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Modeling of Short Term and Long Term Impacts of Freeway Traffic Incidents using Historical Data

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MODELING OF SHORT TERM AND LONG TERM IMPACTS OF FREEWAY TRAFFIC INCIDENTS USING HISTORICAL DATA

By

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ABSTRACT

Modeling of Short Term and Long Term Impacts of Freeway Traffic Incidents using Historical Data

by

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Traffic incidents are major contributors to non-recurring traffic congestion in most urban areas in United States. In addition to losses in terms of injury and property damage, freeway incidents also produce negative effects on the system including increased travel delays, fuel consumption and vehicle emissions. Incident management strategies are aimed at reducing the impacts caused by such incidents. Development of guidelines or models to quantify the impacts of these incidents on the society can aid in analyzing the effectiveness and economic feasibility of such incident management strategies.

The first objective of this study is to calibrate models that relate the short term marginal impacts caused by freeway incidents with incident characteristics such as incident duration and the number of lanes blocked. These models will help in quantifying the impacts of freeway incidents on the system as a part of the evaluation of incident management strategies or other related freeway operation projects. Historical incident data from a Las Vegas freeway is used to calibrate these statistical models. Additionally, freeway operation-related information is obtained from the web-based Dashboard system

maintained by the Regional Transportation Commission of Southern Nevada (RTC). Different statistical regression models calibrated relate freeway travel times, fuel consumption and emissions as functions of incident characteristics including incident duration, number of lanes blocked and time of day. Statistical measures of performance are used to evaluate the models and appropriate models are selected for recommendation. An additional component included in the impacts is the effect of the incident on the opposing direction of flow (rubbernecking).

The second objective of this research is to calibrate the influence of incidents and their corresponding impacts. In this study, various travel time reliability indices are used in quantifying the long term impacts of freeway incidents. Travel time reliability is an important planning tool both from the user point of view as well as transportation planners. The findings of this part of the research can help in operational and economic evaluation of freeway safety and incident management projects from the point of travel time reliability. The models can also be used to quantify system-wide impacts of incident to provide economic justification for acquisition of funding for such projects.

This contribution of this research is two-fold. First, statistical models are calibrated for quantifying the short-term impacts of freeway incidents on travel time, fuel consumption and vehicular emissions exclusively from field data as opposed to simulation and/or mathematical models. These marginal impacts can be used by transportation agencies and public organizations in the evaluation of incident management strategies. Also, given that these models are based on historical field data, accuracy is improved over existing models that are based on computer simulation.

The second contribution of this research is in providing models that quantify the long-term impacts of incidents in terms of travel time reliability. This quantification is a principal benefit since models specific to traffic incident impacts and travel time reliability have rarely been explored previously. In addition, this analysis is also based on field data unlike the very few previous studies and is therefore an improvement in the understanding of relationships between travel time reliability and incident characteristics.

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DEDICATION

To Amma, my husband Avinash and my sister Ramya,

for their endless love, support and encouragement.

Most of all, to Appa,

who dreams for me what I dream for myself, always.

Also to my friends,

for their invaluable companionship and advice.

I love you all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Efforts to provide sustainable transportation and improve system performance and effectiveness have been given much importance in the recent times. According to the World Energy Council, transport systems are among the most important factors that have significant impacts on the environment, contributing to about 20% of world energy consumption and emissions (World Energy Council, 2011).

Traffic incidents are defined as non-recurring events that result in reduction of roadway capacity. Examples include traffic crashes, disabled vehicles, spilled cargo or planned events like work zone activity and special events (Frandrup, Groth, Anderson, Sroga, & Hanzalink, 2002). Traffic incidents can have two types of impacts: short term and long term. Short-term impacts occur immediately during and after the incident. They include vehicle delay, fuel consumption and vehicle emissions. Long term impacts are produced by incident characteristics that influence driver behavior, over time. Drivers' perception of the reliability of travel times experienced on a roadway section is a long term impact of incidents in that location.

Traffic incidents are a major source of non-recurring congestion on freeways. These incidents, along with other non-recurring events like work zone and weather contribute to about 60% of the delay caused by roadway congestion (Federal Highway Administration [FHWA], 2008). In addition to costing millions of dollars in terms of loss of life, injuries and property damage, traffic incidents also cause additional losses due to the resulting traffic delay, excess energy consumption and vehicle emissions. Depending upon the severity of the impact of an incident, in terms of the number and location of travel lanes blocked and the duration of the incident, the resulting congestion can cause significant additional traffic delays, travel time, and associated additional fuel consumption and vehicle emissions. According to the Texas Transportation Institute's Urban Mobility Report, traffic congestion in the US in 2011 caused an estimated 5.5 billion hours of extra time and 2.9 billion gallons of wasted fuel resulting in a cost of $121 billion of travel delay and fuel consumption approximately (Schrank, Lomax & Eisele, 2012).

Congestion and the resulting delays are important problems in most urban locations (Ji, Zhang & Sun, 2011). Reducing recurrent congestion is more challenging since the most common solutions of increased capacity are difficult to enforce. However, non-recurrent congestion can be addressed to an extent by means of practicing incident management strategies and planning construction activities during night-time so as not to interrupt commuter traffic during the day. Many states have incident management strategies in place to reduce the detection and response time of the emergency vehicles resulting in reduction of travel delay due to incidents. Another impact, namely excess fuel consumption is a major concern for sustainability and environmental reasons. Measures to consume fuel efficiently are recommended to aid in reducing the depletion of our natural resources. The Unites States Department of Energy recommends sustainable use of energy to meet the current needs without compromising the need for future (fueleconomy.gov). Vehicle emissions are also of concern since the transportation industry is one the highest producers of pollutant emissions that affect air quality. Hydrocarbons (HC), Carbon Monoxide (CO), Oxides of Nitrogen (NO_x) and Carbon

Dioxide (CO_2) are among the most common vehicle pollutants (Office of Mobile Source, 1994).

For the short term impacts of incidents, a number of efforts have been reported over the years that attempt to model such impacts for the purpose of developing tools for evaluation of the effectiveness of incident management strategies. Most recently such studies have generally involved traffic simulation and/or theoretical models for quantifying impacts of incidents on vehicle travel times, speeds and queues formed as a result of blocked lanes due to incidents. With the existence of real-time and historical freeway traffic data and incident data, this study deviates from the use of simulation models and calibrates statistical impact models using actual field historical incident and traffic data obtained from RTC. Therefore more accurate models can be calibrated and the marginal impacts be estimated. Determining the marginal impacts is essential in understanding the influence of incident and traffic characteristics on the incident impact. Using the marginal impact relationships, agencies can explore various what-if scenarios for reducing incident impacts.

Since congestion is deteriorating in urban areas, estimation of travel time is gaining importance for both the travelers and transportation professionals alike (Lyman & Bertini, 2008). Most drivers that have experienced congestion, plan trips according to an expected delay. However these estimates may not consider non-recurrent congestion components like traffic incidents. In the recent times, interest has turned to travel time measurement followed by an analysis of how reliable they are. Travel time reliability is a measure of consistency in travel times. Road users value reliability highly for work and business reasons. Transportation planners have recently started to consider travel time reliability a key performance measure since it indicates how the users perceive the system performance and is of a lot of importance to many transportation system users (FHWA, 2009).

For long term impacts, the effect on travel time reliability experience by the users is the focal point. Commuters plan trips according the everyday congestion. But the experience of incidents can build up to cause the drivers to plan extra time in order to ensure on-time arrival at their destination. Thus the trip planning by the user is not at the average expected time of travel but higher, allowing for an incident. This impact of incidents on travel time reliability is of use to drivers to plan their trip better. For agencies, this factor can be included while estimating the benefits of a project. Therefore the use of direct impacts of incidents such as excel travel time, emissions and fuel consumption in combination with the indirect impacts of decrease in travel time reliability can better evaluate or forecast project benefits.

1.2 Research Objectives

The first objective of this study is related to the short term impacts and it involves modeling and quantifying the impacts of freeway incidents on measures of effectiveness including travel times, fuel consumption and vehicle emissions. Statistical regression models are calibrated that relate excess travel times, fuel consumption and vehicle emissions as functions of incident characteristics including incident duration, number of lanes blocked, time of day, day of week, peak/off-peak and location of the blocked lanes. These models can be used to estimate the marginal impacts of incidents. For example, for a given incident scenario, the additional travel times, energy consumption and emissions for each minute of incident duration can be estimated. Such information can be used by transportation agencies for project evaluation and justification.

The second objective of this study is to model travel time reliability in order to account for the long term impact of incidents. The objective is to develop models to relate travel time reliability measures as a function of incident characteristics. These models can be used by transportation agencies to be added to the long-term benefits of incident management projects during their evaluation.

1.3 Research Contribution

The first contribution of this research is the development of marginal impacts of traffic incidents on travel time, fuel consumption and vehicle emissions using calibrated statistical models from real-world data. These models quantify the short term or direct impacts of incidents. Archived historical traffic data along with corresponding incident data is used for this modeling.

The second contribution of this study is the model between traffic incidents and travel time reliability. The relations between incident, traffic characteristics and travel time reliability have not been modeled before. The methodology used in this study is novel and the final models from this research are based on archived real data.

1.4 Dissertation Report Organization

Chapter 1 of this document introduces the reader to background information related to the problem and states the objectives of the research. Chapter 2 provides a review of some of the most relevant literature that has been published previously on the study topic. Chapters 3 and 4 present the methodologies for the first and second objectives respectively. Chapters 5 and 6 discuss the data description and collection for short term and long term objectives respectively. This is followed by Chapters 7 and 8, which summarize the descriptive summary statistics of the data used in the analysis. Chapter 9 presents the analysis and statistical modeling results for the first objective and, Chapter 10 for the second. Chapter 11 provides the results for the marginal impacts of the first objective, Chapter 12 for the second. The conclusions drawn, recommendations and suggestions for future work are presented in Chapter 13.

CHAPTER 2

LITERATURE REVIEW

There is a multitude of literature published in the general area of modeling impacts caused by traffic incidents on freeways. This chapter presents a summary of a number of such publications along with other literature related to the topic being addressed in this study, which is the impact of incidents on travel time, fuel consumption, vehicle emissions and travel time reliability. The review has been organized in subdivisions covering some of the relevant focus areas.

2.1 Estimation of Impacts from Incident Management Strategies

Many of the previous attempts to estimate the impacts of incidents have been byproducts of studies that aimed at measuring the effectiveness of incident management programs. The study by Hagen, Zhou and Singh (2005) evaluated the benefits of the Road Ranger freeway service patrol (FSP) program of the Florida Department of Transportation (FDOT) in terms of delay, fuel consumption and reduction of air pollution against the costs of operation, maintenance and administration of the program in the year 2004. The study used a default travel time value of $13.45 in 2004 for each person hour of travel and $71.05 for trucks, in accordance with the Texas Transportation Institute's 2005 Urban Mobility report. For this study, using an assumed occupancy and truck percentage, the average value of travel time was calculated as $22.71. The FSP evaluation (FSPE) model developed by the University of California, Berkeley was used to estimate the savings in delay and fuel consumption. An incident duration of 30 minutes is used by FSPE for the 'without FSP' case. Response time with service patrol is calculated using the FSP beat length, number of FSP trucks and their speed. The study estimated savings for nitrogen oxides (NO_x), carbon monoxide (CO) and reactive organic gases (ROG) as a result of the projected reduction in incident duration (estimated by FSPE) using the traffic profile, incident information, traffic volumes and the FSP beat information as input. Total monthly delay savings for all the sites were found to be $25,863,715 corresponding to 1,138,869 vehicle-hours of travel time saved and savings in fuel consumption of 1,717,064 gallons translating to $3,365,445. Additional benefits not included in the benefit-cost (B/C) ratio calculation included reductions in air pollutant emissions that were found to be 3690 kg of reactive organic gases, 160 kg of CO and 740 kg of NO_x. The B/C ratio of the entire program was found to be in excess of 25:1.

The paper by Fries, Chowdhury and Ma (2007) examined the effectiveness of traffic cameras in the detection and verification of incidents at five different metropolitan freeway sites in the US state of South Carolina by means of benefit-cost analysis. Various incident scenarios were simulated using Parallel Micro Simulation Software (PARAMICS) software. The authors used emission and fuel consumption data from the United States Environmental Protection Agency (EPA) Mobile6 model for the rates of pollutant emission and fuel consumption for vehicles moving at various speeds. Statistical tests were performed on the simulated volumes and measured volumes for the sites and it was found that there was no significant difference in the mean and variance of measured and simulated volume for both freeway and arterial links. The incident detection and verification time for the base case with no early incident detection was a mean of 20 minutes and a standard deviation of 2 minutes. Incidents were then modeled with a range of incident detection time of 180 seconds (std. deviation: 61 s) and verification time of 60 seconds (std. deviation: 15 s). The resulting percentage reduction in delay, fuel and emissions were then computed. The costs considered for economic analyses were: service and maintenance, communication, infrastructure, and personnel. The benefits were categorized as savings in: delay reduction, energy consumption and air pollution (CO emissions, NO_x emissions, Hydrocarbon emissions, Particulate Matter). A vehicle age of 9 years was assumed for the analysis based on Davis and Diegel (2002). With the fuel consumption rates from Moblie6, the dollar values were found using Intelligent Transportation Systems (ITS) Deployment Analysis System (IDAS). Vehicle delay was found to have been reduced by 5.2% and fuel consumption was reduced by 3.8% (diesel) and 3.2% (unleaded gasoline). Total hydrocarbons and volatile organic compounds were both reduced by approximately 14%, CO by almost 10%, NO_x by almost 7%, and particulate matter (PM) by approximately 1% corresponding to 35 kg/day of hydrocarbons (HC), 195 kg/day of CO, and 40 kg/day of NO_x respectively. A benefit-cost analysis based on the simulation results suggested traffic cameras returned $12 for every dollar spent under the prevailing conditions at the study sites.

The study by Dia, Gondwe and Panwai (2008) aimed to quantify the impacts of incident management strategies namely ramp metering, VMS information dissemination combined with route diversions, and variable speed limit systems. The basis for analyses was a calibrated and validated simulation model of a motorway in the Gold Coast region of Australia. A total of 54 incidents were simulated for the AM Peak and 66 incidents for the PM peak. The effectiveness of each of the incident management strategies in reducing the negative impacts of the incidents was reported from the simulation results. Incidents were found to increase travel times by 2.2 percent; delays by 5.7 percent; and number of stops by 11.1 %. In addition to that, incidents resulted in an average increase of 1.5

percent in CO emissions and fuel consumption, and 5 percent increase in operating costs. On an average, each AM-peak incident resulted in an increase of $21,000 (AUD) in operating costs over the duration of the incident. For ramp metering, delays were reduced by 10.5 %, travel times by 2.8 % and number of stops by 23 % when the demand increased by 25 %. Results showed a reduction of delays by 8.8 %, decrease in number of stops by 22 %, and decrease in travel times by 3.3 % when both VMS route diversion and dynamic traffic signal plans on surface roads were implemented simultaneously and 30 percent of the drivers followed the route diversion. Some of the results of implementing variable speed limits indicated 11% improvement in efficiency based on traffic operation and 64 % reduction in the number of stops if the speed was changed from 110 kph (68 mph) to 70 kph (44 mph) over an 8 km (5 mi) road length.

The above mentioned studies develop and demonstrate the use of models estimating the impact of incidents in terms of delays produced and increase in fuel consumption and emissions. Models relating the above variables can be used to compute the effectiveness of incident management strategies and provide for a monetary comparison between viable strategies.

2.2 Measurement of Travel Delays

The study by Lv, Liu and Zhu (2010) explained a methodology to analyze and predict traffic incident impact using historic data. The overall goal was to estimate the impact of traffic incidents in order to improve management strategies to enhance the quality of the transportation system and reduce environmental pollution. The travel speed of the system without any incidents was computed by measuring average under normal circumstances. The impact of the incident was defined in this paper as the difference between the travel speeds with and without the incident under similar conditions. Models to predict the traffic conditions were developed based on an average of historical data with similar conditions. Three classifications of incidents were used: (i) step-type - the incident and the impact lasts for some time with the impact being steady (work zone); (ii) pulse-type - the duration of the incident is short but the impact could last for a long time (traffic incidents) and; (iii) progressive - the incident and the impact duration is long (special events). The autoregressive moving average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH) models were used to model the incident impact value series. The time-sliding matching method was used to predict the traffic pattern. The modeled analyses results compared well with the field data measured from the Beijing Float Car data except for the extremities. The paper concluded that the traffic prediction model developed can simulate traffic conditions under incidents.

Chung and Recker (2011) presented a methodology to estimate the spatial and temporal impact caused by freeway accidents. The paper also identified the causal factors determining the total delay of an incident. Loop detector data from six freeways in Orange County, California was used to demonstrate the method. Speed matrices were plotted under regular conditions and accident conditions from the occupancy measurements and counts collected from inductive loop detectors every 30 seconds. The maximum extent of the incident shockwave was estimated from the speed plots. Accident data was collected from Traffic Accident Surveillance and Analysis System (TSAS) maintained by California Department of Transportation (Caltrans). In order to filter the speed data without the influence of incidents, a threshold was applied. The maximum incident duration was set to 4 hours. The median total delay was 22.27 vehicle hours for

2232 accidents and the maximum total delay, 1379.49 vehicle hours. Based on univariate analysis using nonparametric analysis based on log-rank tests and Kaplan-Meier (KM) estimates, the variables with the most positive influence on delay were peak periods, 3 vehicles involved (function of number of vehicles involved), rear-end collision (type of collision), left lane (location of collision) and speeding (causal factors).

The study by Skabardonis et al. (1995 and 1997) analyzed data from the I-880 (California) field experiment on incidents and freeway traffic-flow characteristics. The field observed data was collected by probe-vehicles traveling a 9.2 mile I-880 freeway section at an average headway of 7 min. Field data during peak hours before and after the introduction of a Freeway Service Patrol (FSP) service was collected. A total of 2181 incidents during the before and after period were recorded along with the incident characteristics. The study found that a Poisson distribution provided an adequate fit for the incident frequency. The study also found that the average response time was 29 minutes in the ‘before’ period and was reduced to 18 minutes after the implementation of FSPs. Without FSP, the impact per assisted incident was 156.74 vehicle hours and with FSP it was reduced to 136.42 vehicle hours. The delay savings per incident were 20.32 vehicle hours.

Chien, Goulias, Yahalom and Chowdhury (2002) presented a simulation-based travel delay estimation at freeway workzones. CORSIM software was use for the simulation and the results were compared with a deterministic queuing model. The methodology was validated using data from a study area in I-80 East, New Jersey. The modeling scenario was a workzone of 0.5 mile blockage of one freeway lane allowing 3 lanes to operate. The total construction activity was for 16 hours. Results for a sample simulation for 4 hours with varying traffic flows of 5000 – 8000 vph showed the resulting queuing delays estimated by to be approximately 5818 vehicle hours (364 vehicle hours per hour of workzone activity).

Wang and Cheevarunothai (2008) quantified travel delays introduced by incidents on freeways. Occupancy data from loop detectors for the study was used for analysis on queuing. The influence of an incident was found by comparing the delays due to different incident types. Loop detector data and incident data was used as input to the deterministic queuing theory based algorithm that was developed to estimate delays. Prevalent traffic conditions were represented using a dynamic volume-based profile developed to more accurately represent non-incident scenario. VISSIM was used to validate the algorithm. Calibration was also performed to replicate the model to field conditions. 18 incidents on the SR-520 Evergreen Point Floating Bridge in Washington, United States were simulated and compared with algorithm-based estimates. The incident induced delay was found to be 173 vehicle hours for each incident. Among incident types, disabled vehicle incidents were found to cause very high incident delays. A drawback of the procedure was that it was based on a deterministic queuing technique which had some discrepancies with the reality and that fatalities were not modeled because none occurred during the 3-month study period.

The objective of the paper by Zhang, Ni and Yang (2012) was to predict freeway traffic incident delay based on simulation. The study used was six freeway incidents that took place on a specific link of the Nanjing-Nantong freeway in China. Traffic Software Integrated Systems (TSIS) software was used for simulation. The input parameter, incident duration data was not readily available. A regression model from a previous study (2009) was used to obtain the incident duration. The simulated delay value was compared with the true delay value measured from toll data. Travel delays were an average of 70,380 vehicle hours per incident corresponding to an average incident duration of 141 minutes. A comparison of the simulated delay with the true delay measured from toll data showed that the results were mostly comparable. The authors recommend the use of simulation methodology owing to its simplicity and practicality. A drawback was that this study used only 6 incidents and did not take into account the characteristics of the incidents.

The paper by Chung (2011) had two objectives. One was to quantify non-recurrent congestion due to a freeway incident as the difference between accident-free speed and the speed during and after an accident. The second objective was to identify the characteristics that affected the non-recurrent congestion due to accidents. The analytical procedure developed for measuring congestion impact was demonstrated using freeway data from South Korea in 2008. The methodology involved the development of speed matrices of normal flow and the accident flow. The shockwave due to the accident was then developed and visualized. The boundary conditions in this study were adopted from a previous study by the author: approximately 20 miles upstream spatially and 3 hours temporally. The case study on the South Korean freeways included 2224 accident records that were used. The non-recurrent delay was estimated to be 161,735.20 vehicle hours in total or 72.72 vehicle hours per incident. For the causal factors influencing the congestion, increase in number of vehicles involved, incident duration and rainy conditions were found to increase congestion. Delay was found to be higher for straight sections when compared to horizontal curves (reasoning being reduced speeds on curves). Night-time accidents had lesser delay than day-time accidents.

Incidents have numerous impacts on freeways including congestion, delays, decreased productivity, increased pollution and reduced safety. Kripalani and Scherer (2007) presented a study on estimating incident related congestion based on incident severity for freeways. The authors used a statistical approach to model congestion with relation to incident severity. The crash data for Virginia, United States for the year 2003 was used for this study along with the corresponding traffic flow data. The model of estimating the 'percent vehicle-hours lost', which was normalized with the traffic volume, was found to be the best (adjusted R2 of 0.64). The model was expressed as a function of the historical volume, number of vehicles, number of people uninjured and number of people with visible injuries. (Percentage of vehicle-hours lost = 0.0000343 * historical volume - 0.0291254 * no. of uninjured people + 0.2401116 * no. of people with moderate injuries + 0.6658071 * no. of overturned vehicles).

Some studies have tried to develop special analysis methodologies for secondary incidents that are caused as a result of deteriorating traffic conditions caused by a primary incident. The reduction of secondary incidents can be an important criterion to evaluate the incident management programs. Sun and Chilukuri (2011) used an Incident Progression Curve (IPC) to find the region of influence. The IPCs were applied on a police crash database to classify the secondary incidents. One challenge faced was that, since the effect of primary incidents can persist long after it has been cleared, it is hard to judge whether the second crash was due to recurrent or non-recurrent congestion. The representative IPC chosen for the whole database was a median because it was less influenced by the extremities and modes. Those incidents that fell under the progression curve starting after the occurrence of a primary incident were identified as secondary. The analysis was also compared to a static threshold of a distance of 3.53 miles and a time of 42 minutes. The analyses results showed that the difference in classification of secondary incidents using both methods was 30%, with the dynamic being higher. This sort of classification is important since incident management can effectively mitigate secondary incidents. Therefore one can analyze the true impact of a primary incident on travelers and the system. One drawback of this study is that it does not differentiate the curve for number of lanes blocked or traffic volume. Also, it may be difficult to obtain queuing information from archived incident data.

Chou and Miller-Hooks (2010) formulated a method to identify secondary incidents. The paper focused on a dynamic methodology to address deficiencies in previously documented (mostly static) methodologies. Some methods like using CCTVs to identify secondary incidents may involve human judgment and visual perspective, producing erroneous results. Static methods involved a setup of spatial and temporal limits (an incident occurring within 15 minutes and 1 mile of the primary incident). In this paper, CORSIM was used to calibrate the regression models developed to indentify the incident impact areas, the motivation being that simulated data can be used to capture a wide range of characteristics rather than field data. The recommendation of the authors was to use this method on large datasets where there is an existing calibrated simulation model duplicating the respective systems.

Based on the review of numerous published literature related to the estimation of delay in terms of travel time due to incidents, it can be seen that a lot of the studies used simulation software to imitate real world situations. Some studies have also used shockwave analysis and delay prediction algorithms to estimate the values. Those studies that used real world data also impose limitations like set temporal and spatial limits. In the current study, historical field data related to incidents and the corresponding traffic conditions is used and impact is computed for each incident selected.

2.3 Excess Fuel Consumption and Vehicle Emissions due to Incidents

Poor air quality and the importance of ambient air quality standards have been well explored in the past few decades. National standards have been established for pollutants like green house gases (most common: CO_2, CH_4, N_2O and hydrofluorocarbons), volatile organic compounds, carbon monoxide, ozone, lead, nitrogen dioxide, particulate matter (also known as particle pollution or PM) and sulfur dioxide. These pollutants are constantly monitored through studies and measurements. Since the transportation industry is a major contributor to the production of many of these pollutants, the study and monitoring of vehicle emissions is very important. Production of atmospheric pollutants from vehicles increases with the increase in fuel consumption. Study of fuel consumption is also important to for sustainable use of energy in order to produce ways to reduce or optimize fuel consumption.

Thomas and Jacko (2007) presented a stochastic model to estimate the impact of highway incidents on air pollution and traffic delay. The study area was the I-94 freeway in Indiana, United States. Incident characteristics such as incident duration, degree of capacity reduction, and the demand-to-capacity ratio were modeled as random variables to estimate excess emissions and traffic delays. Mobile6 model was used for the emission factors and Monte Carlo simulation was used to determine the statistical characteristics of the emissions. The results indicated that an incident caused an average of 126.9 kg of excess CO, 20.8 kg of VOC, 8.8 kg of NO_x and 0.27 kg of $PM_{2.5}$ and delay of 630 vehicle-hours. This corresponds to 138%, 500%, 26% and 43% of increase in CO, VOC, NO_x and $PM_{2.5}$ respectively when compared with normal traffic conditions. The paper also reported that a peak-hour incident was found to have 7 times the estimated CO and VOC of an off-peak-hour incident.

Chung et al. (2013) presented a case study to measure impacts of freeway accidents on carbon dioxide (CO_2). The study area was Orange County in California, United States. The model developed by a previous study by Barth and Boriboonsomsin (2008) was used for estimating CO_2 measured for 2171 incidents that happened during a one-year period (Mar 2001- Feb 2002). The study reported that the average amount of CO_2 emissions for one freeway accident was 398.34 kg. The study also fitted a model and the factors that were found significant (p-value < 0.05) in contributing to CO_2 emissions were five-minute occupancy, AADT for passenger cars and trucks, accidents with three or more vehicles involved, and accidents that occurred at night. All the significant variables except AADT for passenger cars caused an increase in CO_2 emissions with increase in the variable.

The study by M.F. Coelho, Bandera and M.C. Coelho (2011) also evaluated the impact of road traffic incidents on pollutant emissions. The study was based on simulation of incidents using VISSIM for an arterial street in Aveiro, Portugal. The traffic volume and signal timing information were obtained from field studies. Thirteen incidents were modeled and compared with a base no-incident scenario. For peak condition, an increase of 25% and 50% for CO and CO_2 emissions were noted in comparison to no-incident situation in the north direction. For the south direction, an increase of 30% and 45% were noted.

The paper by Nejadkoorki, Nicholson, Lake and Davies (2008) presented an approach for modeling CO_2 emissions in urban areas. The method integrated three software packages namely SATURN, MATLAB and ArcGIS to model the CO_2 emissions at street-level resolution and visualize the results. SATURN is a micro-scale simulation software which uses a trip matrix and the road traffic network as input. The road choice model estimated the total flows in the links. The average speeds, length and density were input from SATURN to MATLAB. In addition, the fleet composition (vehicle and fuel type) and the respective emission factors according to speed from the Transportation Research Laboratory database were also used as input. Total emissions were then computed and visualized using ArcGIS. A case study for the city of Norwich, England was used for demonstration and total CO_2 emissions were found to be 69,100 tons in 2003. The results indicated that 85% of CO_2 emissions were from the main roads with passenger cars contributing to 72.5% of all the CO_2 emissions. Of the total emissions, 41% were attributed to off-peak hours.

This review along with the studies from section 2.1, explain studies to estimate vehicle emissions through simulation and regression analysis methods. This study attempts to look at individual incidents and relate the estimated emissions produced and the incident characteristics. By looking at individual incidents and obtaining the corresponding emissions, then model built in this study presents a good opportunity to perform marginal impact analysis.

2.4 Travel Time Reliability

Reliability is defined by Ebeling (1997) as "the probability that a component or system will perform a required function for a given period of time when used under stated operating conditions. It is the probability of a non-failure over time". Travel time reliability is an important measure of traffic performance and is commonly defined as the extent of consistency in travel times. Since commuters and shippers are averse to unexpected delay, efforts have been made to quantify travel time reliability. Another definition used in conjunction to reliability is the term variability or unreliability which is the measure of variance or dispersion in travel time. Conceptually, higher variability leads to lower reliability. The value of travel time reliability has been investigated by many studies including Carrion and Levinson (2013), Sikka and Hanley (2012), Bates, Jones and Cook (2001), Lam and Small (2001). These studies have explored and reiterated the importance of the travel time reliability to road users.

Bertini and Lyman (2007) and Elefteriadou and Cui (2010) summarized the various measures of reliability. The following are some common definitions of measures of reliability:

- 95^{th} Percentile Travel Time: travel times are lower than this on a given corridor, 95% of the time.
- Travel Time Index: average time taken to travel during peak times defined as the ratio of average travel time to free flow travel time.
- Buffer Time/Planning Time: ratio of 95^{th} percentile travel time divided by free-flow travel time.

- Buffer Index: ratio of the difference between 95th percentile travel time and mean travel time, divided by mean travel time.

Frequency that congestion exceeds some expected threshold: percent of days or time that mean speed falls below a certain speed.

The paper by Chen, Skabardonis and Varaiya (2002) explained the use of travel time reliability as a measure of service. The study used travel statistics to analyze service quality for a section of I-5 in Los Angeles, California. Descriptive statistics were used to represent travel time variability and quantify incidents and travel time predictability, LOS and travel time. The paper reported a wide range of expected travel times and 'what if' scenarios on the freeway study area. In one of the what-if scenarios, for a road-user a trip with a travel time of 40 minutes during 1 PM needed to plan for a travel time of 55 minutes during 6 PM. The cost estimate function combined average travel time as well as the standard deviation because the users placed different costs on travel time experienced and scheduled time. One of the results reported was that it was enough to budget 32 minutes for a certain trip if the driver knew that there were no incidents. However, if that information was not available, the planned travel time would be 45 minutes. Therefore, by knowing that there was no incident, 10 minutes of the trip travel time were saved.

Susilawati, Taylor and Somenahalli (2010) assessed travel time reliability for several corridors in the Adelaide area, Australia. The buffer time and planning indices were used to determine travel time reliability for 8 years' data and the trends were noted. By looking at the distribution, it was found that buffer time index and the planning index seemed to underestimate reliability due to the significant difference between the mean and 95th percentile travel time. Further statistical analyses were performed and it was found that the travel time data did not follow normal distribution. The study found that the log-normal type of distribution fit the data for some of the corridors well. The results of the study included the plots of buffer index and planning index for ten different corridors over 8 years. One drawback of this study is that it did not use time of day or day of week criteria to differentiate the annual travel time data.

Oh and Chung (2006) investigated the use of loop detector data in measuring route and link travel time variability. The study used real-time data from Caltrans in California. A GIS-based database was developed and three measures: day-to-day variability, within-day variability, and spatial variability were investigated. The study area was in Orange County, California for the year 2001. Single-loop detector data for 5-minute intervals was used in this analysis. The standard deviation and normalized standard deviation (normalized for length and travel time) were used as measures of travel time reliability. Time of day analysis showed that reliability was less during morning and afternoon peaks. Day of week analysis did not show significant difference. In terms of analysis across the months of the year, December was found to have lower reliability than the other months.

Very few studies have been dedicated to exploring the effects of incidents on travel time reliability. Two such studies are Tu, Van Lint and Van Zuylen (2008) and Park, Rakha and Guo (2011). Tu et al. investigated the effect of the direct impacts of traffic accidents on travel time reliability under different demand levels. The travel time data was estimated from empirical loop detector data on a freeway in Netherlands and police accident records. The raw data consisted of 10-minute aggregate speed recordings for the year 2004. Travel times were estimated based on the ‘Piecewise Linear Speed Based’ algorithm. The plot results for travel time as a function of inflow levels for the 10th, 50th and 90th percentile volumes showed that traffic accidents increased the travel time. The 90th percentile travel time increased by around 75% due to traffic incidents. Plots of the travel time reliability measure developed and estimated by the study showed that travel time reliability with incidents was much lower than that without traffic incidents. This study made a temporal assumption in that it considers the data for a 3-hour period following the traffic accident to encompass the accident effect.

Park et al. (2011) proposed a multi-state travel time reliability model to quantify the impact of traffic incidents on travel time reliability due to incidents. The study used simulated data for weekdays over a period of 17 days from 5:00 AM to 10:00 AM. A multi-state model was used as opposed to the single-state model since the former fit field measured travel times better as shown in Figure 2-1. The three different states represent uncongested, medium-level congested and heavily congested flows.

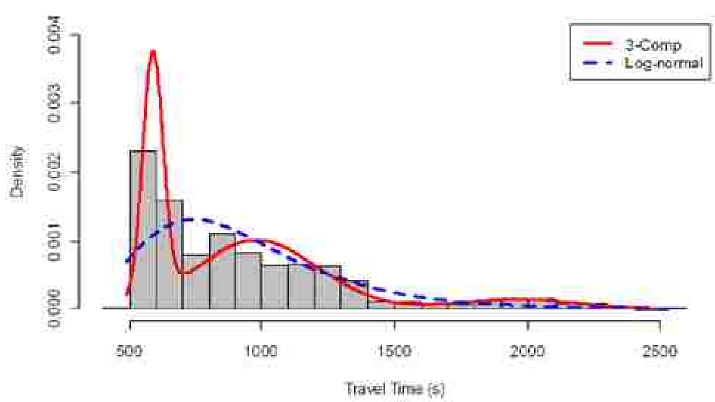


Figure 2-1. Mixed normal and log-normal density function (Park et al., 2011)

The study accounted for incidents of different severities by simulating different incident scenarios with one, two and three lanes blocked. The means and standard deviation of the travel times were reported. The results identified the increase in travel time variability. The difference between mean travel time and 90th percentile travel time increased around 6:00 AM to 8:00 AM. Scenarios with and without incidents were modeled. The study found that in the medium-level congested state, there was 93% increase in the 90th percentile travel time for the incident scenario. In the heavily congested state, once traffic congestion has already onset, traffic incidents did not affect the travel time much. One disadvantage of this study is that it uses an assumed incident duration of 40 minutes based on the average for all incidents in Virginia, United States.

The study by Tsubota et al. (2011) estimated the benefit of reducing accidents due to improvement in travel time reliability. The study used data from a Tokyo Expressway to analyze the relation between traffic accidents and travel time reliability. An additional concept of penalties for late and early arrival was also introduced. A plot with comparison between the incident and non-incident travel time measurements was developed. The estimated costs calculated by the study were compared for incident and non-incident conditions. The results found was that the benefit of reducing one incident was savings of 2.54 million yen (app. 25,670 USD) on an average. Some drawbacks of this study included that the impact measurement was stopped once the vehicle were cleared. The delay that continued after the clearance until normal flow returned was ignored. Also, the incidents that did not produce any noticeable traffic jam were ignored. The study compared the overall travel times and did not include incident characteristics like number of lanes blocked, incident duration of the incidents.

2.5 Summary

The review above presents many papers and reports similar in objective as the current study. The estimation of the short-term impacts of incidents has been well explored. In this study, in addition to presenting a methodology to estimate short-term impacts of incidents, analysis and results for marginal impacts of the measures are modeled. For fuel consumption and vehicle emissions, since real-world measurements are difficult of obtain, simulation software packages are typically used. In this study, fuel consumption and vehicle emissions are modeled using EPA's MOVES software. For long term impacts of incidents, studies that relate incidents and travel time reliability measures are very few. The methodology presented in this study and the incident, traffic characteristics used in developing the statistical models are novel. In both short-term and long term impacts of incidents, archived field-measured traffic data and recorded incidents data are used.

CHAPTER 3

METHODOLOGY FOR ANALYSIS OF SHORT TERM IMPACTS OF INCIDENTS

3.1 Introduction

This chapter presents the methodology for modeling the short term impacts of incidents. In this study, only the impacts of vehicular incidents are considered. The impacts on the opposing direction of traffic due to rubbernecking are also added to the impacts of the primary analysis direction. The term rubbernecking is used to describe the phenomenon where the drivers in one direction of flow are distracted by an incident (and queues) in the opposing direction of flow (Masinick and Teng, 2004). Since the effect is caused due to the incident in the primary direction of flow, the resulting rubbernecking impacts are also added as additional components while computing incident impacts.

3.2 Impacted Measures of Performance

In this study, short term impacts of incidents on travel time, fuel consumption and vehicle emissions are modeled. The following is a description of these measures of performance.

3.2.1 Travel Time

One of the impacts of incidents is increased travel time for vehicles travelling on the impacted segment. The travel time measures used in this study are vehicle-hours of travel, and additional average vehicle travel time over the freeway segment impacted by the incident. The excess of travel time performance measures caused due to traffic incidents is measured by comparing travel time during non-incident and incident conditions.

3.2.2 Fuel Consumption

Another impact of incidents is excess fuel consumption due to reduced vehicle speeds and increased travel time. Figure 3-1 shows the effect of speed on fuel economy with lower and higher speeds indicating reduced fuel economy (USDOE, 2005). Traffic incidents and the ensuing congestion cause lower speeds, therefore resulting in lower fuel economy as shown by Figure 3-1. In this study, EPA's MOVES software is used to estimate the increase in fuel consumption of the impacted vehicles. The excess fuel consumption is computed as the difference between the fuel consumption during incident and non-incident traffic conditions.

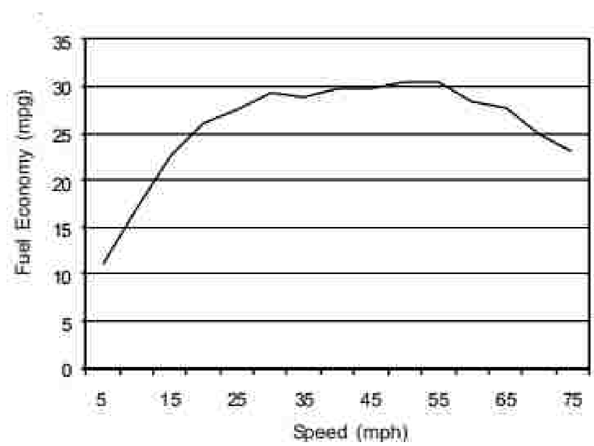


Figure 3-1. Fuel Economy and Speed (Source: USDOE)

3.2.3 Vehicle Emissions

Based on the literature review of related studies and publications, the emission pollutants chosen to be considered in this study are Carbon Dioxide (CO_2), Carbon Monoxide (CO), Oxides of Nitrogen (NO_x) and Particulate Matter of size 10 micrometers or less, (PM_{10}). Vehicular traffic has been found to be a significant contributor to the production of these three pollutants (Rodrigue, 2013). Transportation industry is the highest contributor accounting to about 70% of CO, 40% of NO_x and 25% of PM_{10} production respectively. Oxides of nitrogen contribute to illnesses and react with the atmosphere to affect ozone levels. Also, a component of NO_x namely NO_2 is toxic. PM_{10} causes respiratory illnesses and CO causes oxygen deprivation in human body leading to numerous other illnesses (Gorham, 2002).

Vehicle emissions vary with the speed of vehicle and type of vehicle. Figures 3-2, 3-3 and 3-4 from the California Life-Cycle Benefit Cost Analysis Model (Cal-B/C) show the CO, NO_x and Particulate Matter less than 10 micrometers (PM_{10}) emissions by speed based on UCLA speed measurements for 2003 and 2007 on a highway facility (System Metrics Group, Inc., 2009). The figures show emissions for three types of vehicles, automobiles, buses and trucks, for a highway facility. Traffic incidents can be expected to cause increased emissions due to resulting low operating speeds and sudden acceleration and deceleration.

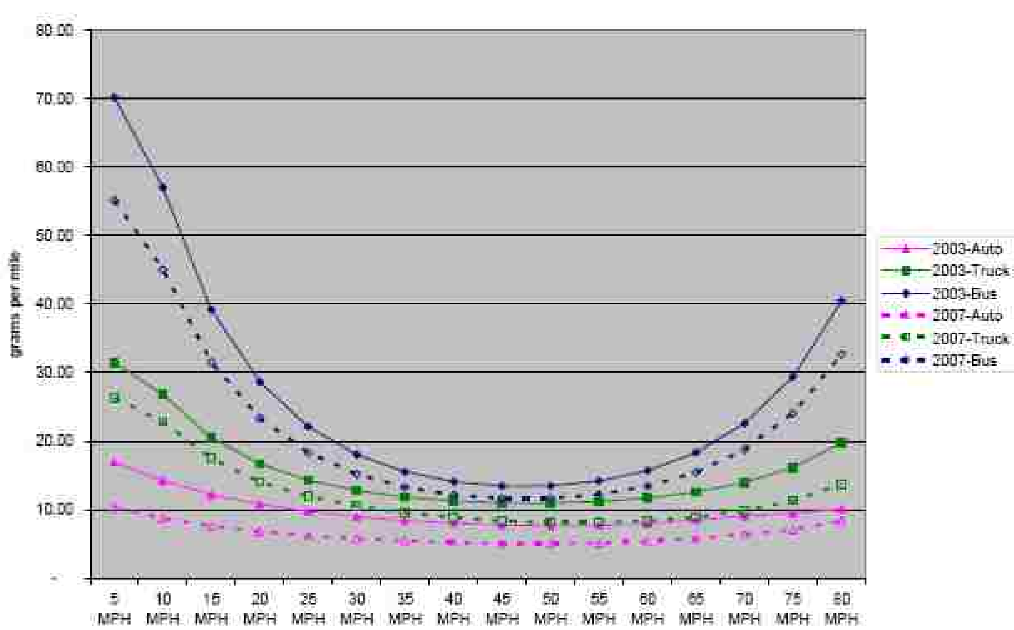


Figure 3-2. CO Emissions versus Speed (System Metrics Group, Inc., 2009)

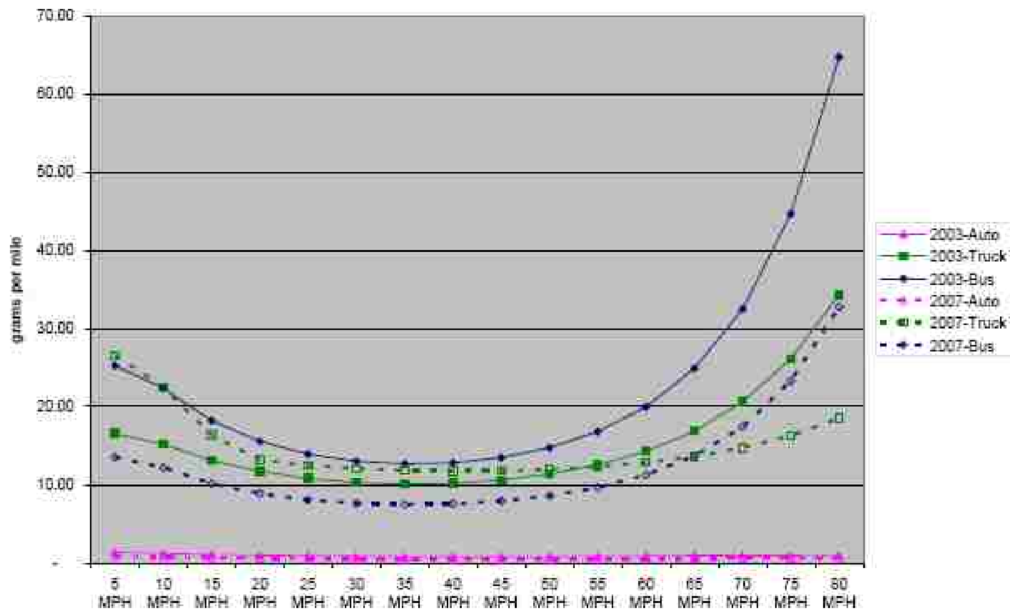


Figure 3-3. NO_x Emissions versus Speed (System Metrics Group, Inc., 2009)

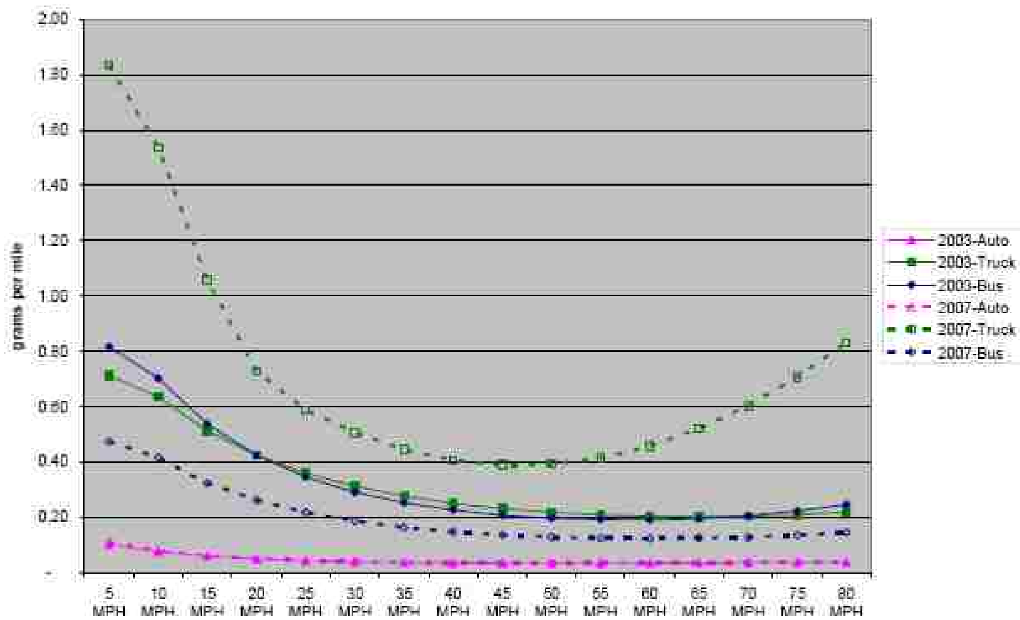


Figure 3-4. PM_{10} Emissions versus Speed (System Metrics Group, Inc., 2009)

As seen in the figures, very low and very high speeds result in higher emissions when compared to normal speeds. The vehicle emissions in this study are modeled using

EPA's MOVES for the incident and non-incident scenarios and the difference between the two is computed as the excess vehicle emissions produced due to that incident.

3.3 Framework of the Study: Impacts of Incidents on Travel Time, Emissions and Fuel Consumption

The flowchart in Figure 3-5 presents the overall methodology for computing the short term impacts considered in this study - travel time, fuel consumption and vehicle emissions.

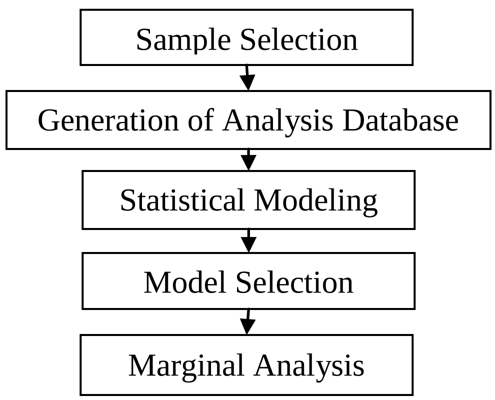


Figure 3-5. Flowchart for Modeling Incident Impacts on Travel Time, Emissions and Fuel Consumption

3.3.1 Sample Selection

The first step in the process is the selection of a suitable sample of incidents from the incident database. All the incidents that occurred in a one- year period are used as the population. Proportional sampling is performed to ensure that the sample has the same proportion of incidents, segment-wise, as the population. After performing proportional sampling on this data, a sample subset is chosen at random according to the requirement for each segment.

3.3.2 Generation of Analysis Database

The flowchart for generation of the analysis database is shown in Figure 3-6.

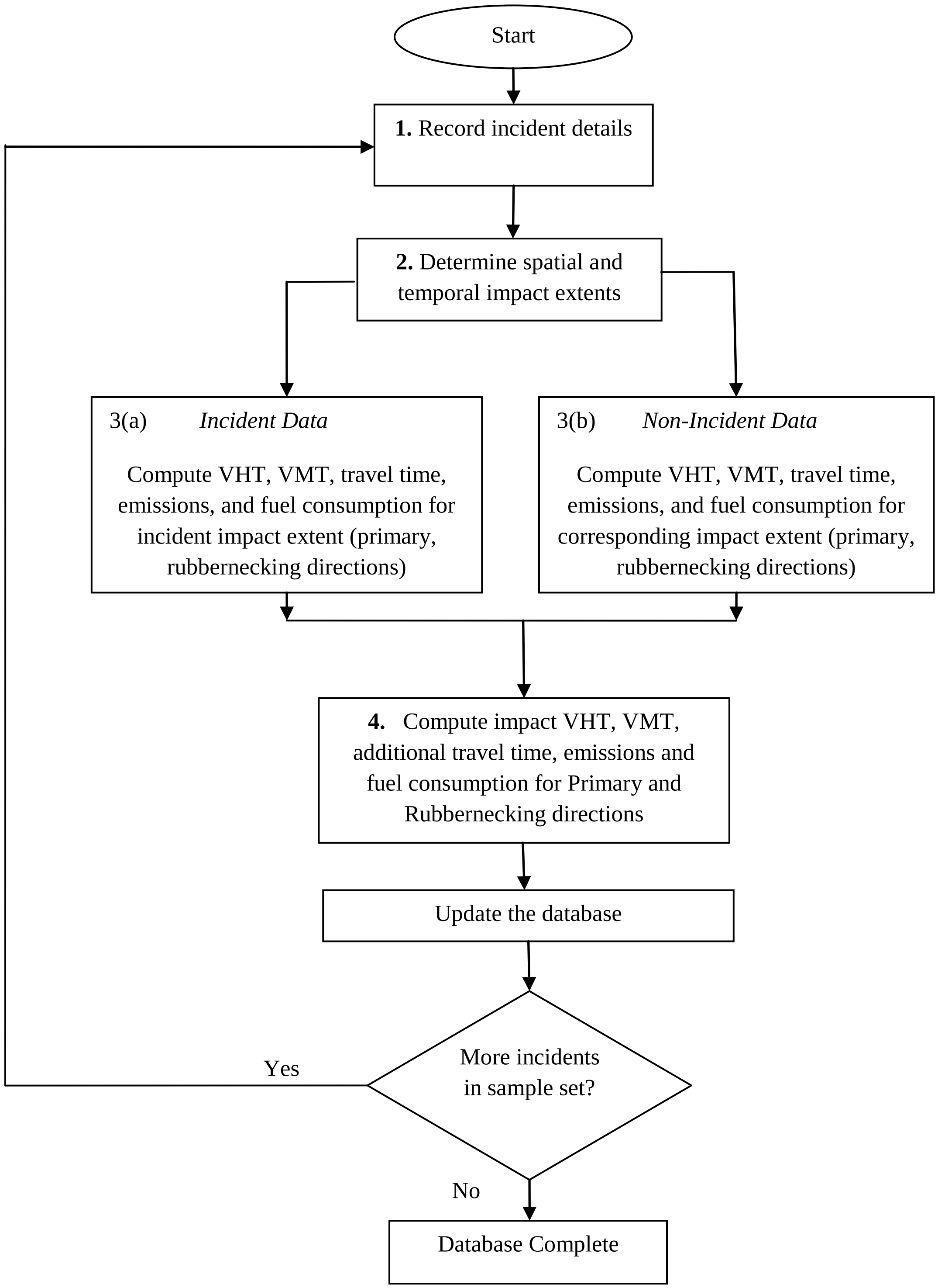


Figure 3-6. Flowchart for Generation of the Analysis Database

Step 1. Recording incident characteristics.

This step is to record the incident characteristics from the incident database. Table 3-1 shows sample incident information for which the procedure for computation of the impact on delay is explained. The incident characteristics recorded include day of week, time of day, location, number of lanes blocked, incident duration, presence of a secondary crash and severity of the incident.

Table 3-1. Sample incident data

Time Stamp	Corridor	Location	Lanes Blocked	Number of lanes	Lane Cleared	Time Elapsed (min)	Secondary	Severity	Roadway ID	Segment ID
12/23/2011 11:26:00 AM	I-15 NB	North of Sahara	Right lanes	2	12/23/2011 1:02:00 PM	96	0	noticeable	110	1

Step 2. Determination of spatial and temporal extents of the incident

This step involves the collection and plotting of speeds for the incident day in order to determine how far upstream the incident had impact (spatial extent) and the total time period impacted (temporal extent). Figure 3-7 shows a typical plot of speeds of the day of an incident under consideration from which the spatial and temporal extents are clearly evident.

The following parameters are extracted from this data, namely,

i. Duration of temporal extent (in minutes), i.e., how long after the occurrence of the incident is the impact felt

ii. Length of spatial extent (in miles), i.e., how far upstream does the incident-induced congestion extend

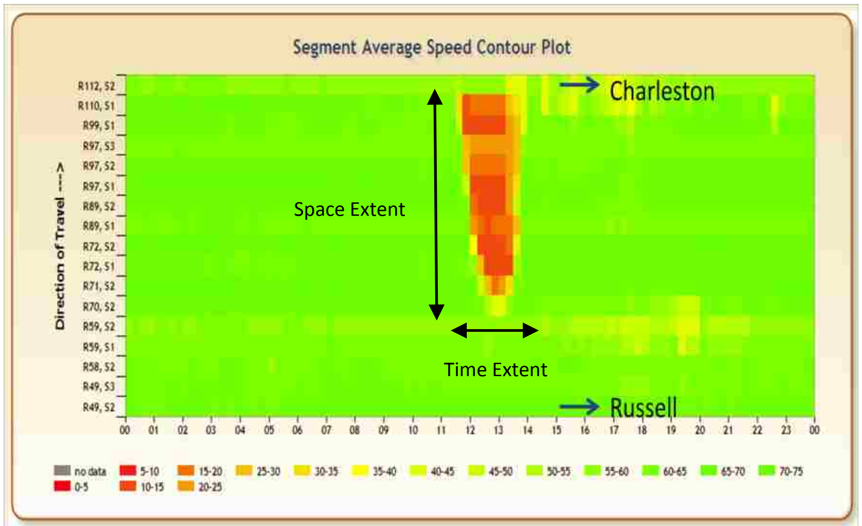


Figure 3-7. Speed Plot for Sample Incident

Step 3. Computing VHT, VMT, travel time, emissions, and fuel consumption for impact extent

a) This step involves the calculation of the traffic parameters for incident condition over the corresponding spatial and temporal extent of the incident. The parameters to be determined include traffic volumes, speeds, travel times, and densities over each segment and time period covering the spatial and temporal extents. Similar data in opposite direction is obtained for the impact of rubbernecking. The following parameters are calculated for the corresponding segments and time periods covered in the spatial and temporal extents.

Volume, $$V_{k,t} = v_{k,t}\frac{60}{T} \quad (3\text{-}1)$$

Average volume, $$VOL_j = \frac{\sum_{t=1}^{N_T}\sum_{k=1}^{N_K} V_{k,t} L_k}{\sum_{k=1}^{N_K} L_k} \text{ vph} \quad (3\text{-}2)$$

Average volume per lane, $vol_j = \dfrac{\sum_{t=1}^{N_T}\sum_{k=1}^{N_K}\dfrac{V_{k,t}}{M_k}L_k}{\sum_{k=1}^{N_K}L_k}$ vphpl (3-3)

Average travel speed, $SPD_j = \dfrac{\sum_{t=1}^{N_T}\sum_{k=1}^{N_K}S_{k,t}L_k}{\sum_{k=1}^{N_K}L_k}$ mph (3-4)

Density, $D_{k,t} = \dfrac{V_{k,t}}{S_{k,t}}$ vpm (3-5)

Average density per lane, $DEN_j = \dfrac{\sum_{t=1}^{N_T}\sum_{k=1}^{N_K}D_{k,t}L_k}{\sum_{k=1}^{N_K}L_k}$ vpmpl (3-6)

Total travel time over impacted segments,

$$TT_j = \frac{1}{N_T}\sum_{t=1}^{N_T}\sum_{k=1}^{N_K}T_{k,t} \text{ minutes} \quad (3\text{-}7)$$

Vehicle-hours-of-travel, $VHT_j = \dfrac{1}{60}\sum_{t=1}^{N_T}\sum_{k=1}^{N_K}v_{k,t}TT_{k,t}$ (3-8)

Vehicle-miles-of-travel, $VMT_j = \sum_{t=1}^{N_T}\sum_{k=1}^{N_K}v_{k,t}L_k$ (3-9)

Rate of fuel consumption and vehicle emissions,

$$fe_j = \frac{FE_{x,j}}{VMTM_j} \quad (3\text{-}10)$$

Where

N_K = the total number of segments over the spatial extent of the incident

L_k = length of segment k in miles

M_k = the number of lanes on segment k

T = length of time period t in minutes

N_T = the total number of time periods over the temporal extent (each time period is approximately 15 minutes)

$v_{k,t}$ = number of vehicles on segment k during time period t

$V_{k,t}$ = volume on segment k during time period t in vph

$S_{k,t}$ = speed, in mph, on segment k during time period t

$D_{k,t}$ = density, in vpm, on segment k during time period t

$TT_{k,t}$ = travel time, in minutes, on segment k during time period t

$FE_{x,j}$ = output from MOVES in grams for emissions and gallons for fuel

x = factor estimated using MOVES: fuel and emissions (CO_2, CO, NO_x, PM_{10})

j is used to distinguish between incident and non-incident parameters and the primary and rubbernecking direction

$VMTM_j$ = vehicle-miles of travel estimated by MOVES

b) For each incident, corresponding non-incident traffic parameters are collected for the same day-of-week, spatial and temporal extent as the incident using the same formulae mentioned above. The days-of-week are divided into four, namely, weekdays (Monday – Thursday), Fridays, Saturdays and Sundays. The non-incident parameters are computed averages over several days' worth of non-incident time periods for corresponding day of week.

The entire process is to be repeated for the rubbernecking direction as well, for the same temporal and spatial extent (plus an extra segment upstream in the rubbernecking direction).

Step 4. Computing impact VHT, VMT, additional travel time, emissions and fuel consumption

In this step, the following incident impact parameters are calculated for each incident:

i. Average additional travel time: This is the difference between the incident and non-incident average total travel time over the all the segments in the spatial and temporal extents, i.e.,

$$\Delta TT = (TT_{inc} - TT_{non}) \tag{3-11}$$

$$\Delta TT_R = (TT_{Rinc} - TT_{Rnon}) \tag{3-12}$$

where

TT_{inc} and TT_{non} are incident and non-incident travel times, respectively.

TT_{Rinc} and TT_{Rnon} are incident and non-incident travel times for the rubbernecking direction, respectively.

ii. The additional vehicle-hours-of-travel and vehicle-miles of travel are calculated as follows, i.e.,

$$\Delta VHT = \sum_{t=1}^{N_t}\sum_{k=1}^{N_k} v_{k,t}\Delta TT \tag{3-13}$$

$$\Delta VHT_R = \sum_{t=1}^{N_t}\sum_{k=1}^{N_k} v_{R\,k,t}\Delta TT_R \tag{3-14}$$

$$\Delta VMT = VMT_{inc} - VMT_{non} \tag{3-15}$$

$$\Delta VMT_R = VMT_{Rinc} - VMT_{Rnon} \tag{3-16}$$

where

VMT_{inc} and VMT_{non} are vehicle-miles of travel for the incident and non-incident condition, respectively.

VMT_{Rinc} and VMT_{Rnon} are vehicle-miles of travel for the incident and non-incident condition in the rubbernecking direction, respectively.

iii. The additional fuel consumption in gallons/vehicle miles is computed by running EPA's MOVES software for incident and non-incident conditions and calculating the difference in fuel consumed per vehicle mile.

$$\Delta_{fuel} = \left(VMT_{inc}\left(fe_{fuel,inc} - fe_{fuel,non}\right) + VMT_{Rinc}\left(fe_{fuel,Rinc} - fe_{fuel,Rnon}\right)\right) \tag{3-17}$$

where

$fe_{fuel,inc}$ and $fe_{fuel,non}$ are incident and non-incident fuel consumption rates in gallons per mile respectively.

$fe_{fuel,Rinc}$ and $fe_{fuel,Rnon}$ are incident and non-incident fuel consumption rates in gallons per mile respectively for the rubbernecking direction.

iv. The additional emissions in grams/vehicle miles are similarly determined by running EPA's MOVES software for incident and non-incident conditions and calculating the difference.

$$\Delta_{emissions} = \left(VMT_{inc}\left(fe_{emnissions,inc} - fe_{emissions,non}\right) + VMT_{Rinc}\left(fe_{emissions,Rinc} - fe_{emissions,Rnon}\right)\right) \tag{3-18}$$

where

$fe_{emissions,inc}$ and $fe_{emissions,non}$ are incident and non-incident emissions in grams per mile respectively.

$fe_{emissions,Rinc}$ and $fe_{emissions,Rnon}$ are incident and non-incident emissions in grams per mile respectively for the rubbernecking direction.

The above procedure is repeated for all incidents considered and corresponding databases are generated.

3.3.3 Statistical Modeling

Regression models are calibrated to obtain the relationship between incident characteristics, such as the duration of blockage and the number of lanes blocked, and the impact on performance measures, such as the average travel time, vehicle-hours-of-travel, fuel consumption and vehicle emissions. These models are then used to estimate marginal impact of the incident parameters. For example, they can be used to estimate the impact on VHT for each additional minute of block duration, or for each lane blocked during an incident. Using Minitab and R statistical packages, regression analysis based on the following functional forms is performed.

3.3.3.1 Linear Regression Models

Linear regression models the mean value of the dependent variable as a linear function of the independent variables. This model is appropriate for analyzing dependent variables that are continuous and normally distributed.

$$Y_d = \beta_0 + \sum_{j=1}^{N} \beta_j X_j \tag{3-19}$$

Where:

Y_d = impact on an MOE parameter, such as VHT, travel time, fuel consumption, or emissions

β_j = regression coefficient for variable j

X_j = predictor/independent variable j

3.3.3.2 Log-Transformed Regression Models

An exponential regression uses an equation of the exponential function to fit a set of data. Exponential regression model takes the form:

$$Y_d = Exp\left(\beta_0 + \sum_{j=1}^{N}\beta_j X_j\right) \tag{3-20}$$

In this analysis an exponential relationship between the dependent and independent variables is subjected to linear transformation by taking logarithm on both sides. This model changes the dependent variable and interpretation should be changed accordingly.

3.3.3.3 Generalized Linear Models

Generalized Linear Models (GLM) models relate the mean of a dependent variable to a linear combination of explanatory variables while allowing for non-constant variance. A generalized linear model is made up of a linear function and two other functions: a link function that describes how the mean depends on the linear predictor, and a variance function that describes how the variance depends on the mean. GLMs are fit to data by the method of maximum likelihood, which is different from the Ordinary Least Squares method used by regular linear models. These models are useful when the dependent variable does not follow normal distribution.

Linear Models: $E(y_d) = \mu_d = \beta_j X_j$ where $y_d \sim N(\mu, \sigma^2)$

GLMs: $E(y_d) = \mu_d = \gamma(\beta_j X_j)$ where $y_d \sim$ Exponential Family (3-21)

Where, γ is the link function.

The exponential family of distributions can include distributions such as Poisson, Gaussian (normal), binomial and gamma. GLMs of the Gaussian and Gamma families are modeled in this study. For the Gamma GLM the link used in inverse and therefore the general model is of the form:

$$Y = (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p)^{-1} \tag{3-22}$$

Minitab software is used for development of the descriptive statistics of the data, their histograms, box plots and correlation matrices. R software is used for calibrating the linear, exponential and GLM models. These software packages are chosen owing to their ability to perform the required analysis and ease of use. Stepwise regression is used to determine the most significant variables, while taking into account the correlation between the predictor variables. A confidence interval of 95% is used to evaluate the statistical significance.

3.3.4 Model Selection

The full model with all the predictor variables is modeled for each of the LMs and GLMs. A nested model is selected by using Adjusted R^2, Akaiake Information Criteria (AIC) and stepwise regression, with the variables being significant at $\alpha = 0.05$. The coefficient of determination R^2 is an indicator of how well the model fits the set of data. In general, a higher R^2 signifies a good model. AIC is another parameter to measure goodness of fit and is applicable to GLM models (Burham and Anderson, 1998). These methods are used, whenever appropriate to select the appropriate regression model in this study. Once the final nested models for each of the functional forms of the LMs and GLMs are modeled, the residual plots are compared to select the best model. The selection of the best model depends upon the list of variables present in the model and its fit.

3.3.5 Marginal Impacts

The final nested model selected is then used to interpret and determine the marginal impacts of the predictor variables on the response variable. The marginal impact analysis is used to determine the rate of change of incident impact (e.g., excess VHT) with percentage or unit change in incident characteristics such as incident duration and number of lanes blocked.

CHAPTER 4

METHODOLOGY FOR ANALYSIS OF LONG TERM IMPACTS OF INCIDENTS

4.1 Travel Time Reliability

Long term impacts in this study are measured by impacts on travel time reliability. The travel time measures used commonly are explained in Chapter 2. In this study, the following measures of travel time reliability are used:

- 95th percentile travel times
- Buffer Time
- Buffer Index

The 95th percentile travel time can be used to indicate the time planned for a trip by a road user. The travel time data for the period under consideration is arranged and accumulated according to the day-of-week and time-of-day categories to facilitate the computation of the travel time reliability indices. The following section describes the analysis methodology for measuring the impacts of incidents on travel time reliability. The methodology involves aggregating all of the data first by weekdays and then by hourly time slots. The incident details are then aggregated for the same time slot. Other traffic characteristics including speeds, volumes and densities are also aggregated in the same manner. To be noted is that the days and times with documented workzone activities, weekends and holidays, night-time (9 PM to 5 AM) are to be excluded from this dataset. This is done in order to ensure that the effect of workzones, holidays or weekends is avoided.

4.2 Framework of the Study

The following text provides a description of the procedure used for calculating the impacts on travel time reliability as shown in the flowchart in Figure 4-1.

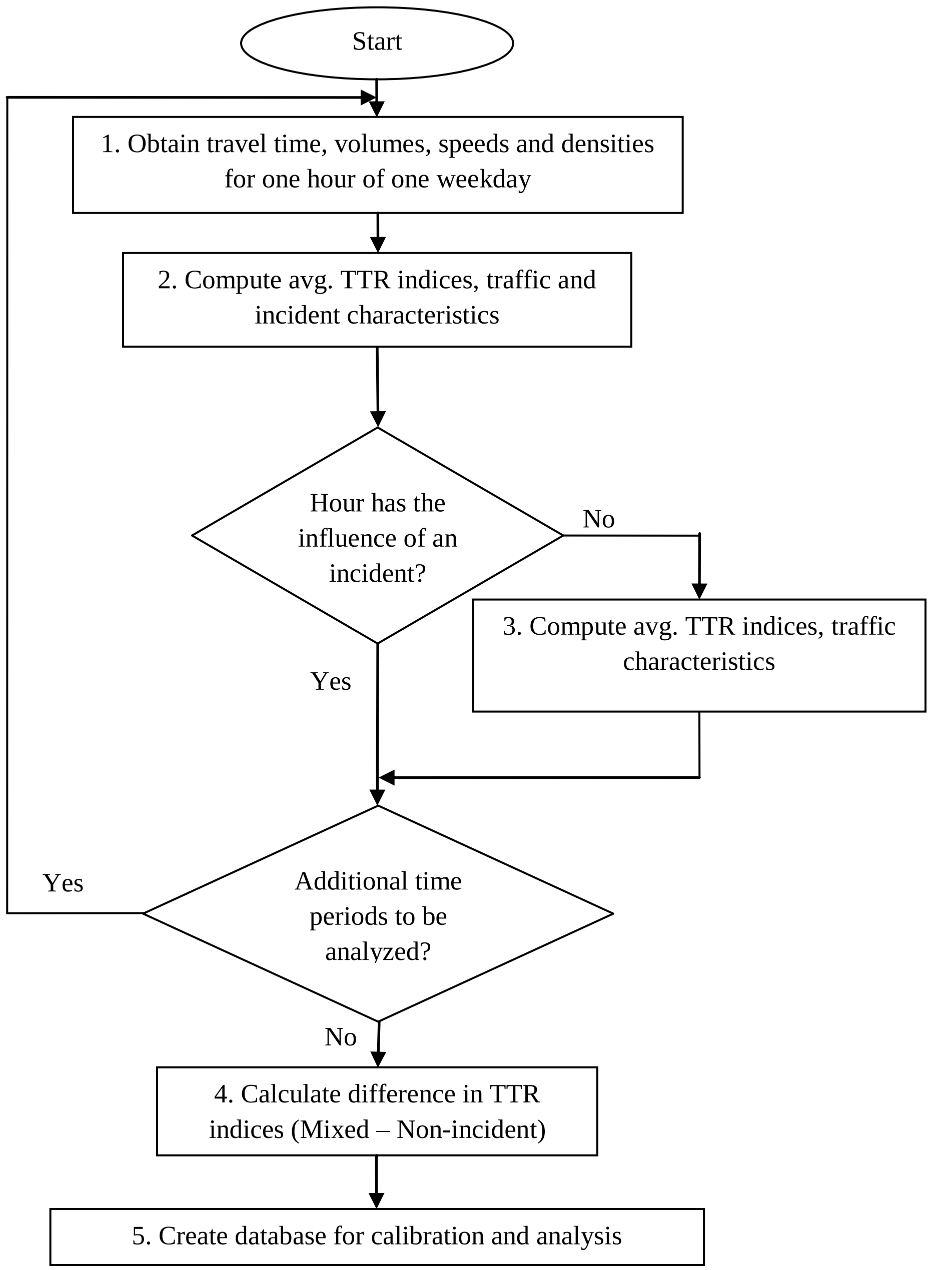


Figure 4-1. Data Processing Flowchart Incident Impacts on Travel Time Reliability

The methodology to compute the impacts of TTR can be applied to a pre-determined segment or corridor selected for consideration. The time period of data collection is also to be decided ahead. Since the concept of reliability is most effective for weekday commuter traffic, analysis for weekdays alone is carried out. The procedure is described as follows:

Step 1: Obtain travel times, volumes, speeds and densities for one hour of one weekday

For the selected weekday, the traffic data from Dashboard is downloaded and arranged by hour. The averages are computed for travel times, volumes, speeds and densities.

Step 2: Compute average TTR indices, traffic and incident characteristics for 'Mixed' data

Since the above dataset contains a mixture of incident and non-incident traffic characteristics, it forms the 'mixed' data. The mixed condition represents the field travel time experienced on an average when incidents might have been experienced. The 95th percentile, buffer/planning time and buffer index reliability measures of travel time reliability are computed for each hour.

Step 3: Compute average TTR indices, traffic and incident characteristics for 'Non-Incident' data

If there was no incident in the current hour and two hours prior to the current hour, the data is deemed fit for use in the non-incident dataset. The travel time and traffic characteristics for the non-incident data are also aggregated in the same manner as mixed data. The travel time reliability measures are computed for the non-incident dataset.

Step 4: Calculate difference in TTR indices

The differences in TTR indices between mixed and non-incident conditions are then computed to account for the influence of incidents on the travel time experience of the road users.

$$\Delta_{TTR} = \left(TTR_{MIXED} - TTR_{NON}\right) \tag{4-1}$$

where TTR_{MIXED} and TTR_{NON} are mixed and non-incident travel time indices respectively.

Step 5: Create database for calibration and analysis

The complete database then contains data for weekdays namely - Mondays, Tuesdays, Wednesdays and Thursdays and hourly time slots from 5 AM to 9 PM yielding 4 x 15 = 60 data points. Summarized along with the TTR impacts are the incident and traffic characteristics to be used as predictor variables in the statistical modeling.

4.3 Statistical Modeling

Statistical modeling for the reliability section, involves the calibration of the travel time reliability (indices) as a function of the incident characteristics and traffic data. The incident characteristics used as predictor variables include: number of incidents in the subject hour, number of lanes blocked and average Incident Duration reported. These characteristics for the previous hour, second hour, two hours combined are also determined. The regression model forms explained in 3.3 are performed for reliability analysis also.

4.4 Model Calibration

Stepwise regression and correlation matrices are used to select the appropriate significant variables. The p-value used is 5%. In some cases, a p-value of 10% is also used so as not to lose variables that are very important for practical purposes.

4.5 Model Selection

The model selection process for reliability analysis is also similar to the model selection for the short term impacts explained in section 3.5. AIC, residual plots and adjusted R^2 are used to select the model that fits the data best.

CHAPTER 5

DATA DESCRIPTION AND COLLECTION FOR SHORT-TERM IMPACT ANALYSIS

5.1 Introduction

In accordance with the methodology described in Chapter 3, the data required for short-term impact analysis include incident data and traffic characteristics. The Regional Transportation Commission of Southern Nevada's Freeway and Arterial System of Transportation (RTC FAST) maintains a web-based system called the PMMS Dashboard which keeps historical incident and traffic data for the Las Vegas valley freeway system (Xie and Hoeft, 2012) in a wide variety of customizable displays for evaluating day-to-day operation, incident management, express lane evaluation, ramp meters operation, ITS devices maintenance and operation data quality control. This Dashboard is the main source of data for this research.

5.2 Data Description for Short Term Impacts of Incidents

5.2.1 Incident Data

The incident database on the Dashboard is a consolidated historical database of all the reported incidents on Las Vegas freeways, including the Interstate 15 (I-15). The I-15 carries a lot of local commuter traffic in and out of the resort corridor from the suburbs. Even though incident information for all the freeways was available from FAST, the I-15 was chosen since the corresponding traffic data was more comprehensive in terms of data entry, when compared to the other freeways. The map of the study location is shown in Figure 5-1.

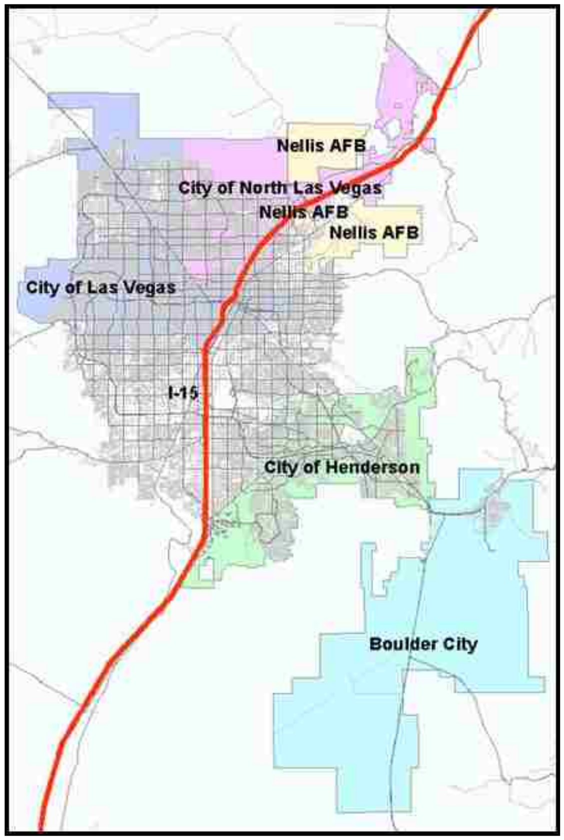


Figure 5-1. Map of Study Location

The following summarizes the study area parameters:

a. Study area: I-15 NB from St Rose to the Speedway.

b. Time period: March 2011 - March 2012.

c. Time of Day: 5 AM – 9 PM. Nighttime was left out because most freeway maintenance activities are conducted at night, and there is lack of reliable data on workzone schedules. In any case, due to low traffic volumes at night, the impact of incidents is expected to be much lower compared to daytime conditions.

During this study period, I-15 NB had 674 incidents and SB had 399 distributed by location as shown in Figure 5-2. The data shows that the segment between Sahara Avenue and Charleston Boulevard had the most number of the incidents. Also, Northbound direction had more number of incidents than the corresponding Southbound direction. The primary segment in this analysis is the Northbound direction, with the impacts on the rubbernecking direction (SB) included in the analysis. Figures 5-3 and 5-4 show the crash distribution by day of week and time of day.

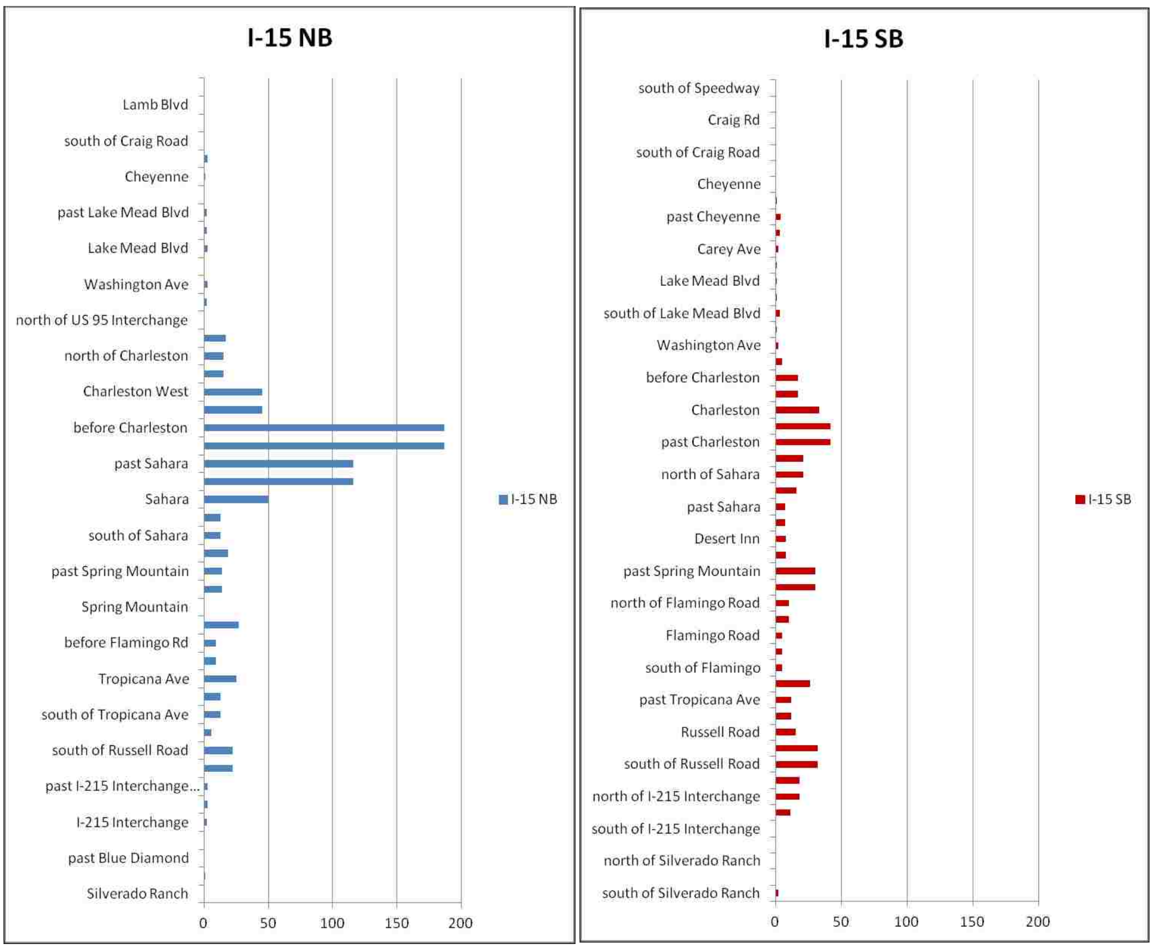


Figure 5-2. Number of Incidents by Segment

Figure 5-5 shows a typical Dashboard report with some incidents that occurred on December 30-31, 2011.

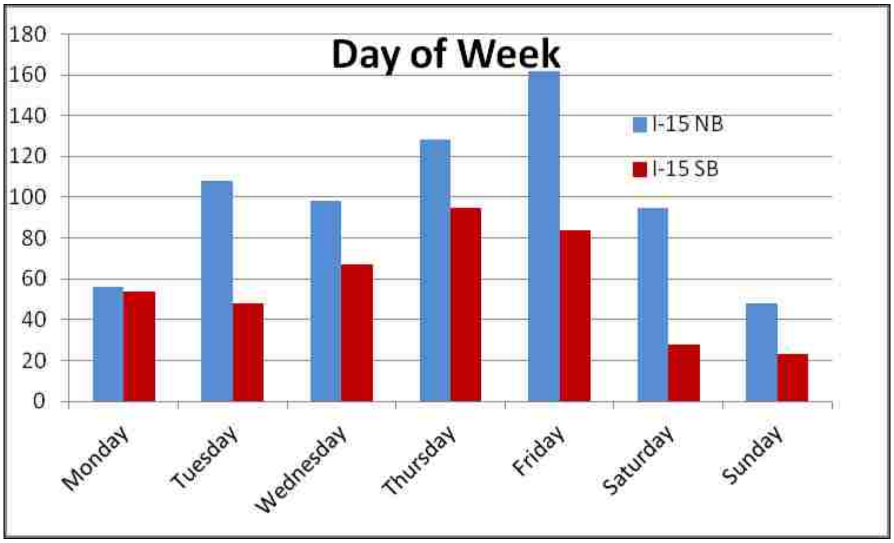


Figure 5-3. Number of Incidents by Day of Week

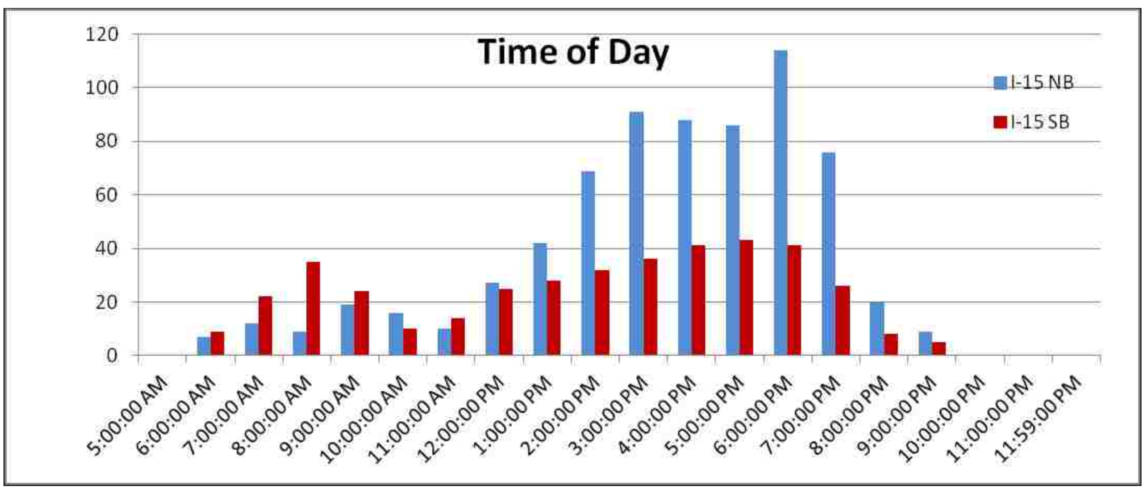


Figure 5-4. Number of Incidents by Time of Day

Year: 2011 Month: 12 Query

Time Stamp	Corridor	Location	Lanes Blocked	Number of Lanes	Tow Truck Arrive	Time Elapsed (min)	Lane Cleared	Time Elapsed (min)	Secondary	Severity	Message	Roadway ID	Segment ID
12/31/2011 5:40:00 PM	US-95 SB	Ann Rd	right lane	1					0	noticeable	12/31/2011 5:40 PM, Crash on US-95 Southbound at Ann Rd, right lane blocked, Expect delays	411	1
12/30/2011 6:31:00 PM	I-15 SB	Charleston	right shoulder	0					0	negligible	12/30/2011 6:31 PM, Crash on I-15 Southbound at Charleston, right shoulder blocked	117	1
12/30/2011 6:15:00 PM	I-215 WB	I-15 Interchange	left lane	1	12/30/2011 6:57:00 PM	42			0	noticeable	12/30/2011 6:15 PM, Crash on I-215 Westbound Southern Beltway, before I-15 Interchange, left lane blocked	7	1
12/30/2011 5:40:00 PM	I-15 NB	north of Sahara	right lanes	2	12/30/2011 6:02:00 PM	22			1	significant	12/30/2011 5:40 PM, Crash on I-15 Northbound north of Sahara, right lanes blocked	110	1
12/30/2011 5:07:00 PM	I-15 NB	north of Sahara	right shoulder	0			12/30/2011 5:52:00 PM	45	0	negligible	12/30/2011 5:07 PM, Crash on I-15 Northbound north of Sahara, right shoulder blocked	110	1

Figure 5-5. Typical Incident Report Page from Dashboard

The following incident details were used in this study:

- Day of the week of occurrence of the incident
- Time of day of occurrence of the incident
- Location of segment on which incident occurred
- Time the incident was cleared: The time duration between the time the incident occurred and when it was cleared gives the incident duration.
- The number of travel lanes-blocked by the incident
- Location of blocked lanes, i.e., left, center, right or shoulder lanes
- Presence of a secondary crash: If an incident occurred in the wake of the congestion of another incident. If the latter incident is within the temporal and spatial extent of the former incident, the latter is termed as a secondary incident.

From the incident data, a random sample of incidents to be used for the study is selected based on proportional sampling by incident location. An additional criterion in the proportional sampling is that each segment should have at least one incident in the study sample. Table 5-1 shows the number of incidents from each segment in the incident database and the corresponding sample size selected for the study. From each segment, the required number of incidents is selected at random. There are a total of 203 incidents in the study sample.

In order to obtain the impacts of the incident in the primary direction exclusively, if a primary direction incident had the presence of an incident in the corresponding rubbernecking (I-15 SB) segment's impact area, it was removed from the dataset.

Table 5-1. Number of Incidents for each Freeway Segment in the Study Area (I-15 NB)

Roadway-Segment ID	Seq ID	Segment	Total Incidents	Proportion	Sample Selection
356-2	56	Silverado Ranch	0	0.0000	0
356-3	57	past Silverado Ranch	1	0.0015	1
355-1	58	past Silverado Ranch	0	0.0000	0
355-3	60	before Blue Diamond	0	0.0000	0
354-1	61	before Blue Diamond	0	0.0000	0
354-2	62	Blue Diamond	0	0.0000	0
354-3	63	past Blue Diamond	1	0.0015	1
32-2	65	past Blue Diamond	0	0.0000	0
34-2	67	before I-215 Interchange (Southern Beltway)	2	0.0030	1
39-2	68	I-215 Interchange (Southern Beltway)	2	0.0030	1
48-2	69	past I-215 Interchange (Southern Beltway)	18	0.0267	5
49-1	70	before Russell Road	5	0.0074	2
49-2	71	Russell Road	3	0.0045	1
49-3	72	Russell Road	15	0.0223	5
58-2	73	before Tropicana Ave	25	0.0371	7
59-1	74	Tropicana Ave	8	0.0119	3
59-2	75	Tropicana Ave	9	0.0134	3
70-2	76	before Flamingo Rd	26	0.0386	8
71-2	77	Flamingo Rd	13	0.0193	4
72-1	78	Flamingo Rd	20	0.0297	6
89-1	80	Spring Mountain	24	0.0356	7
89-2	81	Spring Mountain	14	0.0208	4
97-1	82	past Spring Mountain	18	0.0267	5
97-2	83	Desert Inn	11	0.0163	3
97-3	84	before Sahara	50	0.0742	14
99-1	85	Sahara	116	0.1721	32
110-1	86	past Sahara	181	0.2685	49
112-2	87	before Charleston	45	0.0668	13
113-2	88	Charleston	15	0.0223	5
122-2	89	past Charleston	15	0.0223	5
124-2	90	US 95 Interchange	8	0.0119	3
137-1	92	past US 95 Interchange	2	0.0030	1
138-1	93	D Street	2	0.0030	1
138-2	94	Washington Ave	4	0.0059	2
146-2	96	Owens Ave	3	0.0045	1
148-2	97	Lake Mead Blvd	2	0.0030	1
149-2	98	past Lake Mead Blvd	2	0.0030	1
160-2	100	Carey Ave	0	0.0000	0
396-1	102	before Cheyenne	2	0.0030	1
396-2	103	before Cheyenne	1	0.0015	1
396-3	104	Cheyenne	3	0.0045	1
397-1	105	past Cheyenne	1	0.0015	1
398-1	108	before Craig Road	3	0.0045	1
398-2	109	before Craig Road	1	0.0015	1
399-2	112	past Craig Road	0	0.0000	0
400-1	114	Lamb Blvd	2	0.0030	1
402-1	120	CC 215 (Northern Beltway)	1	0.0015	1
403-3	125	Speedway	0	0.0000	0
		TOTALS	674		203

Another problem with the incident data is the lack of detailed data for some incidents. For instance, about 30% of the incidents do not have the incident duration. Since incident duration is one of the important variables in this study, incidents with no incident duration reported are manually determined from individual plots of speeds and traffic volumes.

5.2.2 Traffic Data

Data regarding traffic characteristics are also obtained from RTC FAST's PMMS Dashboard. The data includes the following parameters at 15 minute intervals for each segment:

- Volume
- Speed
- Travel Time

The data is collected by means of loop detectors for each segment of the freeway. Table 5-2 shows the traffic data from the freeway data plotting section of the Dashboard.

Table 5-2. Dashboard Corridor Traffic Plotting Module Snapshot

Draw Plot | View Table | Export to Excel | Export to Text

1 2 3 4 5 6 7 8 9 10 ... >>

RoadwayID	Segment ID	Slice Time	Avg Speed	Total Volume	Avg Lane Volume	HOV Avg Speed	HOV/Express Avg Lane Volume	GP Avg Speed	GP Avg Lane Volume
39	2	3/16/2012 6:00:00 AM	64	550	0	0	0	64	0
39	2	3/16/2012 6:15:00 AM	65	763	0	0	0	65	0
39	2	3/16/2012 6:30:00 AM	66	1051	0	0	0	66	0
39	2	3/16/2012 6:45:00 AM	66	1238	0	0	0	66	0
39	2	3/16/2012 7:00:00 AM	67	996	0	0	0	67	0
39	2	3/16/2012 7:15:00 AM	67	1256	0	0	0	67	0
39	2	3/16/2012 7:30:00 AM	67	1453	0	0	0	67	0
39	2	3/16/2012 7:45:00 AM	67	1508	0	0	0	67	0

To facilitate the computation of incident impacts, the traffic data is collected separately for: *non-incident* and *incident* conditions.

Incident Data:

Vehicle speeds, volumes and travel times are collected for each segment for the study period. Then, the speed plots are developed for each segment to determine each incident's temporal and spatial extents of the impact. The corresponding densities are computed from the speed and volume data. For each incident, using the formulas described in the methodology, the impacted total volume, impacted average density, and impacted average speed are computed.

Non-Incident Data:

The traffic data for the corresponding non-incident scenario over the same spatial and temporal extent and day-of-week is also collected. Traffic data files for non-incident scenario are created by grouping the data according to weekday and overlapping 8-hour time periods. In order to develop the regular traffic conditions without the presence of an incident, 30 data points (for most categories) are collected for each weekday and each time slot, after removal of outliers. The categories are weekdays (MWTR, Fridays, Saturday and Sunday) for overlapping time periods: 5 AM to 1 PM, 9 AM to 5 PM, 1 PM to 9 PM. The average of this is considered the non-incident data for travel speed, volume and travel time for the corresponding day of week and time of day. Outliers can be detected using the following formulas.

$$f_s = \text{upper fourth} - \text{lower fourth} \tag{5-1}$$

$$\text{Extreme Outlier} = \begin{cases} \text{upper fourth} + 3\,f_s \quad \text{OR} \\ \text{lower fourth} - 3\,f_s \end{cases} \tag{5-2}$$

where:

upper fourth = median of the upper half of the observations when arranged in ascending order

lower fourth = median of the lower half of the observations when arranged in ascending order

In order to obtain the true non-incident travel pattern, it is necessary to filter out the days on which construction activities were planned and carried out. The Nevada Department of Transportation was contacted to obtain the database of recorded work zone activities. One of the problems encountered was the lack of electronic documentation of work zone activities. Since most work zone activities were planned during night time, all night time analysis (9 PM to 5 AM) are removed from the study in order to eliminate the risk of the influence of roadway construction work. In addition, the data for planned work zone activities during day time are also removed from the database. Also, federal holidays are removed from the weekday traffic data since this data would not be representative of the recurrent congestion for weekdays. If federal holidays occurred on weekends, they are retained in the dataset.

5.2.3 Data Collection Procedure for Short Term Impacts of Incidents

In this section the procedure for computing the impacts of incidents on travel time is employed to the data. As mentioned in the methodology described in Chapter 3, each incident is analyzed separately.

Step 1. Record incident characteristics.

Table 5-3 is an example of incident parameters for one incident that took place on February 4, 2012.

Table 5-3. Sample incident parameters

Day	Date	TimeStamp	Corridor	Segment Description	Roadway ID	Segment ID	Blocked Lanes	Blockage Description	Block Duration	TowTruckCome TimeStamp	LaneCleared TimeStamp
Saturday	2/4/12	5:53:00 PM	I-15 NB	before Flamingo Rd	70	2	2	center lanes	25		6:18:00 PM

Step 2. The spatial and the temporal extent of the incident are determined

Figure 5-6 shows the speed segment plots for the example incident.

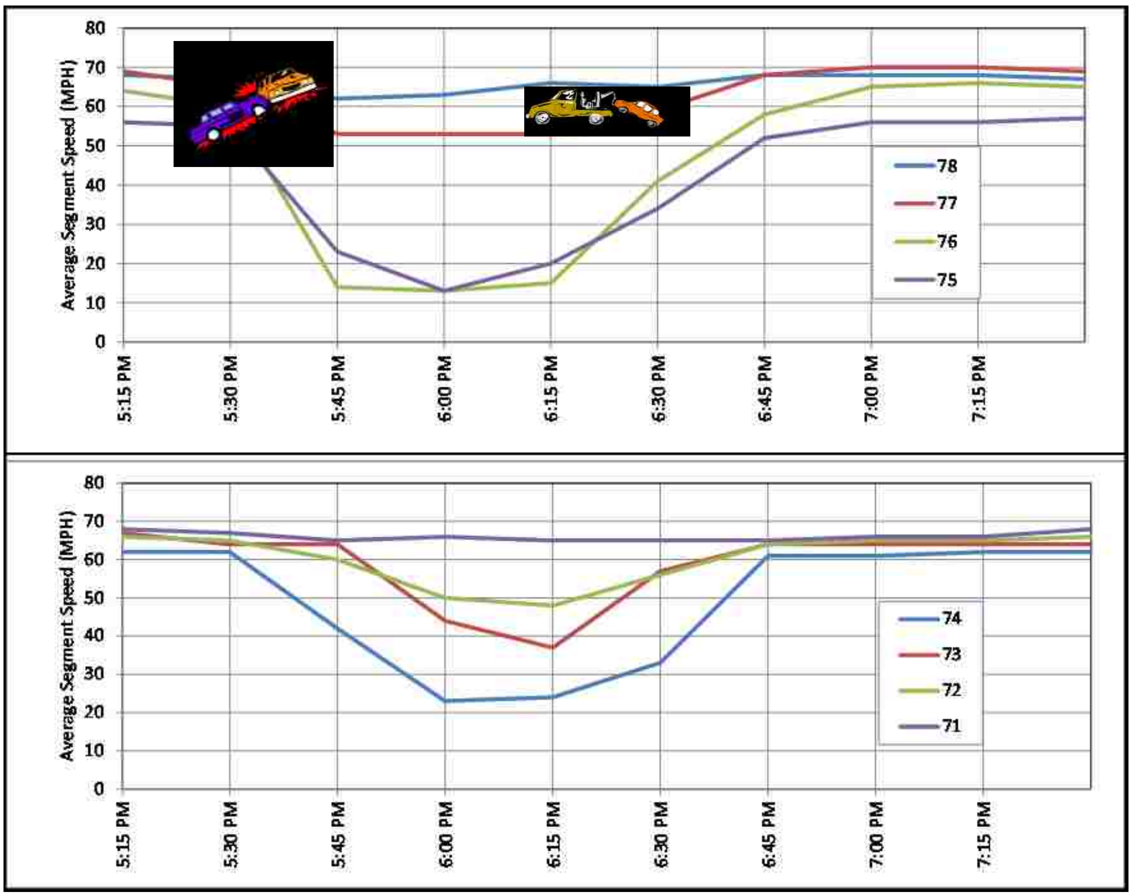


Figure 5-6. Speed-Segment Plot showing Spatial and Temporal extents of Sample Incident

In Figure 5-6, each line represents the speed profile over time for a single segment. The segments are numbered in ascending order from South to North. The incident took place on segment number 76. From Figure 5-6, the temporal extent is from 5:30 PM to 6:45 PM. The spatial extent is from segment 72 to 76. The corresponding extent in the opposing direction including an additional segment downstream of the incident is used to determine the rubbernecking extent. Table 5-4 shows the same for the sample incident under consideration.

Table 5-4. Sample Incident Parameters

Day	Date	TimeStamp	Corridor	Segment Description	RoadwayID	Segment ID	Blocked Lanes	Blockage Description	Block Duration	LaneCleared TimeStamp
Saturday	2/4/12	5:53:00 PM	I-15 NB	Before Flamingo Rd	70	2	2	Center lanes	25	6:18:00 PM

Time Affected		Segments Affected (Spatial extent)		Rubbernecking	
From	5:30:00 PM	From	76	From	50
To	6:45:00 PM	To	72	To	53

Step 3. Computation of incident and non incident impact parameters

Tables 5-5 and 5-6 show examples of spreadsheet calculations for average traffic parameters for incident and non-incident conditions using the formulas from Section 3.3.2 for the sample incident used in the above steps. The process is carried out for rubbernecking direction also.

Step 4. Computation of impacts

The difference between incident and non-incident condition is computed as the impact of each incident. Added to this, are the impacts in the rubbernecking direction as well. Table 5-7 shows the summary of the analysis data for the sample incident.

Table 5-5. Worksheet with Traffic Data for Non-Incident Conditions

					tot v-h	vphpl	vph	mph	vmt
					222.6	961	5,242	60.7	13,478
SeQ ID	tTime	Av Speed	Av TT	Av Volu	Time segs	FMS Distan	Density	Lanes	Vol (vphpl)
72	5:30:00 PM	61	0.3678	1116	1	0.3712	14.74	5	893
72	5:45:00 PM	62	0.3579	1131	2	0.3712	14.54	5	905
72	6:00:00 PM	63	0.3551	1021	3	0.3712	13.02	5	817
72	6:15:00 PM	62	0.3572	1081	4	0.3712	13.86	5	865
72	6:30:00 PM	62	0.3572	1097	5	0.3712	14.07	5	878
72	6:45:00 PM	63	0.3558	1018	6	0.3712	13.00	5	814
73	5:30:00 PM	59	0.4939	1465	1	0.4817	19.95	5	1,172
73	5:45:00 PM	59	0.4949	1483	2	0.4817	20.24	5	1,186
73	6:00:00 PM	59	0.4915	1378	3	0.4817	18.69	5	1,103
73	6:15:00 PM	59	0.4928	1459	4	0.4817	19.82	5	1,167
73	6:30:00 PM	59	0.4921	1469	5	0.4817	19.92	5	1,175
73	6:45:00 PM	59	0.4902	1413	6	0.4817	19.08	5	1,131
74	5:30:00 PM	58	0.2327	809	1	0.2253	11.11	5	647
74	5:45:00 PM	61	0.2234	731	2	0.2253	9.66	5	584
74	6:00:00 PM	61	0.2227	641	3	0.2253	8.45	5	512
74	6:15:00 PM	60	0.2247	704	4	0.2253	9.36	5	563
74	6:30:00 PM	60	0.2240	834	5	0.2253	11.05	5	667
74	6:45:00 PM	60	0.2245	734	6	0.2253	9.74	5	587
75	5:30:00 PM	52	0.2942	1425	1	0.2510	21.87	5	1,140
75	5:45:00 PM	55	0.2730	1359	2	0.2510	19.66	5	1,087
75	6:00:00 PM	56	0.2691	1242	3	0.2510	17.74	5	993
75	6:15:00 PM	56	0.2697	1307	4	0.2510	18.71	5	1,045
75	6:30:00 PM	56	0.2679	1305	5	0.2510	18.56	5	1,044
75	6:45:00 PM	57	0.2636	1253	6	0.2510	17.55	5	1,003
76	5:30:00 PM	64	0.3596	1787	1	0.3851	15.85	7	1,021
76	5:45:00 PM	65	0.3546	1727	2	0.3851	15.15	7	987
76	6:00:00 PM	66	0.3507	1632	3	0.3851	14.13	7	933
76	6:15:00 PM	65	0.3566	1710	4	0.3851	15.06	7	977
76	6:30:00 PM	66	0.3501	1745	5	0.3851	15.11	7	997
76	6:45:00 PM	65	0.3543	1580	6	0.3851	13.83	7	903

Table 5-6. Worksheet with Traffic Data and Impact Travel Time Calculations for Incident Conditions

					tot v-h	add v-h	vpmpl	vphpl	vph	mph
					360.1	153.3	24.86	896	4,873	45.5
Seq ID	tTime	Av Spd	Seg TT	Seg Vol	Diff TT	Time seg	FMS Distai	Density	Lanes	Volume (phpl)
72	5:30:00 PM	65	0.3427	1211	-0.0252	1	0.3712	14.90	5	969
72	5:45:00 PM	60	0.3712	1142	0.0133	2	0.3712	15.23	5	914
72	6:00:00 PM	50	0.4455	1107	0.0903	3	0.3712	17.71	5	886
72	6:15:00 PM	48	0.4640	1002	0.1068	4	0.3712	16.70	5	802
72	6:30:00 PM	56	0.3977	1131	0.0405	5	0.3712	16.16	5	905
72	6:45:00 PM	64	0.3480	1064	-0.0078	6	0.3712	13.30	5	851
73	5:30:00 PM	64	0.4515	1119	-0.0424	1	0.4817	13.99	5	895
73	5:45:00 PM	64	0.4515	1083	-0.0433	2	0.4817	13.54	5	866
73	6:00:00 PM	44	0.6568	1034	0.1653	3	0.4817	18.80	5	827
73	6:15:00 PM	37	0.7810	949	0.2882	4	0.4817	20.52	5	759
73	6:30:00 PM	57	0.5070	1025	0.0149	5	0.4817	14.39	5	820
73	6:45:00 PM	64	0.4515	1003	-0.0387	6	0.4817	12.54	5	802
74	5:30:00 PM	62	0.2179	1287	-0.0147	1	0.2253	16.61	5	1030
74	5:45:00 PM	42	0.3217	1123	0.0983	2	0.2253	21.39	5	898
74	6:00:00 PM	23	0.5875	1169	0.3647	3	0.2253	40.66	5	935
74	6:15:00 PM	24	0.5630	1049	0.3382	4	0.2253	34.97	5	839
74	6:30:00 PM	33	0.4094	1279	0.1855	5	0.2253	31.01	5	1023
74	6:45:00 PM	61	0.2215	1088	-0.0030	6	0.2253	14.27	5	870
75	5:30:00 PM	55	0.2738	1472	-0.0204	1	0.2510	21.41	5	1178
75	5:45:00 PM	23	0.6546	1193	0.3816	2	0.2510	41.50	5	954
75	6:00:00 PM	13	1.1582	1137	0.8891	3	0.2510	69.97	5	910
75	6:15:00 PM	20	0.7528	1190	0.4831	4	0.2510	47.60	5	952
75	6:30:00 PM	34	0.4428	1464	0.1749	5	0.2510	34.45	5	1171
75	6:45:00 PM	52	0.2896	1281	0.0260	6	0.2510	19.71	5	1025
76	5:30:00 PM	60	0.3850	1899	0.0255	1	0.3851	18.09	7	1085
76	5:45:00 PM	14	1.6502	1188	1.2955	2	0.3851	48.49	7	679
76	6:00:00 PM	13	1.7771	1154	1.4264	3	0.3851	50.73	7	659
76	6:15:00 PM	15	1.5402	1267	1.1835	4	0.3851	48.27	7	724
76	6:30:00 PM	41	0.5635	2007	0.2133	5	0.3851	27.97	7	1147
76	6:45:00 PM	58	0.3983	1701	0.0440	6	0.3851	16.76	7	972

Table 5-7. Sample Incident Parameters

Inc No	ExVHrs	AddTT	ImpTime	ImpSpace	NIDensity	NIVol	NISpd	Weekday	Peak
42	145.41	1.2085	75	1.71	16	961	61	0	0

5.2.4 Fuel Consumption and Vehicle Emissions

Simulation of fuel consumption and emissions can be performed by popular software packages, of which EPA's Motor Vehicle Emission Simulator (MOVES) is the most widely used in the United States. Song et al. (2009) conducted a study to compare two simulation software, EMFAC and MOVES, in terms of the production of green house gases in Los Angeles County. The paper compared the characteristics of both software and highlighted the fact that the use of speed bins in MOVES made it a superior analysis tool when compared to the use of Speed Correction Factor in EMFAC.

Therefore the MOVES model is used to estimate the vehicle emissions and fuel consumptions for each incident and the corresponding non-incident scenario in this study. A smaller sample size (116 incidents) was used for the MOVES runs due to fact that the simulation process was very time-consuming. The run-time varies depending upon the number of segments and time periods and the processing speed of the computer. For example, for one incident with 2.5 hours' impact period and 11 segments took around 90 minutes for one run. The following section describes the data used for the estimation of fuel consumption and vehicle emissions using MOVES.

5.2.4.1 About MOVES

MOVES was developed by EPA's Office of Transportation and Air Quality. It is an open source software written in JAVA and MySQL. MOVES can be used to estimate national, state, county and project level emissions and consumption. MOVES has been designed to aid in estimating vehicle emissions from different types and ranges of vehicles under user defined conditions. It is an improvement over EPA's previous model

MOBILE6, with a feature allowing for analysis on a project level, which fits the requirements for the research at hand.

5.2.4.2 Data for Emissions and Fuel Consumption Estimation using MOVES

A MOVES run is performed by creating a run specification (RunSpec) file to define the run details such as place, time, vehicle, road type, fuel etc. The RunSpec file is an XML file type and can be edited and executed either manually or with the use of the MOVES GUI. The data required by MOVES for project-level analyses include:

- Traffic data: Speeds and Volumes
- Geometry: Segment Lengths and Grades
- Meteorology: Temperature and Humidity
- Fuel information
- Vehicle fleet/population
- Vehicle age distribution

Traffic data- Speeds and Volumes:

Traffic data for each incident from Dashboard is used as input in MOVES. Speeds and volumes for each segment and time period are provided in the input file for every MOVES run.

Geometry- Segment Lengths and Grades:

The length of each segment is available from the RCT data. The grades of the individual segments are needed in order for MOVES to compute the emission and fuel consumption estimates, since acceleration and deceleration are major contributing factors. Since this information was not readily available from any source, field measurements of elevations are conducted with the help of Global Positioning System (GPS). In this study, Garmin's eTrex Legend C GPS receiver units are used for measuring the elevation (Figure 5-7). The unit was set to record GPS data, including elevations, at 3 second intervals. In order to improve data accuracy, five GPS runs were made and for each location the elevation was calculated as the average of the elevations from the five runs.

Figure 5-7. Garmin eTrex Legend C handheld GPS unit (Source: www.garmin.com)

The formulas used are shown below:

$$Rise = \frac{E_{end} - E_{start}}{5280} \, miles \tag{5-3}$$

$$SegmentGrade = \frac{Rise}{SegmentLength} \times 100\% \tag{5-4}$$

Where:

E_{start} : elevation of the segment start point in feet

E_{end} : elevation of the segment end point in feet

$SegmentLength$: length of segment in miles

Meteorology data:

Another data requirement for MOVES is the temperature and humidity corresponding to the time and location of the facility being modeled. For this study, this data was acquired from the National Oceanic and Atmospheric Administration's (NOAA)

National Climatic Data Center[1]. Data for the year 2010 for Clark County, Nevada, which is the site of the study,-was downloaded in Excel format. The sources of this data are the recordings at McCarran International Airport, Las Vegas. The data from NCDC contains the temperatures and dew points recorded for every hour of the day. From the temperature and dew point, the humidity is computed by first calculating the saturated vapor pressure and actual vapor pressure, as shown below (Humidity Formulas, n.d.):

$$VP_{Saturated} = 6.11*10^{7.5*\left(\frac{T}{237.7+T}\right)} \quad (5\text{-}5)$$

$$VP_{Actual} = 6.11*10^{7.5*\left(\frac{D}{237.7+D}\right)} \quad (5\text{-}6)$$

$$\text{Relative Humidity} = \frac{VP_{Actual}}{VP_{Saturated}} \quad (5\text{-}7)$$

Where:

T = Temperature in degree Celsius

D = Dew point in degree Celsius

$VP_{Saturated}$ = Saturated Vapor Pressure in Pascal

VP_{Actual} = Actual Vapor Pressure in Pascal

Fuel information

There are two subsets of information entered under the fuel section: fuel type and fuel formulation. The fuel type specifies the kind of fuel (gasoline, electricity, diesel fuel etc.) used. In this study, diesel and gasoline are used. Fuel formulation is a set of data on the characteristics of a fuel subtype such as its sulfur level, benzene content, olefin content etc. The default data for Clark County from the MOVES database is used for fuel

[1] http://gis.ncdc.noaa.gov/map/viewer/#app=cdo&cfg=cdo&theme=hourly&layers=00000001&extent=-139.2:12.7:-50.4:57.8&node=gis) - URL

formulation. This data has been collected and compiled from multiple US counties over the years by EPA.

Vehicle fleet/population:

The various types of vehicles (called Source Types) and their corresponding codes that can be entered in MOVES are shown in Table 5-8. The distribution of vehicle population during the time of the run is required by MOVES for every segment.

Table 5-8. MOVES Vehicle Type Classification

Code	Vehicle Type	Highway Performance Monitoring System Vehicle Class	Axles
11	Motorcycle	Motorcycle	2
21	Passenger Car	Passenger Car	2
31	Passenger Truck	Other Two-Axle/Four Tire, Single Unit	2,3
32	Light Commercial Truck	Other Two-Axle/Four Tire, Single Unit	2,3
41	Intercity Bus	Bus	2
42	Transit Bus	Bus	2,3
43	School Bus	Bus	2
51	Refuse Truck	Single Unit	2
52	Single Unit Short-Haul Truck	Single Unit	2
53	Single Unit Long-Haul Truck	Single Unit	3,4
54	Motorhome	Single Unit	4
61	Combination Short-Haul Truck	Combination	5
62	Combination Long-Haul Truck	Combination	6 or more

The distribution of vehicle types for this study is adopted from NDOT vehicle classification report for the years 2010 and 2011 (shown in Table 5-9). The data for 2012 is estimated from this using the growth rate between the previous two years. This data is matched with the MOVES requirements in Table 5-8 according to the standard FHWA axle and vehicle classification, as shown in the last column of Table 5-8.[2] The appropriate AADTs are then obtained to give the percent distribution in Table 5-10. The same process is used for the other two segments Flamingo to US-95 and US-95 to Speedway.

[2] http://www.fhwa.dot.gov/policy/ohpi/vehclass.htm

Table 5-9. NDOT Vehicle Classification Report, 2011

AADT										Light trucks			Heavy Trucks							
				2010			Avg Wtd AADT	PC-AADT	MC	Buses	2ax	3+ax	4ax	5ax	6+ax				TruckAADT	Year
1	st rose	728	silver	60,000	St Rose Pk Intch.	Flamingo Rd Intch.	167,167	160,017	350	600	425	640	210	4,550	375				6,800	2009
2	silver	**5340**	blue	104,000																
3	blue	453	i215	139,000																
4	i215	1021	russ	225,000																
5	russ	52	trop	220,000																
6	trop	61	flam	255,000																
7	flam	67	spr.mou	257,000	Falmingo Rd. Intch.	Spring Mtn Rd Intch.	257,000	249,230	380	575	450	575	235	4,565	350	265	50	325	6,750	E
8	spr.mou	74	sahara	257,000	Spring Mtn Rd Intch.	Sahara Ave	257,000	248,985	400	600	450	500	260	4,575	325	320	75	510	6,710	E
9	sahara	**1210**	char	254,000	Sahara Ave	L.V. Ex Intch.	252,500	244,295	450	550	425	550	275	4,700	365	300	100	490	6,865	E
10	char	92	us95	251,000																
							254,750	247,503	410	575	442	542	257	4,613	347	295	75	442		
11	us95	98	wash	158,000	L.V. Ex Intch.	Lake Mead Intg	157,000	149,075	400	575	425	575	300	5,200	450				7,525	E
12	wash	424	l.mead	156,000																
13	l.mead	**1230**	chey	125,000	Lake Mead Intg	Speedway-Hollywood	61,400	52,445	375	600	500	980	600	5,000	900				8,580	2010
14	chey	387	craig	78,000																
15	craig	378	lamb	38,000																
16	lamb	1451	XX	33,000																
17	XX	843	speed	33,000																
							109,200	100,760	388	588	463	778	450	5,100	675	265	126	418	8,053	1,005

Table 5-10. Vehicle percent distribution St. Rose-Flamingo, 2011

St. Rose - Flamingo (2011)			
linkID	sourceTypeID	sourceTypeHourFraction	
1	11	267	0.002
1	21	1,53,997	0.937
1	32	3,026	0.018
1	41	839	0.005
1	52	751	0.005
1	53	4,598	0.028
1	54	307	0.002
1	61	362	0.002
1	62	203	0.001
		1,64,350	*1.000*

Vehicle age distribution:

This input lists the fraction of distribution of the vehicle ages for each segment. MOVES stores a default dataset for the national average age distribution from numerous US counties. Owing to lack of data availability from the local DMV and DOT, the default database is used for this input criterion.

5.2.4.3 Data Preparation for MOVES

All the input data for MOVES are required to be arranged in a specific template and format in order to run and be processed by the software without any errors. The default database structure from MOVES is used to obtain the format for each type of input and the data is rearranged to suit the template as required by MOVES. For example, Table 5-8 shows the input format for the meteorology data arranged in the format specified by MOVES. The month ID, zone ID and hour ID gives the details of incident regarding the month, location (county) and time of the incident along with the temperature and relative humidity.

Table 5-11. Sample MOVES Input Format: Meteorology

monthID	zoneID	hourID	temperature	relHumidity
2	320030	15	62.7	25.3

5.2.4.4 Creation of Input files

As explained in the data description for MOVES (Section 5.2.3), the input file needs to be in a specific format. Although two separate runs are performed for the incident and non-incident, the input file is the same for both except for traffic parameters, since all the remaining conditions such as geometry and location are the same. The file has two separate sheets for incident and non-incident with their respective traffic data.

Figure 5-8 presents a snapshot of the MOVES data entry GUI. The list of steps to enter the input and run MOVES and the detailed procedure can be obtained from the MOVES user manual on the EPA website.[3]

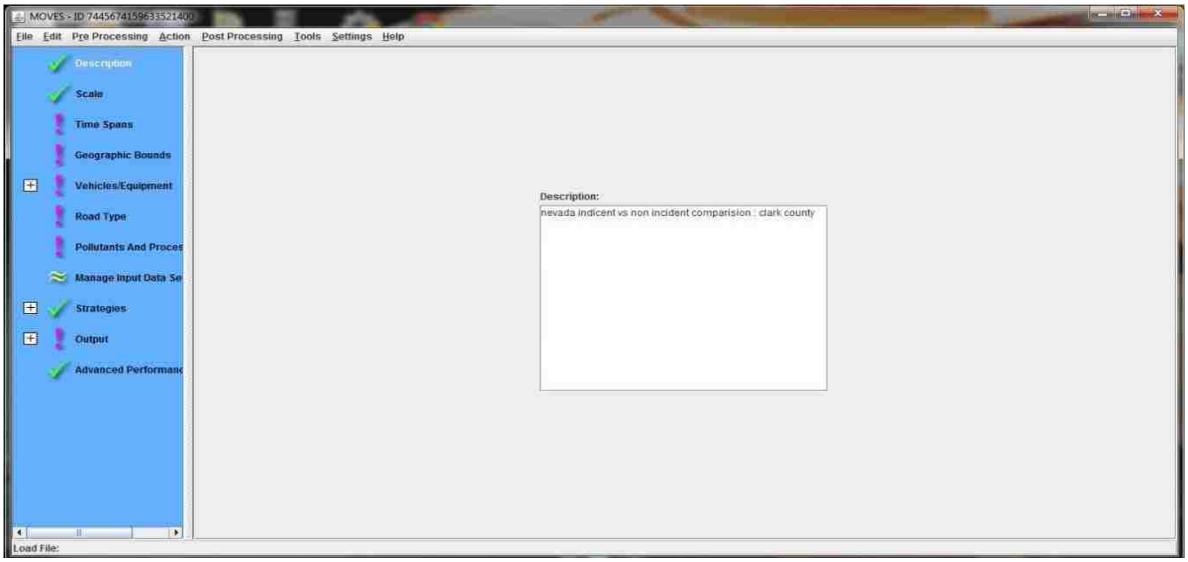


Figure 5-8. MOVES Data Entry Window

MOVES runs are repeated for incident and non-incident conditions for all the incidents in the sample set. Figure 5-9 shows the final database with the excess fuel consumption and vehicle emissions for each incident using the output from MOVES.

[3] MOVES User Guide URL- http://www.epa.gov/otaq/models/moves/documents/420b12001b.pdf

	incident						non-incident					Excess					
Incid	CO2	CO	NO	NOx	PM10	Fuel	CO2	CO	NOx	PM10	Fuel	CO2	CO	NOx	PM10	SO2	Fuel
3	634,192	2,761	603	685	16	64	747,745	3,488	841	17	64	12,109	(141)	(15)	2	0	4
5	786,746	3,348	779	885	18	80	396,542	1,799	453	9	80	(9,304)	(263)	(24)	(0)	(0)	(0)
7	8,395,826	29,921	7,406	8,414	233	841	4,833,846	17,067	5,285	120	841	2,013,917	7,388	1,436	75	35	206
8	1,661,540	6,133	1,550	1,762	42	168	835,814	3,029	909	20	168	101,474	479	65	5	3	19
10	5,862,279	27,385	5,265	5,983	146	585	3,876,057	16,405	4,189	90	585	1,207,296	7,683	952	38	22	123
14	2,641,294	8,674	2,110	2,420	94	264	2,334,407	7,990	2,227	82	264	56,742	(172)	(46)	3	1	7
15	2,432,486	10,389	2,207	2,508	60	240	2,090,256	9,042	2,294	48	240	228,311	854	89	9	5	21
17	8,143,856	36,737	7,170	8,147	202	817	7,216,114	33,911	7,888	162	817	1,245,160	4,318	606	47	22	128
19	7,983,225	37,555	6,526	7,413	196	801	7,875,417	37,953	8,112	175	801	1,631,809	6,946	871	55	28	168
22	8,172,894	35,338	7,373	8,378	202	817	7,870,791	34,877	8,595	179	817	798,433	2,660	325	34	13	82
25	5,056,775	23,048	4,566	5,189	122	504	4,035,096	19,324	4,387	90	504	422,718	856	151	19	8	45
26	17,706,788	82,168	15,747	17,888	446	1,770	13,276,818	65,689	14,797	294	1,770	2,968,527	9,248	1,462	120	51	303
32	546,338	1,845	535	608	22	56	520,450	1,751	578	20	56	1,516	12	3	1	(0)	6
34	1,924,988	6,503	1,782	2,024	72	192	1,545,443	5,073	1,680	54	192	215,688	892	166	12	4	24
35	6,176,623	23,387	5,447	6,186	173	617	4,223,693	16,351	4,709	101	617	1,309,311	4,544	759	57	22	128
36	7,148,707	33,999	6,303	7,162	173	713	5,588,195	28,319	6,001	123	713	682,463	1,230	218	31	12	64
38	9,627,262	35,916	8,753	9,944	260	961	8,355,307	33,449	9,283	198	961	2,563,525	7,638	2,096	93	46	257
40	2,950,064	9,974	2,599	2,953	101	296	2,322,368	7,837	2,571	73	296	673,110	2,290	432	29	12	69
45	952,112	3,240	916	1,041	27	96	1,273,541	4,319	1,388	36	96	0	11	3	0	1	0
46	1,075,334	3,632	1,019	1,172	36	104	1,043,930	3,494	1,188	33	104	111,579	406	75	6	1	8
50	676,156	2,318	562	644	19	64	712,934	2,610	695	21	64	(14,832)	(212)	(30)	(1)	0	(6)
53	857,378	2,917	748	849	19	88	855,386	3,217	869	19	88	(21,562)	(389)	(44)	(1)	(0)	(2)
56	4,487,156	15,934	3,917	4,449	126	448	4,839,225	17,612	4,938	132	448	83,590	(92)	(44)	6	2	11
57	2,785,387	11,733	2,357	2,703	55	280	2,587,047	11,222	2,551	50	280	7,538	(317)	(36)	1	(1)	5
59	5,662,832	19,506	4,861	5,519	133	569	5,623,762	19,814	5,623	128	569	128,837	8	(14)	7	3	17
60	668,802	2,789	630	716	19	64	672,173	2,941	726	19	64	(9,057)	(177)	(16)	(0)	(1)	(1)
65	4,639,041	16,054	3,617	4,149	139	464	4,211,989	15,406	4,108	123	464	667,776	1,528	276	23	11	72
70	253,687	1,220	214	243	5	24	486,560	2,442	488	9	24	19,491	45	8	1	1	1
71	898,882	3,443	811	921	26	88	827,465	3,409	866	24	88	(15,151)	(323)	(36)	(1)	0	(0)
73	3,367,998	16,019	3,056	3,472	66	336	3,367,481	16,585	3,536	65	336	5,939	(539)	(58)	1	0	1

Figure 5-9. Fuel Consumption and Vehicle Emissions: Partial Data

(Excess fuel consumption and vehicle emissions in gallons and grams, respectively)

CHAPTER 6

DATA DESCRIPTION AND COLLECTION FOR LONG-TERM IMPACT ANALYSIS

6.1 Introduction

The analysis for long-term impacts of incidents also uses traffic and incident data from the RTC Dashboard website. Since the concept of reliability is of importance mostly for commuter traffic, analysis is done only for weekdays namely Monday, Tuesday, Wednesday and Thursday. Fridays are not included in the study sample because they typically involve a lot of tourist traffic from out of state. Holidays and night time analysis (9 PM to 5 AM) are again avoided due to construction activities. Also, data for one calendar year, 2011, is used due to availability of data for the complete year. The study area, I-15 NB corridor from I-215 in the South to US-95 (Spaghetti Bowl) in the North, was chosen owing to the busy traffic and the high crash rates typically experienced on that section. This section is about 8 miles long and has a maximum of 6 lanes.

6.2 Data Description for Long Term Impacts of Incidents

6.2.1 Incident Data

The sample set for long term analysis is comprised of all the incidents that occurred on I-15 NB in the calendar year of 2011. The list of the incidents is tabulated by the day-of-week and time-of-day. Each hour of a weekday is a data point. There are a total of 686 recorded incidents in the RTC database for 2011. Specific incident details computed include the number of incidents in each hour, the average and maximum number of lanes blocked, the average incident duration, average and maximum lane-minutes of blockage (product of number of lanes and incident duration) and the average distance of the incidents from the base point, I-215 (Figure 6-1). Incidents that are very close to I-215 do not have as much influence on travel time reliability as those incidents further north in the segment.

Figure 6-1. Average Distance of Incidents from I-215

The number of incidents is tabulated for each day of week and hour of day. Similar spreadsheets for the other incident characteristics including average and maximum lanes blocked, average and maximum lane-minutes of blockage are also created.

6.2.2 Traffic Data

The methodology explained in section 3.3.2 is employed in compiling the study data. The traffic data, namely, speeds, volumes, and travel times for every Monday, Tuesday, Wednesday and Thursday is collected. Table 6-1 presents hourly averages of travel times for all Thursdays in 2011. These values are the averages of four 15-minute periods forming the 'mixed' data. The empty cells in Table 6-1 have either a workzone or a holiday. Similar tables for speeds, volumes and densities are prepared.

Table 6-2 shows the number of incidents for all Thursdays. Using this information the influence of a crash is determined as shown in Table 6-3. Every two hours following an incident is assumed to have the presence of the incident. Table 6-4 shows the average incident durations for the incidents shown in Table 6-2. The hours with the presence or influence of an incident is excluded from the mixed travel time data in Table 6-1. The non-incident travel times are developed as shown in Table 6-4. The empty cells in Table 6-4 either have an incident or followed an incident or are holidays/workzone activities.

Using the mixed and non-incident travel times, the reliability indices namely, 95th percentile, buffer/planning time and buffer index are computed for both. For Thursday, Tables 6-6 a, b and c show the analysis data for each hour of the year.

For the chosen segment (I-15 N between I-215 and US-95), Tables 6-7 and 6-8 show the final data used for performing the statistical analyses on travel time reliability.

Table 6-1. Aggregated Mixed Travel Time data (Thursday)

					Hours															
Date		Non		Week	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1/6/2011	W	-	-	1																
1/13/2011	-	-	1	2	7.25	7.33	7.47	7.69	7.47	7.44	7.50	7.43	7.49	7.57	8.71	9.97	11.34	8.17	7.32	9.30
1/20/2011	-	-	1	3	7.35	7.55	7.73	8.01	7.83	7.61	7.59	7.47	7.58	7.92	11.86	14.23	14.81	12.42	7.47	7.32
1/27/2011	-	-	1	4	7.23	7.37	7.51	7.76	7.61	7.53	7.52	7.48	7.62	13.15	13.19	10.63	13.98	9.21	7.41	7.29
2/3/2011	-	-	1	5	7.23	7.30	7.55	7.80	7.61	7.43	7.46	7.45	7.56	7.88	15.30	14.54	11.04	7.87	7.36	7.27
2/10/2011	-	-	1	6	7.28	7.36	7.66	7.90	7.79	7.57	7.61	7.60	7.65	8.42	9.33	9.99	11.03	9.23	8.10	7.40
2/17/2011	-	-	1	7	7.22	8.04	8.98	7.83	7.75	7.54	7.56	7.57	7.83	8.46	9.83	12.71	13.21	10.75	7.85	7.37
2/24/2011	-	-	1	8	7.30	7.36	7.65	7.88	7.99	7.63	7.60	7.55	7.74	9.30	13.39	11.78	11.08	9.51	7.56	7.33
3/3/2011	-	-	1	9	7.31	7.34	7.54	7.72	7.68	7.92	8.03	7.81	8.16	10.08	11.18	11.84	11.74	10.12	8.16	7.55
3/10/2011	-	-	1	10	7.29	7.29	7.64	7.94	7.95	7.83	8.02	7.81	7.98	9.72	10.71	11.48	11.78	9.15	7.68	7.35
3/17/2011	-	-	1	11	7.35	8.44	8.20	7.97	8.03	7.94	8.14	7.79	8.11	8.53	9.89	11.64	12.33	8.83	7.89	7.58
3/24/2011	-	-	1	12	7.26	7.43	7.72	7.81	7.71	7.65	7.65	7.70	7.72	8.42	10.95	10.67	10.28	8.08	7.58	7.48
3/31/2011	-	-	1	13	8.34	11.22	7.79	7.67	7.73	7.72	7.65	7.65	7.90	9.51	11.87	10.91	11.12	8.80	7.62	7.48
4/7/2011	-	1	1	14	7.30	7.43	7.98	8.62	8.97	7.87	7.90	7.90	8.19	8.60	9.90	8.86	10.04	7.73	7.60	7.52
4/14/2011	-	-	1	15	7.42	7.46	8.10	8.91	8.51	7.98	8.15	8.17	8.42	10.05	11.42	11.78	12.29	8.60	7.71	7.65
4/21/2011	-	-	1	16	7.32	7.29	7.71	8.08	7.95	7.87	7.88	8.15	10.34	10.22	12.04	9.97	9.52	9.81	9.39	7.73
4/28/2011	-	-	1	17	7.32	7.40	7.88	8.02	8.15	7.96	8.04	8.03	8.58	12.63	12.80	11.65	11.44	8.48	7.50	7.54
5/5/2011	-	-	1	18	7.32	7.30	7.72	8.39	8.06	7.81	7.90	8.10	8.20	9.70	10.39	11.06	10.05	9.03	7.93	7.50
5/12/2011	-	-	1	19	7.26	7.34	7.86	8.68	8.20	7.71	7.91	7.87	8.15	9.10	10.12	10.53	11.21	9.84	7.58	7.48
5/19/2011	-	-	1	20	7.31	7.29	8.76	13.71	8.67	7.60	9.59	10.32	7.80	8.44	9.19	9.48	10.20	7.54	7.35	7.44
5/26/2011	-	-	1	21	7.25	7.45	8.80	7.82	7.68	7.62	7.71	7.70	7.95	10.08	11.77	10.68	11.16	8.31	7.68	7.37
6/2/2011	W	-	-	22																
6/9/2011	W	-	-	23																
6/16/2011	-	-	1	24	7.23	7.28	7.58	7.79	8.49	8.18	8.03	8.15	8.38	10.64	10.91	10.48	12.16	9.98	7.87	7.41
6/23/2011	W	-	-	25																
6/30/2011	-	-	1	26	7.20	7.31	7.96	8.12	7.81	7.72	7.89	8.04	8.09	9.23	11.11	11.03	11.53	9.56	7.37	7.37
7/7/2011	W	-	-	27																
7/14/2011	W	-	-	28																
7/21/2011	W	-	-	29																
7/28/2011	W	-	-	30																
8/4/2011	W	-	-	31																
8/11/2011	W	-	-	32																
8/18/2011	W	-	-	33																
8/25/2011	W	-	-	34																
9/1/2011	-	-	1	35	7.45	7.33	7.59	7.64	7.59	7.64	7.59	7.53	7.68	8.32	9.63	9.51	10.40	8.83	7.50	7.55
9/8/2011	-	-	1	36	7.47	7.42	7.59	7.70	7.62	7.72	7.64	7.65	7.73	8.14	9.08	9.31	10.32	8.12	7.53	7.49
9/15/2011	-	-	1	37	7.48	7.41	7.45	7.45	7.53	7.55	7.59	7.47	7.58	7.92	12.47	9.85	8.26	7.44	7.56	7.44
9/22/2011	-	-	1	38	8.26	8.36	7.62	7.54	7.60	7.63	7.55	7.57	7.67	7.73	7.65	7.85	7.90	7.54	7.54	7.39
9/29/2011	-	-	1	39	7.71	7.55	7.58	7.63	7.63	7.67	7.70	7.64	7.74	7.91	11.66	9.97	14.35	10.75	7.65	7.47
10/6/2011	W	-	-	40																
10/13/2011	W	-	-	41																
10/20/2011	W	-	-	42																
10/27/2011	W	-	-	43																
11/3/2011	-	-	1	44	7.30	7.49	7.56	7.64	7.58	7.57	7.58	8.63	7.67	7.92	9.61	11.15	11.27	8.25	7.67	7.42
11/10/2011	-	-	1	45	7.37	7.35	7.49	7.50	7.55	7.55	7.57	9.37	16.98	8.61	8.39	8.58	10.59	11.44	8.58	8.96
11/17/2011	-	-	1	46	7.42	7.43	7.46	7.53	7.54	7.52	7.47	7.60	7.68	11.19	12.70	10.16	11.15	8.60	7.37	7.29
11/24/2011	H	-	-	47																
12/1/2011	-	-	1	48	7.53	7.60	8.13	7.93	7.67	7.86	7.79	7.75	7.84	8.00	8.09	9.19	10.84	8.27	7.47	7.40
12/8/2011	-	-	1	49	7.38	7.34	7.39	7.44	7.50	7.39	7.42	7.44	7.55	7.87	14.15	12.69	11.43	8.09	7.31	7.23
12/15/2011	-	-	1	50	7.36	7.29	7.38	7.43	7.41	7.43	7.43	7.54	9.33	7.82	12.73	11.50	11.04	9.16	7.27	7.20
12/22/2011	-	-	1	51	7.33	7.31	7.39	7.39	7.41	7.50	7.56	13.48	13.77	8.51	8.83	9.56	9.60	9.03	7.46	7.26
12/29/2011	H	-	-	52																
		1	34																	
				Mean	7.40	7.57	7.78	8.03	7.83	7.68	7.77	8.04	8.43	9.05	10.91	10.74	11.19	9.02	7.67	7.52
				Std Ev	0.25	0.70	0.40	1.07	0.37	0.19	0.39	1.12	1.89	1.36	1.82	1.46	1.46	1.14	0.41	0.43

Table 6-2. Number of Incidents for Thursdays - Aggregated

					Hours															
Date		Non		Week	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1/6/2011	W	-	-	1																
1/13/2011		-	1	2											1					2
1/20/2011		-	1	3										1			2			
1/27/2011		-	1	4									1	1			1			
2/3/2011		-	1	5				1				1		1						
2/10/2011		-	1	6														1		
2/17/2011		-	1	7		1									1	2		1		
2/24/2011		-	1	8										2	1		1			
3/3/2011		-	1	9					1	1				1		1				
3/10/2011		-	1	10											1					
3/17/2011		-	1	11												1				
3/24/2011		-	1	12											1					
3/31/2011		-	1	13	1										1		1			
4/7/2011		1	1	14																
4/14/2011		-	1	15												1				
4/21/2011		-	1	16														2		
4/28/2011		-	1	17									1	1						
5/5/2011		-	1	18											1		1	1		
5/12/2011		-	1	19				1										1	1	
5/19/2011		-	1	20			1				1									
5/26/2011		-	1	21													1			
6/2/2011	W	-	-	22																
6/9/2011	W	-	-	23																
6/16/2011		-	1	24					1				1			2				
6/23/2011	W	-	-	25																
6/30/2011		-	1	26							1							1		
7/7/2011	W	-	-	27																
7/14/2011	W	-	-	28																
7/21/2011	W	-	-	29																
7/28/2011	W	-	-	30																
8/4/2011	W	-	-	31																
8/11/2011	W	-	-	32																
8/18/2011	W	-	-	33																
8/25/2011	W	-	-	34																
9/1/2011		-	1	35											1					
9/8/2011		-	1	36					1						1					
9/15/2011		-	1	37			1							1						
9/22/2011		-	1	38												1				
9/29/2011		-	1	39											2	1				
10/6/2011	W	-	-	40																
10/13/2011	W	-	-	41																
10/20/2011	W	-	-	42																
10/27/2011	W	-	-	43																
11/3/2011		-	1	44								1			1	1			2	
11/10/2011		-	1	45	1							1							1	
11/17/2011		-	1	46	1									1						
11/24/2011	H	-	-	47																
12/1/2011		-	1	48													1			
12/8/2011		-	1	49										1	1					
12/15/2011		-	1	50								1			1					
12/22/2011		-	1	51							1	1	1		1					
12/29/2011	H	-	-	52																
				Total	3	1	2	2	3	1	3	5	4	9	14	8	7	6	3	1
				Avg inc/hr (%)	8.82	2.94	5.88	5.88	8.82	2.94	8.82	14.71	11.76	26.47	41.18	23.53	20.59	17.65	8.82	2.94

Table 6-3. Presence or Influence of an Incident (Thursday)

					Hours															
Date		Non		Week	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1/6/2011	W	-	-	1																
1/13/2011		-	1	2											2	1	1			2
1/20/2011		-	1	3										2	1	1	2	1	1	
1/27/2011		-	1	4									2	2	1	1	2	1	1	
2/3/2011		-	1	5				2	1	1		2	1	2	1	1				
2/10/2011		-	1	6														2	1	1
2/17/2011		-	1	7		2	1	1							2	2	1	2	1	1
2/24/2011		-	1	8										2	2	1	2	1	1	
3/3/2011		-	1	9					2	2	1	1		2	1	2	1	1		
3/10/2011		-	1	10											2	1	1			
3/17/2011		-	1	11												2	1	1		
3/24/2011		-	1	12											2	1	1			
3/31/2011		-	1	13	2	1	1								2	1	2	1	1	
4/7/2011		1	1	14																
4/14/2011		-	1	15												2	1	1		
4/21/2011		-	1	16														2	1	1
4/28/2011		-	1	17									2	2	1	1				
5/5/2011		-	1	18											2	1	2	2	1	1
5/12/2011		-	1	19				2	1	1								2	2	1
5/19/2011		-	1	20			2	1	1		2	1	1							
5/26/2011		-	1	21													2	1	1	
6/2/2011	W	-	-	22																
6/9/2011	W	-	-	23																
6/16/2011		-	1	24					2	1	1		2	1	1	2	1	1		
6/23/2011	W	-	-	25																
6/30/2011		-	1	26							2	1	1					2	1	1
7/7/2011	W	-	-	27																
7/14/2011	W	-	-	28																
7/21/2011	W	-	-	29																
7/28/2011	W	-	-	30																
8/4/2011	W	-	-	31																
8/11/2011	W	-	-	32																
8/18/2011	W	-	-	33																
8/25/2011	W	-	-	34																
9/1/2011		-	1	35											2	1	1			
9/8/2011		-	1	36					2	1	1				2	1	1			
9/15/2011		-	1	37			2	1	1					2	1	1				
9/22/2011		-	1	38												2	1	1		
9/29/2011		-	1	39											2	2	1	1		
10/6/2011	W	-	-	40																
10/13/2011	W	-	-	41																
10/20/2011	W	-	-	42																
10/27/2011	W	-	-	43																
11/3/2011		-	1	44								2	1	1	2	2	1	1	2	1
11/10/2011		-	1	45	2	1	1					2	1	1					2	1
11/17/2011		-	1	46	2	1	1							2	1	1				
11/24/2011	H	-	-	47																
12/1/2011		-	1	48													2	1	1	
12/8/2011		-	1	49										2	2	1	1			
12/15/2011		-	1	50								2	1	1	2	1	1			
12/22/2011		-	1	51							2	2	2	1	2	1	1			
12/29/2011	H	-	-	52																
				Total	3	4	6	5	7	5	6	8	10	14	22	25	23	19	14	9

1 presence of incident in previous hour or two

2 presence of incident in subject hour

Table 6-4. Average Incident Duration 2011 incidents (Thursday)

					Hours																
Date		Non		Week	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1/6/2011	W	-	-	1																	2
1/13/2011	-	-	1	2											19.0					56.0	-
1/20/2011	-	-	1	3										35.0			20.0				2
1/27/2011	-	-	1	4									16.0	15.0			17.0				1
2/3/2011	-	-	1	5				43.0				64.0		90.0							-
2/10/2011	-	-	1	6														66.0			2
2/17/2011	-	-	1	7		77.0									41.0	15.0		3.0			2
2/24/2011	-	-	1	8										9.0	14.0		21.0				4
3/3/2011	-	-	1	9					7.0	39.0				54.0		16.0					3
3/10/2011	-	-	1	10											22.0						-
3/17/2011	-	-	1	11												18.0					3
3/24/2011	-	-	1	12											17.0						-
3/31/2011	-	-	1	13	84.0										32.0		52.0				2
4/7/2011	-	1	1	14																	2
4/14/2011	-	-	1	15												39.0					1
4/21/2011	-	-	1	16														11.5			5
4/28/2011	-	-	1	17									38.0	8.0							-
5/5/2011	-	-	1	18											6.0		25.0	17.0			-
5/12/2011	-	-	1	19				9.0										11.0	59.0		2
5/19/2011	-	-	1	20			56.0				83.0										-
5/26/2011	-	-	1	21													22.0				1
6/2/2011	W	-	-	22																	1
6/9/2011	W	-	-	23																	-
6/16/2011	-	-	1	24					2.0				32.0			30.5					2
6/23/2011	W	-	-	25																	-
6/30/2011	-	-	1	26							34.0							19.0			3
7/7/2011	W	-	-	27																	2
7/14/2011	W	-	-	28																	-
7/21/2011	W	-	-	29																	-
7/28/2011	W	-	-	30																	-
8/4/2011	W	-	-	31																	-
8/11/2011	W	-	-	32																	-
8/18/2011	W	-	-	33																	-
8/25/2011	W	-	-	34																	-
9/1/2011	-	-	1	35											29.0						-
9/8/2011	-	-	1	36					4.0						16.0						2
9/15/2011	-	-	1	37			24.0							6.0							5
9/22/2011	-	-	1	38												46.0					-
9/29/2011	-	-	1	39											27.5	19.0					-
10/6/2011	W	-	-	40																	-
10/13/2011	W	-	-	41																	-
10/20/2011	W	-	-	42																	-
10/27/2011	W	-	-	43																	4
11/3/2011	-	-	1	44								15.0			14.0	37.0			31.5		6
11/10/2011	-	-	1	45	53.0							79.0							64.0		2
11/17/2011	-	-	1	46	67.0									24.0							-
11/24/2011	H	-	-	47																	3
12/1/2011	-	-	1	48													41.0				8
12/8/2011	-	-	1	49										20.0	53.0						1
12/15/2011	-	-	1	50								88.0			27.0						3
12/22/2011	-	-	1	51							92.0	7.0	10.0		54.0						1
12/29/2011	H	-	-	52																	-
		1	34		#																
				Mean	68.0	77.0	40.0	26.0	4.3	39.0	69.7	50.6	24.0	29.0	26.5	27.6	28.3	21.2	51.5	56.0	
				Std. Ev.	15.5	-	22.6	24.0	2.5	-	31.2	37.3	13.2	27.5	14.5	12.1	13.1	22.6	17.5	-	

Table 6-5. Aggregated Non-Incident Travel Time data (Thursday)

					Hours															
Date		Non		Week	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1/6/2011	W	-	-	1																
1/13/2011	-	-	1	2	7.25	7.33	7.47	7.69	7.47	7.44	7.50	7.43	7.49	7.57				8.17	7.32	
1/20/2011	-	-	1	3	7.35	7.55	7.73	8.01	7.83	7.61	7.59	7.47	7.58							7.32
1/27/2011	-	-	1	4	7.23	7.37	7.51	7.76	7.61	7.53	7.52	7.48								7.29
2/3/2011	-	-	1	5	7.23	7.30	7.55				7.46						11.04	7.87	7.36	7.27
2/10/2011	-	-	1	6	7.28	7.36	7.66	7.90	7.79	7.57	7.61	7.60	7.65	8.42	9.33	9.99	11.03			
2/17/2011	-	-	1	7	7.22				7.75	7.54	7.56	7.57	7.83	8.46						
2/24/2011	-	-	1	8	7.30	7.36	7.65	7.88	7.99	7.63	7.60	7.55	7.74							7.33
3/3/2011	-	-	1	9	7.31	7.34	7.54	7.72					8.16						8.16	7.55
3/10/2011	-	-	1	10	7.29	7.29	7.64	7.94	7.95	7.83	8.02	7.81	7.98	9.72				9.15	7.68	7.35
3/17/2011	-	-	1	11	7.35	8.44	8.20	7.97	8.03	7.94	8.14	7.79	8.11	8.53	9.89				7.89	7.58
3/24/2011	-	-	1	12	7.26	7.43	7.72	7.81	7.71	7.65	7.65	7.70	7.72	8.42				8.08	7.58	7.48
3/31/2011	-	-	1	13				7.67	7.73	7.72	7.65	7.65	7.90	9.51						7.48
4/7/2011	-	1	1	14	7.30	7.43	7.98	8.62	8.97	7.87	7.90	7.90	8.19	8.60	9.90	8.86	10.04	7.73	7.60	7.52
4/14/2011	-	-	1	15	7.42	7.46	8.10	8.91	8.51	7.98	8.15	8.17	8.42	10.05	11.42				7.71	7.65
4/21/2011	-	-	1	16	7.32	7.29	7.71	8.08	7.95	7.87	7.88	8.15	10.34	10.22	12.04	9.97	9.52			
4/28/2011	-	-	1	17	7.32	7.40	7.88	8.02	8.15	7.96	8.04	8.03					11.44	8.48	7.50	7.54
5/5/2011	-	-	1	18	7.32	7.30	7.72	8.39	8.06	7.81	7.90	8.10	8.20	9.70						
5/12/2011	-	-	1	19	7.26	7.34	7.86				7.91	7.87	8.15	9.10	10.12	10.53	11.21			
5/19/2011	-	-	1	20	7.31	7.29				7.60				8.44	9.19	9.48	10.20	7.54	7.35	7.44
5/26/2011	-	-	1	21	7.25	7.45	8.80	7.82	7.68	7.62	7.71	7.70	7.95	10.08	11.77	10.68				7.37
6/2/2011	W	-	-	22																
6/9/2011	W	-	-	23																
6/16/2011	-	-	1	24	7.23	7.28	7.58	7.79				8.15							7.87	7.41
6/23/2011	W	-	-	25																
6/30/2011	-	-	1	26	7.20	7.31	7.96	8.12	7.81	7.72				9.23	11.11	11.03	11.53			
7/7/2011	W	-	-	27																
7/14/2011	W	-	-	28																
7/21/2011	W	-	-	29																
7/28/2011	W	-	-	30																
8/4/2011	W	-	-	31																
8/11/2011	W	-	-	32																
8/18/2011	W	-	-	33																
8/25/2011	W	-	-	34																
9/1/2011	-	-	1	35	7.45	7.33	7.59	7.64	7.59	7.64	7.59	7.53	7.68	8.32				8.83	7.50	7.55
9/8/2011	-	-	1	36	7.47	7.42	7.59	7.70				7.65	7.73	8.14				8.12	7.53	7.49
9/15/2011	-	-	1	37	7.48	7.41				7.55	7.59	7.47	7.58				8.26	7.44	7.56	7.44
9/22/2011	-	-	1	38	8.26	8.36	7.62	7.54	7.60	7.63	7.55	7.57	7.67	7.73	7.65				7.54	7.39
9/29/2011	-	-	1	39	7.71	7.55	7.58	7.63	7.63	7.67	7.70	7.64	7.74	7.91					7.65	7.47
10/6/2011	W	-	-	40																
10/13/2011	W	-	-	41																
10/20/2011	W	-	-	42																
10/27/2011	W	-	-	43																
11/3/2011	-	-	1	44	7.30	7.49	7.56	7.64	7.58	7.57	7.58									
11/10/2011	-	-	1	45				7.50	7.55	7.55	7.57				8.39	8.58	10.59	11.44		
11/17/2011	-	-	1	46				7.53	7.54	7.52	7.47	7.60	7.68				11.15	8.60	7.37	7.29
11/24/2011	H	-	-	47																
12/1/2011	-	-	1	48	7.53	7.60	8.13	7.93	7.67	7.86	7.79	7.75	7.84	8.00	8.09	9.19				7.40
12/8/2011	-	-	1	49	7.38	7.34	7.39	7.44	7.50	7.39	7.42	7.44	7.55					8.09	7.31	7.23
12/15/2011	-	-	1	50	7.36	7.29	7.38	7.43	7.41	7.43	7.43							9.16	7.27	7.20
12/22/2011	-	-	1	51	7.33	7.31	7.39	7.39	7.41	7.50								9.03	7.46	7.26
12/29/2011	H	-	-	52																
		1	34																	
				Mean	7.36	7.45	7.73	7.84	7.80	7.66	7.70	7.72	7.95	8.81	9.91	9.81	10.55	8.52	7.56	7.41
				Std Ev.	0.20	0.27	0.30	0.35	0.34	0.16	0.21	0.24	0.56	0.83	1.46	0.84	0.99	0.98	0.22	0.12

Table 6-6. Reliability Measures due to Incidents - Thursday

	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Mean	7.395	7.572	7.778	8.028	7.832	7.681	7.771	8.042	8.431	9.047	10.908	10.741	11.191	9.016	7.674	7.524
Std Ev.	0.252	0.702	0.400	1.065	0.373	0.186	0.387	1.122	1.888	1.356	1.816	1.455	1.461	1.141	0.409	0.426
95th Percentile TT	7.901	8.391	8.777	8.763	8.569	7.968	8.143	9.701	11.539	11.693	13.656	13.243	14.109	10.991	8.310	8.158
Buffer Time	0.506	0.819	0.999	0.735	0.737	0.286	0.372	1.660	3.108	2.646	2.748	2.502	2.919	1.975	0.637	0.634
Buffer Index	0.068	0.108	0.128	0.092	0.094	0.037	0.048	0.206	0.369	0.292	0.252	0.233	0.261	0.219	0.083	0.084

(a) Mixed data

	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Mean	7.364	7.447	7.733	7.844	7.796	7.662	7.695	7.722	7.954	8.808	9.910	9.812	10.547	8.515	7.560	7.412
Std Ev	0.198	0.274	0.305	0.346	0.343	0.164	0.215	0.236	0.564	0.830	1.457	0.845	0.985	0.983	0.225	0.120
95th Percentile TT	7.621	8.018	8.176	8.526	8.402	7.954	8.102	8.154	8.384	10.089	11.893	10.889	11.487	9.840	7.903	7.577
Buffer Time	0.257	0.571	0.444	0.682	0.606	0.291	0.406	0.432	0.431	1.281	1.982	1.077	0.940	1.325	0.343	0.165
Buffer Index	0.035	0.077	0.057	0.087	0.078	0.038	0.053	0.056	0.054	0.145	0.200	0.110	0.089	0.156	0.045	0.022

(b) Non-incident data

	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Mean	0.031	0.125	0.045	0.184	0.036	0.019	0.076	0.320	0.477	0.239	0.998	0.929	0.644	0.500	0.113	0.112
95th Percentile TT	0.280	0.373	0.600	0.237	0.167	0.014	0.041	1.547	3.154	1.604	1.763	2.354	2.622	1.151	0.407	0.581
Buffer Time	0.249	0.248	0.555	0.053	0.131	(0.005)	(0.034)	1.227	2.677	1.365	0.765	1.425	1.978	0.650	0.294	0.469
Buffer Index	0.034	0.031	0.071	0.005	0.016	(0.001)	(0.005)	0.150	0.314	0.147	0.052	0.123	0.172	0.064	0.038	0.062

(c) Impacts of Incidents

Table 6-7. Reliability Analysis Dataset (Monday and Tuesday)

	Diff in 95% TT	Diff in Buffer Time	Diff in Buffer Index	Mixed 95% TT	Mixed Buffer Time	Mixed Buffer Index	Number of Inc	Rate of Inc	Avg LNMin of Blockage	Max LnMin of Blockage	Avg Lanes Blocked	Avg Clearance Time	Avg Dist from I-215	NI Speed	NI Volume (Vphpl)	NI Density (Vpmpl)
Monday	-0.0219	-0.0147	-0.0018	8.6181	0.7178	0.0909	1.00	1.00	3.57	15.00	1.00	15.00	4.94	62.44	283.49	4.56
	-0.0161	-0.0097	-0.0011	8.6751	0.6011	0.0744	0.00	0.00	0.00	0.00	0.00	0.00	0.00	61.37	276.35	4.55
	0.2264	0.1960	0.0241	8.6801	0.6163	0.0764	1.00	1.00	3.57	50.00	1.00	50.00	2.69	62.46	247.84	3.99
	0.0243	-0.0274	-0.0039	8.0762	0.3697	0.0480	0.00	0.00	0.00	0.00	0.00	0.00	0.00	62.77	239.10	3.83
	0.2133	0.1759	0.0228	8.0766	0.4021	0.0524	3.00	1.00	14.29	52.33	1.67	28.33	4.59	62.19	245.90	3.98
	0.1674	0.1469	0.0192	7.9181	0.2873	0.0376	2.00	1.00	7.14	41.50	1.50	23.00	5.06	62.18	253.57	4.11
	0.1257	0.1041	0.0136	7.8563	0.2572	0.0338	5.00	1.25	17.86	72.63	1.50	42.88	3.33	60.86	266.11	4.42
	0.1223	0.1170	0.0152	7.9503	0.2733	0.0356	8.00	1.33	28.57	53.75	1.17	43.17	5.08	57.06	292.23	5.28
	-0.0729	-0.0527	-0.0066	8.2095	0.3173	0.0402	2.00	1.00	7.14	23.50	1.00	23.50	3.34	54.01	292.33	5.81
	0.1207	0.1078	0.0134	8.5973	0.5994	0.0749	3.00	1.00	10.71	59.67	2.00	30.67	3.01	52.88	288.79	5.86
	-0.0210	-0.0766	-0.0100	8.5910	0.5340	0.0663	5.00	1.00	17.86	27.80	1.20	26.60	5.44	50.28	283.99	6.44
	0.2067	0.2150	0.0272	8.8582	0.9151	0.1152	2.00	1.00	7.14	68.00	1.50	50.00	6.01	60.40	242.17	4.12
	0.4823	0.4661	0.0576	9.1111	1.0360	0.1283	0.00	0.00	0.00	0.00	0.00	0.00	0.00	63.28	198.30	3.16
	-0.0555	-0.0401	-0.0047	9.1859	0.9949	0.1215	0.00	0.00	0.00	0.00	0.00	0.00	0.00	64.01	175.96	2.77
Tuesday	-0.0584	-0.0306	-0.0038	8.1306	0.3496	0.0449	4.00	1.00	11.43	28.67	1.50	17.50	4.89	61.44	289.91	4.76
	1.2377	1.1590	0.1391	10.1407	1.8543	0.2238	3.00	1.00	8.57	123.50	1.33	68.33	4.71	59.68	280.42	4.97
	1.0481	0.8195	0.0948	10.4061	2.1702	0.2635	2.00	1.00	5.71	75.00	1.50	40.50	4.07	60.54	252.36	4.38
	0.6128	0.4375	0.0548	8.6184	0.7770	0.0991	1.00	1.00	2.86	8.00	2.00	4.00	3.87	61.90	237.93	4.05
	0.0942	0.0218	0.0023	8.1172	0.4190	0.0544	1.00	1.00	2.86	0.00	0.00	0.00	0.00	62.26	245.68	4.09
	0.2630	0.1555	0.0195	8.2175	0.4582	0.0591	3.00	1.00	8.57	28.00	1.00	25.33	5.30	62.11	255.49	4.24
	1.1202	0.6467	0.0740	9.4931	1.2326	0.1492	9.00	1.29	20.00	28.60	1.07	28.57	5.30	61.34	271.26	4.57
	3.8821	3.2787	0.3447	13.8304	4.5838	0.4957	10.00	1.11	25.71	16.75	1.30	31.17	5.14	57.66	296.32	5.39
	0.2210	-0.1834	-0.0288	12.4579	2.3714	0.2351	7.00	1.00	22.86	21.00	1.25	29.71	4.70	53.02	302.18	6.12
	1.6585	1.2033	0.1102	12.8608	2.4718	0.2379	15.00	1.15	37.14	49.33	1.25	39.36	4.78	51.74	294.34	6.18
	3.1650	2.7586	0.2412	15.3315	4.1053	0.3657	9.00	1.00	25.71	68.67	1.11	39.78	4.14	48.57	287.20	6.60
	3.4626	2.8634	0.3116	12.7075	3.7148	0.4131	7.00	1.00	20.00	9.67	1.50	32.43	6.15	58.77	253.53	4.79
	0.3248	0.0573	0.0067	7.8913	0.2180	0.0284	0.00	0.00	0.00	0.00	0.00	0.00	0.00	63.80	207.66	3.44
	0.0054	0.0361	0.0048	7.5122	0.0413	0.0055	1.00	1.00	2.86	59.00	1.00	59.00	4.11	63.57	184.57	2.90

Table 6-8. Reliability Analysis Dataset (Wednesday and Thursday)

	Diff in 95% TT	Diff in Buffer Time	Diff in Buffer Index	Mixed 95% TT	Mixed Buffer Time	Mixed Buffer Index	Number of Inc	Rate of Inc	Avg LNMin of Blockage	Max LnMin of Blockage	Avg Lanes Blocked	Avg Clearance Time	Avg Dist from I-215	NI Speed	NI Volume (Vphpl)	NI Density (Vpmpl)
Wednesday	0.0000	0.0000	0.0000	8.1528	0.1347	0.0168	0.00	0.00	0.00	0.00	0.00	0.00	0.00	60.99	287.83	4.74
	1.0494	0.9752	0.1168	9.8231	1.5138	0.1822	4.00	1.00	13.33	15.00	1.25	12.75	5.26	59.70	285.15	4.87
	0.0164	-0.0050	-0.0010	8.9520	1.0325	0.1304	1.00	1.00	3.33	18.00	2.00	14.50	0.34	60.90	253.76	4.25
	0.2029	0.1399	0.0175	8.3837	0.6432	0.0831	0.00	0.00	0.00	0.00	0.00	9.00	0.00	61.89	239.81	3.95
	0.0943	0.0603	0.0074	8.3943	0.6173	0.0794	2.00	2.00	3.33	0.00	1.50	53.00	4.41	61.64	244.22	4.09
	0.0661	0.0367	0.0043	8.6572	0.8505	0.1089	2.00	2.00	3.33	17.00	0.50	0.00	2.64	61.58	252.18	4.22
	0.3765	0.3229	0.0392	9.1794	1.0641	0.1311	4.00	1.00	13.33	17.50	0.50	36.88	5.97	60.31	267.67	4.61
	0.7094	0.4373	0.0405	11.7733	2.7591	0.3061	9.00	1.00	33.33	54.83	1.33	29.10	4.17	57.47	287.80	5.33
	3.8668	3.1005	0.2700	17.2211	6.8418	0.6592	6.00	1.00	20.00	30.50	1.00	27.29	4.90	54.66	290.51	6.20
	-0.1353	-0.4512	-0.0529	13.2226	2.7808	0.2663	8.00	1.14	23.33	72.90	1.50	32.31	3.93	52.00	291.53	6.46
	-0.3484	-0.4247	-0.0401	14.7525	3.5034	0.3114	9.00	1.29	23.33	41.87	1.00	28.50	4.68	48.93	275.19	6.82
	0.7433	0.5519	0.0537	12.8747	4.0279	0.4553	7.00	1.00	23.33	39.33	0.86	27.75	5.42	58.45	248.28	4.66
	-0.5371	-0.4529	-0.0576	8.2104	0.5267	0.0685	1.00	1.00	3.33	160.00	2.00	80.00	5.44	62.40	209.14	3.41
	0.1387	0.1725	0.0228	7.6857	0.1248	0.0165	0.00	0.00	0.00	0.00	0.00	0.00	0.00	63.25	191.58	3.02
Thursday	0.6004	0.5553	0.0711	8.7766	0.9989	0.1284	2.00	1.00	5.88	0.00	1.00	24.00	4.57	61.71	283.46	4.68
	0.2367	0.0528	0.0046	8.7626	0.7348	0.0915	2.00	1.00	5.88	26.00	1.00	26.00	3.89	60.41	282.42	4.70
	0.1670	0.1306	0.0163	8.5692	0.7371	0.0941	3.00	1.00	8.82	7.00	0.67	4.33	1.71	61.32	252.26	4.19
	0.0141	-0.0049	-0.0007	7.9679	0.2865	0.0373	1.00	1.00	2.94	39.00	1.00	23.50	2.13	61.98	233.48	3.88
	0.0413	-0.0343	-0.0049	8.1428	0.3718	0.0479	3.00	1.00	8.82	0.00	1.00	61.50	4.08	61.58	240.14	3.99
	1.5468	1.2272	0.1504	9.7012	1.6597	0.2064	5.00	1.00	14.71	64.00	1.00	64.00	4.17	61.12	244.66	4.29
	3.1545	2.6771	0.3145	11.5389	3.1080	0.3686	4.00	1.00	11.76	46.00	1.33	32.75	4.23	59.02	257.50	5.08
	1.6042	1.3650	0.1470	11.6929	2.6458	0.2924	10.00	1.11	26.47	50.17	0.93	30.62	6.02	56.50	278.99	5.63
	1.7629	0.7651	0.0518	13.6556	2.7476	0.2519	15.00	1.07	41.18	24.71	0.75	21.14	5.41	49.40	283.63	6.49
	2.3540	1.4253	0.1232	13.2435	2.5024	0.2330	10.00	1.25	23.53	24.00	0.71	23.70	5.22	48.83	292.63	6.69
	2.6218	1.9783	0.1717	14.1092	2.9186	0.2608	8.00	1.14	20.59	31.00	1.00	23.38	4.91	47.89	276.57	6.75
	1.1506	0.6503	0.0635	10.9908	1.9752	0.2191	7.00	1.17	17.65	35.50	1.33	29.75	3.85	56.26	245.66	4.67
	0.4070	0.2937	0.0376	8.3101	0.6365	0.0830	4.00	1.33	8.82	59.00	0.00	59.00	6.15	62.51	204.04	3.55
	0.5808	0.4689	0.0620	8.1577	0.6340	0.0843	2.00	2.00	2.94	83.00	1.50	56.00	5.72	63.57	183.93	3.01

CHAPTER 7

DESCRIPTIVE SUMMARY STATISTICS FOR SHORT TERM IMPACT ANALYSIS

7.1 Introduction

This chapter presents the descriptive summary statistics of the data for short term impacts of traffic incidents. Before embarking on the regression and model calibration, various variable summary statistics are generated to evaluate the distributions and trends between variables are intuitive. The histograms and box-plots presented are applicable to the corresponding variables mentioned when used separately and does not show the interaction and influence of the rest of the variables.

7.2 Summary of Descriptive Statistics

7.2.1 Incident Duration

Figure 7-1 shows the histogram of incident durations for all the incidents in the sample set.

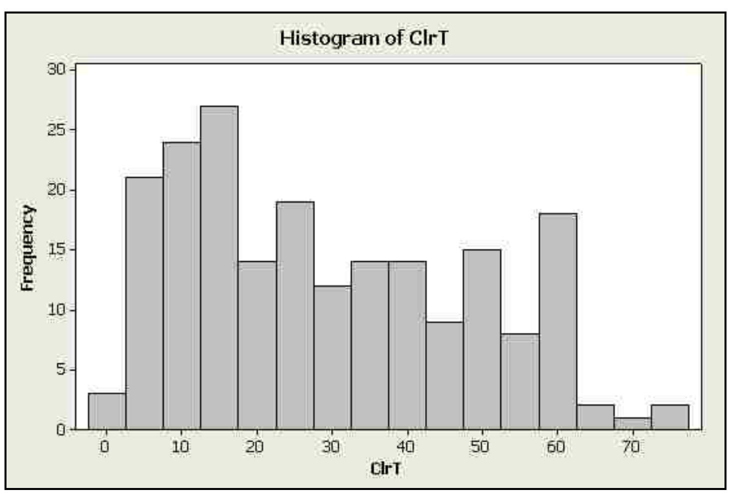


Figure 7-1. Histogram of Incident Clearance Durations (minutes)
(Mean = 29.35; Median = 25.5 minutes)

The distribution is positively skewed as can be expected in the real-world. The average and median durations are 29.35 and 26 minutes, respectively.

7.2.2 Travel Time

This section presents histograms and box-plots of the travel time impact variables for different values of number of blocked lanes and incident duration (duration of blockage). Figures 7-2 and 7-3 show the histograms of impacted vehicle-hours of travel and additional travel time, in minutes/vehicle. The distributions are skewed to the right following the expected trend that typically high-impact incidents are not as frequent as the medium and low impact incidents. The mean impact vehicle-hours of travel is 244.04 per incident (median 134.67), while the mean additional travel time is 1.32 minutes per vehicle (median 1.05) in the primary direction. The latter represents the average *additional* travel time for all the vehicles that are impacted, i.e., those vehicles that are within the temporal and spatial extents of the incident. In the rubbernecking direction, the mean and median additional travel times are 0.06 and 0.01 minutes respectively.

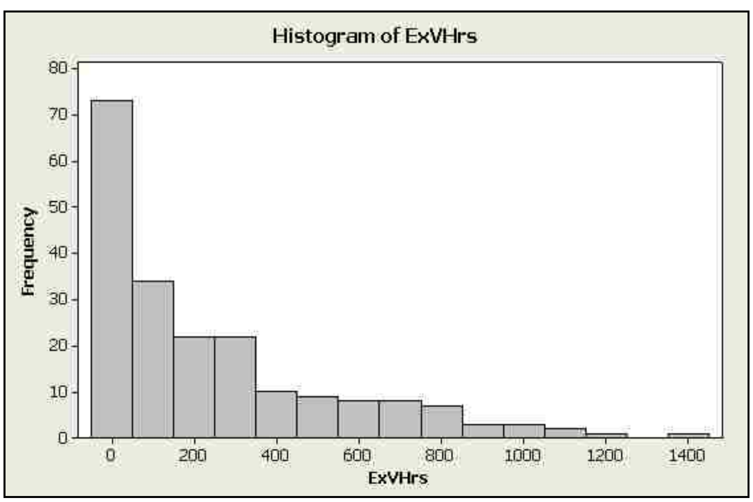


Figure 7-2. Histogram: Impact VHT

(Mean = 244.04; Median = 134.7 veh-hrs/incident)

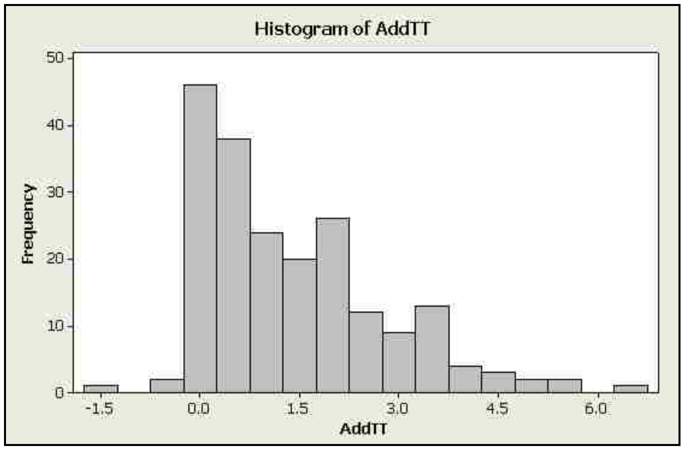


Figure 7-3. Histogram: Additional Travel Time per vehicle
(Mean value = 1.32; Median = 1.05 minutes/vehicle)

Figures 7-4 to 7-9 show box-plots of incident impacts for different numbers of blocked lanes. Box-plots show median values, quartiles and range of values. Upper and lower fences computed using the upper and lower fourth values and the interquartile range are used to signify the boundary limits. The individual points plotted above or below the lower and upper fences are statistically outliers. Zero blocked lanes means the incident occurred on the shoulder and no travel lanes were blocked.

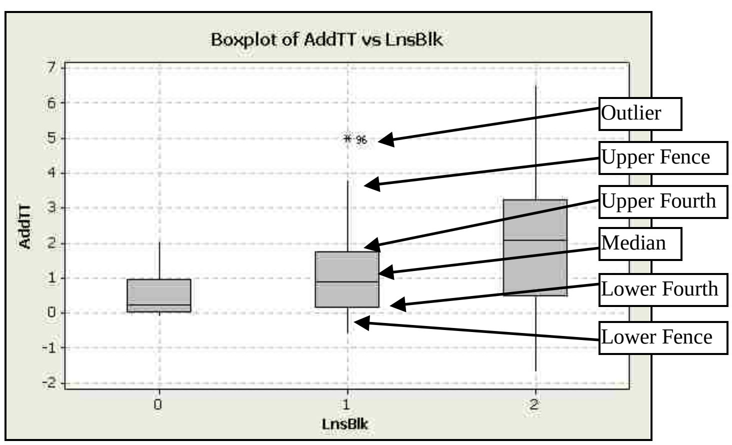


Figure 7-4. Box-plot: Primary Additional Travel Time (in minutes) Vs. Number of Blocked Lanes

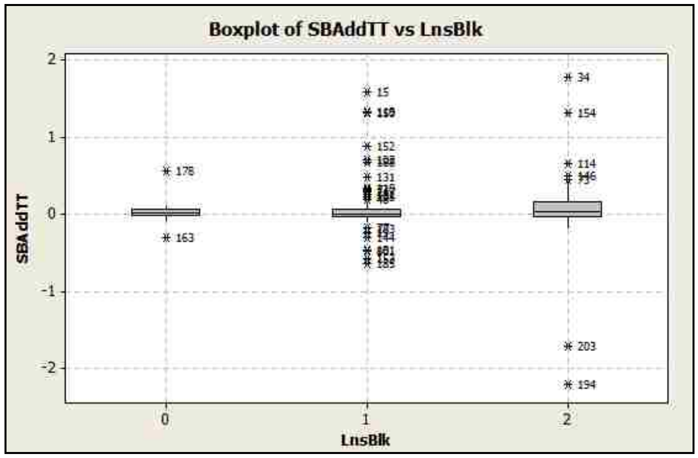


Figure 7-5. Box-plot: Rubbernecking Additional Travel Time (in minutes) Vs. Number of Blocked Lanes

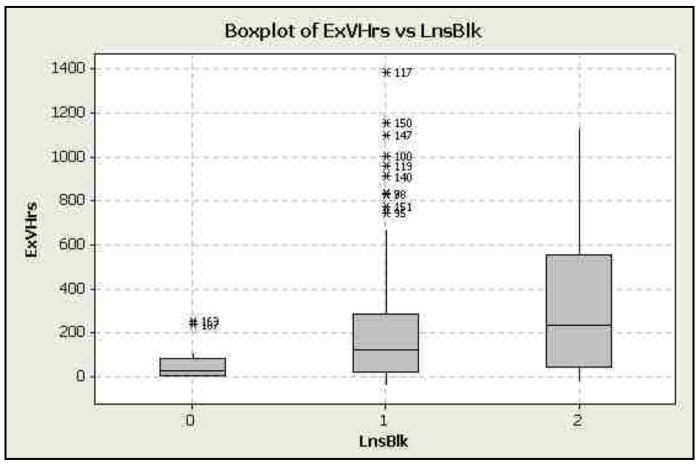


Figure 7-6. Box-plot: Excess VHT Vs. Number of Blocked Lanes

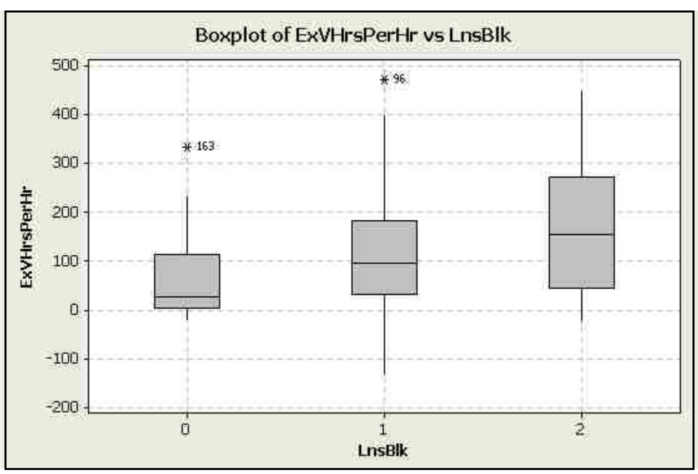


Figure 7-7. Box-plot: Excess VHT per hour of Incident Impact Vs. Number of Blocked Lanes

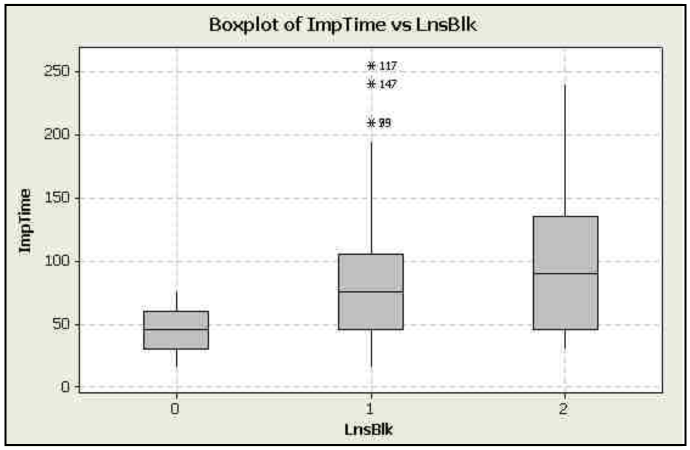


Figure 7-8. Box-plot: Temporal Impact (in minutes) Vs. Number of Blocked Lanes

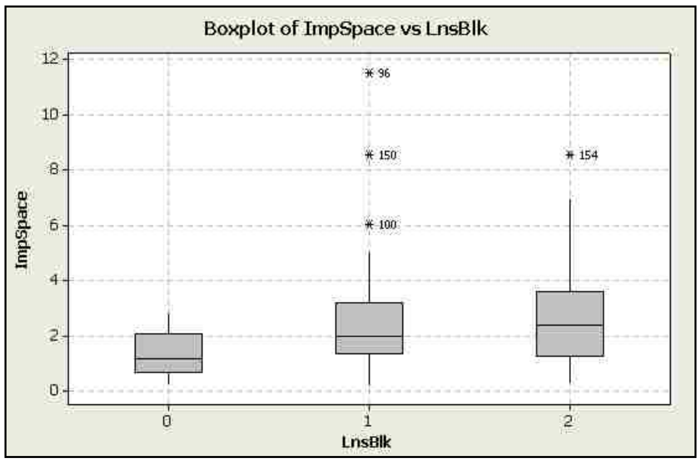


Figure 7-9. Box-plot: Spatial Impact (in miles) Vs. Number of Blocked Lanes

It can be seen from Figures 7-4 to 7-9 that, as expected, the impacts of incident and also the temporal and spatial extents are higher for higher number of blocked lanes. For the rubbernecking additional travel time in Figure 7-5, the trend and the mean/median values are very mild. This indicates that the rubbernecking impacts on additional travel time do not have clear increase with increase in number of lanes blocked.

Figure 7-10 shows that the average incident duration is higher for shoulder incidents (zero blocked lanes) than for one blocked lane. This may indicate a lower sense of urgency for clearing incidents that do not block travel lanes. Figures 7-11 to 7-16 show box-plots of incident impacts for different values of duration of blockage of travel lanes. Incident durations are grouped into five categories 1, 2, 3, 4, and 5 corresponding to incident durations of 15 minutes or less, greater than 15 minutes up to 30, greater than 30 minutes up to 45, greater than 45 minutes up to 60, and finally greater than 60 minutes, respectively. Longer incident durations on an average result in longer spatial and temporal extents and increased incident impacts. Additional travel time for rubbernecking direction (Figure 7-12) does not have a very high clear pattern.

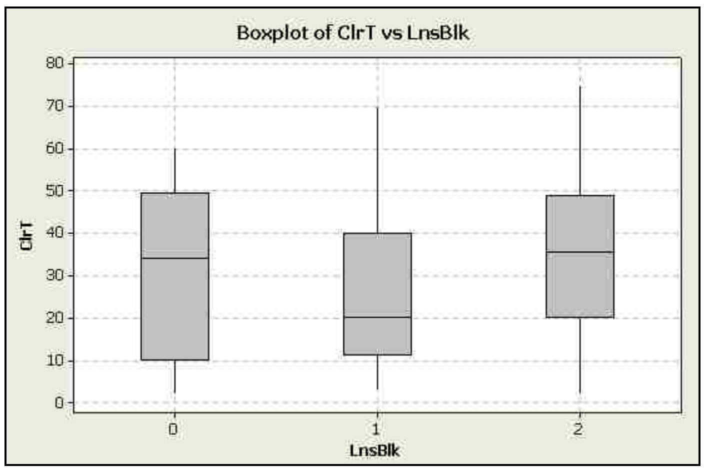


Figure 7-10. Box-plot: Incident Duration Vs. Number of Blocked Lanes

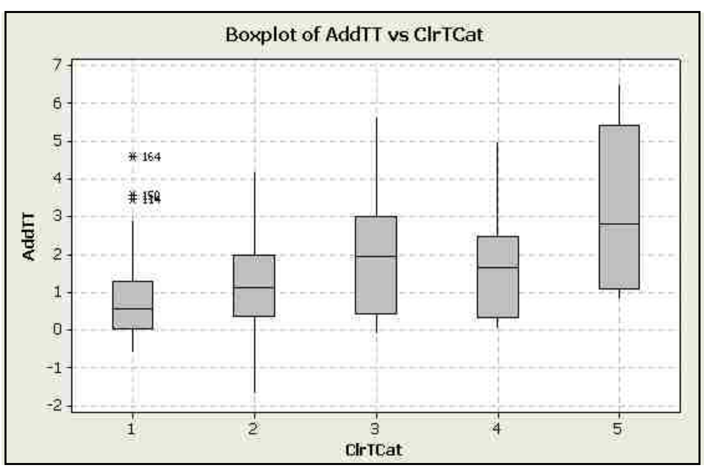


Figure 7-11. Box-plot: Average Primary Additional Travel Time (in minutes/vehicle) Vs. Incident Duration

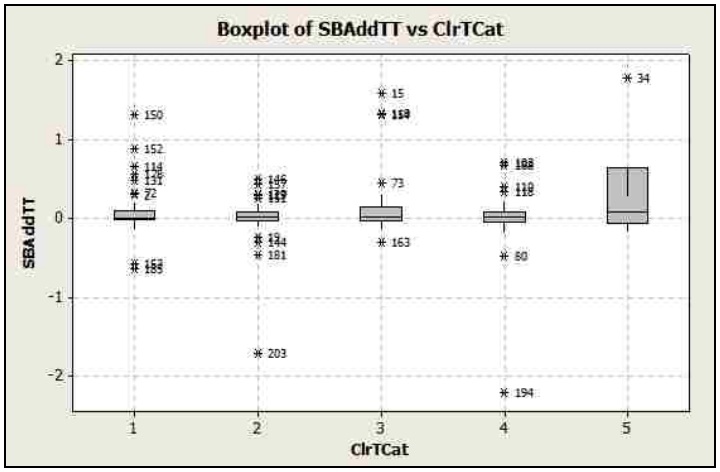


Figure 7-12. Box-plot: Average Rubbernecking Additional Travel Time (in minutes/vehicle) Vs. Incident Duration

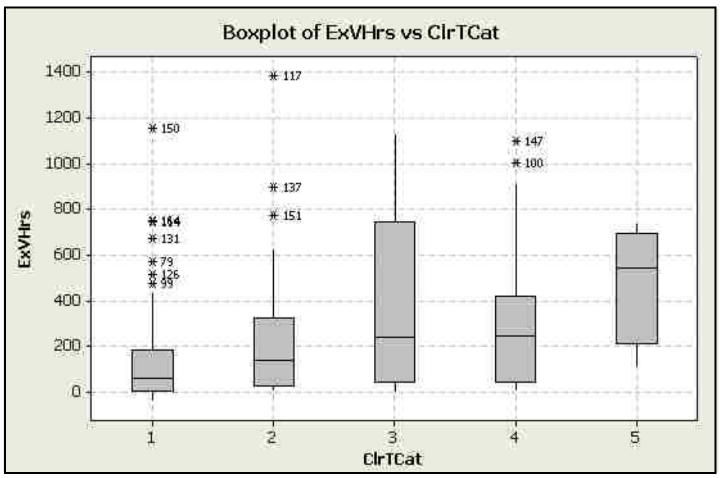


Figure 7-13. Box-plot: Impact in VHT vs. Incident Duration

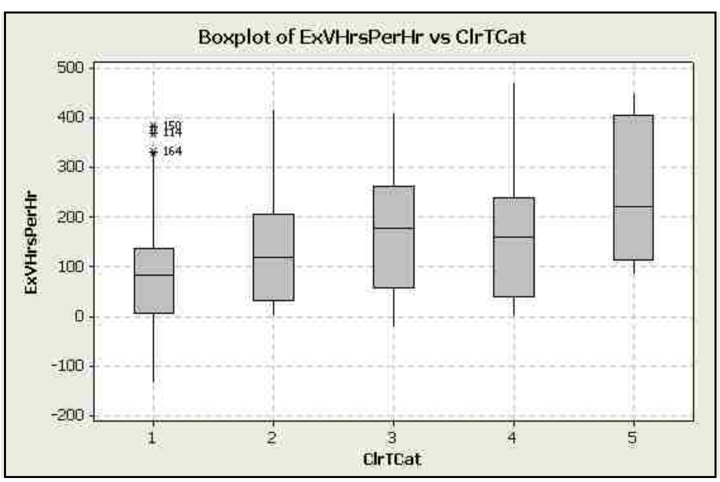


Figure 7-14. Box-plot: Excess VHT per hour of incident impact vs. Incident Duration

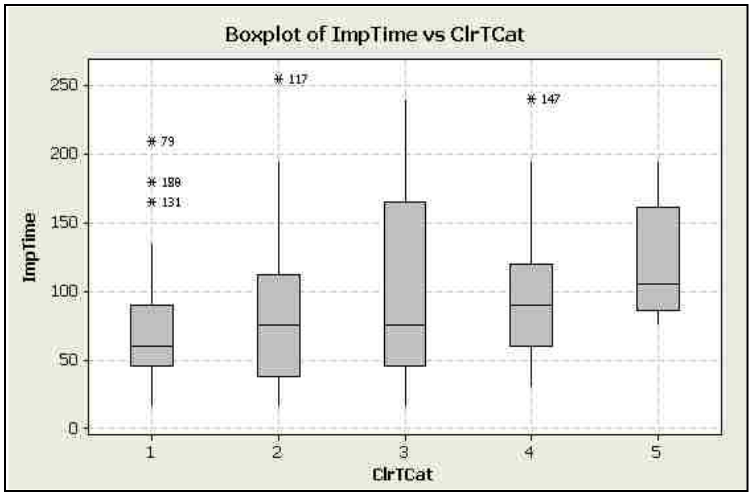


Figure 7-15. Box-plot: Temporal Extent (in minutes) vs. Incident Duration

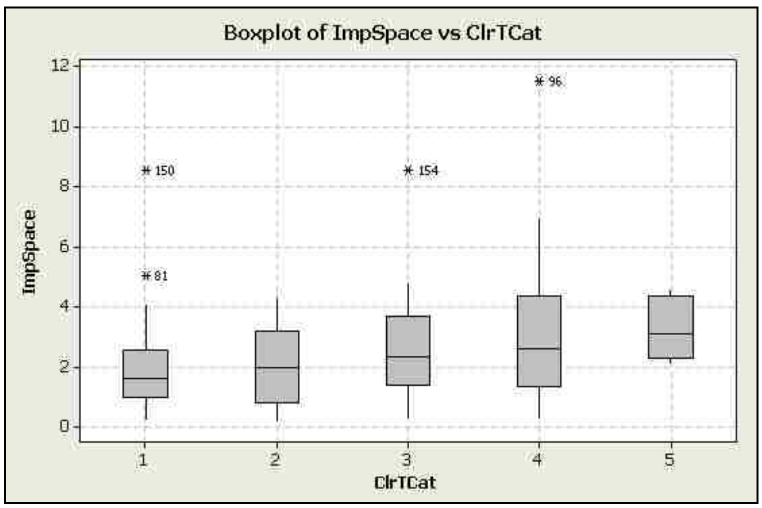


Figure 7-16. Box-plot: Spatial Extent (in miles) Vs. Incident Duration

7.2.3 Fuel Consumption

Figure 7-17 shows a histogram of impacts in terms of fuel consumption (gallons). The histogram is positively skewed as expected, with majority of the cases with lower impacts. The mean excess fuel consumption is around 90.4 gallons per incident (median 37.9). Figure 7-18 and 7-19 also display a general trend of increased impact on fuel consumption with increase in number of lanes blocked and incident duration.

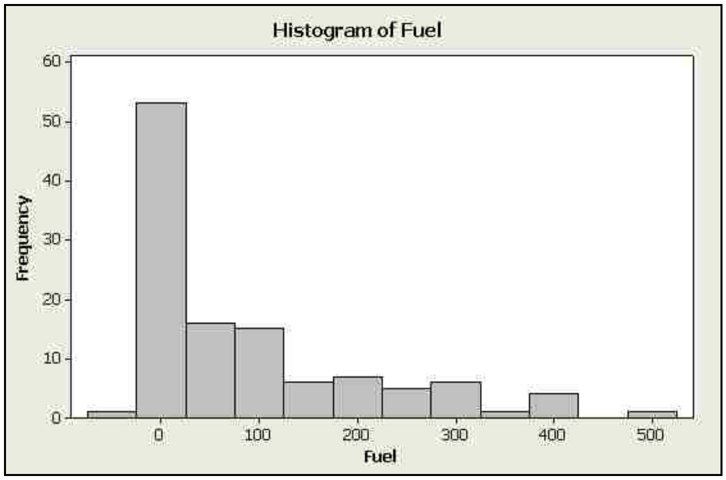


Figure 7-17. Histogram: Excess Fuel Consumption in gallons

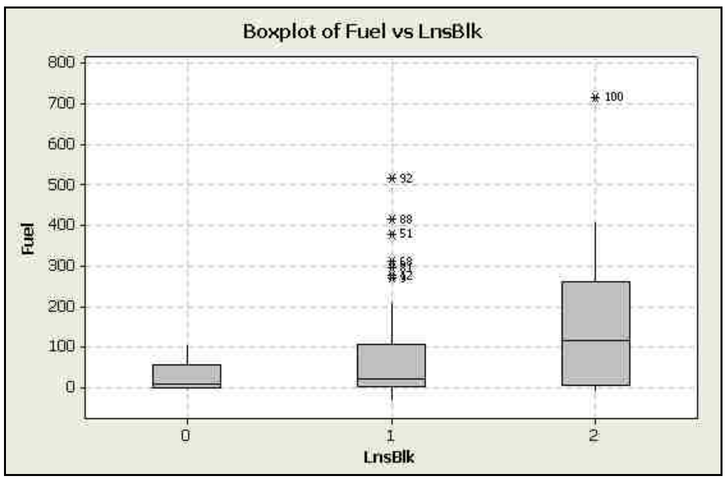


Figure 7-18. Box-plot: Excess Fuel Consumption (in gallons) Vs. Number of Lanes Blocked

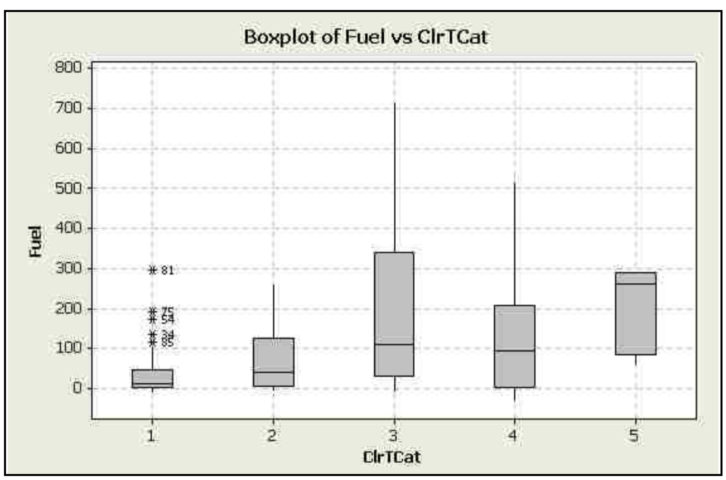


Figure 7-19. Box-plot: Excess fuel consumption (in gallons) Vs. Incident Duration

7.2.4 Vehicle Emissions

The histograms in Figures 7-20 to 7-23 show the trends for emissions of CO_2, CO, and NO_x and PM_{10}.

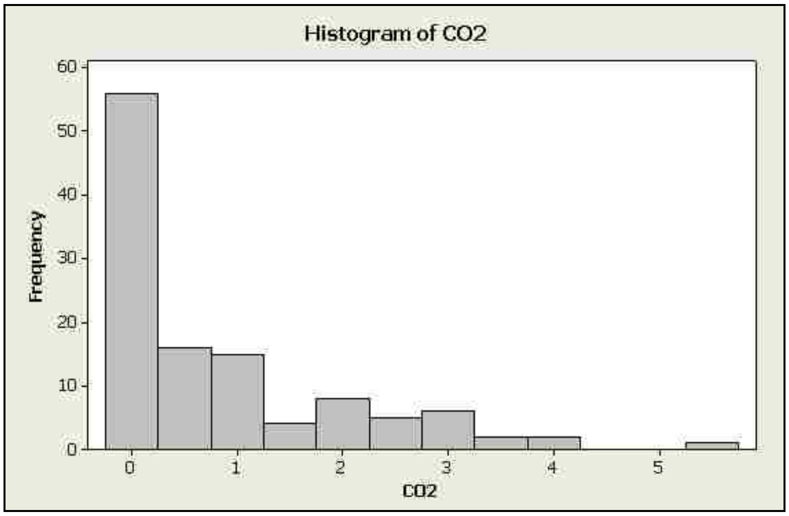


Figure 7-20. Histogram: Excess CO_2 Emissions in Tons

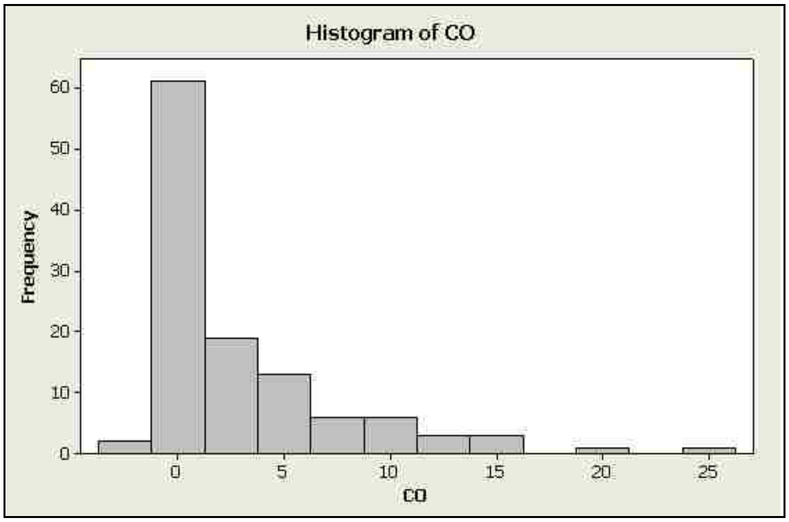


Figure 7-21. Histogram: Excess CO Emissions in Kgs

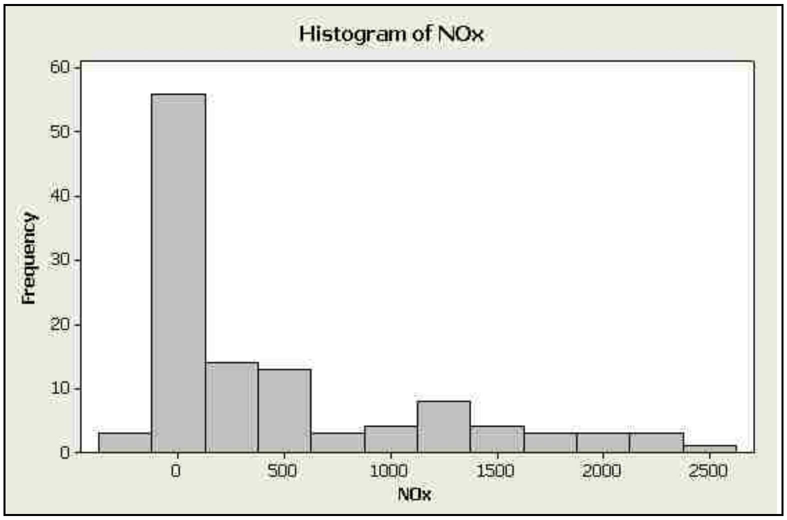


Figure 7-22. Histogram: Excess NO_x Emissions in grams

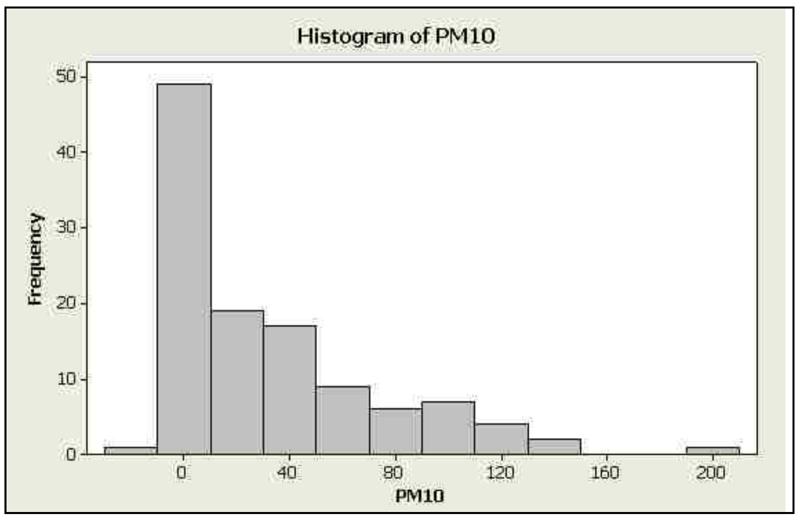


Figure 7-23. Histogram: Excess PM_{10} Emissions in grams

The box-plots in Figures 7-24 to 7-27 and Figures 7-28 to 7-31 show excess vehicle emissions for different numbers of blocked lanes and the incident duration used one at a time, respectively. In general, they all show an increase in impact on vehicle emissions with increase in number of blocked lanes and incident duration. The same categories for incident durations as in the case of fuel consumption are used for the following plots.

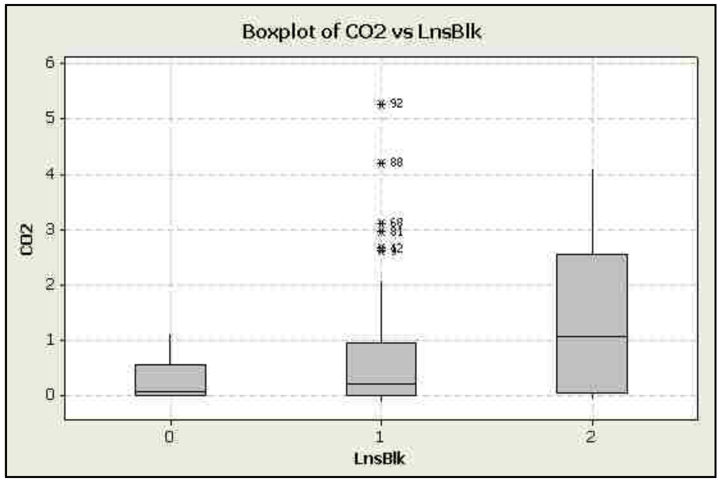


Figure 7-24. Box-plot: Excess CO_2 emissions (in Tons) vs. Number of Blocked lanes

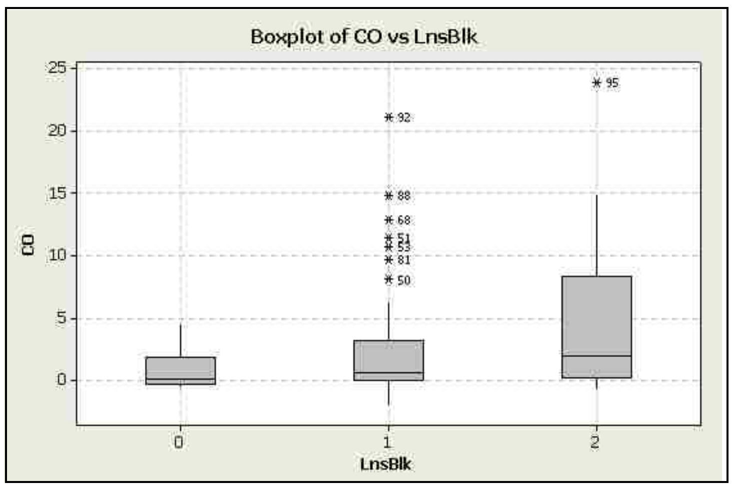


Figure 7-25. Box-plot: Excess CO emissions (in Kgs) vs. Number of Blocked lanes

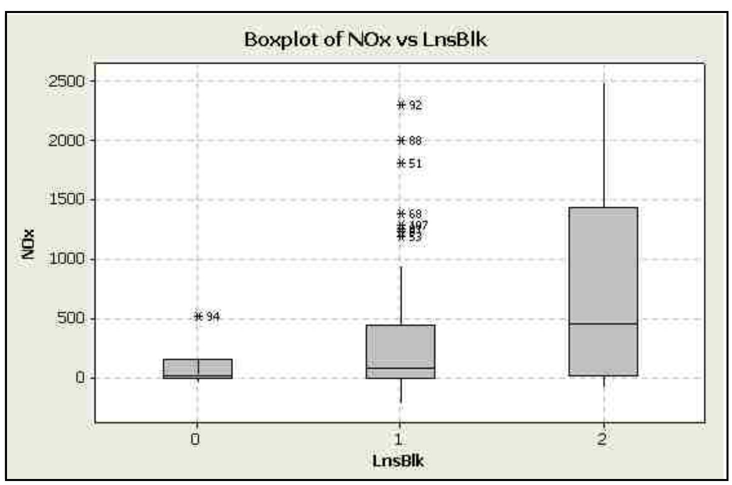


Figure 7-26. Box-plot: Excess NO_x emissions (in Grams) vs. Number of Blocked lanes

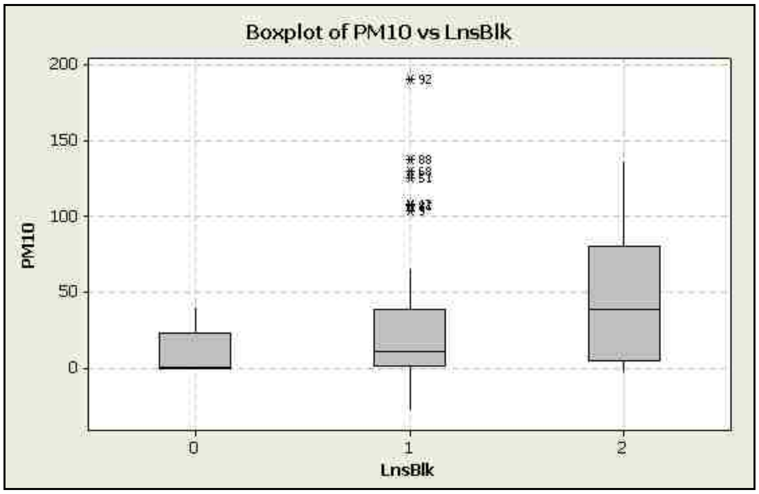


Figure 7-27. Box-plot: Excess PM_{10} emissions (in Grams) vs. Number of Blocked lanes

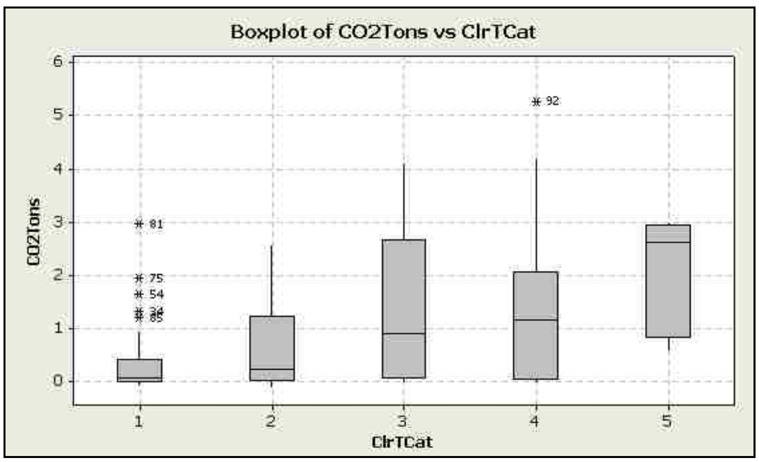


Figure 7-28. Box-plot: Excess CO_2 emissions (in Tons) vs. Incident Duration

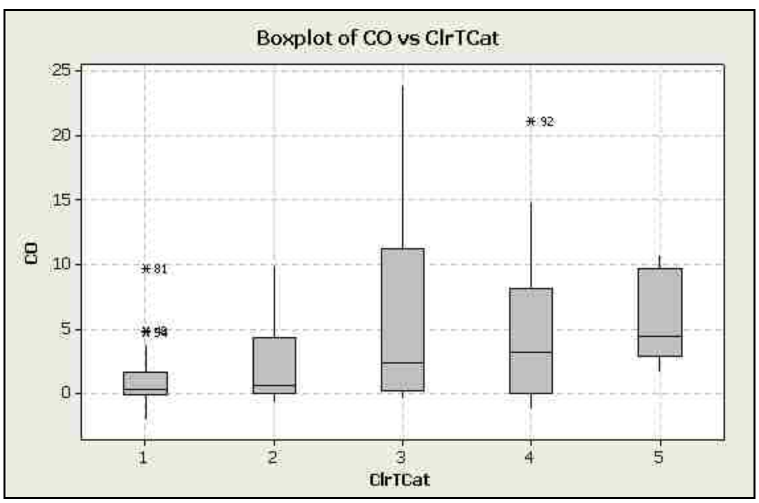


Figure 7-29. Box-plot: Excess CO emissions (in Kgs) vs. Incident Duration

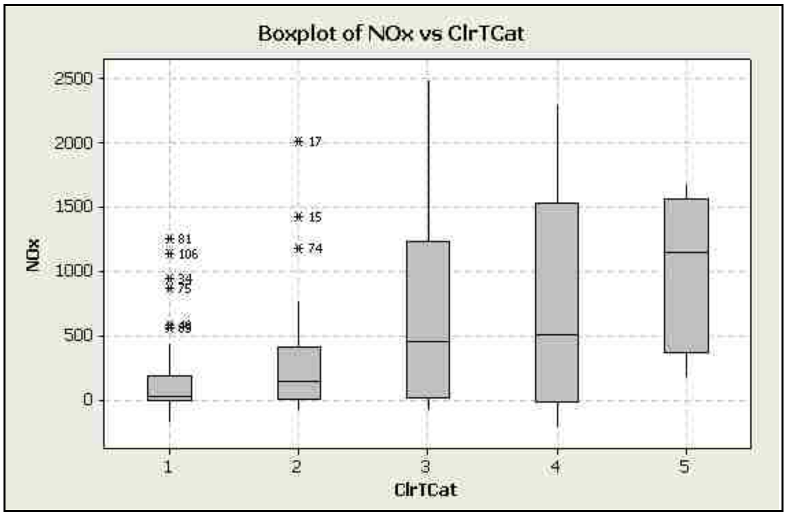


Figure 7-30. Box-plot: Excess NO_x emissions (in Grams) vs. Incident Duration

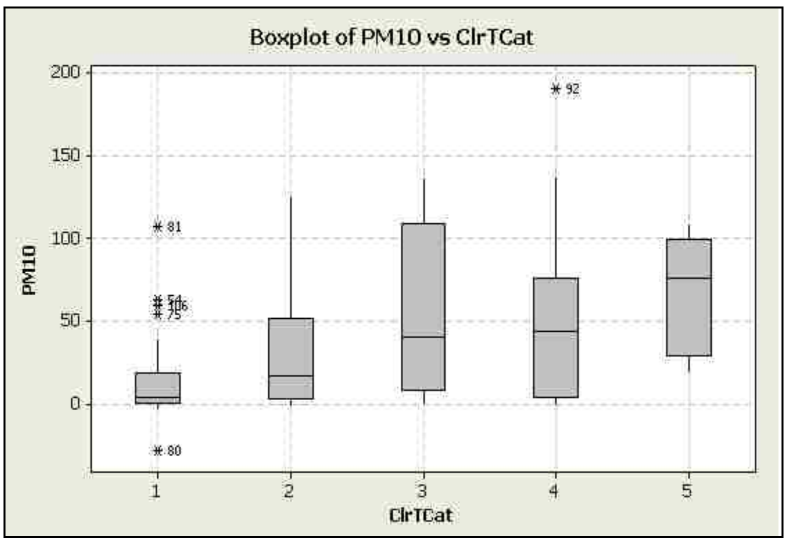


Figure 7-31. Box-plot: Excess PM_{10} emissions (in Grams) vs. Incident Duration

The mean excess vehicle emissions are 0.864 tons of CO_2, 2.985 Kg of CO, 453 grams of NO_x and 33 grams of PM_{10} respectively for an incident. These include the emissions in the rubbernecking direction also.

7.3 Summary

This chapter presented the descriptive summary statistics to observe the general trends among certain among certain incident characteristics and the short term impacts. The impacts of incidents in terms of travel time, fuel consumption and vehicle emissions show an increase with increase in incident duration and number of lanes blocked, as can be expected in the real-world. It is to be noted that these summary statistics do not depict the inter-relationship and influence between other predictor variables and are only for understanding the general trend that can be further studied by statistical modeling.

CHAPTER 8

DESCRIPTIVE SUMMARY STATISTICS FOR LONG TERM IMPACT ANALYSIS

8.1 Introduction

This chapter presents the descriptive summary statistics for long term impacts of incidents. As in the case of the previous chapter, all the plots used the specified variables alone without the interactions of the other predictor variables.

8.2 Summary of Descriptive Statistics

Figures 8-1 to 8-6 show the histograms of the TTR measures (95^{th} percentile travel time, buffer time and buffer index for mixed and also difference between mixed and non-incident). In general, they are all skewed to the right which is according to expectation. In real-world travel time distributions are typically log-normal (Susilawati et al., 2010).

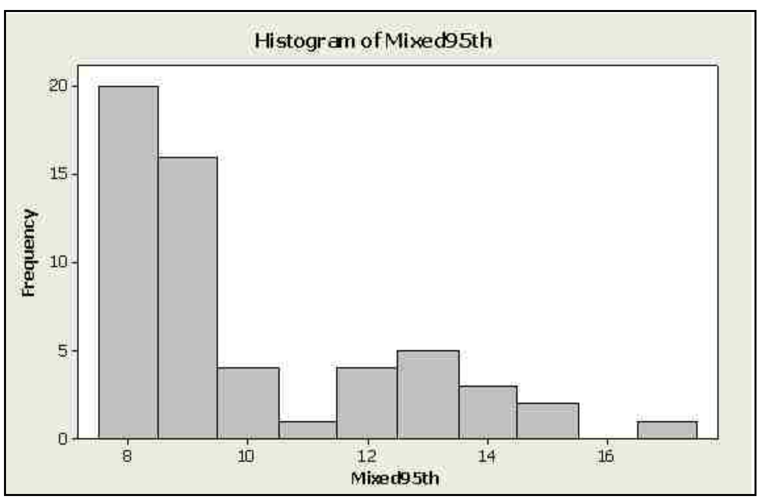


Figure 8-1. Histogram: 95^{th} percentile travel time (mixed)

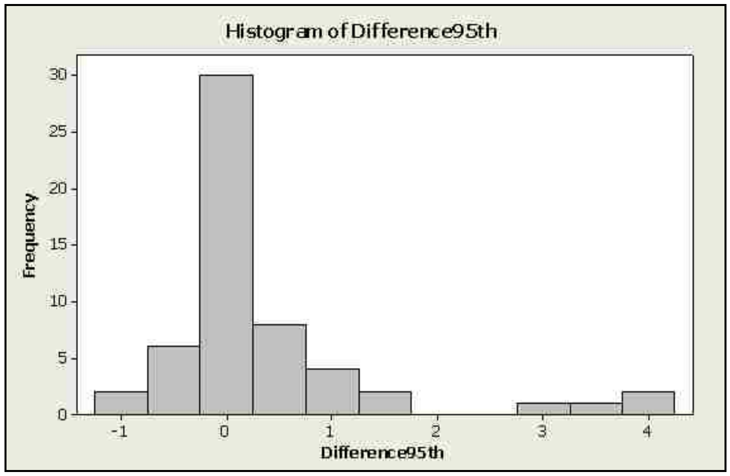


Figure 8-2. Histogram: 95th percentile travel time (difference)

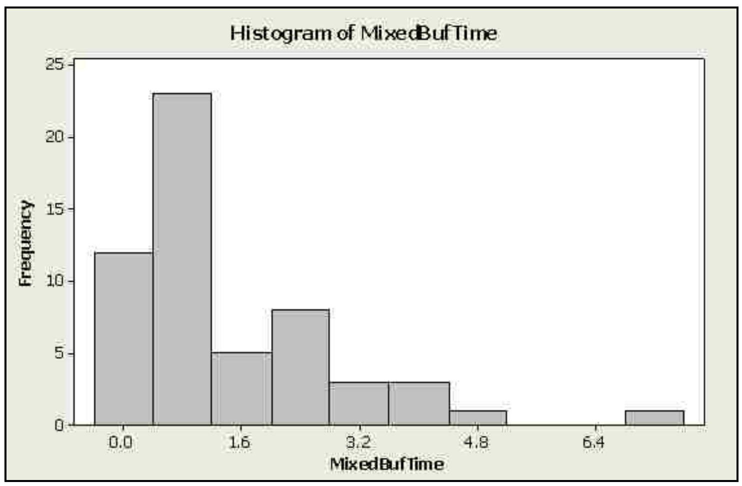


Figure 8-3. Histogram: Buffer Time (mixed)

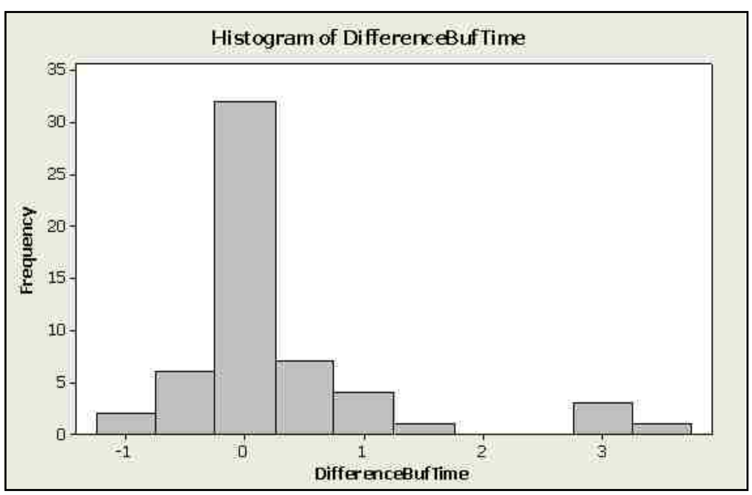


Figure 8-4. Histogram: Buffer Time (difference)

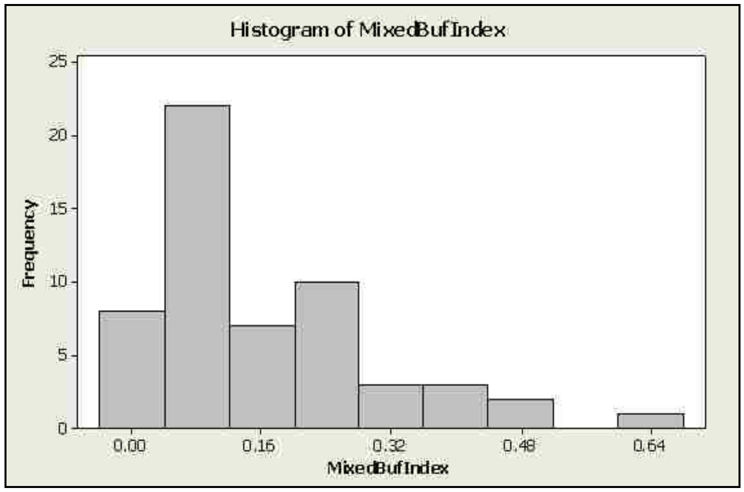


Figure 8-5. Histogram: Buffer Index (mixed)

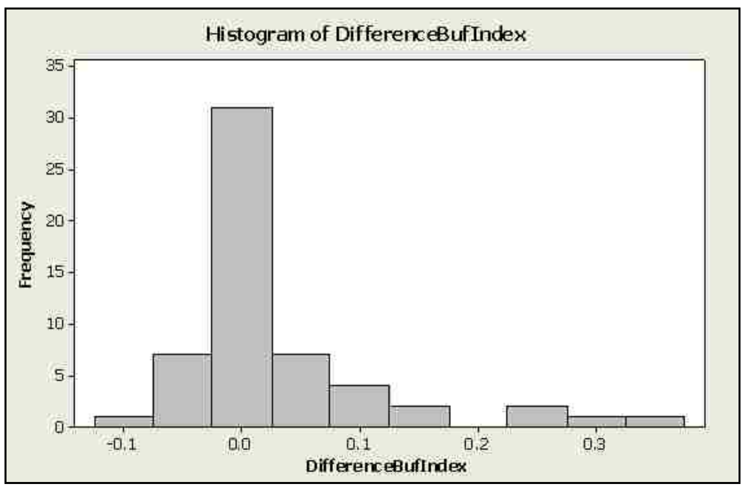


Figure 8-6. Histogram: Buffer Index (difference)

For Figures 8-7 to 8-12, for plotting purposes, the variable average lanes blocked is divided into categories since it is a continuous variable, representing the average number of lanes blocked for a subject hour. For mixed data, the trend is that the TTR measure increases, albeit mildly with increase in lanes blocked (Figures 8-7, 8-9 and 8-11). For the difference between mixed and non-incident, the trends in general stay the same and there is no noticeable increase of the TTR measure with increase in number of lanes blocked (Figures 8-8, 8-10 and 8-12).

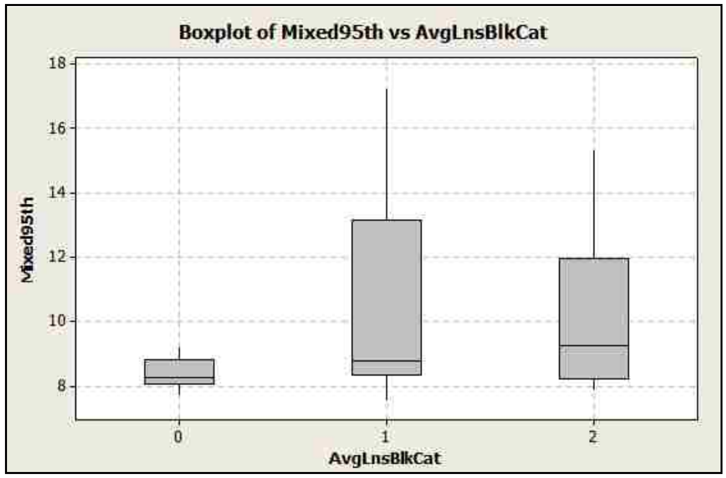


Figure 8-7. Box-plot: 95th Travel Time (mixed) vs. Number of Lanes Blocked

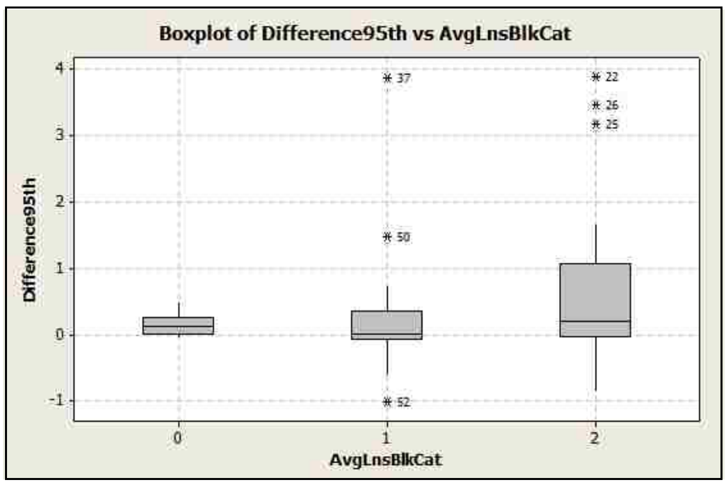


Figure 8-8. Box-plot: 95th percentile TT vs. Number of Lanes Blocked - Difference

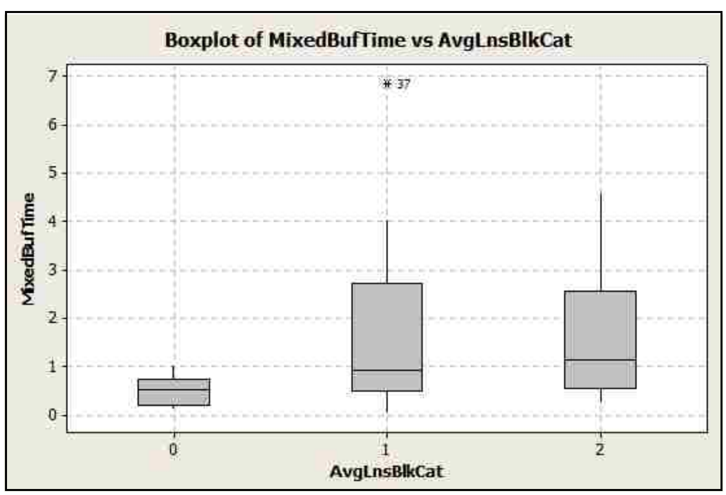


Figure 8-9. Box-plot: Buffer Time (mixed) vs. Number of Lanes Blocked

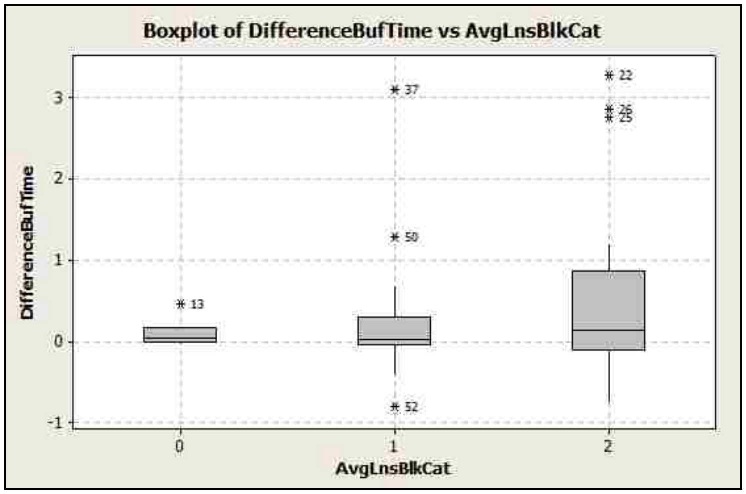


Figure 8-10. Box-plot: Buffer Time vs. Number of Lanes Blocked- Difference

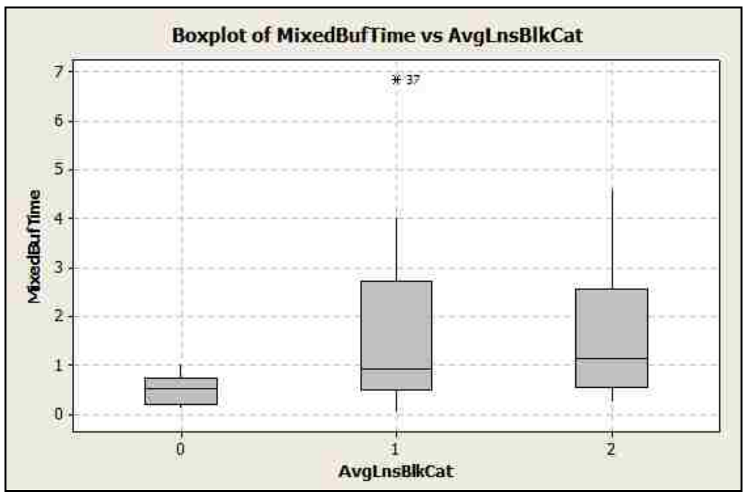


Figure 8-11. Box-plot: Buffer Index (mixed) vs. Number of Lanes Blocked

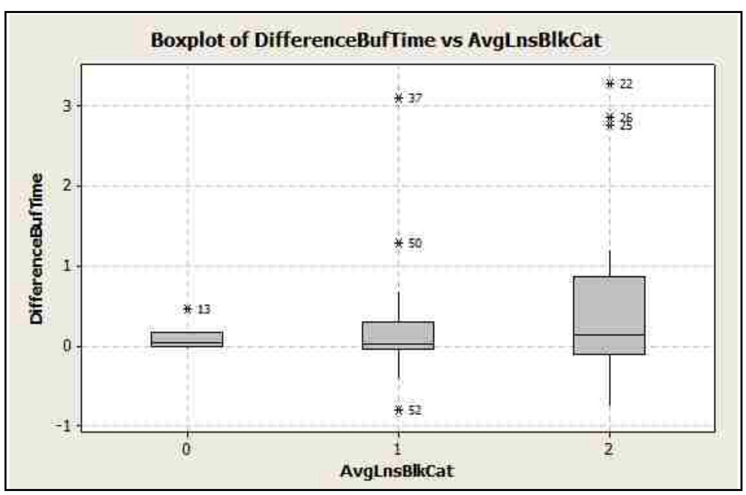


Figure 8-12. Box-plot: Buffer Index vs. Number of Lanes Blocked- Difference

The following box-plots show values of TTR measures with different ranges of incident durations (Figures 8-13 to 8-18). The categories used are the same as short term plots (15 minute bins). With TTR measures, the trend is not as expected. The plots show a general increase with increase in incident duration for incident durations of up to 45 minutes but start to decrease afterward. The count of observations falling in each bin category is shown in boxes in Figure 8-13. This is contrary to the natural expectation that the TTR measures increase with increase in incident duration.

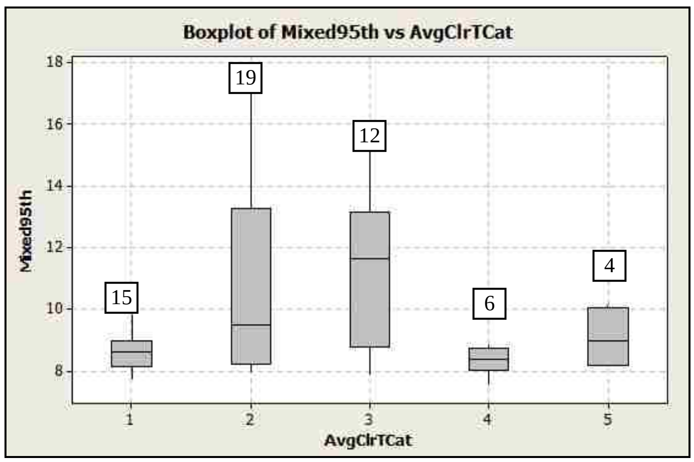


Figure 8-13. Box-plot: 95th percentile Travel Time (mixed) vs. Incident Duration categories

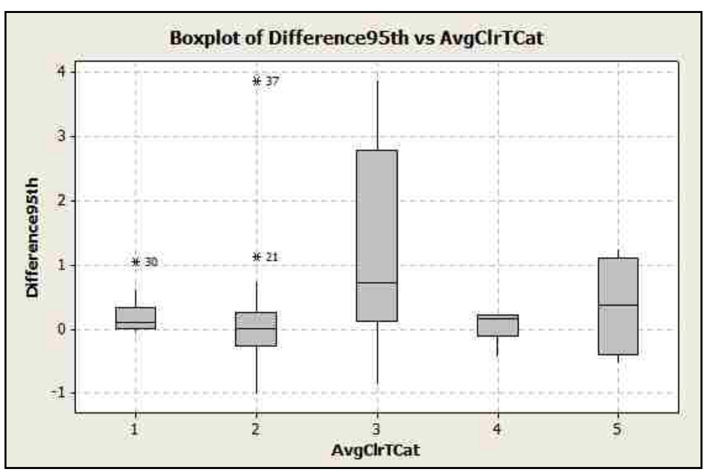


Figure 8-14. Box-plot: 95th percentile Travel Time (difference) vs. Incident Duration categories

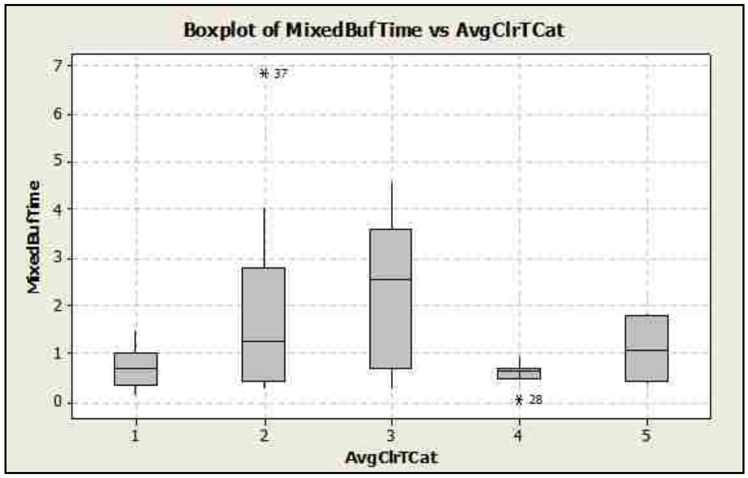


Figure 8-15. Box-plot: Buffer Time (mixed) vs. Incident Duration categories

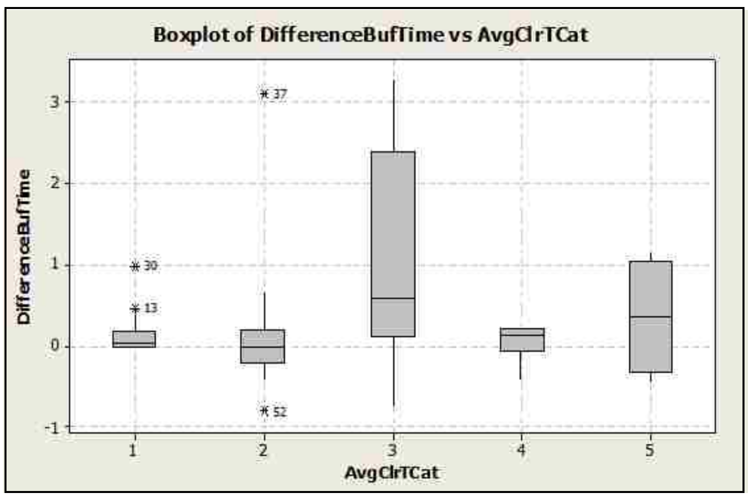


Figure 8-16. Box-plot: Buffer Time (difference) vs. Incident Duration categories

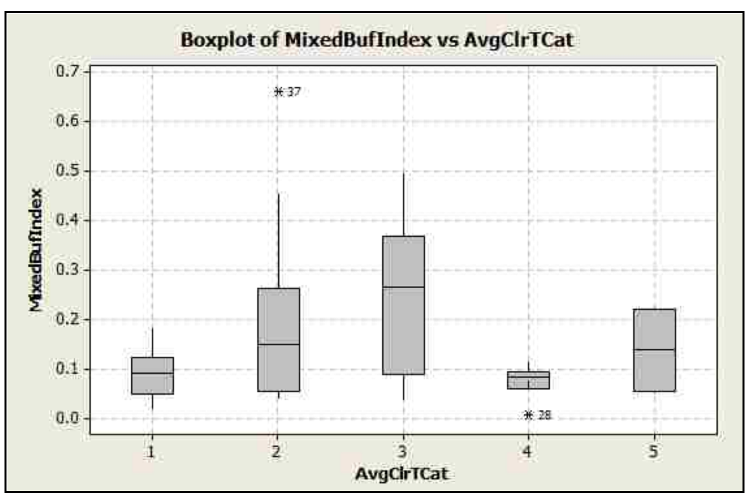


Figure 8-17. Box-plot: Buffer Index (mixed) vs. Incident Duration categories

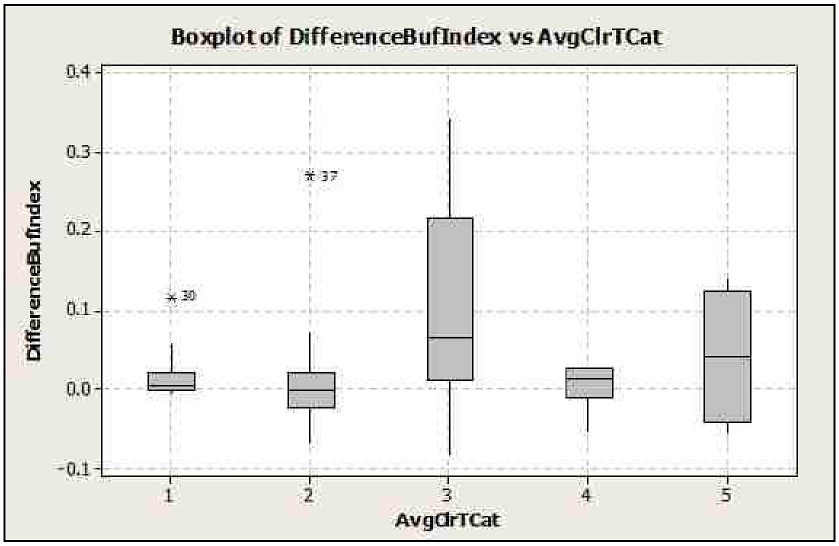


Figure 8-18. Box-plot: Buffer Index (difference) vs. Incident Duration categories

8.3 Summary

The trends for the TTR measures are not entirely as expected. For the difference between incident and non-incident TTR, there is no noticeable increase in TTR measures with increase in incident characteristics. For the incident duration plots, the trends are only partially similar to what can be expected in the real-world. However, these summary statistics do not reflect the interaction of other predictor variables. Since regression modeling includes all the variables and their respective interactions, model results will show the exact relation even though the trends are not visible from these plots. Statistical modeling used to analyze this further is presented subsequently.

CHAPTER 9

RESULTS OF STATISTICAL MODELING FOR SHORT TERM IMPACTS

9.1 Introduction

This chapter presents the statistical modeling results for the short term impacts of incidents. The statistical package used for modeling is R. The models calibrated include the OLS Linear Model, Log-transformed Linear Model, Gamma GLM, Gaussian GLM with Single-Log, and Gaussian GLM with Log-Log. Some response variables have non-positive observations. A constant greater in magnitude than the most negative observed value is added to all the observed values, to make them positive. This step is required for the Gamma and Gaussian GLM models since they can only be used when the response variables are all positive (use of logarithms).

9.2 Description of Response and Predictor Variables

The list of the response and predictor variables used in the analysis of the short term incident impacts, their description and codes in R are presented in the following tables (Tables 9-1 and 9-2). Tables 9-3 and 9-4 show the correlation matrices for the predictor variables for travel time and fuel consumption and vehicle emissions. Though the predictor variables are the same, fuel and emissions have a different sample size from travel time. The highly correlated variables are highlighted by bold text in the correlation matrices. Since the speed for non-incident condition is correlated with density, it is not used in the models (only density and volume are used). As can be seen from the tables, the number of lanes blocked and ratio of lanes blocked are highly correlated, as are incident duration and lane-minutes of blockage.

Table 9-1. List of Response Variables for Short Term Impacts

Variable Code	Variable Name	Explanation
AddTT	Additional Travel Time	Excess travel time during the incident in minutes/incident
SBAddTT	Rubbernecking Additional Travel Time	Excess travel time during the incident in minutes/incident in the rubbernecking direction
ExVHrs	Excess Vehicle Hours	Excess vehicle-hours of travel experienced by all impacted vehicles in veh-hrs
ExVHrsPerHour	VHT per hour of Impact Time	Excess vehicle hours of travel normalized with the Temporal Impact in veh-hrs/hr
ImpTime	Impact Time	Temporal Impact in minutes
ImpSpace	Impact Space	Spatial Impact in miles
NO_x	Excess Oxides of Nitrogen	Excess NO_x due to incident in grams
PM_{10}	Excess Particulate Matter <10 microns	Excess PM_{10} due to incident in grams
CO_2	Excess Carbon dioxide	Excess CO_2 due to incident in Tons
CO	Excess Carbon monoxide	Excess CO due to incident in Kilograms
Fuel	Excess Fuel Consumption	Excess Fuel consumption in gallons

Table 9-2. List of Predictor Variables for Short Term Impacts

Variable Code	Variable Name	Explanation
Weekday	Weekday	Incident happened on a weekday (Yes = 1, No = 0)
Peak	Peak	Incident happened in peak period (Yes = 1, No = 0)
ClrT	Incident duration	Time taken to clear the incident
LNSBLK1	1 Lane Blocked	One travel lane blocked (Yes = 1, No = 0)
LNSBLK2	2 Lanes Blocked	Two travel lanes blocked (Yes = 1, No = 0)
BlkLnMin	Blocked Lane-Minutes	Lanes minutes of blockage (product of "incident duration" and "number of lanes blocked")
LnLoc	Location of Lanes Blocked	Location of blocked lane(s) (Right = 0, Center/Left = 1)
NIDensity	Non-incident Density	Density for non-incident condition in vpmpl
NIVolume	Non-incident Volume	Volume for non-incident condition in vphpl
NISpeed	Non-incident Speed	Speed for non-incident condition in mph
RNIDensity	Rubbernecking Non-incident Density	Density for non-incident condition in vpmpl, for Rubbernecking direction
RNIVolume	Rubbernecking Non-incident Volume	Volume for non-incident condition in vphpl, for Rubbernecking direction

It is to be noted that in all the models, the number of lanes blocked is used as a dummy variable denoted by LNSBLK1 and LNSBLK2 as shown in Table 9-2. Zero lanes blocked (shoulder) has both LNSBLK1 and LNSBLK2 as zero.

Table 9-3. Correlation Matrix for Predictor Variables for Travel Time

	NIDensity	NIVol	NISpd	Weekday	Peak	ClrT	LnsBlk	LnBlkRatio	LnLoc	BlkLnMin	RNIDensity
NIVol	0.102										
(p-value)	0.149										
NISpd	**-0.827**	0.033									
	0.000	0.640									
Weekday	0.369	0.183	-0.327								
	0.000	0.009	0.000								
Peak	0.273	-0.062	-0.445	0.217							
	0.000	0.379	0.000	0.002							
ClrT	-0.089	0.004	0.110	-0.074	-0.132						
	0.208	0.959	0.118	0.297	0.060						
LnsBlk	-0.203	-0.007	0.136	-0.207	-0.046	0.161					
	0.004	0.921	0.053	0.003	0.512	0.022					
LnBlkRatio	-0.206	-0.060	0.122	-0.184	-0.039	0.173	**0.903**				
	0.003	0.391	0.083	0.009	0.580	0.014	0.000				
LnLoc	-0.176	0.169	0.185	0.058	0.008	-0.006	0.045	-0.004			
	0.012	0.016	0.008	0.412	0.909	0.937	0.525	0.956			
BlkLnMin	-0.171	0.041	0.162	-0.157	-0.123	**0.786**	**0.651**	**0.613**	0.018		
	0.015	0.558	0.021	0.025	0.081	0.000	0.000	0.000	0.803		
RNIDensity	**0.748**	0.045	-0.548	0.288	0.056	-0.056	-0.222	-0.217	-0.188	-0.162	
	0.000	0.525	0.000	0.000	0.429	0.430	0.001	0.002	0.007	0.021	
RNIVolume	**0.755**	0.067	-0.513	0.265	0.063	-0.056	-0.239	-0.232	-0.176	-0.182	**0.911**
	0.000	0.342	0.000	0.000	0.369	0.425	0.001	0.001	0.012	0.009	0.000

Table 9-4. Correlation Matrix for Predictor Variables for Fuel and Emissions

	NIDensity	NIVol	NISpd	Weekday	Peak	LnBlkRatio	BlkLnMin	ClrT	LnsBlk	RNIDensity
NIVol	0.126									
(p-value)	0.179									
NISpd	**-0.795**	0.056								
	0.000	0.550								
Weekday	0.362	0.142	-0.273							
	0.000	0.130	0.003							
Peak	0.291	-0.012	-0.459	0.240						
	0.002	0.902	0.000	0.010						
LnBlkRatio	-0.283	-0.136	0.085	-0.238	-0.062					
	0.002	0.147	0.364	0.011	0.512					
BlkLnMin	-0.243	0.004	0.172	-0.221	-0.175	**0.626**				
	0.009	0.970	0.065	0.017	0.062	0.000				
ClrT	-0.185	0.009	0.182	-0.114	-0.179	0.303	**0.862**			
	0.048	0.927	0.052	0.225	0.055	0.001	0.000			
LnsBlk	-0.233	-0.021	0.052	-0.255	-0.055	**0.890**	**0.652**	0.297		
	0.012	0.824	0.580	0.006	0.563	0.000	0.000	0.001		
RNIDensity	**0.816**	0.123	**-0.552**	0.286	0.101	-0.312	-0.224	-0.120	-0.276	
	0.000	0.190	0.000	0.002	0.282	0.001	0.016	0.202	0.003	
RNIVolume	**0.779**	0.149	-0.491	0.253	0.090	-0.313	-0.248	-0.154	-0.273	**0.974**
	0.000	0.111	0.000	0.006	0.337	0.001	0.008	0.100	0.003	0.000

9.3 Model Results

The results are arranged in the same format for all the response variables for short-term analysis. First, is a summary table with the important measures of all the functional forms modeled, followed by the coefficient estimates for the best model selected. The summary table presents the R^2 (regular and adjusted, wherever applicable) and AIC for the Full (model with all predictor variables) and Nested model (model with only the significant predictor variable from stepwise regression). Also presented are the residual and normality plots for the nested models. It is to be noted that models with different functional forms cannot be compared. Also plotted are the plots of Cook's distances to determine the presence of outliers. The main criteria used for selecting the best model are the residual and normality plots, R^2 and AIC and the list of significant and practically useful variables in the final nested model. The results are inclusive of primary and rubbernecking direction for all response variables except additional travel time.

9.3.1 Additional Travel Time – Primary Direction

The model results for the analysis for additional travel time per incident experienced by the impacted vehicles are shown in Table 9-5. The Gaussian Log-Log model has the best fit based on the residual plots, R^2 and AIC measures. Also, since Gaussian log-log model has both incident duration and lanes blocked as significant variables, it is preferred over the Gaussian Single-log model with just the lane-minutes of blockage, though they have very close R^2 and AIC. The model output with the coefficient estimates for the Gaussian Log-log model for additional travel time is presented in Table 9-6 and the diagnostic plots in Figure 9-1. The final model form is presented in equation 9-1.

Table 9-5. Results for Excess Additional Travel Time per Impacted Vehicle

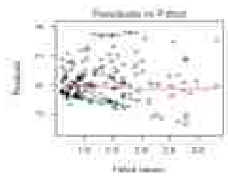
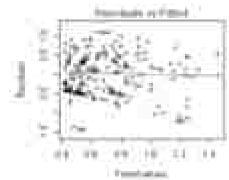
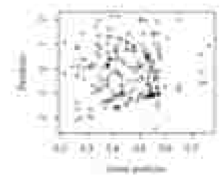
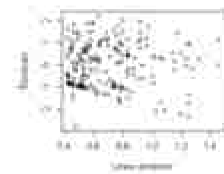
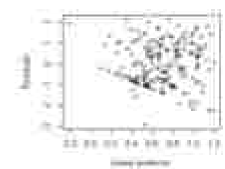
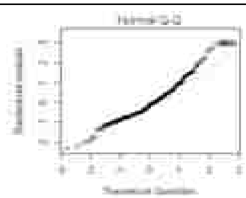
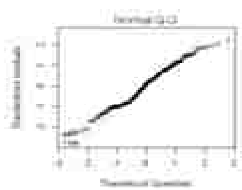
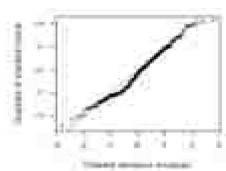
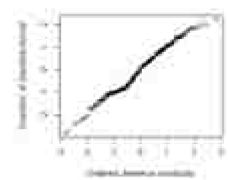
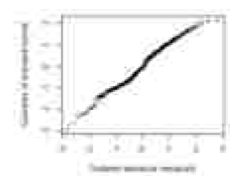
Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)	Gaussian (Log-Log)
			Variable: Additional Travel Time		
Full Model:					
R-sq (%)	26, 22.15	24.07, 20.12	23.87	24.07	23.34
AIC	652.21	298.23	585.48	298.23	298.17
Nested Model:					
R-sq (%)	22.31, 21.93	19.08, 18.68	22.60	19.08	20.96
AIC	644.09	293.16	581.11	293.16	294.37
Model Fit (P-value) Accept Model p >0.05			0.497733	0.4867339	0.486634
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Lane-minutes of Blockage	No. of Lanes Blocked, Incident duration	No. of Lanes Blocked, Incident duration	Lane-minutes of Blockage	Non-incident Density No. of Lanes Blocked, Incident duration

Table 9-6. Best Model: Excess Additional Travel Time per Impacted Vehicle

(Model Form: Gaussian log-log GLM)

<u>Final Nested Model:</u>

```
Call:
glm(formula = lnoneplusTT ~ lnNIDensity + lnClrT + LNSBLK, family =
gaussian(),
    data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.41450  -0.39787  -0.03462   0.37754   1.03566
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.01756    0.36756  -2.768  0.00301 **
lnNIDensity  0.26163    0.10528   2.485  0.00689 *
lnClrT       0.18673    0.04194   4.453 0.71e-05 ***
LNSBLK1      0.30416    0.14373   2.116  0.01779 *
LNSBLK2      0.60272    0.15067   4.000 4.46e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.2412471)
    Null deviance: 60.439  on 202  degrees of freedom
Residual deviance: 47.767  on 198  degrees of freedom

AIC: 294.37

Number of Fisher Scoring iterations: 2
```

<u>AIC:</u>
294.37

<u>R-sq (%):</u>
20.96

The diagnostic plots for the additional travel time model are as follows:

<u>Diagnostic Plots:</u>

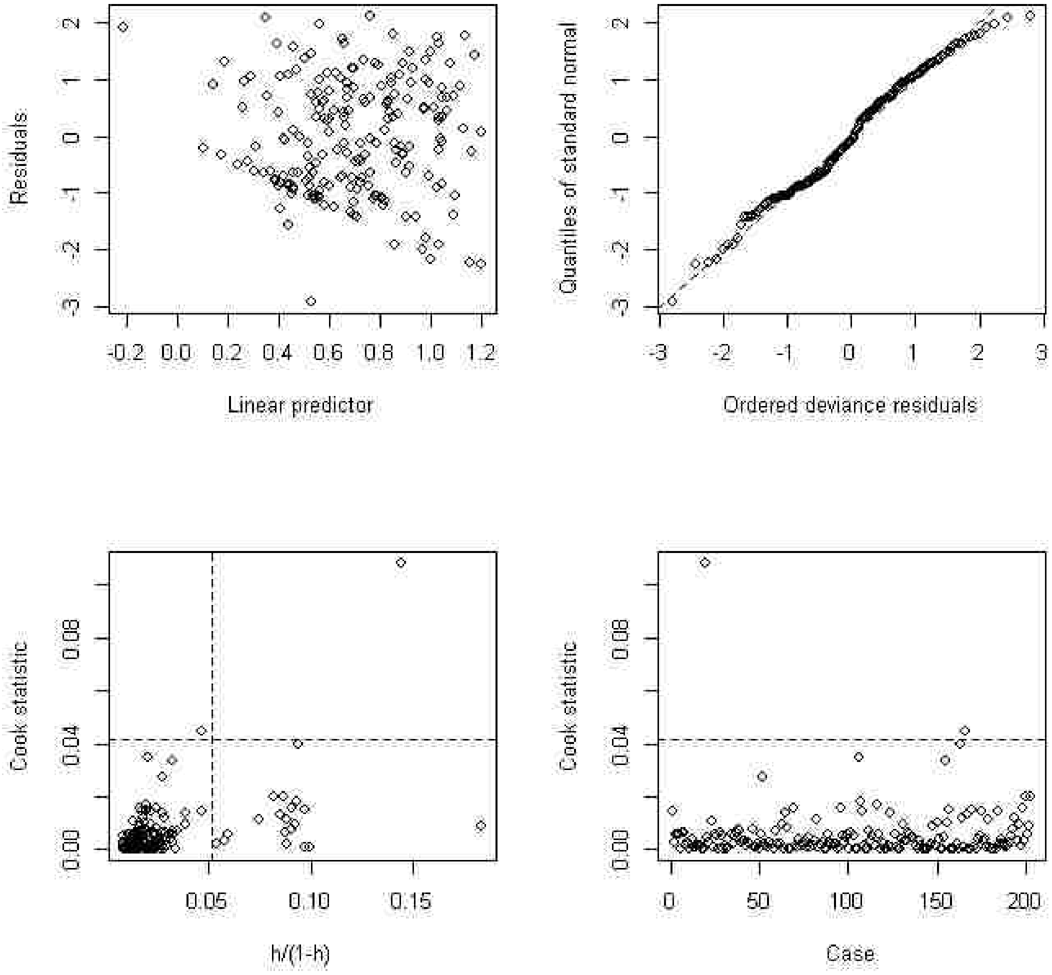


Figure 9-1. Diagnostic Plots: Excess Additional Travel Time per Impacted Vehicle

$$\text{Additional Travel Time} = \text{Exp}\ \{-1.0176 + 0.2616 * \text{Ln (Non-incident Density)} + 0.1867 * \text{Ln (Incident duration)} + 0.3042 * \text{1 lane blocked} + 0.6027 * \text{2 lanes blocked}\} - 1 \qquad (9\text{-}1)$$

Equation 9-1 gives the model form for this model using a constant A = 1 (to make the LHS positive). The coefficient estimates are all positive indicating that additional travel time increases with increase in the incident duration, number of lanes blocked and the non-incident density of traffic. For number of lanes blocked, the coefficient for the dummy variable 2 lanes blocked is higher (approximately by a factor of 2) than for the dummy variable 1 lane blocked, indicating that, additional travel times are higher for an incident with 2 lanes blocked when compared to 1 lane blocked. This conforms to expectation and supports the trend presented in Chapter 7.

9.3.2 Additional Travel Time – Rubbernecking Direction

The model results for the analysis for additional travel time per incident experienced by the impacted vehicles in the rubbernecking direction are shown in Table 9-7. The Gaussian Log-log model is the best as can be seen from Table 9-7, in terms of the R^2 and the significant variables. To be noted is that this model does not have any incident related variables that are significant. Coefficient estimates for the final model are presented in Table 9-8 and the diagnostic plots in Figure 9-2. The final model form is presented in equation 9-2.

$$\text{Rubbernecking Additional Travel Time} = \text{Exp}\{-1.324 + 0.1269 * \text{Ln (Non-incident Density)} - 0.59055 * \text{Ln (Rubbernecking Non-incident Density)} + 0.54118 * \text{Ln (Rubbernecking Non-incident Volume)}\} - 3 \tag{9-2}$$

Table 9-7. Results for Excess Additional Travel Time per Impacted Vehicle in Rubbernecking Direction

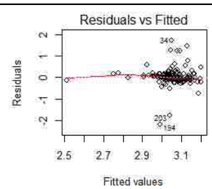
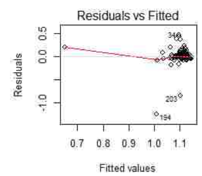
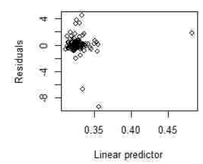
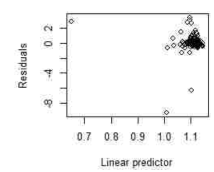
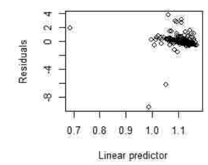
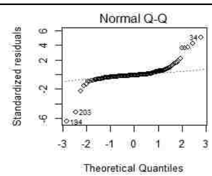
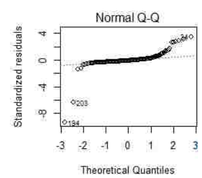
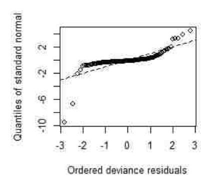
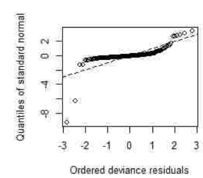
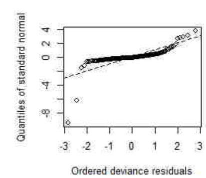
Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)	Gaussian (Log-Log)
			Variable: SB Additional Travel Time		
Full Model:					
R-sq (%)	10.54, 4.89	11.06, 5.44	11.9	11.06	12.75
AIC	155.26	-217.51	198.87	-217.51	-223.41
Nested Model:					
R-sq (%)	4.48, 3.48	7.48, 6.55	8.19	7.48	10.23
AIC	148.66	-229.5	187.19	-229.5	-233.63
Model Fit (P-value) Accept Model p >0.05			0.02482344	0.4867018	0.4866684
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	NIDensity RNIDensity	RNIDensity RNIVolume	NIDensity RNIDensity RNIVolume	RNIDensity RNIVolume	NIDensity RNIDensity RNIVolume

Table 9-8. Best Model: Excess Rubbernecking Additional Travel Time per Impacted Vehicle

(Model Form: Gaussian log-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnthreeplusTT ~ lnNIDensity + lnRNIDensity + lnRNIVolume,
    family = gaussian(), data = x)

Deviance Residuals:
     Min         1Q     Median         3Q        Max
-1.22528  -0.02882  -0.01131   0.02735   0.50029

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.32444    0.66950  -1.978 0.024641 *
lnNIDensity   0.12690    0.05086   2.495 0.006702 *
lnRNIDensity -0.59055    0.12905  -4.576 4.16e-06 ***
lnRNIVolume   0.54118    0.14515   3.728 0.000126 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.01798647)

    Null deviance: 3.9872  on 202  degrees of freedom
Residual deviance: 3.5793  on 199  degrees of freedom
AIC: -233.63

Number of Fisher Scoring iterations: 2
```

AIC:
-233.63

R-sq (%):
10.23

The diagnostic plots for the additional travel time model are as follows:

Diagnostic Plots:

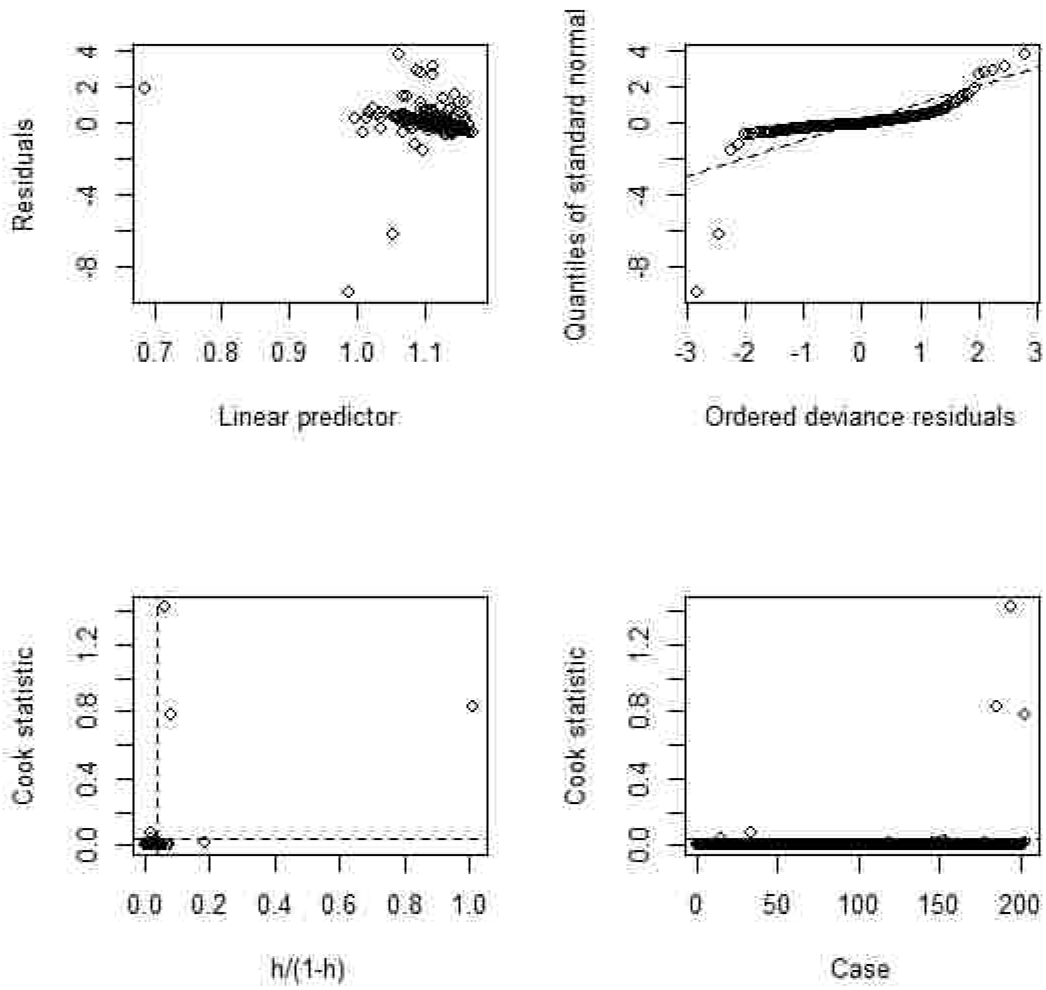


Figure 9-2. Diagnostic Plots: Excess Rubbernecking Additional Travel Time per Impacted Vehicle

Equation 9-2 gives the model form for this model using a constant A = 3 (to make the LHS positive). The coefficient estimate for rubbernecking density is negative indicating that higher densities in the opposing direction of flow experience lower impacts of additional travel time. Although this is contrary to expectation, it is possible that drivers cannot observe the incident in the opposing direction due to higher densities in their own direction of travel.

9.3.3 Excess Vehicle Hours

The model results for the analysis for total excess vehicle hours for all the impacted vehicles are shown in Table 9-9. This is followed by the coefficient estimates for the best model in Table 9-10 and diagnostics plots in Figure 9-3.

From Table 9-9, Gaussian Log-Log model clearly has a better fit when compared to the other model in terms of the residual and normality plots. The R^2 and AIC measures are lesser than the Single-log GLM. Owing to the better fit it provides in comparison to the other functional forms, the Gaussian Log-Log model is recommended for the excess VHT for impacted vehicles.

The coefficient estimates of the model form in Equation 9-3 show that variable vehicle-hours of travel for the impacted vehicles increases with increase in incident duration, lanes blocked and non-incident traffic density. Incidents with 2 lanes blocked have a higher impact than 1 lane blocked, but not by a factor of 2 (As in the case of additional travel time). This is explored further in the marginal impacts presented in Chapter 11.

$$\text{Excess VHT} = \text{Exp}\{1.41944 + 0.66726 * \text{Ln (Non-incident Density)} + 0.35164 * \text{Ln (Incident duration)} + 0.750316 * \text{1 lane blocked} + 1.05008 * \text{2 lanes blocked}\} - 50 \quad (9\text{-}3)$$

Table 9-9. Results for Excess Vehicle Hours of Travel for Impacted Vehicles

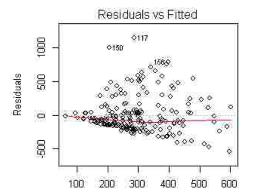
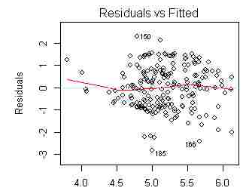
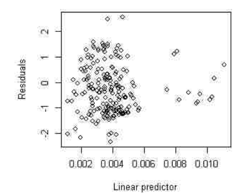
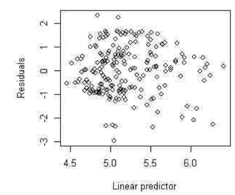
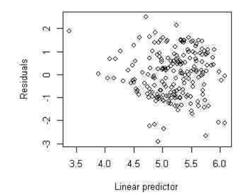
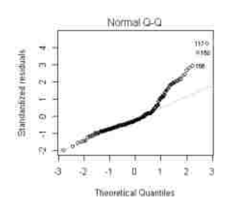
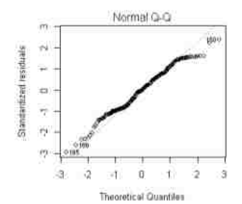
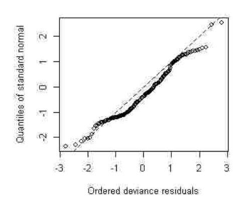
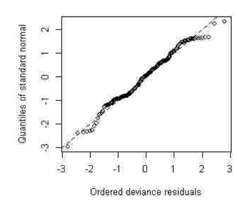
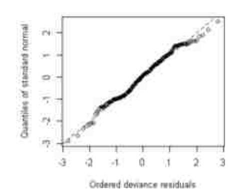
Category	**Linear**	**Transformed (Single Log)**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
		Variable: Excess Vehicle Hours			
Full Model:					
R-sq (%)	21.39, 16.42	27.29, 22.7	13.58	27.29	28.71
AIC	2857.37	555.85	2679.7	555.85	549.85
Nested Model:					
R-sq (%)	13.32, 12.46	15.88, 14.18	8.94	14.54	17.79
AIC	2857.2	569.44	2688.4	568.65	564.79
Model Fit (P-value) Accept Model p >0.05			0.5988775	0.4867013	0.4866341
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density No. of Lanes Blocked, Incident duration	Non-incident Density No. of Lanes Blocked, Incident duration	Non-incident Density, Lane-minutes of Blockage	Non-incident Density No. of Lanes Blocked, Incident duration

Table 9-10. Best Model: Excess Vehicle Hours of Travel for Impacted Vehicles

(Model Form: Gaussian log-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnExVHrsPlus50 ~ lnNIDensity + lnClrT + LNSBLK,
    family = gaussian(), data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.74623  -0.75976   0.05533   0.67780   2.37534

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.41944    0.71547   1.984 0.024322 *
lnNIDensity  0.66726    0.20494   3.256 0.000665 **
lnClrT       0.35164    0.08163   4.308  1.3e-05 ***
LNSBLK1      0.70316    0.27978   2.513 0.006380 *
LNSBLK2      1.05008    0.29328   3.580 0.000216 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.9140856)

    Null deviance: 220.15  on 202  degrees of freedom
Residual deviance: 180.99  on 198  degrees of freedom
AIC: 564.79
Number of Fisher Scoring iterations: 2
```

AIC:

564.79

R-sq (%):

17.79

Diagnostic Plots:

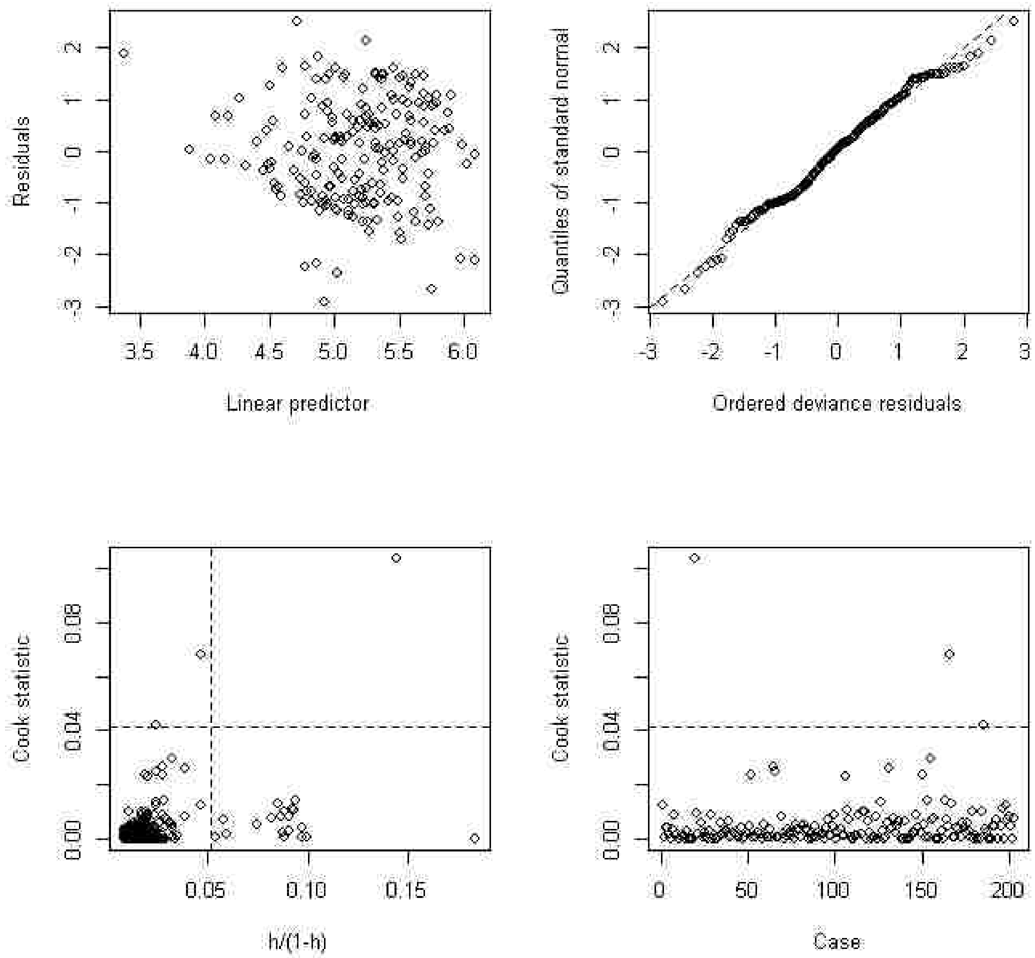
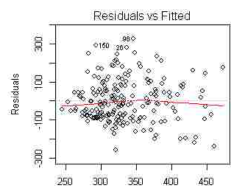
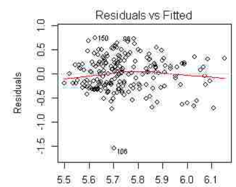
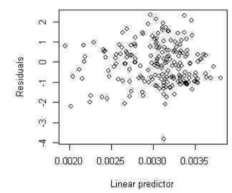
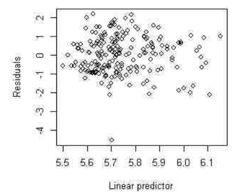
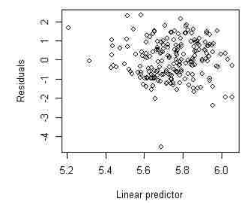
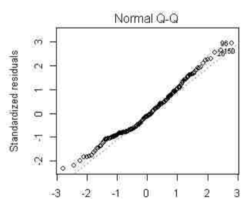
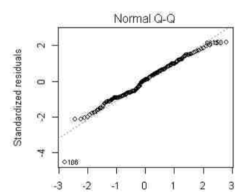
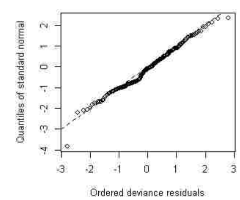
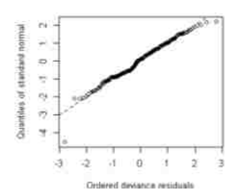
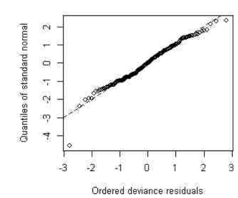


Figure 9-3. Diagnostic Plots: Excess Vehicle Hours of Travel for Impacted Vehicles

9.3.4 Excess Vehicle Hours per Hour of Incident Impact

The model results for excess vehicle hours for all impacted vehicles per hour of incident impact are shown in Table 9-11. The coefficient estimates and the diagnostic plots for the calibrated model are in Table 9-12 and Figure 9-4.

Table 9-11. Results for Excess Vehicle Hours per Hour of Incident Impact

Category	Linear	Transformed (Single Log)	Gamma	Gaussian (Log)	Gaussian (Log-Log)
		Variable: Excess Vehicle Hours Per Hour			
Full Model:					
R-sq (%)	21.65, 16.7	21.23, 16.25	21.09	21.22	21.02
AIC	2495.8	144.81	2473.4	144.81	143.32
Nested Model:					
R-sq (%)	14.65, 13.8	13.31, 12.44	13.17	13.31	15.48
AIC	2493.2	144.25	2474.1	144.25	143.1
Model Fit (P-value) Accept Model p >0.05			0.4292034	0.486701	0.4866337
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density No. of Lanes Blocked, Incident duration

The model selected for the excess VHT per hour of incident impact is the Gaussian Log-log model. In addition to having a high R^2 and low AIC, the model has a good fit and has practically important predictor variables: incident duration and lanes blocked. In Table 9-10, though the dummy variable 1 lane blocked, is significant only at $\alpha = 0.1$, this model is selected owing all the important variables being present and the fit being good.

Table 9-12. Best Model: Excess Vehicle Hours per Hour of Incident Impact

(Model Form: Gaussian log-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnExVHrsPerHrPlus200 ~ lnNIDensity + lnClrT + LNSBLK,
    family = gaussian(), data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.52191  -0.25469  -0.00106   0.24088   0.78586

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.53825    0.25323  17.921  < 1e-16 ***
lnNIDensity  0.23120    0.07253   3.188 0.000834 **
lnClrT       0.11012    0.02889   3.811 0.000092 ***
LNSBLK1      0.16837    0.09903   1.700 0.045326 .
LNSBLK2      0.30868    0.10380   2.974 0.001654 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.1145087)

    Null deviance: 26.824  on 202  degrees of freedom
Residual deviance: 22.673  on 198  degrees of freedom
AIC: 143.1

Number of Fisher Scoring iterations: 2
```

AIC:
143.1

R-sq (%):
15.48

Diagnostic Plots:

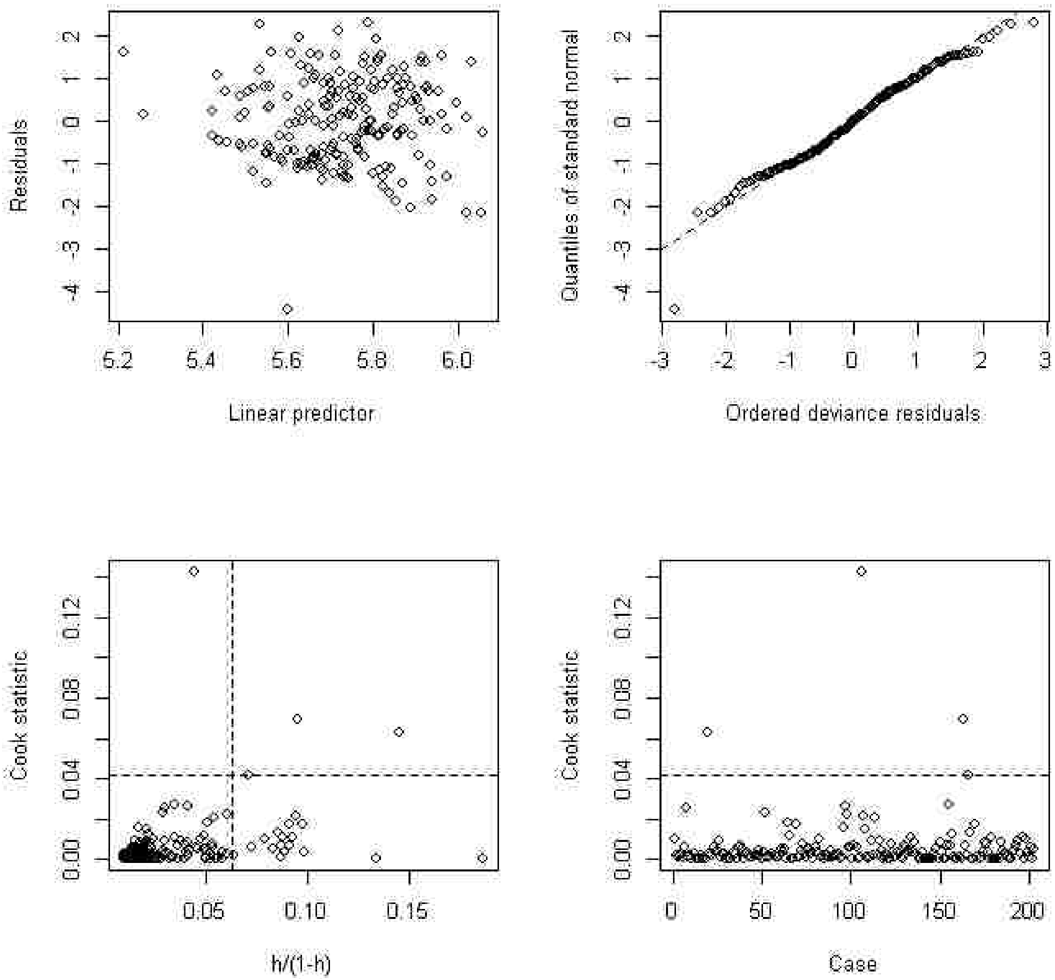


Figure 9-4. Diagnostic Plots: Excess Vehicle Hours per Hour of Incident Impact

Excess VHT per Hour of Incident Impact = Exp {4.53825 +

0.2312 * Ln (Non-incident Density) + 0.11012 * Ln (Incident duration) +

0.16837 * 1 lane blocked + 0.30868 * 2 lanes blocked} – 50 (9-4)

The coefficient estimates in Equation 9-4, indicate that the variable excess vehicle-hours of travel per hour of incident impact, increases with increase in incident duration, lanes blocked and non-incident traffic density.

9.3.5 Temporal Extent

The model results for the analysis for average temporal extent of incidents are shown in Table 9-13. From these results, the final model recommended for the temporal extent of an incident is the Gaussian Single-log model owing to it's higher R^2 and lower AIC than the log-log GLM. Also, the fit for the Single-log model is good in the diagnostic plots. The coefficient estimates for this model are summarized in Table 9-14 and diagnostic plots in Figure 9-5. Equation 9-5 presents the form of the final model.

The coefficient estimates are all positive, except non-incident volume, indicating that the temporal extent of incident impact increases with increase in incident duration, lanes blocked and non-incident traffic density. The coefficient for non-incident volume is negative but also very low. This means that for higher volumes, the impacts are lower which is contrary to expectation.

$$\text{Temporal Extent} = \text{Exp}\{3.244 + 0.02074 * \text{Non-incident Density} + 0.00843 * \text{Incident duration} + 0.53700 * \text{1 lane blocked} + 0.71050 * \text{2 lanes blocked}\} \quad (9\text{-}5)$$

Table 9-13. Results for Temporal Extent

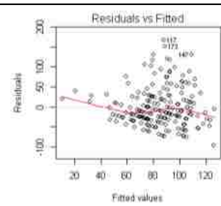
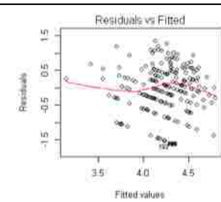
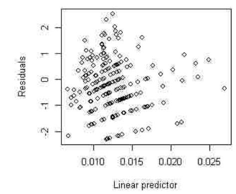
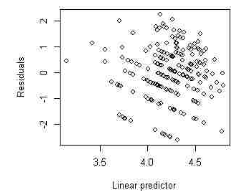
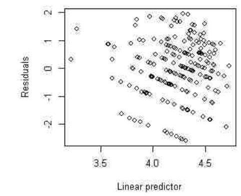
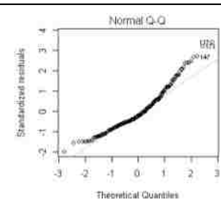
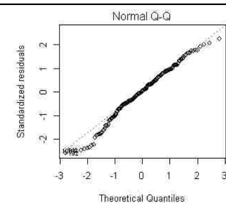
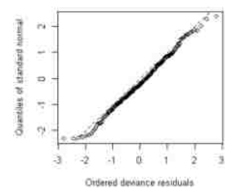
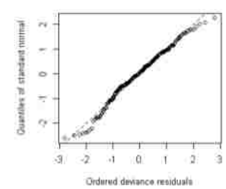
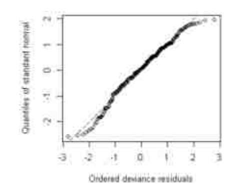
Category	Linear	Transformed (Single log)	Gamma	Gaussian (Log)	Gaussian (Log-Log)
			Variable: Impact Time		
Full Model:					
R-sq (%)	18.13, 12.96	21.71, 16.76	17.98	21.7	19.87
AIC	2168.4	392.68	2108.7	392.68	395.39
Nested Model:					
R-sq (%)	13.54, 11.34	16.98, 14.88	10.86	16.98	15.65
AIC	2165.48	390.57	2108.8	390.57	393.81
Model Fit (P-value) Accept Model p >0.05			0.3454944	0.4866008	0.4866004
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Non-incident Volume, No. of Lanes Blocked, Incident duration	Non-incident Density, Non-incident Volume, No. of Lanes Blocked, Incident duration	Non-incident Density, Non-incident Volume, No. of Lanes Blocked, Incident duration	Non-incident Density, No. of Lanes Blocked, Incident duration	Non-incident Density, No. of Lanes Blocked, Incident duration

Table 9-14. Best Model: Temporal Extent

(Model Form: Gaussian Single-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnImpTime ~ NIDensity + NIVol + ClrT + LNSBLK,
    family = gaussian(), data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.60338  -0.31559   0.03039   0.43403   1.35017

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.244e+00  2.570e-01  12.620  < 1e-16 ***
NIDensity    2.074e-02  8.323e-03   2.492 0.006768 *
NIVol       -1.283e-04  4.022e-05  -3.190 >0.05
ClrT         8.425e-03  2.370e-03   3.555 0.000237 ***
LNSBLK1      5.370e-01  1.823e-01   2.946 0.001802 **
LNSBLK2      7.105e-01  1.901e-01   3.737 0.000122 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.3856351)

    Null deviance: 91.512  on 202  degrees of freedom
Residual deviance: 75.970  on 197  degrees of freedom
AIC: 390.57

Number of Fisher Scoring iterations: 2
```

AIC:
390.57

R-sq (%):
16.98

Diagnostic Plots:

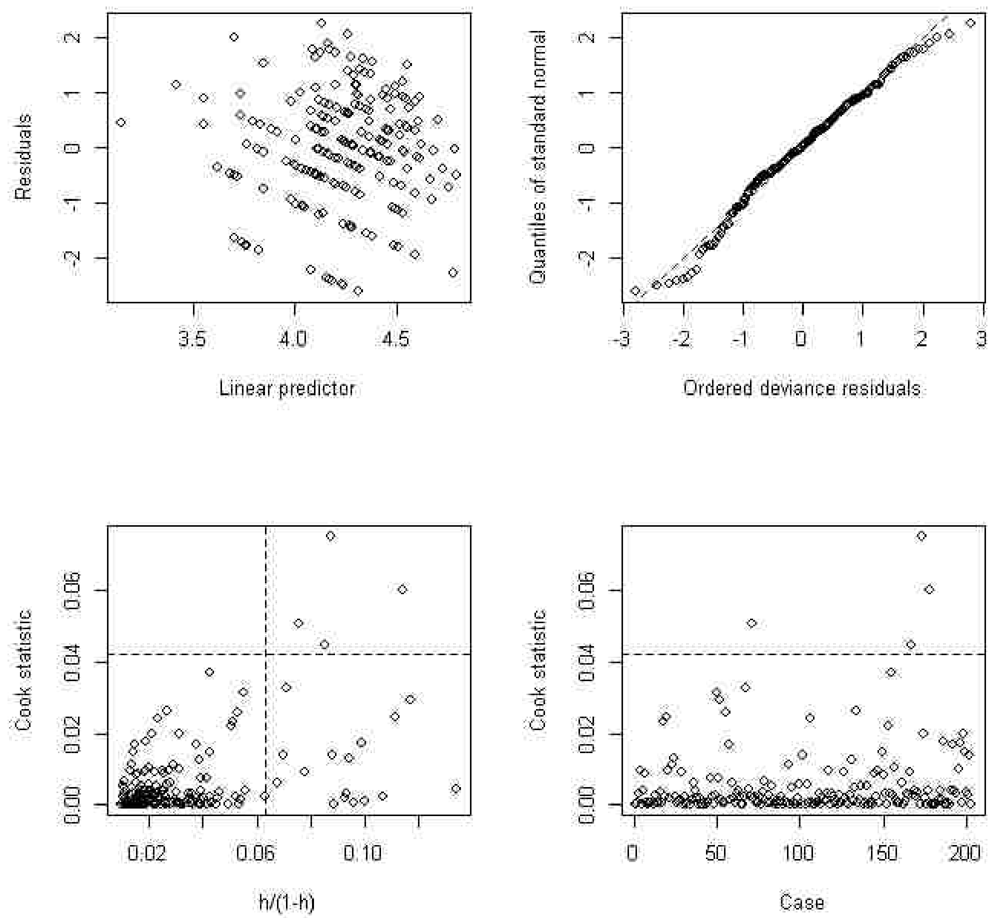


Figure 9-5. Diagnostic Plots: Temporal Extent

9.3.6 Spatial Extent

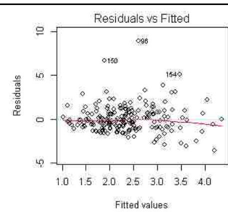
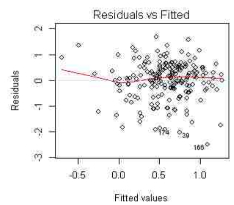
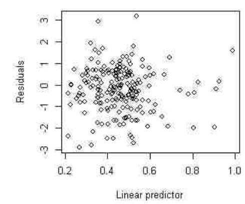
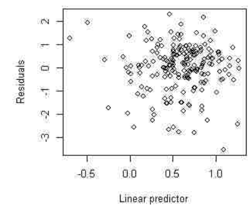
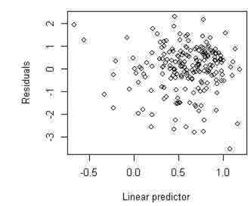
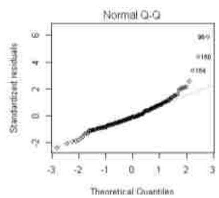
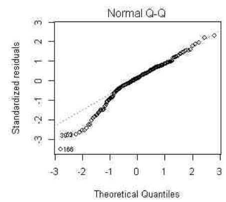
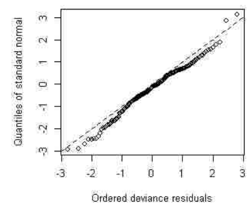
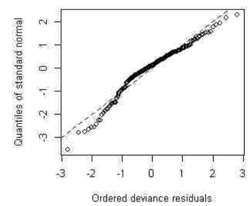
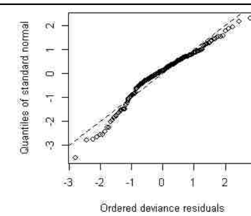
The summary of model results is shown in Table 9-15. The model chosen for the spatial extent of a incident is the Gaussian Single-log model since it has the best fit from the diagnostic plots. Also, it has a higer R^2 and lower AIC than the log-log model. The significant variables are also as expected.

Spatial Extent = Exp {-0.8622 + 0.035 * (Non-incident Density) +

0.0102 * (Incident duration) + 0.7286 * 1 lane blocked + 0.8024 * 2 lanes blocked}

(9-6)

Table 9-15. Results for Spatial Extent

Category	Linear	Transformed (Single Log)	Gamma	Gaussian (Log)	Gaussian (Log-Log)
			Variable: Impact Space		
Full Model:					
R-sq (%)	21.6, 16.64	21.39, 16.42	19.19	21.39	18.76
AIC	756.86	460.11	680.84	460.11	464.79
Nested Model:					
R-sq (%)	16.39, 15.13	16.85, 14.74	13.05	16.85	15.62
AIC	751.91	457.51	681.72	453.23	460.49
Model Fit (P-value) Accept Model p >0.05			0.1743228	0.4866004	0.4866003
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Non-incident Volume, Lane-minutes of Blockage	Non-incident Density, Non-incident Volume, No. of Lanes Blocked, Incident duration	Non-incident Density, No. of Lanes Blocked, Incident duration	Non-incident Density, Non-incident Volume, No. of Lanes Blocked, Incident duration	Non-incident Density, No. of Lanes Blocked, Incident duration

The results of the recommended model are shown in Table 9-16, Figure 9-6 and equation 9-6. Since all the response variables are positive, there was no need for the use of a constant. The coefficient estimates are once again, all positive, except non-incident volume. Therefore, the spatial extent of incident impact increases with increase in incident duration, lanes blocked and non-incident traffic density.

Table 9-16. Best Model: Spatial Extent

(Model Form: Gaussian Single-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnImpSpace ~ NIDensity + NIVol + ClrT + LNSBLK,
    family = gaussian(), data = x)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4820  -0.3022   0.0864   0.4879   1.6842

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -8.622e-01  3.031e-01  -2.844 0.002456 **
NIDensity    3.501e-02  9.815e-03   3.567 0.000227 ***
NIVol       -1.247e-04  4.743e-05  -2.630 >0.5
ClrT         1.018e-02  2.795e-03   3.643 0.000173 ***
LNSBLK1      7.286e-01  2.149e-01   3.390 0.000424 ***
LNSBLK2      8.024e-01  2.242e-01   3.579 0.000217 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.536283)

    Null deviance: 127.05  on 202  degrees of freedom
Residual deviance: 105.65  on 197  degrees of freedom
AIC: 457.51
Number of Fisher Scoring iterations: 2
```

AIC:

453.23

R-sq (%):

16.85

Diagnostic Plots:

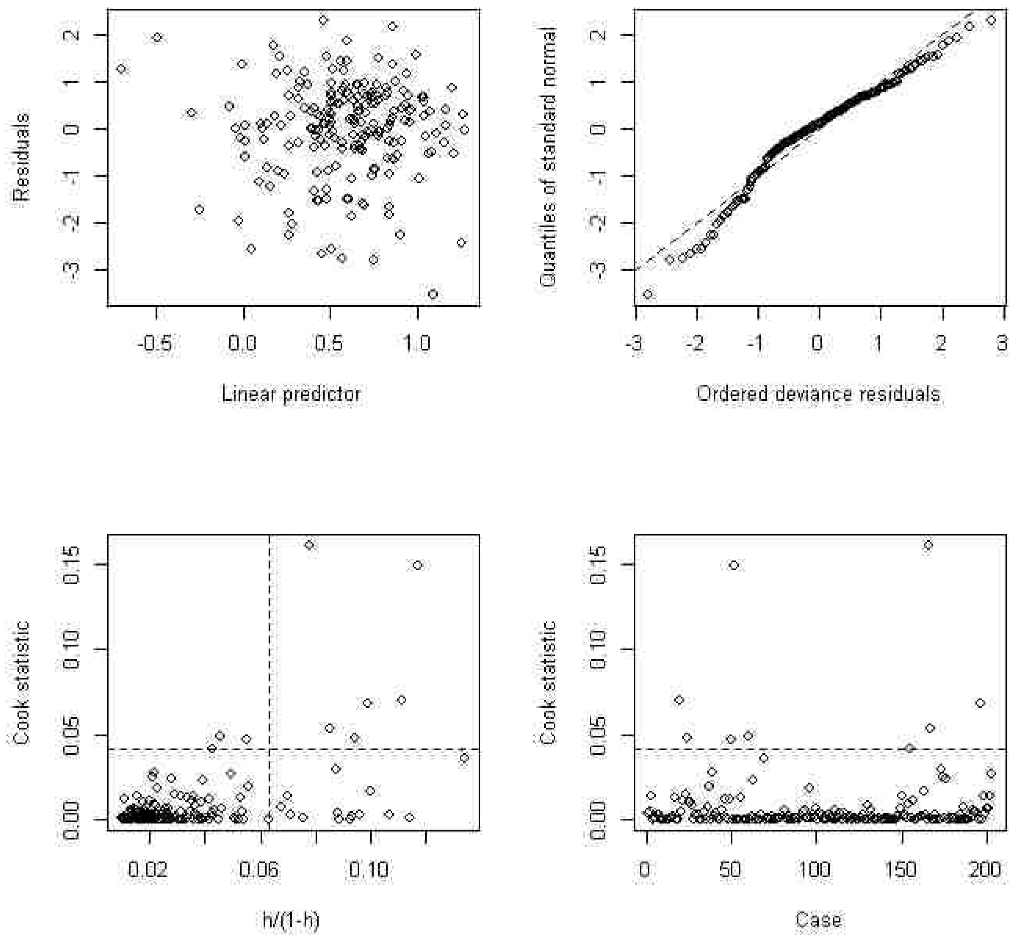


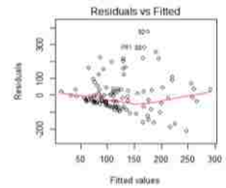
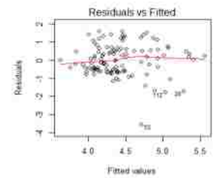
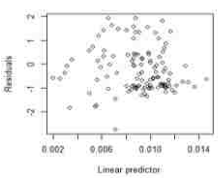
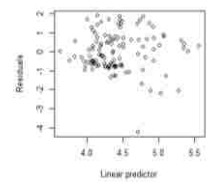
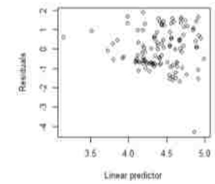
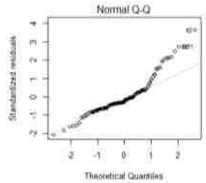
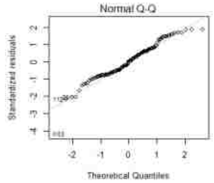
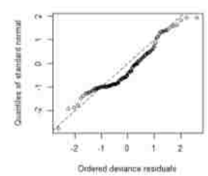
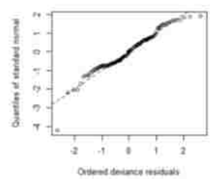
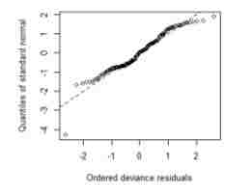
Figure 9-6. Diagnostic Plots: Spatial Extent

9.3.7 Excess Fuel Consumption

Table 9-17 presents the comparison of the results for all the models for excess fuel consumption in gallons. For fuel, a constant A=35 is used to make LHS positive.

Excess Fuel Consumption = Exp {3.36649 + 0.010554 * Lane-Minutes of Blockage + 0.036113 * Non-incident Density} – 35 (9-7)

Table 9-17. Results for Excess Fuel Consumption

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
			Variable: Fuel		
Full Model:					
R-sq (%)	30.2, 22.75	28.44, 20.8	23.54	26.77	27.52
AIC	1406.05	294.25	1315.2	292.91	293.72
Nested Model:					
R-sq (%)	21.71 , 20.31	16.96 , 15.48	15.33	28.44	11.77
AIC	1401.257	293.3693	1317.7	294.25	300.34
Model Fit (P-value) Accept Model p >0.05			0.7121132	0.482228	0.4822278
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Incident duration

The Gaussian Single-log model represents the excess fuel consumption (in gallons) the best as can be seen from the R^2 and AIC measures. The model fit is also the best when compared to the rest of the models. The coefficient estimates for the best model are shown in Table 9-18, the diagnostic plots in Figure 9-7 and the model form in equation 9-7. The significant variables in the model are lane-minutes of blockage and non-incident traffic density.

Table 9-18. Best Model: Excess Fuel Consumption (gallons)

(Model Form: Gaussian Single-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnFuelPlus35 ~ BlkLnMin + NIDensity, family = gaussian(),
    data = fe)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.5452  -0.5659  -0.0015   0.5343   1.5915

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.366490   0.311134  10.820  < 1e-16 ***
BlkLnMin    0.010554   0.002301   4.586 0.59e-05 ***
NIDensity   0.036113   0.014858   2.430   0.0084 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.7189439)

    Null deviance: 96.967  on 114  degrees of freedom
Residual deviance: 80.522  on 112  degrees of freedom
AIC: 293.37

Number of Fisher Scoring iterations: 2
```

AIC:
293.37

R-sq (%):
16.96

Diagnostic Plots:

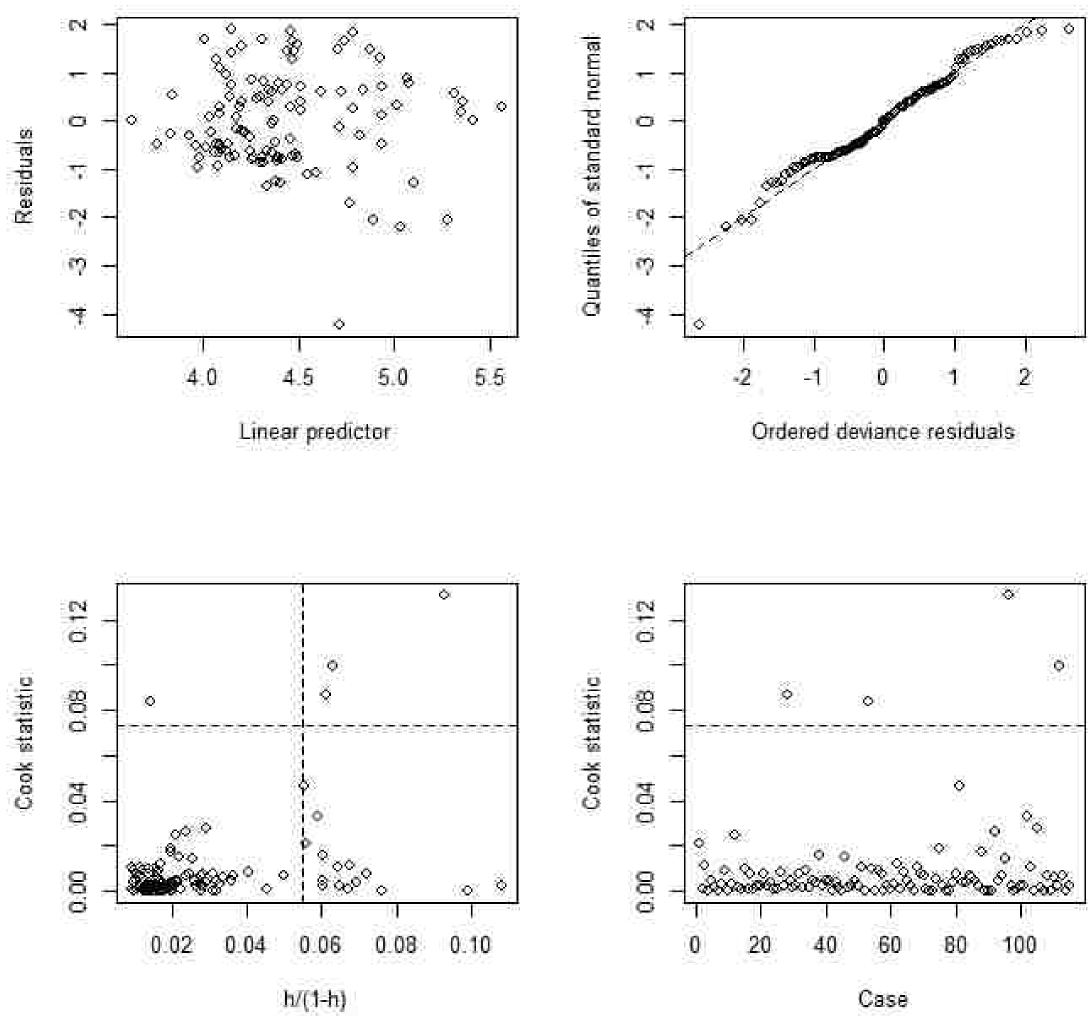


Figure 9-7. Diagnostic Plots: Excess Fuel Consumption (gallons)

Lane-minutes of blockage is the product of incident duration and number of lanes blocked (for shoulder incidents, lane-minutes of blockage is zero). The model indicates a positive relationship, with the increase in lane-minutes of blockage and non-incident density leading to increased excess fuel consumption.

9.3.8 Excess CO_2 Emissions

Table 9-19 gives a summary of the results for excess carbon dioxide (CO_2) in metric tons for the different modeling forms. All of the models do not have a very good fit for excess CO_2 emissions (metric tons). Out of them, the Gaussian Single-Log GLM model provides the better fit where the outliers in the normality plots are a little closer to the normality line than the Gaussian log-log or Gamma. R^2 is higher and AIC is lower for the Gaussian single-log when compared to the log-log.

The coefficient estimates for the recommended model and diagnostics plots are summarized in Table 9-20 and Figure 9-8, respectively. Equation 9-8 gives the form of the final model. The significant variables in the model are lane-minutes of blockage and non-incident traffic density. The model indicates a positive relationship, with the increase in lane-minutes of blockage and non-incident density leading to increased excess CO_2 emissions due to incidents.

$$\text{Excess } CO_2 \text{ Emissions} = \text{Exp}\,\{3.38 + 0.00146 * \text{Non-incident Density} + 0.00050 * \text{Lane-Minutes of Blockage}\} - 30 \qquad (9\text{-}8)$$

Table 9-19. Results for total Excess CO_2 Emissions

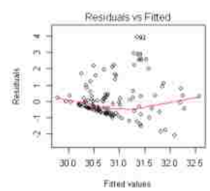
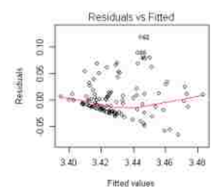
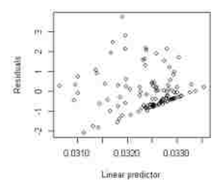
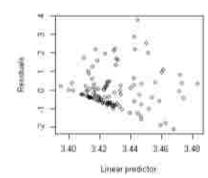
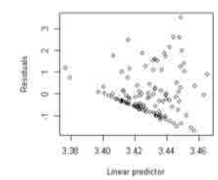
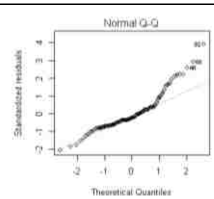
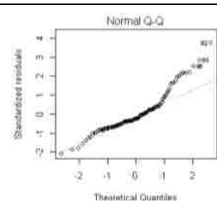
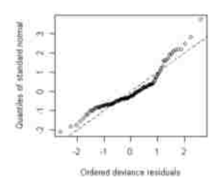
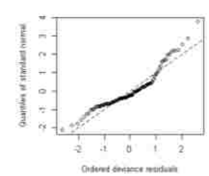
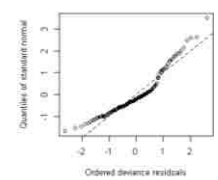
Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
Variable: CO_2 Scaled to Tons					
Full Model:					
R-sq (%)	30.26, 22.81	30.59, 23.18	30.47	30.59	27.9
AIC	341.92	-453.40	336.3	-453.4	-451.03
Nested Model:					
R-sq (%)	23.61, 22.24	23.81, 22.44	23.56	23.8	17.09
AIC	334.39	-460.68	329.41	-460.68	-451.81
Model Fit (P-value) Accept Model p >0.05			0.5555897	0.4822266	0.4821482
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Incident duration, Lane block ratio

Table 9-20. Best Model: Excess CO_2 Emissions (Tons)

(Model Form: Gaussian Single-Log GLM)

Final Nested Model:

```
Call:
glm(formula = lnCO2TonsPlus30 ~ NIDensity + BlkLnMin, family =
gaussian(),
    data = fe)

Deviance Residuals:
      Min          1Q      Median          3Q         Max
-0.065443  -0.019731  -0.007994   0.010539   0.119018

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.383e+00  1.173e-02 288.550  < 1e-16 ***
NIDensity   1.455e-03  5.600e-04   2.598   0.0053 *
BlkLnMin    5.018e-04  8.673e-05   5.786 3.35e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.001021062)

    Null deviance: 0.15009  on 114  degrees of freedom
Residual deviance: 0.11436  on 112  degrees of freedom
AIC: -460.68

Number of Fisher Scoring iterations: 2
```

AIC:
-460.68

R-sq (%):
23.80

Diagnostic Plots:

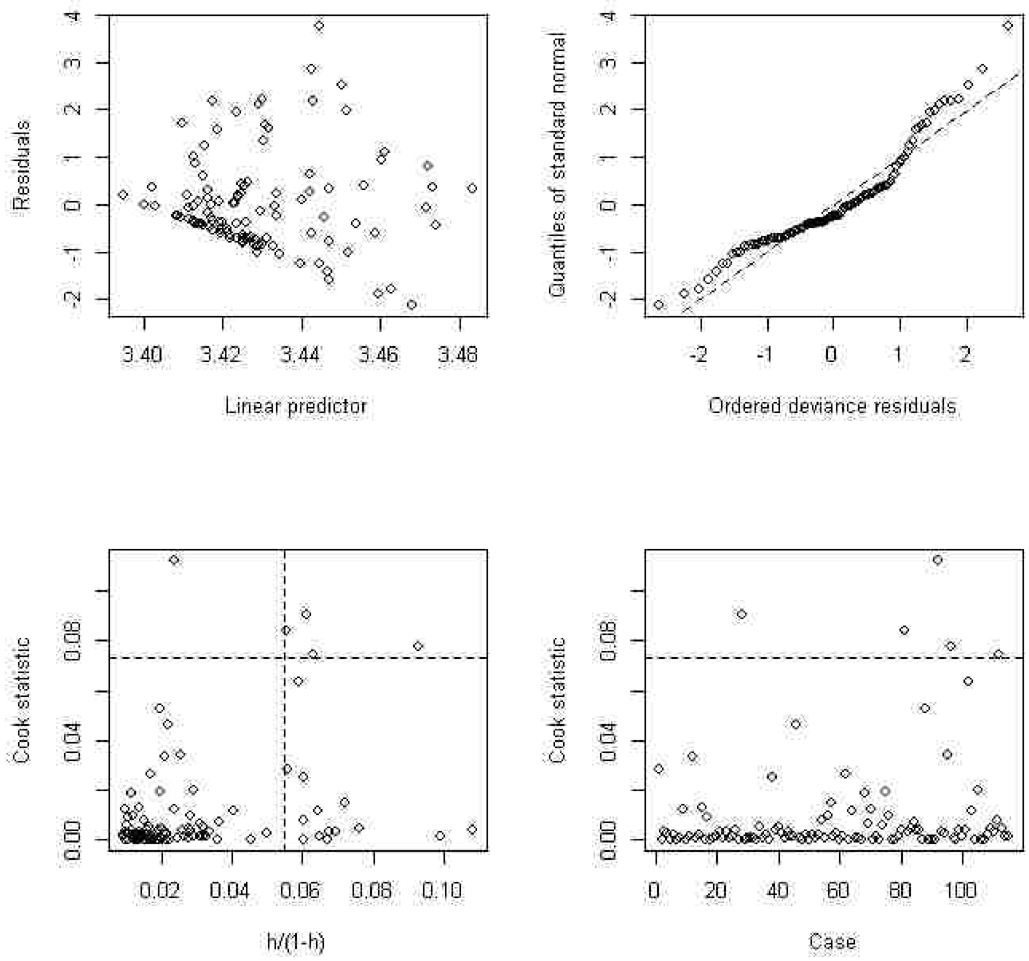


Figure 9-8. Diagnostic Plots: Excess CO_2 Emissions (Tons)

9.3.9 Excess CO Emissions

Table 9-21 gives a summary of the results for excess carbon monoxide (CO) emissions for the different regression models. The Gaussian Single-Log model clearly has the better fit, R^2 and AIC. The original data was scaled to kilograms. The results for the recommended model are presented in Table 9-22, Figure 9-9 and equation 9-9.

Excess CO Emissions = Exp {0.511946 + 0.039209 * Non-incident Density +

0.009008 * Lane-Minutes of Blockage} – 3 (9-9)

Table 9-21. Results for total Excess CO Emissions (Kg)

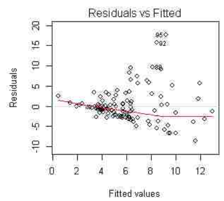
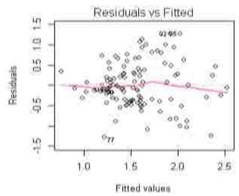
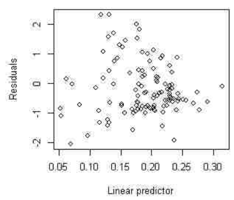
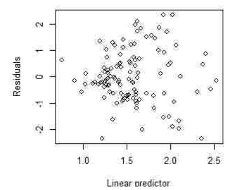
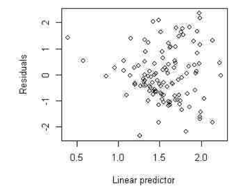
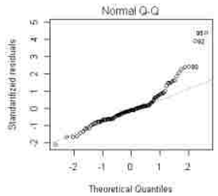
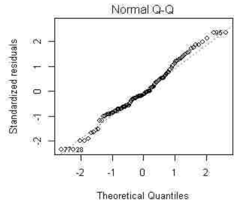
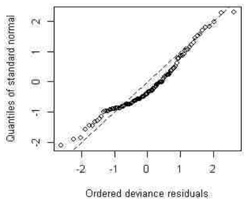
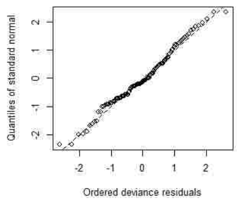
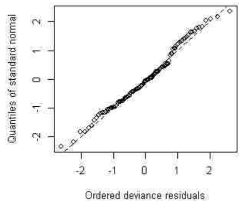
Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
		Variable: CO Scaled to 1K			
Full Model:					
R-sq (%)	32.63, 25.44	36.86, 30.12	30.47	36.86	34.89
AIC	662.52	194.75	561.66	194.75	196.3
Nested Model:					
R-sq (%)	26.19, 24.87	28.52 , 27.24	17.39	28.52	23.57
AIC	655.02	191.03	568.18	191.03	200.72
Model Fit (P-value) Accept Model p >0.05			0.9105878	0.4822277	0.4821479
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Incident duration, Lane block ratio

Table 9-22. Best Model: Excess CO Emissions (Kgs)

(Model Form: Gaussian Single-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnCOKgPlus3 ~ NIDensity + BlkLnMin, family = gaussian(),
    data = fe)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.26781  -0.36017  -0.07009   0.32182   1.26871

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.511946   0.199389   2.568   0.0058 *
NIDensity   0.039209   0.009522   4.118 3.68e-05 ***
BlkLnMin    0.009008   0.001475   6.108 0.75e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.2952593)

    Null deviance: 46.262  on 114  degrees of freedom
Residual deviance: 33.069  on 112  degrees of freedom
AIC: 191.03
Number of Fisher Scoring iterations: 2
```

AIC:
191.03

R-sq (%):
28.52

The model uses a constant of A = 3 added to make LHS positive. The significant variables in the model are lane-minutes of blockage and non-incident traffic density. The model indicates a positive relationship, with the increase in lane-minutes of blockage and non-incident density leading to increased excess CO emissions.

Diagnostic Plots:

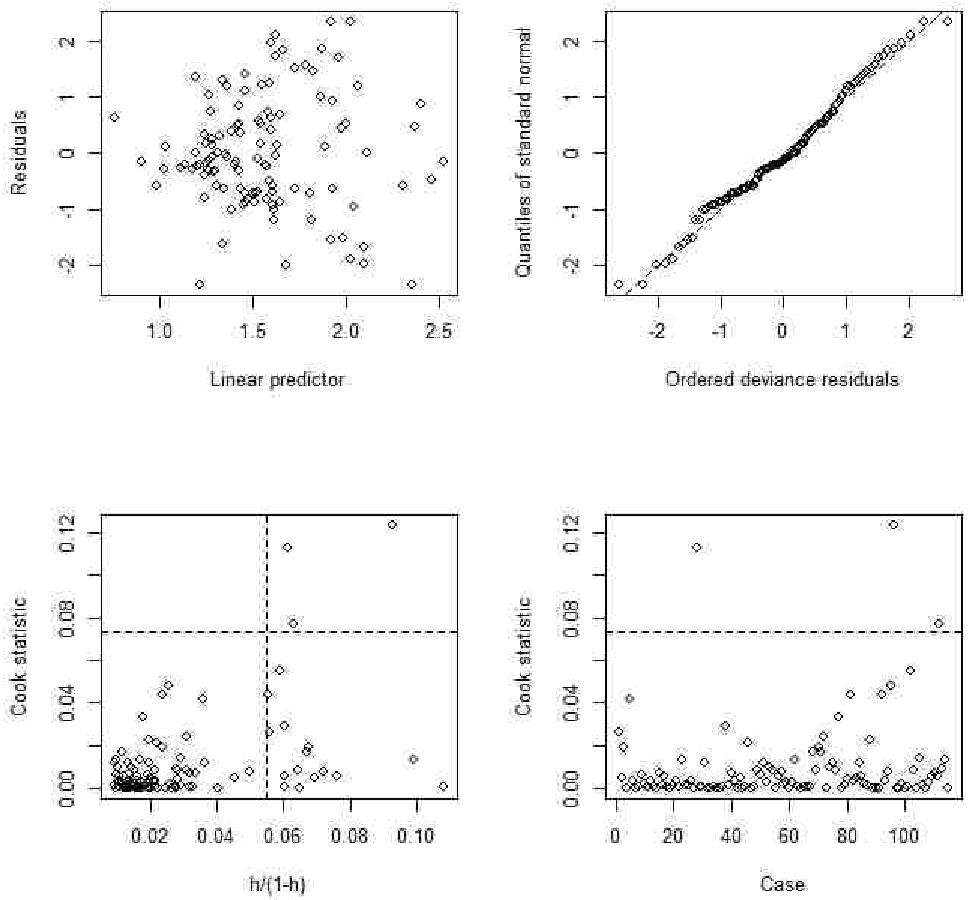


Figure 9-9. Diagnostic Plots: Excess CO Emissions (Kgs)

9.3.10 Excess NO_x Emissions

Table 9-23 gives a summary of results for excess NO_x emissions for the different regression models. Based on the summary of results from Table 9-23, the Gaussian Single-log and log-log model have the best fit among all models. Of this, the Gaussian Single-log has the lower AIC and higher R^2 and is therefore, recommended. The final model results are shown in Table 9-24, Figure 9-10 and equation 9-10.

Excess NO_x Emissions = Exp {5.03591 + 0.038019 * Non-incident Density +

0.012057 * Lane-Minutes of Blockage} – 250 (9-10)

Table 9-23. Results for total Excess NO_x Emissions (grams)

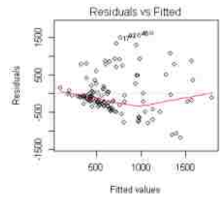
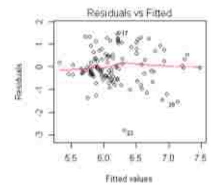
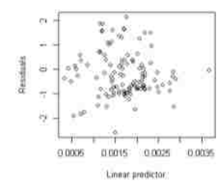
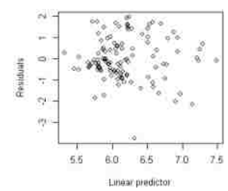
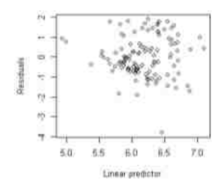
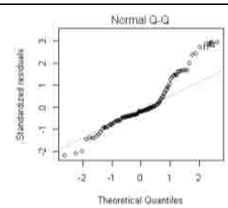
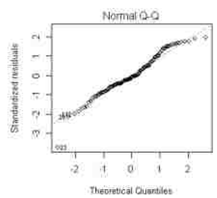
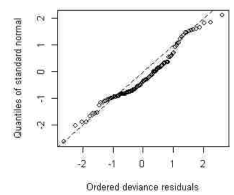
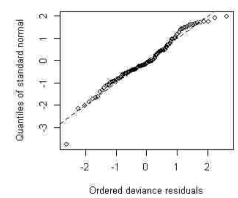
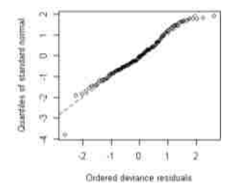
Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)	Gaussian (Log-Log)
			Variable: NO_x		
Full Model:					
R-sq (%)	39.02, 31.51	35.23,28.21	38.88	35.22	34.15
AIC	1783.92	266.28	1691.7	266.28	266.17
Nested Model:					
R-sq (%)	28.83, 27.56	25 , 23.66	29.06	25	19.50
AIC	1783.695	265.14	1693.9	265.14	275.27
Model Fit (P-value) Accept Model p >0.05			0.771368	0.508903	0.5089433
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Incident duration, Lane block ratio

Table 9-24. Best Model: Excess NO_x Emissions (grams)

(Model Form: Gaussian Single-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnNOxPlus250 ~ NIDensity + BlkLnMin, family = gaussian(),
    data = fe)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.7968  -0.4239  -0.0944   0.4826   1.4785

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 5.035910   0.275194  18.299  < 1e-16 ***
NIDensity   0.038019   0.013142   2.893  0.00230 **
BlkLnMin    0.012057   0.002036   5.923 1.77e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.5624454)

    Null deviance: 83.992  on 114  degrees of freedom
Residual deviance: 62.994  on 112  degrees of freedom
AIC: 265.14

Number of Fisher Scoring iterations: 2
```

AIC:

265.14

R-sq (%):

25

The constant, used to make all the response variables positive, is A = 250. The significant variables in the model are lane-minutes of blockage and non-incident traffic density, similar to the previous two models. An increase in either of the two variables produces an increase in excess NO_x emissions due to incidents.

Diagnostic Plots:

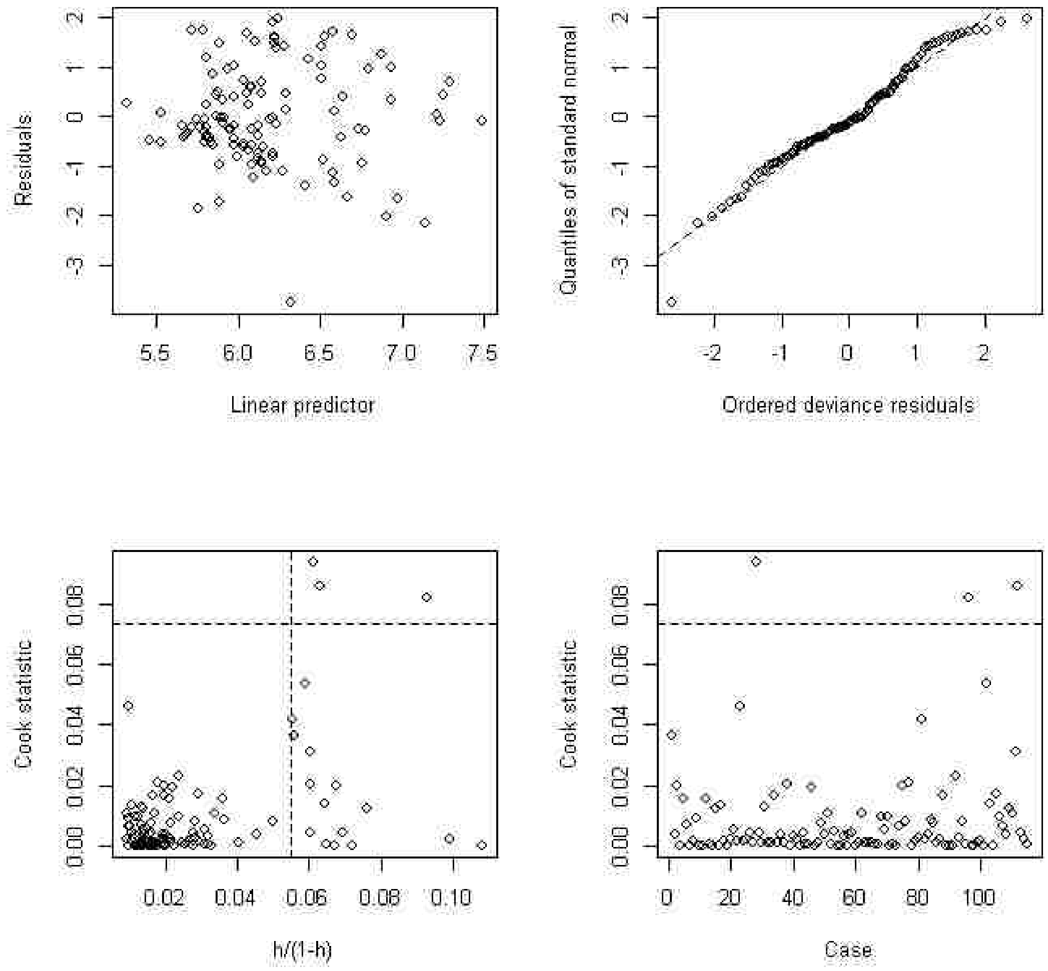


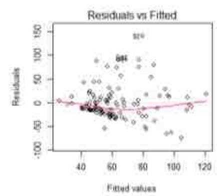
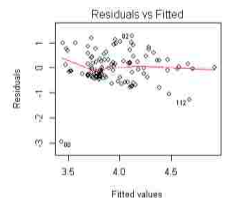
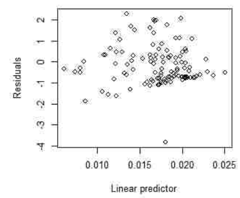
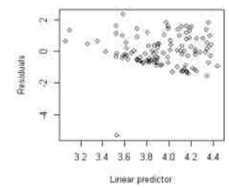
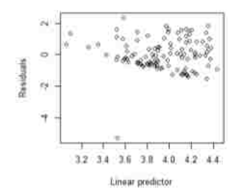
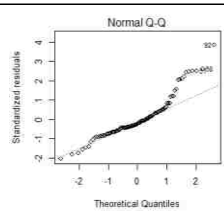
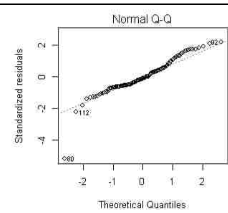
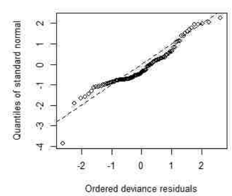
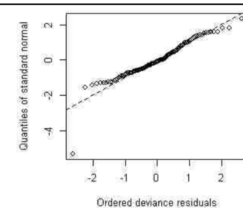
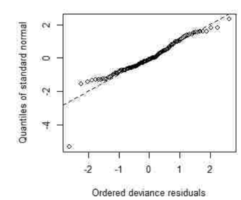
Figure 9-10. Diagnostic Plots: Excess NO_x Emissions (grams)

9.3.11 Excess PM_{10} Emissions

Table 9-25 gives a summary of the results for PM_{10} emissions for the different regression models. Gaussian Single-log and log-log GLMs have the best fit. Both of these have R^2 and AIC that is almost equal.

$$\text{Excess } PM_{10} \text{ Emissions} = \text{Exp}\,\{3.399096 + 0.293358 * \text{Weekday} + 0.008231 * \text{Lane-Minutes of Blockage}\} - 30 \qquad (9\text{-}11)$$

Table 9-25. Results for total Excess PM_{10} Emissions (grams)

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
			Variable: PM10		
Full Model:					
R-sq (%)	28.63 , 22.52	27.71 , 21.51	25.92	27.70	29.56
AIC	1163.449	210.6274	1110.2	210.63	209.65
Nested Model:					
R-sq (%)	21.31 , 19.9	20.16, 18.74	13.31	20.16	19.53
AIC	1160.688	208.05	1113	208.05	208.95
Model Fit (P-value) Accept Model p >0.05			0.6885185	0.4822277	0.4822281
Residual Vs Fitted					
Standardized Residuals					
Significant Variables	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Lane-minutes of Blockage	Non-incident Density, Incident duration

The log-log model has no representation of the number of lanes blocked which is a very important incident characteristic for practical purposes. Therefore, Gaussian Single-log model is selected for recommendation for excess 'PM_{10}' emission owing to the variable lane-minutes of blockage in it. The model results are summarized in Table 9-26, Figure 9-11 and equation 9-11. The constant used is A = 30.

Table 9-26. Best Model: Excess PM_{10} Emissions (grams)

(Model Form: Gaussian Single-log GLM)

Final Nested Model:

```
Call:
glm(formula = lnPM10Plus30 ~ Weekday + BlkLnMin, family = gaussian(),
    data = fe)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.93732  -0.33493  -0.06319   0.30781   1.27335

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.399096   0.142301  23.887  < 1e-16 ***
Weekday     0.293358   0.133757   2.193   0.0015 *
BlkLnMin    0.008231   0.001580   5.210 4.34e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.3423557)

    Null deviance: 48.027  on 114  degrees of freedom
Residual deviance: 38.344  on 112  degrees of freedom
AIC: 208.05

Number of Fisher Scoring iterations: 2
```

AIC:
208.05

R-sq (%):
20.16

Diagnostic Plots:

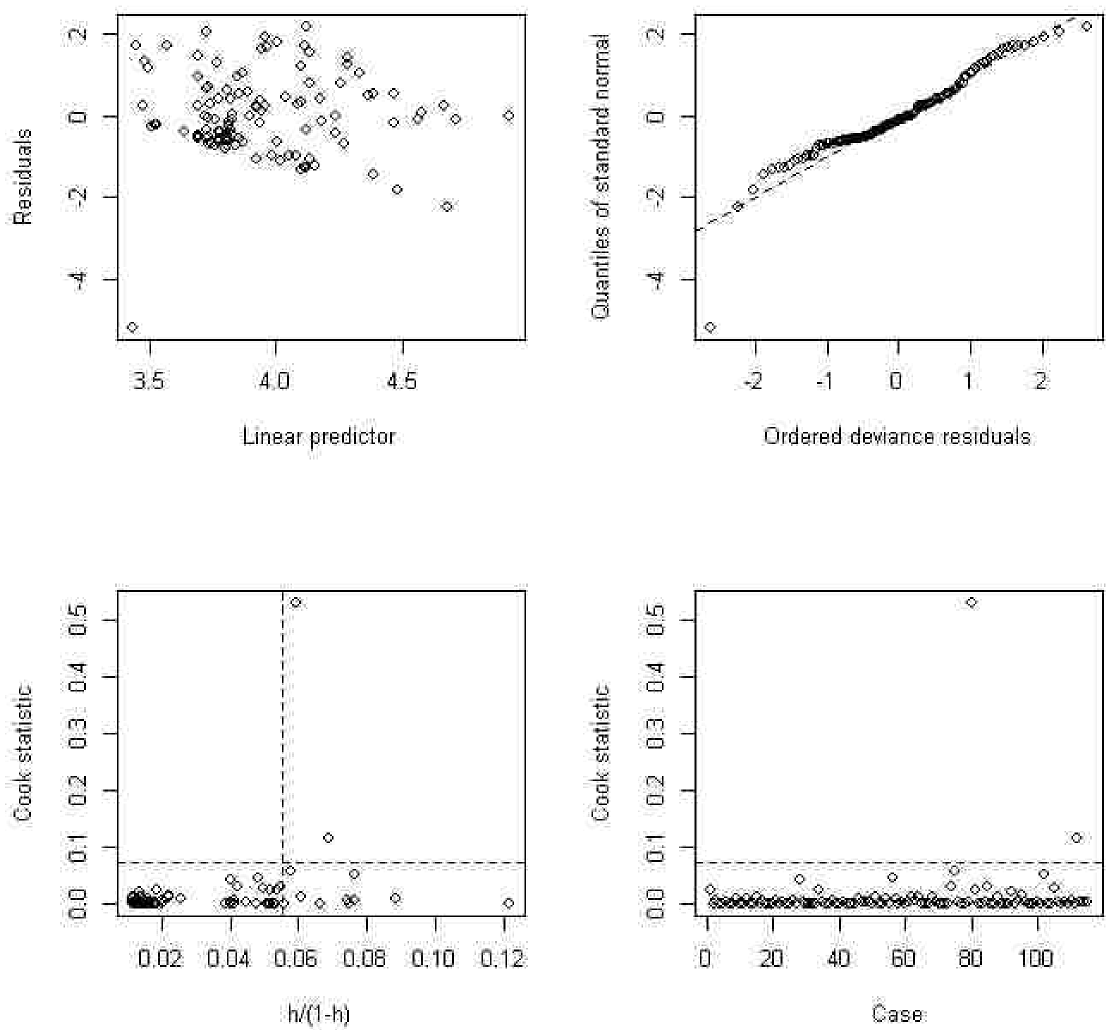


Figure 9-11. Diagnostic Plots: Excess PM_{10} Emissions (grams)

The calibrated model has two significant variables, lane-minutes of blockage and a dummy variable indicating if the incident day happened on a weekday or weekend. Both of these variables have positive coefficients. If an incident happened on a weekday, the impact on the excess PM_{10} emissions is more than on a weekend.

9.4 Summary

All the models for short term incident impacts have positive coefficient estimates indicating that the short-term impacts of incidents (travel time, fuel consumption and vehicle emissions) increase with the increase in incident characteristics. This follows the logic that an incident of bigger magnitude (more number of lanes blocked and more incident duration experienced) will cause more short term impacts than an incident with lower incident duration and number of lanes blocked. The interpretation and marginal impacts of these models are discussed in Chapter 11.

CHAPTER 10

STATISTICAL MODELING RESULTS FOR LONG TERM IMPACTS

10.1 Introduction

This chapter presents the statistical modeling results for the long term incident impacts. The response variables in this category are 95th percentile travel time, buffer time and buffer index values for mixed data, and difference between mixed and non-incident data. Similar to the previous chapter, a summary table for all the models are presented followed by coefficient estimation of the recommended nested model. Since many of the predictor variables had zeros, the Gaussian Log-Log GLM could not be modeled because logarithms do not apply for zeros. Therefore four functional forms Linear, Log-Transformed, Gamma GLM and Gaussian Single-log GLM are summarized. For GLMs, appropriate constants are used, as necessary, to make the modeling possible.

10.2 Description of Response and Predictor Variables

The list of the response and predictor variables used in the analysis of the long term impacts of incidents and their codes in R are presented in Tables 10-1 and 10-2. For the predictor variables in long term impacts, there was a lot of correlation among the variables, especially the previous hour, previous 2nd hour and previous 2 hours as shown in Table 10-3. During stepwise regression, these sets of variables are modeled one at a time manually, and the best one is recommended.

Table 10-1. List of Response Variables for Long Term Impacts

Variable Code	Variable Name	Explanation
Mixed95%ile	Mixed 95th TT	95th percentile TT for mixed data
95%ile	Diff 95th TT	Excess 95th percentile TT due to incident
MixedBufTime	Mixed Buffer Time	Buffer time TTR for mixed data
BufTime	Diff Buffer Time	Excess buffer time TTR measure due to incident
MixedBufIndex	Mixed Buffer Index	Buffer index TTR for mixed data
BufIndex	Diff Buffer Index	Excess buffer index TTR measure due to incident

Table 10-2. List of Predictor Variables for Long Term Impacts

Variable Code	Variable Name	Explanation
TotNoOfInc	Number of Incidents	Total Number of incidents in the hour
IncRate	Rate of Incidents	Rate of incidents - inc/hr in the hour
AvgLnMin	Average Lane-Minutes	Average Lane minutes of blockage in the hour
MaxLnMin	Maximum Lane-Minutes	Maximum Lane minutes of blockage in the hour
NoOfIncPrvHr	Incidents in previous hour	Total Number of incidents in the previous hour
IncRatePrvHr	Rate of incidents in previous hour	Rate of incidents - inc/hr in the previous hour %
AvgLnMinPrevHr	Average Lane-Minutes in previous hour	Average Lane minutes of blockage in the previous hour
NoOfIncPrv2ndHr	Incidents in previous 2nd hour	Total Number of incidents in the previous 2nd hour
IncRatePrv2ndHr	Rate of incidents in previous 2nd hour	Rate of incidents - inc/hr in the previous 2nd hour %
AvgLnMinPrev2ndHr	Average Lane-Minutes in previous 2nd hour	Average Lane minutes of blockage in the previous 2nd hour
NoOfIncPrv2Hrs	Incidents in previous 2 hours	Total Number of incidents in the previous 2 hours combined
IncRatePrv2Hrs	Rate of incidents in previous 2 hours	Rate of incidents - inc/hr in the previous 2 hours combined %
AvgLnMinPrev2Hrs	Average Lane-Minutes in previous 2 hours	Average Lane minutes of blockage in the previous 2 hours combined
AvgLnBlk	Average Lanes Blocked	Average number of lanes blocked
MaxLnBlk	Maximum Lanes Blocked	Maximum number of lanes blocked
AvgClrT	Average Incident duration	Average Incident duration of incidents in the hour
AvgDist	Average Distance	Average distance from 215.
NISpeed	Non-incident Speed	Speed for non-incident scenario
NIVolume	Non-incident Volume	Volume for non-incident scenario
NIVolVphpl	Non-incident Volume -vphpl	Volume (vphpl) for non-incident scenario
NIDensity	Non-incident Density	Density for non-incident scenario
NIDensVpmpl	Non-incident Density -vpmpl	Density (vpmpl) for non-incident scenario

Table 10-3. Correlation Matrix for Predictor Variables for Long Term Impacts

	No OfI	Inc Rat e	Avg Ln Min	Ma xLn Min	OfI ncP rvH	Rat ePr	Ln Min Pre	OfI ncP rv2	Rat ePr	Ln Min Pre	OfI ncP rv2	Rat ePr	Ln Min Pre	Avg Ln Blk	Avg Clr T	Avg Dist	NIS pee d	NI Vol ume	Vol Vph	NI Den sity
IncRate (p-value)	0.40 0.00																			
AvgLnMin	**0.97** 0.00	-0.09 0.53																		
MaxLnMin	-0.14 0.38	0.05 0.74	-0.12 0.45																	
NoOfIncPrvHr	**0.99** 0.00	0.35 0.01	**0.98** 0.00	-0.15 0.35																
IncRatePrvHr	**0.61** 0.00	0.25 0.09	**0.56** 0.00	0.00 0.99	**0.61** 0.00															
AvgLnMinPrev	-0.13 0.42	-0.09 0.56	-0.08 0.64	0.07 0.68	-0.14 0.36	-0.11 0.47														
NoOfIncPrv2n	0.40 0.00	0.09 0.52	0.38 0.01	0.22 0.16	0.38 0.00	**0.78** 0.00	0.02 0.91													
IncRatePrv2n	0.27 0.06	-0.03 0.83	0.29 0.07	0.09 0.59	0.25 0.09	0.57 0.00	-0.01 0.97	**0.86** 0.00												
AvgLnMinPrev	-0.19 0.24	-0.09 0.59	-0.20 0.23	-0.15 0.40	-0.19 0.24	-0.19 0.26	0.15 0.40	-0.08 0.61	-0.07 0.68											
NoOfIncPrv2H	**0.57** 0.00	0.13 0.35	**0.53** 0.00	0.05 0.78	**0.56** 0.00	**0.88** 0.00	-0.06 0.72	**0.93** 0.00	**0.88** 0.00	-0.10 0.51										
IncRatePrv2H	**0.55** 0.00	0.12 0.38	**0.52** 0.00	0.08 0.63	**0.54** 0.00	**0.89** 0.00	-0.04 0.82	**0.93** 0.00	**0.89** 0.00	-0.09 0.56	**0.99** 0.00									
AvgLnMinPrev	-0.09 0.54	-0.07 0.64	-0.06 0.69	-0.03 0.84	-0.09 0.54	-0.07 0.67	**0.65** 0.00	0.01 0.92	-0.06 0.72	**0.86** 0.00	-0.03 0.85	0.00 0.99								
AvgLnBlk	0.24 0.07	**0.58** 0.00	-0.08 0.59	0.31 0.04	0.26 0.05	0.17 0.25	0.02 0.90	0.08 0.55	0.07 0.65	0.04 0.83	0.11 0.43	0.12 0.38	0.05 0.72							
AvgClrT	0.22 0.10	**0.52** 0.00	-0.05 0.72	**0.83** 0.00	0.22 0.11	0.23 0.12	-0.04 0.79	0.21 0.13	0.01 0.97	-0.34 0.03	0.17 0.24	0.17 0.23	-0.24 0.10	**0.51** 0.00						
AvgDist	0.35 0.02	0.04 0.78	0.34 0.02	0.14 0.38	0.35 0.02	0.26 0.10	0.21 0.23	0.21 0.15	0.22 0.17	0.01 0.94	0.32 0.03	0.32 0.04	0.12 0.46	-0.19 0.21	0.29 0.05					
NISpeed	**-0.75** 0.00	-0.25 0.07	**-0.71** 0.00	0.12 0.43	**-0.75** 0.00	**-0.71** 0.00	0.09 0.57	**-0.55** 0.00	-0.44 0.00	0.15 0.35	**-0.67** 0.00	**-0.68** 0.00	0.01 0.95	-0.22 0.11	-0.08 0.58	-0.12 0.41				
NIVolume	**0.52** 0.00	0.22 0.10	**0.54** 0.00	-0.32 0.03	**0.54** 0.00	0.27 0.07	-0.24 0.13	-0.11 0.43	-0.06 0.68	0.07 0.68	0.15 0.30	0.15 0.28	0.03 0.81	0.29 0.03	-0.04 0.79	0.01 0.95	**-0.59** 0.00			
NIVolVphpl	**0.55** 0.00	0.23 0.09	**0.58** 0.00	-0.34 0.03	**0.58** 0.00	0.32 0.03	-0.25 0.11	-0.05 0.74	-0.01 0.95	0.06 0.72	0.20 0.15	0.21 0.14	0.03 0.86	0.28 0.04	-0.04 0.75	0.03 0.86	**-0.64** 0.00	1.00 0.00		
NIDensity	**0.74** 0.00	0.27 0.05	**0.73** 0.00	-0.22 0.15	**0.75** 0.00	**0.62** 0.00	-0.14 0.37	0.35 0.01	0.27 0.06	-0.06 0.70	**0.53** 0.00	**0.54** 0.00	0.02 0.87	0.25 0.06	0.03 0.83	0.13 0.40	**-0.94** 0.00	**0.81** 0.00	**0.85** 0.00	
NIDensVpmpl	**0.74** 0.00	0.27 0.05	0.73 0.00	-0.22 0.16	**0.75** 0.00	**0.62** 0.00	-0.14 0.37	0.36 0.01	0.28 0.06	-0.06 0.69	**0.53** 0.00	**0.54** 0.00	0.02 0.87	0.25 0.06	0.03 0.82	0.13 0.38	**-0.94** 0.00	**0.81** 0.00	**0.84** 0.00	**1.00** 0.00

10.3 Model Results

10.3.1 The 95th Percentile Travel Time for Mixed Data

Table 10-4 presents the results for the 95th percentile travel time for mixed data. The Gaussian Single-log GLM is selected as the best model for the 95th percentile travel time for mixed data since it has the best fit. The extreme values in the residual and normality plots are much closer to the normal line than the other models as seen in plots in Table 10-4. The coefficient estimates for the Single-log GLM are presented in Table 10-5, the diagnostic plots in Figure 10-1 and the model form in Equation 10-1.

The significant variables are average lane-minutes of blockage and the rate of incident in the previous hour. Both coefficients are positive showing that there is an increase in the 95th percentile travel time (therefore, a decrease in travel time reliability) with increase in the average lane-minutes of blockage in the subject hour and the rate of incidents in the previous hour.

95th Percentile Travel Time Mixed = Exp {2.045 + 0.009 * Average Lane-Minutes of Blockage + 0.00882 * Rate of Incidents in Previous Hour} (10-1)

Table 10-4. Results for 95th Percentile Travel Time (Mixed)

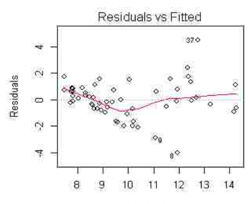
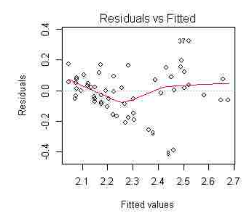
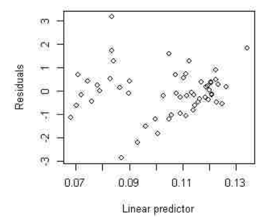
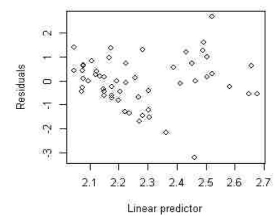
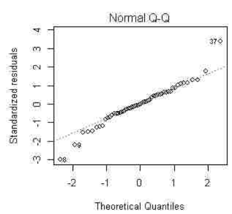
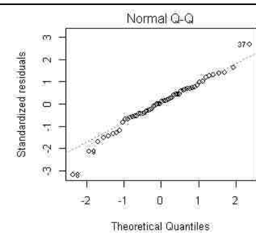
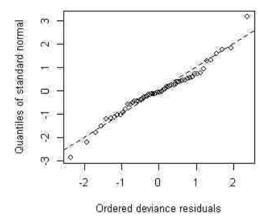
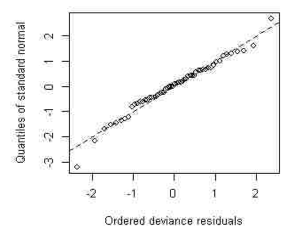
Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**
Full Model:				
R-sq (%)	71.35, 62.48	71.04, 62.07	74.76	71.04
AIC	214.12	-56.25	196.59	-53.19
Nested Model:				
R-sq (%)	67.33, 66.1	67.17, 65.93	68.96	67.17
AIC	199.46	-68.16	183.35	-68.163
Model Fit (P-value) Accept Model p >0.05			0.506291	0.4741632
Residual Vs Fitted				
Standardized Residuals				
Significant Variables	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour

Table 10-5. Best Model: 95th Percentile TT - Mixed

(Model Form: Gaussian Single-Log GLM)

Final Nested Model with variables for PrevHr and Prev2ndHr:

```
Call:
glm(formula = lnMixed95th ~ AvgLnMin + IncRatePrvHr, family =
gaussian(),
    data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.38824  -0.06357   0.00682   0.07832   0.32592

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.044984   0.027343  74.789  < 1e-16 ***
AvgLnMin     0.009064   0.002072   4.373 2.88e-05 ***
IncRatePrvHr 0.008820   0.001900   4.642 1.16e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.01587711)

    Null deviance: 2.56289  on 55  degrees of freedom
Residual deviance: 0.84149  on 53  degrees of freedom
AIC: -68.163

Number of Fisher Scoring iterations: 2
```

AIC:
-68.163

R-sq (%):
67.17

Diagnostic Plots:

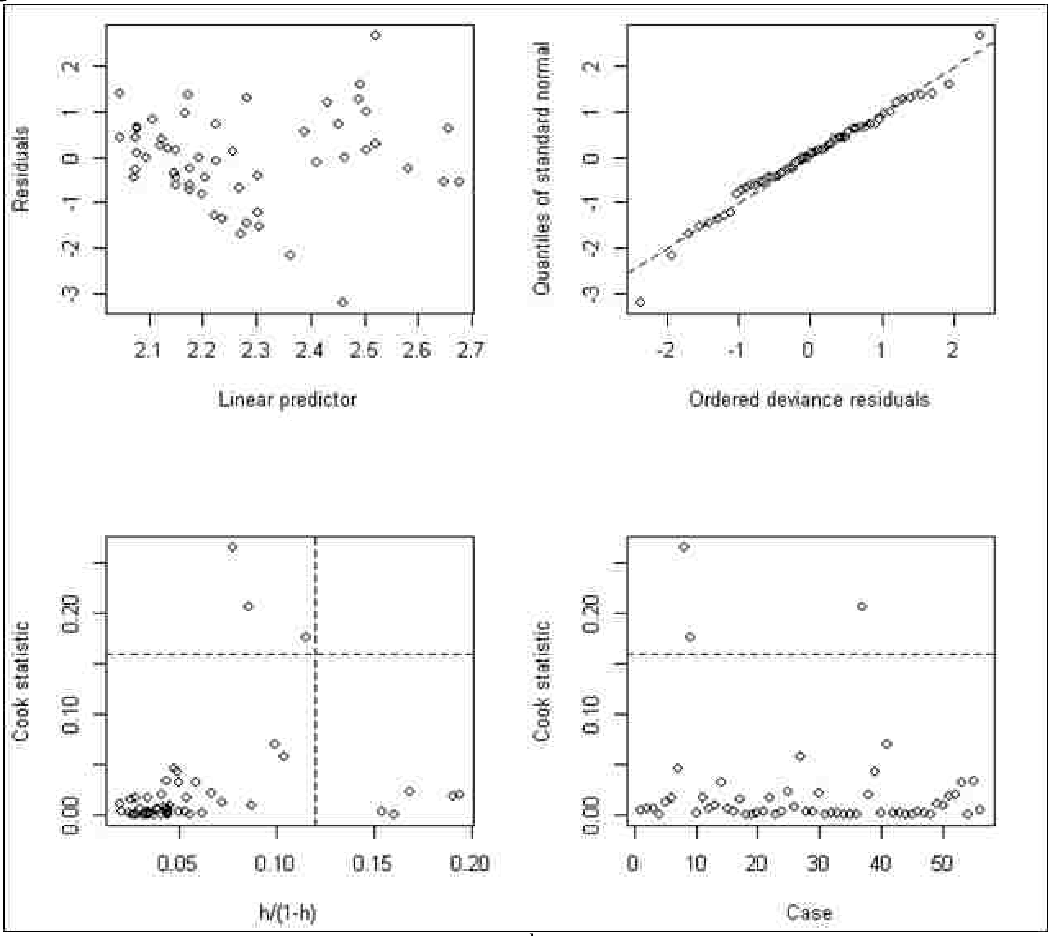


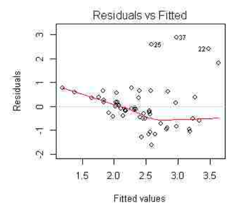
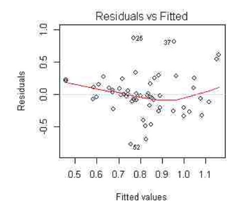
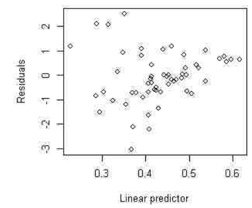
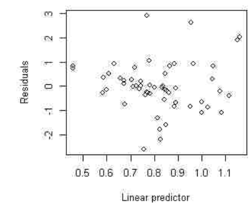
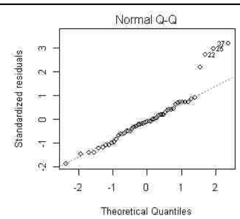
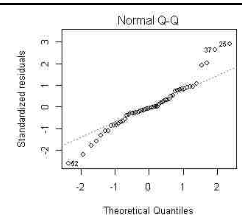
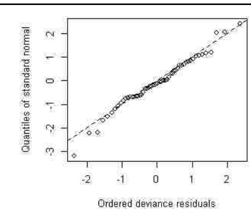
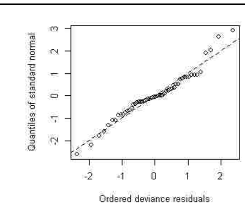
Figure 10-1. Diagnostic Plots: 95th Percentile Travel Time - Mixed

10.3.2 Difference in 95th Percentile Travel Time

Table 10-6 presents a summary of the results for the difference in 95th percentile travel time between mixed and non-incident data. For this case, the Gamma GLM model is recommended. It has a higher R^2 and a very good fit in the normality and residual plots. The constant used is A=2 and the final model results are shown in Table 10-7, Figure 10-2 and equation 10-2.

Diff in 95th percentile TT = {1/ (2.58 -0.00471 * Average Lane-Minutes of Blockage - 0.00723 * Rate of Incidents in Previous Hour - 0.02519 * Non-incident Speed - 0.00039 * Non-incident volume)} – 2 (10-2)

Table 10-6. Results for 95th Percentile Travel Time - Difference

Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)
Full Model:				
R-sq (%)	30.31, 8.73	26.52, 3.78	45.5	26.52
AIC	170.62	52.13	139.46	52.13
Nested Model:				
R-sq (%)	24.79, 18.89	21.49, 15.33	35.54	21.49
AIC	156.89	37.84	127.95	37.84
Model Fit (P-value) Accept Model p >0.05			0.3877355	0.4736602
Residual Vs Fitted				
Standardized Residuals				
Significant Variables	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume

The Gamma GLM model uses an inverse link function. Therefore, the negative signs in the coefficient estimates indicate an increase in difference in 95th percentile for the significant variables, namely, average lane-minutes of blockage, the incident rate in the previous hour, non-incident speed and volume.

Table 10-7. Best Model: 95th percentile TT- Difference

(Model Form: Gamma GLM)

Final Nested Model:

```
Call:
glm(formula = TwoPlus95th ~ AvgLnMin + IncRatePrvHr + NISpeed +
    NIVolume, family = Gamma(), data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.87240  -0.20079  -0.03805   0.18544   0.66258

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.5812057  0.5665623   4.556 3.28e-05 ***
AvgLnMin     -0.0047131  0.0023488  -2.007  0.01253 .
IncRatePrvHr -0.0072320  0.0022504  -3.214  0.00057 **
NISpeed      -0.0251897  0.0072574  -3.471  0.00027 **
NIVolume     -0.0003917  0.0001491  -2.626  0.00569 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.09347843)

    Null deviance: 7.3819  on 55  degrees of freedom
Residual deviance: 4.9775  on 51  degrees of freedom

AIC: 127.95
Number of Fisher Scoring iterations: 5
```

AIC:
127.95

R-sq (%):
35.54

Diagnostic Plots:

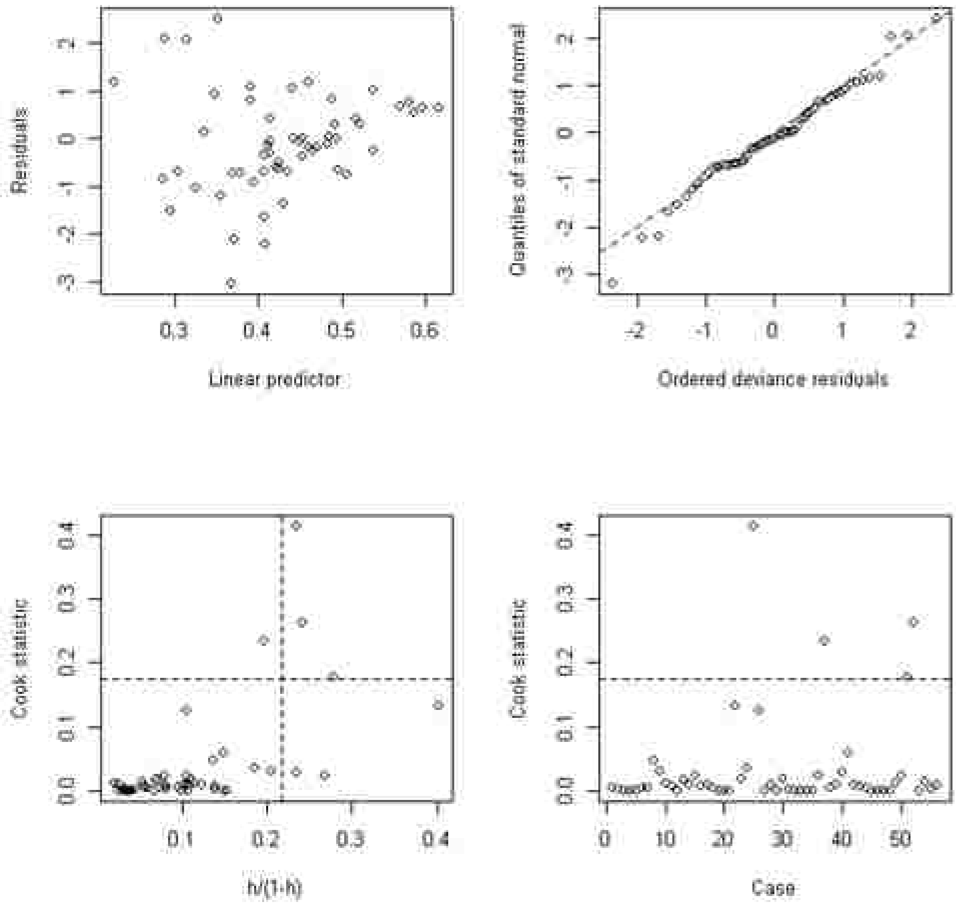


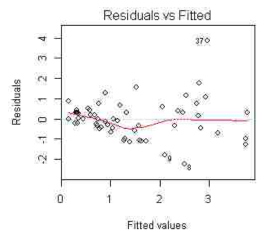
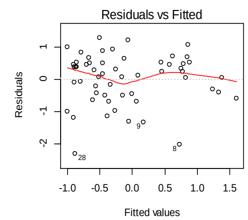
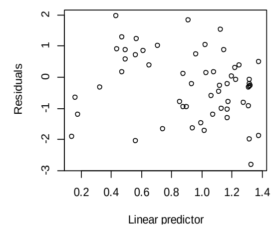
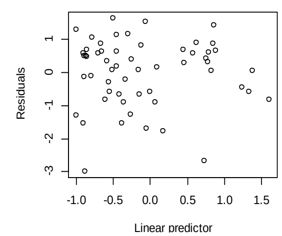
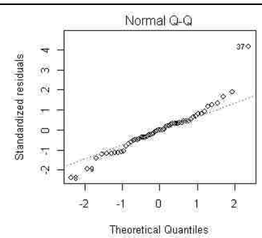
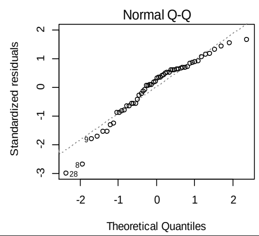
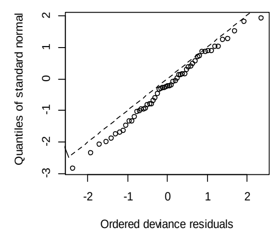
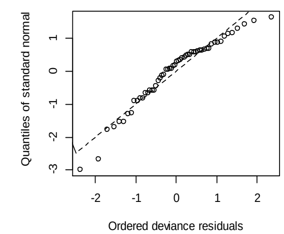
Figure 10-2. Diagnostic Plots: Difference in 95th percentile TT

10.3.3 Buffer Time for Mixed Data

Table 10-8 shows the summary of results for buffer time for mixed data. The Gaussian Single-log GLM is the model selected for the Buffer Time owing to its better fit in the residual and normality plots. The results of the final model are shown in Table 10-9, Figure 10-3 and equation 10-3.

Buffer Time Mixed = Exp {-3.00209 + 0.03583 * Average Lane-Minutes of Blockage + 0.02607 * Rate of Incidents in Previous Hour} (10-3)

Table 10-8. Results for Buffer Time (Mixed)

Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)
Full Model:				
R-sq (%)	58.97, 46.27	49.78, 34.23	66.21	49.78
AIC	175.83	154.52	135.77	154.52
Nested Model:				
R-sq (%)	54.44, 52.72	45.74, 43.69	31.33	45.74
AIC	159.69	136.86	127.55	136.86
Model Fit (P-value) Accept Model p >0.05			0.4969493	0.6176565
Residual Vs Fitted				
Standardized Residuals				
Significant Variables	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour

The significant variables are average lane-minutes of blockage and the rate of incident in the previous hour. Equation 10-3 shows that buffer time increases with increase in the average lane-minutes of blockage in the subject hour and the rate of incidents in the previous hour. Increase in the buffer time measure corresponds to a decrease in travel time reliability and is therefore indicating that the incidents reduce travel time reliability.

Table 10-9. Best Model: Buffer Time - Mixed

(Model Form: Gaussian Single-log GLM)

Final Nested Model for PrevHr, PRev2ndHr and α = 0.05:

```
Call:
glm(formula = lnMixedBufTime ~ AvgLnMin + IncRatePrvHr, family = 
gaussian(), 
    data = x)
Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-2.3048  -0.4630   0.1895   0.4976   1.2747  

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  -0.99912    0.17055  -5.858 1.52e-07 ***
AvgLnMin      0.04093    0.01293   3.166  0.00128 ** 
IncRatePrvHr  0.03099    0.01185   2.615  0.00580 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 
(Dispersion parameter for gaussian family taken to be 0.6176565)

    Null deviance: 60.328  on 55  degrees of freedom
Residual deviance: 32.736  on 53  degrees of freedom

AIC: 136.86
Number of Fisher Scoring iterations: 2
```

AIC:
136.86
R-sq (%):
45.74

Diagnostic Plots:

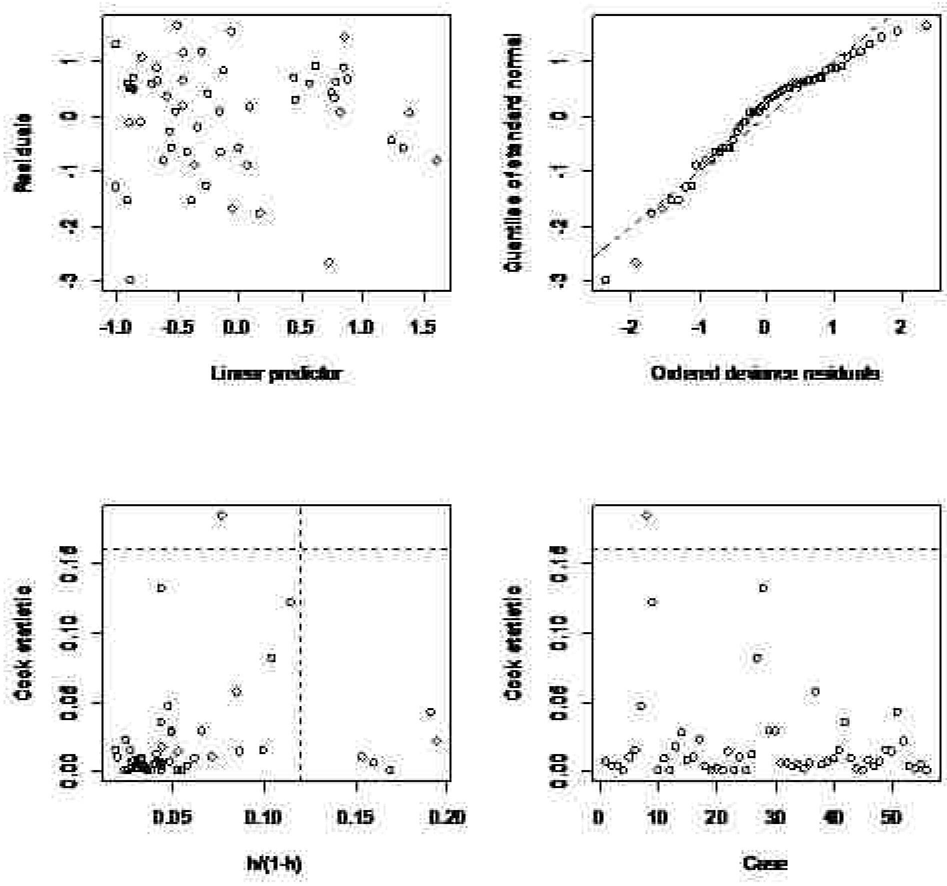


Figure 10-3. Diagnostic Plots: Buffer Time - Mixed

10.3.4 Difference in Buffer Time

The summary of results for the difference in buffer time between mixed and non-incident data is shown in Table 10-10. The model selected is the Gamma GLM since it has the best normality plot of all the models and a high R^2. The coefficient estimates and diagnostic plots are shown in Table 10-11 and Figure 10-4. The constant used to make the LHS positive is A=2. Equation 10-4 presents the form of the final model.

Diff in Buffer Time = {1/ (2.34 -0.00421 * Average Lane-Minutes of Blockage - 0.0064 * Rate of Incidents in Previous Hour - 0.02245 * Non-incident Speed - 0.00034 * Non-incident Volume)} – 2 (10-4)

Table 10-10. Results for Buffer Time - Difference

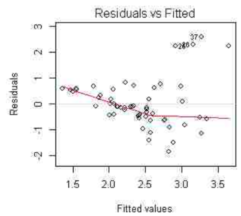
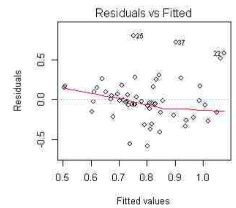
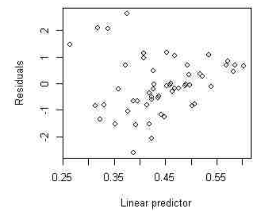
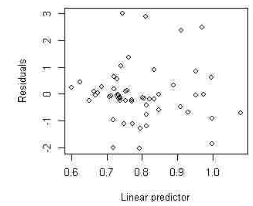
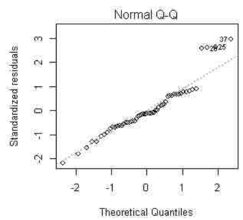
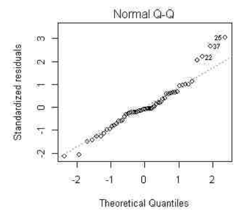
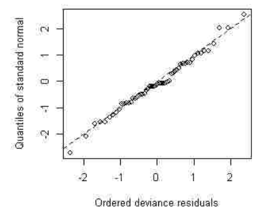
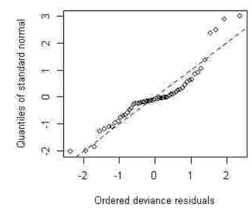
Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)
Full Model:				
R-sq (%)	27.98, 5.69	25.42, 23.41	40.6	25.42
AIC	152.75	37.40	123.87	37.405
Nested Model:				
R-sq (%)	22.65, 16.58	19.25, 12.92	31.33	12.13
AIC	138.75	23.86	112.31	24.59
Model Fit (P-value) Accept Model p >0.05			0.4954747	0.4741625
Residual Vs Fitted				
Standardized Residuals				
Significant Variables	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume

Table 10-11. Best Model: Buffer Time - Difference

(Model Form: Gamma GLM)

Final Nested Model:

```
Call:
glm(formula = BufTimePlus2 ~ AvgLnMin + IncRatePrvHr + NISpeed +
    NIVolume, family = Gamma(), data = x)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.68258  -0.18642  -0.03844   0.17390   0.64202

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.3435925  0.5437544   4.310 3.73e-05 ***
AvgLnMin     -0.0042124  0.0022778  -1.849  0.03510 .
IncRatePrvHr -0.0063994  0.0021718  -2.947  0.00242 **
NISpeed      -0.0224492  0.0069712  -3.220  0.00112 **
NIVolume     -0.0003374  0.0001418  -2.380  0.01055 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Gamma family taken to be 0.07861903)

    Null deviance: 5.6485  on 55  degrees of freedom
Residual deviance: 3.9662  on 51  degrees of freedom

AIC: 112.31

Number of Fisher Scoring iterations: 5
```

R-sq (%):
31.33

For the Gamma GLM, as explained in the previous section, negative signs in the coefficient estimates indicate an increase in difference in buffer time (therefore, a decrease in travel time reliability) for the significant variables, namely, average lane-minutes of blockage, the incident rate in the previous hour, non-incident speed and volume.

Diagnostic Plots:

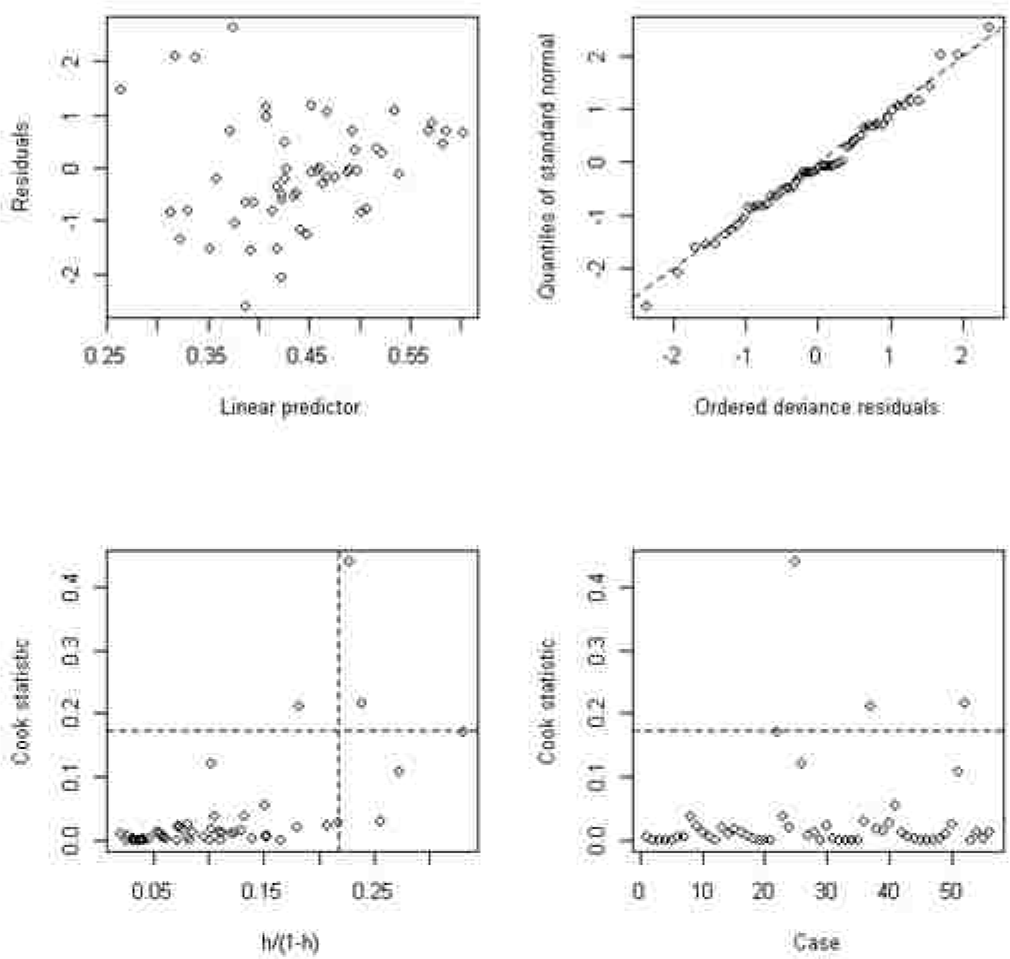


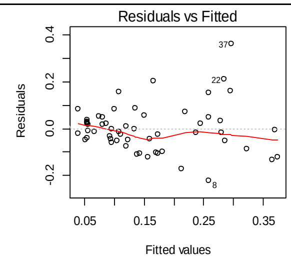
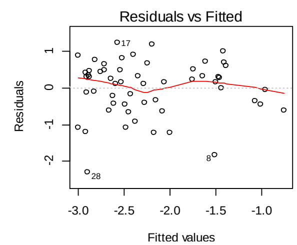
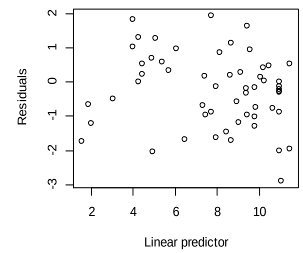
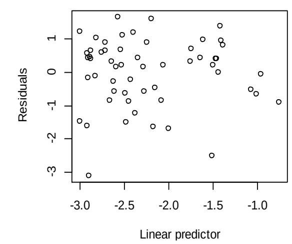
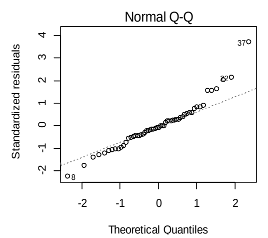
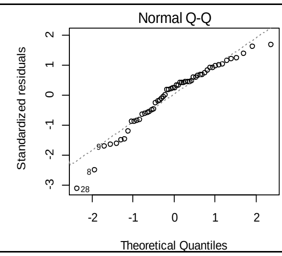
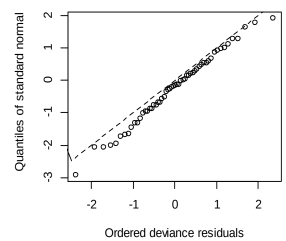
Figure 10-4. Diagnostic Plots: Buffer Time - Difference

10.3.5 Buffer Index for Mixed Data

The summary of the results for the buffer index for mixed data is presented in Table 10-12. The Gaussian GLM with Single-log is chosen as the best model since it has the better normality plot. The coefficient estimates, diagnostic plots and model form are presented in Table 10-13 and Figure 10-5 and equation 10-5 respectively.

Buffer Index Mixed = Exp {-0.99912 + 0.04093 * Average Lane-Minutes of Blockage + 0.03099 * Rate of Incidents in Previous Hour} (10-5)

Table 10-12. Results for Buffer Index (Mixed)

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**
Full Model:				
R-sq (%)	54.09, 39.88	45.3, 28.37	62.46	45.3
AIC	-77.46	149.52	-108.17	149.53
Nested Model:				
R-sq (%)	47.27, 45.28	40.32, 38.07	22.69	40.32
AIC	-91.70	132.41	-117.52	132.41
Model Fit (P-value) Accept Model p >0.05			0.444908	0.5704758
Residual Vs Fitted				
Standardized Residuals				
Significant Variables	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour

The positive coefficients in equation 10-5 show an increase of buffer index (therefore, a decrease in travel time reliability) for the two significant variables, average lane-minutes of blockage and the incident rate in the previous hour.

Table 10-13. Best Model: Buffer Index - Mixed

(Model Form: Gaussian Single-log GLM)

Final Nested Model with PrevHr and Prev2ndHr:

```
Call:
glm(formula = lnMixedBufIndex ~ AvgLnMin + IncRatePrvHr, family =
gaussian(),
    data = x)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3034  -0.4340   0.1644   0.4932   1.2403

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  -3.00209    0.16390 -18.316  < 1e-16 ***
AvgLnMin      0.03583    0.01242   2.885  0.00283 **
IncRatePrvHr  0.02607    0.01139   2.289  0.01304 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.5704758)

    Null deviance: 50.664  on 55  degrees of freedom
Residual deviance: 30.235  on 53  degrees of freedom
AIC: 132.41

Number of Fisher Scoring iterations: 2
```

AIC:
132.41

R-sq (%):
40.32

Diagnostic Plots:

Figure 10-5. Diagnostic Plots: Buffer Index - Mixed

10.3.6 Difference in Buffer Index

The summary of model results for the difference in buffer index as the response is summarized in Table 10-14. The Gamma GLM has marginally better residual plots and higher R^2 when compared to all the models and is selected for recommendation. The Gamma GLM results are given in Table 10-15 and plots in Figure 10-6. Equation 10-6 shows the model form using a constant A = 2 to make the LHS positive.

Table 10-14. Results for Buffer Index - Difference

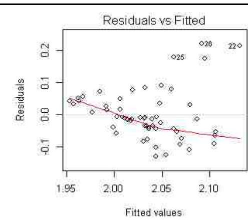
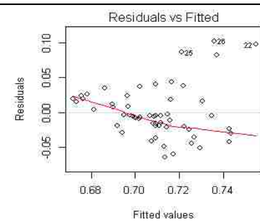
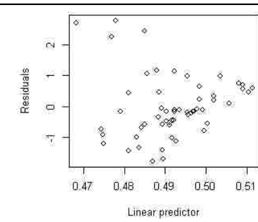
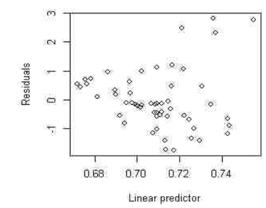
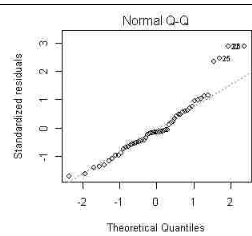
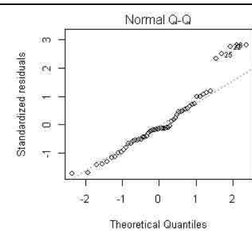
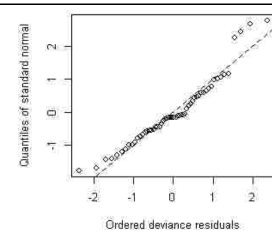
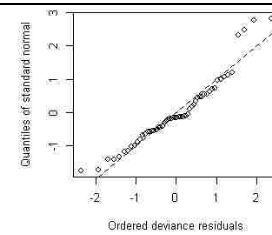
Category	Linear	Transformed Single Log	Gamma	Gaussian (Log)
Full Model:				
R-sq (%)	28, 5.7	27.66, 5.27	29.3	27.66
AIC	-104.82	-118.38	-108.94	-188.39
Nested Model:				
R-sq (%)	21.85, 15.72	21.44, 15.28	22.68	21.44
AIC	-118.24	-201.77	-122	-201.77
Model Fit (P-value) Accept Model p >0.05			0.5145734	0.473661
Residual Vs Fitted				
Standardized Residuals				
Significant Variables	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume	Average Lane-Minutes of Blockage, Rate of Incidents in Previous Hour, Non-incidnet Speed, Non-incident Volume

Table 10-15. Best Model: Buffer Index - Difference

(Model Form: Gamma GLM)

Final Nested Model:

```
Call:
glm(formula = BufIndexPlus2 ~ AvgLnMin + IncRatePrvHr + NISpeed +
    NIVolume, family = Gamma(), data = x)

Deviance Residuals:
      Min          1Q      Median          3Q         Max
-0.063890   -0.021259   -0.005933    0.018291    0.101388

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.428e-01  8.212e-02   9.046 3.51e-12 ***
AvgLnMin     -6.969e-04  3.809e-04  -1.830  0.07315 .
IncRatePrvHr -7.556e-04  3.478e-04  -2.173  0.03446 *
NISpeed      -3.044e-03  1.063e-03  -2.864  0.00605 **
NIVolume     -4.066e-05  2.099e-05  -1.937  0.05831 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Gamma family taken to be 0.001450574)

    Null deviance: 0.094113  on 55  degrees of freedom
Residual deviance: 0.072485  on 51  degrees of freedom
AIC: -122

Number of Fisher Scoring iterations: 4
```

R-sq (%):

22.68

Diagnostic Plots:

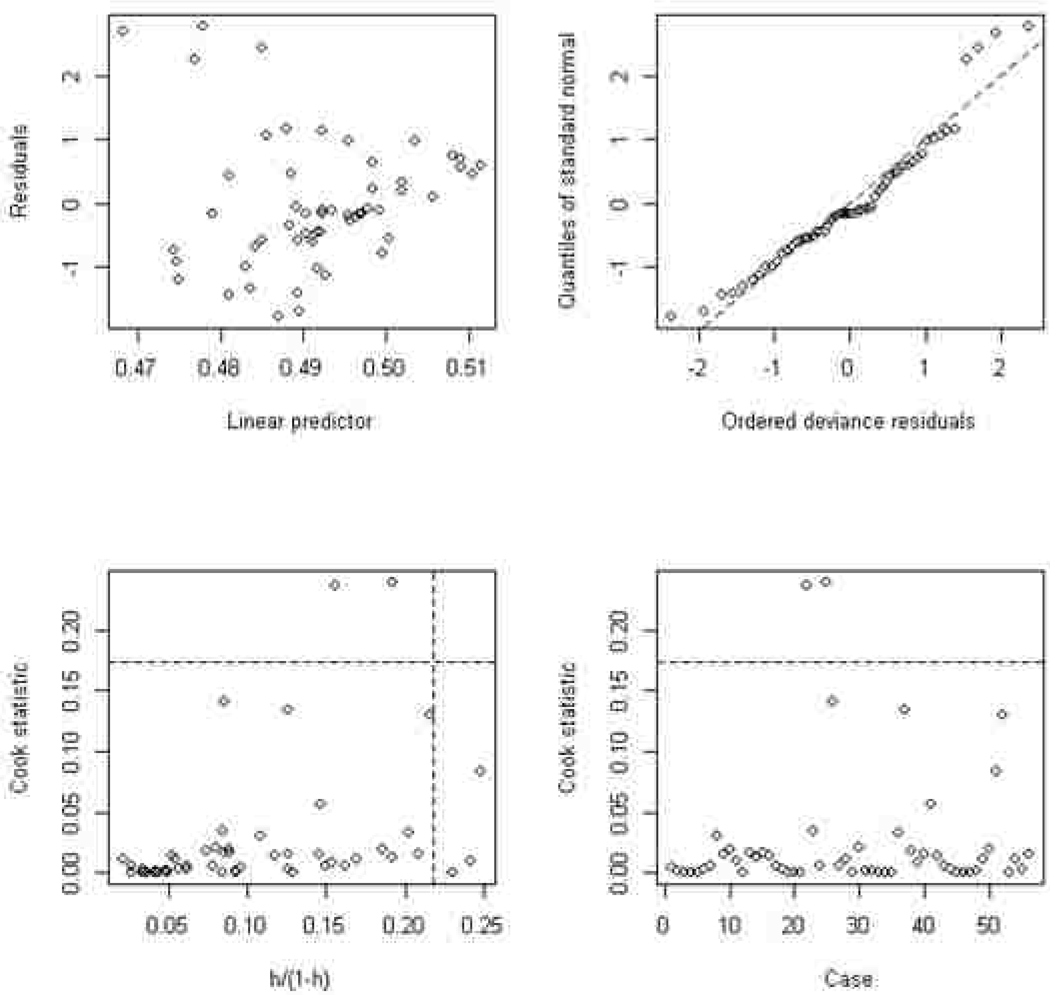


Figure 10-6. Diagnostic Plots: Buffer Index - Difference

Diff in Buffer Index = {-1/(0.7428 -0.0007 * Average Lane-Minutes of Blockage - 0.0008 * Rate of Incidents in Previous Hour - 0.0030 * Non-incident Speed - 0.00004 * Non-incident Volume)} – 2 (10-6)

Negative signs in the coefficient estimates indicate an increase in difference in buffer time (therefore, a decrease in travel time reliability) for the significant variables, namely, average lane-minutes of blockage, the incident rate in the previous hour, non-incident speed and volume (Since Gamma GLM uses an inverse link).

10.4 Summary

In all the models for the TTR measures, the significant variables are lane-minutes of blockage, incident rate in the previous hour, non-incident speed and non-incident volume in combinations. The TTR measures have a positive trend with these variables and therefore increase with the corresponding increase in these variables. Since the TTR measures are a representation of travel time unreliability (or variability), increase in TTR measures results in decrease of travel time reliability. The interpretation and marginal impacts of these models are discussed in Chapter 12.

CHAPTER 11

MARGINAL IMPACTS AND DISCUSSION OF RESULTS FOR SHORT TERM ANALYSIS

11.1 Introduction

This chapter describes the interpretation of the models selected for analysis of the marginal impacts of incident characteristics on the response variables. Marginal impact measures the effect on the response variable with a change in one of the predictor variables. Elasticity is defined as the rate of change in a dependent variable with a percent change in a predictor variable. This chapter describes the derivation of the effect of the predictor variable on the original response variable, after the addition of the constant for the Gamma, Gaussian Single-log and Gaussian Log-log GLMs.

11.2 Derivation of Elasticity for Gamma GLM

The interpretation of the Gamma GLM with an inverse link function, as in the case of the statistical modeling in this study, is given below. The Gamma model requires the response variables to be positive. Hence the interpretation for the model with the addition of a constant A on the left-hand side is as shown in the following derivation.

Elasticity of a variable Y with respect to predictor variable X_j is given as

$$\varepsilon_j = \frac{dY}{dX_j}\left(\frac{X_j}{Y}\right)$$

Here the response variable is A + Y

The Gamma model is of then general form

$$(A+Y) = (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p)^{-1} \quad (11\text{-}1)$$

Taking the A to RHS,

$$Y = (\beta_0 + \beta_j X_j)^{-1} - A$$

Differentiating,

$$\frac{dY}{dX_j} = -(\beta_0 + \beta_j X_j)^{-2} \times \beta_j$$

$$= \ -(Y + A)^2 \times \beta_j$$

Hence,

$$\varepsilon_j \quad = -\beta_j X_j \frac{(Y + A)^2}{Y} \tag{11-2}$$

where:

Y is the response variable

A is the constant added to make the LHS positive

X_j are the predictor variables

11.3 Derivation of Elasticity for Gaussian Single-Log GLM

The functional form for the Gaussian Single-log model in this study is given by the following equation:

$$\ln(A + Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p \tag{11-3}$$

Where A is the constant used to make LHS positive. Taking exponentiation on both sides,

$$A + Y = e^{\beta_0 + \beta_j X_j}$$

$$Y = e^{\beta_0 + \beta_j X_j} - A$$

Differentiating,

$$\frac{dY}{dX_j} = \beta_j \times e^{\beta_0 + \beta_j X_j}$$

$$= \beta_j (A + Y)$$

$$\varepsilon_j = \beta_j \times (A + Y) \times \frac{X_j}{Y} \qquad (11\text{-}4)$$

For a dummy variable that takes the value of 0 or 1, the derivation for rate of change of Y with unit change in X_j is as follows:

$$\frac{\Delta Y}{Y} = \frac{Y_1 - Y_0}{Y_0} = \frac{(e^{\beta_0 + \beta_j X_j} - A) - (e^{\beta_0} - A)}{(e^{\beta_0} - A)}$$

$$= \frac{(e^{\beta_0 + \beta_j X_j} - e^{\beta_0})}{(e^{\beta_0} - A)}$$

$$= \frac{(e^{\beta_0} e^{\beta_j X_j} - e^{\beta_0})}{(e^{\beta_0} - A)}$$

$$= \frac{e^{\beta_0} (e^{\beta_j X_j} - 1)}{Y_0}$$

$$= \frac{Y_0 + A}{Y_0} (e^{\beta_j X_j} - 1)$$

$$\frac{\Delta Y}{Y} = \left(1 + \frac{A}{Y_0}\right)(e^{\beta_j X_j} - 1) \qquad (11\text{-}5)$$

11.4 Derivation of Elasticity for Gaussian Log-Log GLM

The functional form for the Gaussian log-log model in this study is given by the following equation:

$$\ln(A + Y) = \beta_0 + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + ... + \beta_p (X_p) \qquad (11\text{-}6)$$

Where A is the constant used to make LHS positive. Taking the exponentiation on both sides,

$$A + Y = e^{\beta_0 + \beta_j \ln(X_j)}$$

$$Y = e^{\beta_0 + \beta_j \ln(X_j)} - A$$

Differentiating,

$$\frac{dY}{dX_j} = \frac{\beta_j}{X_j} \times e^{\beta_0 + \beta_j \ln(X_j)}$$

$$= \frac{\beta_j}{X_j}(A+Y)$$

$$\varepsilon_j = \frac{\beta_j}{X_j}(A+Y) \times \frac{X_j}{Y}$$

$$= \beta_j \times \left(1 + \frac{A}{Y}\right) \qquad (11\text{-}7)$$

For a dummy variable, the derivation is the same as the previous section (Equation 11-3) since the log (X_j) in the log-log model only applies to the continuous variables.

11.5 Marginal Impacts for Short Term Impacts of Incidents

This section presents the marginal analysis results for each of the variables in this category as recommended in Chapter 9. Each of the chosen models for travel time, fuel and vehicle emissions are used to explain the marginal impacts of the incident characteristics on the corresponding response variable.

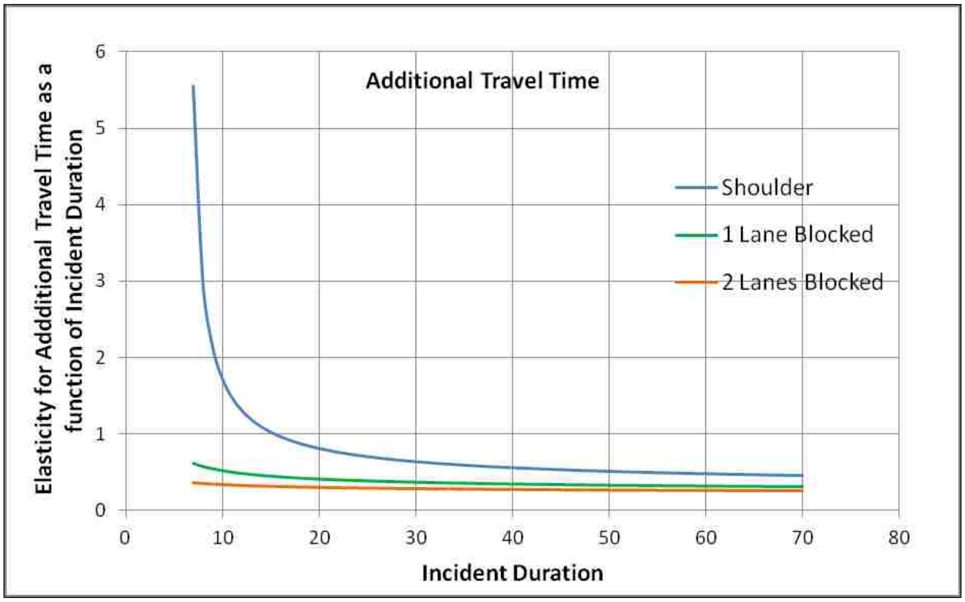
11.5.1 Additional Travel Time

The best model selected for this variable is the Gaussian Log-log model given by equation 9-1. The corresponding relationship for elasticity is given by equation 11-7. Based on the equation, the values of elasticity for different values of incident duration are plotted. Figure 11-1 (a) and (b) show the values of elasticities for different values of incident duration, with shoulder, one and two lanes blocked. The plots show that the elasticities of additional travel time are lower at higher incident durations.

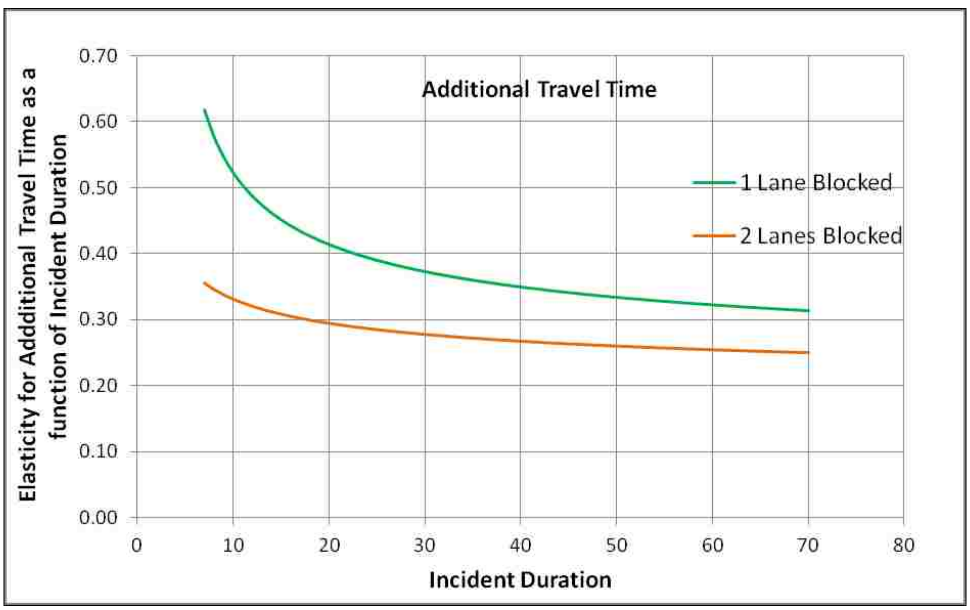
The percent change in additional travel time for different numbers of lanes blocked – shoulder, 1 and 2 lanes blocked are shown in Figure 11-2. From the figure, at a incident duration of 20 minutes, a 1 minute change in incident duration will produce 1.5% change in the additional travel time for a shoulder incident, 2.1% change in the additional travel time for an incident with 1 lane blocked and 4.2% change in the additional travel time for an incident with 2 lanes blocked.

The rate of change of additional travel time with unit change in the number of lanes blocked is shown in Figure 11-3. The ratio of the excess impacts for 1 lane blocked to the impacts for shoulder incident is given by the blue line. In the same way the rate of change of additional ravel time with increase in number of lanes blocked from zero to 2 and 1 to 2 are also calculated and shown in Figure 11-3.

Table 11-1 presents the marginal impacts of each of the incident characteristics at the average values of the predictor variables. While computing the marginal impacts of one variable, all the values of the other predictor variables are kept at the same average values. For example, for a shoulder incident, if the average incident duration of 29.35 minutes is decreased by 1 minute (a 3.41% decrease), the corresponding decrease in additional travel time per impacted vehicle is 2.2% which amounts to 0.012 minutes. Similarly for lanes blocked, if one lane is blocked instead of zero lanes, it results in a 97% increase in additional travel time corresponding to 0.57 minutes. Similarly, if two lanes are blocked it results in a 196% increase corresponding to 1.28 minutes.



(a)Shoulder, 1 lane, 2 lanes blocked



(b) 1 lane and 2 lanes blocked (zoomed)

Figure 11-1. Elasticity of Additional Travel Time as a function of Incident Duration

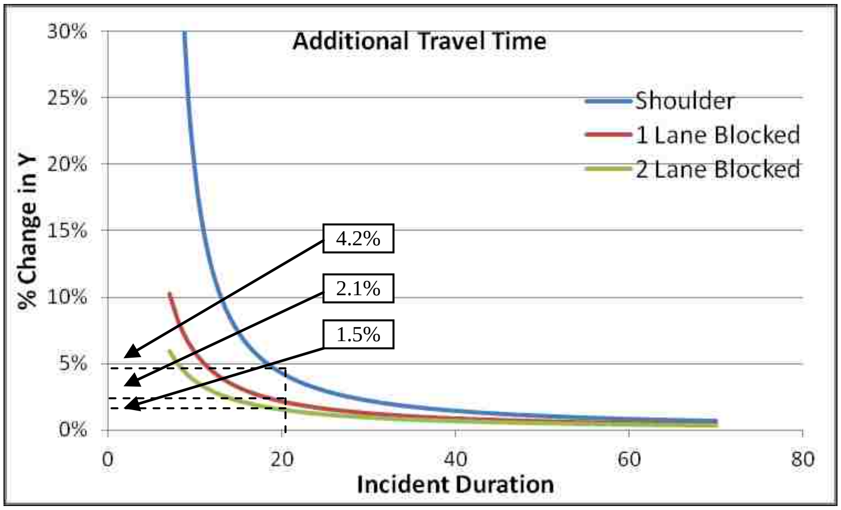


Figure 11-2. Percent Change in Additional Travel Time for unit change in Incident Duration

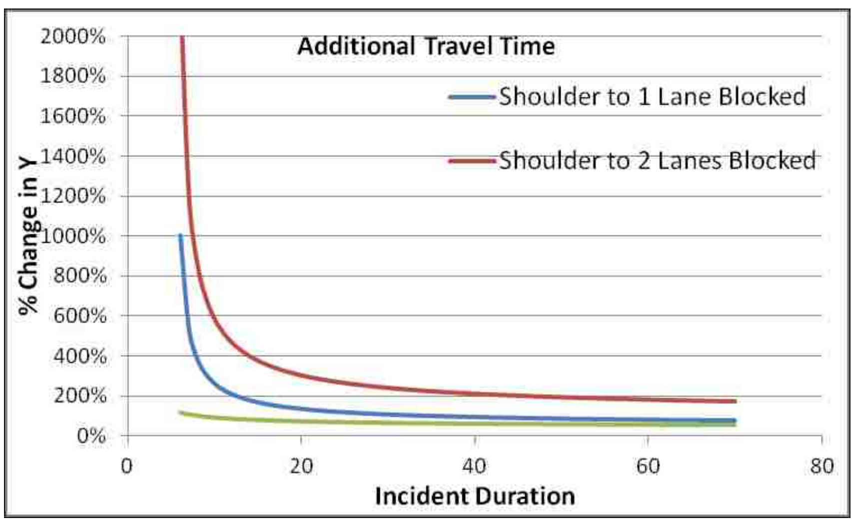


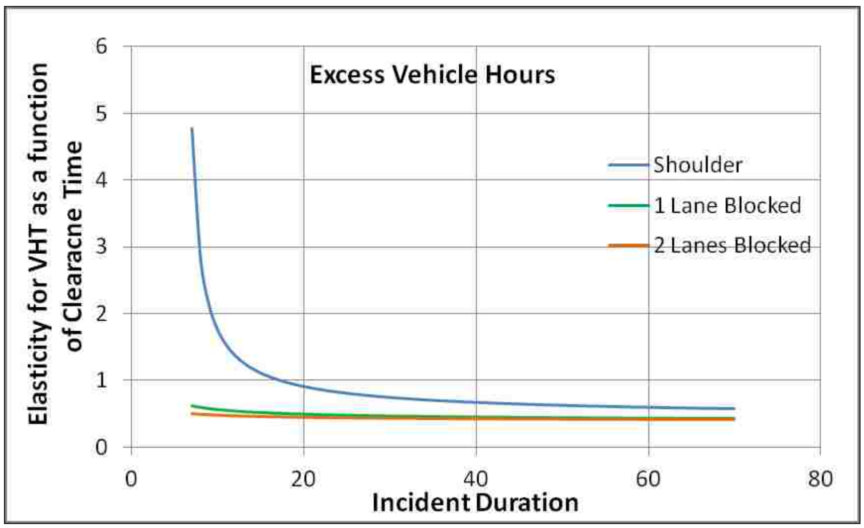
Figure 11-3. Percent Change in Additional Travel Time for unit change in Number of Lanes Blocked

Table 11-1. Marginal Impacts for Additional Travel Time

Variable	**BETA**	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ **(regression)**	$\frac{\Delta Y}{Y}\%$ **(elasticity)**	**Notes**
Intercept	-0.324							
NIDensity	0.2763	18.15		-				
ClrT	0.1334	29.35	0.53	(1.00)	-3.41%	-2.21%	-2.18%	Reduction of 1 minute of ClrT
LNSBLK1	0.2034	0	0.53	1.00	N/A	107.75%	97.17%	Change from Shoulder incident to 1 lane blocked
LNSBLK2	0.4096	0	0.53	1.00	N/A	241.83%	195.68%	Change from Shoulder incident to 2 lanes blocked

11.5.2 Excess Vehicle Hours

The best model selected for this variable is also of the Gaussian Log-log GLM model form given by equation 9-2. Using the elasticity relationship given in equation 11-7, Figure 11-4 (a and b) show the plots for the elasticites of incident duration for the model for zero, one and two lanes blocked.



(a) Shoulder, 1 lane and 2 lanes blocked

(b) 1 lane and 2 lanes blocked

Figure 11-4. Elasticity of Excess VHT as a function of Incident Duration

The percent change in excess vehicle-hours of travel for all impacted vehicles with unit change in incident duration for different numbers of lanes blocked is shown in Figure 11-5. Figure 11-6 shows the elasticity of excess VHT with respect to number of lanes blocked from shoulder to 1 lane, 1 lane to 2 lanes and shoulder to 2 lanes. When a an incident changes from having zero lanes blocked (shoulder) to having 2 lanes blocked, the impact is much higher (as can be expected) compared to the change of shoulder to 2 lanes blocked. For an incident with 2 lanes blocked instead of 1 lane, the rate of change is not as much compared to the 2 lanes instead of shoulder (about 1.5 higher than from zero to 1 lane blocked).

Table 11-2 shows the marginal impacts for the excess VHT with a change in the values of predictor variables for the average conditions. From Table 11-2, if an incident blocks one lane, it would lead to a 218.3% increase in excess VHT with an estimated increase of 95.75 veh-hours of excess VHT when compared to a shoulder incident.

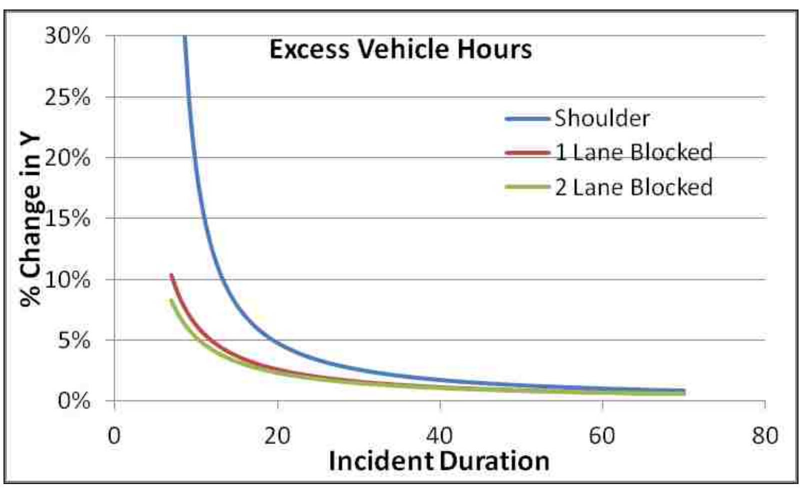


Figure 11-5. Percent Change in Excess VHT for unit change in Incident Duration

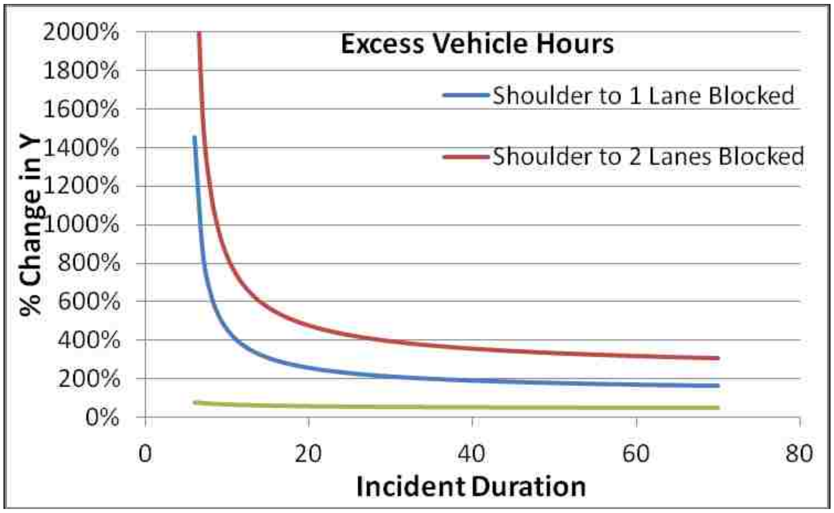


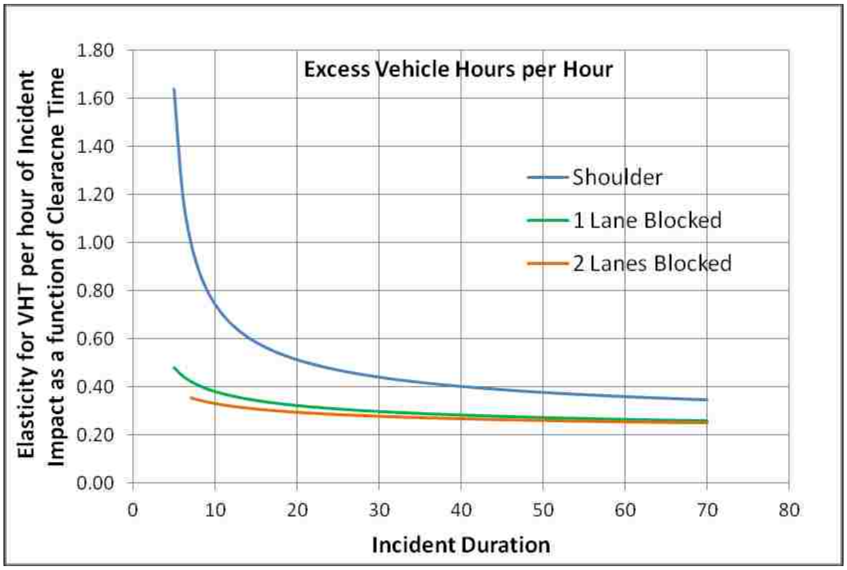
Figure 11-6. Percent Change in Excess VHT for unit change in Number of Lanes Blocked

Table 11-2. Marginal Impacts for Excess Vehicle Hours

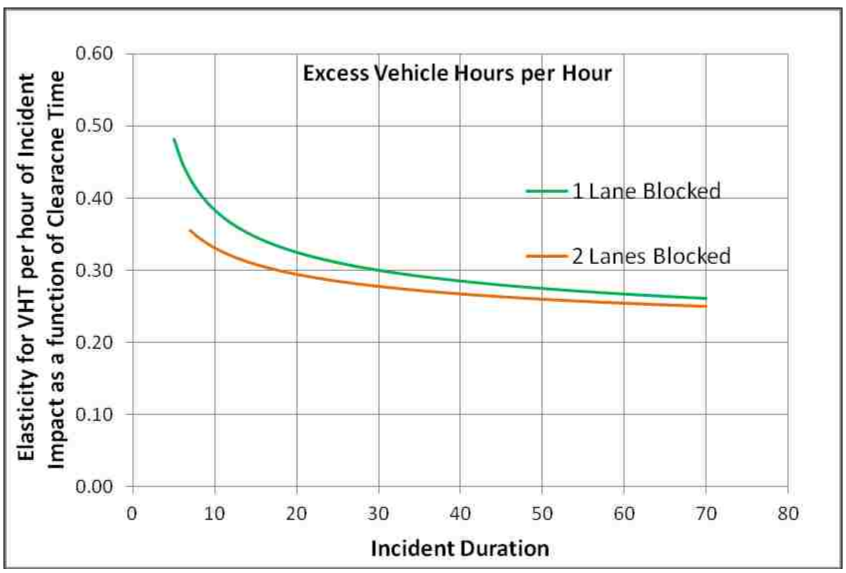
Variable	**BETA**	$\mathbf{X_0}$	$\mathbf{Y_0}$	**ΔX**	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ **(regression)**	$\frac{\Delta Y}{Y}\%$ **(elasticity)**	**Notes**
(Intercept)	1.419							
NIDensity	0.667	18.15		-				
ClrT	0.352	29.35	43.86	-1	-3.41%	-2.59%	-2.56%	Reduction of 1 minute of ClrT
LNSBLK1	0.703	0	43.86	1	N/A	218.30%	150.5%	Change from Shoulder incident to 1 lane blocked
LNSBLK2	1.050	0	43.86	1	N/A	397.58%	224.7%	Change from Shoulder incident to 2 lanes blocked

11.5.3 Excess Vehicle Hours per Hour

The best model for excess VHT per hour of incident impact is of the Gaussian log-log GLM form as presented in equation 9-3. Using the elasticity relation presented in equation 11-7, Figures 11-7 (a) and (b) show the plots for the elasticites of incident duration, for different number of lanes blocked. These are point elasticities and applicable only to small changes in incident duration. The elasticity for shoulder lane is higher when compared to 1 and 2 lanes blocked, respectively.



(a) Shoulder, 1 lane and 2 lanes blocked



(b) 1 lane and 2 lanes blocked

Figure 11-7. Elasticity for predictor variables in Excess VHT per hour of incident impact model

The percent change in excess VHT per impact hour for with 1 minute change in incident duration is shown in Figure 11-8. At an incident duration of 20 minutes the percent change in excess VHT per hour of incident impact is 2.7%, 1.7% and 1.3% for incident with shoulder, 1 lane blocked and 2 lanes blocked respectively.

For different values of number of blocked lanes, Figure 11-9 shows the corresponding percent changes in excess VHT per hour of incident impact. The trend is the same as before with the increase of number of blocked lanes from zero to two having a higher percent change than from zero to 1 and 1 to 2.

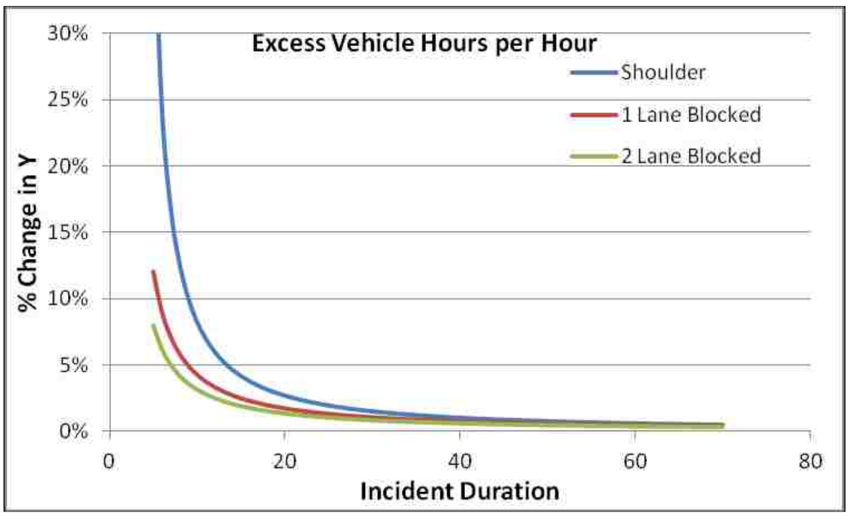


Figure 11-8. Percent Change in Excess VHT per hour of incident impact for unit change in Incident Duration

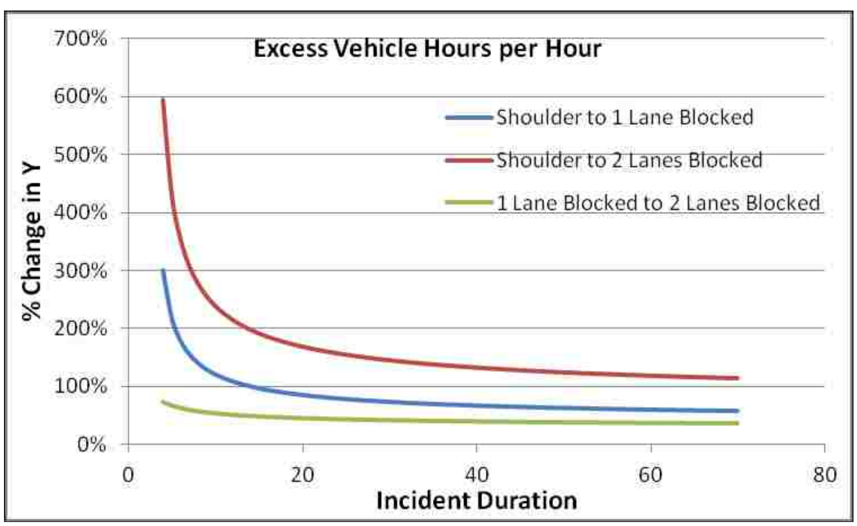


Figure 11-9. Percent Change in Excess VHT per hour of incident impact for unit change in Number of Lanes Blocked

Table 11-3 shows the marginal impacts for the excess VHT per hour of incident impact for the base scenario being the average incident conditions. If the incident duration is reduced by 1 minute under the average incident duration (29.35 minutes), it results in a 1.55% decrease in excess VHT per hour of incident impact amounting to 1.2 excess veh-hours/hr.

Table 11-3. Marginal Impacts for Excess Vehicle Hours per Hour

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (elasticity)	Notes
(Intercept)	4.538							
NIDensity	0.231	18.15		-				
ClrT	0.110	29.35	65.21	-1	-3.41%	-1.55%	-1.53%	Reduction of 1 minute of ClrT
LNSBLK1	0.168	0	65.21	1	N/A	74.58%	68.48%	Change from Shoulder incident to 1 lane blocked
LNSBLK2	0.309	0	65.21	1	N/A	147.07%	125.54%	Change from Shoulder incident to 2 lanes blocked

11.5.4 Temporal Extent

The Gaussian Single-log GLM model is the functional form (equation 9-4) selected for the temporal extent of incidents. Since this model does not use a constant, the rate of change of temporal extent with change in a variable is given just by its coefficient (β_j). From equation 11-4, if A=0, elasticity is $\beta_j X_j$. For incident duration, β_{ClrT} of 0.84% is the percent change in Y. Table 11-4 shows the marginal impacts in the values of temporal extent while only the variable under consideration is changed and the rest are held constant. If the average incident duration is reduced by 1 minute (from 29.35 minutes), temporal extent reduces by 0.84% (0.5 minutes, for 1 lane-blocked incident).

Table 11-4. Marginal Impacts for Temporal Extent

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (elasticity)	Notes
(Intercept)	3.244							
NIDensity	0.021	18.15		-				
NIVol	0.000	1,507.56		-				
ClrT	0.008	29.35	39.42	-1	-3.41%	-0.84%	-0.84%	Reduction of 1 minute of ClrT
LNSBLK1	0.537	0	39.42	1	N/A	71.09%	53.70%	Change from Shoulder incident to 1 lane blocked
LNSBLK2	0.711	0	39.42	1	N/A	103.50%	71.05%	Change from Shoulder incident to 2 lanes blocked

11.4.5 Spatial Impact

For the spatial impact model also, the Gaussian Single-log GLM model (equation 9-5) is the functional form calibrated. From equation 11-4, if A=0, elasticity is $\beta_j X_j$. For incident duration, β_{ClrT} is 1.02%. Table 11-5 gives the marginal impacts under the average incident conditions. For example, for a shoulder incident, if incident duration is decreased by 1 minute the spatial extent of incidents will be 0.88 miles (instead of 0.89 miles).

Table 11-5. Marginal Impacts for Spatial Extent

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (elasticity)	Notes
(Intercept)	-0.862							
NIDensity	0.035	18.15		-				
NIVol	0.000	1,508		-				
ClrT	0.010	29.35	0.89	-1	-3.41%	-1.01%	-1.02%	Reduction of 1 minute of ClrT
LNSBLK1	0.729	0	0.89	1	N/A	107.22%	72.86%	Change from Shoulder incident to 1 lane blocked
LNSBLK2	0.802	0	0.89	1	N/A	123.09%	80.24%	Change from Shoulder incident to 2 lanes blocked

11.4.6 Fuel Consumption

The model with the best fit for excess fuel consumption during an incident is the Gaussian Single-log model in equation 9-6. Using the elasticity relation in equation 11-4, Figure 11-10 presents the elasticities for different average lane-minutes of blockage. The plot shows that for higher values of lane-minutes of blockage, the elasticity is higher.

Figure 11-11 shows the percent change in excess fuel consumption with 1 lane-minute change in lane-minutes of blockage. This also shows higher rate of excess fuel consumption for higher values of lane-minutes of blockage, which suggests that, by reducing high incident durations (therefore reducing, lane-minutes), more fuel savings are generated. The marginal impacts of the incident-related predictor variables (in this case, only lane-minutes of blockage) for the average incident conditions are presented in the following Table 11-6. If, from the average conditions, lane-minutes of blockage is decreased by 1 lane-minute, the corresponding decrease in excess fuel consumed is 1.82% (0.88 gallons).

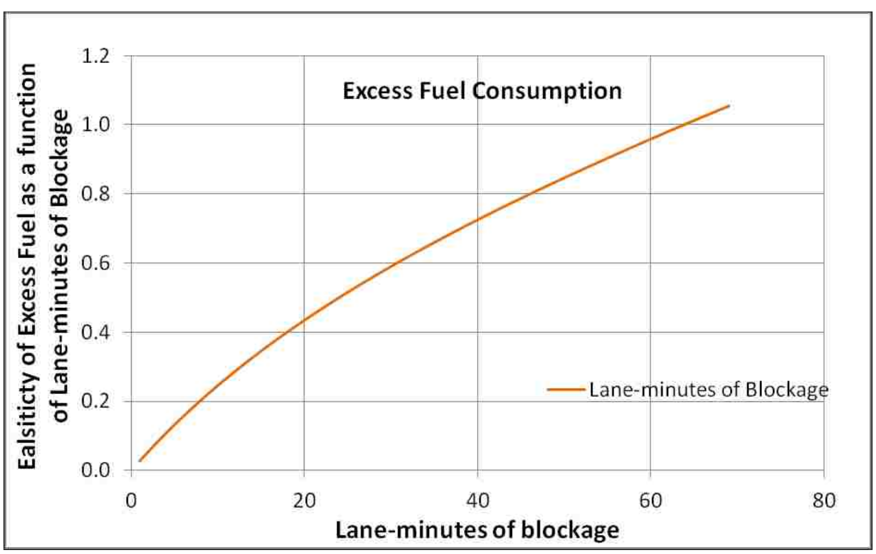


Figure 11-10. Elasticity for Lane-Minutes of Blockage in Excess Fuel Consumption

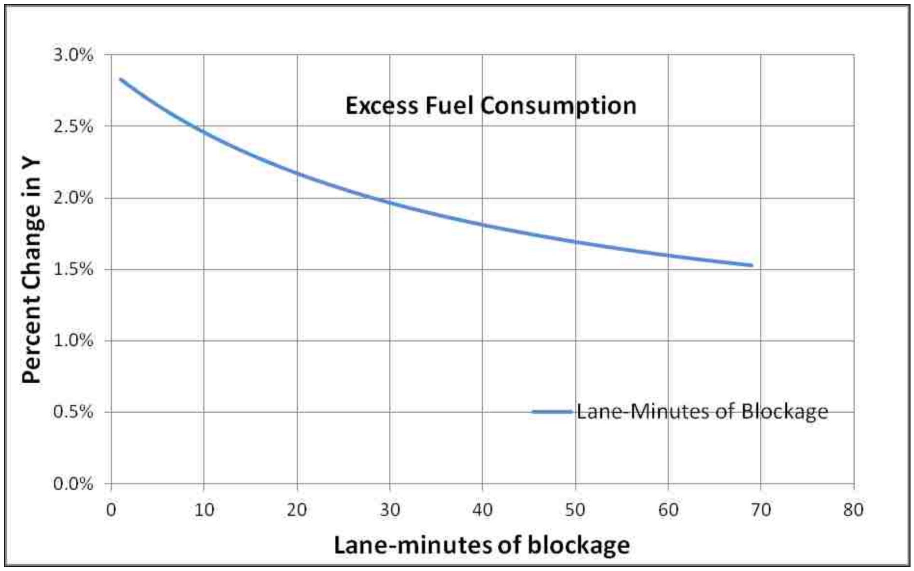


Figure 11-11. Percent Change in Excess Fuel Consumption for unit change in Lane-Minutes of Blockage

Table 11-6. Marginal Impacts for Excess Fuel Consumption

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (elasticity)	Notes
(Intercept)	3.36649							
BlkLnMin	0.010554	38.77	48.38	-1	-2.58%	-1.81%	-1.82%	Reduction of 1 lane-minute of BlkLnMin
NIDensity	0.036113	17.94	48.38					

11.5.7 Carbon dioxide (CO_2) Emissions

Excess CO_2 emissions are scaled to metric tons for this analysis. The model recommended for CO_2 is the Gaussian Single-log GLM model shown in equation 9-7. Using the elasticity formula from equation 11-4, Figure 11-12 presents the various values of elasticity for different lane-minutes of blockage. Presented in Figure 11-13 are the percent changes in CO_2 emissions for 1 lane-minute change.

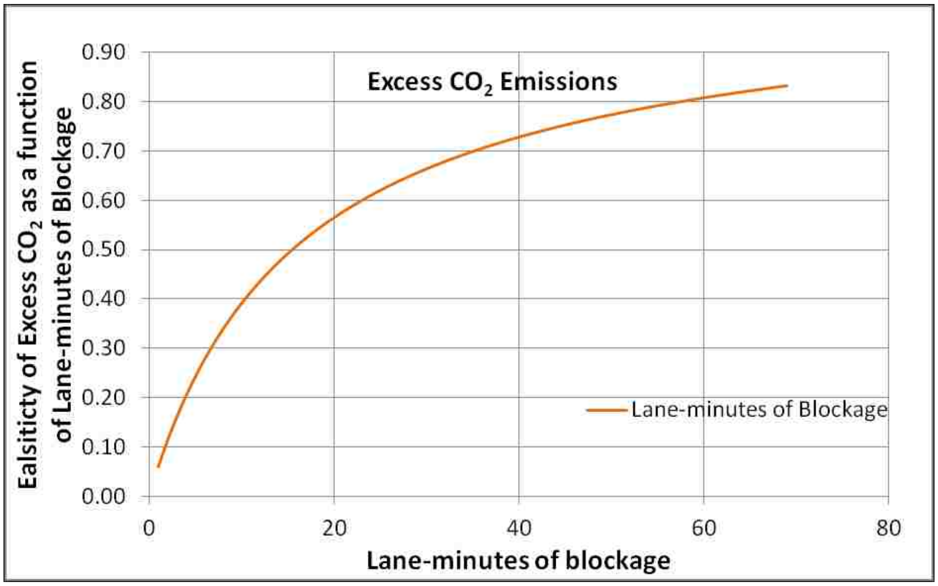


Figure 11-12. Elasticity for Lane-Minutes of Blockage in Excess CO_2 Emissions

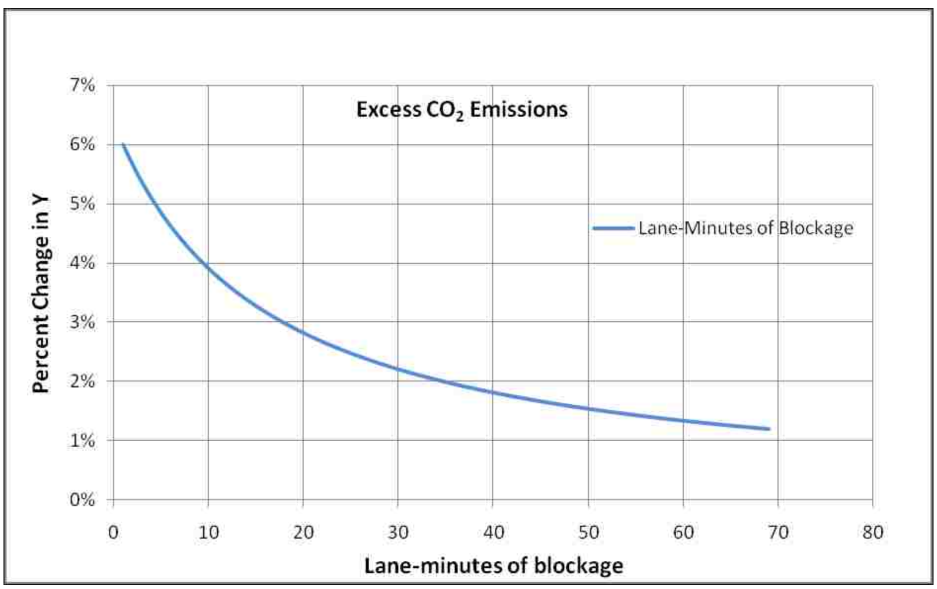


Figure 11-13. Percent Change in Excess CO_2 Emissions for unit change in Lane-Minutes of Blockage

The percent change of CO_2 emissions are higher for higher lane-minutes of blockage showing that CO_2 emissions can be reduced at a bigger scale by reducing high incident durations. The marginal impacts are presented in Table 11-7. With the use of mean incident characteristics, decreasing the lane-minutes of blockage by 1 lane-minute results in reduction of CO_2 emissions by 1.86% (0.015 Tons).

Table 11-7. Marginal Impacts for Excess CO_2 Emissions

Variable	**BETA**	$\mathbf{X_0}$	$\mathbf{Y_0}$	$\mathbf{\Delta X}$	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ **(regression)**	$\frac{\Delta Y}{Y}\%$ **(elasticity)**	**Notes**
(Intercept)	3.38							
NIDensity	0.00146	17.94	0.83					
BlkLnMin	0.00050	38.77	0.83	-1	-2.58%	-1.86%	-1.86%	Reduction of 1 lane-minute of BlkLnMin

11.4.8 Carbon monoxide (CO) Emissions

Excess CO emissions also has the Gaussian Single-log model form (equation 9-8). Figure 11-14 presents the various values of elasticity for different values of lane-minutes of blockage. Figure 11-15 gives the percent change in excess CO emissions for changes in lane-minutes of blockage by 1 lane-minute. The trend is similar to CO_2 emissions with higher percent changes in CO excess for high lane-minutes of blockage.

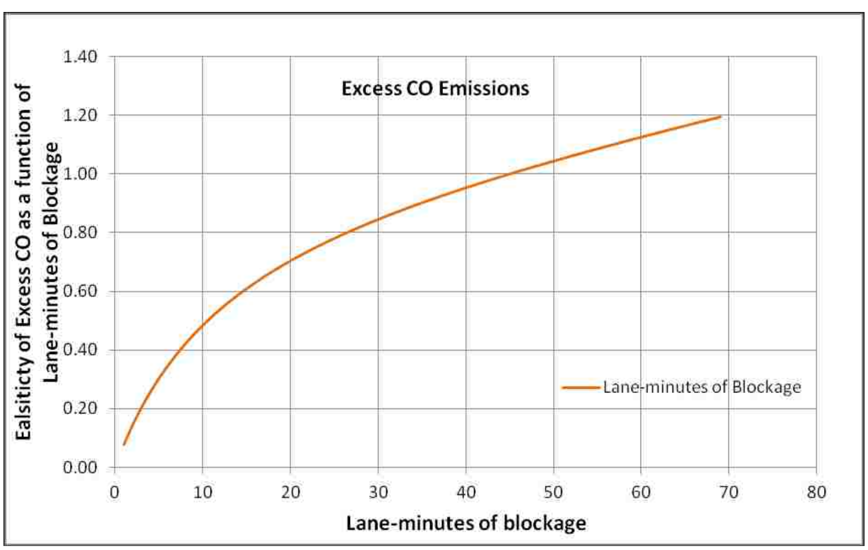


Figure 11-14. Elasticity for Lane-Minutes of Blockage in Excess CO Emissions

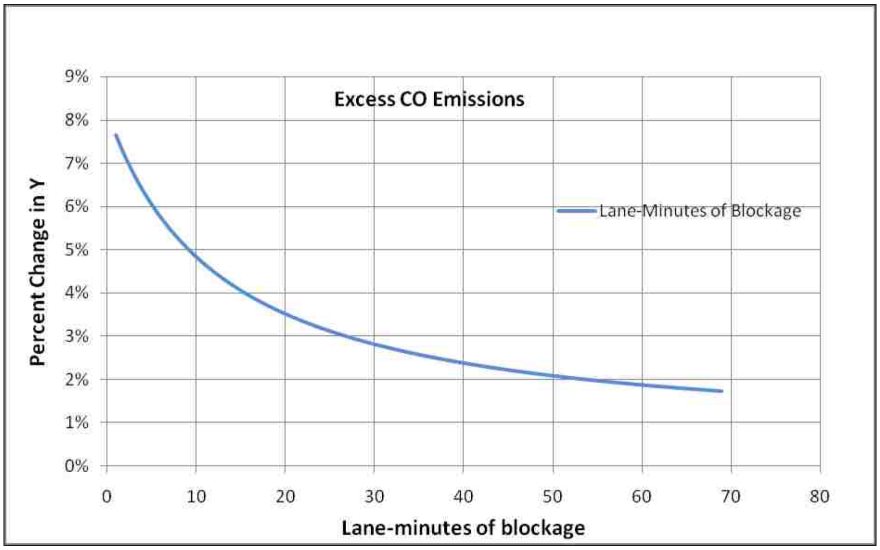


Figure 11-15. Percent Change in Excess CO Emissions for unit change in Lane-Minutes of Blockage

The marginal impact of lane-minutes of blockage is shown in Table 11-8. If lane-minutes of blockage is decreased by 1 lane-minute from the average conditions, the corresponding decrease in excess CO emissions is 2.41% amounting to 43 grams.

Table 11-8. Marginal Impacts for CO

Variable	**BETA**	**X_0**	**Y_0**	**ΔX**	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ **(regression)**	$\frac{\Delta Y}{Y}\%$ **(elasticity)**	**Notes**
(Intercept)	0.511946							
NIDensity	0.039209	17.94						
BlkLnMin	0.009008	38.77	1.78	-1	-2.58%	-2.41%	-2.42%	Reduction of 1 lane-minute of BlkLnMin

11.5.9 Oxides of Nitrogen (NO_x) Emissions

Using the Gaussian Single-log model shown in equation 9-9 and the elasticity formula from equation 11-4, the values of elaticities are plotted. Figure 11-16 shows the elasticity of lane-minutes of blockage for the NO_x model. Figure 11-17 shows the percent change in NO_x emissions with 1 lane-minute changes in lane-minutes of blockage.

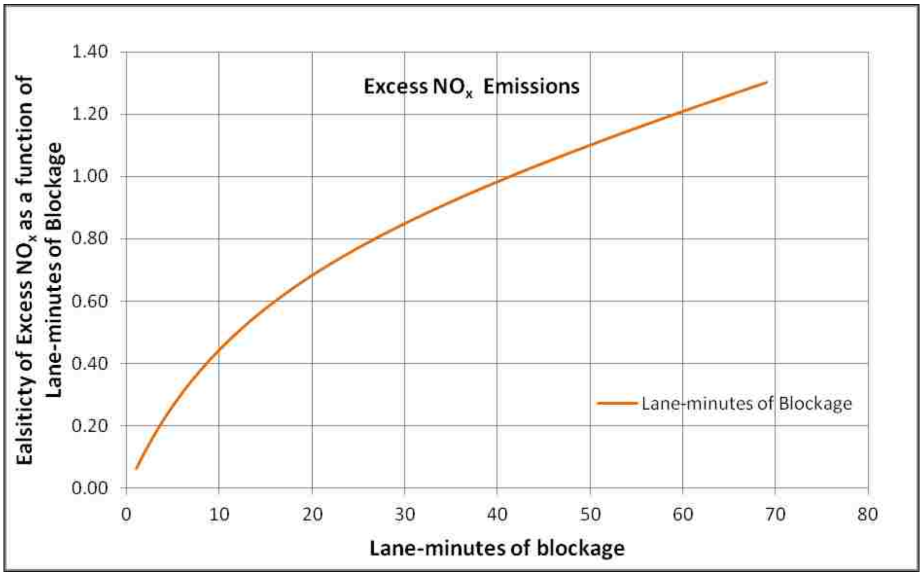


Figure 11-16. Elasticity for Lane-Minutes of Blockage in Excess NO_x Emissions

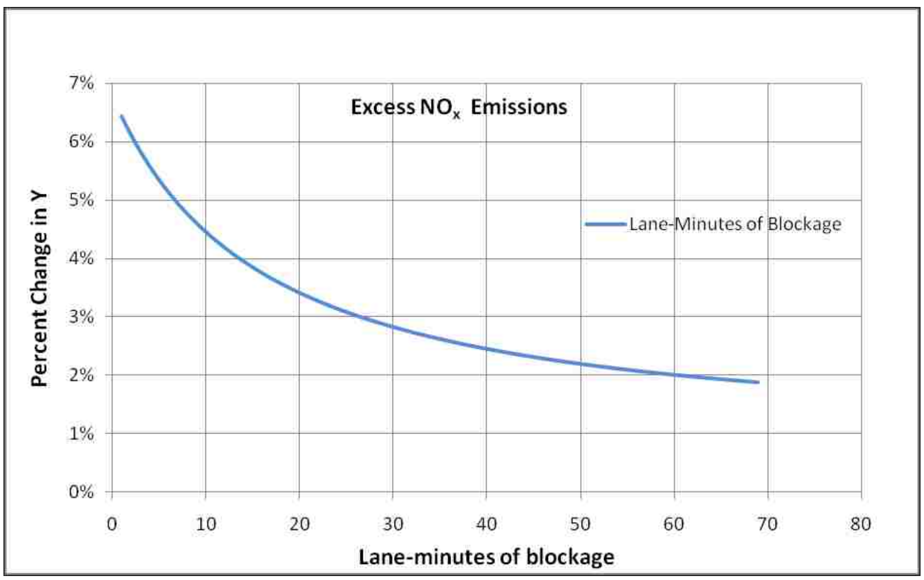


Figure 11-17. Percent Change in Excess NO_x Emissions for unit change in Lane-Minutes of Blockage

Table 11-9 shows the marginal impact of the incident-related predictor variable, lane-minutes of blockage. From Table 11-9, if lane-minutes of blockage is decreased by 1 lane-minute, the corresponding decrease in excess NO_x emissions is 2.47% (5.8 grams of reduction for the base scenario using average incident characteristics).

Table 11-9. Marginal Impacts for Excess NO_x Emissions

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (elasticity)	Notes
(Intercept)	5.03591							
NIDensity	0.038019	17.94		-				
BlkLnMin	0.012057	38.77	235.57	-1	-2.58%	-2.47%	-2.49%	Reduction of 1 lane-minute of BlkLnMin

11.5.10 Particulate matter (PM_{10})

The model for estimating excess PM_{10} emissions in grams is also the Gaussian Single-log GLM (equation 9-10). The elasticity plot (Figure 11-18), percent change plot (Figure 11-19) and the marginal impacts (Table 11-10) are presented subsequently.

For lane-minutes of blockage, a unit decrease (2.58%) causes a 30.2% decrease in excess PM_{10} emissions (0.34 grams) as shown in Table 11-10, which presents the marginal impacts under average incident conditions.

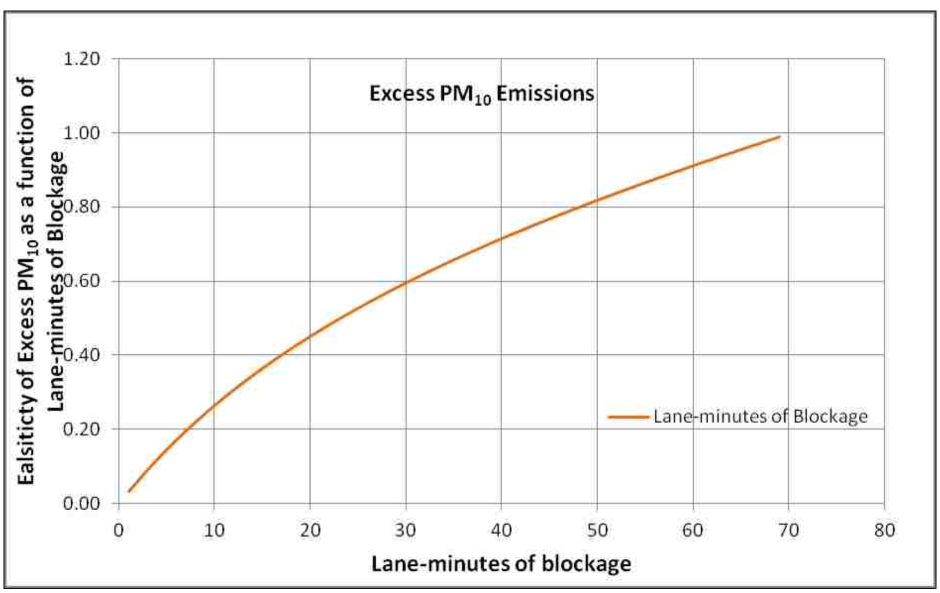


Figure 11-18. Elasticity for Lane-Minutes of Blockage in Excess PM_{10} Emissions

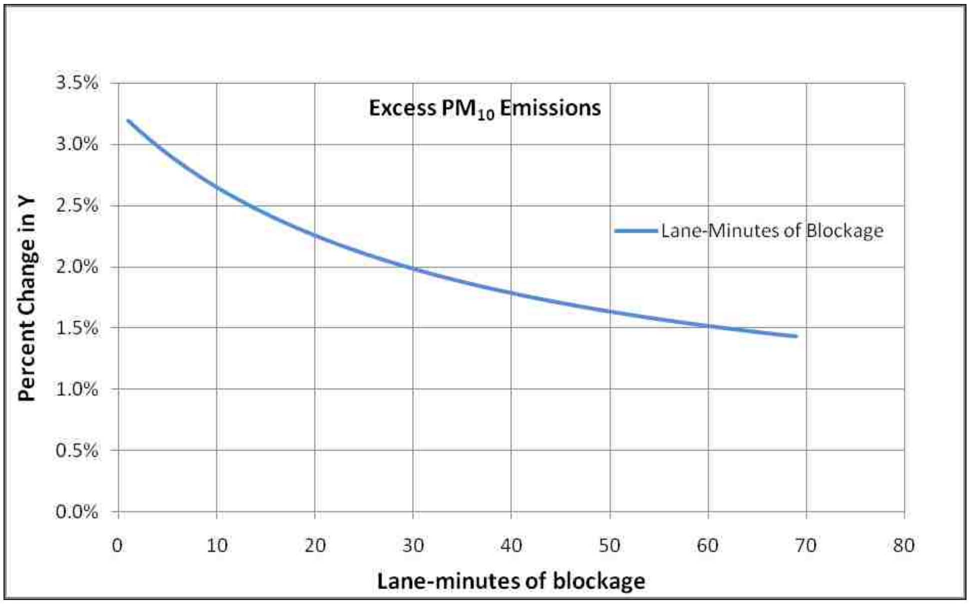


Figure 11-19. Percent Change in Excess PM_{10} Emissions for unit change in Lane-Minutes of Blockage

Table 11-10. Marginal Impacts for PM_{10}

Variable	**BETA**	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ **(regression)**	$\frac{\Delta Y}{Y}\%$ **(elasticity)**	**Notes**
(Intercept)	3.399096							
Weekday	0.293358	-	11.19	-				
BlkLnMin	0.008231	38.77	11.19	-1	-2.58%	-3.02%	-3.03%	Reduction of 1 lane-minute of BlkLnMin

11.6 Use of the Calibrated Models

The impacts of an average incident with one lane blocked are given in Table 11-11. Also tabulated are the corresponding marginal impacts when the incident duration is altered by one minute. Table 11-12 provides a comparison of average impacts with those reported by other studies. Incident impacts reviewed from different studies for VHT, Fuel and the different emissions are tabulated. For emissions, the rate per mile comparison is shown. To be noted is that the assumptions and characteristics for each study are different.

Table 11-11. Impacts for a 1-lane incident - Average and Marginal (for 1 minute change in incident duration)

Impact	**Average Impacts**	**Marginal Impacts**	**Units**
Additional Travel Time	1.10	0.01	Minutes
Excess Vehicle Hours	139.61	2.30	Vehicle-Hours
Excess Vehicle Hours per Hour of Incident Impact	113.84	1.20	Vehicle-Hours/Hour
Temporal Extent	67.44	0.57	Minutes
Spatial Extent	1.85	0.02	Miles
Excess Fuel Consumption	48.38	0.88	Gallons
Excess CO_2 Emissions	832.02	15.47	Kilograms
Excess CO Emissions	1.78	0.04	Kilograms
Excess NO_x Emissions	235.57	5.82	Grams
Excess PM_{10} Emissions	25.23	0.34	Grams

Table 11-12. Comparison of Average Incident Impacts

				Emission Factors (gallons/ grams per mi)					**Impact per incident**					
	Study	**Location**	**Year**	**Fuel**	**CO_2**	**CO**	**NO_x**	**PM_{10}**	**Delay (veh-hours)**	**Fuel (gal)**	**CO_2 (Kg)**	**CO (Kg)**	**NO_x (g)**	**PM_{10} (g)**
1	Skabardonis et. al.	Orange County	1997						157					
2	Wang, Cheevarunothai	Washington	2008						173					
3	Kripalani, Scherer	Virginia	2007						64					
4	Thomas, Jacko	Indiana	2011						630			127	9	
5	Hagen et al	Florida	2005						52	79				
6	Chung, Cho, Choi	Orange County	2013								398			
7	Barth et. al.	Riverside	1999			1.0	0.40							
8	Bigazzi, Figliozzi	Oregon	2011		375	2.0	1.00							
9	Rakha et. al.	Michigan	2004		300	3.0	0.50							
10	California Air Resource Board	California	2013	Similar										
11	Chiang et. al.	Taiwan	2007			1.2	0.45	0.03						
12	Chiang , Huang	Taiwan	2009					0.01						
	Current Study				**356**	**1.3**	**0.34**	**0.01**	**140**	**48**	**832**	**2**	**236**	**25**

The calibrated models can be of use to transportation agencies during project evaluation for incident management strategies. For example, if a proposed incident management strategy is expected to result in 5-minute reduction of incident duration, the savings from marginal impacts of the calibrated models are presented in Table 11-13.

Table 11-13. Savings in Marginal Impacts for Sample Proposed Incident Management Project with 5 min reduction in incident duration

Impact	Savings	Unit
Additional Travel Time	0.07	Minutes
Excess Vehicle Hours	11.49	Vehicle-Hours
Excess Vehicle Hours per Hour of Incident Impact	5.98	Vehicle-Hours/Hour
Temporal Extent	2.83	Minutes
Spatial Extent	0.09	Miles
Excess Fuel Consumption	4.38	Gallons
Excess CO_2 Emissions	77.34	Kilograms
Excess CO Emissions	0.21	Kilograms
Excess NO_x Emissions	29.10	Grams
Excess PM_{10} Emissions	1.69	Grams

For savings in terms of monetary purposes, a value of $16.79 for every hour of excess VHT is used from the Texas Transportation Institute's Urban Mobility Report (Shrank, Lomax & Eisele, 2012). Therefore, from Table 11-12, the proposed reduction of incident duration by 5 minutes from the average results in an estimated 11.49 vehicle-hours of delay or $192.86 in VHT savings for one incident.

Similarly, if a fuel pricing of $3.24 per gallon (American Automobile Association, 2011) is used, the proposed project will result in 4.38 gallons or $14.18 in fuel savings per incident.

11.7 Summary

This chapter presents the analysis of the marginal impacts for the calibrated for short term impacts. These marginal impacts are presented in a form that can be used by agencies to see the effect of an incident management strategy that reduces the incident duration by a certain number of minutes.

CHAPTER 12

MARGINAL IMPACTS AND DISCUSSION OF RESULTS FOR LONG TERM ANALYSIS

12.1 Introduction

In this chapter, the marginal impacts for the TTR measures are presented. The models are: 95th percentile travel time, buffer time and buffer index for mixed data alone and difference in 95th percentile travel times, difference in buffer times, difference in buffer indices. It is to be noted that these TTR measures quantify variability in travel times. Therefore, a decrease in the TTR measures used in this study indicates improved travel time reliability.

12.2 Marginal Impacts for Long Term Impacts of Incidents

12.2.1 The 95th Percentile Travel Time for Mixed Data

The Gaussian Single-log model is found to be the best fit for the 95th percentile travel time for mixed data given in equation 10-1. For Gaussian Single-log model with no constant in equation 11-4, a percent change in X_j causes $X_j * \beta_j$ % change in Y. Using this for 95th percentile travel time (mixed), the elasticity measurements under average incident conditions are

i. decreasing average lane-minutes of blockage by 1 minute will cause a 0.9% decrease;

ii. decreased the rate of incidents in the previous hour by 1% will cause a 0.882% decrease

The marginal impacts of the predictor variables are shown in Table 12-1. Under average incident conditions, if the average lane-minutes of blockage is decreased by 1 lane-minute, one would need to plan for 0.9% of 10 minutes, which translates to a savings of 0.9 minutes of planned travel time.

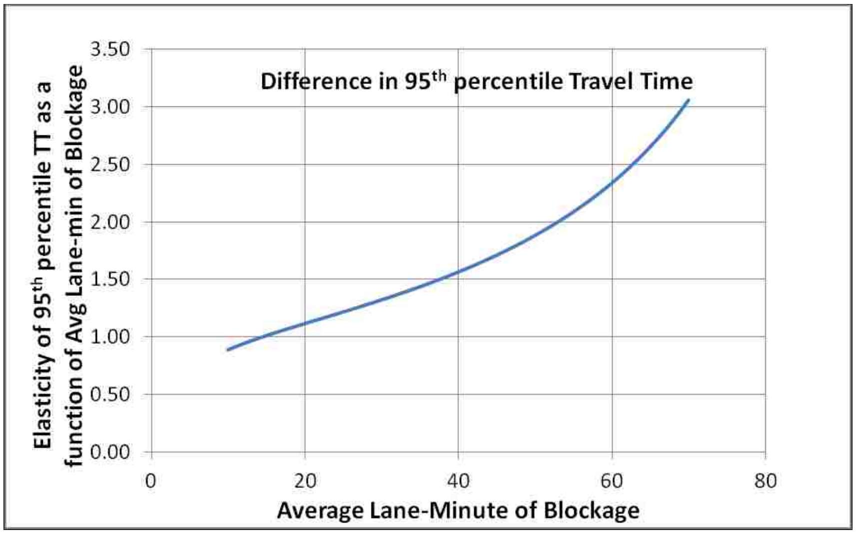
Table 12-1. Marginal Impacts for 95th percentile TT - Mixed

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (formula)	Notes
(Intercept)	2.045							
AvgLnMin	0.009	12.06	9.67	-1	-8.29%	-0.90%	-0.91%	Reduction of 1 lane-minute of AvgLnMin
IncRatePrvHr	0.009	13.03	9.67	-1	-7.67%	-0.88%	-0.88%	Reduction of 1% of incident rate in previous hour

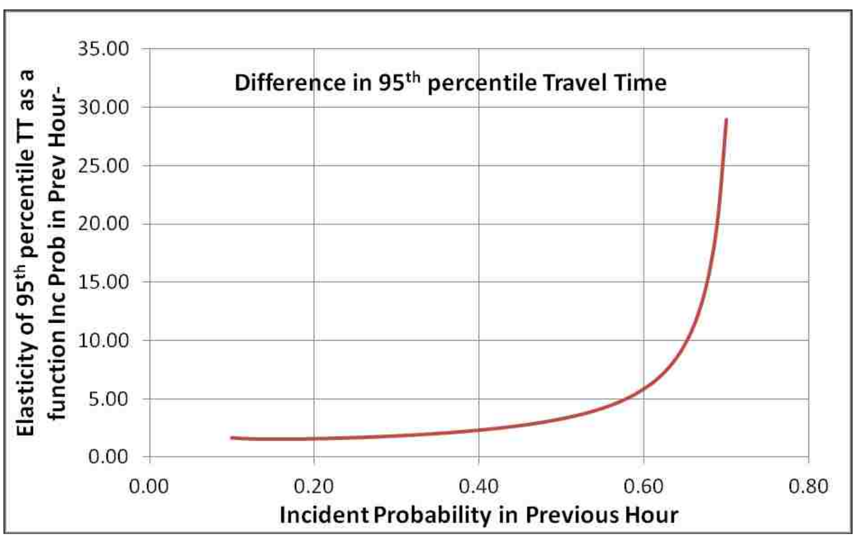
12.2.2 Difference in 95th percentile Travel Time

The Gamma GLM model provides the best fit for the difference in 95th percentile travel time response variable given in equation 10-2. For the Gamma GLM, using the elasticity formula in equation 11-2, elasticities are plotted for different values of X. Figures 12-1 (a) and (b) give the elasticity plots for average lane-minutes of blockage and rate of incidents in the previous hour (probability). For lane-minutes of 10 minutes and over, the elasticity (percent change in Y with small percent change in X) increases with increase in X.

The percent changes in the difference of 95th percentile travel time with unit increase in average lane-minutes of blockage and rate of incidents in the previous hour (probability) are shown in Figure 12-2 (a) and (b). For very high incident durations, the rate of savings in difference of 95th percentile is not as high as that for lower incident durations. The marginal impact of the predictor variables are shown in the following table (Table 12-2). If the average lane-minutes of blockage is decreased by 1 minute from the average conditions overall, the 95th percentile TT (difference) is decreased by 7.75% (0.025 minutes). Therefore if there was an incident, one needs plan 0.025 minutes lesser than what he/she would have ordinarily, due to the reduction in the overall average lane-minutes of blockage for the incident. Contrarily, if the overall percentage of incidents in the segment is reduced by 1, the driver needs to plan 0.04 (11.8%) minutes lesser during an incident.

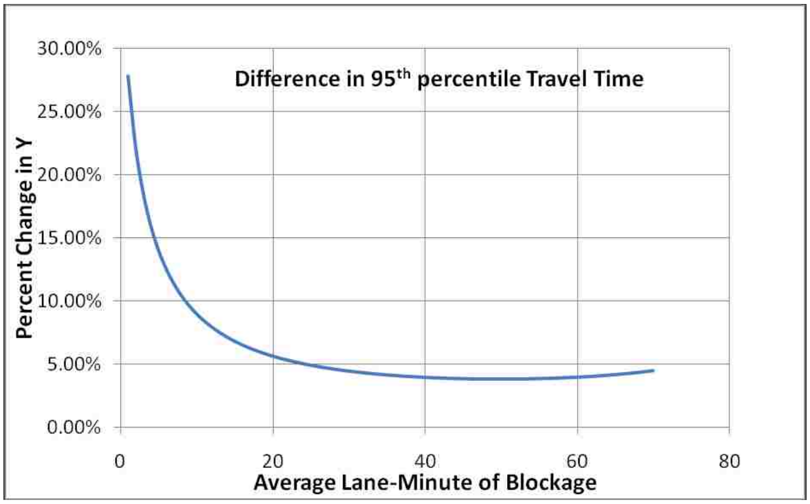


(a) Average Lane-minutes of Blockage

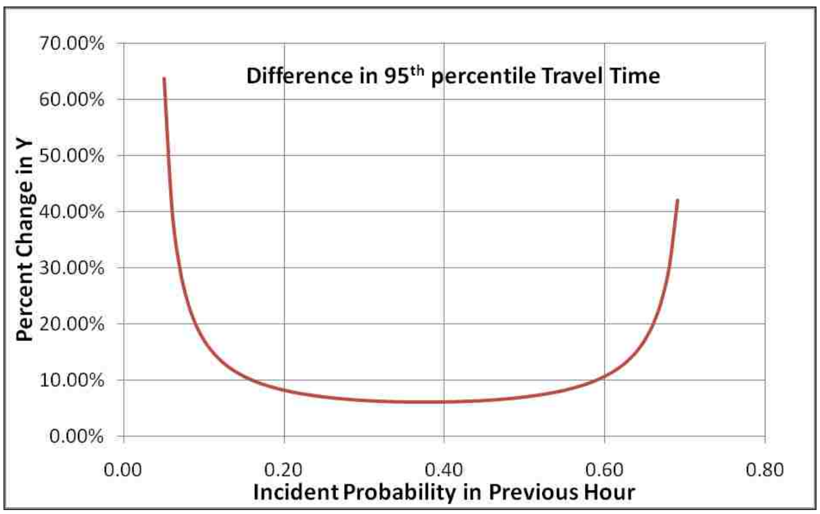


(b) Probability of Incidents in Previous Hour

Figure 12-1. Elasticities of Incident Characteristics for Difference in 95th Percentile Travel Time



(a) Average Lane-minutes of Blockage



(b) Probability of Incidents in Previous Hour

Figure 12-2. Percent Change in Difference in 95th percentile Travel Time with unit change in Incident Characteristics

Table 12-2. Marginal Impacts for 95th percentile TT - Difference

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (formula)	Notes
(Intercept)	2.581206							
AvgLnMin	-0.00471	12.06	0.32	(1.00)	-8.29%	-7.75%	-7.84%	Reduction of 1 lane-minute of AvgLnMin
IncRatePrvHr	-0.00723	13.03	0.32	(1.00)	-7.67%	-11.83%	-12.03%	Reduction of 1% of incident rate
NISpeed	-0.02519	58.91	0.32	-				
NIVolume	-0.00039	1,318	0.32	-				

12.2.3 Buffer Time for Mixed Data

Similar to the 95th percentile travel time for mixed data, the Gaussian Single-log model is the best fit for the Buffer Time reliability measure for mixed data (equation 10-3). The elasticity measurements using elasticity from equation 11-4 (with A = 0) are:

i. decreasing average lane-minutes of blockage by 1 minute will cause a 3.58% decrease in mixed buffer time

ii. decreased the rate of incidents in the previous hour by 1% will cause a 2.61% decrease in mixed buffer time

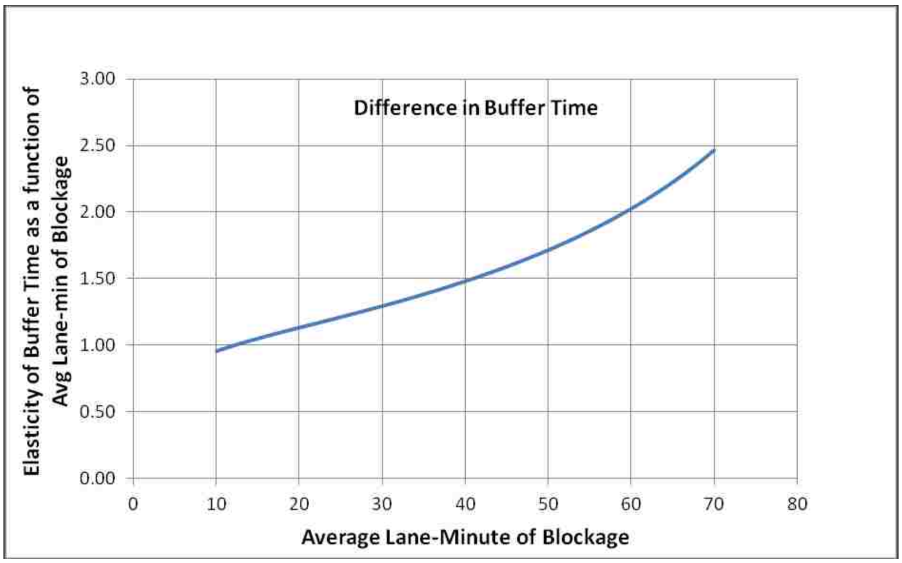
The marginal impacts of the predictor variables are shown in the following table (Table 12-3). So, if the rate of incidents in the previous hour is decreased by 1% overall (probability of incidents is reduced by 0.01), the mixed buffer time is decreased by 2.57% (0.003 minutes, with the base scenario being average incident and traffic characteristics).

Table 12-3. Marginal Impacts for Buffer Time - Mixed

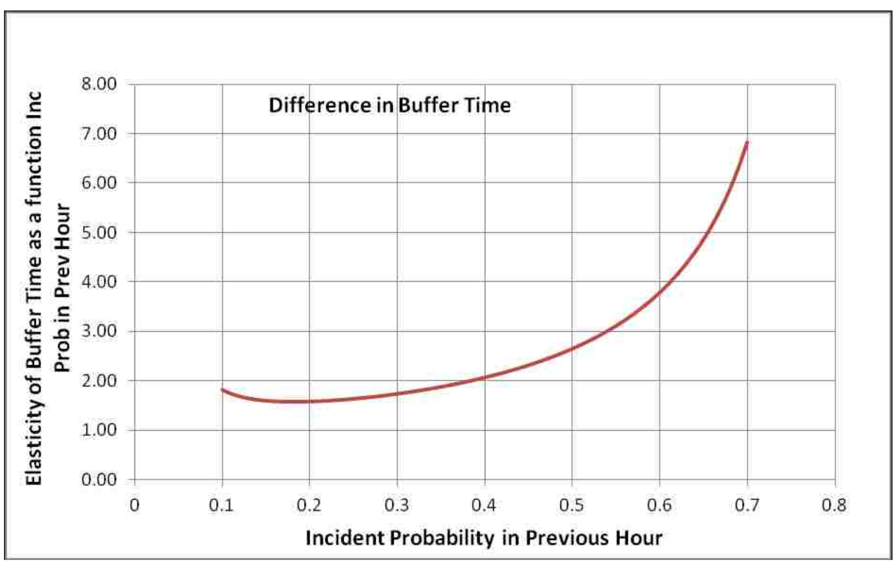
Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (formula)	Notes
(Intercept)	-3.00209							
AvgLnMin	0.03583	12.06	0.11	-1	-8.29%	-3.52%	-3.58%	Reduction of 1 lane-minute of AvgLnMin
IncRatePrvHr	0.02607	13.03	0.11	-1	-7.67%	-2.57%	-2.61%	Reduction of 1% of incident rate in previous hour

12.2.4 Difference in Buffer Time

The Gamma GLM model is selected for the difference in Buffer time TTR measure (equation 10-4). Figures 12-3 (a) and (b) give the elasticity plots for average lane-minutes of blockage and the incident rate in previous hour with a range of X values using equation 11-2. Once again, the elasticity values increase for higher values of the incident characteristics. The percent changes of difference in buffer time for unit changes in the incident characteristics are plotted in Figures 12-4 (a) and (b). The percent changes in buffer time (difference) decrease with increase in lane-minutes of blockage and rate (probability) of incidents.

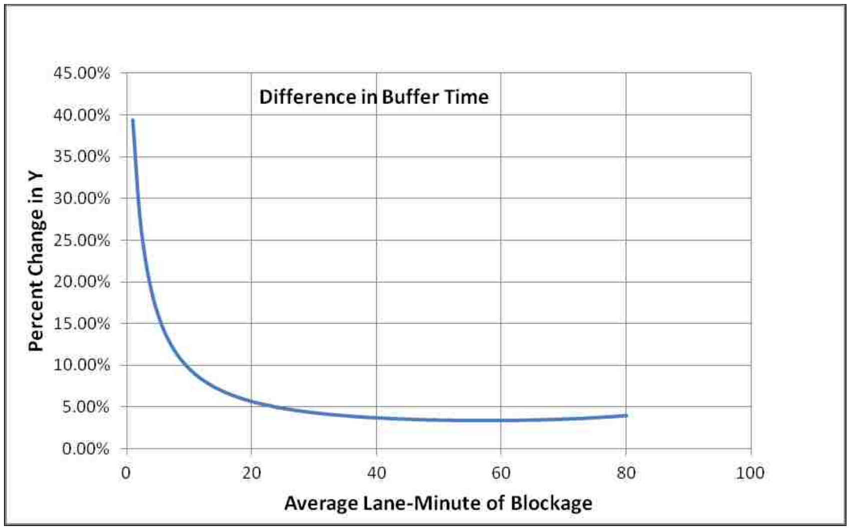


(a) Average Lane-minutes of Blockage

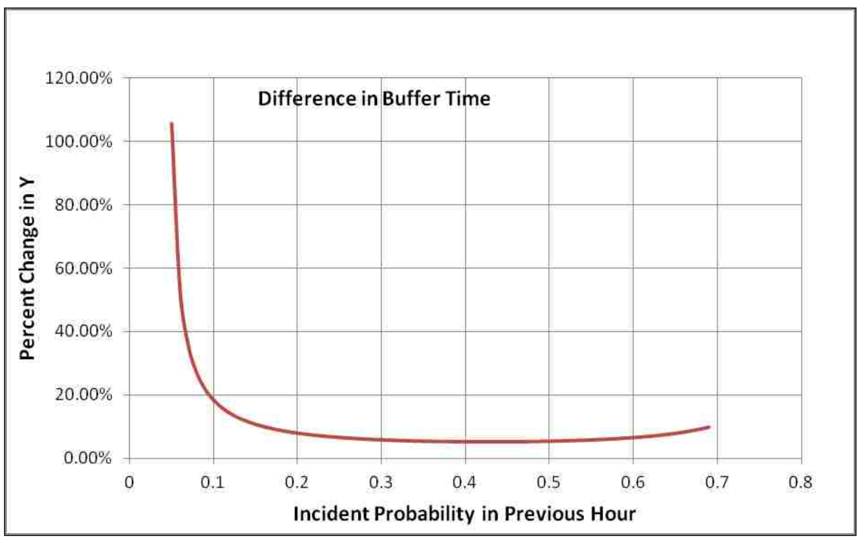


(b) Probability of Incidents in Previous Hour

Figure 12-3. Elasticities of Incident Characteristics for Difference in Buffer Time



(a) Average Lane-minutes of Blockage



(b) Probability of Incidents in Previous Hour

Figure 12-4. Percent Change in Difference in Buffer Time with unit change in Incident Characteristics

The marginal impact of the predictor variables are shown in the Table 12-4. If the rate of incidents in the previous hour is reduced by 1% from the average conditions (the probability is reduced by 0.01), the Buffer Time (difference) is decreased by 12.3 % (0.021 minutes).

Table 12-4. Marginal Impacts for Buffer Time - Difference

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (formula)	Notes
(Intercept)	2.3436							
AvgLnMin	-0.00421	12.06	0.26	-1	-8.29%	-8.18%	-8.26%	Reduction of 1 lane-minute of AvgLnMin
IncRatePrvHr	-0.0064	13.03	0.26	-1	-7.67%	-12.37%	-12.55%	Reduction of 1% of incident rate
NISpeed	-0.02245	58.91	0.26	-				
NIVolume	-0.00034	1,318	0.26	-				

12.2.5 Buffer Index for Mixed Data

The Buffer Index for mixed data is also of the Gaussian Single-log GLM form (equation 10-5). The elasticity measurements using equation 11-4 for Gaussian Single-log (with A=0) are:

i. decreasing average lane-minutes of blockage by 1 minute will cause a 4.09% decrease;

ii. decreased the rate of incidents in the previous hour by 1% will cause a 3.1% decrease

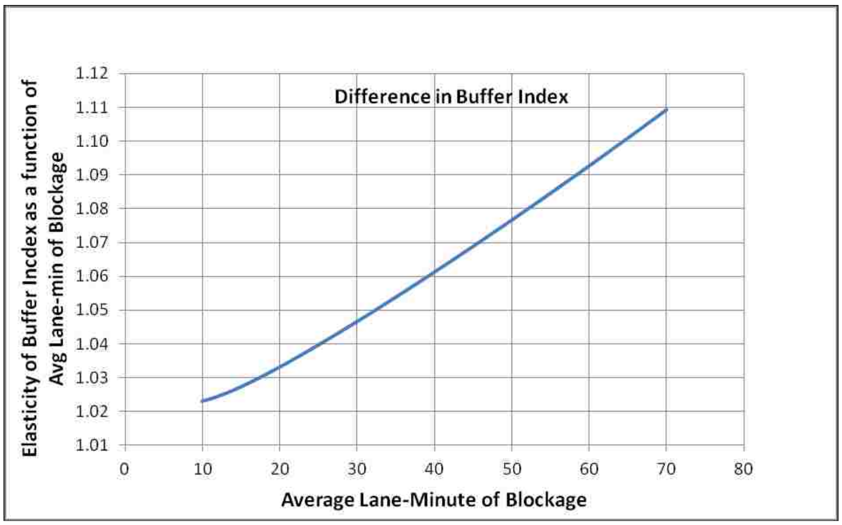
Table 12-5 shows the marginal impacts for average incident conditions. From Table 12-5, if average lane-minutes of blockage is decreased by 1 minute, the buffer index (mixed) is decreased by 0.04 (with the base scenario being average incident and traffic characteristics).

Table 12-5. Marginal Impacts for Buffer Index - Mixed

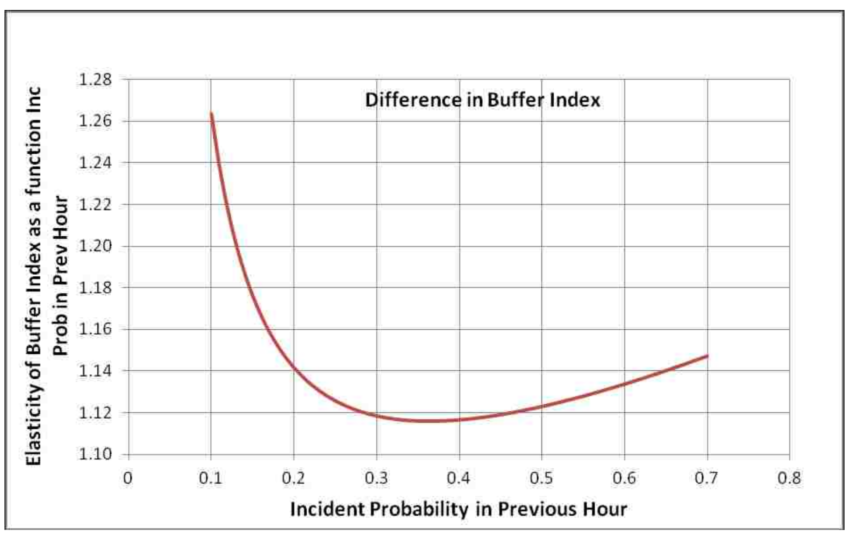
Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (formula)	Notes
(Intercept)	-0.99912							
AvgLnMin	0.04093	12.06	0.90	-1	-8.29%	-4.01%	-4.09%	Reduction of 1 lane-minute of AvgLnMin
IncRatePrvHr	0.03099	13.03	0.90	-1	-7.67%	-3.05%	-3.10%	Reduction of 1% of incident rate in previous hour

12.2.6 Difference in Buffer Index

For the difference in Buffer Index, the Gamma GLM provides the best fit (equation 10-6). Figure 12-5 (a) and (b) give the elasticity plots for average lane-minutes of blockage and incident probability in previous hour and Figures 12-6 (a) and (b) give the percent changes in the buffer index (difference) with unit changes in the X values.

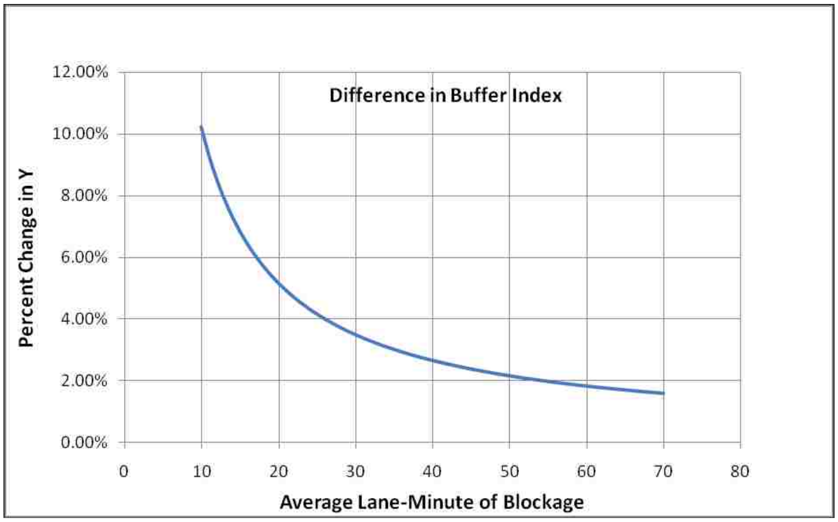


(a) Average Lane-minutes of Blockage

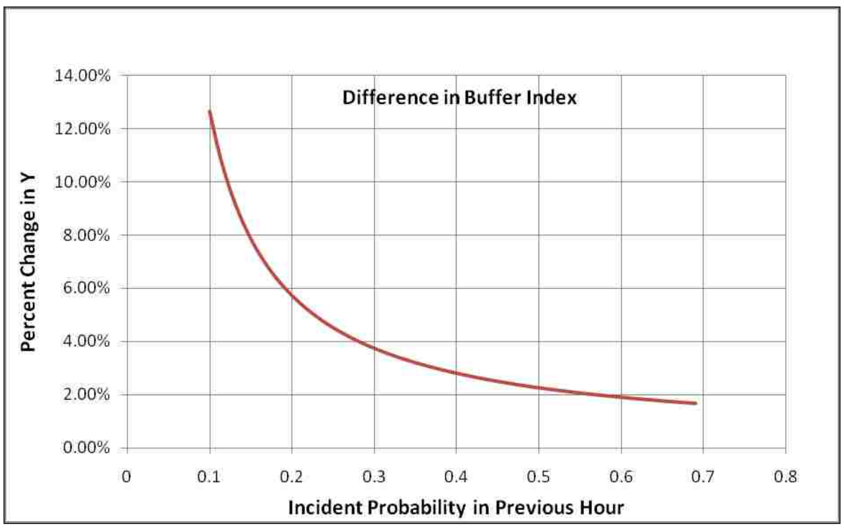


(b) Probability of Incidents in Previous Hour

Figure 12-5. Elasticities of Incident Characteristics for Difference in Buffer Index



(a) Average Lane-minutes of Blockage



(b) Probability of Incidents in Previous Hour

Figure 12-6. Percent Change in Difference in Buffer Index with unit change in Incident Characteristics

The marginal impact of the predictor variables are shown in Table 12-6. A 1 lane-minute reduction in the average lane-minutes of blockage results in 8.5% reduction in the difference of buffer index between mixed and non-incident data (8.5% of buffer index difference of 0.034, resulting in 0.003 or 0.3%).

Table 12-6. Marginal Impacts for Buffer Index - Difference

Variable	BETA	X_0	Y_0	ΔX	$\frac{\Delta X}{X}\%$	$\frac{\Delta Y}{Y}\%$ (regression)	$\frac{\Delta Y}{Y}\%$ (formula)	Notes
(Intercept)	0.7428							
AvgLnMin	-0.0007	12.06	0.03	-1	-8.29%	-8.48%	-8.49%	Reduction of 1 lane-minute of AvgLnMin
IncRatePrvHr	-0.0008	13.03	0.03	-1	-7.67%	-9.19%	-9.21%	Reduction of 1% of incident rate
NISpeed	-0.0030	58.91	0.03					
NIVolume	-0.00004	1,318	0.03					

12.3 Use of the Calibrated Models

Using the same hypothetical project mentioned in Section 11.6, the savings in terms of travel time reliability are summarized in Table 12-7.

Table 12-7. Savings in Long Term Marginal Impacts for Sample Proposed Incident Management Project

Impact	Savings	Unit
95^{th} Percentile TT (Mixed)	0.44	Minutes
95^{th} Percentile TT (Difference)	0.13	Minutes
Buffer Time (Mixed)	0.02	Minutes
Buffer Time (Difference)	0.11	Minutes
Buffer Index (Mixed)	0.18	-
Buffer Index (Difference)	0.01	-

Using a monetary value of travel time reliability of $23.5 per hour (Lam & Small, 2001), the project will result in a travel time reliability savings of 0.44 minutes or $2.05 per driver in 95^{th} percentile travel time. In other words, if the proposed project is implemented, each road user needs to plan 0.44 minutes lesser than before, saving $2.05 per driver.

12.4 Summary

This chapter presented the marginal impact analysis for the travel time reliability measures for the long term impacts of incidents. Models of this form can also be used to quantify the benefits of reducing the incident characteristics. These are long term benefits, which are accumulated over time unlike the short term impacts. Therefore the results in the form of benefits to uses while planning a trip, if the incident characteristics are improved overall.

CHAPTER 13

CONCLUSIONS AND RECOMMENDATIONS

13.1 Conclusions

In this study, statistical models for the impact of freeway incidents on vehicle travel time, emissions and fuel consumption are calibrated. Two types of incident impacts are modeled: short term, and long term. The first objective of the study is to model the short term impacts that occur immediately during and after an incident. The short term impacts are quantified by excess travel time measures, fuel consumption and vehicle emissions produced due to the incident. Included in the short-term impacts are the rubbernecking impacts of the incident. The second objective is to calibrate models to relate the long term impacts of incidents to incident and traffic characteristics. Long-term impacts are accumulated over time due to incidents. They affect the travel time reliability and hence the user's perceived travel time. In this study, the different measures of travel time reliability are modeled as long term impacts.

The I-15 freeway from St. Rose Parkway to Speedway Boulevard in Metropolitan Las Vegas, Nevada, is selected for the study. Archived field data from RTC's Dashboard is used to calibrate the statistical models. The incident database for I-15 for a twelve-month period between March 2011 and March 2012 is used for analysis.

13.1.2 Short-term Impacts

For short-term impact analysis, models are calibrated for (i) excess travel time per vehicle (ii) total vehicle-hours of travel (iii) excess fuel consumption and (iv) excess vehicle emissions (CO_2, CO, NO_x and PM_{10}) for all vehicles over the spatial and temporal extent of incidents. The predictor variables used are incident duration, number of lanes blocked, lane-minutes of blockage, location of blocked lanes, ratio of lanes blocked, peak/off-peak period, day-of-week (weekday versus weekend), traffic volume, speed and density for non-incident conditions over the corresponding spatial and temporal extents of incidents.

The statistical model results indicate, as expected, that the most significant predictor variables are the incident duration, number of lanes blocked and the non-incident traffic density. In certain models, the incident duration and lanes blocked were replaced by the product of the two, namely, the lane-minutes of blockage. The resulting functional forms are the Gaussian Single-Log and Log-Log GLMs. Using the marginal impact analysis, these models can be used for benefit-cost analyses or effectiveness of incident management projects. For example, decreasing the incident duration by one minute results in a 1.7% reduction in additional travel time per vehicle, 2.59% decrease in total vehicle-hours of travel. In terms of fuel and emissions, the same 1 minute reduction in incident duration results in a 2.58% reduction in excess fuel consumption, 1.86% in excess CO_2, 2.41% in excess CO, 2.47% in excess NO_x, and 3.02% in excess PM_{10} emissions.

In terms of absolute values, decreasing the incident duration by 1 minute for an average incident with 1 lane blocked, results in a decrease of 2.3 vehicle-hours of travel. The models calibrated in the study can be used to estimate incident impacts on travel time, fuel consumption, and vehicle emissions and travel time reliability for any freeway region. For example, if a certain proposed incident management strategy such as a new highway patrol program is considered to be implemented, then the reduction of incident duration due to the proposed program can be used in the calibrated statistical models to estimate the corresponding savings in quantities of travel time, fuel consumption and emissions. These estimates can be used to perform benefit-cost analyses of proposed incident management strategies and justify potential project implementation.

13.1.2 Long-term Impacts

For this analysis, models are calibrated for the travel time reliability measures, namely, excess and actual 95th percentile travel time, buffer time and buffer index. The predictor variables used are average number of incidents per hour and average number of lanes and minutes of blockage for the subject hour, previous hour and previous 2nd hour, average speed, volume, density and the location of incidents on the study segment. The resulting functional forms are the Gamma and Gaussian-Log GLM.

Typically, the most significant characteristics of incidents affecting all the measures of travel time reliability for a subject hour are the average lane-minutes of blockage, rate of incidents in the previous hour and the traffic volume and speed under non incident conditions. The marginal impact of reducing the average lane-minutes of blockage for incidents by 1 lane-minute, causes a reduction of 0.9% in 95th percentile travel time (mixed), 3.52% in Buffer Time (mixed), 4.09% in Buffer Index (mixed), 0.58% in difference of 95th percentile travel time between mixed and non-incident, 0.5% in Buffer Time and 3.02% in Buffer Index difference between mixed and non-incident scenarios.

For additional 95th percent travel time, 0.09 minutes in the savings when incident duration is reduced by 1 minute on an average. So, the benefit of improving average incident duration by 1 minute is that each driver on the segment can save 0.09 minutes of planned trip time. With respect to the long-term impacts the savings is users' planned travel time (due to reduced 95th travel time) can also be used to quantify economic benefits of proposed projects and their economic and/or financial feasibility.

13.2 Contributions of this Research

For the analysis of short-term impacts of incidents, the contribution of this research is the development of marginal impacts of incidents and its implications. The marginal impacts and the models are derived using archived real-world data for the Las Vegas. The models and their usefulness are demonstrated. For long-term impacts of incidents, this study presents models to relate travel time reliability measures to incident and characteristics unlike previous studies. The contributions of this study are the statistical models themselves, since calibration of models directly relating travel time reliability measures and incident characteristics have not been attempted before, to the best of our knowledge. Also, the marginal impacts for travel time reliability are computed. These can be used as an additional benefit of implementing incident management strategies.

13.3 Recommendation for Future Research

Some of the limitations of the current study and suggestions for future work in this topic are discussed in this section.

The first recommendation for future research related to this study is in the data collection effort. This study uses data collected every 15 minutes. Using a shorter data collection interval can improve the accuracy of the calibrated models.

Second, among the challenges encountered in the course of collecting and processing data for this study, the biggest issue is related to the accuracy of the incident durations or duration of blockage especially with respect to multiple lane blockages. In these cases, this study has assumed that the start and end of blockage occur at the same time for all the blocked lanes. We know this is not always the case, as occasionally, the lanes may be cleared at different times. This lack of detail results in some overestimation of the blockage. However, the researchers are aware that, since the beginning of 2013, FAST has started keeping snapshot images of the incident scenes for most incidents. These images have the potential to provide more detail information related to the sequence and timing of lane blockages and incident durations during incidents. More accurate models can be calibrated using this more detailed data.

The third recommendation is the need for more detailed work-zone database to ensure that their influence is not included in the analysis. In this study, the researchers are forced to exclude all night-time analysis as work-zone activities are typically scheduled after 9 PM, and due to unavailability of accurate work-zone data that would have helped in isolating impacts due to work-zones.

Fourth, since secondary incidents occur as a result of primary incidents, this study adds the impact of a secondary incident to the primary incident. But the characteristics of the secondary incident itself are not included in the model. Future studies can address this issue by including the characteristics of the secondary incident in the analysis.

Finally, for rubbernecking direction, the inclusion of parameters like median type, geometric location, incident location, and weather and pavement conditions is recommended, since they are not addressed in this study.

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