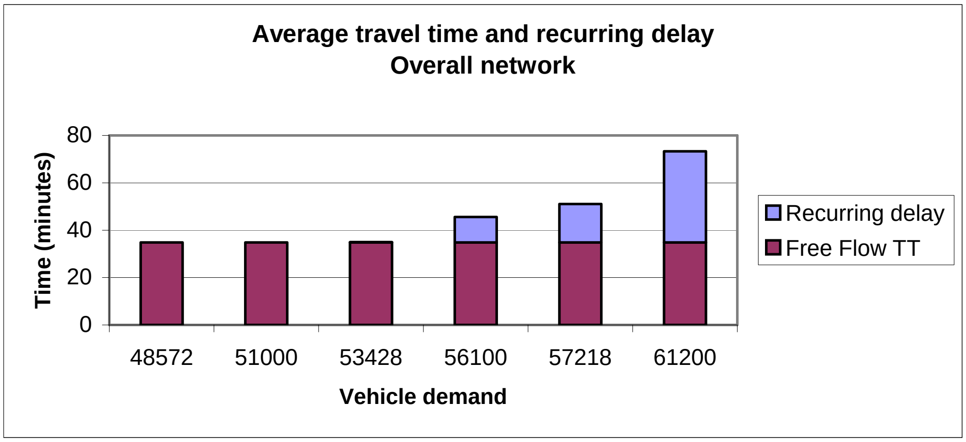

Figure 5.5.1 Average travel time and recurring delay at network level (base case)

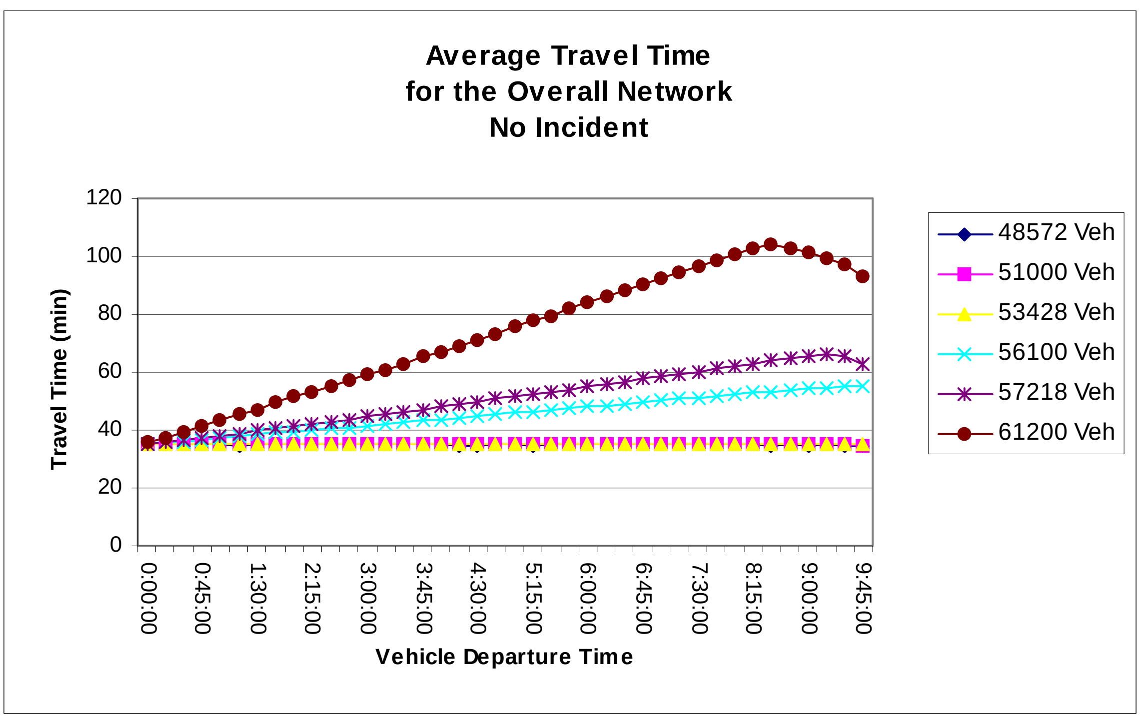

Figure 5.5.2 Temporal distribution of travel time at the network level (base case)

An incident with a duration of 30 minutes that closes three lanes on link #4 is simulated for all demand levels illustrated above. The chart displayed on Figure 5.5.3 shows the average travel time on the network as a function of the demand level under the incident conditions. It is observed that the average travel time per vehicle increases with the demand level.

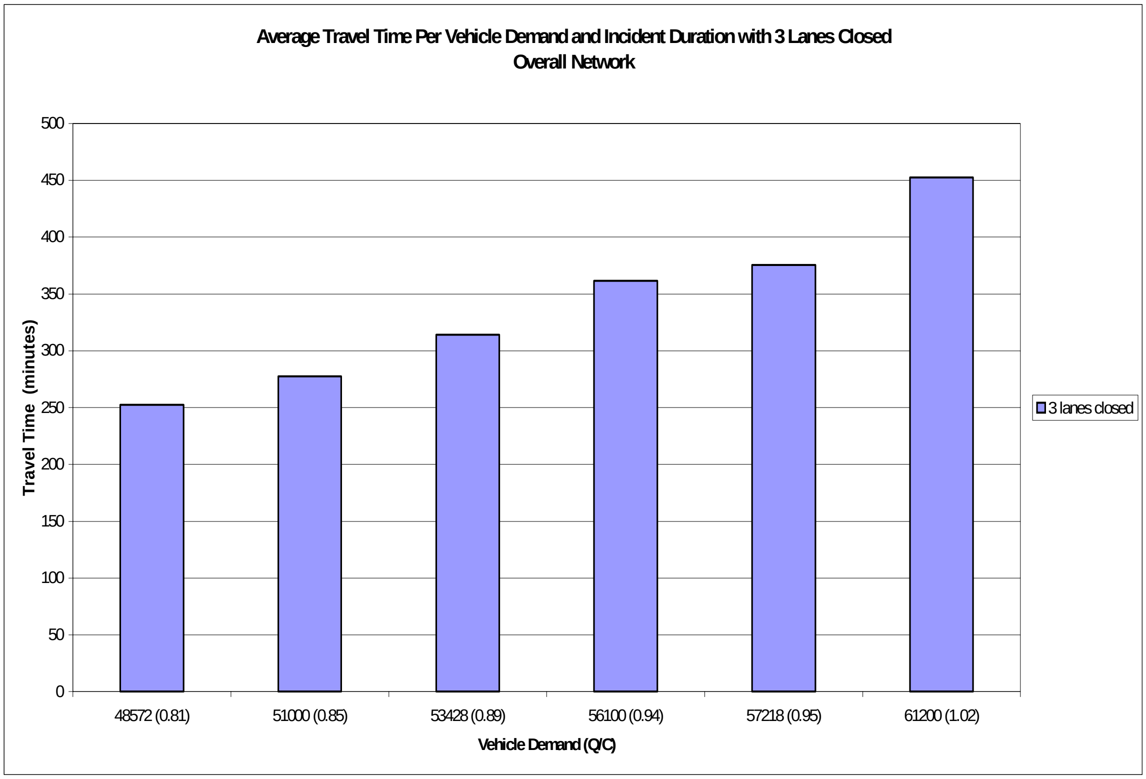

Figure 5.5.3 Average travel time per demand for the overall network (incident case)

Figure 5.5.4 displays a breakdown of average travel time per vehicle under incident conditions. The travel time is composed of three components: travel time at free flow, recurring delay, and incident-induced delay. At demand level under non-congested conditions, the incident travel time is composed only of free flow and incident delay times. At demand close or exceeding capacity, the incident travel time is composed of all three-travel time components. The percentage of the recurring delay time of the total delay increases while the percentage of the incident-induced delay time decreases with the increase of the network demand (Table 5.5.2).

Some studies in the literature have stated that the delay will also increase when the roadway operates close to capacity and does not have alternatives for diverting traffic (e.g., see Hall, 2000). It is important to state that although total delay will increase when the roadway operates close to capacity, the incident-induced delay may decrease.

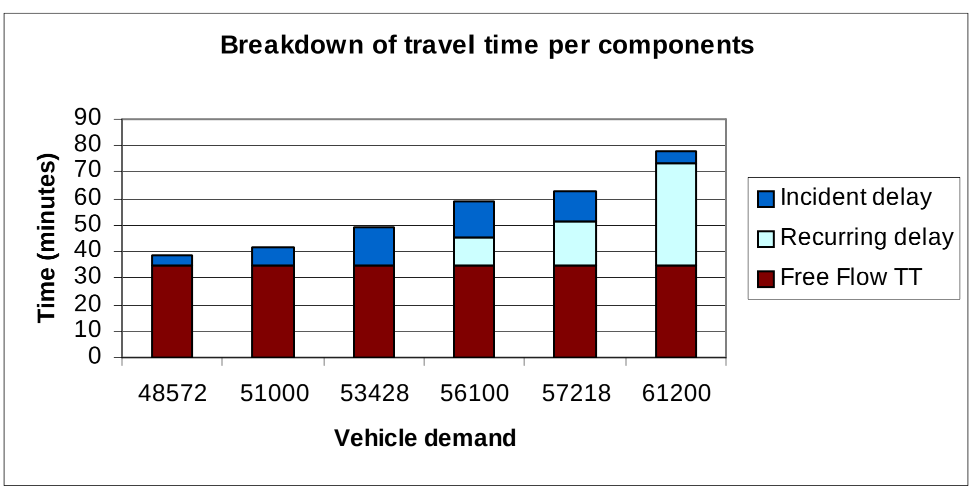

Figure 5.5.4 Breakdown of average travel time per demand for the overall network (incident case)

Table 5.5.2 Percentage of delay as a function of the total delay (incident case)

Demand (vehicles)	Percentage of recurring delay on the total delay	Percentage of incident delay on the total delay
48,572	0%	100%
51,000	0%	100%
53,428	0%	100%
56,100	44%	56%
57,218	59%	41%
61,200	89%	11%

The two terms “delay” and “incident-induced delay” are used interchangeably in the remainder of the section to mean the same thing: a delay resulting from the occurrence of an incident. The calculated incident-induced delay for the above conditions is shown in the following chart. The chart reveals that the impact of the incident depends on prevailing traffic conditions. Under non-congested conditions, the incident induced delay, for the overall section of the freeway, increases with the demand. However, under congested conditions, the delay decreases with the demand. In general, the incident delay is not proportional to the demand on the network (see Figure 5.5.5). It is shown that when the network is operating near capacity conditions, the incident delay may be less than the corresponding delay if the network is operating in non-congested conditions. This observation implies the importance of discriminating between the total delay and the true incident-induced delay that is the true measure of the incident impact.

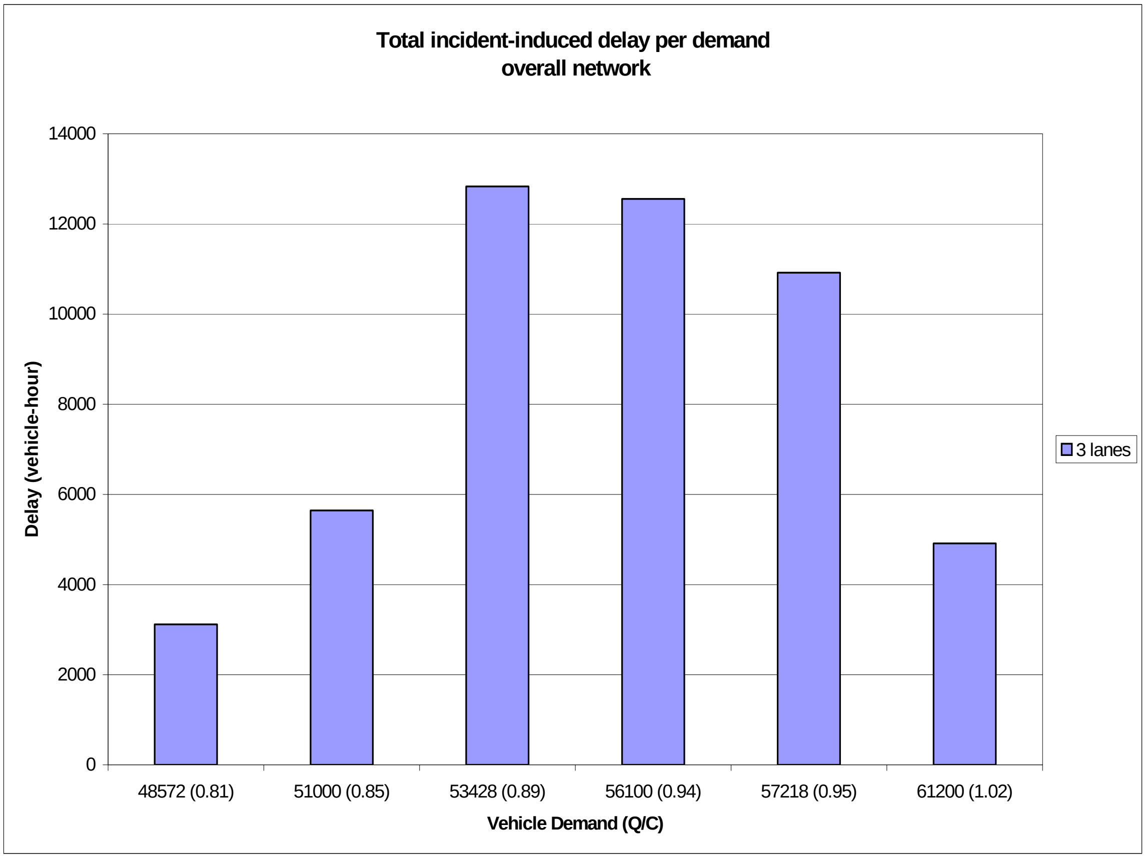

Figure 5.5.5 Total incident-induced delay per demand for the overall network

Figures 5.5.6 and 5.5.7 depict the temporal distribution of the total delay per demand for the network under incidents that blocked 3 and 2 lanes respectively. For the overall network, when the network is operating at non-congested conditions, the temporal distribution of the delay reveals that the impact of incident is severe from the occurrence through the duration of the incident and dissipates at a later time. However, when the network is operating near or over capacity, the impact of the incident may be moderate, but last longer than on under non-congested conditions. An incident has a longer-lasting impact on a network under congested conditions than it has under non-congested conditions.

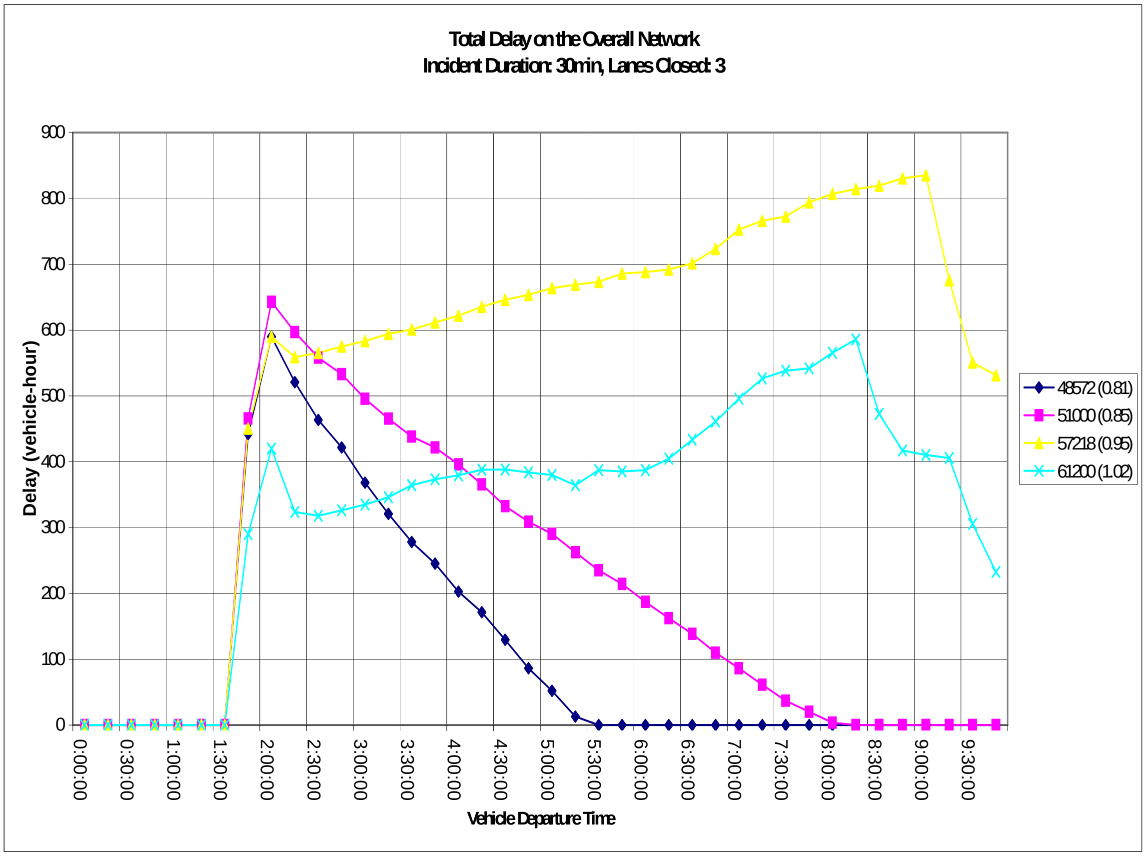

Figure 5.5.6 Temporal distribution of incident-induced delay per demand for the overall network; 3 lanes closed

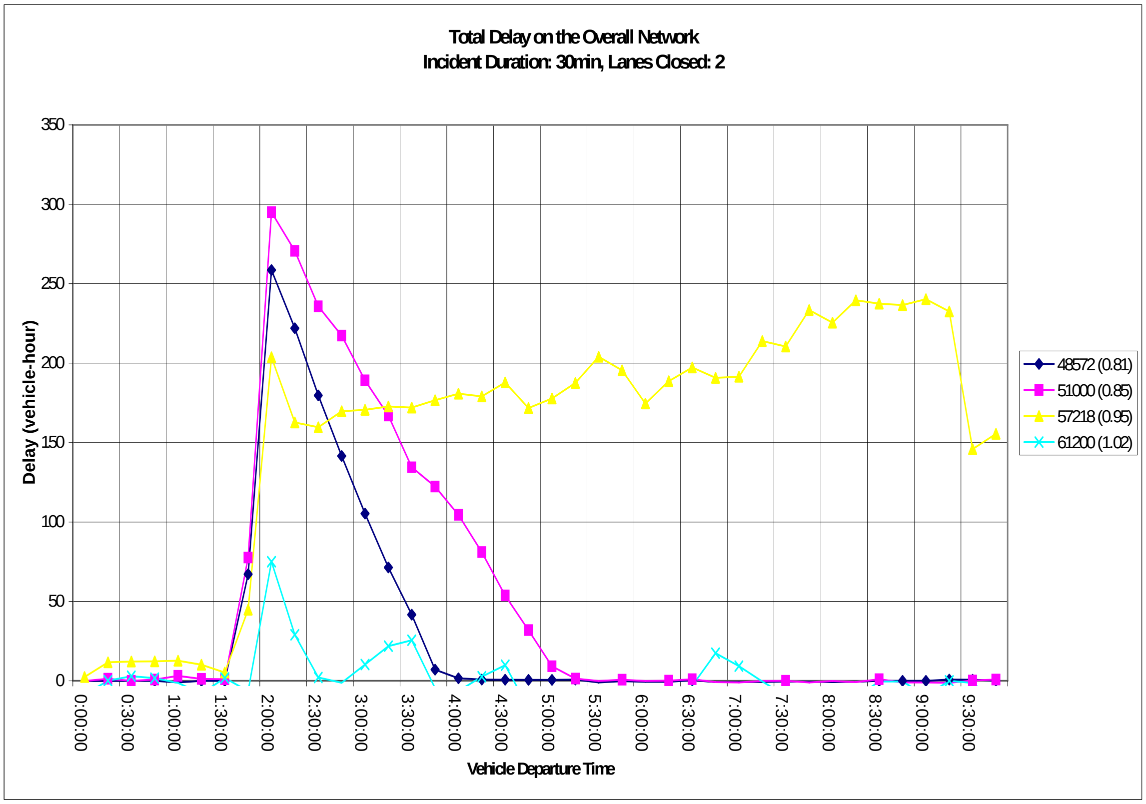

Figure 5.5.7 Temporal distribution of incident-induced delay per demand for the overall network; 2 lanes closed

The following charts (Figures 5.5.8, and 5.5.9) present the spatial and temporal distribution of the 30 minutes incident delay for OD pairs originating upstream and for those originating downstream of the incident location respectively. Under non-congested conditions, vehicles originating upstream of the incident location experience a severe delay that dissipates later after its clearance, while downstream vehicles are experiencing much more moderate delay. Under congested conditions, upstream vehicles experience moderate delay that lasts longer while downstream vehicles are benefiting from the occurrence of the incident in term of average travel time. Therefore, while incidents generally have a negative impact for vehicles upstream of its location and for the overall network, it may at the same time have a positive impact on downstream vehicles which otherwise would have experienced recurring delay due to the high demand of the network.

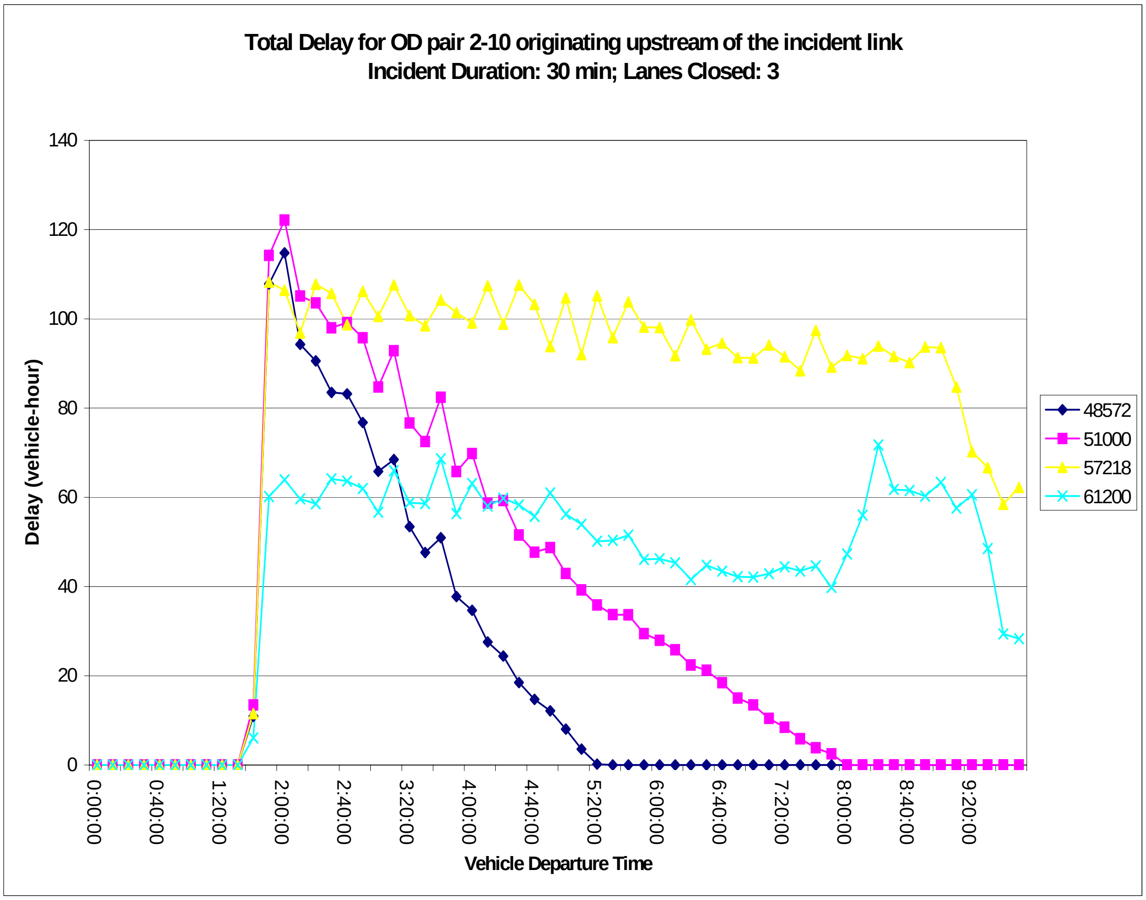

Figure 5.5.8 Temporal distribution of incident-induced delay per demand for an OD originating upstream of the incident; 3 lanes closed

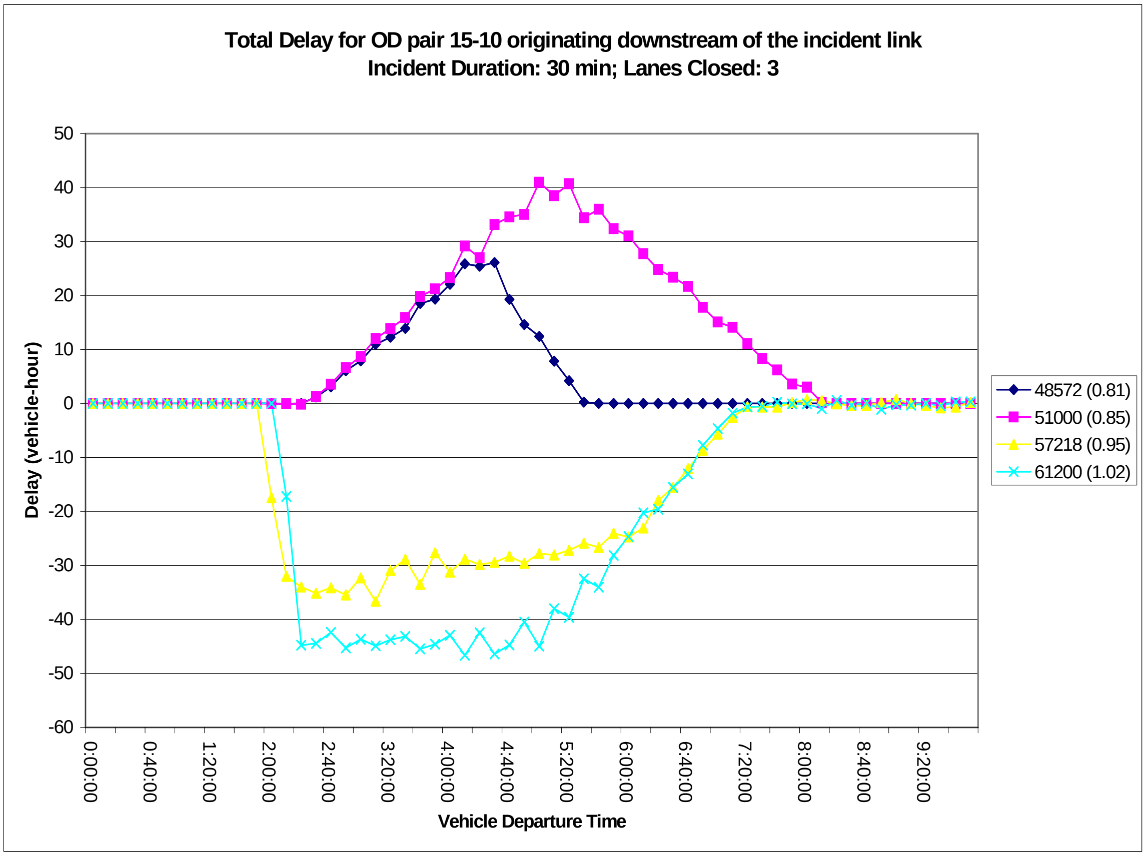

Figure 5.5.9 Temporal distribution of incident-induced delay per demand for an OD originating downstream of the incident; 3 lanes closed

5.6 Incident Impacts with Influencing Factors – Incident Duration, Lanes Blockage, and Demand

In the previous sections, the impacts resulting from the occurrence of incidents on the network have been determined for each of the influencing factors separately. In this section, a more comprehensive analysis of the incident-induced delay is being explored by taking into account all the influencing factors. The following tables show summary results of the travel time, the incident-induced delay and their standard deviations for all scenarios simulated at the network level. The analysis is done with varying the vehicle demand, the incident duration and the number of lanes closed (or incident severity). The section of freeway (Network #1) is used for the analysis. For each demand level with Demand-to-Capacity (Q/C) ratio varying from 0.81 to 1.02, the network is simulated for incident blocking one to three lanes and lasting from 15 to 120 minutes. Consistent with findings in the literature, the average travel time of vehicle for the overall section of the freeway increases with the demand, the number of lanes closed and the duration of the incident as shown in the Table 5.6.1 and Figure 5.6.1 below.

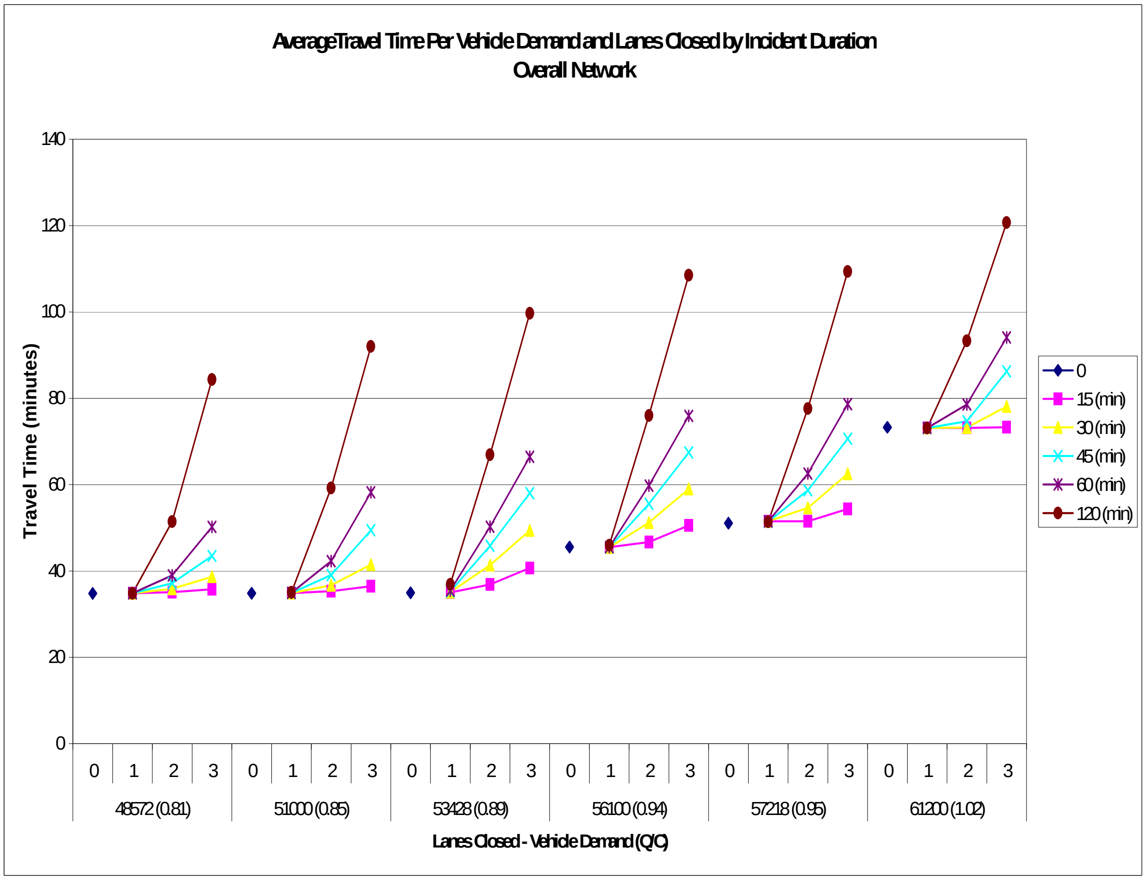

Figure 5.6.1 Average travel time per incident duration categorized by lanes blocked and demand at the network level

Table 5.6.1 DTA – Summary results for Network #1 with incidents

Incident Duration	# of Lanes Closed	Demand (veh)	Travel Time (minutes)					
			48,572 (Q/C=0.81)	51,000 (Q/C=0.85)	53,428 (Q/C=0.89)	56,100 (Q/C=0.94)	57,218 (Q/C=0.95)	61,200 (Q/C=1.02)
15 minutes	1	AVG	34.84	34.88	35.02	45.50	51.52	73.14
		STD	5.03	5.04	5.07	8.10	12.49	31.09
	2	AVG	35.10	35.34	36.87	46.70	51.52	73.14
		STD	5.25	5.39	5.72	8.98	13.18	31.09
	3	AVG	35.78	36.48	40.67	50.57	54.38	73.31
		STD	6.13	6.54	7.04	11.66	15.62	31.18
30 minutes	1	AVG	34.84	34.89	35.12	45.43	51.5	73.14
		STD	5.03	5.05	5.11	8.14	12.55	31.09
	2	AVG	35.90	36.70	41.38	51.2	54.61	73.23
		STD	6.23	6.76	7.48	12.29	16	31.78
	3	AVG	38.68	41.50	49.39	59.00	62.51	78.10
		STD	9.92	10.95	12.13	18.51	22.25	35.83
45 minutes	1	AVG	34.85	34.91	35.27	45.47	51.46	73.14
		STD	5.03	5.06	5.17	8.28	12.65	31.09
	2	AVG	37.19	39.06	45.86	55.55	58.68	74.7
		STD	7.95	8.95	10.13	16.06	19.56	33.65
	3	AVG	43.49	49.45	58.03	67.46	70.67	86.23
		STD	15.09	15.88	18.91	25.69	29.28	42.85
60 minutes	1	AVG	34.85	34.93	35.49	45.49	51.48	73.14
		STD	5.03	5.07	5.27	8.44	12.87	31.09
	2	AVG	39.01	42.29	50.25	59.76	62.58	78.60
		STD	10.17	11.49	13.35	19.90	23.13	36.97
	3	AVG	50.23	58.2	66.44	75.93	78.66	94.11
		STD	20.61	21.76	26.13	32.76	36.37	51.72
120 minutes	1	AVG	34.86	35.05	36.92	45.98	51.41	73.12
		STD	5.04	5.15	5.91	9.91	13.55	31.24
	2	AVG	51.44	59.23	66.94	76.00	77.62	93.32
		STD	20.72	23.32	28.55	35.74	38.12	54.31
	3	AVG	84.37	92.01	99.72	108.5	109.36	120.7
		STD	45.86	50.84	57.62	64.54	67.27	72.39

The delay on the network is calculated for each scenario and shown in Figure 5.6.2 and Table 5.6.2.

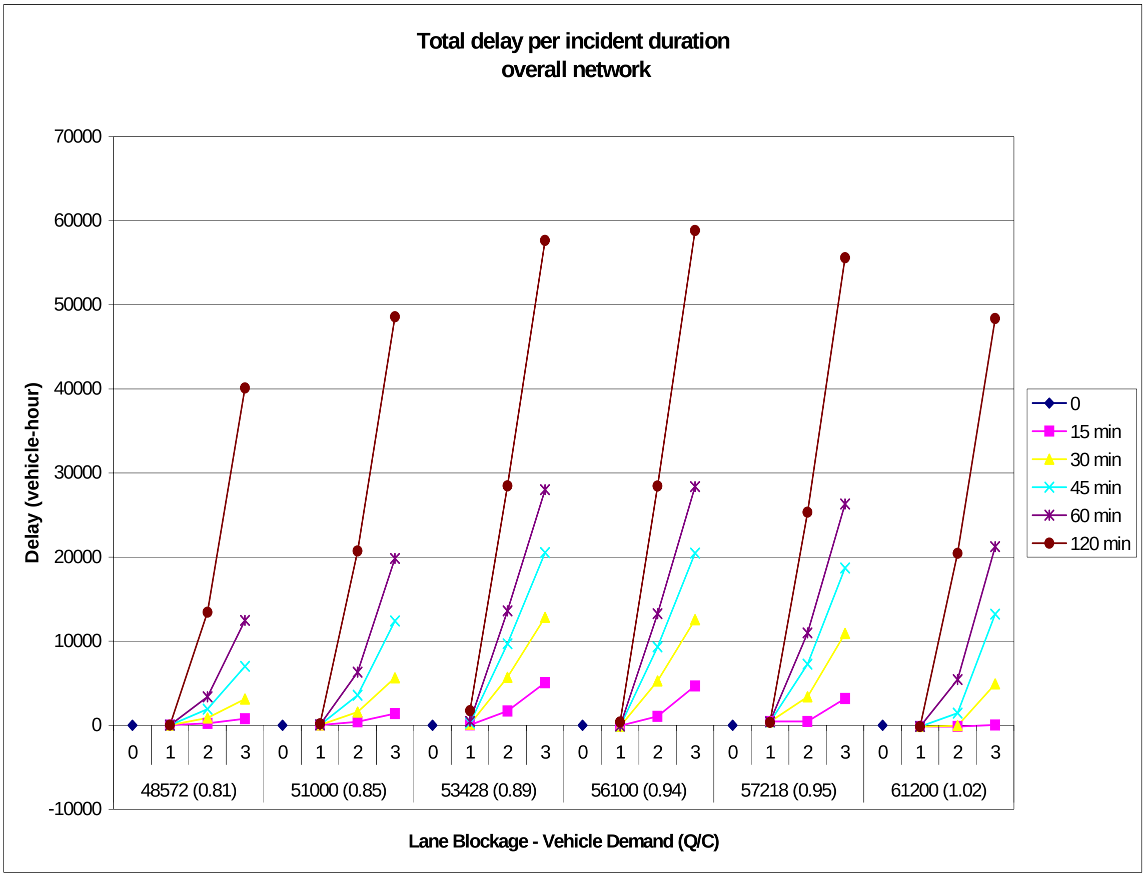

Figure 5.6.2 Total delay per incident duration categorized by lanes blocked and demand at the network level

Table 5.6.2 Average delay per vehicle for Network #1 under incident conditions

Incident Duration	# of Lanes Closed	Demand (veh)	Average Delay (minutes/vehicle)					
			48,572 (Q/C=0.81)	51,000 (Q/C=0.85)	53,428 (Q/C=0.89)	56,100 (Q/C=0.94)	57,218 (Q/C=0.95)	61,200 (Q/C=1.02)
15 minutes	1	AVG	0.01	0.02	0.04	0.24	0.46	-0.14
		STD	10.05	10.07	10.12	16.15	24.83	62.27
	2	AVG	0.27	0.48	1.89	1.13	0.46	-0.14
		STD	10.27	10.42	10.77	17.10	25.52	62.27
	3	AVG	0.95	1.62	5.69	5.00	3.32	0.03
		STD	11.15	11.57	12.09	19.78	27.96	62.75
30 minutes	1	AVG	0.01	0.03	0.14	0.17	0.44	-0.14
		STD	10.05	10.08	10.16	16.19	24.89	62.27
	2	AVG	1.07	1.84	6.40	5.63	3.55	-0.05
		STD	11.25	11.79	12.53	20.41	28.34	62.96
	3	AVG	3.85	6.64	14.41	13.43	11.45	4.82
		STD	14.94	15.98	17.18	26.63	34.59	67.01
45 minutes	1	AVG	0.02	0.05	0.29	0.21	0.40	-0.14
		STD	10.05	10.09	10.22	16.33	24.99	62.27
	2	AVG	2.36	4.20	10.88	9.98	7.62	1.42
		STD	12.97	13.98	15.18	24.18	31.9	64.83
	3	AVG	8.66	14.59	23.05	21.89	19.61	12.95
		STD	20.11	20.91	23.96	33.81	41.62	74.03
60 minutes	1	AVG	0.02	0.07	0.51	0.23	0.42	-0.14
		STD	10.05	10.10	10.32	16.49	25.21	62.27
	2	AVG	4.18	7.43	15.27	14.19	11.52	5.32
		STD	15.19	16.52	18.40	28.02	35.47	68.15
	3	AVG	15.40	23.34	31.46	30.36	27.60	20.83
		STD	25.63	26.79	31.18	40.88	48.71	82.90
120 minutes	1	AVG	0.03	0.19	1.94	0.72	0.35	-0.16
		STD	10.06	10.18	10.96	17.96	25.89	62.42
	2	AVG	16.61	24.37	31.96	30.43	26.56	20.04
		STD	25.74	28.35	33.60	43.86	50.46	85.49
	3	AVG	49.54	57.15	64.74	62.93	58.30	47.42
		STD	50.88	55.87	62.67	72.66	79.61	103.57

A correlation analysis was performed on all the variables. The results are displayed in Table 5.6.3.

Table 5.6.3 Coefficients of correlation between the incident influencing variables

	Q/C	Incident Duration	Lanes Closed	Average Travel Time	Average Incident Delay
Q/C	1.0000	0.000	0.000	0.644	0.0205
Incident Duration	0.0000	1.000	0.182	0.461	0.6090
Lanes Closed	0.0000	0.182	1.000	0.435	0.5750
Average Travel Time	0.6440	0.461	0.435	1.000	0.7230
Average Incident Delay	0.0205	0.609	0.575	0.723	1.0000

There are fair correlations between the average travel time in the network and Q/C, the incident duration and the lanes closed, and high correlation between the average travel time and the incident delay. These observations are to some extent consistent with those made by Guiliano (1989). Guiliano found that the delay caused by an incident is a function of the duration of the incident, the extent of capacity reduction, and the level of demand at the time of the incident. There are fair correlations between the incident delay and the incident duration and the lanes closed. But, there is a weak correlation between the incident delay and Q/C ratio. This suggests that the level of demand affects in great length the total delay, but not necessarily the incident delay. If one is to group the Q/C in two categories, one for Q/C less than 0.90 and one for Q/C greater than 0.9, the following results illustrated in Tables 5.6.4 and 5.6.5 are obtained for the correlation analysis.

Table 5.6.4 Coefficients of correlation between the incident influencing variables (Q/C < 0.9)

	Q/C	Incident Duration	Lanes Closed	Average Travel Time	Average Incident Delay
Q/C	1.000	0.000	0.000	0.182	0.178
Incident Duration	0.000	1.000	0.182	0.610	0.610
Lanes Closed	0.000	0.182	1.000	0.557	0.558
Average Travel Time	0.182	0.610	0.557	1.000	0.999
Average Incident Delay	0.178	0.610	0.558	0.999	1.000

Table 5.6.5 Coefficients of correlation between the incident influencing variables (Q/C > 0.9)

	Q/C	Incident Duration	Lanes Closed	Average Travel Time	Average Incident Delay
Q/C	1.000	0.000	0.000	0.547	-0.143
Incident Duration	0.000	1.000	0.182	0.514	0.609
Lanes Closed	0.000	0.182	1.000	0.501	0.592
Average Travel Time	0.547	0.514	0.609	1.000	0.748
Average Incident Delay	-0.143	0.609	0.592	0.748	1.000

There is a very high correlation between the travel time and the incident delay for Q/C less than 0.9 or when the network is operating under non-congested conditions. There is practically no recurring delay on traffic operating at non-congested conditions. Therefore, the incident-induced delay is equal to the total delay in the network. The coefficient of correlation between the incident delay and Q/C is higher than for the previous case where Q/C is not grouped. It can be concluded that for traffic operating under non-congested conditions, the level of demand at the time of the incident may have an influence on the incident-induced delay.

When Q/C is higher than 0.9 or the traffic operating close to capacity, there is a poor correlation between the incident delay and Q/C and there is a fair correlation between the incident delay and the travel time. Under these conditions, the recurrent delay shares a greater percentage of the total delay compared to the incident delay. For both Q/C levels, the incident delay is fairly correlated with the incident duration and number of lanes blocked. Therefore, the main factors that influence the incident-induced delay are the number of lanes blocked and the duration of the incident.

The following figures (Figures 5.6.3, 5.6.4, and 5.6.5) present charts of the total delay per vehicle as a function of the demand and incident duration for three schemes of lane blockage. It is observed that closing one lane of a three-lane roadway has insignificant impact on the overall network especially if the Q/C ratio is greater than 1 or less than 0.85. Closing two lanes of a three-lane roadway for less than 30 minutes result in inconsequential impact, if Q/C is greater than 1 or less than 0.81. These figures provide a telling example of the effect that a lane-blocking incident has on traffic congestion, in addition to the potential benefit reaped by quick clearance practices.

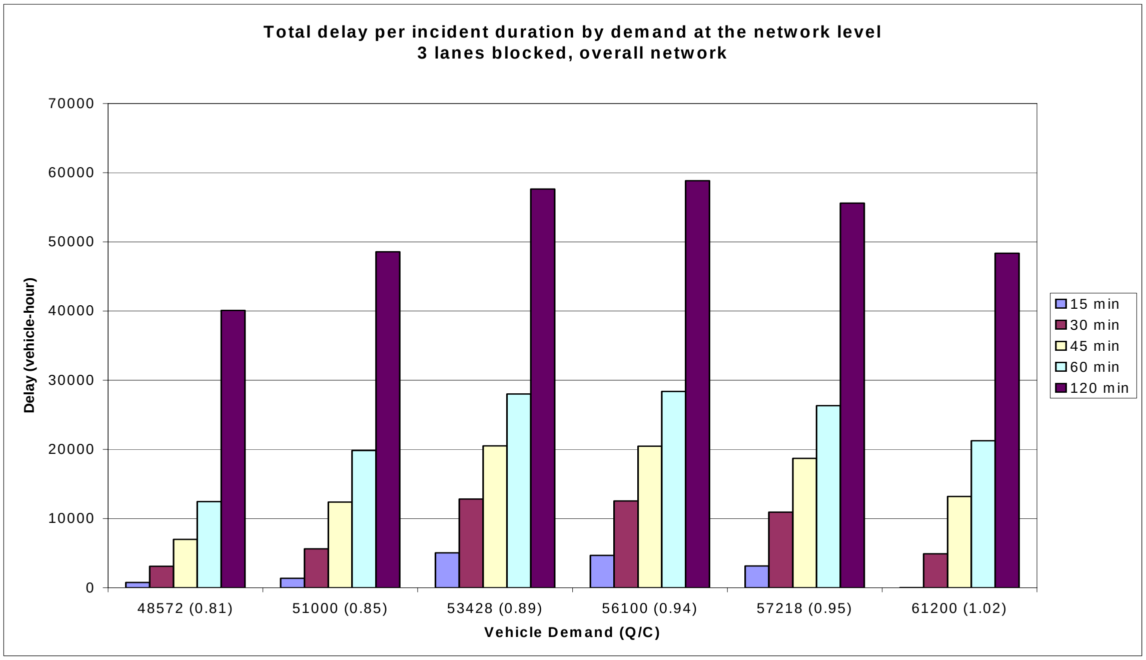

Figure 5.6.3 Total delay per incident duration by demand at the network level; 3 lanes blocked

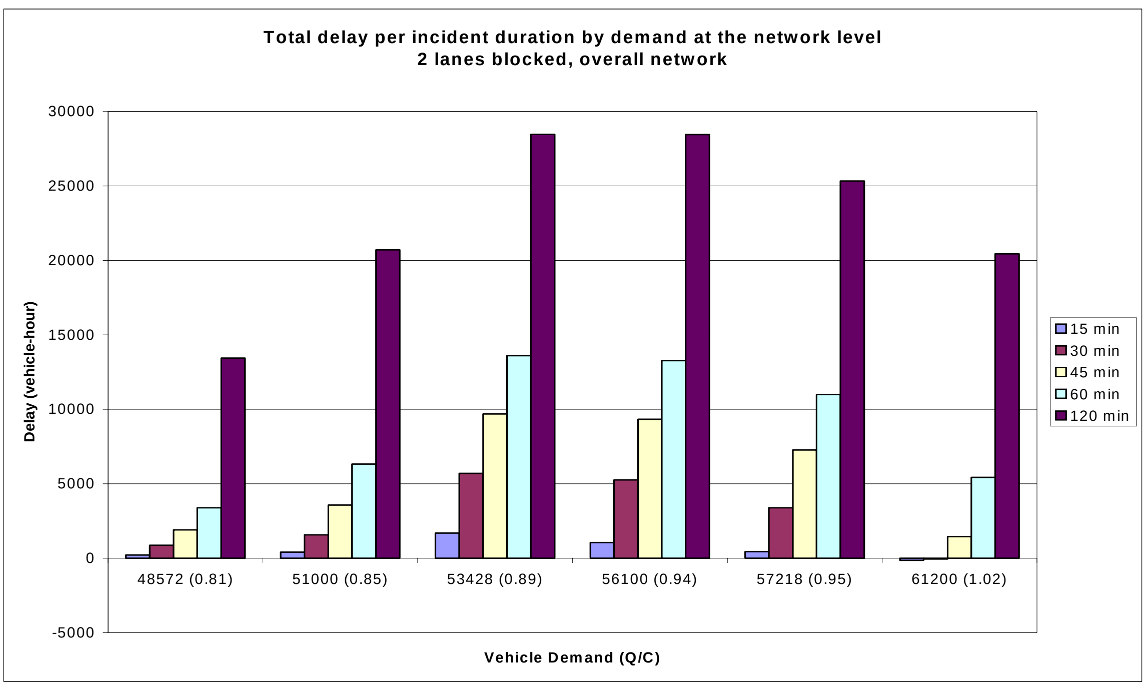

Figure 5.6.4 Total delay per incident duration by demand at the network level; 2 lanes blocked

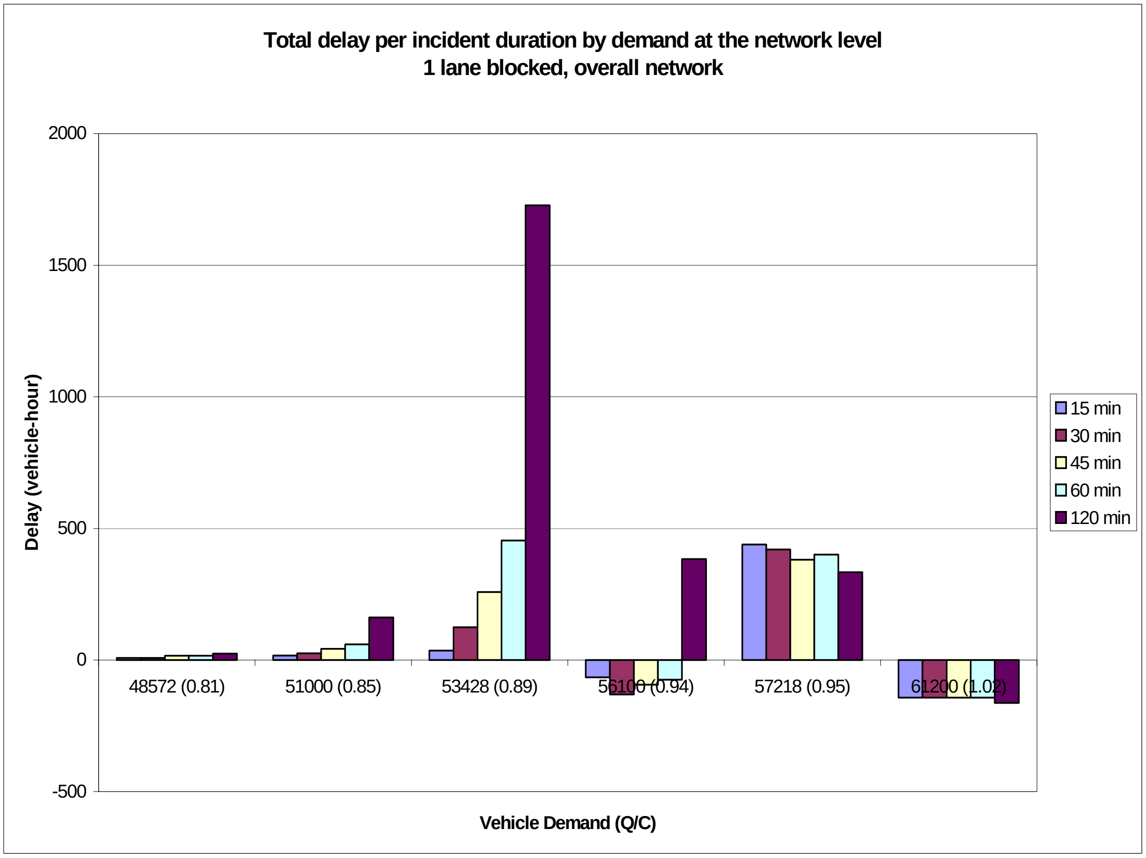

Figure 5.6.5 Total delay per incident duration by demand at the network level; 1 lane blocked

An analysis of incident delay as a function of the incident duration is performed for varying schemes of demand and lane blockage. It was observed that there is a quadratic or cubic relationship between the incident delay and the incident duration for a demand of 56100 with 3 lanes closed. Table 5.6.6 show the coefficients for cubic linear regression models of incident delay as a function of the incident duration for varying demand and lane blockage. All models are showing a high correlation between the incident delay and the incident duration. The incident duration is one of the main factors that affect the impact of an incident.

$D = \mathrm{K} + \mathrm{A}X + \mathrm{B}X^2 + \mathrm{C}X^3$

where,

D is the average incident delay in the network in minute and X is the incident duration in minute.

Table 5.6.6 Parameters for the cubic linear regression models

Demand	Lanes Closed	Intercept (K)	Parameter of Duration (A)	2nd Power of Duration (B)	3rd Power of Duration (C)	**R-Sq**
48,572	1	0.00051572	0.00055595	-0.00000475	1.801797E-8	**0.9583**
48,572	2	-0.00135	0.00140	0.00113	6.66246E-8	**1.0000**
48,572	3	0.05253	-0.03198	0.00583	-0.00001776	**1.0000**
51,000	1	0.00103	0.00107	-0.00000198	5.143953E-8	**0.9992**
51,000	2	0.02711	-0.01400	0.00275	-0.00000786	**1.0000**
51,000	3	-0.03412	-0.02061	0.00960	-0.00004549	**1.0000**
53,428	1	-0.00270	0.00019189	0.00014576	-1.03781E-7	**0.9999**
53,428	2	-0.18870	0.12693	0.00332	-0.00001785	**0.9993**
53,428	3	-0.23168	0.38664	0.00360	-0.00001923	**0.9997**
56,100	1	-0.00641	-0.00539	0.00008479	-9.2275E-8	**0.9537**
56,100	2	-0.25230	0.08252	0.00401	-0.00002137	**0.9986**
56,100	3	-0.23440	0.32863	0.00456	-0.00002425	**0.9997**
57,218	1	0.03752	0.02962	-0.00057928	0.00000295	**0.8645**
57,218	2	-0.19015	0.02344	0.00355	-0.00000994	**0.9994**
57,218	3	-0.34395	0.22091	0.00617	-0.00003287	**0.9993**
61,200	1	-0.00981	-0.00938	0.00017948	-9.31341E-7	**0.9227**
61,200	2	0.21646	-0.11783	0.00419	-0.00001523	**0.9974**
61,200	3	-0.16111	-0.12731	0.01175	-0.00006157	**0.9996**

CHAPTER 6 CONCLUSIONS

In this dissertation, a method for estimating the impact of incident on a traffic network through calculation of incident-induced delay is introduced. The method is applied to two transportation networks and the resulting impacts are analyzed and discussed. In this section, a summary of the study, some policy implications and future research are presented.

6.1 Summary of the Study

The reduction of incident-induced delay is one of the main objectives of transportation management in many states. The success of a Transportation Incident Management (TIM) program cannot be achieved without a good estimation and prediction of prevailing traffic conditions. The estimation of non-recurring incident delay becomes an essential component in the successful implementation of TIM. In the past, many studies were performed that developed models to estimate the delay resulting from an incident on the roadway. Non-recurring incident delay models found in the literature are either difficult to implement due to the non-availability of data and parameters used in the model or the complexity of finding a comprehensible solution to the formulation of the problem is difficult to overcome. These methods estimate the incident impacts on links upstream of the incident location or on the affected link. The impacts on the downstream links are not considered and the variability in demand is not taken into consideration. In addition, these models are not taking into account the spatial and temporal distribution of traffic and do not consider the behavior of the motorists after the time of incident occurrence. The implementation of advanced traveler information systems to manage the traffic after the occurrence of an incident cannot be considered in these models.

With a research motivation to better estimate the incident impact on a transportation system, this dissertation introduces a comprehensive and effective methodology to estimate the incident delay for network-wide, OD pair and link levels. The method can be applied to a wide range of operational traffic condition. The incident impact is estimated by calculating the incident delay that is the difference of the average travel times between the travel times under normal and incident conditions. This procedure avoids some of the problems in using the queuing diagram and directly provides the delay perceived by the motorists. Using the VISTA computer transportation simulation DTA model, two transportation networks are simulated under a range of traffic demand levels, incident durations, lanes blockages, and deployment of ATIS. Dynamic Traffic Assignment (DTA) has been studied extensively over the years because it can provide a more realistic representation of the traffic patterns on a network given the time-dependent demand. The importance of DTA is evident, since travel demand changes by time of day. The assumption that demand is steady state within a relatively long period of time is not realistic and a model system built upon such an assumption cannot adequately capture the traffic dynamics in the network.

The main characteristic of DTA is that it produces the time-space trajectory of each individual vehicle from its origin to its destination. Each vehicle trajectory includes the departure time from the origin, the arrival time at the destination, the vehicle's chosen path and the location of the vehicle at any time of interest along this path. The estimates of travel times, vehicle volumes, and corresponding statistics were obtained under varying incident schemes. The incident-induced delay is computed using the proposed methods to estimate the incident impacts on the roadway at the link, OD pair, and network levels. The key results from the incident scenarios are summarized in the following section.

6.2 Contributions and Results

This dissertation introduces a more comprehensive estimation method to quantify the incident impacts on a transportation network by developing a procedure to produce some measures of effectiveness (MOE) for traffic incident management. The impacts caused by an incident are estimated through the calculation of the travel time and the incident delay at the network level, per origin-destination pair, and per user group using a Dynamic Traffic Assignment Model. A methodology to estimate incident delay distribution for the network, OD, and user group, per time interval of the day and incident type that takes into account the impact of the implementation of the advanced traffic information systems has been presented. It is found that this method can be applied to more types of operational traffic conditions. The following MOEs are more useful towards the evaluation of TIM programs, as well as short term and long term transportation planning.

- Total travel time on the network before and after the incident
- Total incident delay for all vehicles in the network under the incident conditions
- Total travel time for OD pairs before and after the incident
- Total incident delay for OD pairs under the incident conditions
- Travel time distribution per time interval on the network before and after the incident
- Incident delay distribution per time interval on the network before and after the incident
- Travel time distribution per time interval for OD pairs before and after the incident
- Incident delay distribution per time interval for OD pairs before and after the incident

All of the above MOEs can be expressed for each user groups. Emergencies medical services (EMS), fire department, police, towing services, homeland security, hazardous materials (HAZMAT) have a perspective on the incident delay different from other user groups such as passenger and commercial vehicles.

This research has demonstrated the followings:

Incidents have a different impact on different OD pairs. By considering the OD pair distribution, one can determine the impact of the incident on vehicles depending of their departure origin, their travel path in the network, and their arrival destination. Impacts of incident on the network depend on the points of origin and destination of the vehicles. It is found that vehicles originating or accessing the freeway or the network at locations upstream of the incident and traversing the incident link are negatively impacted.

Vehicles originating downstream and not traversing the incident link are insignificantly impacted by it and in some cases, may even be positively impacted. OD pairs with paths including the incident link are severely impacted compared to OD pairs that do not traverse the incident.

The temporal distribution of the impacts of incident is an important factor in the analysis of incident delay. Delay that a vehicle will experience as a result of an incident depends on the time when the vehicle enters the affected transportation network.

Incident delay has a network-wide impact on the transportation system. Incident delay often is reported only for the affected and upstream link. Most studies on incident delay extrapolate the incident delay estimates by using only the vehicles that are severely affected by the incident. Incidents may affect upstream traffic as well as downstream. Incidents may affect vehicles not traversing its location.

The impact of the incident depends on prevailing traffic demand levels. Under non-congested conditions, the incident induced delay, for the overall section of the freeway, increases with the demand. However, under congested conditions, the incident delay decreases with the demand. In general, the incident delay is not proportional to the demand on the network. It is shown that when the network is operating near capacity conditions, the incident delay may be less than the corresponding delay, if the network is operating on non-congested conditions.

In addition, under the research objective, the relationship of the impact of incident severity, duration, and demand on the abovementioned MOEs has been investigated. The following observations illustrated in this study reiterate some of the previous results found in the literature:

The delay that a vehicle experiences as a result of an incident is affected by factors related to the characteristics of the transportation network, the incident, and the prevailing traffic conditions during its occurrence. These factors include the incident severity, the capacity reduction, the incident duration, the arrival pattern, the traffic volume, and the future time when the vehicle arrives at the incident location.

Incidents may cause an increase of the total travel time for vehicles in the network. It is observed that at the network level in general, the total travel time may increase when an incident occurred. Some vehicles in the network, especially those located upstream of the incident link are experiencing higher travel times when an incident occurred compared to travel time under normal traffic conditions. The percentage of increased travel time depends on the prevailing traffic conditions, the location of the incident, its duration and severity, and the number of lanes blocked.

Incident impacts may last beyond its duration and clearance time. An incident may have impact on the network that lasts longer than its duration and its clearance time. The recovery time of the network after an incident may not always be proportional to its duration as generally expected. Short incidents may generate lasting recovery time as those of longer duration times. An incident has a longer-lasting impact on a network under congested conditions than it has under non-congested conditions.

An effective traveler information system can alleviate the impacts of an incident on various travelers to varying degrees. These results demonstrate that the dissemination of information could help reduce the negative impact of an incident on traffic operations at the network level. The diverting of vehicles helps reduce considerably the average travel time for most vehicles traversing the incident, therefore reducing the total delay in the network. However, it is also found that vehicles with paths not traversing the incident location do not benefit from the information provided. A few of them even experience slightly higher delay resulting from the rerouting of other vehicles that generate an increased vehicle volume in some links.

Incident-induced delay depends of the incident duration. The average travel time per vehicle and the total travel time for all vehicles in the network during a period of time will increase with the duration of the incident. The incident duration has an effect on both the travel time and the incident-induced delay for the overall network. The total travel time and delay at the network level increase with the duration of the incident. A strong correlation also exists between the incident duration and the average delay per vehicle.

Even though the severity of the delay increases with the duration of the incident, the effect on the recovery time may not always depend on the incident duration. It is observed that the recovery time does not increase nor decrease with the incident duration.

The cubic linear models are found to be the best for describing the incident-induced delay versus incident duration curve at the network level. The models produce a good R-Square value of above 0.9. However, any use of these models for any other transportation segment or transportation network, incident location would require calibration.

It was also observed that delay caused by incidents depends on how quickly the incident can be cleared.

Incident-induced delay depends on the number of lanes blocked. Incidents occurring within the traveled way and blocking lanes create severe capacity restrictions, leading to excessive delays if not attended to and cleared as quickly as possible. It is observed that the incident impact increases with the number of lanes closed. As the number of lanes blocked increases, the intensity of the impact will increase accordingly. A blockage of one lane does not exhibit any impact on the three-lane freeway for this incident scenario. The closure of two or three lanes creates a delay in the network.

6.3 Policy Implications

The cost of delay on freeways caused by non-recurring incidents is significant. Lindley (1986) estimated that it would had reached $35 billion/year in 2005. Jurisdictions across the country have instituted incident management programs to address incidents requiring a cooperative and multi-agency response. Major incident response efforts collectively provide victim assistance, traffic management, dissemination of traveler information, and incident removal.

The results of this study strengthen the importance of a comprehensive approach that considers the impacts of incident network wide and not only on upstream or immediately affected links. The network wide effect of incidents will have some policy implications for the location of variable message signs, emergency vehicle locations, medical service centers, and the proportion of roadway maintenance funds for local aid programs.

To reduce the impact of an incident, a traffic management center (TMC) needs to quickly detect and remove it from the freeway. A policy for quick and safe removal of obstructions from the roadway must be enacted. Incident management is important due to its direct effect in saving life, property and the environment and due to its indirect effect on the entire highway system, including congestion and travel time. Responding to or clearing incidents more quickly reduces both the economic cost of congestion and the associated aggravation. The result is more reliable travel, shorter trips, and an ability to accommodate more trips within the existing roadway infrastructure.

The study findings show that a short incident clearance time requiring more closures of lanes has less impact on the overall network than an incident with a longer clearance time involving the blockage of fewer lanes. A policy of quick clearance that may require more lanes to be blocked should be implemented. These practices may increase the safety of incident responders and victims by minimizing their exposure to adjacent passing traffic. Also, it may reduce the probability of a secondary incident.

The study findings suggest that provision of traveler information only upstream of the incident may not always be beneficial for vehicles with paths not traversing the incident link. Few of them may experience slightly more delay resulting from the rerouting of affected vehicles that generates an increase vehicle volume in uncongested alternate routes. Therefore, the location of variable message signs (VMS) and the strategy of information provision should take this effect into account. In addition, the diversion of vehicles from the main roadway to alternate routes during an incident will increase their incremented damage and influence life cycle maintenance costs. A policy for allocation of funds for road construction and maintenance that take into account the diversion impact on the pavement of the road, should be established. The allocation of funds may be based on the frequency of occurrence of incident in some locations, duration of incidents, and percentage of vehicles per class that are likely to be rerouted to alternate roads. This area is yet to be further investigated and it is an interesting subject for future research.

6.4 Areas for Future Research

This thesis has demonstrated the importance of a comprehensive approach to estimate the incident impact by calculating the incident-induced delay on the network, origin-destination, and link levels using a Dynamic Traffic Assignment model. This method takes into account the spatial and temporal characteristics of the transportation systems and the change in demand and route that may result from the provision of traveler information to motorists during incident conditions. However, there are several areas in which continued research can improve the applicability of this approach.

In the current research, all vehicles must complete their trip or exit the network in order to apply the proposed method. The simulation time is extended beyond the assignment period to allow all vehicles to arrive at their destination or exit the network. This creates a challenge for real time implementation. More research should be done to estimate incident delay with vehicles that have not yet reached their destination during the time period of analysis.

The departure of vehicles is assumed to be uniformly distributed in this study for simplification purposes. For further research, stochastic processes can be assumed for departure time to develop a more realistic incident delay model. In addition, incident duration models should be incorporated in the model instead of being treated as an exogenous variable, as done in this study.

The potential benefits of providing traveler information to user groups during the occurrence of incidents can be further evaluated. This study has determined that the deployment of ATIS can alleviate the negative impact of incident.

In addition, further research should be done to improve the real time deployment of this approach. For example, a development of an incident management module in DTA software to aid transportation agencies in analyzing the impacts of incidents using this approach should be investigated. This module will enable the user to conduct parametric analysis based on the incident (location, severity, duration) and IM characteristics such as: potential diversion routes plus the percentage of travelers that are expected to follow each route, location and content of VMS, and percentage of travelers informed of the incident.

The author expects to submit papers on findings of this dissertation for publication to peer review transportation journals such as the Transportation Research Board and the Institute for Transportation Engineers.

APPENDICES

VISTA Modules

The main modules that have been implemented in VISTA are:

Time –dependent OD Matrix Estimation Module

The VISTA system incorporates an OD matrix estimation/calibration algorithm that is based on: (1) an estimated OD matrix that is usually provided by the metropolitan planning organizations and traditionally they reflect a static OD matrix for the peak and off-peak periods of the day; and (2) fifteen-minute traffic counts at various links of the network for various time periods of the day and day of the week. The VISTA algorithm projects the static OD matrix to reproduce the 15-minute roadway link traffic counts resulting in a dynamic OD matrix per vehicle category.

Infrastructure Changes Module

One of the principal characteristics of transportation planning is the evaluation of various infrastructure improvements such as: lane additions/deletions; addition/deletion of roadways into the network; interchange changes such as changes in geometry and/or in traffic control; location of data collection devices and type. The principal concern of the transportation planner is how would the traffic be redistributed based on the new network changes and who will be affected in terms of the specific *Measures of Effectiveness (MOEs)* such as the network wide total travel time per vehicle class, or the OD path travel time per vehicle class and time period of the day.

3.4.3.3 Construction Management Module

One of the main concerns of the transportation agencies is how to optimize the construction schedule in order to minimize the impact of construction on the travelers. The VISTA construction module provides the user the ability to define a construction schedule and evaluate it based on its impact for each user class.

Traffic Information Module

VISTA can be used to evaluate the location of Variable Message Signs through the identification of the OD paths that pass through a VMS location. It can also be used to evaluate the impact of traffic information to the users by conducting parametric analyses on the percentage of users who will decide to change their original routes; all others are assumed to follow their ordinary routes and this percentage of drivers are reassigned onto the network producing new OD paths.

Incident Management Module

The incident management module has similar characteristics with the construction module and is further associated with the traffic information module. The module allows the user to evaluate various incident management strategies such as route diversion strategies under severe incidents, off-line and/or real time route-planning optimization for emergency vehicles (police, EMS, fire department, towing truck(s), etc.), to/from the scene of an incident, evaluation of corridor control optimization strategies (ramp metering, variable speed limit, signal timing) under incident and various congestion conditions.

Weather Module

The principal driver behavioral change under rainy conditions is the change in average speed. The VISTA system allows the user to observe the impact(s) of a change in the average speed per vehicle class for the network or roadway under rainy conditions. Under ice and snow conditions the reduction in average speed may be more severe for local roads rather than freeways therefore the user may specify different reductions based on historical information for these roadways. Furthermore, the user may specify reductions in roadway capacity especially in cases of severe snowfall where the number of lanes is reduced due to the inability of the plowing trucks to remove the snow. The VISTA system may be used to evaluate various snow plowing and roadway sanding and salting strategies employed to reduce the impact on the transportation network. It is emphasized here that historical information on roadway conditions under different snowfall amounts and ice conditions are very important to be able to utilize the model effectively.

Flooding Module

Flood impacts the network in different ways. First some roadways can only be driven by a certain category of vehicles such as sport utility vehicles (SUV) or trucks; Second, it will affect only certain roadways due to terrain conditions. Third it may be combined with rain affecting the entire network. The VISTA system has the capability to model various classes of vehicles and determine the flood impact based on the level of the water that exists on the roadways of the network. The user could then use the model to evaluate various emergency strategies such as emergency evacuations and route planning for emergency vehicles to stranded citizens or animals, taking into consideration that some of the links of the network will not be accessible based on the projection of the water level on different roadways.

Truck Routing Module

The trucks usually are allowed only to drive at certain roadways. In addition, under various traffic or safety conditions they may be required to go through certain roadways to arrive to their destination. This module allows the user to evaluate existing and proposed new truck routes and produce the measures of effectiveness for both the trucks and passenger cars. The module allows the user to model different types of trucks based on their configuration, which is very important especially at narrow turns in urban and suburban areas.

Signal Optimization Module

This module allows the user to optimize the traffic signals of the transportation network under based on the VISTA optimization tool or it allows the user to use to interface with another optimization software (e.g. SYNCHRO, TRANSYT). In addition, the module allows the user to conduct a signal warrant analysis for unsignalized intersections and if needed to also optimize the signalized intersection under consideration. This procedure is activated automatically (could be easily suppressed by the user) and is very helpful in cases where the transportation agency does not have any data for an intersection (very common in many cities). The system provides the user with new signal timing and notifies the user that this particular intersection(s) has changed traffic control characteristics (from unsignalized to signalized).

Transit Module

The transit module allows the user to model bus and train operations. The user includes the transit route, transit schedule, transit stations, dwelling time distribution (average and variance) at each station. The module allows the user to compare one or more transit scenarios such as changes to the schedule or transit route. The analyst can change one or more transit parameters and evaluate them under various traffic flow conditions such as changes in demand or roadway capacity.

The Transit Signal Priority (TSP) Module allows the user to evaluate various types of transit signal priority schemes such as: (1) Extension, truncation, (2) Extension, truncation, return to correct timing, (3) Compensation, (4) Conditional (route or schedule). The main questions related to transit signal priority schemes are: (1) What is the impact of TSP on transit, (2) What is the impact of TSP on general traffic, (3) How do impacts of TSP vary with different levels of congestion?

REFERENCES

1. Abdelghany, K.F. and Mahmassani, H.S. (2001) “Dynamic trip assignment-simulation model for inter-modal transportation networks.” Transportation Research Record 1771: pp. 2-60.

2. Abdelghany, K.F., Abdelghany, A.F., Mahmassani, H.S., and Abdelfatah, A.S. (2001) “Evaluating Bus Preemption Strategies at Signalized Intersections Using a Multi-modal Dynamic Network Assignment-Simulation Methodology.” 80th Annual Meeting of the Transportation Research Board, Washington D.C.

3. Agrawal, B.B., Waller, S.T., and Ziliaskopoulos, A.K. (2002) “A Modeling Approach for Transit Signal Preemption.” 81st Annual Meeting of the Transportation Research Board, Washington D.C.

4. Al-Deek, H. M., Kanafani, A. (1993). “Modeling the Benefits of Advanced Traveler Information Systems in Corridors with Incidents,” Transportation Research – C, Vol. 1, No. 4, pp. 303-324.

5. Al-Deek, H.M., Khattak, A., and Thananjeyan, P. (1998). “A Combined Traveler Behavior and System Performance Model with Advanced Traveler Information Systems, Transportation Research – A, Vol. 32, No. 7, pp. 479-493.

6. Balke, K., Fenno D., and Ullman B. (2002). Incident Management Performance measures, Texas transportation Institute, The Texas A&M University System, College Station, Texas.

7. Ben-Akiva, M., H. Koutsopoulos, R. Mishalani, and Q. Yang. (1997). "Simulation Laboratory for Evaluating DynamicTraffic Management Systems," ASCE Journal of Transportation Engineering, 123:4

8. Ben-Akiva, M., H.N. Koutsopoulos and A. Mukudan. (1994). “A dynamic traffic model system for ATMS/ATIS operations.” IVHS Journal 2 (1), pp. 1-19.

9. Bertini Robert, Rose Michael, El-Geneidy Ahmed, (2005). "Using Archived ITS Data Sources to Measure the Effectiveness of a Freeway Incident Response Program," 84th Annual Meeting of the Transportation Research Board, Washington, DC.

10. Bertini, R. Tantiyanugulchai, S. Anderson, E. Lindgren, R. Leal, M. (2001). "Evaluation of Region 2 Incident Response Program Using Archived Data". Portland State University, Transportation Research Group, Research Report.

11. Carson, J.L., Legg, B., Mannering, F.L., et al. (1999). "Are Incident Management Effective? Findings from Washington State," 78th Annual Meeting, TRB, January 10-14, Washington, DC.

12. Chang G., Petrov A., Lin P. and Zou N., (2002). "Performance Evaluation of CHART – The Real-Time Incident Management System-year 2000," Dept. of Civil and Environmental Engineering, University of Maryland, College Park.

13. Cheu, Ruey L. and Ritchie Stephen G. (1995) "Automated Detection of Lane-Blocking Freeway Incidents Using Artificial Neural Networks," Transportation Research, part C, Vol. 3, No. 6, pp. 371-388.

14. Chow, W. M. (1976). "Study of Traffic Performance Models Under an Incident Condition." Highway Research Record 567, TRB, National Research Council, Washington, D.C., pp. 31–36.

15. Cohen S. and Nouveliere C., (1997). "Modelling incident duration on an urban expressway," M. Papageorgiu and A. Pouliezos (eds) Proceeding of the 8th International Federation of Automatic Control (IFAC) Symposium on Transportation Systems, 16-18 June, Chania, Greece.

16. Congestion Needs Analysis Model, CNAM's INCIDENT DELAY SUBMODEL manual, version 4/2/99, 1999.

17. Daganzo, C.F. (1994). "The cell transmission model: a dynamic representation of highway traffic consistent with the hydrodynamic theory." Transportation Research Part B, Vol.28, No. 4, pp. 269-287.

18. Derr, B. R. (1987). "Delay Analysis for Freeway Corridor Surveillance, Communication, and Control Systems", Transportation Research Record 1132, pp 77-81.

19. El-Geneidy, A. and Bertini, R.L. (2003). "Integrating Geographic Information Systems and Intelligent Transportation Systems to Improve Incident Management and Life Safety". The 8th International Conference on Computers in Urban Planning and Urban Management.

20. Epps, A., Cheng, J. C., and May, A. D. (1994). "Developing methodologies for quantifying freeway congestion delay." Technical Report UCB-ITS-RR-94-2, Institute of Transportation Studies, University of California, Berkeley.

21. Federal Highway Administration (1984). "FRESIM user guide, Version 4.5, Office of Research And Development," U.S. Dept. of Transportation, Washington, D.C.

22. Federal Highway Administration (2000). "Traffic Incident Management Handbook." U.S. Department of Transportation. Publication No. DOT-T-01-01.

23. Fu, Liping (2004). "A Fuzzy Queuing Model for Real-Time, Adaptive Prediction of Incident Delay for ATMS/ATIS," Transportation Planning and Technology, Vol. 27, No. 1, pp. 1-23.

24. Fu, Liping and Rilett, Laurence R. (1997). "Real-Time Estimation of Incident Delay in Dynamic and Stochastic Networks," Transportation Research Record 1603, pp. 99-105.

25. Garib, A., Radwan, A.E., Al-Deek, H. (1997). "Estimating Magnitude and Duration of Incident Delays." Journal of Transportation Engineering. v 139 n 6 November/December pp 459-465.

26. Giuliano, G. (1989) "Incident Characteristics, Frequency, and Duration on a High Volume Urban Freeway." Transportation Research A, 23A, No. 5.

27. Goolsby M. E., and Smith W. (1971). "Influence of incidents on freeway quality of service," Highway Research Record, 349, Transportation Research Board, Washington D.C., pp. 41-46.

28. Gordon, R., Reiss, R., Haenel, H., Case, E.R., French, R.L., Mohaddes, A., and Wolcott, R. (1996). "Traffic Control Systems Handbook." Report FHWA-SA-95-032, Federal Highway Administration, Washington, D.C.

29. Hall, Randolph (2000). "Incident Dispatching, Clearance and Delay," California PATH Working Paper UCB-ITS-PWP-2000-14, California Path program, ITS, University of California, Berkeley, California.

30. Jayakrishnan, R, Chen, A, and Tsai, WK (1994). "Dynamic Traffic Equilibrium: Definition and Solution Algorithms", paper presented at the 41st North American Meeting of the Regional Science Association International, Niagara Falls, Canada.

31. Jones, B., Janssen, L., and Mannering, F. (1991). "Analysis of the Frequency and Duration of Freeway Accidents in Seattle." Accident Analysis & Prevention. Vol. 23, No. 4, pp. 239-255.

32. Jovanis, P., Chang, H.-L. (1989) "Disaggregate model of highway accident occurrence using survival theory." Accident Analysis and Prevention 21, pp.445-458.

33. Juge J., Kennedy K. and Wang T. (1974). "Early Detection and Road Removal of Disabled Vehicles and Other Hazards from the Freeway," Final Report, California Department of Transportation and Department of California Highway Patrol.

34. Khattak, A., Schofer, J., Wang, M-H. (1995). "A Simple time sequential procedure for predicting freeway incident duration." IVHS Journal 2 (2), pp. 113-138.

35. Kockelman, S., Kara M., Waller, T., Ukkusuri, S.V., and Boyles, S. (2006) A Comparison of Static and Dynamic Traffic Assignment Under Tolls: A Study of the Dallas-Fort Worth Network, TRB Annual meeting, CD-ROM, Washington D.C.

36. Li, J., Lan, CJ., and Gu, X. (2005). "Estimation of Incident Delay and its Uncertainty on Freeway Networks." TRB 2006 Annual Meeting CD-ROM, Washington, D.C.

37. Lindley, J. (1987). “Urban Freeway Congestion: Quantification of the Problem and Effectiveness of Potential Solutions.” ITE Journal-Institute of Transportation Engineers. v 57 n 1 Jan pp 27-32.

38. Lindley, J. A. (1986). "Quantification of Urban Freeway Congestion and Analysis of Remedial Measures." Report RD/87- 052. FHWA, U.S. Department of Transportation.

39. List, G. and Cho, H. (2004). “Quantifying Non-Recurring Delay on New York City’s Arterial Highways.” Technical Memoradum, Task 1: Goals and Objectives, NYSDOT Project C-01-29, Rensselaer Polytechnic Institute, Troy, NY.

40. Maas, Gerard C. Jr. (1998). "Estimating Benefits of ITS Technology in Incident Management: The Case of Northern Virginia," 77th Annual Meeting, January 11-15, TRB, Washington, D.C.

41. Mahmassani H.S., Srinivas Peeta, Ta-Yin Hu, Athanasios Ziliaskopoulos, (1993) Dynamic traffic assignment with multiple user classes for real-time ATIS/ATMS applications. Proceedings of the Advanced Traffic Management Conference.

42. Mahmassani, H.S. (2001.) “Dynamic network traffic assignment and simulation methodology for advanced system management applications.” Networks and Spatial Economics Vol. 1, pp. 267-92.

43. Mahmassani, H.S., S. Peeta, Hu, T.Y. and Ziliaskopoulos, A.K. (1993) “Dynamic traffic assignment with multiple user classes for real-time ATIS/ATMS applications.” Proceedings of the Advanced Traffic Management Conference, St. Petersburg, Florida. Federal Highway Administartion.

44. McShane, W. R., and Roess, R. P. (1990). "Traffic Engineering," Prentice-Hall, Inc., Englewood Cliffs, N.J.

45. Messer, C. J., Dudek, C. L., and. Friebele, J. D. (1973). "Method for Predicting Travel Time and Other Operational Measures in Real-Time During Freeway Incident Conditions." In Highway Research Record 461, TRB, National Research Council, Washington, D.C.

46. Morales, J. (1987). “Analytical Procedures for Estimating Freeway Traffic Congestion.” ITE Journal-Institute of Transportation Engineers. v 57 n 1 Jan pp 45-49.

47. Nam, Doohee and Fred Mannering. (2000). “An Exploratory Hazard-Based Analysis of Highway Incident Duration.” Transportation Research – A. Vol. 34A, No. 2, pp 85-102.

48. Nee, J. and Hallenbeck, M. (2001). "Evaluation of the Service Patrol Program in the Puget Sound Region." Report WARD 518.1. FHWA, U.S. Department of Transportation.

49. Olmstead, T. (2001). "Freeway management systems and motor vehicle crashes: a case study of Phoenix, Arizona," Accident Analysis and Prevention 33, pp. 433–447.

50. Ozbay, Kaan and Pushkin Kachroo. (1999). "Incident Management in Intelligent Transportation Systems." Boston, MA: Artech House.

51. Peeta, S. and A.K. Ziliaskopoulos. (2001). “Foundations of dynamic traffic assignment: The past, the present and the future.” Networks and Spatial Economics 1 (3/4), pp. 233-65.

52. Peng, Zhong-Ren; Beimborn, Edward; and Neluheni, Malindi. (2000) "A Framework for the Evaluation of the Benefits of Intelligent Transportation Systems," Center for Urban Transportation Studies, University of Wisconsin-Milwaukee, Milwaukee, Wisconsin.

53. Petty Karl, Ostland Michael, Kwon Jaimyoung, Rice John, and Bickel Peter, (2002). "A new methodology for evaluating incident detection algorithms," Transportation Research Part C 10, pp. 189-204.

54. Pierce, Ryan A., Sun, Carlos C., and Lemp, Jason D. (2005) "Incident Delay Modeling with the Use of Video Reidentification," 84th Annual Meeting of the Transportation Research Board, Washington, D.C.

55. Qi, Y. (2002). "Incident Delay Analysis and Estimation." Dissertation for Doctor of Philosophy in Civil Engineering, Polytechnic University, Brooklyn, NY.

56. Raub, Richard A. and Schofer, Joseph L. (1997) "Managing Incidents on Urban Arterial Roadways," Transportation Research Record 1603, pp. 12-19.

57. Robinson, J. (1990) "What’s New in Freeway Incident Detection and Response. Technical Papers from ITE Specialty Conferences 1990, 1989, and 1988." Institute of Transportation Engineers, Washington, DC, pp 244-257.

58. Sengupta, Raja, and Hongola, Bruce (1998). "Estimating ATIS Benefits for the smart corridor," California Path Program, Report UCB-ITS-PRR-98-30, University of California, Berkeley.

59. Sherali, Hanif D. and Subramaniam, Shivaram. (1999). "Opportunity Cost-Based Models for Traffic Incident Response Problems," ASCE, Journal of Transportation engineering, Vol. 125, No. 3.

60. Shi, H. (2004). "Online Dynamic Traffic Assignment Based Algotithms for Managing Real-Time Traffic Networks." Dissertation for Doctor of Philosophy in Civil Engineering, Northwestern University, Evanston, IL.

61. Skabardonis, A. Noeimi, H. Petty, K. Rydzewski, D. Varaiya, P. and Al-Deek, H. (1995) "Freeway Service Patrol Evaluation." PATH Research Report UCB-ITS-PRR-95-5 University of California, Berkley.

62. Skabardonis, A. Petty, K. Varaiya, P. and Bertini, R. (1998) "Evaluation of the Freeway Service Patrol (FSP) in Los Angeles." PATH Research Report UCB-ITS-PRR-98-31 University of California, Berkley.

63. Skabardonis, A., Petty, K., Noeimi, H., Rydzewski, D., and Varaiya, P. (1996). “I-880 Field Experiment: Data-Base Development and Incident Delay Estimation Procedures.” Transportation Research Record 1554, Transportation Research Board, Washington D.C. pp 204-212.

64. Smith, B., Qin, L., and Venkatanarayana, R. (2003). “Characterization of Freeway Capacity Reduction Resulting from Traffic Accidents.” Journal of Transportation Engineering. v 129 n 4 July/August pp. 362-368.

65. Stephanedes, Yorgos J., and Chassiakos, Athanassios P. (1993) "Freeway Incident Detection Through Filtering," Transportation Research Part C, Vol. 1, No. 3, pp. 219-233.

66. Sullivan, E. (1997). “New Model for Predicting Freeway Incidents and Incident Delays.” Journal of Transportation Engineering. v 123 n 4 July/August pp 267-275.

67. Taylor, William C., Saif, Mohammed A., and Sisiopiku, Virginia P. (1999) "Development of Freeway Incident-Based Congestion Measures." 78th TRB Annual Meeting, Washington, D.C.

68. Teng, Hualiang, Qi, Yi (2003). "Detection-delay-based freeway incident detection algorithms," Transportation Research Part C 11 pp. 265-287.

69. TRB (2000). "Highway Capacity Manual: 2000." Transportation Research Board; Ringbound edition (December 1, 2000).

70. Urbanek, G. L. and Rogers R.W. (1978) "Alternative surveillance concepts and methods for freeway incident management," Executive Summary, FHWA, Report # FHWA-RD-77-58, Vol. 1, Washington, D.C.

71. Wardrop J. G.(1952). "Some theoretical aspects of road traffic research." Proceedings of the Institute of Civil Engineers, pp. 325-378.

72. Wen, Huimin; Yang, Zhaosheng; Jiang, Guiyan and Shao, Changfeng. (2001). "A New Algorithm of Incident Detection on Freeways," IEEE. pp. 197-202.

73. Wickes, D., and Lieberman, E. (1980) "Development and testing of INTRAS, a microscopic freeway simulation model, Vol. 1, program design, parameter calibration and freeway dynamic component development," Rep. No. FHWA/RD-80/106, Federal Highway Administration, U.S.

74. Wirasinghe, C. S. (1978); "Determination of Traffic Delays from Shock Wave Analysis." Transportation Research, Vol. 12.

75. Ziliaskopoulos, A.K. and Waller, S.T. (2000). “An internet based geographic information system that integrates data, models and users for transportation applications.” Transportation Research Part-C Vol. 8, No. 1, pp. 427-44.

76. Zografos, K.G, and Vasilakis, G.M. (1997). “Theoretical and Practical Issues in Incident Response Operations,” IFAC Transportation Systems, Chania, Greece.

77. Zografos, K.G., Nathanail, T., and Michalopoulos, P. (1993). “Analytical Framework for Minimizing Freeway Incident Response Time,” Journal of Transportation Engineering, ASCE, Vol. 119, No. 4.