NDOT Research Report

Report No. 001-13-803

Development of an Analysis Tool for Evaluation of Marginal Impacts of Freeway Incidents in the Las Vegas Area Using FAST's Dashboard Freeway Data

January 2014

Nevada Department of Transportation
1263 South Stewart Street
Carson City, NV 89712

Disclaimer

UNLV

UNIVERSITY OF NEVADA LAS VEGAS

FINAL REPORT

Development of an Analysis Tool for Evaluation of Marginal Impacts of Freeway Incidents in the Las Vegas Area using FAST's Dashboard Freeway Data

Submitted to

NEVADA DOT

The Nevada Department of Transportation

Submitted by

Mohamed Kaseko, Associate Professor
Hualiang "Harry" Teng, Associate Professor
Vidhya Kumaresan, Graduate Research Assistant
Saketh Chigurupati, Graduate Research Assistant

Dept of Civil and Environmental Engineering and Construction (CEEC)
University of Nevada Las Vegas (UNLV)
4505 Maryland Parkway, Box 45015
Las Vegas, NV 89154-4015

January 21st, 2014

EXECUTIVE SUMMARY

Incidents are a major source of non-recurring congestion on freeways. In addition to costing millions of dollars in the loss of life, injuries and property damage, traffic incidents also cause additional losses due to the resulting traffic congestion, delay and energy consumption. Depending on the severity 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. The objective of the proposed research is to model and quantify the impacts of freeway incidents on measures of effectiveness including system-wide traffic travel times, fuel consumption and vehicle emissions. Statistical regression models are calibrated that relate freeway travel times, fuel consumption and emissions as functions of incident characteristics that include incident duration, number of lanes blocked and corresponding non-incident traffic characteristics. One year worth of data for a section of the northbound I-15 freeway in Las Vegas metropolitan area is used for the study. The data is retrieved from Dashboard, an interactive website maintained by RTC's FAST.

Non-linear regression models are calibrated for each impact variable using the statistics software package R. Models are calibrated for (i) excess travel time per vehicle (ii) excess 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 full set of predictor variables used included incident duration, number of lanes blocked, lane-minutes of blockage (product of incident duration and number of travel lanes blocked), 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 statistical functional forms are the Gaussian Single-Log and Double-log Generalized Linear Models (GLMs). Use of the models is demonstrated by showing examples of using the equations to compute the impact of an average incident. The results show, for example, that an average incident that has one travel lane blocked on the section of the freeway modeled results in approximately 149.2 excess vehicle-hours of travel and 41.45 gallon of excess fuel consumed by impacted vehicles. Further analysis using elasticity derived equations can be done to estimate marginal impacts with respect to small changes in the values of the predictor variables, such as the incident duration and n umber of travel lanes blocked. Such analysis can be used for planning purposes and for evaluation of the overall performance of a freeway network, as well as for benefit-cost evaluation of incident management projects.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 : INTRODUCTION

1.1 Problem Statement

Incidents are a major source of non-recurring congestion on freeways. In addition to costing millions of dollars in the loss of life, injuries and property damage, traffic incidents also cause additional losses due to the resulting traffic congestion, delay and energy consumption. Depending on the severity 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 produced an estimated cost of $121 billion of travel delay and fuel consumption in 2011 corresponding to 5.5 billion hours of extra time and 2.9 billion gallons of wasted fuel (Shrank et. al., 2012).

A number of efforts have been reported over the years that attempt to model such impacts for purposes of developing tools for evaluation of the effectiveness of incident management strategies. Most recent 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 the extensive freeway traffic data in Las Vegas maintained by FAST and accessible online (Dashboard interactive website), this study deviates from the use of simulation models and calibrate statistical impact models using actual field historical incident and traffic data to be obtained from the website. Moreover, there is no guarantee that an impact model calibrated for traffic in one region can be transferable for use in another region due to potential differences, such driver behavior, climate, whether and other location specific variable.

1.2 Research Objective

The objective of the proposed research is to use FAST's historical Dashboard data to model and quantify the impacts of freeway incidents on measures of effectiveness including system-wide traffic travel times, fuel consumption and vehicle emissions. Statistical regression models will be calibrated that will relate freeway travel times, speeds, energy consumption and emissions as functions of incident characteristics that include incident duration, number of lanes blocked and time of day. The models will produce “marginal” impacts of key incident parameters, such as incident duration, traffic volumes and number and lateral location of blocked lanes, on travel times, vehicle emissions and fuel consumption. Ultimately, the goal of this study is to develop models that can be used in evaluating the effectiveness (economical or otherwise) of proposed new and/or improved incident management strategies.

1.3 Research Tasks

Overall, the research procedure involves calculating the differences in the traffic measures of performance between incident and non-incident conditions. Differences traffic performance measures are obtained for various incident conditions and statistical regression models are calibrated to obtained relationships between the incident/traffic characteristics during incidents and the resulting impacts in terms of additional travel times, fuel consumption and emissions. The project is divided into the following main tasks

1. Literature Review
2. Data Collection
3. Statistical Analysis and Model Calibration
4. Analysis of Results and Models Summary
5. Final Report

1.4 Report Organization

This report is organized in the following chapters. Chapter 2 presents a literature review of relevant technical publications and reports. Chapter 3 presents the research methodology. Chapter 4 describes the data requirements, how the data is collected and processed for analysis. Chapter 5 has descriptive summary statistics for all the impact variables with respect to variables of incident characteristics. Chapter 6 has model calibration results. In Chapter 7, marginal impact analysis is presented for each impact variable. An example application is also presented in the chapter. Finally, Chapter 8 presents conclusions and recommendations.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

Apart from direct costs of injury, fatalities and property damage due to incidents, there are also additional economic impacts due to increased travel times, increased fuel consumption and vehicle emissions, which have long and short term impact on the environment and quantifiable health impacts. Several previous studies have addressed different aspects of freeway incidents and their effect on freeway measures of effectiveness, such as delays and queue lengths, and other impacts such as vehicle emissions and fuel consumption. The studies have used a combination of empirical methods based on field data and/or theoretical statistical, queuing, statistical, mathematical optimization and/or computer simulation models. The papers reviewed for this study are grouped into two categories, namely, (1) those that presented procedures and/or analysis of the impact of incidents of vehicle delays, emissions and/or fuel consumption, and (2) papers that presented benefit-cost analysis studies of various freeway incident management programs.

2.2 Quantification of impacts of freeway incidents

Garib and Radwan (1997) presented two statistical models for predicting incident delays and estimating the impact of incidents on vehicle delays. This research was supposed to be part of the study to evaluate the impact or effectiveness of the freeway service patrol (FSP). Two months of data, one month before and one month after implementation of FSP was collected for a 7.3 mile segment of I-880 in Alameda County, California. Incident data was collected by a fleet of moving observes during the morning and evening peak periods. In addition, 30 second loop detector data was collected which included traffic speeds, flow and occupancy. Statistical regression models were then calibrated to relate the total traffic delays (in vehicle-hours) as a function of traffic and incident characteristics, including the number of lanes affected by the incident, he number of vehicles involved in the incident, the incident duration (difference between the time an incident is detected and the time it is cleared), and the traffic demand upstream of the incident in the 15 minutes before the incident starting time. They also calibrated a model for estimation of incident duration in minutes, as a function of the number of lanes affected, police response time, the number of vehicles involved in the incident, and dummy variables for whether or not a truck (heavy vehicle) was involved, the time of day (morning vs. afternoon peaks), and weather conditions (rain or no-rain). Both sets of models were found to be statistically significant.

Xia and Chen (2007) used shockwave analysis to predict freeway travel times based on loop detector and historical incident data. The objective of the study was to develop a reliable methodology to make use of single-loop detector data and estimate travel time and the impact of incidents on travel time. Conventionally, corridor travel times have been estimated as the total of the link travel times estimated during the same time interval. Since the effects of traffic progression is not considered, the authors deemed this method as not reliable. During the time of an incident, sudden changes in flow pattern and non-recurrent congestion occur. This report focuses on estimating the effect of incident on travel time to provide accurate travel time estimation for purposes such as advanced traveler information system. The corridor selected for travel time estimation is a 9-mile freeway segment located in the Bay area of California on eastbound Interstate-80. In the methodology presented, travel time on the freeway corridor is first estimated based on short-term prediction of traffic parameters which is performed based on historical trends of the parameters without considering the impact of an incident overtly. If an incident is considered likely to have a significant impact, then the travel time is adjusted for the segment by the projected queue formed at the bottleneck. The results of this study showed that the factors that have significant impacts on the duration of an incident are day-of-week and incident type. The results also show that the trend of graph that does not consider the incident impacts on travel time usually underestimates the actual corridor travel times. After using the report's methodology and adjusting the travel time for impact due to incident, the prediction was much closer to real-time measured values. Therefore the queuing theory-based methodology was able to capture the real-time characteristics of traffic and provide more accurate travel time estimates during an incident occurrence when compared to static methods.

Thomas and Jacko (2007) developed a stochastic model to estimate the average excess emissions of carbon monoxide (CO), volatile organic compounds (VOC), oxides of nitrogen (NO_X) and particulate matter ($PM_{2.5}$) and the traffic delay due to incidents. Monte Carlo simulation and statistical models of incident and traffic characteristics were used to derive the statistical characteristics of the excess emissions and traffic delays due to incidents. Data from the Borman Expressway, a heavily travelled 16-mile segment of the Interstate 80/94 freeway in Northern

Indiana was used. The study found that for the average incident with average clearance duration of 26 minutes, the average incident impact was 126.9 kg of excess CO emissions, 20.8 kg of excess VOC, and 8.8 kg of excess NOx, and 0.27 kg of excess PM2.5 emissions and 630 vehicle-hours of traffic delay.

Wang and Cheevarunothai (2008) developed an algorithm based on deterministic queuing of 1-minute loop detector data for quantifying the travel delays resulting from different categories of incidents on freeways. They used data recorded by the incident response team from the Washington State Department of Transportation (WSDOT). Since a major portion of congestion is due to traffic incidents, the research was focused on incident-related congestion and its reduction by means of management and emergency response strategies. The influence of an incident is found by comparing the delays due to different incident types. 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. It is interesting to note that the authors found that the median impact of all incidents, except non-injury commissions, was zero vehicle-hours. The median for non-injury collisions was 1.07 vehicle hours per incident. The maximum impact was 8,376 vehicle-hours. No fatal collisions were analyzed, as there were none reported during the study period. A drawback of the procedure is that it is based on a deterministic queuing technique which causes some discrepancies with the reality and that fatalities were not modeled because none occurred during the 3-month study period.

Chung and Recker (2012) presented an approach for estimating temporal and spatial extent of the delays caused by freeway accidents. The objective of the paper was to develop methods for estimating the delays as well as the spatial and temporal impacts of an incident as part of the overall goal of analysis and evaluation of incident management strategies. Another objective of the study was to identify the causal factors determining the delay of an incident. Loop detector data from six freeways in Orange County, California was used to demonstrate the method. There were no details on the incident characteristics, such as incident severity (number of lanes affected) and duration. Hence the temporal and spatial impacts of the incidents were estimated by plotting speed matrices and modeling and solving binary integer programming (BIP) problems. The methodology was employed on one-year data of a section of the freeway network in Orange County, California. The study found that for the 2,232 accidents that were studied over that time period, the median total delay was 22.27 vehicle-hours per accident, with corresponding minimum and maximum delays of 0 and 1,379.49 vehicle hours. In addition, the study found that the variables with the most positive influence on the total delay were peak periods, 3 or more vehicles involved (function of number of vehicles involved), rear-end collision (type of collision), left lane (location of collision) and speeding (causal factors). However, no clear results were presented in the paper with respect to the temporal and spatial impacts of the incidents.

2.3 Benefit-cost studies

The following papers were selected from a number of studies whose primary objectives were to evaluate the performance and/or economic effectiveness (in terms of benefit-cost ratios) of various incident management programs. These studies generally involved “before-and-after” or “with vs without” comparative evaluations of various performance measures as a result of the incident management activities.

Skabardonis, et. al (1996) reported a study whose objectives were (1) develop a large and comprehensive database on freeway incidents and operational characteristics, (2) develop an improved methodology for estimating incident delay, and (3) apply the methodology to determine the effectiveness of freeway service patrols (FSP) at a section of freeway I-880 in the San Francisco Bay Area. Loop detector data complemented by travel time data using probe vehicles was collected for during the peak periods for 24 weekdays before and 22 weekdays after the deployment of FSPs at the test site. Information on incidents was obtained from observations of the probe vehicle drivers. A total of 1,616 incidents were observed during the study period. Deterministic queuing models were used to obtain estimates of traffic delays due to the incidents by comparing traffic data with and without incidents. The results showed deployment of FSP resulted in that a reduction of the total delay impact from 154.74 vehicle hours to 136.42 vehicle-hours per assisted incident, a reduction of 20.32 vehicle-hours per incident.

Later, Skabardonis, et. al (1998) followed-up the study above with a similar one to evaluate the effectiveness of the FSP on a 7.8 mile section of I-10 freeway (Beat 8) in Los Angeles. Field data for 32 weekdays, 6 hours per day from loop detectors and probe vehicles was used to obtain estimates of savings in performance measures in the absence of data for before FSP conditions. This 192-hour database includes detailed descriptions for 1,560 incidents. An average of 41 incidents/day was observed during the peak periods in the study area with an average duration per incident of 20 minutes. FSP assisted 1,035 incidents during the field study (1.44 assists/truck-hr), mostly vehicles with mechanical or electrical problems, flat tires and those that had run out of gas. About 21 percent of the assists were for accidents. The average response time of FSP tow trucks was 10.8 minutes. Analysis indicated that FSP assisted incidents were shorter than non-assisted incidents by 7 to 20 minutes on the average. The estimated benefit/cost ratios based on delay and fuel savings for a range of typical reductions in incident durations was greater than 5:1. In addition, the reduction in incident duration was estimated to translate to daily reductions in air pollutant emissions of a total of 60 kg of hydrocarbons, 462 kg of carbon monoxide and 122 kg of oxides of nitrogen.

Hagen et al. (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 value of travel time of $13.45 for each person hour of travel and $71.05 for each truck hour, in accordance with the Texas Transportation Institute's 2005 Urban Mobility report. Using an assumed occupancy and truck percentage, the average value of travel time was calculated as $22.71 per vehicle-hour. The Freeway Service Patrol Evaluation (FSPE) model developed by the University of California, Berkeley was used to estimate the savings in delay, emissions and fuel consumption (Skabardonis and Mauch, 2005). The FSPE model is implemented in a Microsoft Excel workbook using visual basic routines to evaluate impacts based on deterministic queuing models and emission sub-models to calculate reductions in emissions. Total monthly delay savings from a total of 21,759 incidents from all the sites were found to be 1,138,869 vehicle-hours of travel time and 1,717,064 gallons of fuel saved due to the FSP program, corresponding to monetary savings of $25,863,715 and $3,365,445 respectively. The B/C ratio of the entire program was found to be in excess of 25:1. Additional benefits not included in the benefit-cost (B/C) ratio calculation included monthly reductions in air pollutant emissions that were found to be 3,690 kg of reactive organic gases, 160 kg of CO and 740 kg of NO_x.

Fries et al. (2007) examined the economic effectiveness of traffic cameras to detect and verify incidents at five different metropolitan freeway sites in the State of South Carolina. Various incident scenarios were simulated using Parallel Micro Simulation Software (PARAMICS) software. The authors used the MOBILE6 model developed by the Environmental Protection

Agency (EPA) for the rates of pollutant emissions 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 costs considered for economic analyses were: service and maintenance, communication, infrastructure, and personnel. The benefits were categorized as savings in: vehicle delays, energy consumption and air pollution (CO emissions, NO_x emissions, HC emissions, PM). The dollar values were found using Intelligent Transportation Systems (ITS) Deployment Analysis System (IDAS). The incident scenarios were compared to the base scenarios and the differences were attributed to the incident. The study found that use of the cameras reduced vehicle delays by 5.2% and fuel consumption by 3.8% (diesel) and 3.2% (unleaded gasoline). Total hydrocarbons and volatile organic compounds were both reduced by approximately 14%, carbon monoxide by almost 10%, nitrous oxide by almost 7%, and particulate matter by approximately 1% corresponding to 35 kg/day of hydrocarbons, 195 kg/day of carbon monoxide, and 40 kg/day of nitrous oxides 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.

Dougald and Demetsky (2008) developed methods to quantify the benefits of safety service patrols (SSPs) for the Northern Virginia region. The procedure developed included determining incident durations with and without SSPs and applying the results to the Freeway Service Patrol Evaluation (FSPE) model to quantify the benefits resulting from the reduced traffic delays attributable to SSPs. The FSPE model uses deterministic queuing models to estimate traffic delays associated with queues that form during incident conditions (Skabardonis and Mauch, 2005). The models takes as input the geometric and traffic characteristics of the route, and the type and frequency of SSP assisted incidents. From one of the area freeway analyzed, the results indicated an overall average reduction in incident duration of 17.3% with associated savings of 290,765 vehicle-hours and 438,598 gallons of fuel resulting in total benefits of approximately $6,488,126. With a corresponding SSP cost of $1,193,511, this represented a B/C ratio of 5.4:1. As expected, the savings were a function of the type of incident, traffic characteristics and time of day.

Chou, Miller-Hooks and Promisel (2010) did a benefit-cost analysis of the effectiveness of the freeway service patrol within New York State, known as the "Highway Emergency Local

Patrol (H.E.L.P.)". They performed a CORSIM simulation-based study for a 10-mile segment of the freeway network and found that there was an average reduction of 20 minutes in the duration of each incident, i.e., incidents were being cleared faster due to the prompt arrival and service of H.E.L.P. personnel. This resulted in estimated annual savings of 24,000 vehicle-hours of travel delay, 2,900 gallons of fuel consumed, 0.32 tons of hydrocarbons (HC), 3.6 tons of carbon monoxide (CO), 0.2 tons of nitrogen oxide and 18 secondary incidents. These are very significant economic as well as environmental benefits and a benefit-cost analysis clearly showed justification for use of the funds for the H.E.L.P. program.

2.4 Summary

Table 1 below provides a summary of selected incident impact studies. In general, these studies, with the exception of the one by Garib and Radwan (1997), only reported average or aggregate measures for the impact of incidents on traffic delays, travel times, emissions and/or fuel consumption. The results from these studies may not be usable in analysis of incremental improvements in incident management activities. None of the studies have reported "marginal" impacts of, for example, reduction in incident duration, or number of blocked lanes. Also, most of these studies used a combination of field data as well as theoretical models and simulation models of traffic performance measures, such as queue lengths, which limits their ability to more accurately reproduce real world conditions. Garib and Radwan (1997) came closest to answering these issues, however, the study was based on only two-months' worth of data and analysis was during the peak periods only. They also did not evaluate vehicle emissions or fuel consumption. Overall, one can also observe from these studies the wide range in reported measures of impacts per incident, reflecting the regional differences as well as methodologies used in the analysis.

Table 2-1: Summary of Selected Incident Impact Studies

Author(s)	Setting and methodology	Modeling delays, emissions and fuel Consumption	Impact Results
Skabardonis, et. Al (1996)	California's I-880 Freeway; 250 hours of detector data (speeds, flow, occupancy); Travel times, and incident data collected using probe vehicles; 1,616 incidents;	Incident delays – deterministic queuing analysis used to estimate delays and recorded difference in travel speeds with/without incidents	Without FSP, impact per assisted incident: 156.74 veh-hrs With FSP, 136.42 veh-hrs, savings of 20.32 veh-hrs per incident No regression models.
Garib, A.; Radwan, Essam and Al-Deek, Haitham (1997)	Statistical Models	Modeling: SPSS Statistical Software	Separate regression models for predicting incident delay and incident duration
Hagen, Larry; Zhou, Huaguo and Singh, Harkanwal. (2005)	FL Road Ranger FSP Program	California's Freeway Service Patrol Evaluation (FSPE) software Travel Time value: Texas Transportation Institute (TTI)	Total monthly delay savings of 1,138,869 vehicle-hours of travel time, and 1,717,064 gallons of fuel consumed 3,690 kg of reactive organic gases, 160 kg of CO and 740 kg of NO_x.
Thomas, Salimol and Jacko, Robert B. (2007)	Study area was a 3-lane highway with 6,000 vph capacity and 10,000 incidents	Monte Carlo simulation was used to derive statistical characteristics of excess emissions and traffic delays	Each incident averages 126.9 kg of excess CO, 20.8 kg of VOC, 8.8 kg of NO_x 0.27 kg of $PM_{2.5}$ and 630 vehicle-hours This corresponds to 500%, 26% and 43% of increase in VOC, NO_x and $PM_{2.5}$respectively when compared with normal traffic conditions.

Table 2.1: Summary of Selected Incident Impact Studies (Continued…..)

Author(s)	Setting and methodology	Modeling delays, emissions and fuel Consumption	Impact Results
Dougald, Lance E. and Demetsky, Michael J. (2008)	Northern Virginia Interstates 395, 495, 96, 66 and State Route 267, a total of 198 centerline miles. Study period of 1 year with a total of 22,233 incidents.	Delays: Queuing models to estimate queues and delays Emissions: MOBILE6	Average reduction in incident duration of 17.3% with associated annual delay savings of 290,765 veh-hrs and 438,598 gallons of fuel; Emissions savings of 36,614 kg ROG (reactive organic gases), 1,934 kg CO and 8,153 kg NOx
Chou, Chihsheng; Miller-Hooks, Elise and Promisel, Ira (2010)	CORSIM-simulation-based study for a 10-mile segment of the freeway network; NY HELP program	Delays and Fuel Consumption: CORSIM Emissions: Rates from Maryland DOT	Average reduction of 20 minutes in the duration of each incident; Estimated annual savings of 24,000 veh-hrs of travel delay, 2,900 gallons of fuel consumed, 0.32 tons of hydrocarbons (HC), 3.6 tons of carbon monoxide (CO), 0.2 tons of nitrogen oxide, and 18 secondary incidents

CHAPTER 3 : METHODOLOGY

3.1 Introduction

This chapter presents the methodology for modeling the 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, 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.

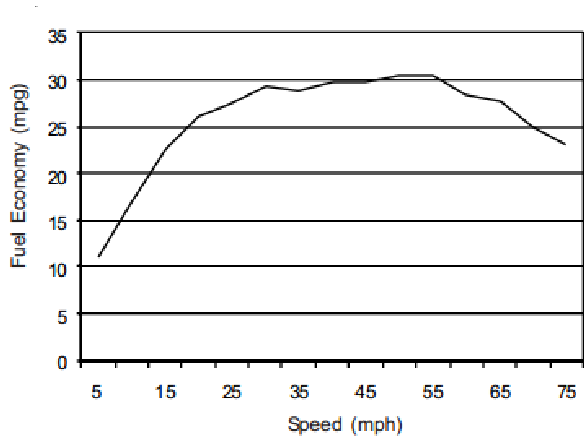


Figure 3-1. Fuel Economy and Speed (Source: USDOE)

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.

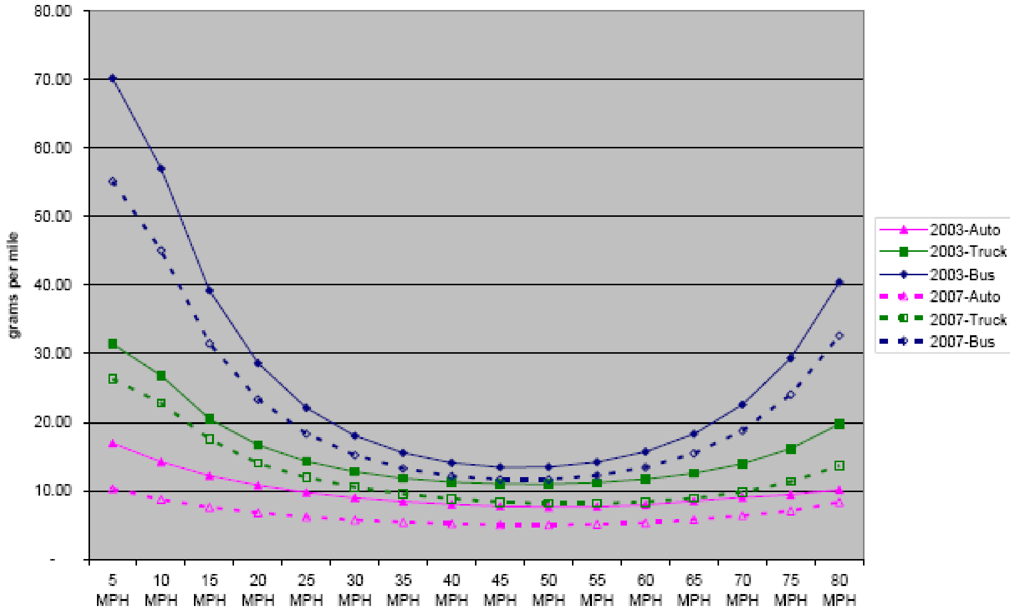


Figure 3-2. CO Emissions versus Speed

(System Metrics Group, Inc., 2009)

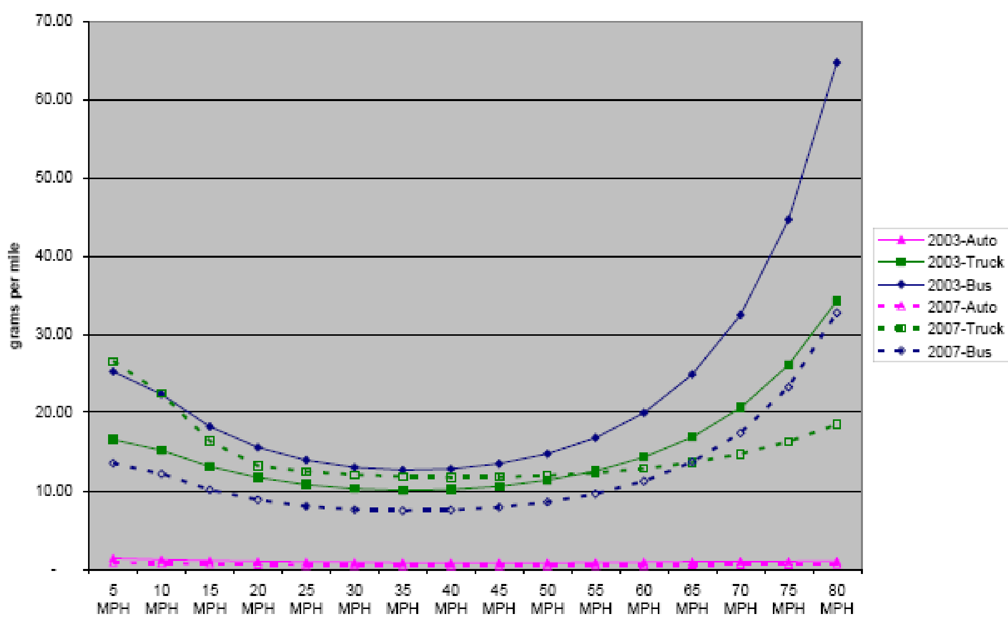


Figure 3-3. NO_x Emissions versus Speed

(System Metrics Group, Inc., 2009)

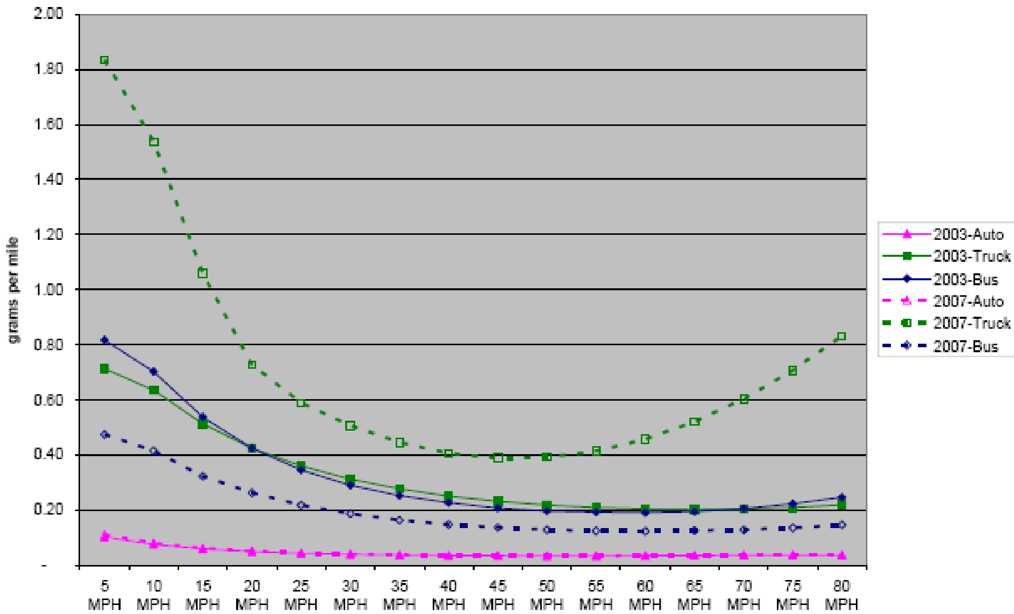


Figure 3-4. PM_{10} Emissions versus Speed

(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 Study Methodology

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

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.

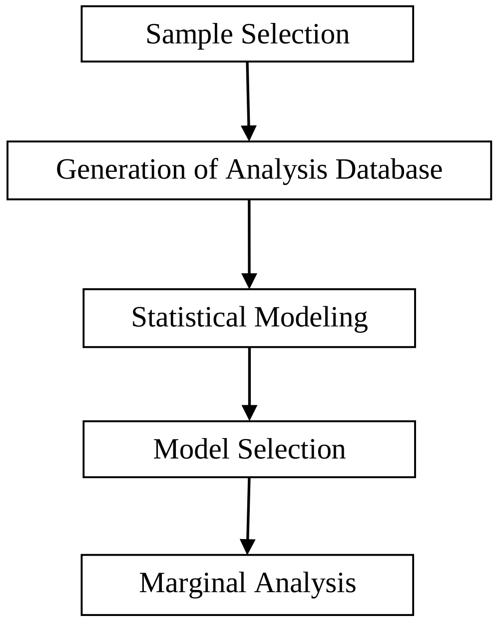


Figure 3-5. Flowchart for Modeling Incident Impacts on Travel Time, Emissions and Fuel Consumption

3.3.2 Generation of Analysis Database

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

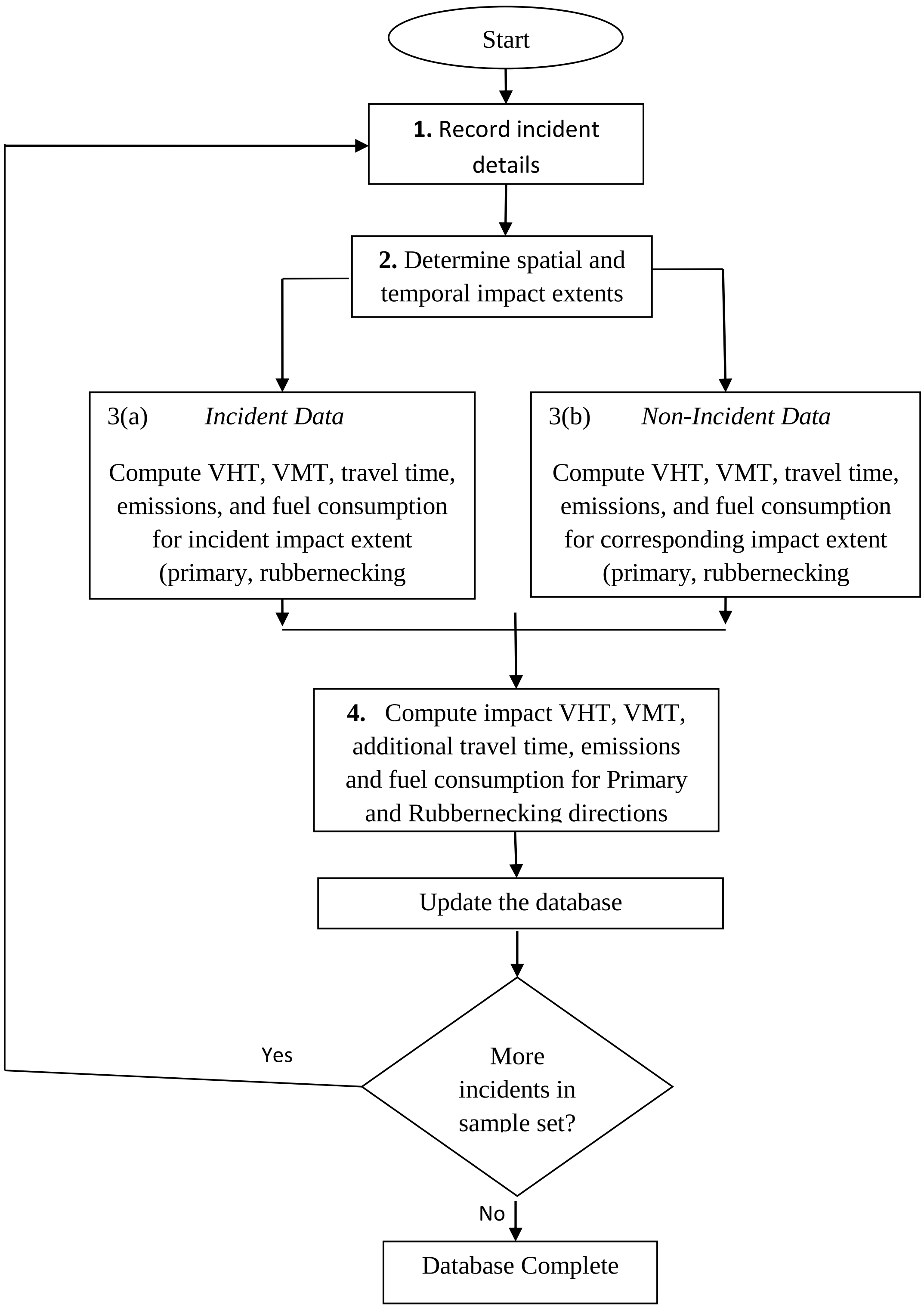


Figure 3-6. Flowchart for Generation of the Analysis Database

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

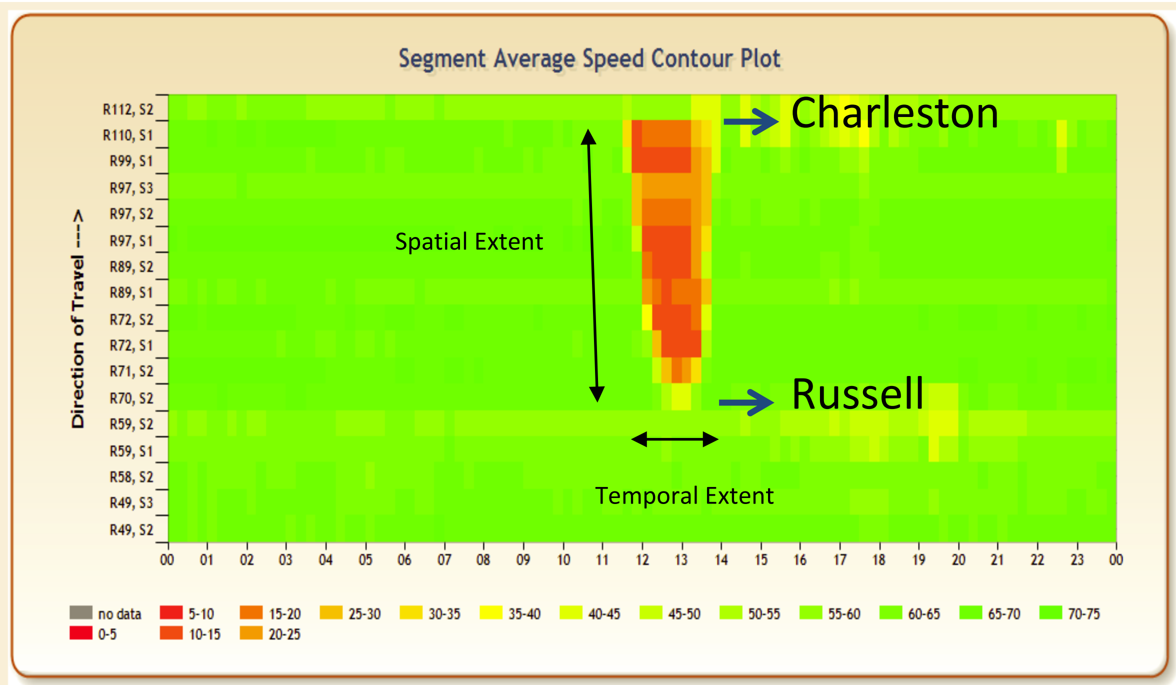


Figure 3-7. Speed Plot for Sample Incident

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, $$V_{k,t} = v_{k,t}\frac{60}{T} \tag{3-1}$$

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

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

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

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

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

Total travel time over impacted segments,

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

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

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

Rate of fuel consumption and vehicle emissions,

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

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:

a) 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.

b) 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.

c) 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.

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

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.

d) 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.

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

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.

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

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.

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:

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

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 Impact Analysis

The final nested model selected is then used to interpret and determine the marginal impact 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 : DATA COLLECTION AND PROCESSING

4.1 Introduction

In accordance with the methodology described in Chapter 3, the data required for 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.

4.2 Data Description and Collection

4.2.1 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 4-1.

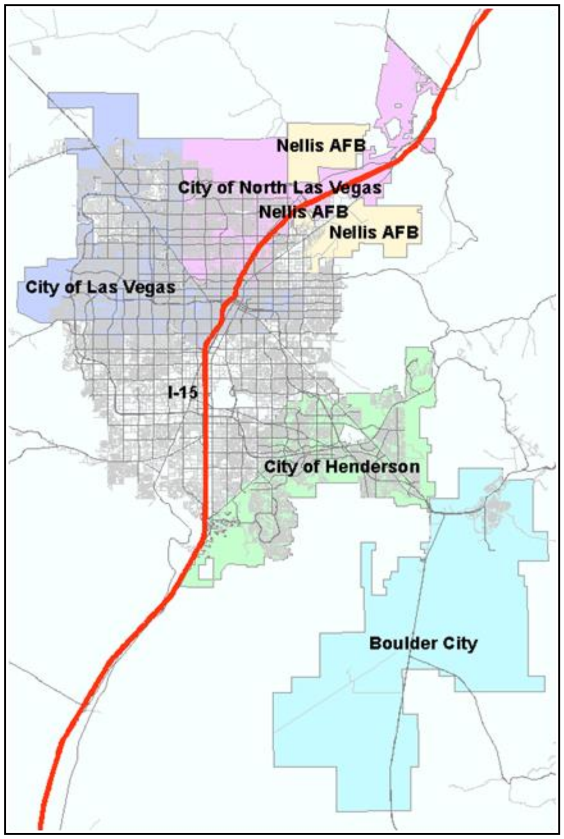
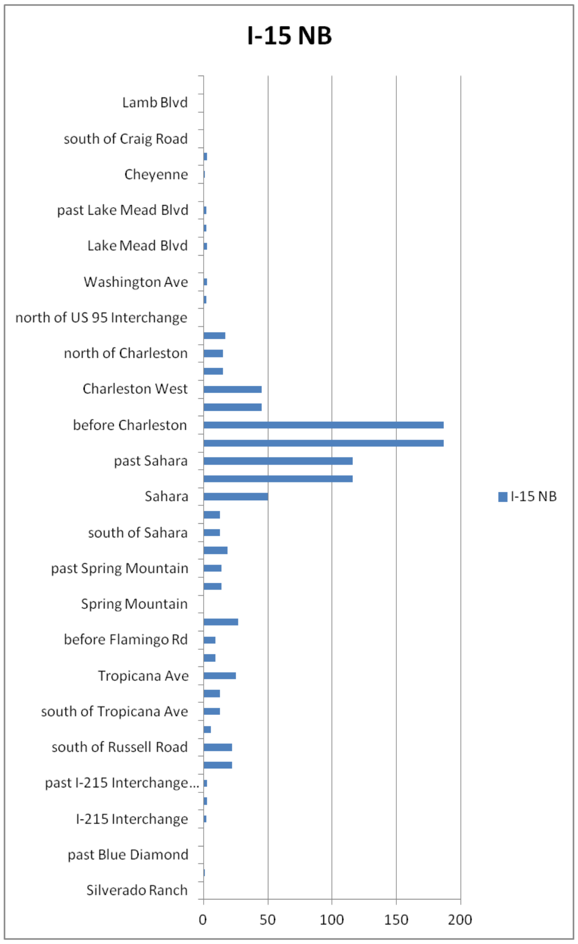


Figure 4-1. Map of Study Location

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 4-2. The data shows that the segment between Sahara Avenue and Charleston Boulevard had the most number of the incidents. Also, the 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 4-3 and 4-4 show the crash distribution by day of week and time of day.



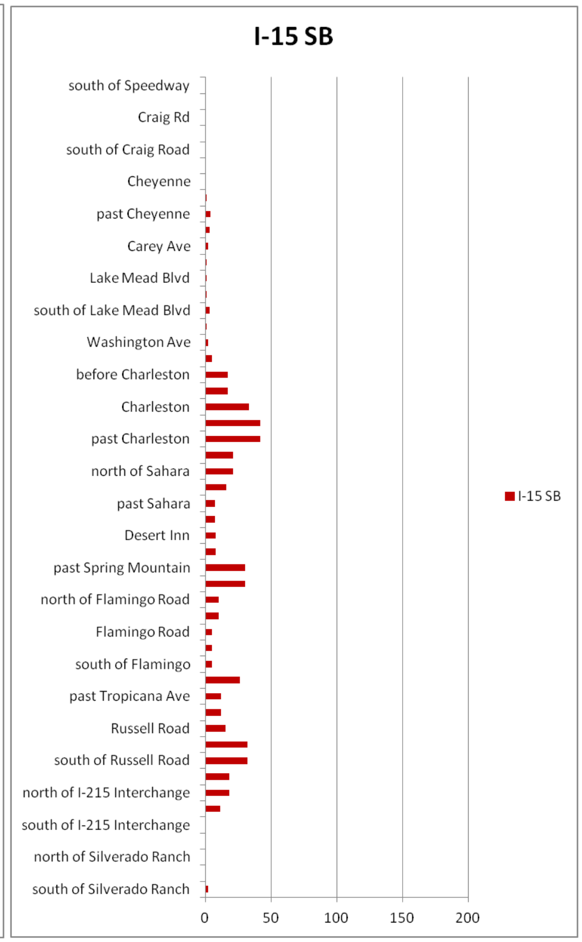


Figure 4-2. Number of Incidents by Segment

Figure 4-5 shows a typical Dashboard report with some incidents that occurred on December 30-31, 2011.

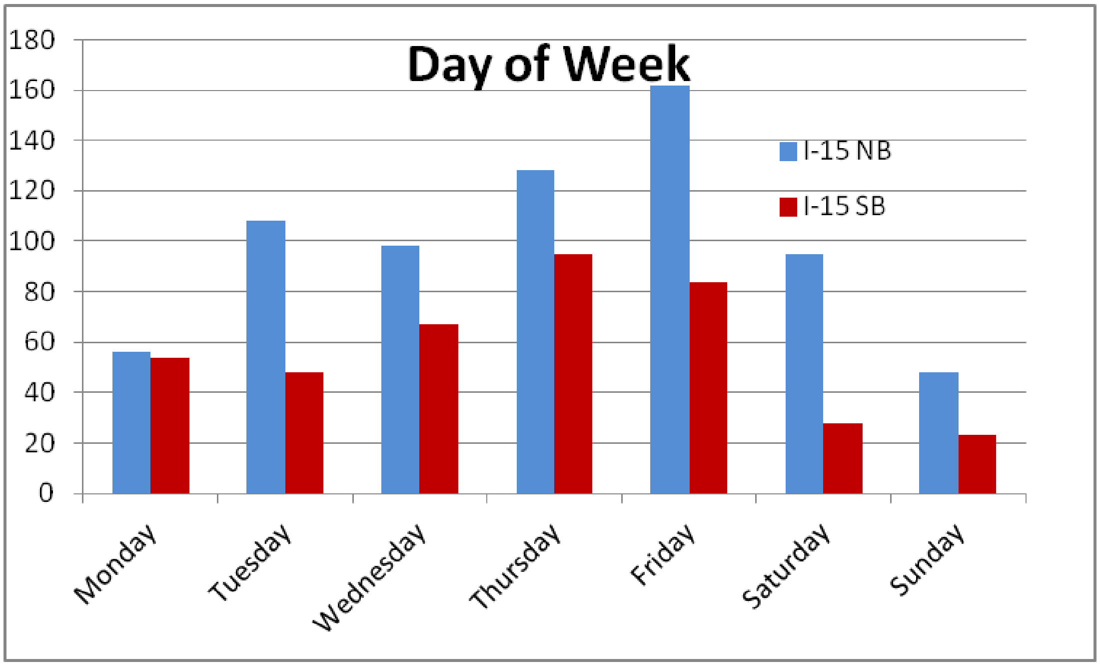


Figure 4-3. Number of Incidents by Day of Week

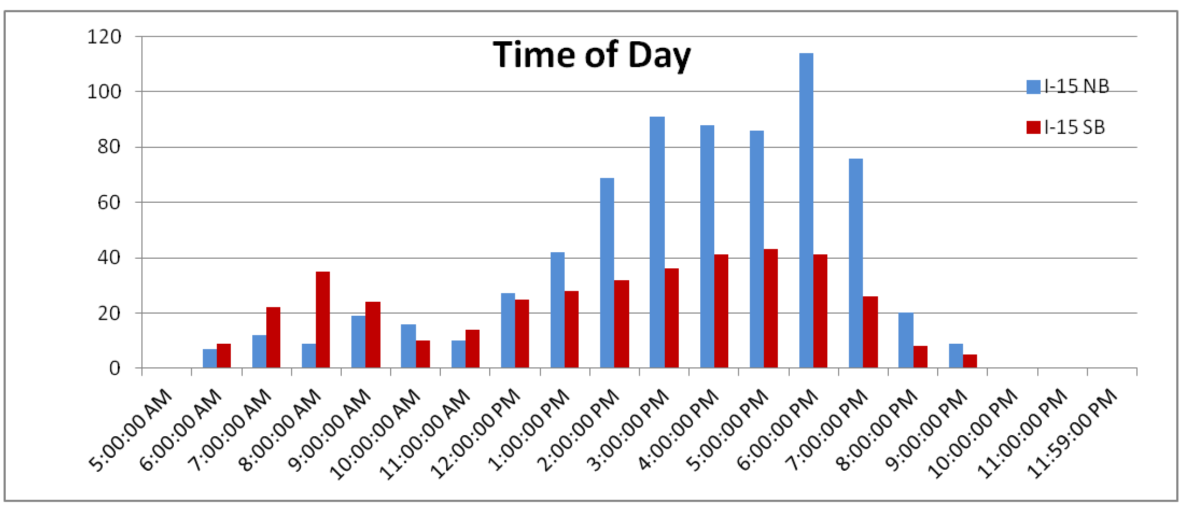


Figure 4-4. Number of Incidents by Time of Day

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 4-5. 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. Column 6 in Table 4-1 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. The process of sampling the 203 incidents also included a criteria that for each selected incident, there is no incident in the opposite direction at around the same time and location as the selected incident. This is to ensure that the impact observed is only for the primary incident, and not a possible incident in the adjacent opposite direction.

One of the problem with the incident data that was acquired was that about 30% of them did not have incident duration recorded. In such cases, the duration was estimated manually by examining the individual speed and traffic volume data.

Table 4-1. Number of Incidents for each Freeway Segment in the Study Area (I-15 NB)

Roadway-Segment ID	Seq ID	Segment	I-15 NB	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

4.2.2 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 4-2 shows the traffic data from the freeway data plotting section of the Dashboard.

Table 4-2. 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.

<u>Incident Data:</u>

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.

$$f_s = \text{upper fourth} - \text{lower fourth} \tag{4-1}$$

$$\text{Extreme Outlier} = \begin{cases} \text{upper fourth} + 3\, f_s \quad \text{OR} \\ \text{lower fourth} - 3\, f_s \end{cases} \tag{4-2}$$

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.

4.2.3 Data Collection Procedure for 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 4-3 is an example of incident parameters for one incident.

Table 4-3. 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 4-6 shows the speed segment plots for the example incident. Each line in the figure 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 4-6, 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 4-4 shows the same for the sample incident under consideration.

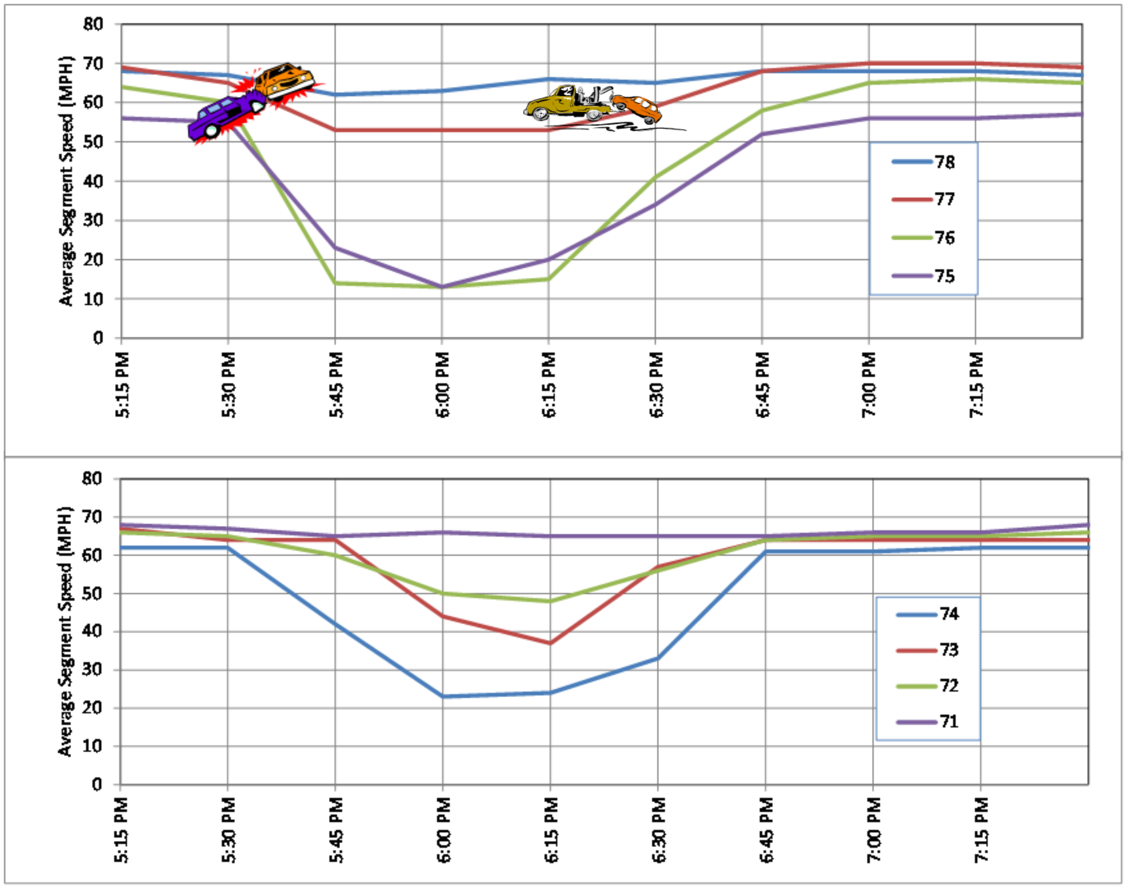


Figure 4-6. Speed-Segment Plot showing Spatial and Temporal extents of Sample Incident

Table 4-4. 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	
From	5:30:00 PM
To	6:45:00 PM

Segments Affected (Spatial extent)	
From	76
To	72

Rubbernecking	
From	50
To	53

Step 3. Computation of incident and non-incident impact parameters

Tables 4-5 and 4-6 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 4-7 shows the summary of the analysis data for the sample incident.

4.2.4 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 greenhouse 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.

Table 4-5. 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 4-6. 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 Dista	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 4-7. 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

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.

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

<u>Traffic data- Speeds and Volumes:</u>

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.

<u>Geometry- Segment Lengths and Grades:</u>

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 4-7). 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 4-7. Garmin eTrex Legend C handheld GPS unit (Source: www.garmin.com)

The formulas used are shown below:

$$Rise = E_{end} - E_{start} \quad \text{feet} \tag{4-3}$$

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

Where:

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

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

Segmentlength: The length of the road segment in feet.

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], which maintains the data on a website accessible by the general public. Data for the year 2010 for Clark

[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

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.):

$$VP_{Saturated} = 6.11 * 10^{7.5*\left(\frac{T}{237.7+T}\right)} \tag{4-5}$$

$$VP_{Actual} = 6.11 * 10^{7.5*\left(\frac{D}{237.7+D}\right)} \tag{4-6}$$

$$\text{Relative Humidity} = \frac{VP_{Actual}}{VP_{Saturated}} \tag{4-7}$$

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 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 4-8. The distribution of vehicle population on the segment during the time of the run is required by MOVES for every segment.

The distribution of vehicle types for this study is adopted from NDOT vehicle classification report for the years 2010 and 2011 (shown in Table 4-9). 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 4-8 according to the standard FHWA axle and vehicle classification, as shown in the last column of Table 4-8.[2] The appropriate AADTs are then obtained to give the percent distribution in Table 4-10. The same process is used for the other two segments Flamingo to US-95 and US-95 to Speedway.

<u>Vehicle age distribution:</u>

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

Table 4-8. 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

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

Table 4-9. 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 4-10. 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*

4.2.5 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 4-11 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 4-11. Sample MOVES Input Format: Meteorology

monthID	zoneID	hourID	temperature	relHumidity
2	320030	15	62.7	25.3

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 4-8 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]

MOVES runs are repeated for incident and non-incident conditions for all the incidents in the sample set. Table 4-12 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

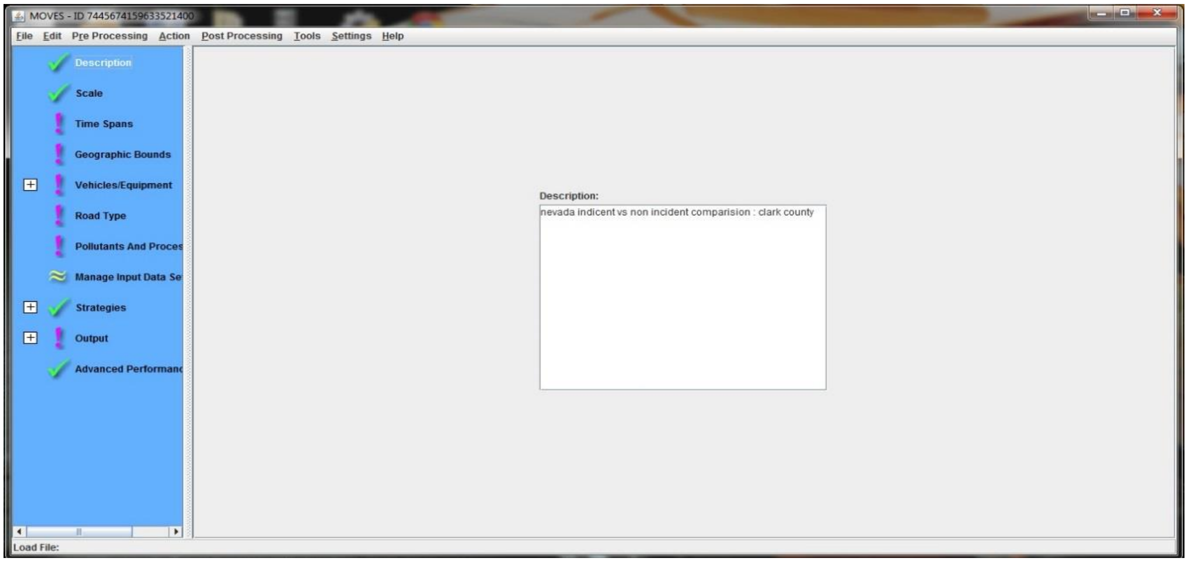


Figure 4-8. MOVES Data Entry Window

Table 4-12. Fuel Consumption and Vehicle Emissions: Partial Data

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

	incident						non-incident					Excess (grams)					
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

CHAPTER 5 : DESCRIPTIVE SUMMARY STATISTICS

5.1 Introduction

This chapter presents the descriptive summary statistics of the data for impacts of traffic incidents. Before embarking on the regression and model calibration, various variable summary statistics are generated to evaluate whether or not the distributions and trends between variables are intuitive. However, it should be noted that the histograms and box-plots presented are applicable to the corresponding variables mentioned when used separately and do not show the interaction and influence of the rest of the variables.

5.2 Summary of Descriptive Statistics

5.2.1 Introduction

Except for the additional travel time, spatial and temporal extents, the summary statistics for each of the other impact variables presented here are for the combined primary incident direction and the rubbernecking (i.e., opposite) directions. For example, the excess vehicle –hours of travel is the sum of the excess VHT in the primary direction and the excess VHT in the rubbernecking direction. This was dome primarily due to what was observed in the preliminary analysis that there were no significant observed trends between the rubbernecking impacts by themselves and the incident characteristics.

5.2.2 Incident Duration

Figure 5-1 shows the histogram of incident durations for all the incidents in the sample set.

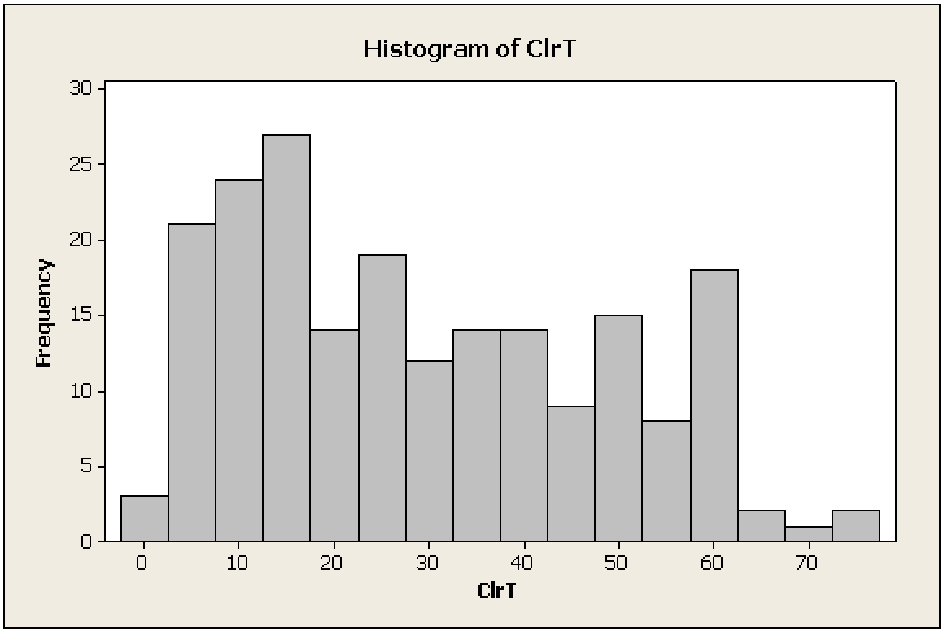


Figure 5-1. Histogram of Incident Clearance Durations (minutes)

(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.

Figure 5-2 shows that the average incident duration for two lanes blocked is higher than for one lane, implying, as expected, that two lane incidents are typically more severe than single lane incident resulting in higher incident duration. However it should be noted also that the incident duration for shoulder incidents (zero blocked lanes) are higher than the single blocked travel lane incidents. This may indicate a lower sense of urgency for clearing incidents that do not block travel lanes.

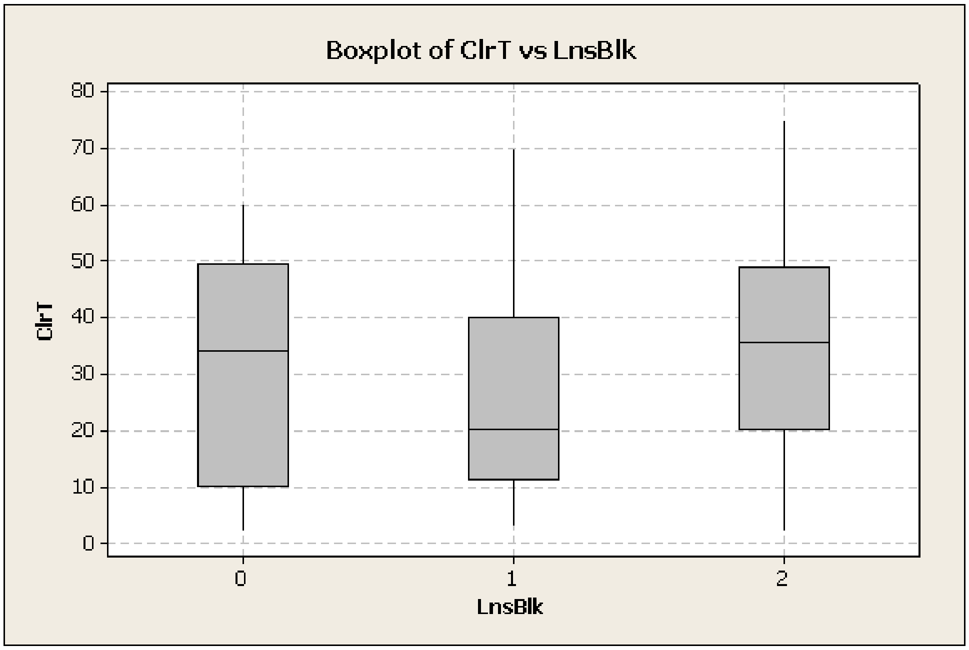


Figure 5-2. Box-plot: Incident Duration Vs. Number of Blocked Lanes

5.2.3 Additional Average Travel Time

This section presents histograms and box-plots of the impact in terms of the additional average travel time over the impacted segment in the primary direction, i.e., same travel direction as the incident location. Figures 5-3 show the histogram of the additional travel time, in minutes/vehicle. The distribution is skewed to the right following the expected trend that typically high-impact incidents are not as frequent as the lower impact incidents. 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

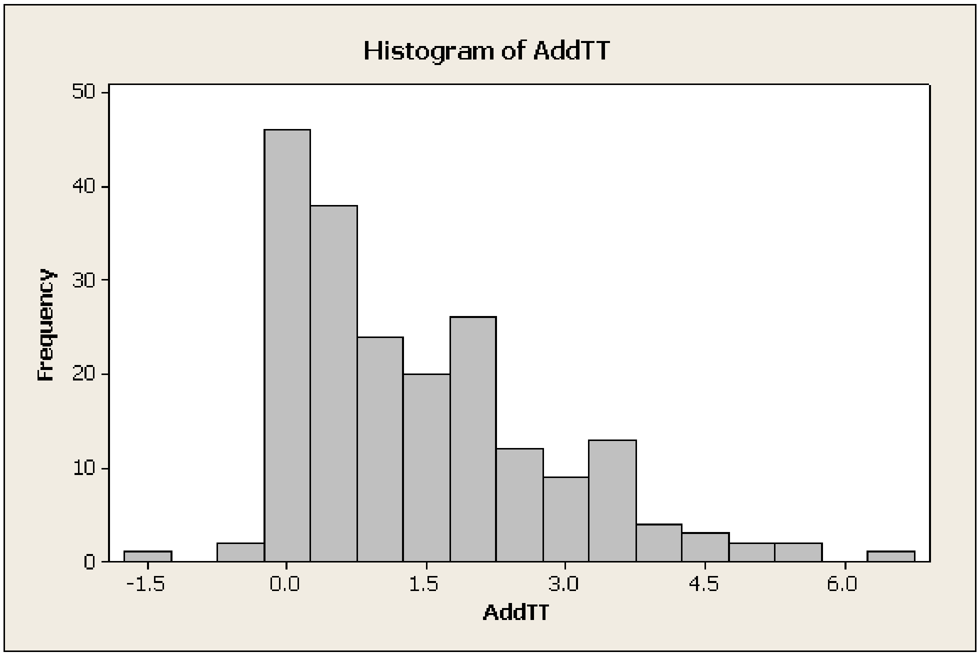


Figure 5-3. Histogram: Additional Travel Time per vehicle

(Mean value = 1.32; Median = 1.05 minutes/vehicle)

Figures 5-4 show box-plots of travel time impact for different numbers of blocked lanes. Box-plots show median values (the horizontal lines in the middle of the box) of the response variable, quartiles and range of values. 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. The figures show an expected trend, namely, the more the number of travel lanes blocked the higher the impact in terms of the additional travel time.

Similarly, Figure 5-5 Shows box-plots of the additional travel times as functions of the incident duration. 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 minutes, greater than 45 minutes up to 60, and finally greater than 60 minutes, respectively. Again the plot show the expected trend, namely, the higher the incident duration, the higher the impact in terms of the additional travel time.

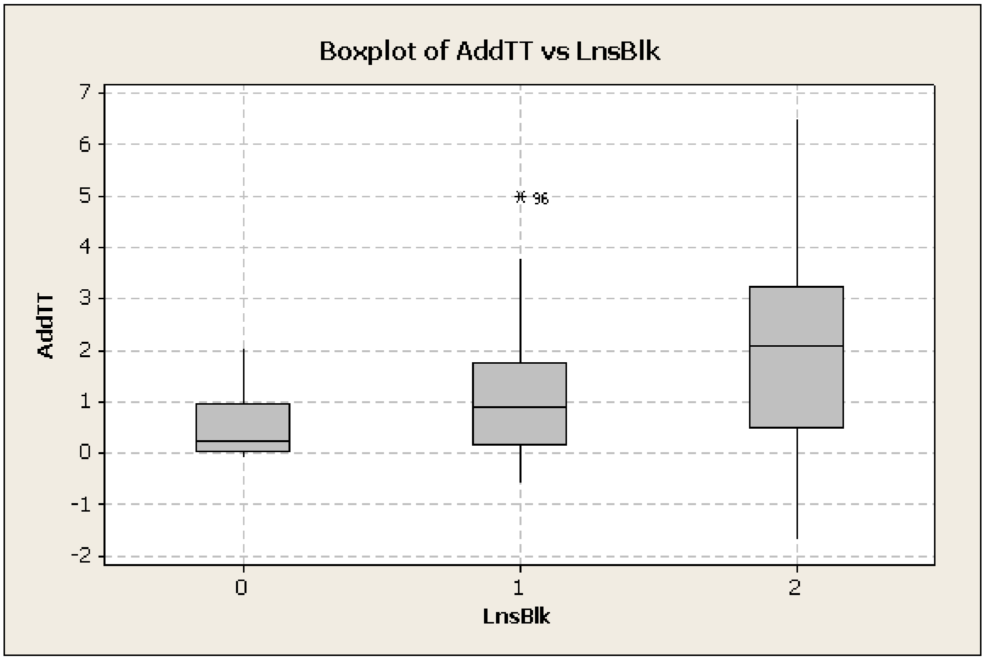


Figure 5-4. Box-plot: Primary Additional Travel Time (in minutes) Vs. Number of Blocked Lanes

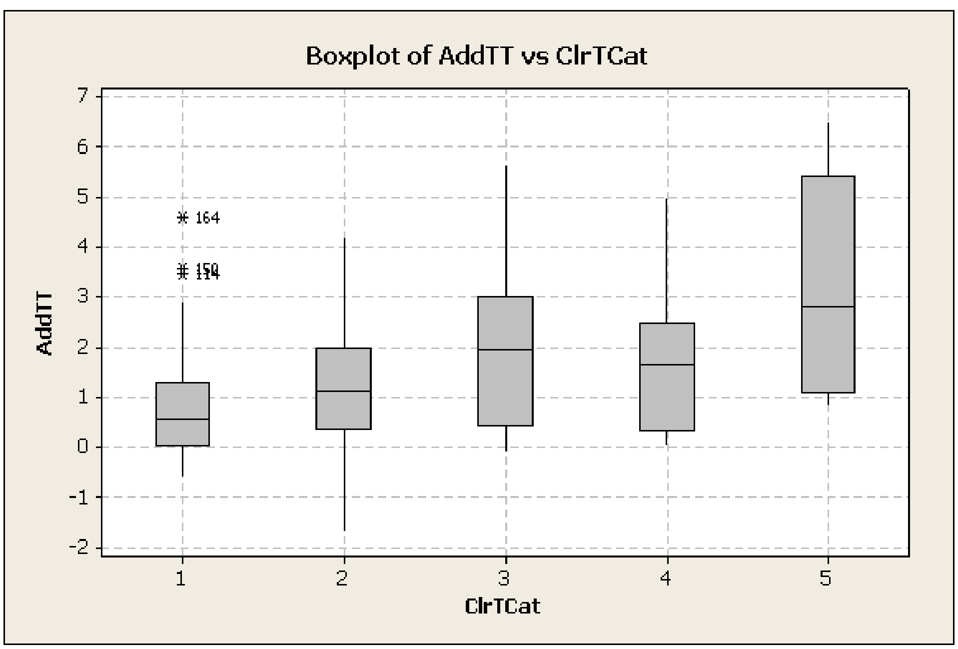


Figure 5-5. Box-plot: Average Primary Additional Travel Time (in minutes/vehicle) Vs. Incident Duration

5.2.4 Excess Vehicle-Hours of Travel (VHT)

This section presents histograms and box-plots of the impact in terms of the excess total vehicle-hours of travel for all the impacted vehicles combined. Figure 5-6 shows the histogram of the excess vehicle hours of travel. Again, as expected, 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).

Figures 5-7 and 5-8 show box-plots of the excess VHT impact for different numbers of blocked lanes and incident durations, respectively. Also, here the trends are as expected, the higher the number of travel lanes blocked, the higher the impact. The same trend is true for the incident duration.

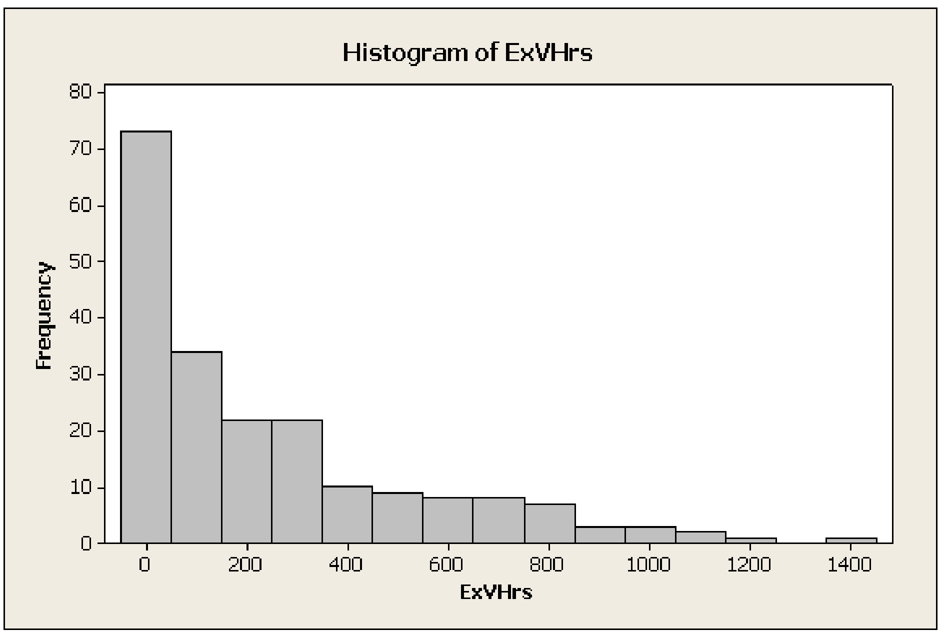


Figure 5-6. Histogram: Impact VHT

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

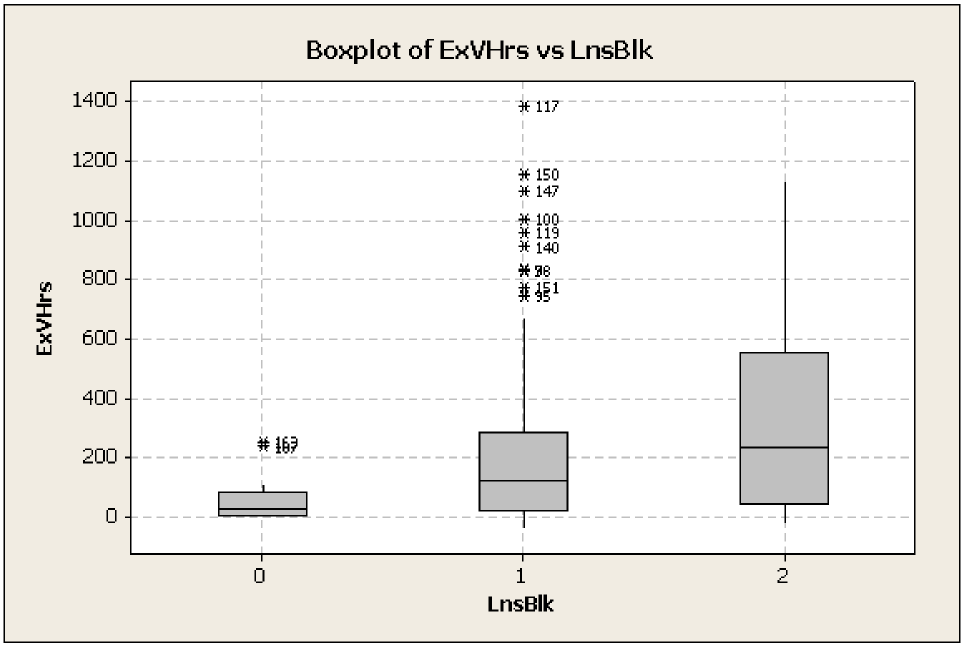


Figure 5-7. Box-plot: Excess VHT Vs. Number of Blocked Lanes

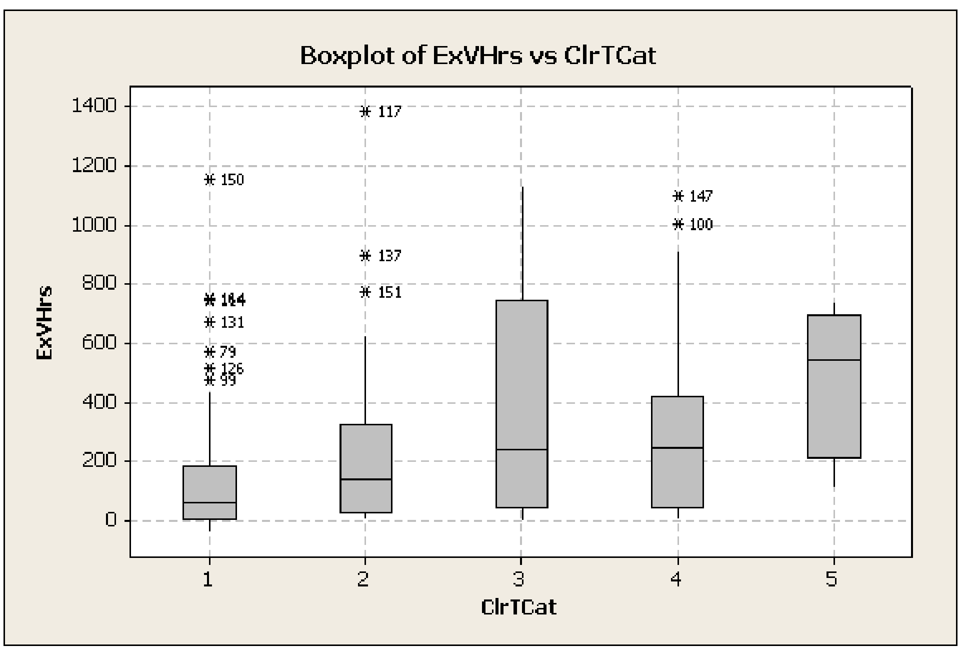


Figure 5-8. Box-plot: Impact in VHT vs. Incident Duration

5.2.5 Temporal and Spatial Extents

Figures 5-9 to 5-12 are box-plots of the temporal and spatial extents for different values of the number of blocked lanes and for different incident duration categories, as earlier explained. Again, the trends observed are as expected, the higher the number of blocked travel lanes, the longer will be the length of the temporal and spatial extents. Similar trends are observed with respect to the incident durations.

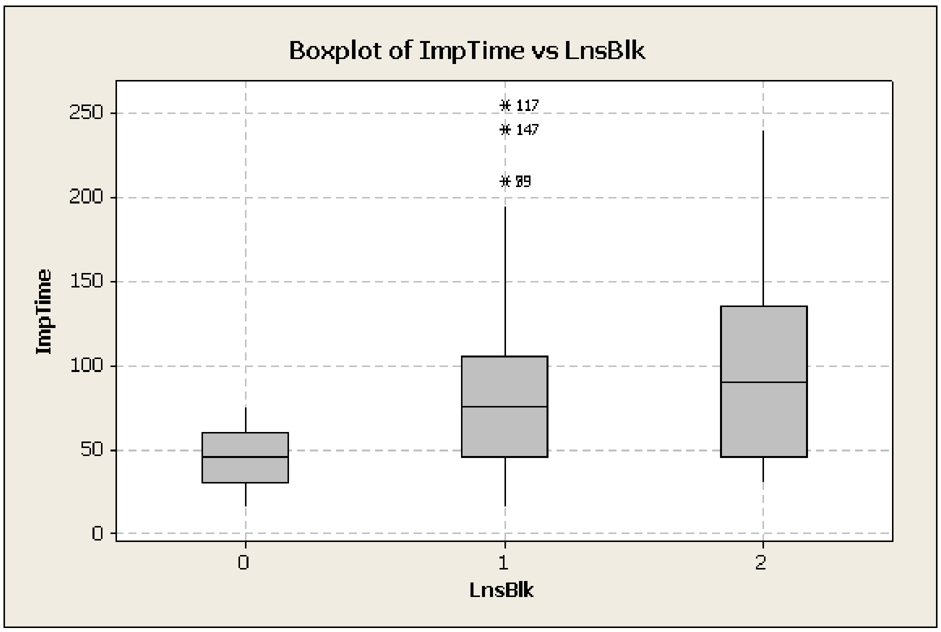


Figure 5-9. Box-plot: Temporal Impact (in minutes) Vs. Number of Blocked Lanes

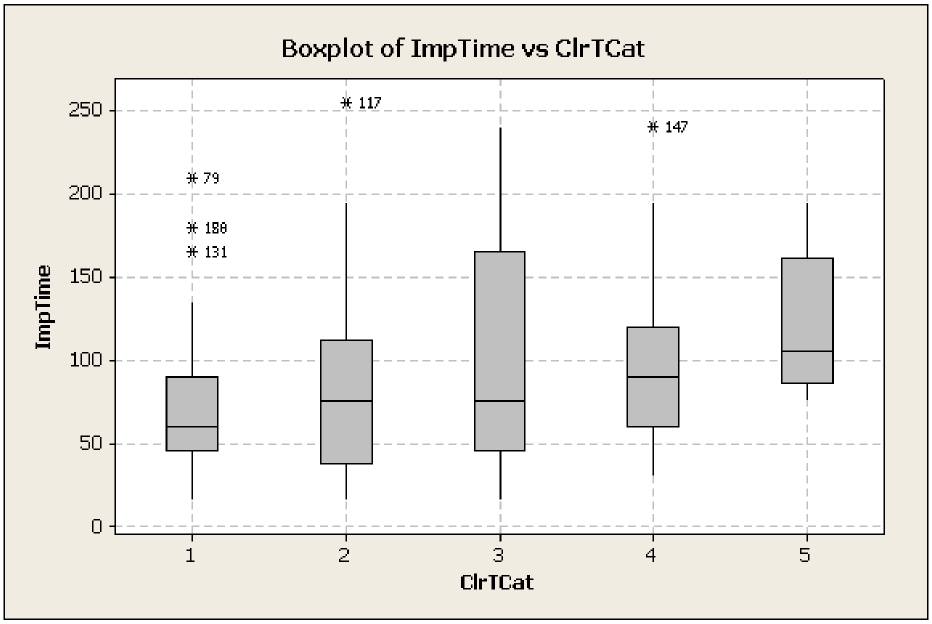


Figure 5-10. Box-plot: Temporal Extent (in minutes) vs. Incident Duration

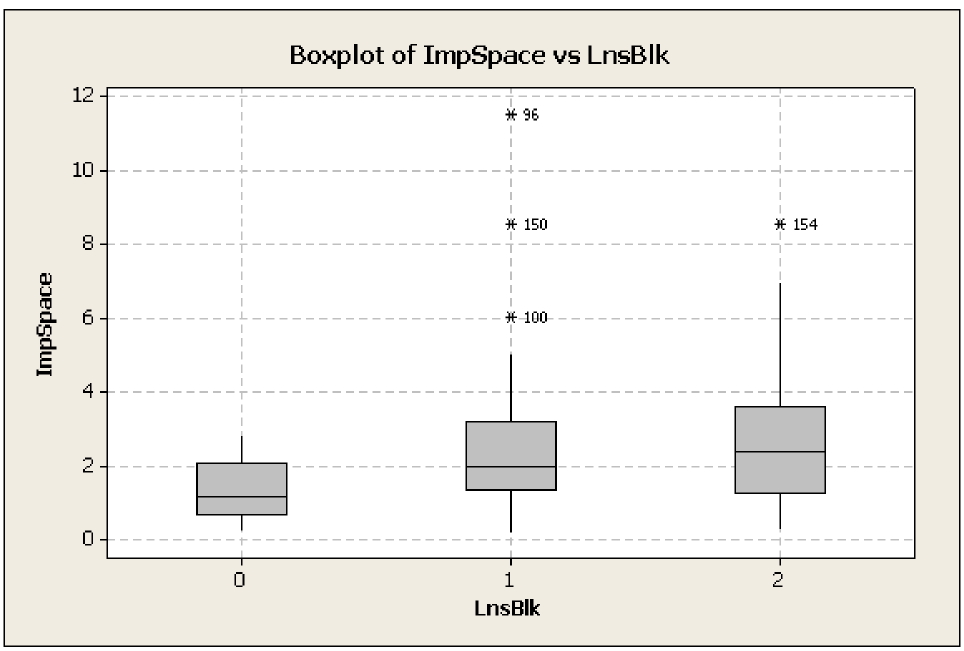


Figure 5-11. Box-plot: Spatial Impact (in miles) Vs. Number of Blocked Lanes

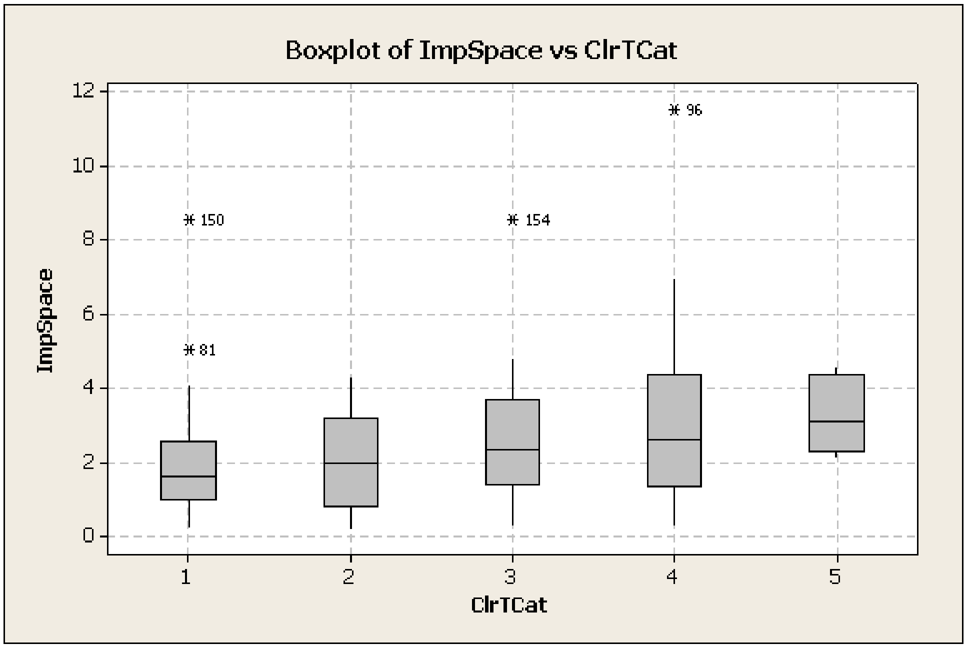


Figure 5-12. Box-plot: Spatial Extent (in miles) Vs. Incident Duration

5.2.6 Fuel Consumption

Figures 5-13 to 5-15 show a histogram and box-plots of incident impacts in terms of fuel consumption. Again, the trends are in general are similar to what is observed with the other variables.

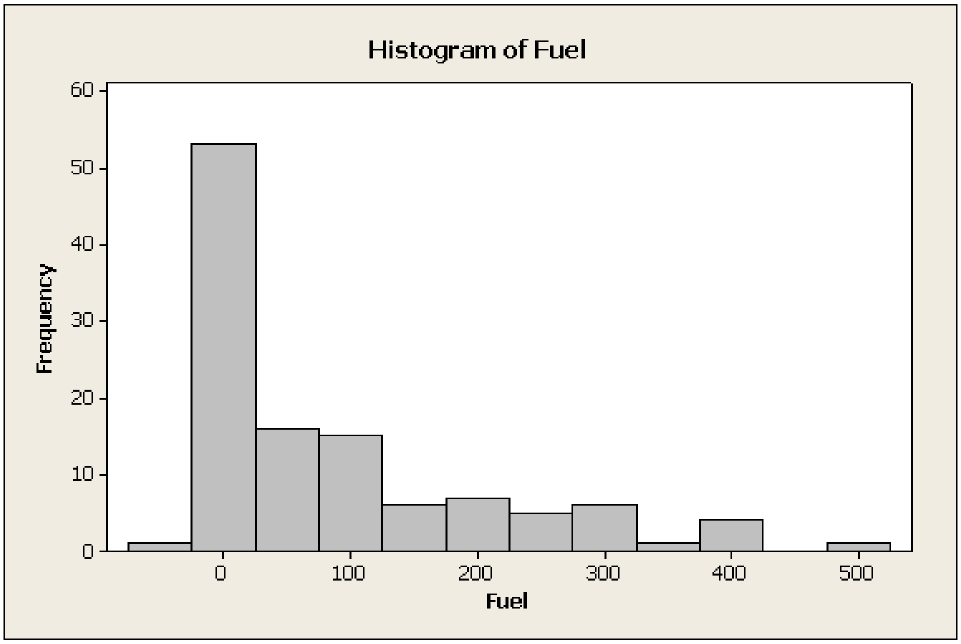


Figure 5-13. Histogram: Excess Fuel Consumption in gallons

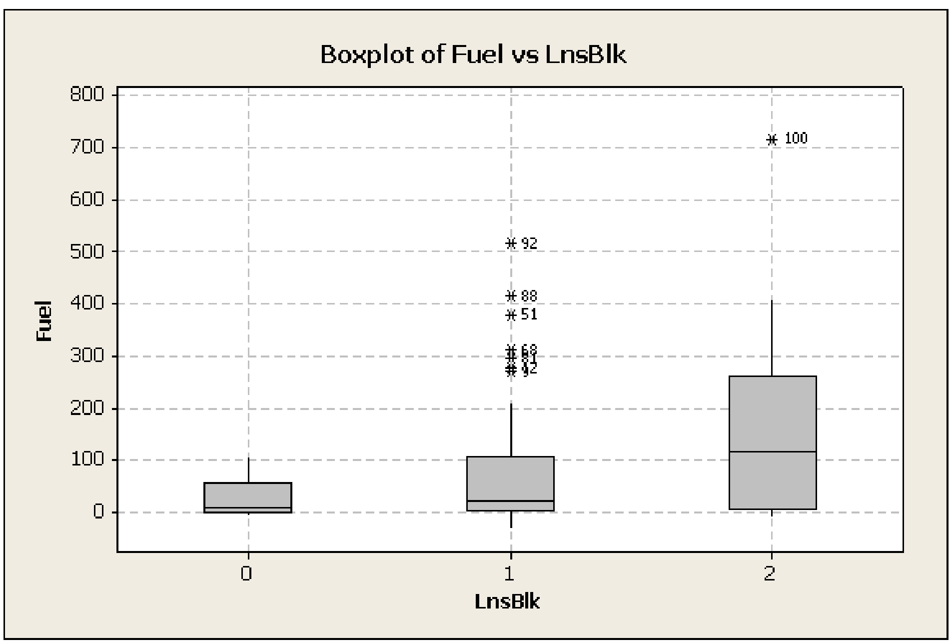


Figure 5-14. Box-plot: Excess Fuel Consumption (in gallons) Vs. Number of Lanes Blocked

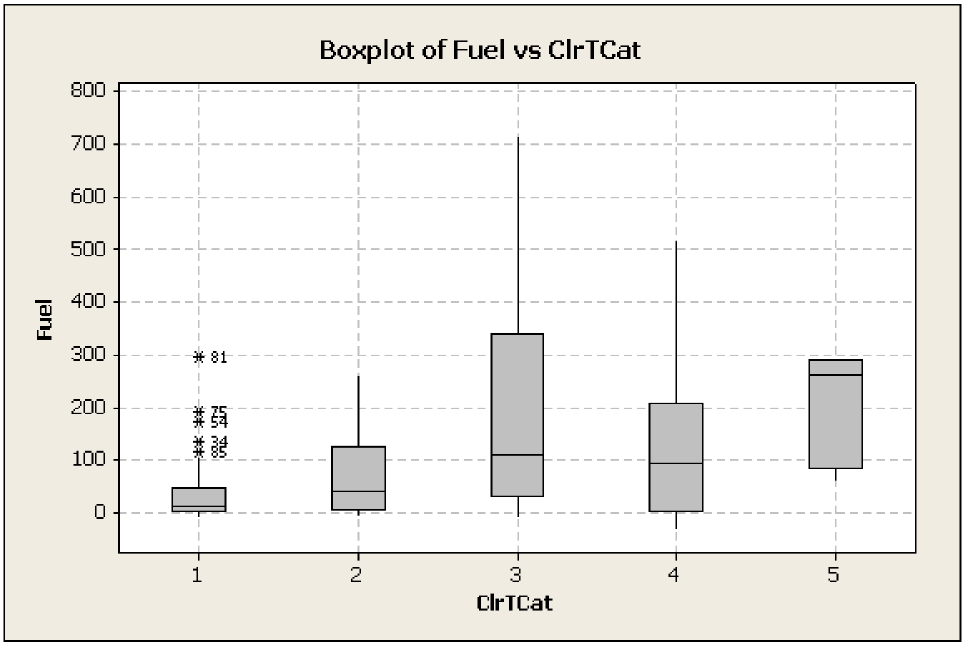


Figure 5-15. Box-plot: Excess fuel consumption (in gallons) Vs. Incident Duration

5.2.7 Vehicle Emissions

Figures 5-16 to 5-27 show histograms and box-plots of incident impacts in terms of fuel consumption. Again, the trends are in general are similar to what is observed with the other variables. The impacts median of the impacts increase as the number of lanes blocked or the incident durations increase.

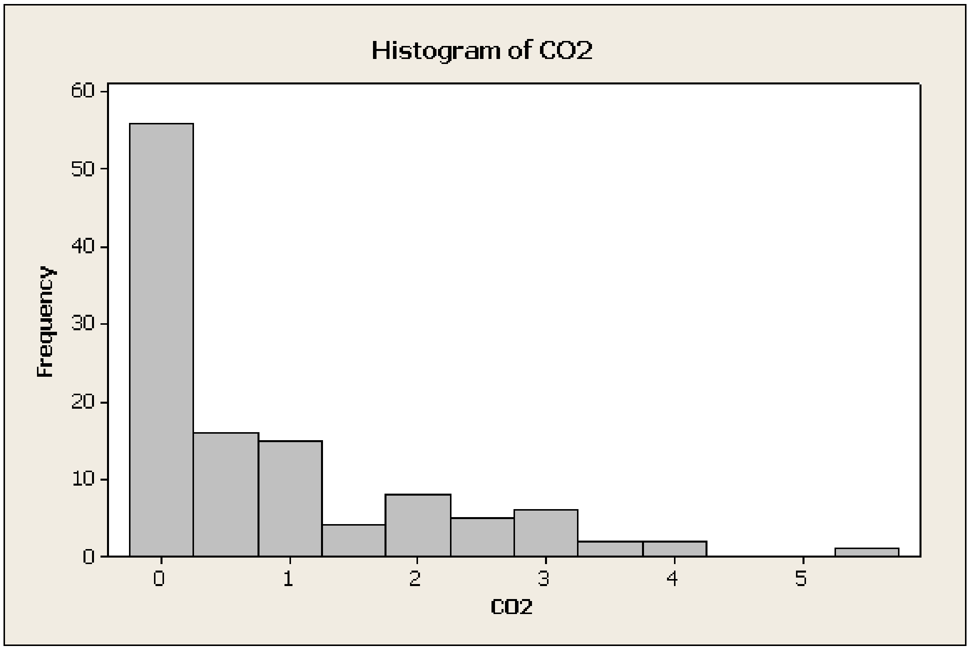


Figure 5-16. Histogram: Excess CO_2 Emissions in Tons

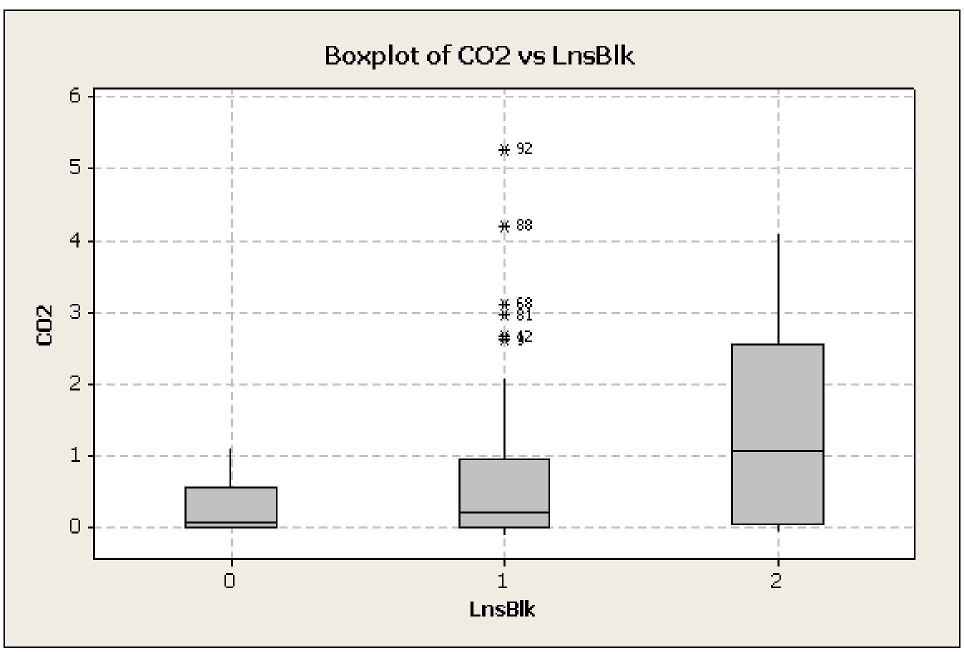


Figure 5-17. Box-plot: Excess CO2 emissions (in Tons) vs. Number of Blocked lanes

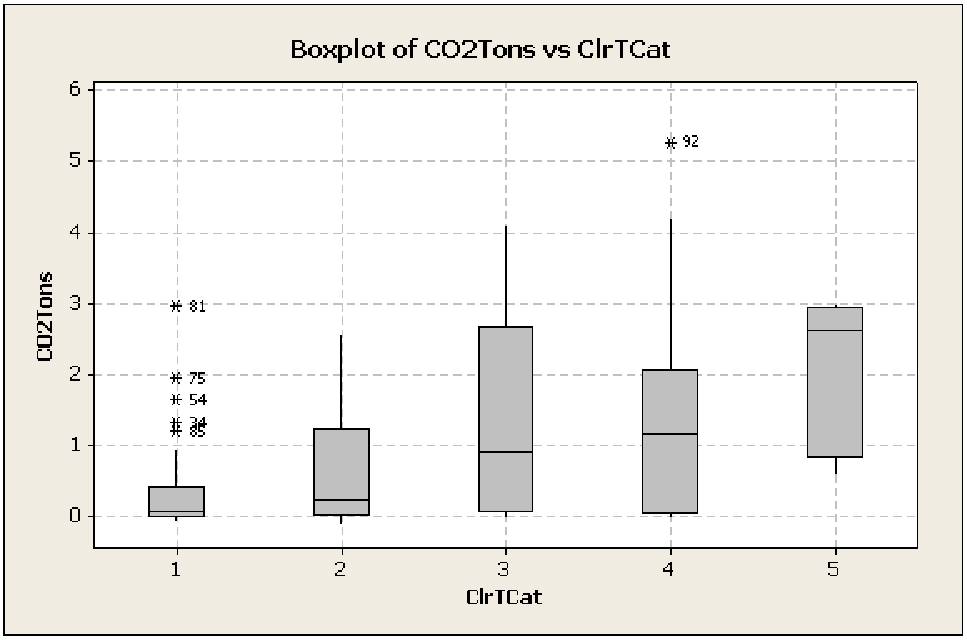


Figure 5-18. Box-plot: Excess CO_2 emissions (in Tons) vs. Incident Duration

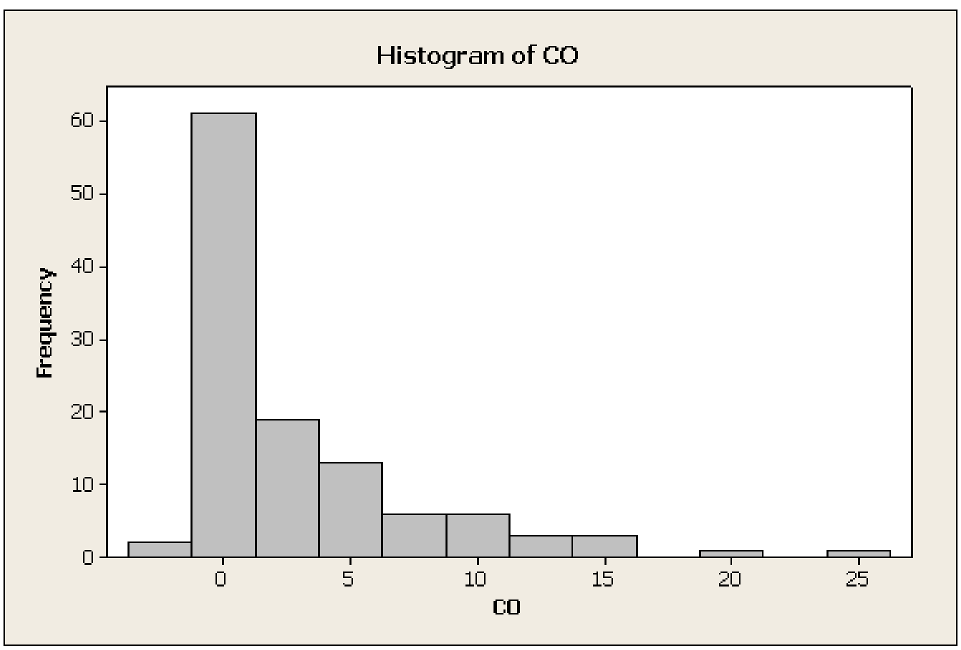


Figure 5-19. Histogram: Excess CO Emissions in Kgs

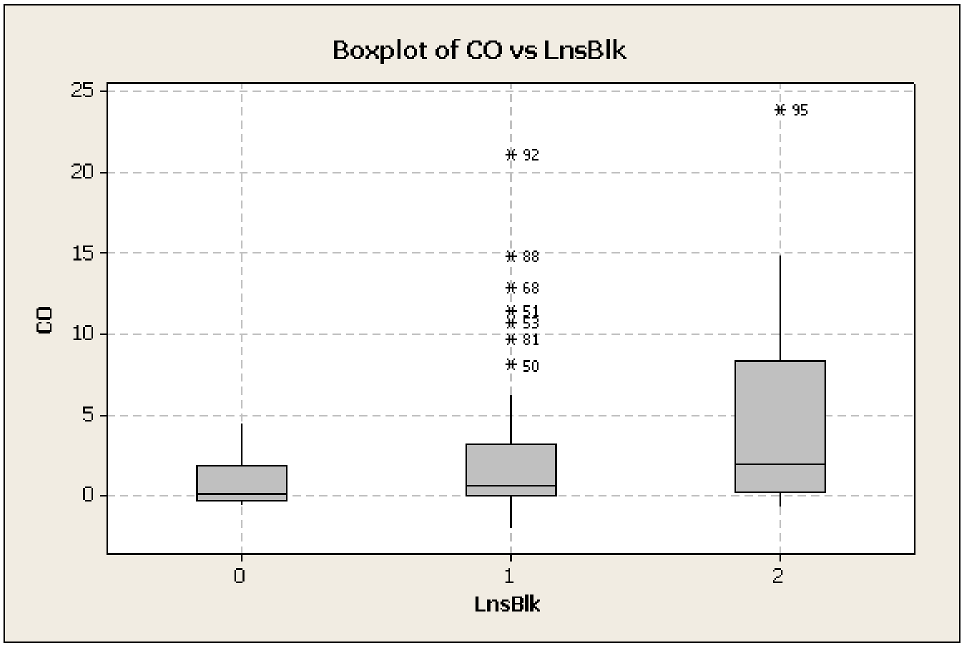


Figure 5-20. Box-plot: Excess CO emissions (in Kgs) vs. Number of Blocked lanes

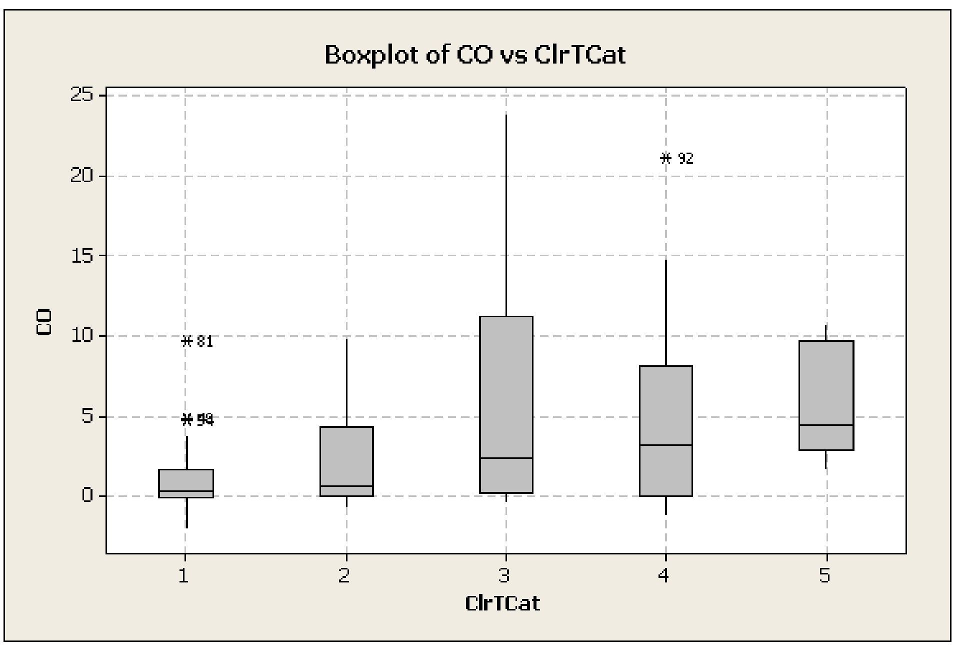


Figure 5-21. Box-plot: Excess CO emissions (in Kgs) vs. Incident Duration

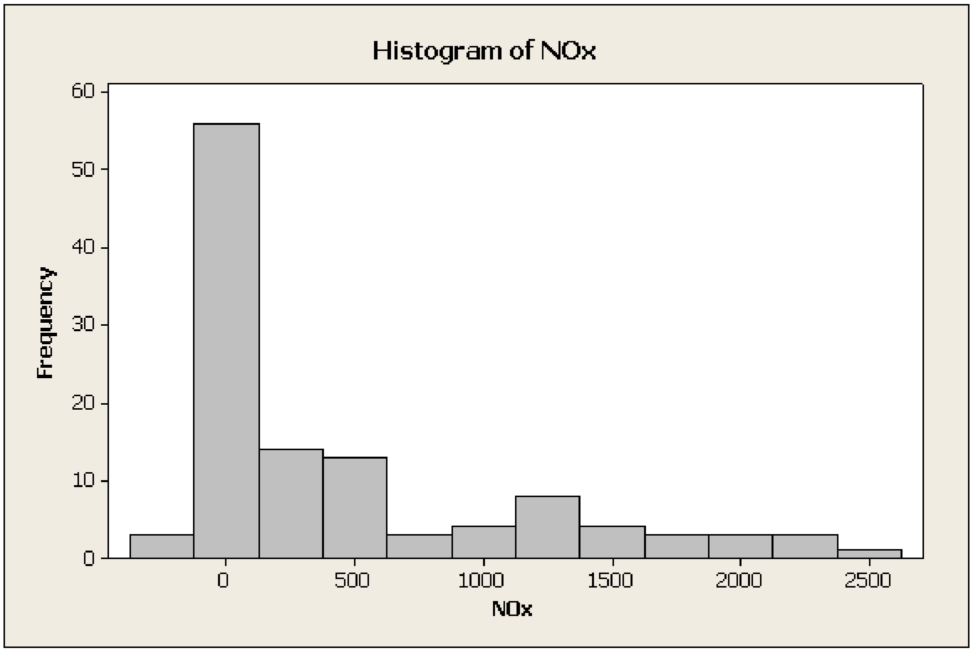


Figure 5-22. Histogram: Excess NO_x Emissions in grams

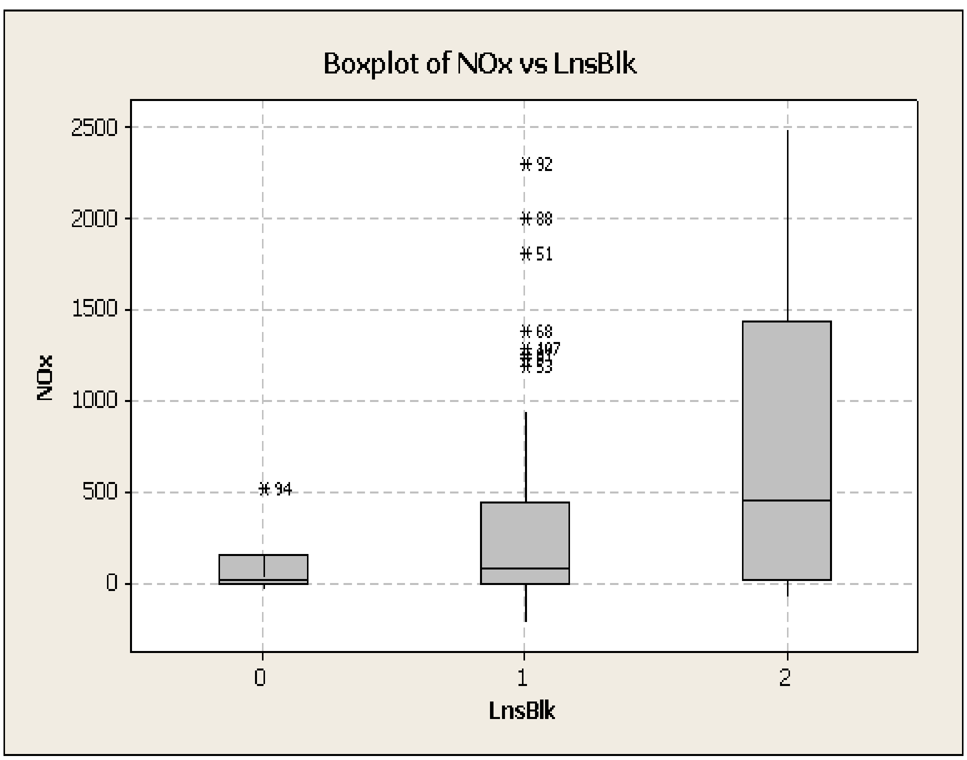


Figure 5-23. Box-plot: Excess NO_x emissions (in Grams) vs. Number of Blocked lanes

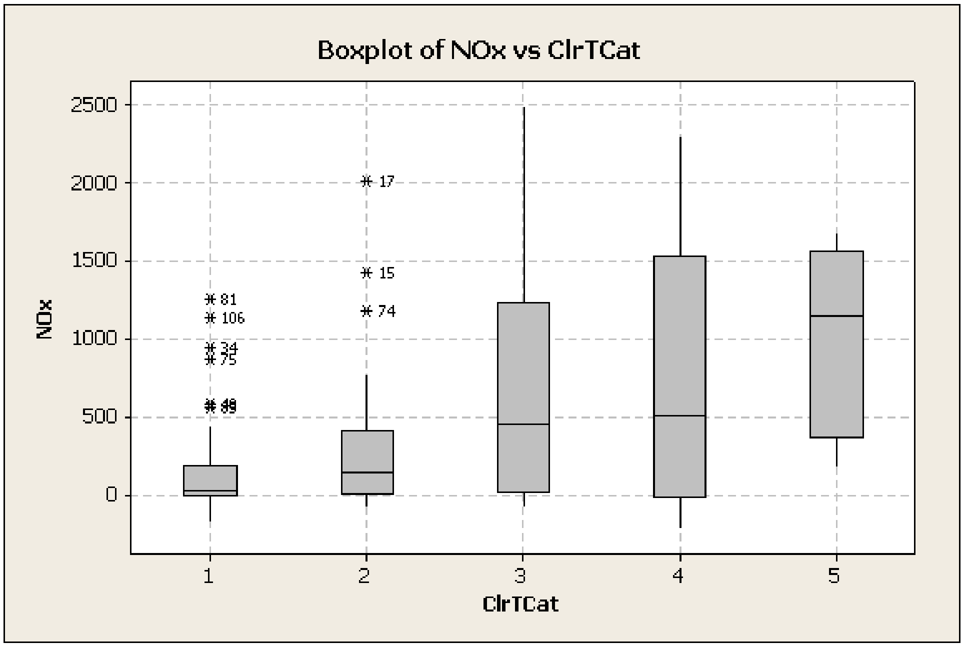


Figure 5-24. Box-plot: Excess NO_x emissions (in Grams) vs. Incident Duration

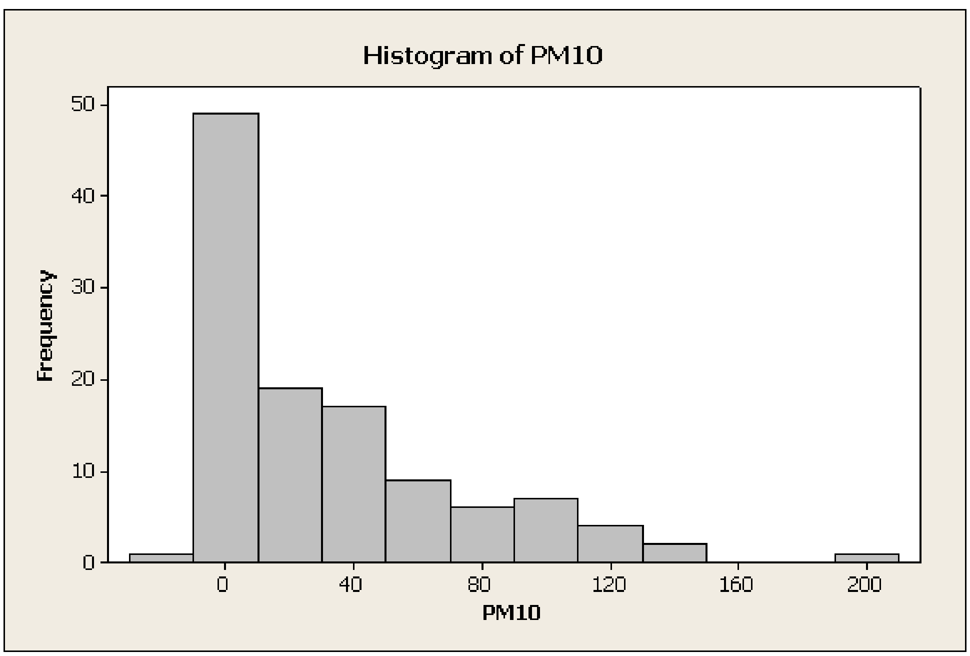


Figure 5-25. Histogram: Excess PM_{10} Emissions in grams

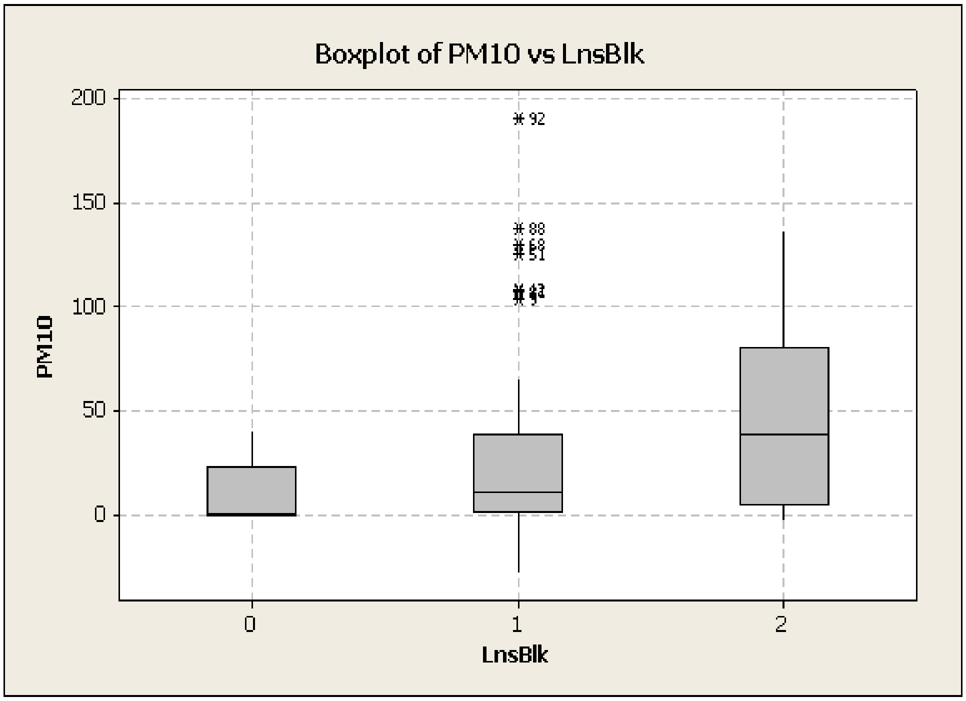


Figure 5-26. Box-plot: Excess PM_{10} emissions (in Grams) vs. Number of Blocked lanes

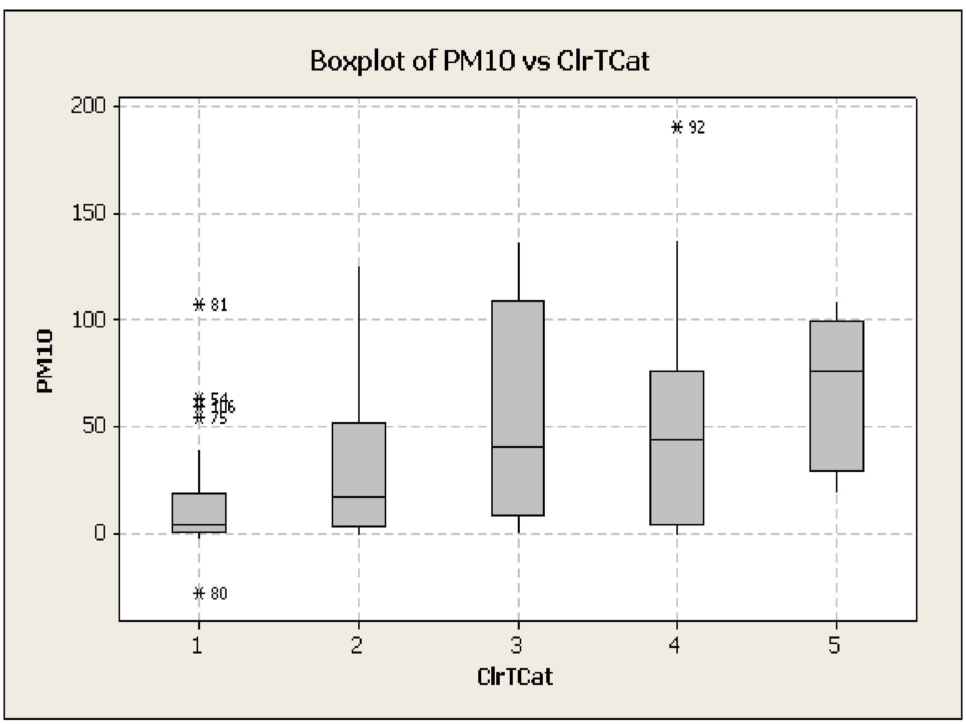


Figure 5-27. Box-plot: Excess PM_{10} emissions (in Grams) vs. Incident Duration

5.3 Summary

This chapter presented the descriptive summary statistics to observe the general trends among certain among certain incident characteristics and the 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 trends that can be further studied by statistical modeling.

CHAPTER 6 CALIBRATION MODELING RESULTS

6.1 Introduction

This chapter presents the statistical modeling results for the 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 Double-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).

6.2 Description of Response and Predictor Variables

The list of the response and predictor variables used in the analysis of the incident impacts, their description and codes in R are presented in the following tables (Tables 6-1 and 6-2). It is to be noted that in all the models, the number of travel lanes blocked is used as a dummy variable, as denoted by the variables LNSBLK1 and LNSBLK2. Zero travel lanes blocked (i.e., shoulder incident) will have both variables equal to zero. On the other hand if one travel lane is blocked, then LNSBLK1 will have a value of 1, and if two lanes are blocked LNSBLK2 will be the one to take the value 1.

Tables 6-3 and 6-4 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.

Statistical models were calibrated for each response variable using the functional forms described in Section 3.3.3. Stepwise regression analysis was used to identify the significant predictor variables for each response variable for each functional form. The statistical parameters R^2, AIC, and residual plots were then used to select the most appropriate function form for each response variable.

Table 6-1. List of Response Variables

Variable Code	Variable Name	Explanation
AddTT	Additional Travel Time	Excess travel time during the incident in minutes/incident
ExVHrs	Excess Vehicle Hours	Excess vehicle-hours of travel experienced by all impacted vehicles in veh-hrs
ImpTime	Temporal extent	Total time of incident impact in minutes
ImpSpace	Spatial extent	Freeway segment impacted in miles
NO_X	Excess Oxides of Nitrogen	Excess NOx due to incident in grams
PM_{10}	Excess Particulate Matter <10 microns	Excess PM10 due to incident in grams
CO_2	Excess Carbon di-oxide	Excess CO2 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 6-2. List of Predictor Variables

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

Table 6-3. 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 6-4. 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

6.3 Model Results

The results are arranged in the same format for all the response variables for 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 (model with all predictor variables) and Nested model (the final model with only the significant predictor variable from stepwise regression). Also presented are the residual and normality plots for the nested models, as well as 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.

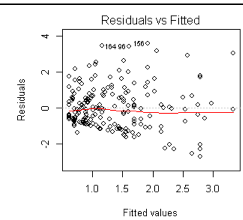
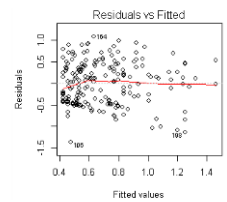
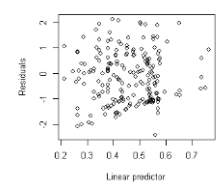
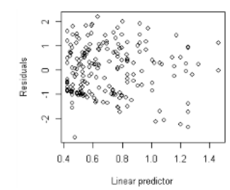
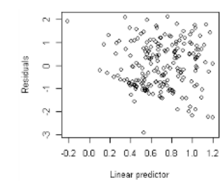
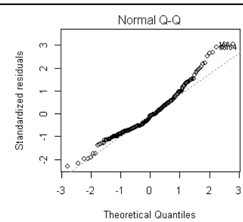
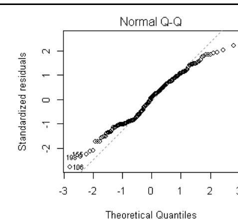
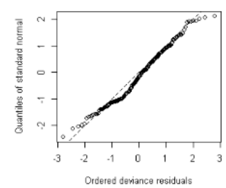
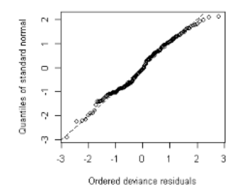
6.3.1 Additional Travel Time

The model results for the analysis for additional travel time per incident experienced by the impacted vehicles are shown in Table 6-5. The Gaussian Double-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 Figure 6-1. The final model form selected is the Gaussian log-log function and is presented in Equation 6-1 below.

$$\text{Additional Travel Time} = \text{Exp}\,\{-1.01756 + 0.2616 * \text{Ln (Non-incident Density)} + 0.1867 * \text{Ln (Incident duration)} + 0.3042 * \text{1 lane blocked} + 0.6027 * \text{2 lanes blocked}\} - 1 \quad (6\text{-}1)$$

The results show that the coefficient estimates are all positive indicating that, as expected, additional travel time increases with increase in each of the predictor variables. 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.

Table 6-5. 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^2 / Adj-R^2 (%)	26.0 / 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^2 / Adj-R^2 (%)	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	BlkLnMin	LNSBLK ClrT	LNSBLK ClrT	BlkLnMin	lnNIDensity lnClrT LNSBLK

Final Nested Model:

```
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
```

AIC:
294.37

R-Sq:
20.96%

Diagnostic Plots:

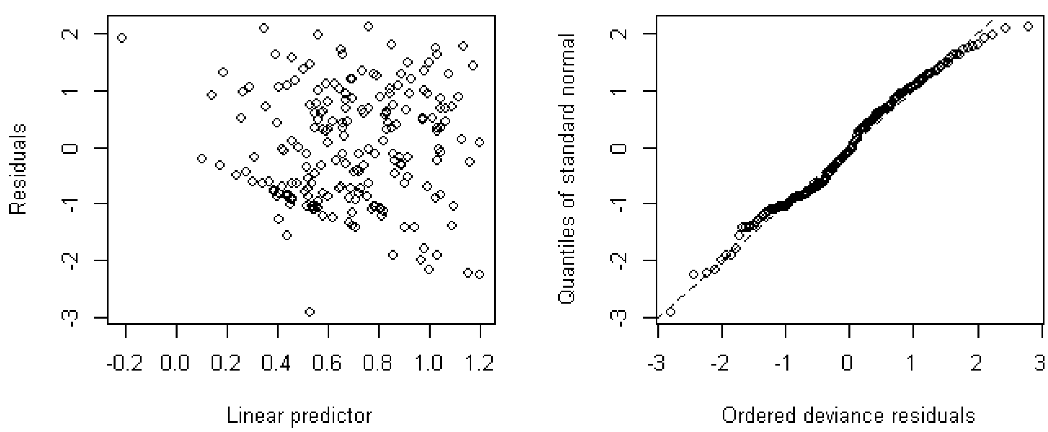


Figure 6-1. Best Model: Excess Additional Travel Time per Impacted Vehicle

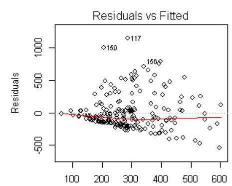
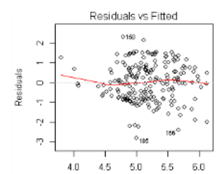
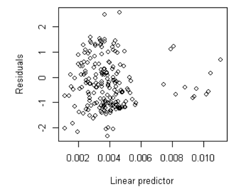
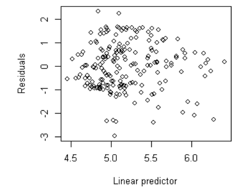
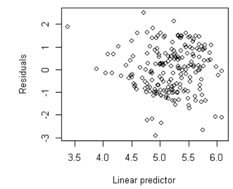
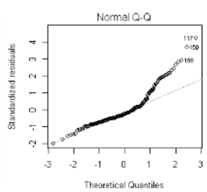
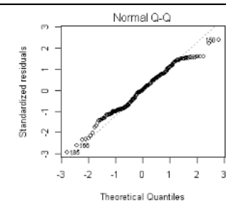
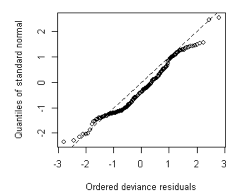
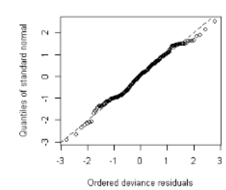
(Model Form: Gaussian log-log GLM)

6.3.2 Excess Vehicle Hours

The model results for excess vehicle hours of the impacted vehicles are shown in Table 6-6. This is followed by the coefficient estimates for the best model and the diagnostic plots in Figure 6-2. The Gaussian Log-Log model clearly shows the best fit when compared to the other models in terms of the residual and normality plots. The R^2 and AIC measures are lower than the Single-log GLM. Therefore, the Gaussian Log-Log model is recommended for estimation of excess vehicle hours of impact (Equation 6-2). The significant variables are the incident duration, the number of travel lanes blocked and the non-incident density. All the signs of the coefficients are positive, indicating, as expected, that the higher the values of these variables, the higher the impact vehicle hours. The results also show that the impact for two lanes blocked is higher than that for only one lane blocked.

$$\text{Excess VHT} = \text{Exp}\,\{1.41944 + 0.66726 * \text{Ln (Non-incident Density)} + 0.35164 * \text{Ln (Incident duration)} + 0.750316 * \text{1 lane blocked} + 1.05008 * \text{2 lanes blocked}\} - 50 \qquad (6\text{-}2)$$

Table 6-6. 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^2 / Adj-R^2 (%)	21.39 / 16.42	27.29 / 22.7	13.58 /	27.29 /	28.71 /
AIC	2857.4	555.85	2679.7	555.85	549.85
Nested Model:					
R^2 / Adj-R^2 (%)	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 $p > 0.05$			0.5989	0.4867	0.4866
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

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:

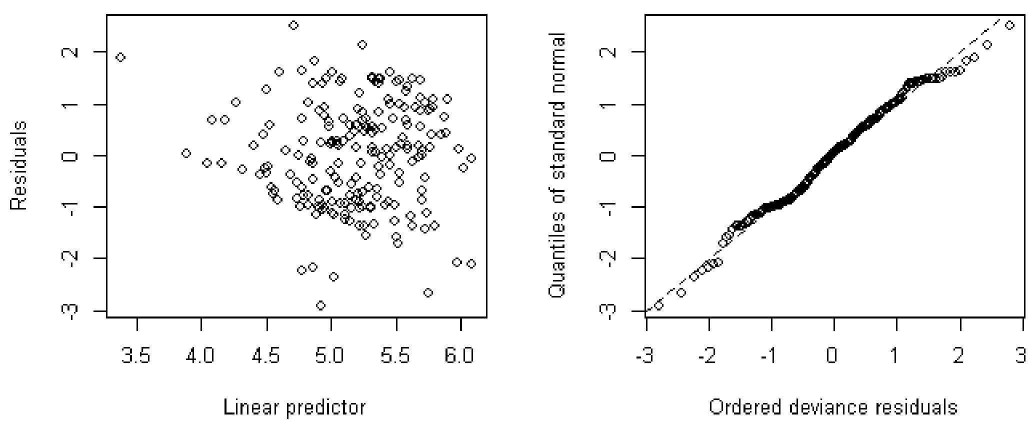


Figure 6-2. Best Model: Excess Vehicle Hours of Travel for Impacted Vehicles

(Model Form: Gaussian log-log GLM)

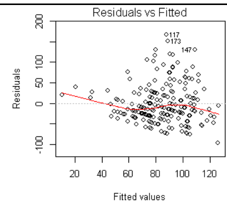
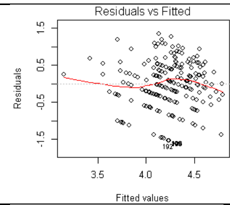
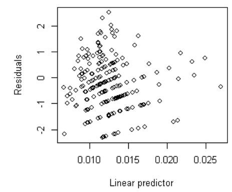
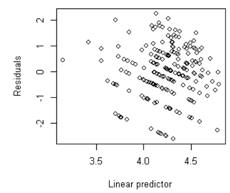
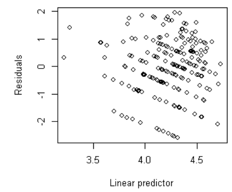
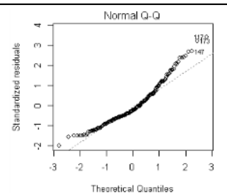
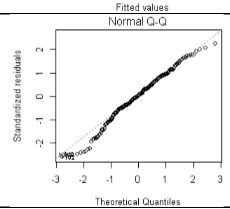
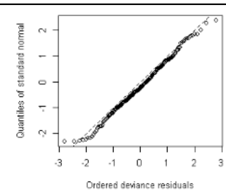
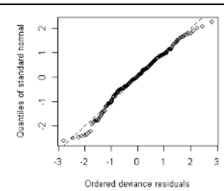
6.3.3 Temporal Extent

The model calibration results for the analysis for average temporal extent of incidents are shown in Table 6-7. 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 Figure 6-3. Equation 6-3 presents the calibrated equation for the selected 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.

$$\text{Temporal Extent} = \text{Exp}\,\{3.244 + 0.02074 * \text{Non-incident Density} + 0.00843 * \text{Incident duration} + 0.53700 * 1\ \text{lane blocked} + 0.71050 * 2\ \text{lanes blocked}\} \qquad (6\text{-}3)$$

Table 6-7. Results for Temporal Extent

Category	**Linear**	**Transformed (Single log)**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
Variable: Impact Time					
Full Model:					
R^2 / Adj-R^2 (%)	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^2 / Adj-R^2 (%)	13.54 / 11.34	16.98 / 14.88	10.86 /	16.98 /	15.65 /
AIC	2165.5	390.6	2108.8	390.6	393.8
Model Fit (P-value) Accept Model p >0.05			0.3455	0.4866	0.4866
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

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:

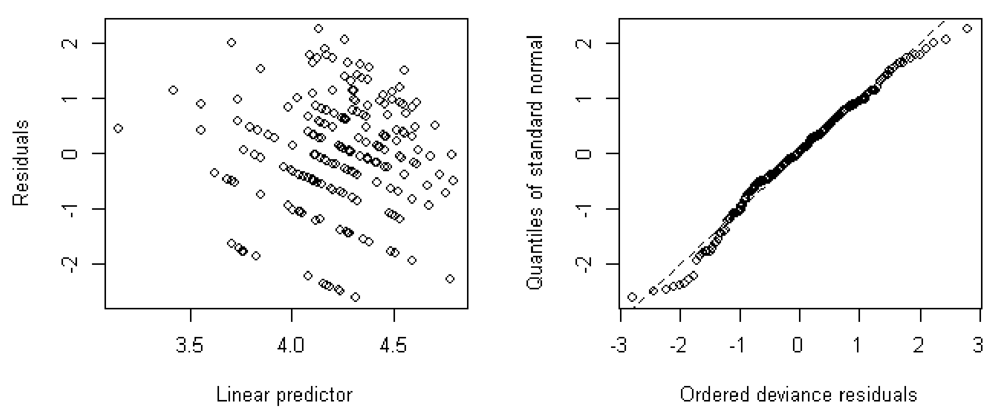


Figure 6-3. Best Model: Temporal Extent

(Model Form: Gaussian Single-log GLM)

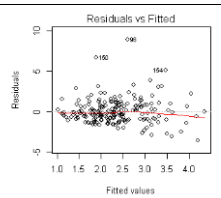
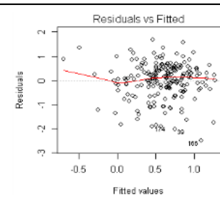
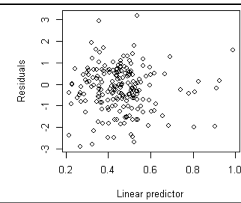
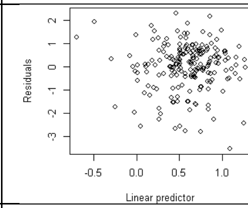
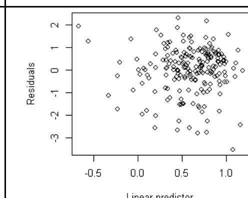
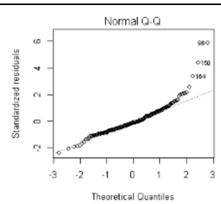
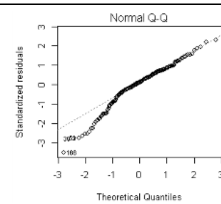
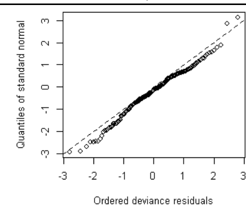
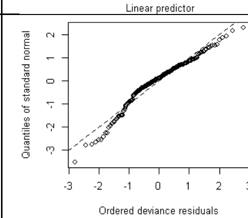
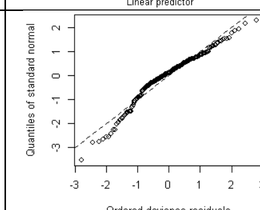
6.3.4 Spatial Extent

The summary of model results is shown in Table 6-8. The model chosen for the average spatial extent of an 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.

The results of the recommended model are shown in Figure 6-4 and Equation 6-4. The coefficient estimates are once again, all positive, except non-incident volume. Therefore, the spatial extent increases with increase in incident duration, lanes blocked and non-incident traffic density.

$$\text{Spatial Extent} = \text{Exp}\,\{-0.8622 + 0.035 * (\text{Non-incident Density}) + 0.0102 * (\text{Incident duration}) + 0.7286 * 1\text{ lane blocked} + 0.8024 * 2\text{ lanes blocked}\} \qquad (6\text{-}4)$$

Table 6-8. Results for Spatial Extent

Category	Linear	Transformed (Single Log)	Gamma	Gaussian (Log)	Gaussian (Log-Log)
Variable: Spatial Extent					
Full Model:					
R^2 / Adj-R^2 (%)	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^2 / Adj-R^2 (%)	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			0.1743	0.4866	0.4866
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

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:

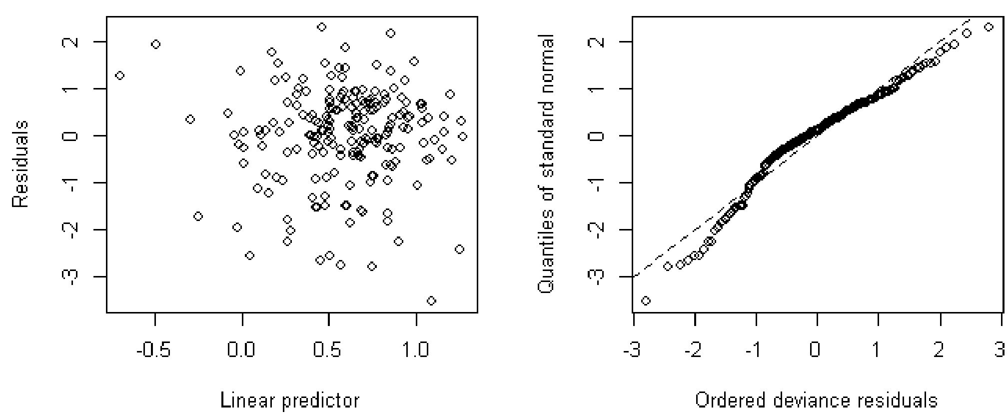


Figure 6-4. Best Model: Spatial Extent

(Model Form: Gaussian Single-log GLM)

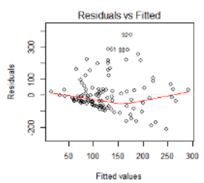
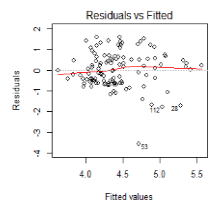
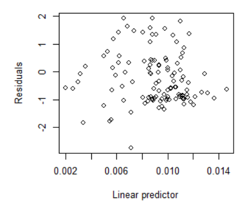
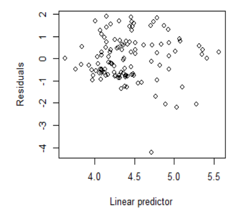
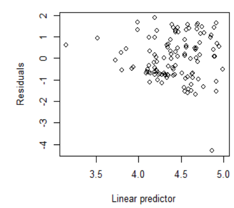
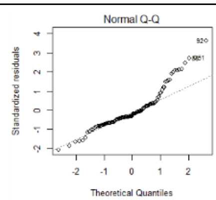
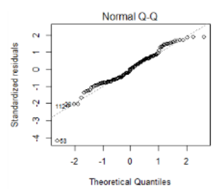
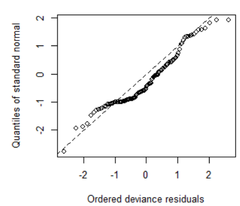
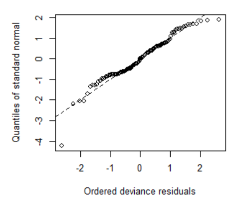
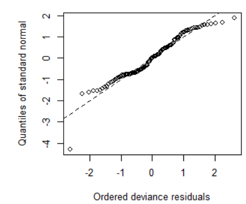
6.3.5 Excess Fuel Consumption

Table 6-9 presents the comparison of the results for all the models for excess fuel consumption in gallons. 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 Figure 6-5 and the model form in equation 6-5. The significant variables in the model are lane-minutes of blockage and non-incident traffic density.

$$\text{Excess Fuel Consumption} = \text{Exp}\,\{3.36649 + 0.010554 * \text{Lane-Minutes of Blockage} + 0.036113 * \text{Non-incident Density}\} - 35 \tag{6-5}$$

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.

Table 6-9. Results for Excess Fuel Consumption

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
			Variable: Fuel Consumption		
Full Model:					
R^2 / Adj-R^2 (%)	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^2 / Adj-R^2 (%)	21.71 / 20.31	16.96 / 15.48	15.33 /	28.44 /	11.77 /
AIC	1401.3	293.4	1317.7	294.3	300.3
Model Fit (P-value) Accept Model p >0.05			0.7121	0.4822	0.4822
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

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:

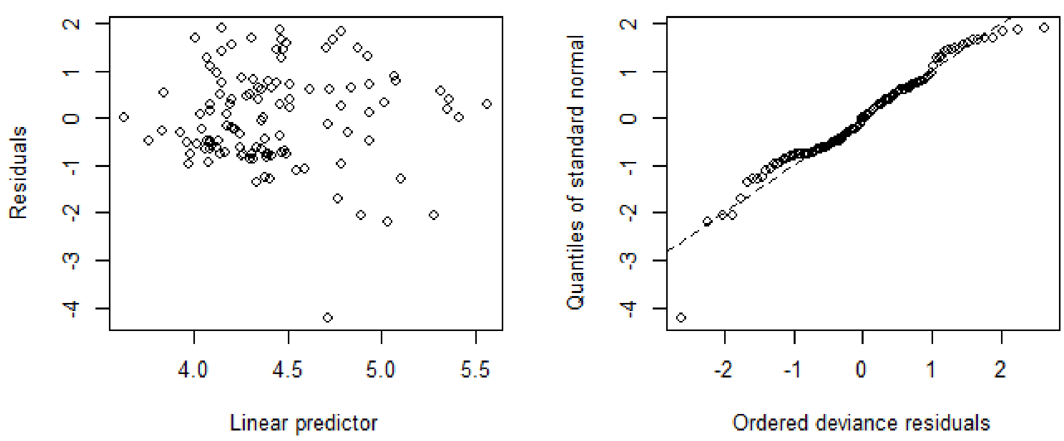


Figure 6-5: Best Model Results Excess Fuel Consumption (gallons)

(Model Form: Gaussian Single-log GLM)

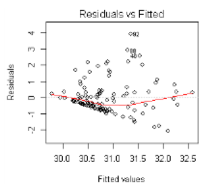
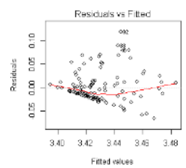
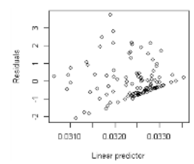
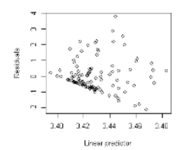
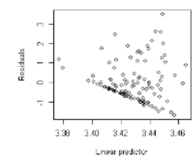
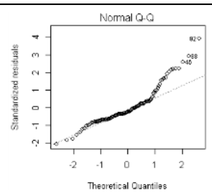
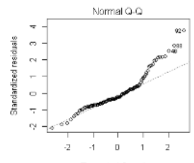
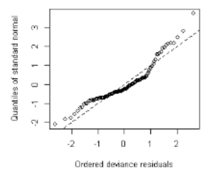
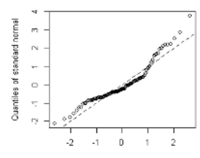
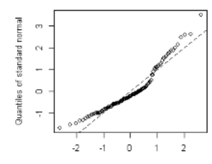
6.3.6 Excess CO_2 Emissions

Table 6-10 gives a summary of the results for excess carbon di-oxide (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 best 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 Figure 6-6. Equation 6-6 is the final form of the selected 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.

$$\text{Excess } CO_2 \text{ Emissions} = \text{Exp}\,\{3.38 + 0.00146 * \text{Non-incident Density} + 0.00050 * \text{Lane-Minutes of Blockage}\} - 30 \qquad (6\text{-}6)$$

Table 6-10. 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^2 /Adj-R^2 (%)	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^2 / Adj-R^2 (%)	23.61 / 22.24	23.81 / 22.44	23.56 /	23.8 /	17.09 /
AIC	334.4	-460.7	329.4	-460.7	-451.8
Model Fit (P-value) Accept Model p >0.05			0.5555	0.4822	0.4821
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

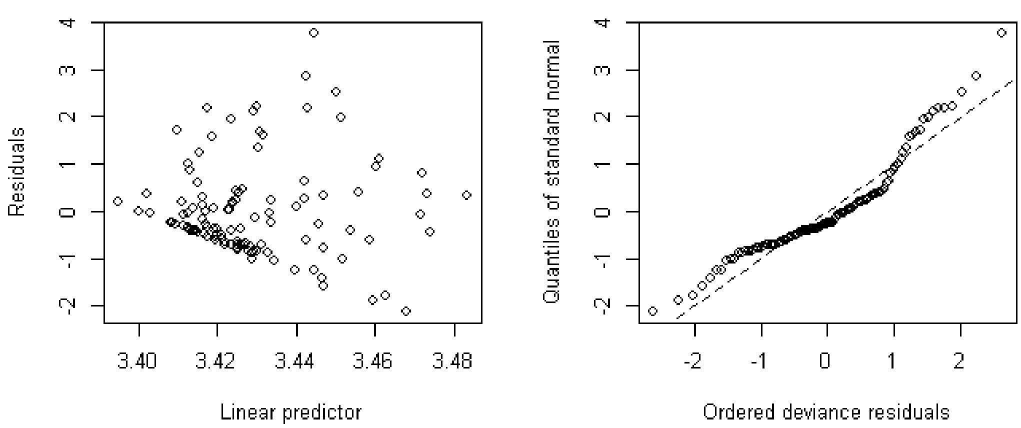
Final Nested Model:

```
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 6-6. Best Model: Excess CO_2 Emissions (Tons)

(Model Form: Gaussian Single-Log GLM)

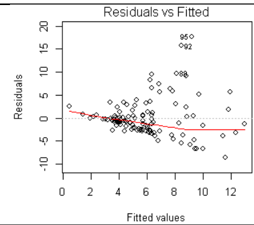
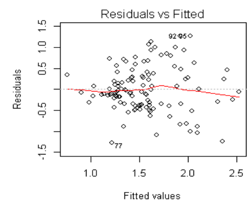
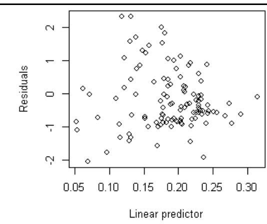
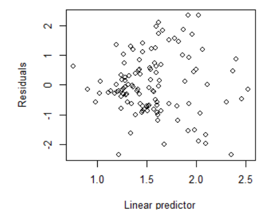
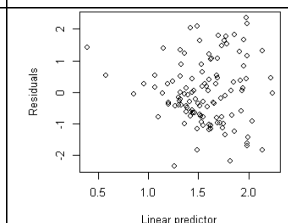
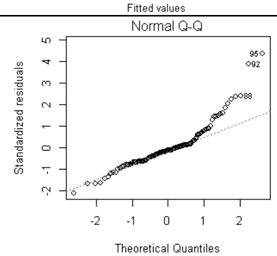
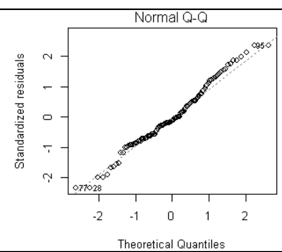
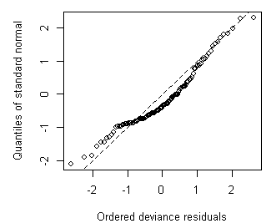
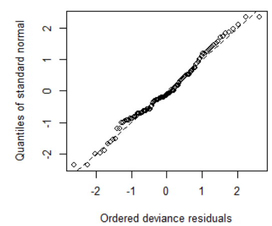
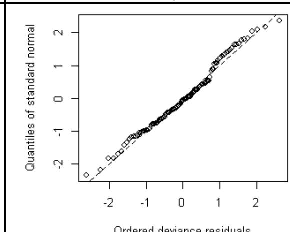
6.3.7 Excess CO Emissions

Table 6-11 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 Figure 6-7 and equation 6-7.

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.

$$\text{Excess CO Emissions} = \text{Exp}\{0.511946 + 0.039209 * \text{Non-incident Density} + 0.009008 * \text{Lane-Minutes of Blockage}\} - 3 \qquad (6\text{-}7)$$

Table 6-11. Results for total Excess CO Emissions (Kg)

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
Variable: CO Emissions					
Full Model:					
R^2 / Adj-R^2 (%)	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^2 / Adj-R^2 (%)	26.19 / 24.87	28.52 / 27.24	17.39 /	28.52 /	23.57 /
AIC	655.0	191.0	568.2	191.0	200.7
Model Fit (P-value) Accept Model p >0.05			0.9105	0.4822	0.4821
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

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%

Diagnostic Plots:

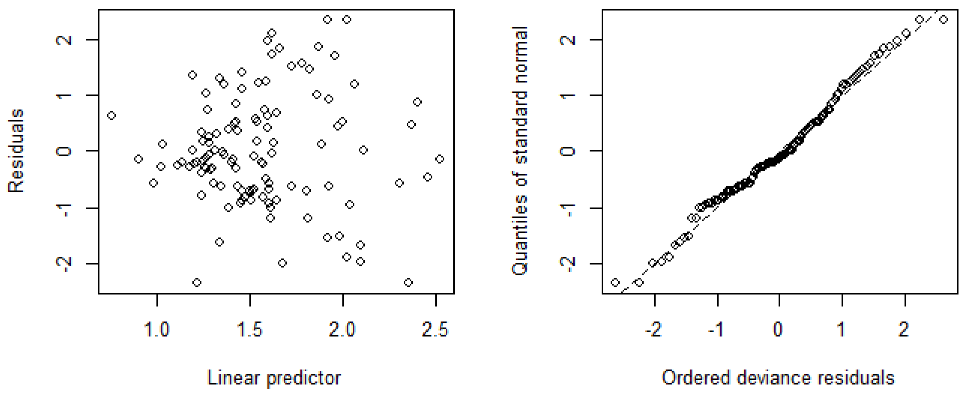


Figure 6-7. Best Model: Excess CO Emissions (Kgs)

(Model Form: Gaussian Single-log GLM)

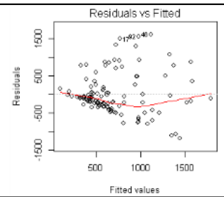
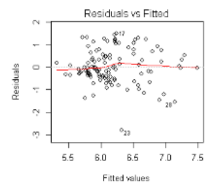
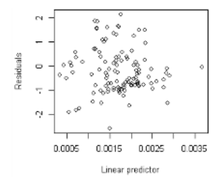
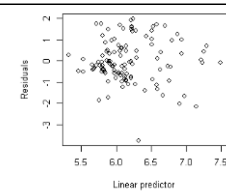
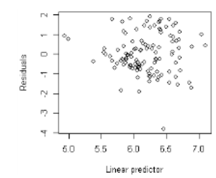
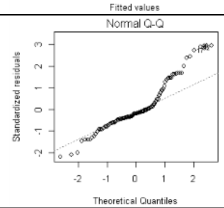
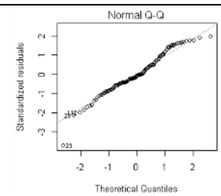
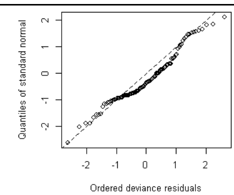
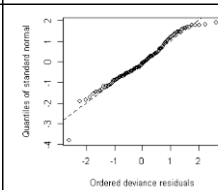
6.3.8 Excess NOx Emissions

Table 6-12 gives a summary of results for excess NO_x emissions for the different regression models. Based on these results, 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 Figure 6-8 and equation 6-8.

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.

$$\text{Excess } NO_x \text{ Emissions} = \text{Exp}\,\{5.03591 + 0.038019 * \text{Non-incident Density} + 0.012057 * \text{Lane-Minutes of Blockage}\} - 250 \qquad (6\text{-}8)$$

Table 6-12. Results for total Excess NO_x Emissions (grams)

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
Variable: NOx Emissions					
Full Model:					
R^2 / Adj-R^2 (%)	39.02 / 31.51	35.23 / 28.21	38.88 /	35.22 /	34.15 /
AIC	1783.9	266.3	1691.7	266.3	266.2
Nested Model:					
R^2 / Adj-R^2 (%)	28.83 / 27.56	25.0 / 23.66	29.06 /	25.0 /	19.50 /
AIC	1783.7	265.1	1693.9	265.1	275.3
Model Fit (P-value) Accept Model p >0.05			0.7713	0.5089	0.5089
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

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:
25.0%

Diagnostic Plots:

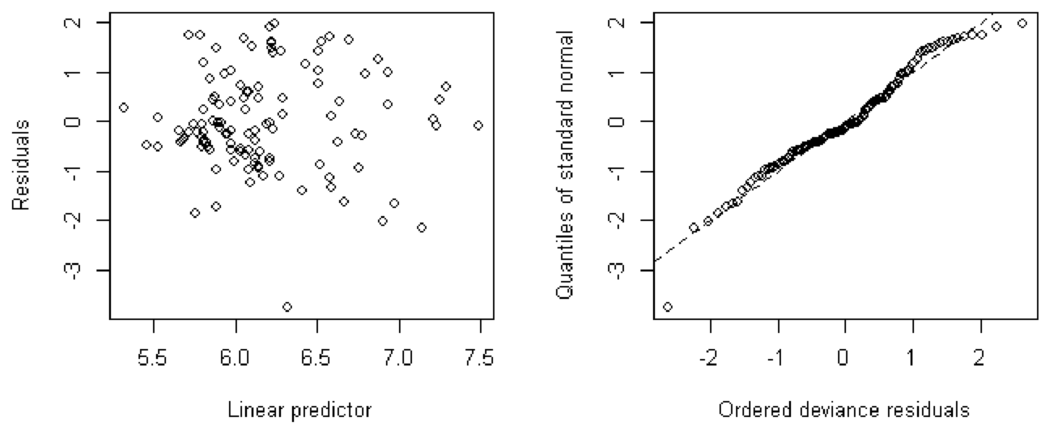


Figure 6-8. Best Model: Excess NO_x Emissions (grams)

(Model Form: Gaussian Single-log GLM)

6.3.9 Excess PM_{10} Emissions

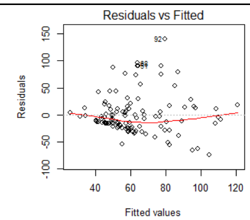
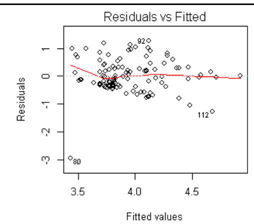
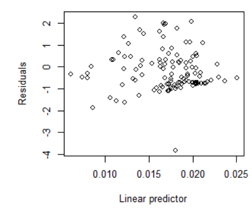
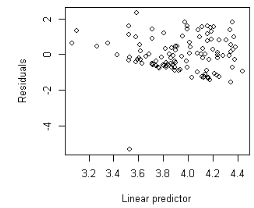
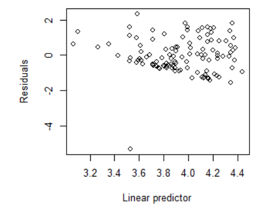
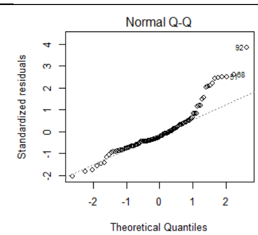
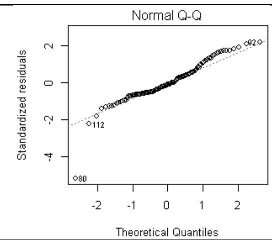
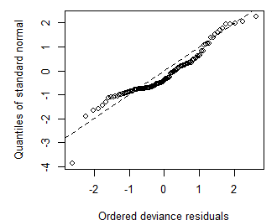
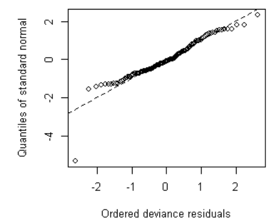
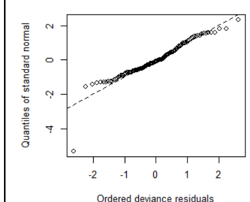
Table 6-13 gives a summary of the results for PM_{10} emissions for the different regression models. Gaussian Single-log and log-log GLMs have the best fit. Both of these have R^2 and AIC that is almost equal.

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 Figure 6-9 and equation 6-9.

Excess PM_{10} Emissions = Exp {3.399096+ 0.293358 *Weekday + 0.008231* Lane-Minutes of Blockage} – 30 (6-9)

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.

Table 6-13. Results for total Excess PM_{10} Emissions (grams)

Category	**Linear**	**Transformed Single Log**	**Gamma**	**Gaussian (Log)**	**Gaussian (Log-Log)**
Variable: PM_{10} Emissions					
Full Model:					
R^2 / Adj-R^2 (%)	28.63 / 22.52	27.71 / 21.51	25.92 /	27.70 /	29.56 /
AIC	1163.4	210.6	1110.2	210.6	209.65
Nested Model:					
R^2 / Adj-R^2 (%)	21.31 / 19.9	20.16 / 18.74	13.31 /	20.16 /	19.53 /
AIC	1160.7	208.1	1113.0	208.1	209.0
Model Fit (P-value) Accept Model p >0.05			0.6885	0.4822	0.4822
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

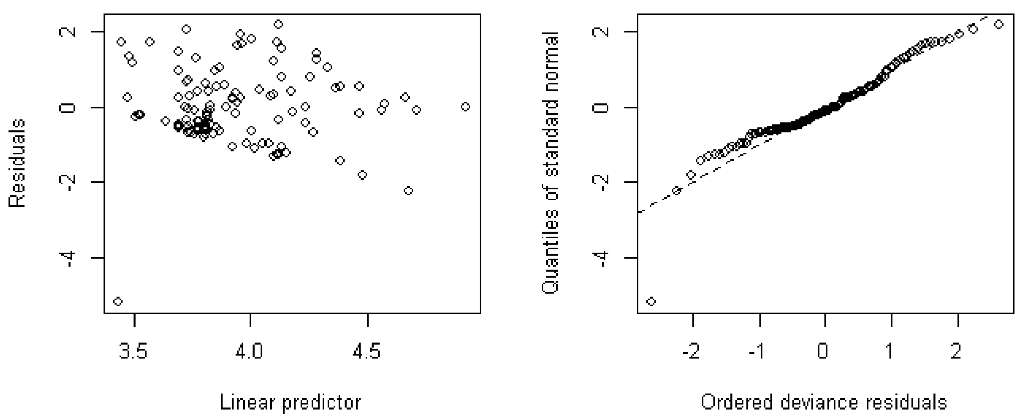
Final Nested Model:

```
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 6-9. Best Model: Excess PM_{10} Emissions (grams)

(Model Form: Gaussian Single-log GLM)

6.4 Summary

All the models for incident impacts have positive coefficient estimates indicating that the 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 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 7.

CHAPTER 7 MARGINAL IMPACTS ANALYSIS AND DISCUSSION

7.1 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 Gaussian Single-log and Gaussian Double-log GLMs.

7.2 Derivation of Elasticity for Gaussian Single-Log GLM

In general, the elasticity of a dependent variable Y with respect to predictor variable X_j is given as

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

This means that the value of *Y* changes by ε_j % for a 1% change in the value of X_j. For the Gaussian single-log model used in this study, the functional form of the model is

$$\ln(Y + A) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p \tag{7-1}$$

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

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

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

Differentiating,

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

Therefore,

$$\varepsilon_j = \frac{dY}{dX_j}\left(\frac{X_j}{Y}\right) = \beta_j (Y + A)\left(\frac{X_j}{Y}\right) = \beta_j X_j \left(1 + \frac{A}{Y}\right) \tag{7-2}$$

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

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

This simplifies to

$$R_j = \left(1 + \frac{A}{Y_0}\right)\left(e^{\beta_j} - 1\right) \qquad (7\text{-}3)$$

i.e., If the dummy variable changes from 0 to 1, the change in Y_0 is by $100R_j$%.

7.3 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:

$$\ln(A + Y) = \beta_0 + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + ... + \beta_p (X_p) \qquad (7\text{-}4)$$

Where A is the positive constant added to the dependent variable Y to make sure the LHS of the equation is always positive and there are no errors when taking logs. Taking the exponentiation on both sides,

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

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

Differentiating,

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

Therefore

$$\varepsilon_j = \frac{\beta_j}{X_j}(Y + A) \times \frac{X_j}{Y} \quad = \beta_j \times \left(1 + \frac{A}{Y}\right) \qquad (7\text{-}5)$$

For a dummy variable, the derivation is the same as the previous section (Equation 7-3) since the log (X_j) in the log-log model only applies to the continuous variables.

7.4 Quantification of Impacts

This section presents calculations for the average and marginal impacts of incident for a given incident scenario. The example below shows the calculations for excess vehicle-hours of travel for an incident blocking one travel lane, lasting 30 minutes with a corresponding non-incident density of 18 vpmpl, the last two parameters being about the average values for the incidents used in this study. Equation 6-2 is used for computing the average impact while the elasticity equation 7-5 is used for estimating the marginal impacts for a 1% change in the incident duration and for a 1 minute change in incident duration. Using equation 6-2,

Excess VHT = Exp{1.41944 + 0.66726 * Ln (Non-incident density) + 0.35164 * Ln (Incident duration) + 0.750316 * 1 lane blocked + 1.05008 * 2 lanes blocked} – 50

Substituting for the following values: Incident duration = 30 minutes; Non-incident density = 18 vpmpl; 1 lane blocked = 1; and 2 lane blocked = 0.

Then

Excess VHT = Exp {1.41944+ 0.66726 * Ln (18) + 0.35164 * Ln (30) + 0.750316 * 1 + 1.05008 *0} – 50

= 149.2 veh-hrs

This 149.2 vehicle-hours is the average excess vehicle-hours of travel for an incident of average duration and non-incident density.

Using elasticity equation 7-5,

$$\varepsilon_j = \beta_j \times \left(1 + \frac{A}{Y}\right) = 0.35164 \times \left(1 + \frac{50}{149.2}\right) = 0.4695$$

This means that for each 1% change in incident duration, there is a 0.4695% change in the excess VHT. In absolute values, a 1% change in the incident duration results in,

Actual change = (0.4695/100)x149.2 = 0.70 veh-hrs

This analysis can be extended to calculate the change in excess VHT for a 1 minute change in the incident duration. A 1 minute change in incident duration from the 30 minutes is equivalent to (1/30)% = 3.33% change. Using the elasticity for excess VHT computed above, this will result in 0.4695x3.33% = 1.57% change in the excess VHT, which translates to 149.2 x 1.57% = 2.335 excess VHT.

These calculations are repeated for all the impact variables using appropriate calibrated models and elasticity equations and for 1 and 2 blocked travel lanes. The results are summarized in Tables 7-1 and 7-2.

Table 7-1. Calculated impacts corresponding to average incident conditions[1]

Impact Variable	Units	Excess (1 lane)	Excess (2 lanes)
Excess VHT	Veh-hours	149.20	218.84
Excess Fuel Consumption	Gallons	41.45	69.91
Excess CO_2 Emissions	Kgs	613	1,076
Excess CO Emissions	Kgs	1.45	2.82
Excess NO_x Emissions	Grams	189.60	381.22
Excess PM_{10} Emissions	Grams	21.39	35.78

[1]Appliable for the following incident conditions:
Incident duration = 30 minutes; Non-incident density = 18 vpmpl

Table 7-2. Marginal Impacts for a 1 minute change in incident duration[2]

Impact Variable	Units	Marginal (1 lane)	Marginal (2 lanes)
Excess VHT	Veh-hours	2.33	3.15
Excess Fuel Consumption	Gallons	0.80	2.21
Excess CO_2 Emissions	Kgs	15.30	31.10
Excess CO Emissions	Kgs	0.040	0.105
Excess NO_x Emissions	Grams	5.30	15.23
Excess PM_{10} Emissions	Grams	0.423	1.083

[2]Appliable for the following incident conditions:
Incident duration = 30 minutes; Non-incident density = 18 vpmpl

7.5 Project application example

Using the results from Table 7-2 above, one can evaluate a scenario where, for example, an economic analysis has to be conducted to evaluate the economic feasibility of an incident management project that is designed, for example, to reduce the average incident duration from, for example the current 30 minutes to 25 minutes, a reduction in 5 minutes. The resulting reductions or "savings" in impacts will be as summarized in Table 7-3. The values in this table are calculated using the elasticity equations, similar to those obtained for Table 7-2. However, it should be noted that elasticity equations are only applicable for "small" changes in the predictor variable. SO for big changes in the values of the predictor variables, the original calibrated equations may have to be used to calculate the corresponding changes in the impacts.

Table 7-3. Reduction in Impacts for a 5 minute reduction in average incident duration[3]

Impact Variable	Units	Marginal (1 lane)	Marginal (2 lanes)
Excess VHT	Veh-hours	11.65	15.75
Excess Fuel Consumption	Gallons	4.00	11.05
Excess CO_2 Emissions	Kgs	76.50	155.5
Excess CO Emissions	Kgs	0.200	0.525
Excess NO_x Emissions	Grams	26.50	76.15
Excess PM_{10} Emissions	Grams	2.12	5.42

[3]Appliable for the following incident conditions: Average incident duration reduced from 30 to 25 minutes; Non-incident density = 18 vpmpl

7.6 Elasticity and Marginal Impact Plots

Impact and elasticity analysis done in the previous section is repeated for different values of the incident duration and the results plotted. The resulting plots show how the elasticity changes as the incident duration is increased or decreased. Figures 7-1 to 7-12 show these plots for each of the impact variables.

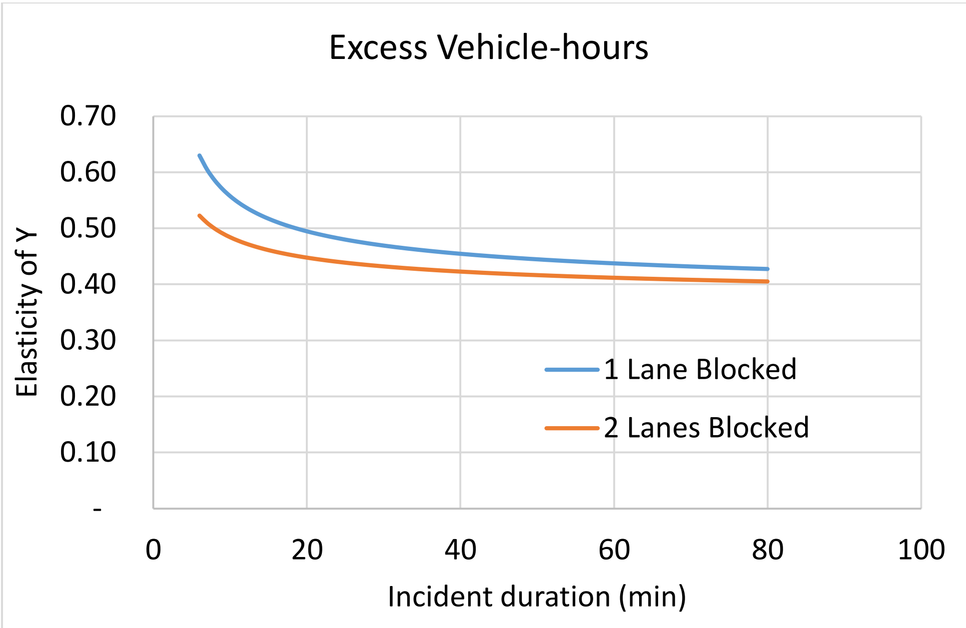


Figure 7-1. Elasticity of Excess VHT as a function of Incident Duration

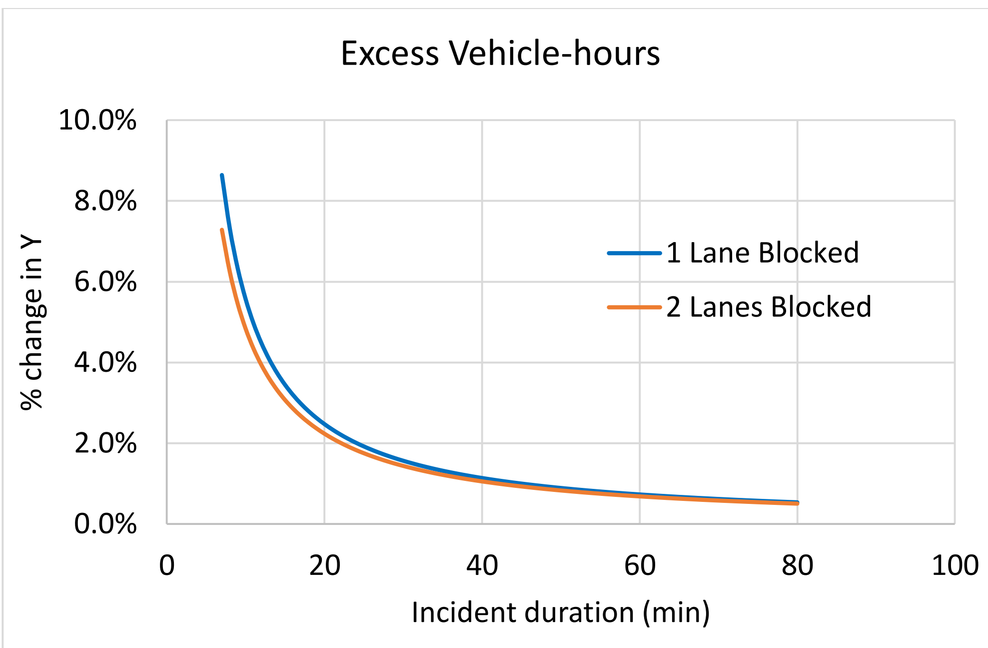


Figure 7-2. Percent Change in Excess VHT for unit change in Incident Duration

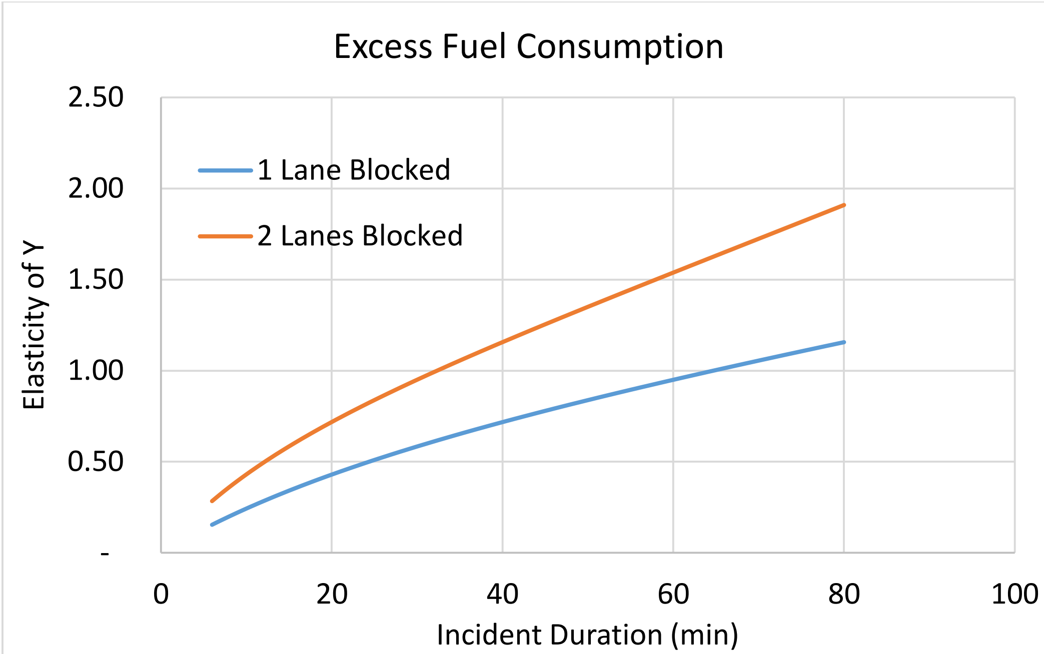


Figure 7-3. Elasticity for Lane-Minutes of Blockage in Excess Fuel Consumption

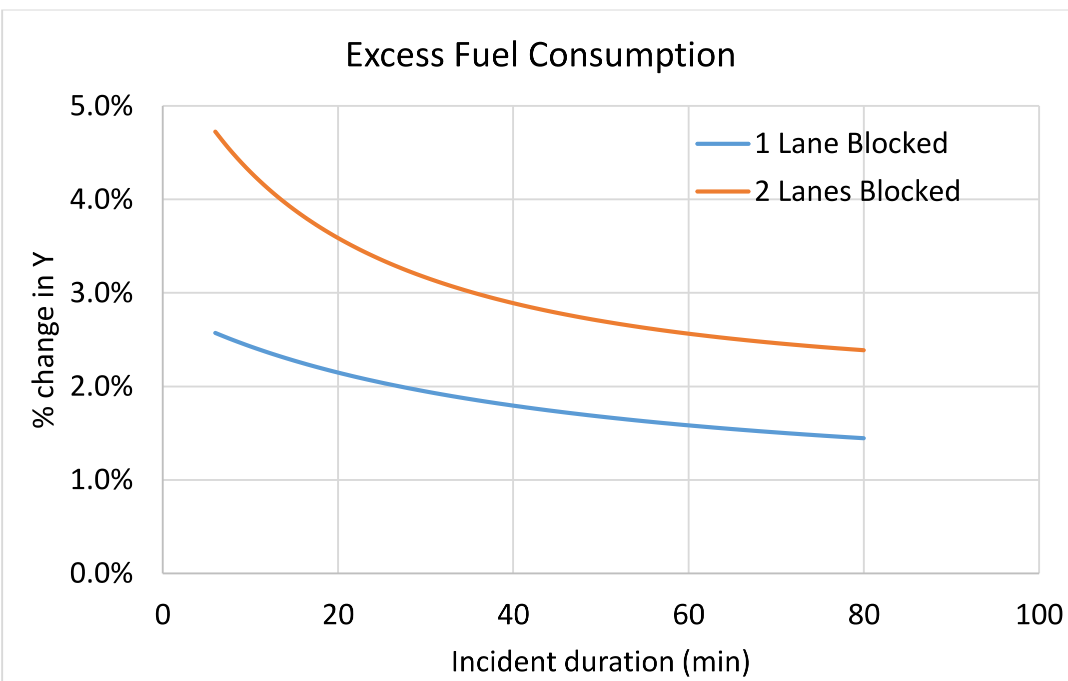


Figure 7-4. Percent Change in Excess Fuel Consumption for unit change in Lane-Minutes of Blockage

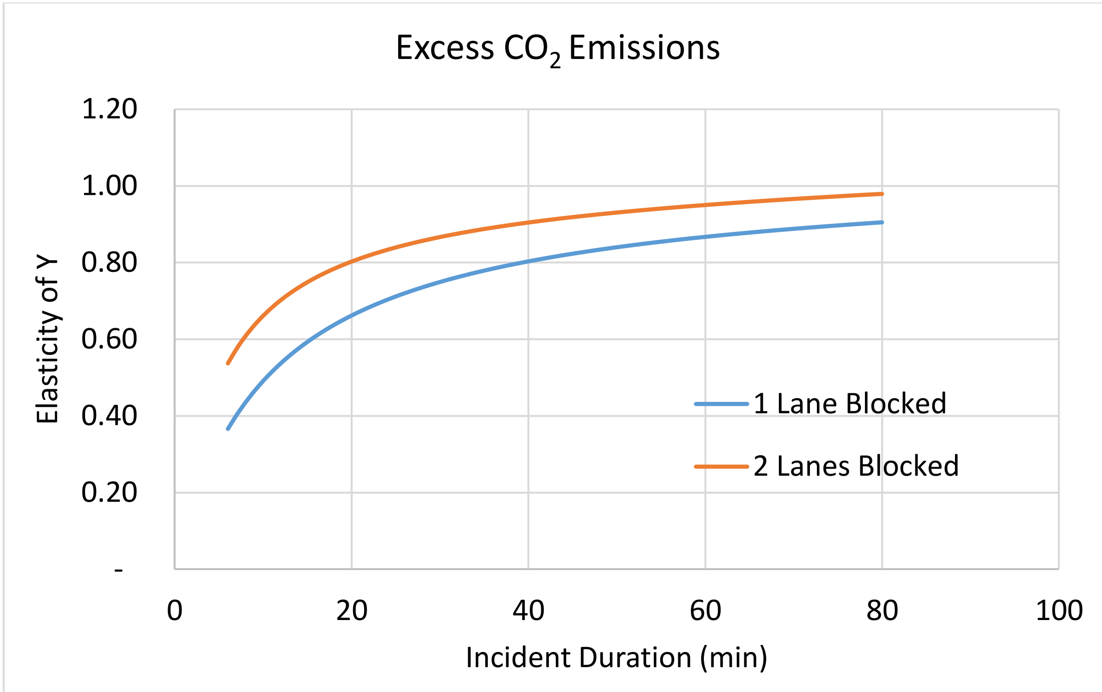


Figure 7-5. Elasticity for Lane-Minutes of Blockage in Excess CO_2 Emissions

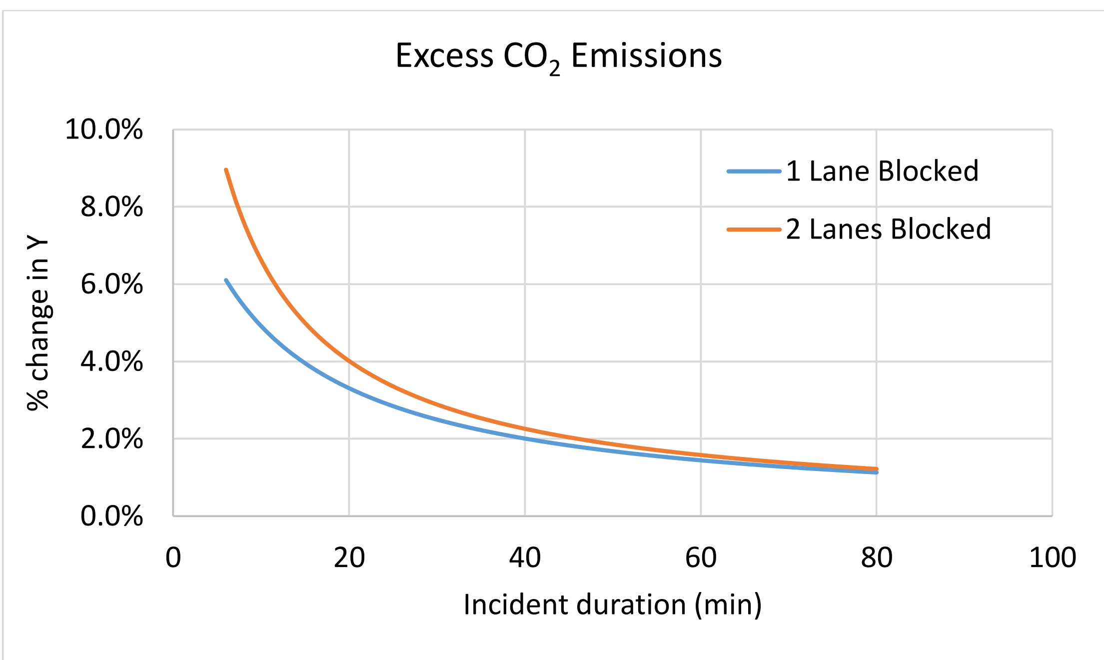


Figure 7-6. Percent Change in Excess CO_2 Emissions for unit change in Lane-Minutes of Blockage

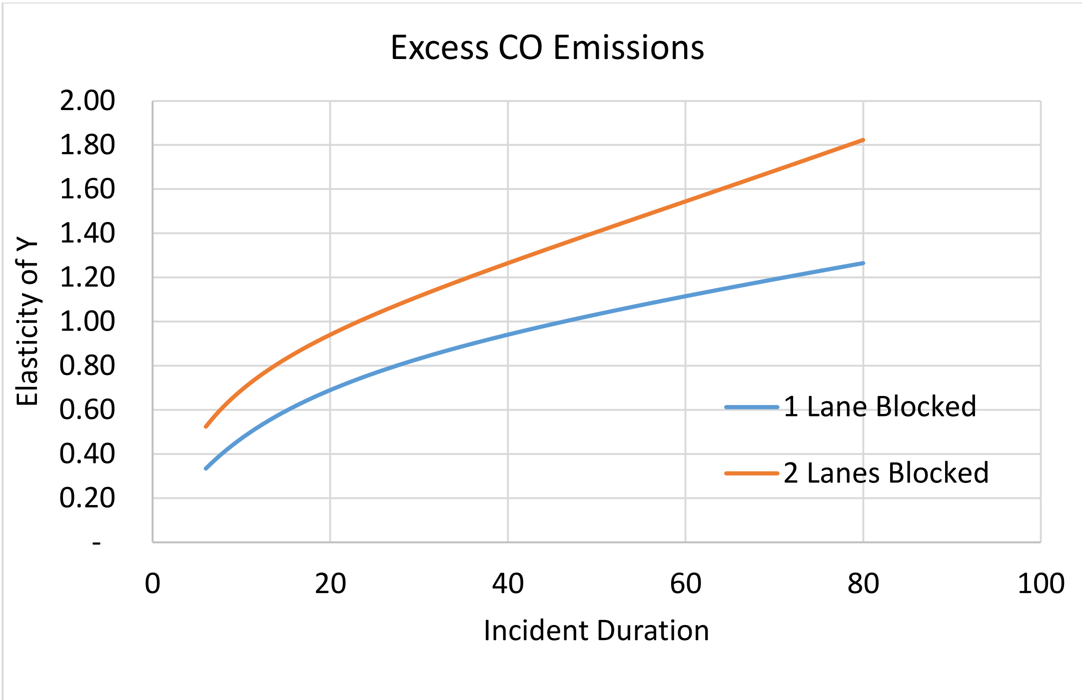


Figure 7-7. Elasticity of Excess CO Emissions with respect to incident duration

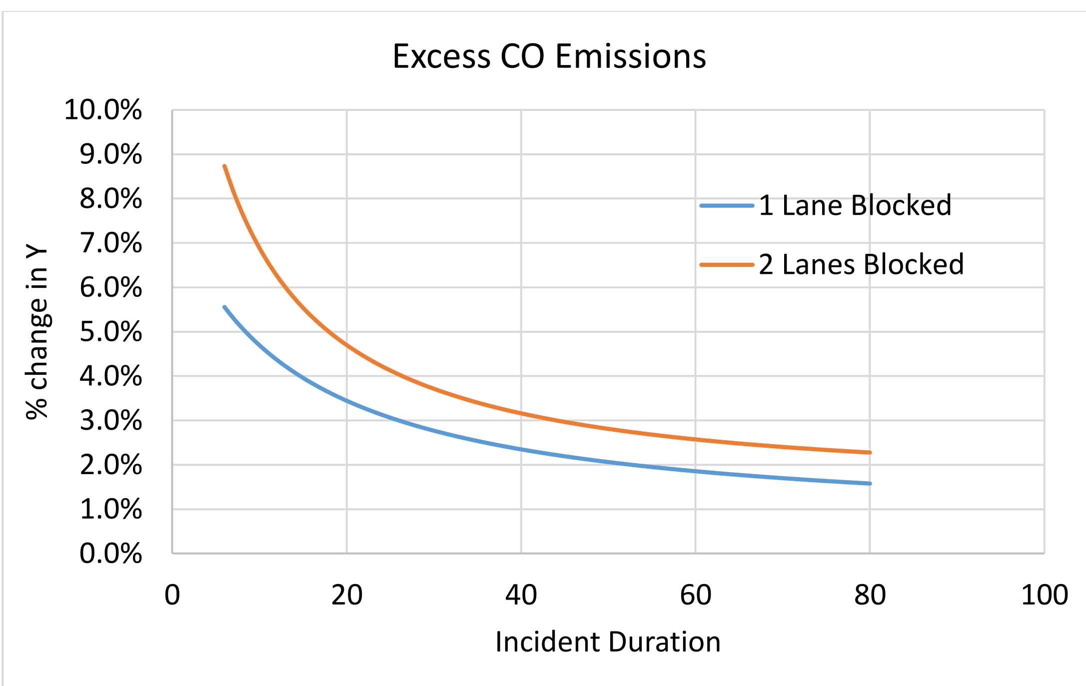


Figure 7-8. Percent Change in Excess CO Emissions for 1 minute change in incident duration

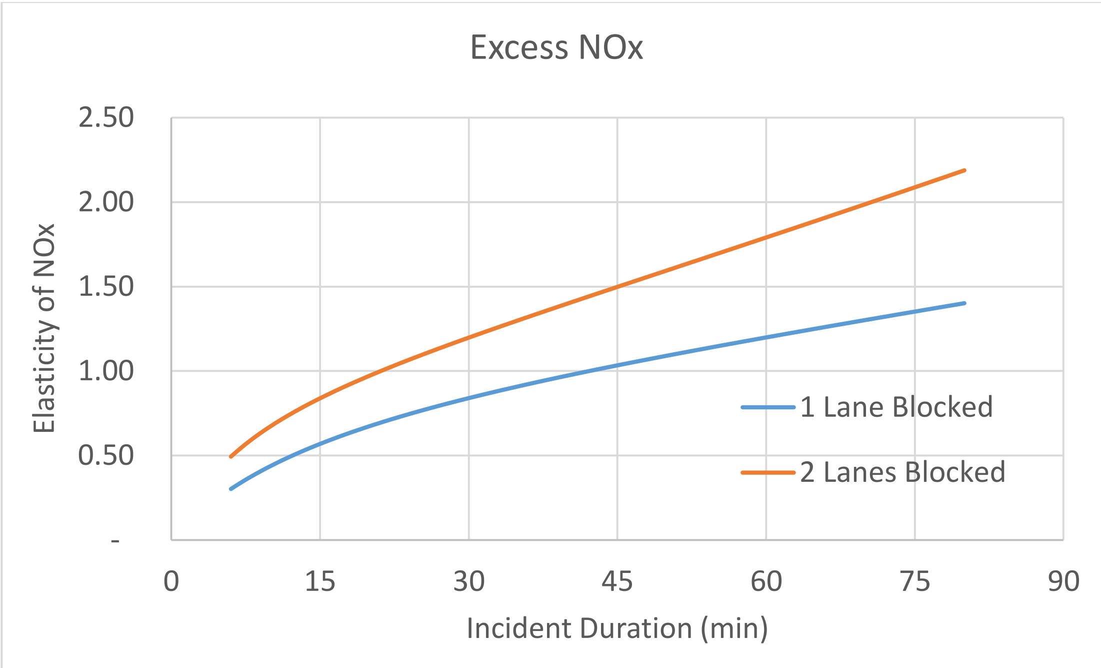


Figure 7-9. Elasticity of Excess NO_x Emissions with respect to incident duration

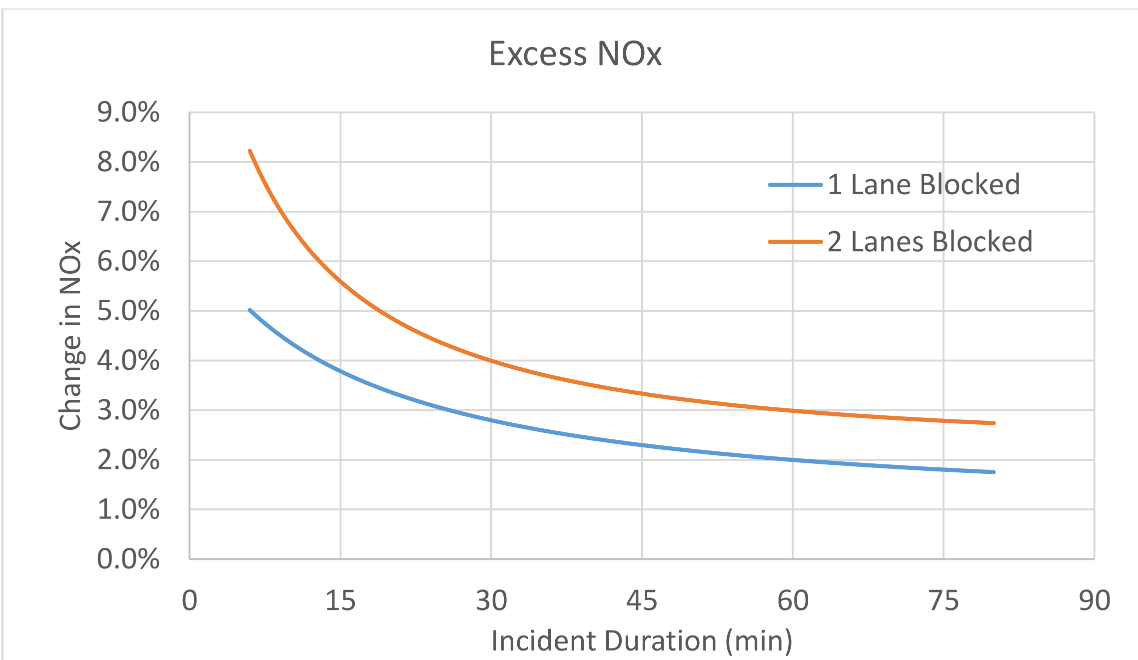


Figure 7-10. Percent Change in Excess NO_x Emissions for 1 minute change in incident duration

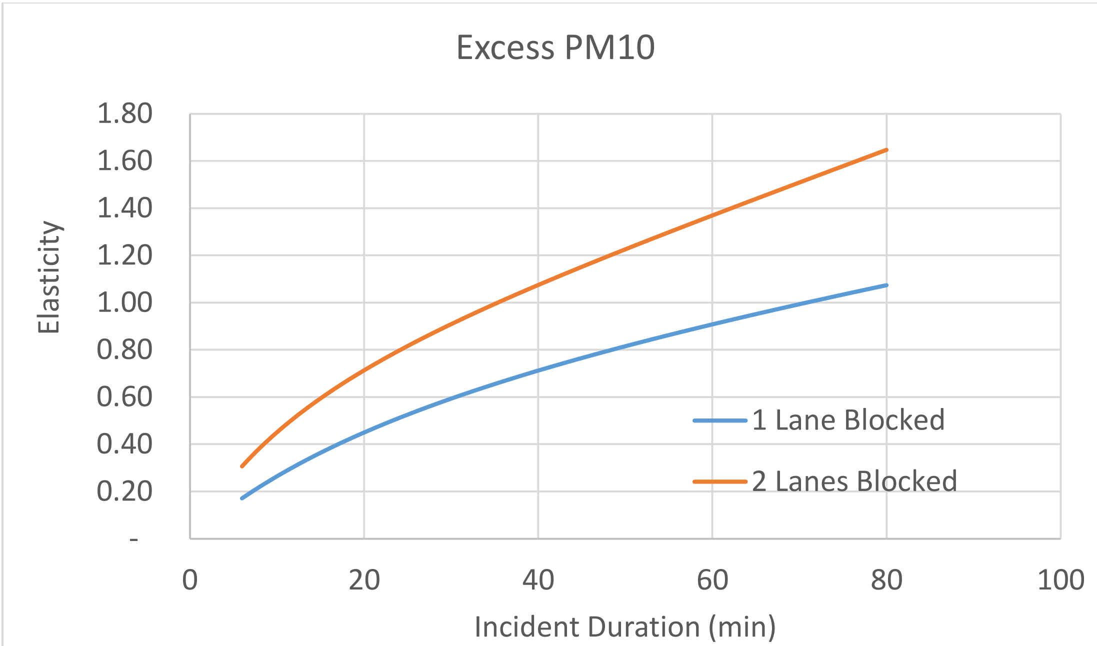


Figure 7-11. Elasticity for Excess PM10 emissions with respect to Incident Duration

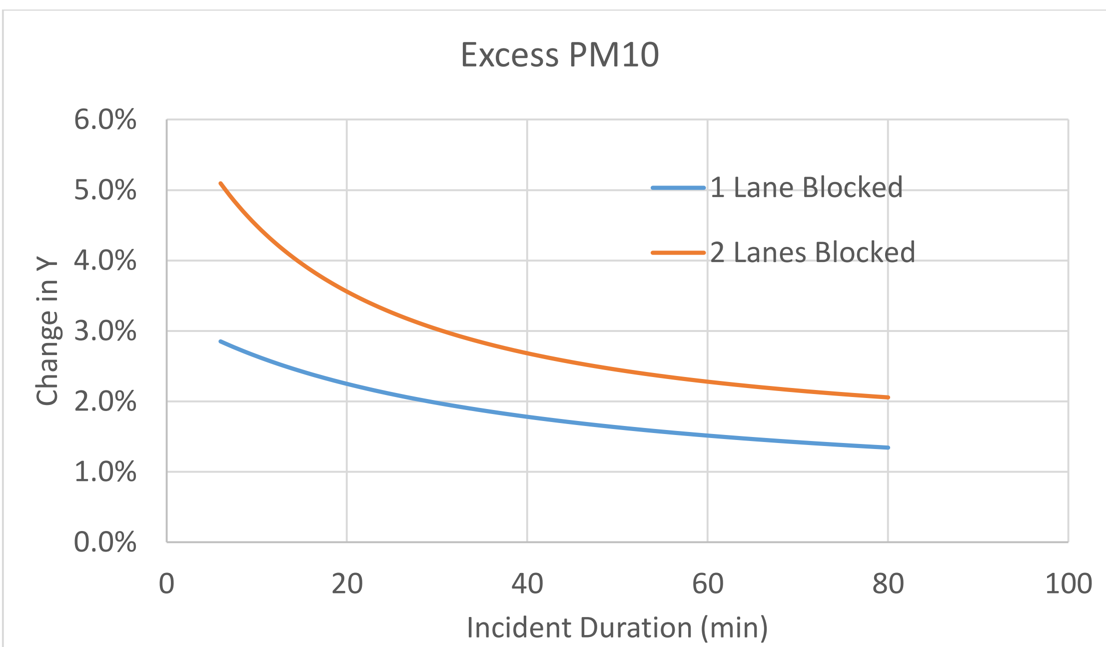


Figure 7-12. Percent Change in Excess PM_{10} Emissions for 1 minute change in incident duration

7.7 Summary

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

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

8.1 Concluding Remarks

In this study, statistical models for the impact of freeway incidents on vehicle travel time, fuel consumption and emissions are calibrated. The impacts are quantified by excess travel time measures, fuel consumption and vehicle emissions produced due to the incident. Also included in the analysis are impacts due to rubbernecking in opposite travel direction of the incident direction. Separate regression models are calibrated for each impact. 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.

Models are calibrated for (i) excess travel time per vehicle (ii) excess 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 full set of predictor variables used included incident duration, number of lanes blocked, lane-minutes of blockage (product of incident duration and number of travel lanes blocked), 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 Double-log GLMs. Use of the models is demonstrated in Chapter 7 by showing examples of using the equations to compute the impact of an average incident. Such analysis can be used for planning purposes and for evaluation of the overall performance of a freeway network. The economic feasibility of any strategies designed to improve safety and reduce such incidents can be performed using these models. Furthermore, elasticity analysis is used to demonstrate use of the models for estimating marginal impacts of incidents for small changes in the values of the incident characteristics, such as the incident duration and number of blocked lanes. This kind of analysis is used to quantify the reduction in impacts due to incremental changes in incident characteristics, such as reduction in incident duration due to new incident management strategies. In such cases, one can perform a benefit-cost analysis for a proposed incident management project and evaluate its economic feasibility.

8.2 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 data, especially the incident durations and duration of travel lane blockages especially when multiple travel lanes are affected. 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.

REFERENCES

Chou, Miller-Hooks and Promisel, 2010, "Benefit-cost Analysis of Freeway Service Patrol Programs: Methodology and Case Study", *Advances in Transportation Studies*, Section B 20.

Chung, Younshik and Recker, Wilfred W. 2012. A Methodological Approach for Estimating Temporal and Spatial Extent of Delays Caused by Freeway Accidents. IEEE Transactions on Intelligent Transportation Systems, Vol. 13, No. 3, September 2012.

Dougald, Lance and Demetsky, Michael (2008). Assessing Return on Investment of Freeway Safety Service Patrol Programs. TRR no. 2047, pp. 19-27

Fries, R., Chowdhury, M. and Ma, Y. (2007). Accelerated Incident Detection and Verification: A Benefit to Cost Analysis of Traffic Cameras. Journal of Intelligent Transportation Systems, 11(4):191–203, 2007

Garib, A; Radwan, A. E; and Al-Deek H., (1997) Estimating Magnitude and Duration of Incident Delays, ASCE Journal of Transportation Engineering, Vol 123, p459-466.

Gorham, R. (2002). *Air Pollution from Ground Transportation – An Assessment of Causes, Strategies and Tactics, and Proposed Actions for the International Community*. Division for Sustainable Development, Department of Economic and Social Affairs, United Nations. Retrieved December 12, 2012 from the World Wide Web: http://www.un.org/esa/gite/csd/gorham.pdf.

Hagen, L., Zhou, H. and Singh. H. (2005). Road Ranger Benefit Cost Analysis. Florida Department of Transportation

Lv, W., Liu, X. and Zhu, T. (2010). A history data based traffic incident impact analyzing and predicting method. Proceedings of the 2010 International Conference on Electronics and Information Engineering, Volume 2, pp 219 to 223, 2010

Masinick , J. P. & Teng, H. (2004). An Analysis on the Impact of Rubbernecking on Urban Freeway Traffic. Research Report No. UVACTS-15-0-62. Center for Transportation Studies, University of Virginia.

Nejadkoorki, F., Nicholson, K., Lake, I. and Davies, T. 2008. An approach for modeling CO_2 emissions from road traffic in urban areas. Science of The Total Environment, Volume 406, Issues 1–2, Pages 269–278, 15 November 2008

Shrank, D., Lomax, T. & Eisele, B. (2012). TTI's 2012 Urban Mobility Report: Powered by INRIX Traffic Data. Texas Transportation Institute, Texas A&M University System. December 2012. URL: http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-report-2012.pdf

Skabardonis, Alexander; Petty, Karl F.; Noeimi, Hisham; Rydzewski, Daniel; and Varaiya, Pravin (1996) I-880 Field Experiment: Data-base Development and Incident Delay Estimation Procedures. *Transportation Research Record No. 1554, p.204-212*

Skabardonis, Alexander; Petty, Karl; Varaiya, Pravin; and Bertini, Robert. (1998) Evaluation of the Freeway Service Patrol (FSP) in Los Angeles. *PATH Research Report* UCB-ITS-PRR-98-31. University of California, Berkeley

Skabardonis, Alexander; and Mauch, Michael, (2005) FSP Beat Evaluation and Predictor Models: Methodology and Parameter Estimation, *University of California at Berkeley,* Research Report: UCB-ITS-RR-2005-XX

System Metrics Group, Inc. (2009). *California Life-Cycle Benefit/Cost Analysis Model (Cal-B/C) - Technical Supplement to User's Guide: Volume 3: Traffic Operations Consistency, Network and Corridor Analysis, New Capabilities, and Economic and Parameter Value Updates*, California Department of Transportation.

Thomas, S; and Jacko, R.B. (2007). A stochastic Model for Estimating the Impact of Highway Incidents on Air Pollution and Traffic Delay. Transportation Research Record, No. 2011, Transportation Research Board, Washington D.D.

United States Department of Energy (USDOE). *Fuel Economy Guide - Model Year 2005*. (2005). Retrieved from: http://www.fueleconomy.gov/FEG/FEG2005.pdf

Wang, Yinhai and Cheevarunothai, Patikhom. (2008). Quantifying Incident-Induced Travel Delays on Freeways Using Traffic Sensor Data- Final Report. Washington State Transportation Commission and Transportation Northwest (TransNow). 2008

Xia, J. and Chen, M. (2007). Freeway Travel Time Forecasting Under Incident: Final Report. Southeastern Transportation Center. 2007.

Xie, G. & Hoeft, B. (2012). FAST Dashboard – Web-based Freeway & Arterial Performance Measurement System. Proceedings of the *91st Transportation Research Board Annual Meeting*, Washington D.C.

Nevada Department of Transportation
Rudy Malfabon, P.E. Director
Ken Chambers, Research Division Chief
(775) 888-7220
kchambers@dot.nv.gov
1263 South Stewart Street
Carson City, Nevada 89712