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Examination Of Factors Affecting The Frequency, Response Time, And Clearance Time Of Incidents On Freeways

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EXAMINATION OF FACTORS AFFECTING THE FREQUENCY, RESPONSE TIME, AND CLEARANCE TIME OF INCIDENTS ON FREEWAYS

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DEDICATION

To my lovely parents, affectionate brother, and beautiful wife
for their unconditional love
without which it was not possible to achieve this goal in my life

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PREFACE

The objective of this research is to assess freeway operations in metropolitan Detroit, particularly as it relates to traffic incidents. A software interface has been developed to combine traffic flow data with incident data available from various sources. A framework is proposed to analyze the relationship between traffic incidents and the resultant congestion, as well as to identify important factors that impact the frequency of incidents and the time required by Freeway Courtesy Patrol (FCP) operators to respond and clear such incidents on various freeway sections. The developed framework is evaluated using data obtained from four freeways in southeastern Michigan.

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FCP : Freeway Courtesy Patrol

MDOT : Michigan Department of Transportation

MITS : Michigan Intelligent Transportation Systems

DMS : Dynamic Message Sign

CCTV : Closed Circuit Television

Chapter 1 Introduction

1.1 Background and motivation

Freeways serve as the major surface transportation corridors for most metropolitan areas in the United States. Over the past several decades, constantly increasing congestion on these freeways has caused considerable direct and indirect costs to businesses, commuters, and the environment (Hellinga et al., 2004). One mobility study conducted by the Texas Transportation Institute (TTI) estimated the total cost of traffic congestion, in terms of wasted fuel and lost efficiency, in the United States to be $87.2 billion (Schrank and Lomax, 2009). Congestion generally occurs when demand exceeds capacity supplied by the transportation facilities. Congestion can be classified into two categories: recurring and nonrecurring (Carvell et al., 1997; Skabardonis et al., 2003). Recurring congestion refers to the situation where normal traffic demand exceeds the physical capacity of the freeway. This congestion typically occurs due to systematic capacity shortages during high traffic volume periods (e.g., morning and afternoon peak periods) and is predictable in terms of its location, duration, time, and effect (Carvell et al., 1997; Skabardonis et al., 2003). Commuters have reasonable knowledge of recurring congestion based upon their daily experiences and are capable of making their travel plan based upon this knowledge. Conversely, nonrecurring congestion is the result of a short-term reduction in the capacity of a roadway (e.g., closure due to traffic incidents, work zones, etc) or a temporary excess of demand in the case of special events (e.g., sporting events, concerts, festivals, etc). Factors responsible for nonrecurring congestion can be either unpredictable (e.g., a stalled vehicle) or planned (e.g., a construction activity). The distinctive factor differentiating nonrecurring and recurring congestion is that nonrecurring congestion is unanticipated by motorists and can result in a significant safety hazard and cause excessive delays to uninformed motorists (Carvell et al., 1997). Many of the events contributing to nonrecurring congestion can be categorized as traffic incidents. Traffic incidents are generally described as any planned or unplanned event affecting traffic flow on the roadway (Sethi et al., 1994). These events result in the reduction of traffic flow, thus affecting the roadway capacity either directly by lane closure or indirectly by motorists slowing down to view the incident (Giuliano, 1988). Incidents include traffic crashes, vehicle breakdowns, the presence of debris on the road, and other factors that cause temporary reduction of roadway capacity (Hellinga et al., 2004). As per Highway Capacity Manual, incidents are of major concern as they disrupt the level of service of provided by the traffic facilities, diminish capacity drastically, and create risk for those drivers directly involved (TRB, 1994). Incidents are responsible for a significant proportion of the delays and costs to the motoring public. Non-recurring congestion due to freeway incidents such as crashes, disabled vehicles, and weather events has been found to be accountable for one-half to three-fourths of the total congestion on metropolitan freeways in the United States (Giuliano, 1988). Basically the majority (approximately 60 percent) of congestion is caused by traffic incidents (Lindley, 1987). In most of the urban areas, incident-related delay accounts for 50 to 60 percent of total congestion delay. In smaller urban areas, it can account for an even larger proportion

(Farradyne, 2000). Besides being responsible for excessive delays, incidents can result in a significant safety hazards to uninformed motorists (Carvell et al., 1997), as well as to personnel responding to incidents (Neudorff et al., 2003). The risk of secondary crashes is also a critical problem. Incidents also have effects on the environment through increased fuel consumption and reductions in air quality. Other long-term effect of incidents include increased costs of commodities, services, and vehicle maintenance, as well as reduced productivity and negative impressions of the public agencies responsible for incident management (Wang et al., 2005b).

In response to the growing and adverse impacts of incidents, many communities have initiated incident management programs which detect and respond to incidents and restore the freeway to full capacity by clearing the incident scene as soon as possible (Khattak and Rouphail, 2004). In other words, one method of fighting nonrecurring congestion problems is to carry out an effective incident management program. Incident management can be broadly described as a coordinated and well planned approach for restoring traffic to its normal operations as quickly as possible after an incident has occurred (Carvell et al., 1997). A Traffic incident management program tries to pacify the impact of an incident on motorists by clearing the scene of an incident with timely activities. Such programs play an important role in the operation of the transportation system and require collaboration and efficient communication among various agencies, including fire and rescue, police, towing and recovery, transportation engineers, and freeway service patrol (Dougald and Demetsky, 2008). They involve an organized use of human and mechanical processes for spotting and confirming the incident, judging the magnitude and identifying the requirement to restore the normal operation, as well as supplying a suitable response in the form of control, information, and aid (Carvell et al., 1997). Effective incident management programs can reduce the duration and impacts of incidents, consequently improving the safety for roadway users, incident victims, and responders.

The Detroit metropolitan area, is home to one of the first ever freeway incident management program in the United States, established by the Michigan Department of Transportation (MDOT). Detroit is currently subject to the highest levels of traffic congestion in the State of Michigan, and disruptions to the Detroit freeway network, such as those caused by traffic incidents, create adverse impacts that can last for minutes or hours and may result in additional secondary incidents if not identified and cleared in a reasonable time period. During the 1980s, MDOT implemented a program to reduce congestion during rush hours, offer immediate management, and provide traffic information to motorists. This system included surveillance cameras, dynamic message signs (DMS), motorists aid telephones, and ramp metering (Robinson and Nowak, 1993). Presently, MDOT operates the Freeway Courtesy Patrol (FCP) program as part of its larger freeway incident management program from the Michigan Intelligent Transportation Systems (MITS) Center in downtown Detroit. FCP program has become an increasingly crucial component of the incident management program. Such FCP programs are widely used to help mitigate the effects of nonrecurring congestion (Dougald and Demetsky, 2008). They are normally active in high traffic volume areas, especially freeways, and are responsible for the task of clearing obstructions such as debris and disabled vehicles from roadways and assisting police with traffic control in the case of crashes (Dougald and Demetsky, 2008). Several State Departments of

Transportation have carried out return-on-investment evaluations of their FCP programs and found the benefit-to-cost ratios (B/C) ranging from 1.1:1 to 36:1 (Dougald and Demetsky, 2008). The benefits considered in these studies generally include reduction in motorist delay, fuel consumption, emissions, and reductions in secondary incidents (Dougald and Demetsky, 2008).

The MITS Center, serves as the hub of ITS applications at MDOT where personnel administer a traffic surveillance system that covers 200 freeway miles. The center is able to monitor freeway performance through a series of in-pavement and roadside traffic detectors, as well as closed-circuit cameras. The cameras are used to identify incidents in combination with a hotline by which motorists can phone in incidents and other issues that they encounter on the road. When incidents are identified, FCP vans are dispatched to respond to the incident and provide assistance to affected motorists in a timely manner such that the freeway network can maintain operations at or near its capacity. Established in 1994, the MDOT FCP provides service to the motorists in southeastern Michigan region by helping out stranded motorists, keeping freeways clear of vehicle breakdowns and traffic crashes, thus helps commuters and other drivers alleviating traffic congestions, reduces travel time and improves motorists' safety by forming safe and sound driving situations. Followings are the general services provided by the MDOT FCP to the motorists (SEMCOG, 2009):

- Provides gas and other fluids to the disabled vehicles;
- Removes abandoned vehicles and debris from roadways;
- Fixes flat tires;
- Supplies minor mechanical assistance;

- secure the area around your vehicle;
- Provides cell phone assistance;
- Provides up to five miles of towing at no charge;
- Transports stranded motorists;
- Provides directions.

In addition to reacting to dispatch calls, FCP vans roam the freeway network during the day and are thus able to respond to remote incidents in a more timely manner. Figure 1.1 illustrates the FCP coverage area within the Southeast Michigan freeway network. The locations of dynamic message signs (DMSs) for dissemination of messages/information to the motorists and close-circuit TV cameras (CCTV) to detect incidents are also illustrated in Figure 1.1.

It is estimated that the FCP saved commuters 11.5 million hours of delay in 2008, in addition to reducing 2,094 kilograms per day of volatile organic compounds (VOC), 999 kilograms per day of nitrogen oxides (NOx) and 15,411 kilograms per day of carbon monoxide (CO) pollutants. The Southeastern Michigan Council of Governments (SEMCOG) estimates that for each dollar spending on FCP operation, a profit of $15.20 was realized in 2008. Since 1994, the FCP has assisted 230,149 stranded motorists, made 108,440 unoccupied vehicle stops, and stopped to clear debris 12,460 times on southeastern Michigan freeways. Based on recent data, the average time required for FCP responders to clear an incident is approximately 12.5 minutes (SEMCOG, 2009).

Figure 1.1. Freeway Courtesy Patrol Coverage Area (MDOT, 2010a)

Incident response time and clearance time are two critical components of the overall incident duration, which is primary concern of transportation agencies and the traveling public. Incident duration is generally defined as the time elapsed between the occurrence of an incident and the time at which roadway is restored to its capacity (Garib et al., 1997; Nam and Mannering, 2000; Smith and Smith, 2001; Chung, 2010). The Highway Capacity Manual (TRB, 1994) divides a traffic incident into four distinct phases as shown in Figure 1.2:

- Incident detection time (time between the incident occurrence and the incident detection),
- Response time (difference between incident detection time and the time when incident response team arrived on the incident site),
- Clearance time (time required for the incident response team to clear the incident site) and
- Recovery time (time between incident clearance and recovery of the incident site to normalcy).

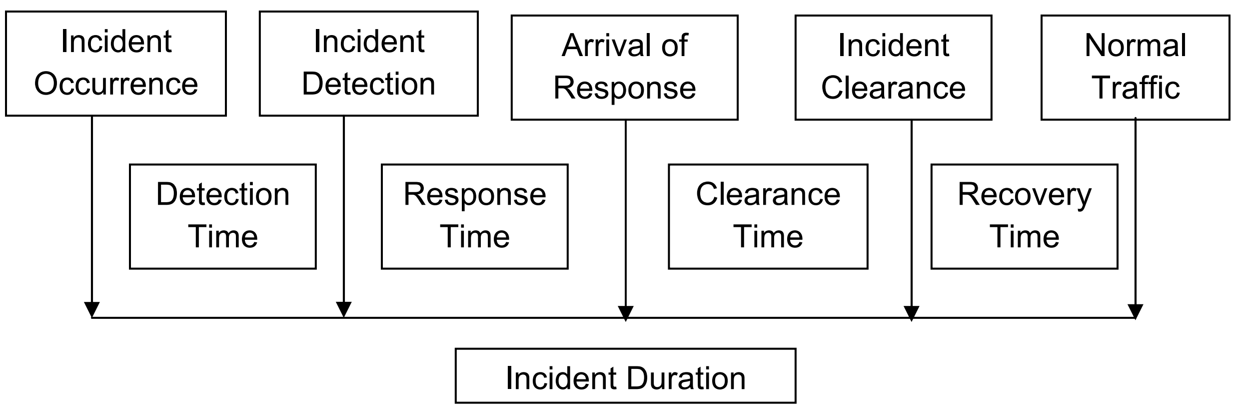

Figure 1.2. Components of a Typical Incident Duration (Nam and Mannering, 2000; Chung, 2010)

Though incident duration typically involves four phases, it is possible to have circumstances where an incident does not experience all of these four aforementioned phases. For example, if an incident took place within the sight of police or response teams while patrolling the area, then both the detection and response times may be negligibly small. Similarly, if an incident is observed by surveillance camera by Traffic

Operation Center personnel, there will not be a detection phase. Incidents with short detection, response, and clearance stages may not affect traffic flow conditions and consequently may not have any recovery stage. In some cases of minor incidents, incident response team does not need to arrive at the incident site which therefore eliminates the clearance phase and the situation on the incident scene can be handled by the people involved without getting support from police or response teams (Smith and Smith, 2001). These types of circumstances have been referred as gone-on-arrival scenarios in the incident database used in the present research.

Incident durations can be significantly reduced through effective incident management. Analyzing each phase of the incident duration as opposed to the overall incident duration provides additional information useful for agencies involved in incident management program. Response time and clearance time for incidents are the most critical parts of incident duration as they can be directly affected by the road agency. Response time refers to the period from incident detection until the arrival of FCP operators on the scene. In other words, response time measures the duration from the time FCP operators are dispatched until they arrive on-site. Response time is critical to incident management strategies as the longer an incident affects traffic flow, the higher the chance of a secondary incident. The incident clearance stage which constitutes the safe and timely removal of stalled vehicles, wreckage, spilled materials and debris from the roadway or shoulders and reinstates the roadway to its full capacity is usually the most time consuming portion of the incident management process (Pearce, 2000). Quick clearance practices ensure the safety of responders and motorists involved in the incident by minimizing their exposure to the adjacent passing traffic (NCHRP, 2003).

This necessitates the reduction of incident clearance to improve incident management operation. It has been found that the incident clearance process takes at least twice the duration of other steps in incident management process (Pearce, 2000).

In the current study, incident detection time and recovery time durations could not be modeled due to the absence of detailed traffic flow data obtained from sensors that could be helpful to identify incident occurrence time and the time when freeway is restored to its capacity which can be determined based upon the distinct change in traffic flow characteristics over time.

1.2 Problem statement and research objectives

Freeway incident management programs aim to minimize user delay by quickly reinstating the capacity of freeways in case of incident occurrence (Konduri et al., 2003). To do so requires a systematic understanding of incident patterns, in order to restore roadways to full capacity (Konduri et al., 2003; Jones et al., 1991). Consequently, the collection and examination of incident-related data, as well as the development of incident forecasting models are really important for freeway incident management systems. Such data and models are helpful in the selection of program strategies, and allocation of personnel in case of incident occurrence (Konduri et al., 2003; Jones et al., 1991). Compared to crash modeling, very little amount of work has been done in the field of modeling the incidents (Konduri et al., 2003). The primary reason behind it is the process of acquiring incident data using expensive field surveillance procedures and extensive data processing, whereas crash data is available from Federal and State agencies (Konduri et al., 2003).

The MITS Center in Downtown Detroit maintains a series of databases that detail freeway operations, as well as the activities of the FCP. However, these databases are independent of one another and no research has concurrently examined the interrelationships between freeway operations and the services provided by the MITS Center. This study aims at analyzing operations on the Detroit freeway network, including inputs related to the occurrence of incidents. Initially, a software interface is proposed which can be used to combine data from these various sources. These data include traffic flow information obtained from side-fire detectors, as well as data related to FCP operations in the Detroit freeway network. In addition to linking these independent data sources, primary data analyses along a stretch of freeway in Detroit metro area helps identifying important factors influencing the occurrence of incidents as well as the response time of FCP responders and incident clearance time. Developing larger models using collected data for the Detroit freeway network allows for a determination of what factors may impact the frequency of incidents as well as response time of the responders and incident clearance time on particular freeway sections in Detroit metro area.

The purpose of this research is to examine incident data along with side-fire detector data and to identify factors affecting the frequency, response time and clearance time of incidents on major freeways in the Detroit metro area, specifically.

The research objectives are:

1) To develop a software interface that can be used to link traffic flow and incident data.
2) To identify factors that affect the frequency of incidents on particular freeway sections in the Detroit metro area.
3) To determine the impacts of various factors on incident duration, including traffic flow, geometric characteristics and type of incidents.
4) To evaluate the operation of the MITS Center, specifically the FCP, and propose recommendations for improving traffic safety and operations.
5) To examine whether incident impacts are similar across different freeways.

1.3 Organization of the research

The report is organized into six chapters. Having outlined the importance of this study and the research objectives, the remainder of the study is organized as follows. Chapter 2 provides a state-of-the-art literature review of previous research in the area of freeway safety and operations. Chapter 3 describes the study area and the data obtained from different sources and utilized in the study. The research methodology is presented in Chapter 4. Chapter 5 includes the results of various statistical analyses conducted as a part of the study. Chapter 6 provides conclusions together with future research directions.

Chapter 2 State-of-the-Art Literature Review

Past research on incident characteristics include analyses of the frequency and duration of incidents and the resulting effect of congestion on the roadway capacity. Similar to traffic crashes, the numbers of incidents experienced on a particular road segment during a given time period are well modeled as a Poisson random variable (Jones et al., 1991; Skabardonis et al., 1997). Concurrently, numerous approaches have been utilized by researchers to model the time duration caused by freeway traffic incidents. Most of the primitive studies conducted in this field used merely descriptive statistics for the data obtained from time-lapse cameras, closed-circuit television (CCTV), and police logs (Giuliano, 1988). Various more advanced analytical techniques have also been applied to study incident duration, including multiple regression (Golob et al., 1987; Giuliano, 1988; Garib et al., 1997), truncated regression (Khattak et al., 1995), survival analyses (Jones et al., 1991; Nam and Mannering, 2000; Stathopoulos and Karlaftis, 2002; Chung, 2010), nonparametric regression, and classification tree models (Smith and Smith, 2001). This chapter presents a summary of prior research related to incident frequency and duration.

2.1 Past research on congestion caused by incidents and incident frequency

Goolsby (1971) analyzed about 2,000 lane-blocking incidents on Gulf Freeway in Houston. An average of 4.5 lane-blocking incidents occurred on each weekday during daylight hours. The maximum numbers of vehicle breakdowns were found to occur in the outside lanes while, conversely, crashes tended to occur near the median. Non-injury crashes were found to impact traffic for approximately 45 minutes on average and the average time for the detection and reporting of crashes was found to be one minute. After the reporting of any crashes, it took an average of 12 minutes for the police to arrive on the scene and the average time between the police arrival and crash removal was seven minutes. Minor crashes or stalled vehicles that blocked one of three available lanes reduced capacity by 50 percent and those crashes blocking two lanes reduced capacity by an average of 79 percent. “Gaper delay” was responsible for a 33 percent reduction of normal flow in the presence of a crash on freeway shoulders. Most incidents were found to occur during the morning (26.7 percent stalls, 25.6 percent crashes) and afternoon (48.2 percent stalls, 40.8 percent crashes) peak periods.

As a part of a study in the Seattle metro area, Jones et al. (1991) developed Poisson regression models to examine crash frequency and identify the effects of factors including day of week, month, weather, road surface condition, and the occurrence of special events (football, baseball, and basketball games).

Ullman and Ogden (1996) studied about 600 major traffic incidents in Houston blocking travel lanes for a duration of 45 min or more. Higher numbers of incidents were observed at freeway-to-freeway interchange areas than between them. About 81 percent of these incidents involved trucks alone (single or multiple trucks), and another 17 percent involved both trucks and automobiles. 70 percent of the incidents involved single vehicle, spilled loads and/or overturned trucks accounted for 57 percent of the incidents.

Skabardonis et al. (1997) carried out a field experiment on I-880 freeway in Los Angeles to determine factors affecting incident frequency. More incidents were experienced during the PM peak hours, especially breakdowns on the right shoulder. Crashes accounted for about 10 percent of all incidents and almost half of all crashes involved more than two vehicles.

Another study by Skabardonis et al. (1999) on I-20 in Los Angeles examined incident patterns and identified significant factors affecting incident frequency. Crashes constituted over 6 percent of all incidents and occurred more frequently at sections with weaving area and lane drops. The Poisson distribution was observed to provide sufficient fit for the incident frequency data.

Chen et al. (2003) assessed the effect of incidents on travel times along I-5 North in Los Angeles through the incident records from the California Highway Patrol (CHP). Higher incident rates were found during the peak hours. The occurrence of incidents accounted for an additional 5 minutes of travel time on average for most trips. Incidents also strongly affected the variance of travel time during midday non-peak hours. No congestion was observed due to incidents during the late night and early morning hours.

Skabardonis et al. (2003) used data from loop detectors on freeway corridors in California to estimate average delay on urban freeways. Weekday data during the peak periods were utilized for all study corridors. Non-recurrent congestion was found to account for 13 to 31 percent of total congestion delay during peak hours. Non-recurrent congestion delay was found to be dependent on roadway segment characteristics, frequency and type of incidents, and the occurrence of recurrent congestion.

Smith et al. (2003) measured the capacity reduction due to over 200 crashes occurring on urban freeways in Virginia. Crashes blocking one of the three freeway lanes reduced capacity by 63 percent while crashes blocking two lanes reduced capacity by 77 percent. It was recommended that capacity reduction be modeled as a random variable as opposed to assuming a deterministic value.

2.2 Past research on the incident duration analysis

Golob et al. (1987) analyzed over 9,000 crashes involving trucks in the greater Los Angeles area and found that the log-normal distribution fit the duration of each groups of freeway truck crashes well, though the sample size of each group was relatively small.

Giuliano (1988) expanded upon the study conducted by Golob et al. and applied a log-normal distribution in a duration analysis of 876 incidents in Los Angeles. Crashes and lane closure related incidents accounted for 11 percent and 18 percent of all incidents, respectively, and were responsible for 17 percent and 14 percent of the total duration. Results showed that the factors affecting incident duration included incident type, lane closures, time of day, day of week, accident type, and truck involvement. The durations of incidents were found to be highly skewed and only 2 percent of incidents had durations of more than 2 hrs.

Jones et al. (1991) assessed the effectiveness of various statistical techniques to study crash duration and evaluate accident management strategies in the Seattle metro area. The results showed that the duration of incidents was better characterized by a log-logistic distribution than a log-normal. The time of year, time of day, lighting conditions, and characteristics related to the driver, vehicle, and type of crash were all found to impact crash duration. Drunk drivers were found to be associated with shorter clearance times due to the higher urgency of law enforcement response to alcohol-related crashes.

Khattak et al. (1995) used truncated regression to model incident duration on roads in Chicago. Numerous factors were found to impact incident duration, including time of day, location, weather and visibility conditions, response time of the first rescue vehicle, damage to the freeway facility, and severity of injuries.

Ullman and Ogden (1996) found clearance times to be considerably longer when incidents involved four or more responding agencies. The median clearance time was found to be slightly less than 2.5 hours and, of that time, 1.75 hours was found to be related to blockage of travel lanes. The distribution of incident duration was found to be slightly right-skewed, as a number of incidents lasted more than the median clearance time. A median clearance time of more than 3 hours was estimated for overturn trucks related incidents. Property damage only (PDO) crashes were found to have relatively minor impacts on traffic.

Garib et al. (1997) carried out an analysis of about 200 incidents on I-880 in California and developed linear regression models for freeway incident delay. Results showed that the factors affecting incident duration included number of lanes affected, involved vehicles, truck involvement, time of the day, police response time, and weather conditions.

Madanat and Feroze (1997) developed truncated regression models to predict incident clearance time using data from approximately 4,000 incidents on the Borman

Expressway in Indiana. Three separate models were developed for different types of incidents: overheating vehicles, debris on the roadway and crashes. The mean clearance time of overheating related incidents was slightly over 12 minutes. Average clearance time for incidents involving debris on roadways and crashes were about 4 minutes and 20 minutes, respectively. Injuries associated with incidents, truck and bus involvement, adverse weather conditions, and higher average traffic speeds increased incident duration.

Skabardonis et al. (1997) found that after the implementation of a Freeway Service Patrol (FSP) program on the I-880 freeway in Los Angeles, the average response time was reduced from 29 minutes to 18 minutes. The average clearance time of incidents and lane-blocking crashes was found to be 20 minutes, while the average time to clear breakdowns on the shoulder was 7 minutes. Weather was found to be a significant factor affecting incident rates. Implementation of the FSP reduced the response time of assisted breakdowns by 57 percent, though no significant effects of the FSP has been observed on the duration of all incidents. This may be due to the fact that the FSP is primarily involved in assisting with minor incidents.

A subsequent study by Skabardonis et al. (1999) on the I-20 freeway in Los Angeles found that average response time and clearance time for the incidents assisted by FSP were 11.4 minutes and 13.4 minutes respectively. Breakdowns on shoulders were cleared in about 10 minutes, whereas crashes and lane-blocking incidents were cleared in 20 minutes. Assisted and non-assisted incidents lasted for 24.8 minutes and 14.4 minutes respectively. Incident duration was found to follow a log-normal distribution. The type and location of incidents, as well as FSP assistance were found to affect incident duration.

Nam and Mannering (2000) developed hazard duration models for 700 incidents from Washington State. They developed separate models for the detection/reporting, response, and clearance durations. Incidents occurring during the afternoon peak period, nighttime hours, and weekends tended to have longer response times. For the incident detection and response models, a Weibull distribution with gamma heterogeneity provided the best fit when compared to all other parametric models and both of these models exhibited positive duration. The log-logistic distribution provided the best fit for the clearance time duration model. Longer clearance times were observed during commuting and nighttime hours, as well as when fatalities or lane closures were involved.

Kim and Choi (2001) developed a fuzzy incident response model using incident data on the freeway in the Los Angeles area. Involved vehicle types, type of incident, incident vehicle location were considered to analyze the incident service time. Their study showed that fuzzy system can be effectively used in the freeway incident management process with fewer numbers of explanatory variables. This study did not consider the incident types separately; rather they categorized ten different incident types (crash, vehicle fire, abandoned, debris removal, flat tire, mechanical, electrical, over-heated, out of-gas, locked out) into three discrete levels. Additionally, they did not include other important variables that could be deciding factors (time of day, day of week, environmental conditions, traffic flow condition, etc) in the freeway incident management strategy.

Smith and Smith (2001) used stochastic model, nonparametric regression model and classification tree model for the prediction of clearance time of freeway crashes in Virginia using about 6,800 accident data. Chi-square goodness-of-fit test results showed that available crash clearance time data does not support the Weibull or lognormal distributions for the stochastic models. The other two types of developed models performed unsatisfactorily in predicting the clearance time of future accidents due to large prediction errors and lower percentage of accurate predicted clearance time.

Stathopoulos and Karlaftis (2002) developed hazard-based duration models using data collected on a major road in the City of Athens, Greece to examine congestion resulting from an incident. This study showed that the log-logistic distribution best described the congestion duration in comparison to Weibull and Exponential distributions. It was found that congestion was most likely to diminish at 6 minutes and less likely to diminish when it persisted to more than 12 minutes.

Wang et al. (2002) developed a vehicle breakdown duration model using fuzzy logic (FL) theory due to limited availability of incident related data for over 200 incidents on a motorway in UK. Vehicle breakdown duration for all vehicle types considered were observed to follow Weibull distribution, though they are statistically significantly different. Incident report mechanism, location of breakdown and time of breakdown were factors affecting the durations. Breakdown reported by emergency telephone service had lower average duration than not reported by it. Vehicle breakdown at the middle of a link experienced higher duration. Vehicle breakdown duration lasted longer in the morning and at night for all types of vehicles.

Wang et al. (2005a) extended their previous analysis of factors affecting the breakdown duration using data of over 200 vehicle breakdowns on one of the most important motorways in UK. In addition to fuzzy logic (FL) theory, artificial neural networks (ANN) was utilized to develop duration models. Kolmogorov-Smirnov test conformed that breakdown duration followed Weibull distribution instead of log-normal distribution. Out of the four breakdown characteristics (type of vehicle, location, time of day and report mechanism) considered, ANN model showed that the reporting mechanism and location of breakdowns had the greatest and least effect on the duration, respectively. Though both the models provided reasonable estimates of breakdown duration with fewer number of variables, the ANN model was found to out-perform the FL model. Both the models could not predict outliers well due to limited number of explanatory variables thus suggesting requirement of more information/data.

Chung (2010) used the log-logistic accelerated failure time metric model to develop an accident duration prediction model for the Korean Freeway System. Duration was found to increase with the number of injuries and involved vehicles, as well as when fatalities were involved. A likelihood ratio test showed that the estimated parameters in the duration model were stable over time.

Valenti et al. (2010) used a database of 237 incidents in Italy and compared the results of five statistical models in the process of estimating the incident duration. Multiple Linear Regression was observed to be the best predictor for incidents with shorter duration. For medium and medium-long duration incidents, Support/Relevance Vector Machine model exhibited the best prediction. Artificial Neural Network offered the best results in case of incidents having duration more than 90 minutes. The other two models, namely, Prediction/Decision Tree Model (CHAID) and K-Nearest-Neighbor did not show satisfactory performances in the prediction of incidents having durations more than 90 minutes. Good prediction accuracy was obtained for all the developed models while considering the incidents having duration of 90 minutes or less because of smaller proportion of severe incidents in the database. It is apparent from the result that these prediction models are capable of showing best performance for different incident duration range.

2.3 Summary

The research literature demonstrates that various analytical techniques can be utilized to examine the frequency of incident occurrence on a particular road section as it relates to roadway geometry, traffic volumes, and other characteristics. No other studies have been found related to frequency analysis of incidents on freeways. All the earlier studies worked with the analysis of crash frequency. As incident frequency data consists of non-negative integers, application of standard ordinary least-square regression is inappropriate as it assumes a continuous dependent variable (Washington et al., 2003). More appropriately, Poisson and negative binomial regression models can be used as tools to evaluate the relationship among highway geometry, traffic-related elements, and other factors with incident frequencies.

When analyzing the duration of incidents, standard linear regression methods may be inappropriate due to the assumption of a simple linear relationship between incident duration and various predictor variables. While regression analysis may be easier to understand and interpret than survival analysis (Khattak et al., 1995), hazard-based duration models allow the explicit study of the relationship between how long an incident has lasted and the likelihood of the incident ending soon (Jones et al., 1991; Nam and Mannering, 2000; Stathopoulos and Karlaftis, 2002; Chung, 2010). Hazard-based duration models are well suited for analyzing time-related data that include well-defined start and end points (Collett, 2003).

Some researchers have used fuzzy logic, artificial neural networks to develop incident duration models. Comparing previous study results is difficult for a number of reasons: different variables have been used by various researchers; results may not be transferrable across different locations; and there is generally dissimilarity in the data collection and reporting process. The survival analysis considered in the earlier studies found several factors (incident characteristics, environmental conditions, time of day, monthly variation, roadway characteristics, traffic flow condition, operational and response characteristics, information broadcasting, etc.) to significantly affect incident duration.

This research aims to build upon previous studies and develop analytical models to examine both the frequency of incidents and the time required by the MDOT Freeway Courtesy Patrol to respond and clear them. The inclusion of a wide range of factors (e.g., traffic flow, roadway geometry, service provided by incident response team, etc.) will allow for a determination of the impacts of such factors on incident frequency, response time as well as clearance time of incidents. The results of these analyses will aid decision makers in optimizing the operations of the MITS Center and, as a result, the Detroit freeway network.

Chapter 3 Data for Study Area

The primary objective of this research is to assess the data that is being collected and maintained by the Michigan Department of Transportation (MDOT) Michigan Intelligent Transportation Systems (MITS) Center and to use these data to examine traffic operations on the southeastern Michigan freeway network. A software interface is developed in order to integrate two databases for subsequent data analysis activities. To analyze the freeway operations in Detroit metro area, data are obtained from two primary sources: traffic flow data from roadside sensors collected by Traffic.com and Freeway Courtesy Patrol (FCP) operational data maintained by the MITS Center.

The MITS Center is located in downtown Detroit and serves as the primary hub of MDOT ITS-related applications. The Center staff monitors a network of twelve freeways in southeastern Michigan using a series of closed circuit television (CCTV) cameras, inductive loop detectors, and side-fire roadside traffic detectors. This monitoring system is used to aid the MDOT FCP in providing assistance to nearly 35,000 stranded motorists in the Detroit metro region each year and responding to many of the more than 10,000 crashes which are experienced annually on a sophisticated network of interconnected freeways as shown in Figure 3.1.

Figure 3.1. Map of Detroit Metropolitan Area (Bing.com, 2010)

3.1 Traffic.com Traffic Flow Data

Traffic.com provides information on traffic conditions for a specific metropolitan area by utilizing a map of the Detroit metro area, including traffic flow data, as well as a summary of incidents, events, and roadwork. The Traffic.com sensor manager feature provides MDOT with detailed data related to traffic on those corridors that are covered by their side-fire detectors. Table 3.1 provides a list of important variables along with a brief description of each. Sensor data are available in 5 minute intervals for each sensor. This results in up to 288 observations for a specific day for each sensor. Traffic.com maintains a total of 110 sensors along four local major freeways (Interstate 75, Interstate 94, Interstate 275 and Interstate 696) in the Detroit metro area. A map showing the locations of these sensors is shown in Figure 3.1. For this study, traffic flow data from a sample of the 110 active sensors were extracted and analyzed. Each of these sensors provides data related to time, number of lanes, average vehicular speed, total number of vehicles along with vehicle classes (Class I, Class II, Class III and Class IV), and detection zone occupancy information for each direction of travel. Mile markers along each freeway for these 110 sensors are also available from Traffic.com.

Table 3.1. List of Variables Included In the Sensor Database (Traffic.Com, 2010)

Name	**Description**
Time	Timestamp
Sensor	Unique sensor ID number (for all lanes)
Device	Sensor device ID (per lane, or zero for all lanes combined)
Direction	Direction of vehicular travel
Lane Position	Location of incident within lane
Lane Type	Type of lane: Thru (mainline), on-ramp, off-ramp, etc.
Speed	Average speed in MPH
Volume	Total count of all vehicles that were measured by vehicle class
Occupancy	The percentage of time that a roadway detection zone was “occupied”

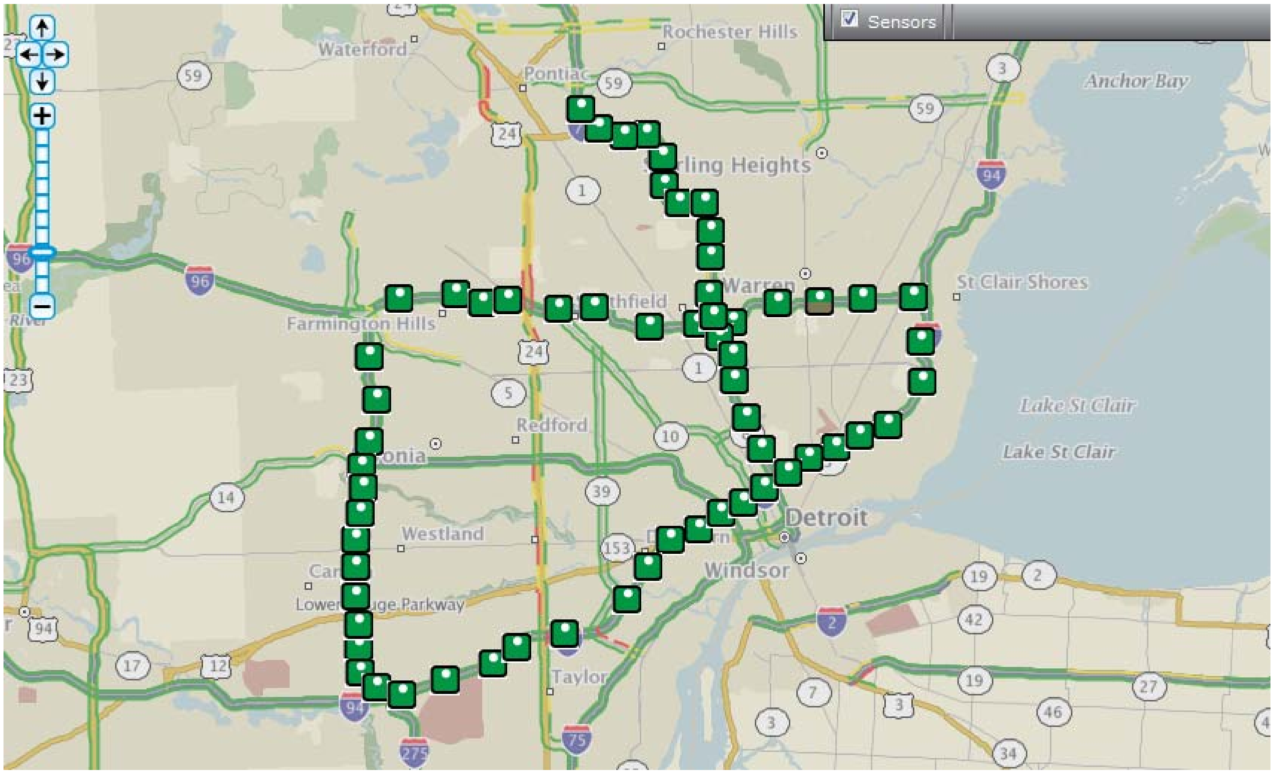

Figure 3.2. Location of Traffic.com Maintained Sensors (Traffic.com, 2010)

3.2 MDOT Traffic Flow Data

In addition to the sensors owned and maintained by Traffic.com, MDOT maintains a series of in-pavement loop detectors/sensors along the freeway network. While these data are also available through Traffic.com, the data are very sparse. Due to the very limited number of sensors that can be used to extract traffic condition related information data for the evaluation study of transportation operations in Detroit metro area, MDOT owned sensors were not included for the present study.

3.3 Freeway Courtesy Patrol (FCP) Data

Incident-related data for 2009 are obtained from a database maintained by the MDOT MITS center for its FCP program. During each FCP call, data are recorded related to each incident. These data include information related to each vehicle (vehicle classification, state of vehicle registration, year, model, color as well as manufacturer of vehicle), incident location (county name, name and type of freeway, direction, nearest cross street, mile marker on freeways), incident type (abandoned vehicle, flat tire, out of gas, mechanical trouble, debris, crash, other, etc), type of service provided by the response team and total time taken by the operator to reach the incident scene and to clear the incident. Table 3.2 provides a list of variables present in the FCP database along with their description.

Table 3.2. List of Variables Included In the FCP Database

Name	**Description**
Day of Week	Day that the Call occurred
ccDateDD	Date the Call occurred
ccDispatched	The time FCP operator was dispatched
ccArrived	The time FCP operator arrived on the scene
ccCleared	The time FCP operator left the scene
typVehicleType	Type of vehicle
ccVehicleYear	Model year of the vehicle
vmMake	Manufacturer of the vehicle
vmmModel	Model of the vehicle
ccOccupants	Number of persons in the vehicle
fwdDirection	The route direction of the freeway
ccMileMarker	Mile marker of the Call location
ccLaneBlocked	Whether any lanes/shoulders were blocked
ccTroubleType	Problem which prompted Call
ccServiceType	Service performed by the FCP operator
ResponseTime	Time taken by FCP operator to arrive on the scene from the place of dispatch
ClearTime	Time taken by the FCP operator to clear the incident
fcp_Longt	Longitude of the Call location
fcp_Lati	Latitude of the Call location

In order to assess the impact of incidents on freeway operations, the FCP incident data must be linked to traffic flow data from the impacted freeway sections. The procedure for linking and subsequently analyzing these data are described in Chapter 4.

Chapter 4 Methodology

In order to accomplish the stated research objectives discussed in Chapter 1, the methodology illustrated in Figure 4.1 is followed as a guideline for the present research. Initially, a software interface is developed to link data from several sources and to identify when incidents have occurred. Using this software interface, sample data is collected for a small section of freeway. A procedure is developed to determine the occurrence of incidents. Then, preliminary hazard-based duration models are developed to examine the duration of incidents clearance time. Larger models using data for Detroit metro area freeway network are developed to identify factors affecting incident frequency and duration on different sections of freeways. The specific tasks associated with this study are described in detail in the following sections.

4.1 Task 1 – Development of a software interface

The previously described data in chapter 3 provide rich source of information that can be utilized to improve the effectiveness and efficiency of MITS Center operations in Detroit metro area. However, until this point, these separate databases were not integrated and much of the available data was not utilized for research purposes. As such, the initial task of this study is to develop a software interface program combining the Traffic.com sensor data and MDOT FCP data into a single integrated database.

The software interface, shown in Figure 4.2, allows users to extract traffic flow data during the time of incidents from the 110 active sensors maintained by Traffic.com along

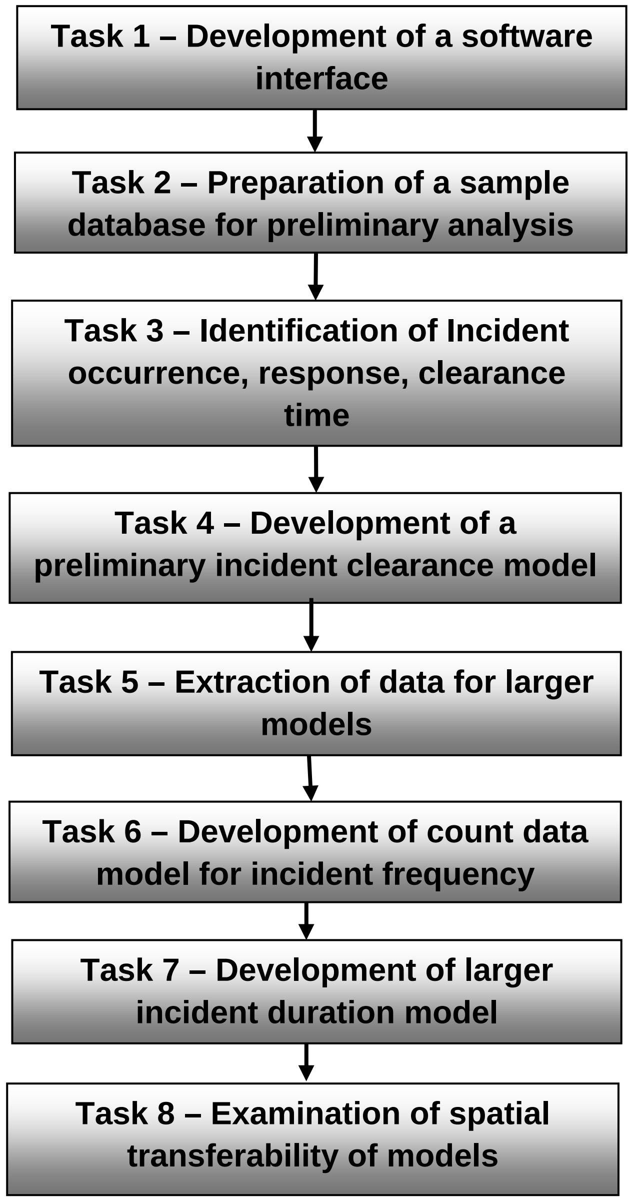

Figure 4.1. Research Methodology

four local freeways (Interstate 75, Interstate 94, Interstate 275 and Interstate 696) in Detroit metro area. Traffic.com provides the mile marker data for each sensor. The mile markers for each incident location are also provided in the FCP database, though there are numerous incident cases with no mile markers information. Mile markers of such incidents are found manually as part of this research. FCP database maintained by the MITS center has latitude and longitude information for each incident occurrence. Google map (2010) was used to find the mile marker of the incidents utilizing latitude and longitude information. For a particular section and a given date range, this software compares the mile markers of each incident location with those of the Traffic.com maintained sensors, identifying the nearest downstream sensor to an incident within a distance specified by the user and extracts the traffic flow information from that particular sensor for each lane type and position for a certain time range.

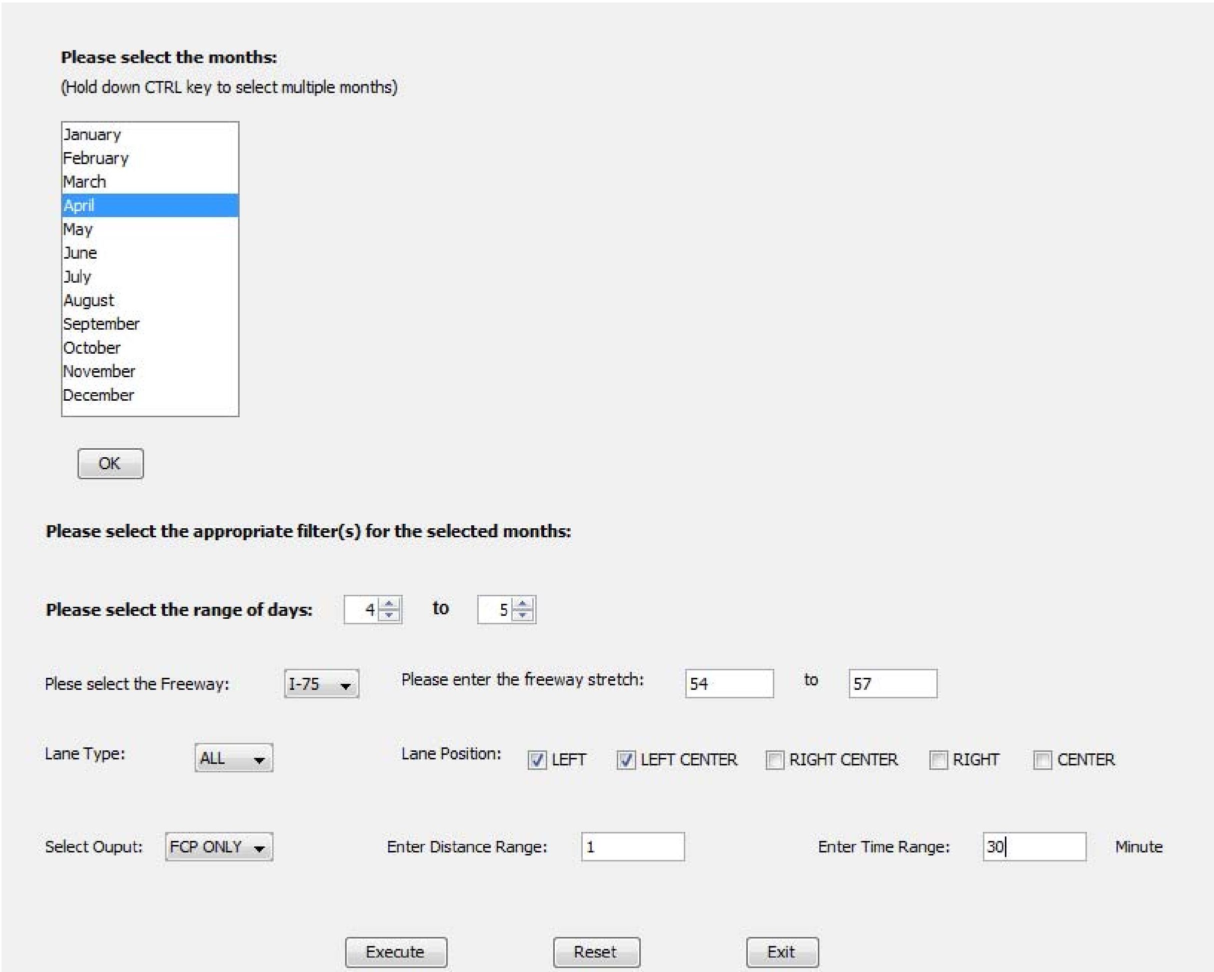

Figure 4.2. Screenshot of Software Interface

The FCP database provides the users several timestamps related to an incident. In addition to providing the timestamps of FCP vehicle's arrival time in the incident location and departure time from the scene, almost 15 percent of incidents in the FCP database also include a dispatch time for incident response team. The time of incident occurrence may also be determined based on sudden changes in traffic flow data (speed, total volume and occupancy) obtained from the sensors.

4.2 Task 2 – Preparation of a sample database for preliminary analyses

Traffic.com provides data for each sensor on each freeway over 5-minute intervals. Due to the large volume of data available for the Detroit freeway network, sample data are extracted for a section of Interstate 75 (I-75) in southeastern Michigan north of the City of Detroit for preliminary analyses aimed at determining the feasibility of the study approach and providing direction for the subsequent larger scale analysis. The sample data are related to those incidents that occurred along the six-mile stretch of I-75 between 8 Mile Road and 14 Mile Road between January and September of 2009. This particular stretch of I-75 is chosen for the study as it has a large volume of traffic and incident management for this stretch of freeway is extremely critical as incidents and the resulting congestion may lead to other incidents, as well as excessive delay to road users. The study section yields a data set of 1,549 incidents, of which 62 cases are removed from the dataset because of incomplete information. The final analysis dataset includes the FCP data for each of the remaining 1,487 incidents. Additionally, weather condition around the time of incident occurrence was obtained for each of the incidents from Weather Underground (2010). Table 4.1 provides summary information related to these incidents.

Table 4.1. Summary Statistics of Freeway Incidents Considered in Preliminary Analysis

Variable	**Number (percentage)**	**Variable**	**Number (percentage)**
Day of Week		*Area of Roadway Affected*	
Weekend	299 (20.11%)	Shoulder only	1,330 (89.44%)
Weekday	1,188 (79.89%)	Exactly one travel lane	135 (9.08%)
Number of Vehicles Involved		More than one travel lane	22 (1.48%)
One Vehicle	1,427 (95.97%)	*Service type*	
Multiple vehicles	60 (4.03%)	Abandoned vehicle	436 (29.32%)
Weather		Flat tire	194 (13.05%)
Clear	1,324 (89.04%)	Out of gas	103 (6.93%)
Rain	101 (6.79%)	Mechanical problems	119 (8.00%)
Snow/icy	40 (2.69%)	Clearing debris	69 (4.64%)
Foggy	22 (1.47%)	Directing traffic	61 (4.10%)
Direction of travel		Towing	107 (7.20%)
Northbound	797 (53.60%)	Standby for EMS	24 (1.61%)
Southbound	690 (46.40%)	Transporting motorist	14 (0.94%)
FCP operator arrival time		Providing cell phone	11 (0.74%)
First shift (10 p.m. - 6 a.m.)	127 (8.54%)	Gone on arrival	8 (0.54%)
Second shift (6 a.m. - 2 p.m.)	665 (44.72%)	Providing directions	21 (1.41%)
Third shift (2 p.m. -10 p.m.)	695 (46.74%)	Service declined by driver	133 (8.94%)
Incident clearance time		Other services	38 (2.56%)
First shift (10 p.m. - 6 a.m.)	128 (8.61%)	Multiple services required	149 (10.02%)
Second shift (6 a.m. - 2 p.m.)	646 (43.44%)		
Third shift (2 p.m. -10 p.m.)	713 (47.95%)		

Table 4.1 shows that only 20 percent of incidents occurred on weekends. Higher weekday traffic volumes are the primary reason for the higher percentage of incidents experienced on weekdays. About 96 percent of the incidents involved only a single vehicle. Approximately 89 percent of incidents occurred under clear weather conditions, with the remainder comprised of rainy, snowy, or icy weather. These proportions are similar to the crash involvement rates in these respective weather categories. Nearly 54 percent of the incidents occurred in the northbound direction of I-75, which may be due to greater congestion in this direction during high-activity periods. Over 89 percent of

the incidents occurred on the shoulders, with 9 percent of incidents impacting a single lane, and the remainder affecting multiple travel lanes. About 91 percent of incidents occurred during the morning (6 am to 2 pm) and afternoon (2 pm to 10 pm) shifts as traffic volume are reduced in the late evening and into the early morning.

The most commonly occurring incidents were in response to abandoned vehicles (29 percent), followed by flat tires (13 percent), mechanical problems (8 percent), or vehicles running out of gas or requiring a tow (7 percent). Multiple services were required for 10 percent of incidents. In approximately 9 percent of cases where the FCP responded, the driver of the incident-involved vehicle declined any assistance. The remaining incident types each comprised less than 5 percent of the total sample. This includes standby service, which generally included situations where a FCP operator stayed on the incident scene while emergency medical services were dispatched to the scene or when the owner does not give the towing company consent to remove a vehicle. These extracted data were combined with the related traffic flow data from Traffic.com in order to conduct some preliminary investigations.

4.3 Task 3 – Identification of incident occurrence, response, and clearance times

Approximate incident occurrence times can be determined by examining traffic flow characteristics over time. As the Traffic.com data are aggregated in 5-minute intervals, vehicle breakdown-related incidents tend to have very little effect on traffic flow, whereas crashes generally result in greater impacts due to their severity. To illustrate this fact, traffic data are presented during two incidents as shown in Figures 4.3 and 4.4. These figures show the plot of vehicular speed, traffic volume and detection zone occupancy information with respect to the time of day for the lanes on which two types of incidents occurred and try to assess potential to automatically identify incidents using the traffic flow profiles. Traffic flow data for the lanes blocked by these two incidents were obtained from the nearest downstream sensor using the software interface. The first incident (Figure 4.3), which is related to a vehicle breakdown was attended by a response team that arrived on the scene at 12:57 PM and cleared the incident at 1:01 PM. This particular incident is shown to have very little effect on traffic flow conditions. No distinct change in any of the traffic flow characteristics can be found from Figure 4.3. Conversely, the approximate occurrence time of the second incident (Figure 4.4), which is a traffic crash, can be detected by the drastic change in the profile of traffic flow characteristics. So, Figure 4.4 shows the traffic flow profile for an “identifiable” incident. The FCP database confirms that the response team arrived on the scene at 3:00 PM and the incident was cleared at approximately 3:48 PM. Figure 4.4 shows a sudden change in traffic volume and mean speed at approximately 2:50 PM and again at 3:50 pm.

Several recent studies have used detector data to identify or predict crashes on a near real-time basis and to identify major factors and conditions that lead to crashes (Lee et al., 2002; Lee et al., 2003; Abdel-Aty and Pande, 2005; Abdel-Aty and Pande, 2009). These studies mainly utilized 30-seconds loop detector data and found that various traffic conditions measured in terms of coefficient of variations in speed, standard deviation of volume and average lane occupancy for different time slices prior to crash occurrence and for upstream sensors act as significant crash precursors on freeways. Conversely, some other studies did not observe any abnormal patterns in pre-crash traffic flow characteristics (e.g., speed and its variation) prior to occurrence of crashes on freeways (Lu et al., 2006; Kockelman and Lu, 2007). For the present study, sensor data from Traffic.com can be obtained for a minimum pooling interval of 5 minutes. As shown in Figure 4.3, these 5-minute intervals are not suitable to identify incidents based upon variations in real-time traffic flow characteristics prior to incident occurrence, with the exception of very severe incidents.

Given these limitations, the occurrence times could not be accurately determined in an automated fashion and the time at which the freeway was restored to its capacity could also not be readily identified for similar reasons. As such, this research focuses specifically upon the duration of incident response and clearance, the two components of the total incident duration that are most directly affected by the transportation agency. If more precise traffic detector data were to become available, analyzing the total incident duration would provide a promising avenue for future research, though this task is outside the scope of this study.

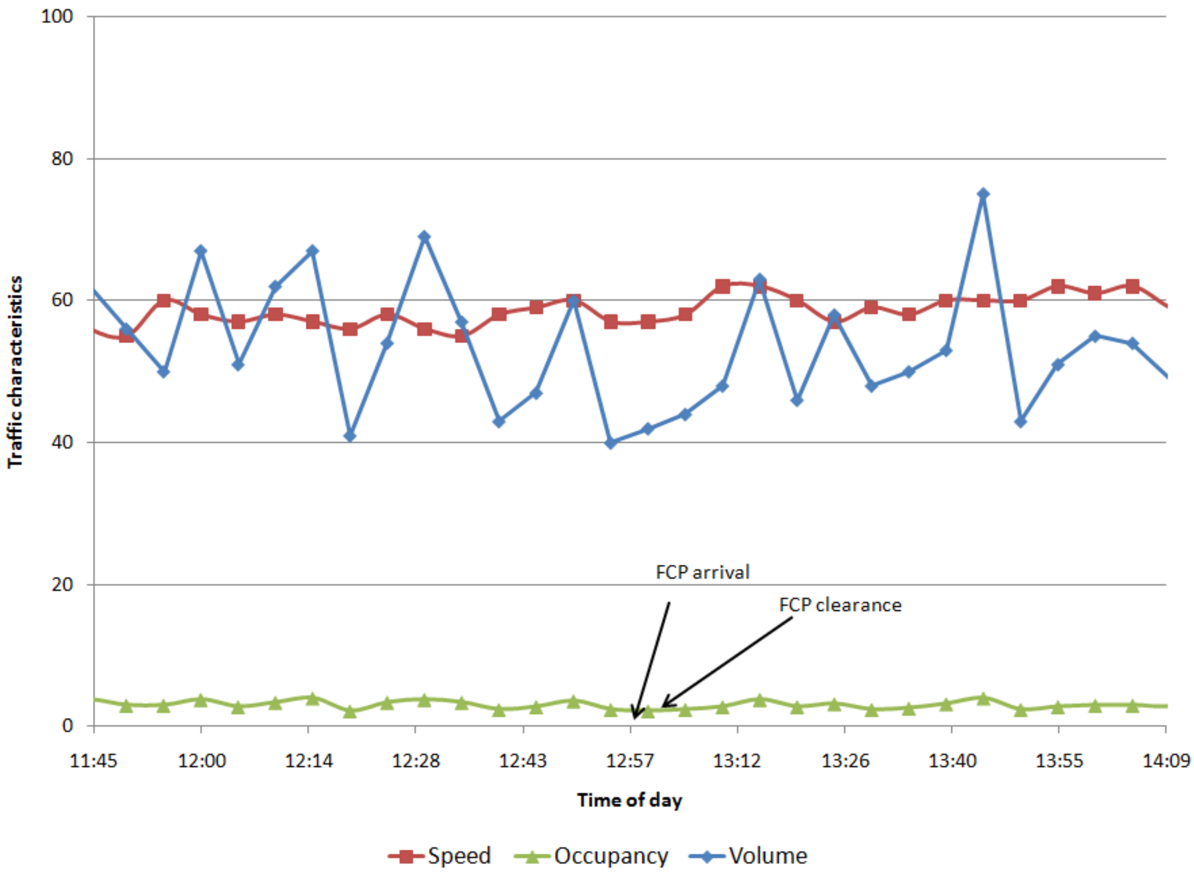

Figure 4.3. Traffic Flow Profile With Respect to Time of Day for Incident # 1

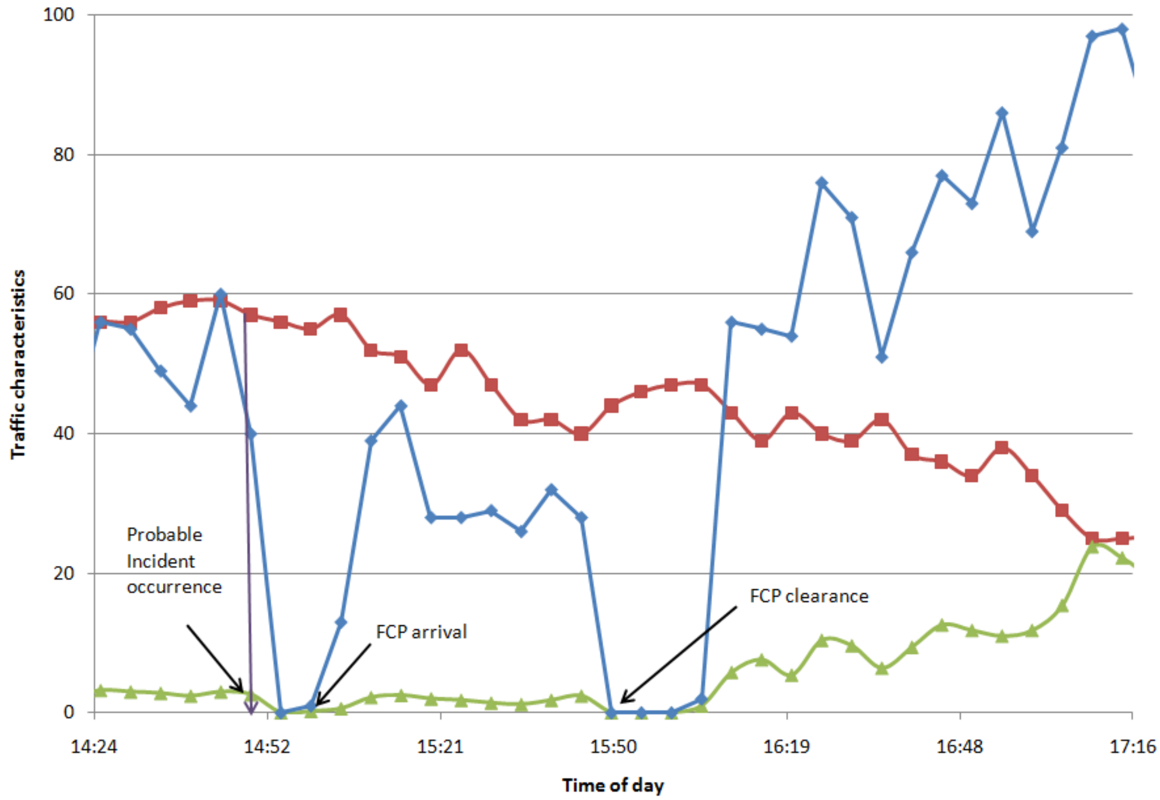

Figure 4.4. Traffic Flow Profile With Respect to Time of Day for Incident # 2

4.4 Task 4 – Development of a preliminary incident clearance model

In addition to determining which factors affect incident frequency, it is also important to identify those factors which increase (or decrease) the clearance time of an incident. For example, delays encountered during the clearance process may be due to weather conditions, traffic characteristics, or other factors. Such time interval data are well-suited to analysis by hazard duration models, which allow for an assessment of the impacts of covariates on the duration of an event. One of the ultimate goals of the FCP is to restore each roadway facility to its capacity as quickly as possible when clearing an incident. Duration models are examined as a part of the study to address the time intervals required for incidents to get cleared and for traffic to recover to pre-incident levels following the occurrence of an incident.

4.4.1 Hazard-based duration model

Hazard-based duration models are well suited for analyzing time-related data that include well-defined start and end points (Collett, 2003). In the field of transportation engineering, hazard-based duration models have been applied for the analysis of traffic crashes (Jovanis and Chang, 1989; Chang et al., 1990; Mannering, 1993), trip-making decisions (Mannering and Hamed, 1990; Hamed and Mannering, 1993; Bhat, 1996a, 1996b; Bhat, 2004), and vehicle ownership (Mannering and Winston, 1991; Gilbert, 1992; De Jong, 1996; Yamamoto and Kitamura, 2000), vehicular delay at an international border crossing (Paselk and Mannering, 1994) as well as incident durations (Jones et al., 1991; Nam, 1997; Nam and Mannering, 2000, Stathopoulos and Karlaftis, 2002; Chung, 2010).

For the task of developing a preliminary incident duration model, hazard models are applied to analyze the time between when the FCP vehicle arrives on the scene and the time the incident is cleared. These models are used to examine the likelihood that an incident will be cleared during the time period *(t +Δt)* given that it has already lasted until time *t*. Following the work of Jones et al. (1991), the central concept for a hazard duration model is not the unconditional probability (i.e., the probability of an incident lasting exactly ten minutes), but its conditional probability (i.e., the probability of an incident ending in the tenth minute given that it has lasted nine minutes). Defining a duration period precisely requires an explicit origin (in this case, the time the FCP vehicle arrives on the scene), as well as an end (the time the FCP has cleared the incident and leaves the scene). Within the context of preliminary incident clearance duration model, the incident clearance time is impacted by several factors of interest, including the type of incident, service performed by the FCP operator, time-of-day, and others, the effects of which can be captured by the hazard model.

As a general, for the hazard duration models, a function is defined of the following form:

$$F(t) = \int_0^t f(u)du = \Pr(T < t), \qquad 0 < t < \infty \tag{1}$$

This equation specifies the probability that a random variable, *T*, is less than some specified value, *t*. In this case, it is the probability that an incident has a duration less than *t*. For all points that *F(t)* is differentiable, a probability density function *f(t)* is defined as:

$$f(t) = \frac{\partial F(t)}{\partial t} = \lim_{\Delta t \to 0} \frac{P(t \le T \le t + \Delta t)}{\Delta t} \tag{2}$$

This gives the instantaneous probability that an incident (duration) will end in the infinitesimally small interval *[t, t + Δt]*.

Another basic function in hazard-based duration modeling is the survivor function, *S(t)*, which gives the probability that an incident has a duration greater than or equal to *t,* and is expressed as follows:

$$S(t)=1-F(t)=Pr(T \ge t) \tag{3}$$

The relationship between failure times and the survivor function is captured through the hazard function (Collett, 2003). The hazard function provides the instantaneous probability that an incident will end during the infinitesimally small time interval between t and $t+\Delta t$, and this function is expressed as:

$$h(t) = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{Pr(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t} \tag{4}$$

In incident duration analysis, *h(t)* can be approximately interpreted as the rate at which the incident duration will end at time *t,* given that it has already lasted for *t* minutes. This function is also referred to as the hazard rate (Collett, 2003).

The slope of the hazard function captures dependence of the probability of a duration ending based upon the current duration, termed as duration dependence. When the slope of the hazard function, *dh(t)/dt*, is greater than 0, the hazard function is termed to have positive duration dependence, which indicates that the longer the duration of the incident is, the more likely the incident is to be ended soon. The converse case is termed negative duration dependence, which indicates that the longer the incident duration, it is less likely to end soon. When *dh(t)/dt*=0, the probability of incident duration ending soon is constant and independent of time. Hazard-based duration models can also explain the effect of covariates on these probabilities (Washington et al., 2003).

The models developed herein are referred to as proportional hazards models. The data used in the present study do not contain any sort of censoring and there are no time varying covariates, so no method can be preferred over the other among the two methods namely, proportional hazards model and accelerated lifetime model (Jones et al., 1991). In proportional hazards models, the effects of the explanatory variables are multiplicative and the hazard function is of the form:

$$h(t \mid X) = h_0(t)y(\beta X) \tag{5}$$

where t is time, X is a vector of explanatory variables, β is a vector of estimable parameters, $h_0(t)$ is the baseline hazard model (i.e., the hazard at $\beta X = 0$), and $y(\beta X)$ is a scaling factor of the form $\exp(\beta X)$. This approach is illustrated in Figure 4.5.

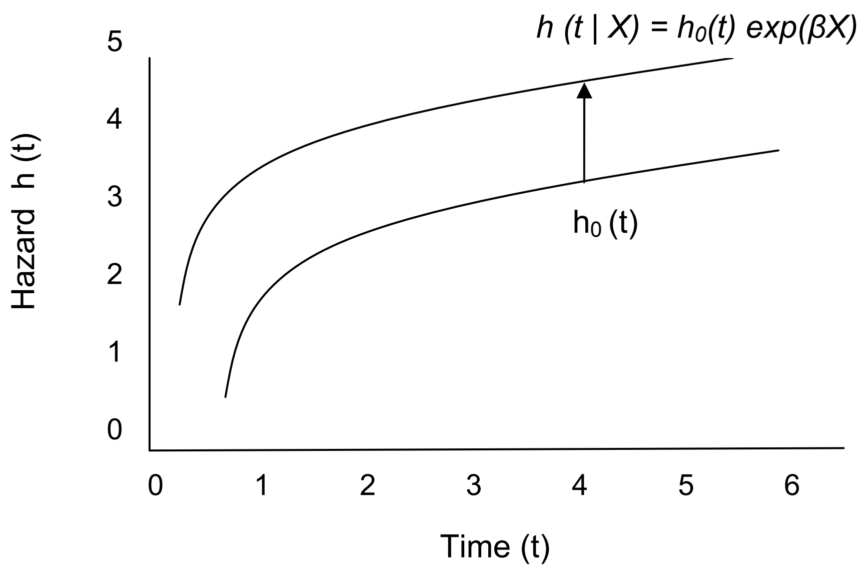

Figure 4.5. Proportional Hazards Model (Washington et al., 2003)

Fully parametric and semiparametric models are used to implement proportional hazard models. Fully parametric models assume a distribution of duration time in addition to having a parametric assumption on the functional form of the influence of the covariates on the hazard function. On the contrary, semiparametric models do not assume a distribution for the duration time, though they hold the parametric assumption of the covariate influence (Washington et al., 2003).

4.4.2 Fully parametric models

The fully parametric models employed as a part of this research assume a variety of distributional alternatives for the hazard function, namely the Weibull, the log-normal, and log-logistic distributions (Nam, 1997; Greene, 2002; Kalbfleisch and Prentice, 2002; Stathopoulos and Karlaftis, 2002; Collett, 2003; Lee and Wang, 2003; Washington et al., 2003). Some other alternatives are gamma, exponential, Gompertz distributions. Table 4.2 provides corresponding hazard function and survival function of various parametric duration models.

Table 4.2. Hazard and Survival Functions for Parametric Duration Models (Nam, 1997)

Name of distribution	**Hazard function, h(t)**	**Survivor function, S(t)**
Exponential	λ	e-λt
Weibull	$\lambda P(\lambda t)^{P-1}$	$e^{-(\lambda t)P}$
Log-logistic	$\lambda P(\lambda t)^{P-1}/[1+(\lambda t)^{P}]$	$1/[1+(\lambda t)^{P}]$

The exponential distribution is the simplest one to use and interpret for the duration modeling purposes. With parameter shift parameter λ>0, its density function is

$$f(t) = \lambda \exp(-\lambda t) \tag{6}$$

With hazard function

$$h(t) = \lambda \tag{7}$$

This hazard function is not a function of implying that the probability of an incident will end is independent of the time and there is no duration dependence (Washington et al., 2003).

The Weibull distribution which is most commonly used in the survival analyses is a more generalized form of the exponential distribution. It allows for positive duration dependence (hazard is monotonic increasing in duration and probability of the duration ending increases over time), negative duration dependence (hazard is monotonic decreasing in duration and probability of the duration ending decreases over time), or no duration dependence (hazard is constant and probability of the duration ending does not change over time). Hazard functions of Weibull distribution have been shown in the Figure 4.6. In Figure 4.6, Weibull I shows positive duration dependence, while Weibull II shows negative duration dependence. With shift parameter $\lambda>0$ and scale parameter $P>0$, its density function is

$$f(t) = \lambda P(\lambda t)^{P-1} \exp[-(\lambda t)^{P}] \tag{8}$$

With hazard function

$$h(t) = \lambda P(\lambda t)^{P-1} \tag{9}$$

Equation 9 says that when Weibull parameter P is greater than 1, the hazard is monotone increasing in duration (designated as Weibull I in Figure 4.6). If P is less than 1, it is monotone decreasing in duration (shown as Weibull II in Figure 4.6); and if P is equal to 1, the hazard is constant in duration and reduces to exponential distribution's hazard (Equation 7). Being a generalized form of exponential distribution, Weibull distribution allows for more flexible means of capturing duration dependence. The major limitation Weibull distribution has is that it requires the hazard to be monotonous over time, whereas in the real world application a non-monotonic hazard is theoretically reasonable (Washington et al., 2003).

The log-logistic distribution allows for non-monotonic hazard functions and is often used to approximate the more computationally unmanageable lognormal distribution. The log-logistic with parameters $\lambda>0$ and $P>0$ has the density function

$$f(t) = \lambda P(\lambda t)^{P-1}[1 + (\lambda t)^{P}]^{-2} \quad (10)$$

And hazard function

$h(t) = \lambda P(\lambda t)P\text{-}1/[1+(\lambda t)P]$ (11)

The hazard function of log-logistic distribution is identical to that of the Weibull distribution except for the denominator. One example of log-logistic hazard function has been shown in Figure 4.6. Equation 11 shows that if P is less than 1, then the hazard is monotone decreasing in duration. If P is greater than 1, then the hazard is monotone increasing in duration from parameter λ; and if P is equal to 1, then the hazard increases in duration from zero to an inflection point, $t = [(P-1)^{1/P}]/\lambda$ (shown in Figure 4.6) , and decreases towards zero thereafter (Washington et al., 2003).

The lognormal distribution does not have a closed form hazard function and therefore cannot be solved analytically. It has the density function

$$f(t) = \left(\frac{P}{t}\right)\phi[Pln(\lambda t)] \quad (12)$$

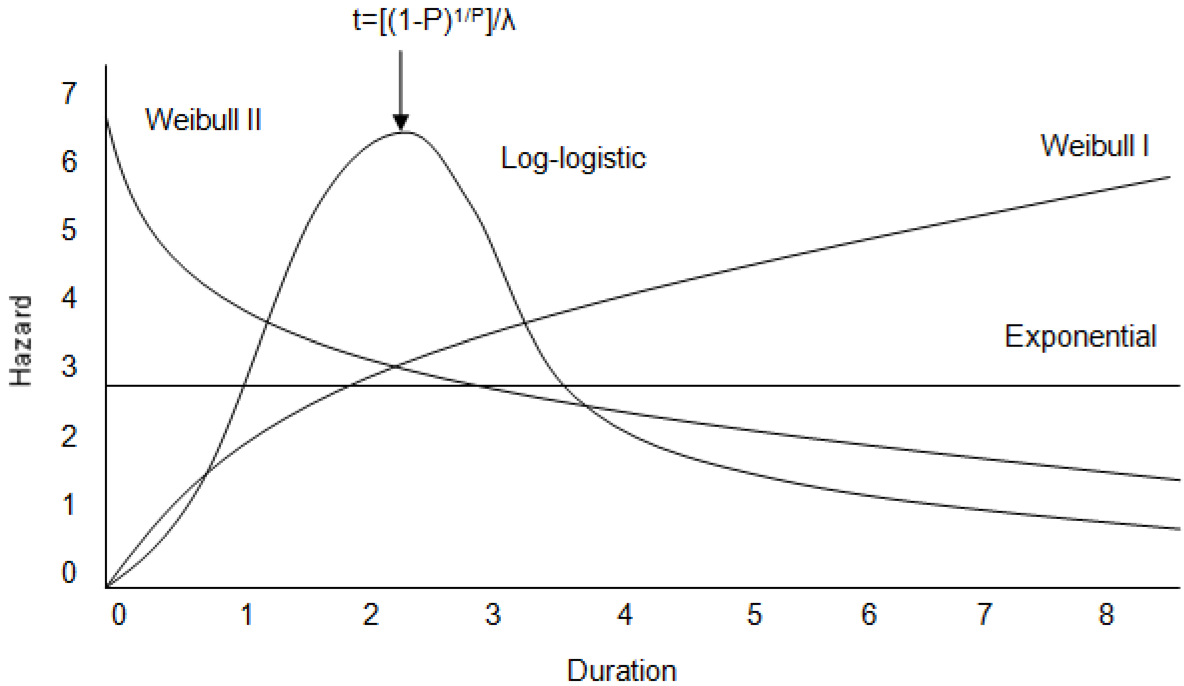

Figure 4.6. Hazard Functions for Different Distributions (Washington et al., 2003)

4.4.3 Comparisons of fully parametric models

The choice of any one of these distributional alternatives is based on theoretical grounds or statistical evaluation. The selection of an appropriate functional form for the duration distribution is a crucial aspect of duration analysis as it not only defines the shape of the underlying hazard, but also affects the efficiency and potential bias of the estimated parameters (Washington et al., 2003). For the present research, the model that provides the best fit was selected based on likelihood ratio statistics.

Likelihood ratio statistics is given by $-2(LL_i - LL_c)$ where LL_i is the initial log-likelihood (with all coefficients equal to zero) and LL_c is the log-likelihood at convergence. This statistic is χ^2 distributed with degrees of freedom equal to the number of estimated coefficients included in the model. The distribution which provides the highest level of significance for this statistics can be selected as the best-fit distribution (Washington et al., 2003).

Another approach of selecting appropriate parametric distribution suggested by Cox and Oakes (1982) is to utilize the plots of the survival and hazard distributions obtained from nonparametric methods. Shapes and characteristics of the survival and hazard curves can be visually compared to choose the appropriate parametric distribution (Washington et al., 2003).

Akaike information criterion (AIC) and Bayesian information criterion (BIC) obtained as values in the output of duration models using Limdep 9 can also been used to select a model among a class of parametric models with different numbers of parameters. Model with lowest AIC or BIC is preferred over others (Burnham, 2002).

4.4.4 Heterogeneity

In the formulation of proportional hazard models, the survival function is assumed to be homogeneous across observations. It implies that all variation in duration is implicitly captured by the vector of explanatory variables, *X*. However, problem occurs when some of the unobserved factors that are not included in the vector *X*, have an effect on durations. This is termed as an unobserved heterogeneity. In the presence of unobserved heterogeneity, it can result in major specification error leading to erroneous inferences on the shape of the hazard function and inconsistent parameter estimates. In fully parametric models, a heterogeneity term can be introduced to capture unobserved effects across the data and to work with the resulting conditional survival function (Gourieroux et al., 1984; Washington et al., 2003).

Assuming a heterogeneity term, *w*, is distributed over the observations with some function *g(w)*, along with a conditional survival function, *S(t|w)*, the unconditional survival function is (Washington et al., 2003),

$$S(t) = \int S(t|w)g(w)dw \tag{13}$$

A common assumption to account for heterogeneity is to consider *w* as gamma distributed (Hui, 1991). Such a model (Weibull distribution with gamma heterogeneity) is developed as a part of this study and compared to three other model specifications.

4.4.5 Semiparametric models

Nonparametric survival analysis methods can model survival or duration data without depending on any particular statistical distributions. As discussed earlier, fully parametric models assume a distribution of duration times and also have a parametric assumption on the functional form of the covariates on the hazard function exp(βX). On the contrary, semiparametric models are more general as they do not assume a duration time distribution, but they retain the parametric assumption of the covariate influence (Washington et al., 2003).

Semiparametric modeling approach is convenient to apply when little or almost no knowledge is obtainable about the underlying hazard distribution. This approach is based on proportional hazards approach and was developed by Cox (1972). The Cox proportional hazards model is semiparametric as exp(βX) is used as the functional form of the covariate influence. This model is based on the ratio of hazards. The probability of an incident i exiting a duration at time t_i, given that at least one incident exits at time t_i, is given as

$$\frac{\exp(\beta X_i)}{\sum_{j \in R_i} \exp(\beta X_j)} \quad (14)$$

where R_i denotes the set of incidents, j, with durations greater than or equal to t_i. This model is readily estimated using standard maximum likelihood methods. If only one incident completes its duration at each time (no tied data), and no incidents are censored, the partial log likelihood is

$$LL = \sum_{i=1}^{I} \left[\beta X_i - \sum_{j \in R_i} \exp(\beta X_j) \right] \quad (15)$$

If no incidents are censored and tied data are present with more than one incident exiting at time t_i, the partial log likelihood is the sum of individual likelihoods of the n_i incidents that exit at time t_i

$$LL = \sum_{i=1}^{I} \left[\beta \sum_{j \in t_i} X_j - n_i \sum_{j \in R_i} \exp(\beta X_j) \right] \quad (16)$$

Semiparametric models have two limitations. First, they do not provide information about the duration dependence. As a consequence, when primary interest of a study is to find out the probability of duration exits with respect to duration, it is not of much use. Second, there is a chance of potential loss in efficiency. When underlying survival distribution is known, Cox semiparametric proportional hazards model does not result in efficient parameter estimates in case of censored data (Washington et al., 2003). Nevertheless, this efficiency loss has been found to be usually small by various researchers (Efron, 1977; Oaks, 1977).

4.5 Task 5 – Extraction of data for larger models

Based on the results obtained from the pilot study using the sample data, larger scale models are developed for the Detroit Metropolitan area. The purpose of developing larger models is to expand the analysis across the freeway network to examine the transferability of the models and determine how the impacts of significant factors vary across freeways and across sections on specific freeways. These expanded models are developed using data for several sections of different freeways. Numerous freeway sections are examined to determine how site-specific factors impact incident frequency and duration and how these impacts vary across locations. Including data from different freeways also allows for a further examination of model transferability, which provides an opportunity for a broad examination of freeway operations in metro Detroit and a determination of how incident characteristics vary across freeways. Analyzing larger models by utilizing data from several freeway sections provide a more comprehensive assessment of incident management on metro area freeways and can allow for an identification of avenues for optimizing incident management practices.

During 2009, the Detroit metro area experienced approximately 51,407 incidents that were responded to by the MDOT Freeway Courtesy Patrol (FCP). In the FCP database for Detroit freeway network, several incidents were found with no lane or shoulder blockage information. After removal of these incidents with incomplete information, this number is reduced to 48,116. Table 4.3 shows the frequency of incidents by type.

Table 4.3. Frequency of Incident Types in Detroit Freeway Network

Incident type	**Frequency**	**Percentage**
Abandoned vehicle	14,435	30%
Flat tire	9,319	19%
Ran out of gas	5,201	11%
Mechanical failure	10,919	23%
Debris on road	2,587	5%
Crash	1,743	4%
Other	2,845	6%
Multiple	1,067	2%
Total	48,116	100%

Table 4.4 shows the frequency of incidents on each freeway and shows that Interstate 94 (I-94) experienced the highest frequency of incidents in 2009, followed by Interstate 75 (I-75).

Table 4.4. Incident Frequency for Detroit Freeway Network

Freeways	**Number of incidents**	**Percentage**
I-275	3,829	8.0%
I-375	79	0.2%
I-696	5,005	10.4%
I-75	10,761	22.4%
I-94	12,983	27.0%
I-96	6,909	14.4%
M-5	3,812	7.9%
M-8	665	1.4%
M-10	2,876	6.0%
M-14	421	0.9%
M-39	88	0.2%
M-59	688	1.4%
Total	48116	100.0%

The four local freeways (Interstate 75, Interstate 94, Interstate 275 and Interstate 696) where Traffic.com maintains sensors experienced a total of 32,578 of these incidents. Four cases have been deleted from the overall database due to excessive high values of FCP response time and incident clearance time. Average response time for the FCP operators and clearance time for the incidents on these four freeways are observed as 11.51 minutes and 9.81 minute, respectively. Summary statistics of the remaining 32,574 incidents are shown in Table 4.5. Data related to these incidents are utilized to develop larger-scale models and examine freeway operations in southeastern Michigan region. Each of these four freeways is divided into finite-length sections of each 1-Mile length and these sections are examined to determine how site-specific variables (e.g., number of lanes, presence of horizontal curves, number of horizontal curves, maximum and minimum radii of horizontal curves, number of entrance and exit ramps, etc.) impact incident frequency, response and clearance times and how these impacts vary across freeway sections. Northbound and southbound, eastbound and westbound freeway sections are considered separately. Consequently, total freeway network consisting of the four local freeways (I-75, I-94, I-275 and I-696) is disaggregated into 422 sections of 1-Mile length. The geometric features and traffic related information (85th and 15th percentile speed, peak hour volume) are collected for each of these sections. Traffic flow related information cannot be obtained for some sections (especially the end sections for a particular freeway) due to the absence of side-fire detectors in these sections. In cases where a section with no detector falls between two sections having detectors, traffic related information is calculated by taking the average of traffic flow information for the previous and next sections. The summary statistics of these 422 freeway sections are presented in Table 4.6.

Table 4.5. Summary Statistics of Incidents in Study Network (I-75, I-275, I-94, I-696)

Variable	**Number (percentage)**	**Variable**	**Number (percentage)**
Day of Week		*Area of Roadway Affected*	
Weekend	5,492(16.86%)	Shoulder only	28,900(88.72%)
Weekday	27,082(83.14%)	Exactly one travel lane	3,258(10.00%)
Month		More than one travel lane	416 (1.28%)
January	2,214(6.80%)	*Service type*	
February	2,158(6.62%)	Abandoned vehicle	9,862(30.28%)
March	2,404(7.38%)	Flat tire	4,313(13.24%)
April	2,941(9.03%)	Out of gas	2,757(8.46%)
May	2,721(8.35%)	Mechanical problems	2,038(6.26%)
June	2,710(8.32%)	Clearing debris	1,678(5.15%)
July	2,832(8.69%)	Directing traffic	740(2.27%)
August	3,295(10.12%)	Towing	2,052(6.30%)
September	2,963(9.10%)	Standby for EMS	675(2.07%)
October	3,042(9.34%)	Transporting motorist	278(0.85%)
November	2,720(8.35%)	Providing cell phone	126(0.39%)
December	2,574(7.90%)	Gone on arrival	222(0.68%)
Number of Vehicles Involved		Providing directions	404(1.24%)
One Vehicle	32,208(98.88%)	Service declined by driver	3,202(9.83%)
Multiple vehicles	366(1.12%)	Other services	859(2.64%)
		Multiple services required	3,368(10.34%)
Freeway		*FCP operator dispatch time*	
I-75	10,760(33.03%)	First shift (10 pm - 6 am)	305(8.47%)
I-275	3,828(11.75%)	Second shift (6 am - 2 pm)	1,453(40.33%)
I-94	12,981(39.85%)	Third shift (2 pm -10 pm)	1,845(51.21%)
I-696	5,005(15.37%)	*FCP operator arrival time*	
Direction of travel		First shift (10 pm - 6 am)	2,875(8.83%)
Northbound	7,520(23.09%)	Second shift (6 am - 2 pm)	15,469(47.49%)
Southbound	7,068(21.70%)	Third shift (2 pm -10 pm)	14,230(43.69%)
Eastbound	8,803(27.02%)	*Incident clearance time*	
Westbound	9,183(28.19%)	First shift (10 pm - 6 am)	2,875(8.83%)
		Second shift (6 am - 2 pm)	15,301(46.97%)
		Third shift (2 pm -10 pm)	14,397(44.20%)

Table 4.5 shows that only 17 percent of incidents occurred on weekends due to lower weekend traffic as compared to weekdays. Only a single vehicle was involved in about 99 percent of the incidents. Nearly 23 percent and 28 percent of the total incidents occurred in the northbound and westbound direction of these freeways, respectively, which may be due to greater congestion in these two directions during high-activity periods. Over 88 percent of the incidents occurred on the shoulders, with 10 percent and 1.3 percent of incidents impacting a single lane and multiple travel lanes, respectively. About 91 percent of incidents occurred during the morning (6 am to 2 pm) and afternoon (2 pm to 10 pm) shifts as traffic volume are reduced in the late evening and into the early morning. Month of August and February were found to experience the highest (10 percent) and lowest (6.6 percent) percentage of incidents, respectively. 33 percent and 39 percent of the incidents were observed on Interstate 75 and Interstate 94, respectively.

The most frequently occurring incidents were in response to abandoned vehicles (30 percent), followed by flat tires and incidents requiring multiple services (13 percent), vehicles running out of gas (8 percent), mechanical problems or requiring a tow (7 percent). In approximately 10 percent of the cases, the driver of the incident-involved vehicle declined any assistance from the FCP responder. Other remaining incident types each consisted of less than 6 percent of the total sample.

Table 4.6. Summary Statistics of Characteristics of Freeway Sections

Variable	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Incident frequency (per month)	0	43	6.4	6.3
85th percentile speed	59	76	68.5	3.3
15th percentile speed	48	68	58.7	3.8
Peak hour volume	2,892	6,720	4,494.2	910.8
Number of lanes	2	4	3.1	0.4
Number of horizontal curves	0	3	0.8	0.8
Maximum radius of the horizontal curve	0	4,365	1,412.3	1,344.3
Minimum radius of the horizontal curve	0	4,365	1,328.1	1,287.4
Number of entrance ramps	0	3	0.9	0.8
Number of exit ramps	0	3	0.8	0.7

Note: Data represents 422 freeway sections of one mile length on I-75, I-275, I-94, I-696

The Table 4.6 provides the summary statistics of different characteristics for the 422 sections (each of one mile length) considered in this study. In 2009, the maximum number of incidents that a freeway section experienced was 43, whereas there are 46 sections with no history of incident occurrence in 2009. Peak hour volume was found to vary between 2,892 vehicles per hour to 6,720 vehicles per hour. For different freeways considered in this study, maximum of three horizontal curves were found on a one mile section. For the analysis of incident frequency data, same maximum and minimum radius of horizontal curves have been used for freeway sections with only one horizontal curve. The tangent sections are referred to the freeway sections of one mile length with no horizontal curves. Maximum of three entrance ramps and three exit ramps were observed for freeway sections.

4.6 Task 6 – Development of larger incident duration model

Incident response and clearance processes are very critical elements of traffic management for road agencies, particularly in large urban environments where the effects of incidents can create long-lasting impacts on congestion in addition to contributing to secondary incidents. Hazard duration models are developed (both fully parametric and semiparametric) using data for four major local freeways in Detroit freeway network to examine the factors affecting clearance times for incidents responded to by the FCP as well as the response time of the FCP operators and to assess the transferability of these impacts across other freeway sections in southeastern Michigan region. In the case of fully parametric models, four types of distributions are assumed for the underlying hazard functions namely, Weibull distribution, Weibull distribution with gamma heterogeneity, log-normal distribution and log-logistic distribution. For semiparametric models it is not necessary to assume any distribution. So it is not possible to obtain any information related to duration dependence and interpret duration effects from the semiparametric model results, though a semiparametric framework does provide greater flexibility, which is important if some of the parametric assumptions may not be appropriate for particular duration data. Preliminary incident clearance models are already developed utilizing incident data for a stretch of Interstate 75 in Detroit metro region. But no traffic flow related information was not considered during this preliminary work. So, additional site specific factors, such as number of lanes, presence of horizontal curves, maximum and minimum radii of horizontal curves, presence of entrance and exit ramps, and traffic flow related variables, such as 85th percentile and 15th percentile speed, as well as peak hour traffic volume data are considered as a part of subsequent models.

4.7 Task 7 – Examination of model transferability

The stability of incident duration over location is an essential theoretical and empirical concern as incident duration pattern changes over location. If it is not taken into account, the prediction of incident duration as obtained from developed models can be incorrect. Spatial transferability is examined as detailed in this section.

4.7.1 Spatial transferability

The spatial transferability of the model is checked by using data for other locations. Likelihood ratio test is conducted based on data for other locations to check the spatial transferability of the developed models and to use it for future forecasting. If it is not done, coefficients of developed model can be resulted in incorrect forecasting.

4.7.2 Likelihood ratio test

For any model it is imperative to check if the estimated parameters are transferable spatially (among places or areas) or temporally (over time). Spatial transferability guarantees the use of estimated parameters to be utilized in other places, saving cost of further data collection and estimation. On the other side, temporal transferability is favored to confirm that the model estimated parameters are stable over time. Likelihood ratio test is generally conducted to check spatial and temporal transferability (Washington et al., 2003).

Incident duration patterns can change over place (region/section) and time due to variation in factors such distance of nearest traffic management centers from where FCP operators are dispatched, allotment of FCP operators along certain freeways, geometrical characteristics (presence of horizontal and vertical curves, number of lanes, shoulder width, etc), educational programs for drivers, and incorporation of modern technologies for roads and vehicles. The duration model developed for the study should be checked for its spatial transferability to ensure presence of stability in the models over locations.

To test the transferability of parameters between two regions or time periods, following likelihood ratio test should be carried out (Washington et al., 2003):

$$X^2 = -2[LL(\beta_T) - LL(\beta_a) - LL(\beta_b)] \qquad (17)$$

where $LL(\beta_T)$ is the log-likelihood value at convergence of the model using data from both region *a* and *b* (or both time periods *a* and *b*), $LL(\beta_a)$ is the log-likelihood value at convergence of the model using region *a* data (or time *a* data) and $LL(\beta_b)$ is the log-likelihood value at convergence of the model using region *b* data (or time *b* data). Same variable should be used in all three models- total, region a model and region b model. The test statistic follows the chi-square distribution (X^2) and has degrees of freedom equal to the total number of estimated parameters in region *a* and region *b* models (or all periodical models) minus the number of estimated parameters in the overall model. The resulting X^2 statistic provides the probability of the models having different parameters (Washington et al., 2003).

The likelihood ratio test gives forth a good evaluation of the model's transferability. Before checking the spatial and temporal transferability, it has to be made sure that the models are well specified because the omitted variables and other specification errors can lead to rejection of transferability erroneously. For the present research, spatial transferability is checked using likelihood ratio test.

4.8 Task 8 – Development of count data model for incident frequency

Statistical modeling is undertaken to predict incident frequency based upon segment-specific information on roadway geometry, traffic characteristics and other factors. This work attempts to identify the conditions under which freeway sections tend to experience a higher frequency of incidents on monthly basis. As incident frequency data consists of non-negative integers, application of standard ordinary least-square regression is inappropriate as it assumes a continuous dependent variable (Washington et al., 2003). Poisson regression and negative binomial regression models are used as predictive tools to evaluate the relationship among month of incident occurrence, highway geometry, traffic-related elements, other incident characteristics and incident frequencies per month. These models allow for a determination of what segment-specific factors have the greatest impact on incident frequency. This information may provide useful to MDOT for the purposes of FCP routing and in determining means of reducing incidents in particular locations. In many situations, the zero outcomes of the data are undoubtedly different from the non-zero ones (Greene, 1994, 2000). If the possibility of a zero-inflated counting process is ignored, it can lead to biased estimation of Poisson and negative binomial regression coefficients. But it was observed that out of 422 finite length sections considered for this study, only 46 sections (11%) have zero incidents for the year 2009. So, zero-inflated probability processes, such as the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) regression models, are not developed as a part of the study to determine the relative incident likelihoods of freeway sections having incidents and having no history of incident.

4.8.1 Poisson regression model

Poisson regression model is applied to wide range of transportation count data. In a Poisson regression model, the probability of roadway entity (for example, section) i having n_i incidents per some time period (where n_i is a non-negative integer) is given by:

$$P(n_i) = \frac{exp(-\lambda_i){\lambda_i}^{n_i}}{n_i!} \tag{18}$$

where $P(n_i)$ is the probability of roadway section *i* having n_i incidents per time period and λ_i is the Poisson parameter for roadway section *i*, which is equal to roadway section *i*'s expected number of incidents per month, $E[n_i]$. Poisson regression models are estimated by specifying the Poisson parameters λ_i (the expected number of incidents per period) as a function of explanatory variables. The most common relationship between explanatory variables and the Poisson parameter is the log-linear model,

$\lambda_i = exp(\beta X_i)$ or , equivalently $LN(\lambda_i) = \beta X_i$, (19)

where X_i is a vector of explanatory variables and β is a vector of estimable coefficients. With this form of λ_i, the coefficient vector β can be estimated by the maximum likelihood method with the likelihood function being

$$L(\beta) = \prod_i \frac{\exp[-\exp(\beta X_i)][\exp(\beta X_i)]^{n_i}}{n_i!} \tag{20}$$

The log the likelihood function is simpler to manipulate and more appropriate for estimation,

$$LL(\beta) = \sum_{i=1}^{n} [-\exp(\beta X_i) + y_i \beta X_i - LN(y_i!)] \tag{21}$$

The important characteristic of Poisson probability distribution is that the mean and variance of a Poisson probability distribution are equal. When the variance is significantly larger than the mean, the data are said to be overdispersed. In many cases, overdispersed count data are successfully modeled using a negative binomial model (Washington et al., 2003).

4.8.2 Negative binomial model

To overcome the overdispersion problem, negative binomial regression has been commonly used by various researchers which relaxes the assumption that the mean of incident frequencies is equal to the variance. The negative binomial distribution assumes that the Poisson parameter follows a gamma probability distribution. The model results in a closed-form equation and the mathematics to manipulate the relation between the mean and variance structures is relatively simple (Lord and Mannering, 2010). An error term is added to the expected incident frequency λ_i. Equation 19 then becomes

$$\lambda i = exp(\beta X_i+\varepsilon_i) \tag{22}$$

where $\exp(\varepsilon_i)$ is a gamma-distributed error term with mean one and variance *α*. The formulation of the negative binomial distribution is

$$P(n_i) = \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta).\mathrm{n_i}!]}.u_i^{\theta}(1-u_i)^{n_i} \tag{23}$$

where $u_i = \theta/(\theta + \lambda_i)$ and $\theta = 1/\alpha$, and $\Gamma(\cdot)$ is a value of gamma distribution. The corresponding likelihood function is

$$L(\lambda_i) = \prod_{i=1}^{N} \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta).\mathrm{n_i}!]} \left[\frac{\theta}{\theta + \lambda_i}\right]^{\theta} \left[\frac{\lambda_i}{\theta + \lambda_i}\right]^{n_i} \tag{24}$$

where N is the total number of freeway sections. The coefficient estimates can be obtained by the maximum likelihood method. This model structure allows the mean to differ from the variance such that,

$$var[n_i]=E[n_i][1+\alpha E[n_i]] \tag{25}$$

where α is used as a measure of dispersion. If α is not significantly different from zero, the negative binomial model simply reduces to a Poisson model with $var[n_i] = E[n_i]$. If α is significantly different from zero, the negative binomial model is the correct choice.

4.9 Calculation of Elasticities

Elasticity values are computed to measure how specific variables affect outcome probabilities. Elasticity values represent the percentage change in the probability of an outcome due to a 1% change in an explanatory variable. For a continuous variable x_{ki}, the elasticity is calculated as

$$E_{x_{ki}}^{P(i)} = \frac{\partial P(i)}{\partial x_{ki}} \times \frac{x_{ki}}{P(i)} \tag{26}$$

where $P(i)$ is the probability of outcome i, x_{ki} is the value of variable k for outcome i in the vector of variables X_i. For indicator variables (those variables that take on values of 0 and 1) the elasticity cannot be determined using Equation 24. Some measure of the sensitivity of indicator variables is conducted by computing a pseudo-elasticity. Pseudo-elasticity is defined as the percentage change in the probability of an outcome when an indicator variable is changed from zero to one. It is calculated for the set of observations where x_{ki} = 0. The following equation (Equation 27) is used to calculate pseudo-elasticity

$$E_{x_{ki}}^{P(i)} = \frac{exp[\Delta(\beta_i x_i)] \sum_{\forall I} \exp(\beta_{kI} x_{kI})}{exp[\Delta(\beta_i x_i)] \sum_{\forall I_n} \exp(\beta_{kI} x_{kI}) + \sum_{\forall I \neq I_n} \exp(\beta_{kI} x_{kI})} - 1 \qquad (27)$$

where I_n is the set of alternate outcomes with x_k in the function determining the outcome, and I is the set of all possible outcomes (Washington et al., 2003).

For count data models also elasticities are calculated to assess the marginal effect of the indicator variables. Elasticities are the suitable way to evaluate the relative effect of each variable in the model and provide estimation of the impact of a variable on the expected frequency and are interpreted as the effect of a 1% change in the variable on the expected frequency λ_i (Washington et al., 2003). Elasticity of frequency λ_i is defined as

$$E_{x_{ik}}^{\lambda_i} = \frac{\partial \lambda_i}{\partial x_{ik}} \times \frac{x_{ik}}{\lambda_i} = \beta_k x_{ik} \qquad (28)$$

where x_{ik} is the value of variable the *k*th independent variable for observation *i*, β_k is the estimated parameter *for k*th independent variable and λ_i. is the expected frequency for observation *i*,.

The elasticity for noncontinuous indicator variables (those variables that take on values of 0 and 1) cannot be determined using Equation 28. In such cases, a pseudo-elasticity is computed to estimate an approximate elasticity of the variables. It gives the incremental change in the frequency caused by changes in indicator variables. The elasticity for indicator variables, is computed as (Washington et al., 2003)

$$E_{x_{ik}}^{\lambda_i} = \frac{\exp(\beta_k) - 1}{\exp(\beta_k)} \quad (29)$$

Chapter 5 Results and Discussions

As described in the previous chapter (Chapter 4), count data models have been developed in the present study to analyze factors affecting the incident frequency per month on Detroit freeway network. Modeling count data as continuous one by applying standard least squares regression is inappropriate. Both the Poisson regression and negative binomial regression models have been used for the modeling purposes. One limitation of using the Poisson regression model for the count data is that it requires the mean of the count process to be equal to its variance. Overdispersion occurs at situations when variance of the data is significantly larger than the mean. Overdispersed count data are successfully modeled by developing negative binomial model (Washington et al., 2003).

Additionally, hazard-based duration model approach has been used in the present study to analyze incident duration. Though duration data are usually continuous and thus can be modeled using least square regression, estimation techniques based on hazard functions provide additional information about underlying duration problem. Hazard-based duration models study the conditional probability of a time duration ending at some time t, given that the duration has already lasted for time t. Incorporating these models in the present study not only identify important factors influencing the response time taken by the FCP operators and clearance time of the incidents, but also provide insights about the probability of a duration ending on the length of the duration (i.e., duration dependence) from the slope of the hazard function (Washington et al., 2003).

5.1 Results of incident clearance duration model

As discussed in the previous chapter, preliminary incident clearance duration models are developed using incident related data for a stretch of freeway in Detroit metro area. Afterwards, using the comprehensive database for four local freeways in the southeastern Michigan freeway network, larger clearance duration models have been developed and examined to identify the major significant factors affecting clearance times. Results of both preliminary incident clearance model and larger incident clearance models are discussed in the following sub-sections.

<u>5.1.1 Preliminary incident clearance model</u>

5.1.1.1 Fully parametric models

The preliminary work is focused on examining the factors influencing the time required to clear incidents along the study section of Interstate 75 by developing four hazard duration models, each with a different assumption regarding the underlying distribution for the hazard function. The distributions that are compared include the Weibull, both with and without heterogeneity effects, as well as the log-normal and log-logistic distributions. LIMDEP Version 9 software is used for the analysis as it allows flexibility in terms of model specification (Greene, 2007).

Figure 5.1, 5.2, 5.3 and 5.4 present plots of each of these four hazard functions versus incident duration. As mentioned earlier, hazard function is the conditional probability that an event will clear between time *t* and *t+dt*, given that the incident already lasted up to time t. In other words, hazard function on the y-axis of Figure 5.1, 5.2, 5.3 and 5.4 gives the rate at which incident clearance durations are ending at time *t,* given that the incident clearance process has not ended up to time t (Washington et al., 2003). From visual inspection of Figure 5.1, it is apparent that in case of the Weibull distribution, hazard function increases monotonically, which indicates that as incident clearance duration increases, the likelihood of the incident being cleared over the following time period also increases continuously. However, when introducing heterogeneity effects based upon the gamma distribution, the distribution appears more reasonable as shown in Figure 5.2. The hazard function peaks at between 9 and 10 minutes, after which the likelihood of the incident being cleared decreases monotonically. Figure 5.3 and Figure 5.4 present the hazard functions of log-normal and log-logistic distribution. For both the distributions, the hazard functions (probability of incidents getting cleared at time *t*, given that it already lasted up to time *t*) initially increase, and then decrease monotonically after a certain inflection point.

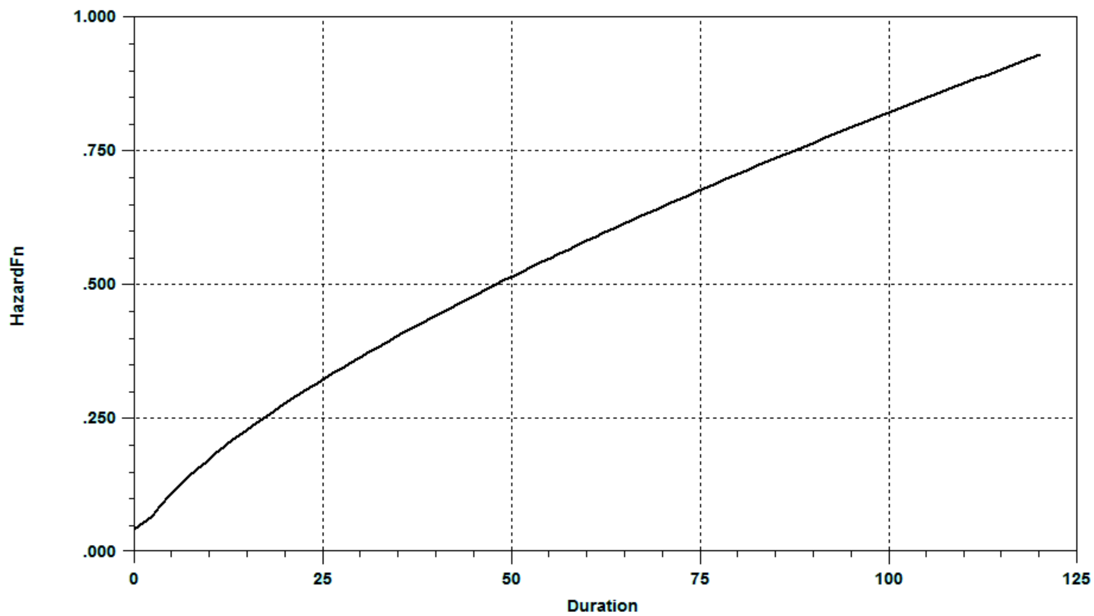

Figure 5.1. Hazard Distribution Function for Weibull Distribution I (No Heterogeneity Effects)

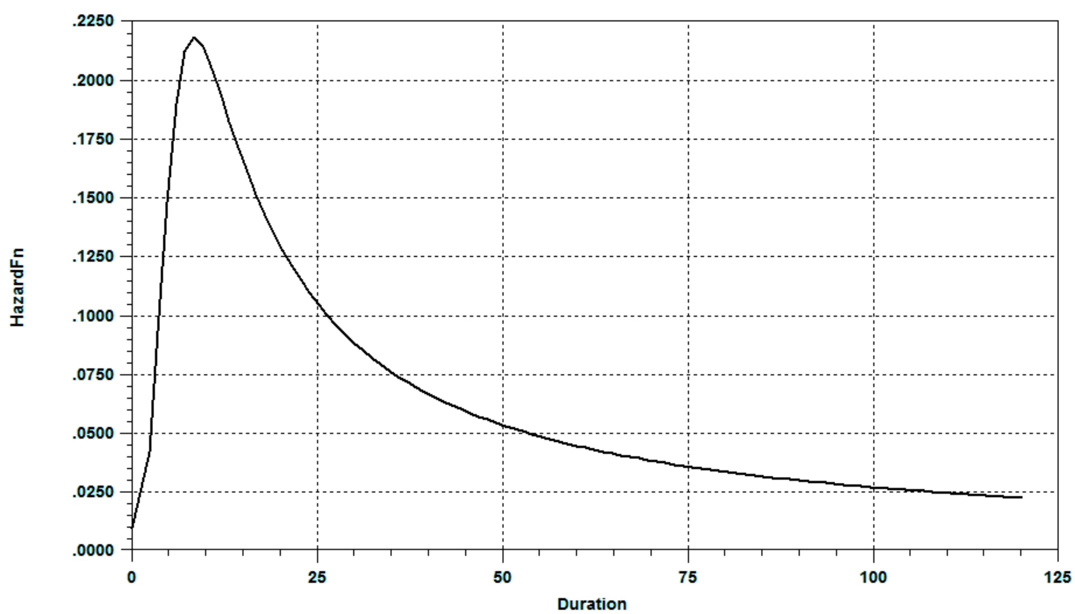

Figure 5.2. Hazard Distribution Function for Weibull Distribution with Gamma Heterogeneity I

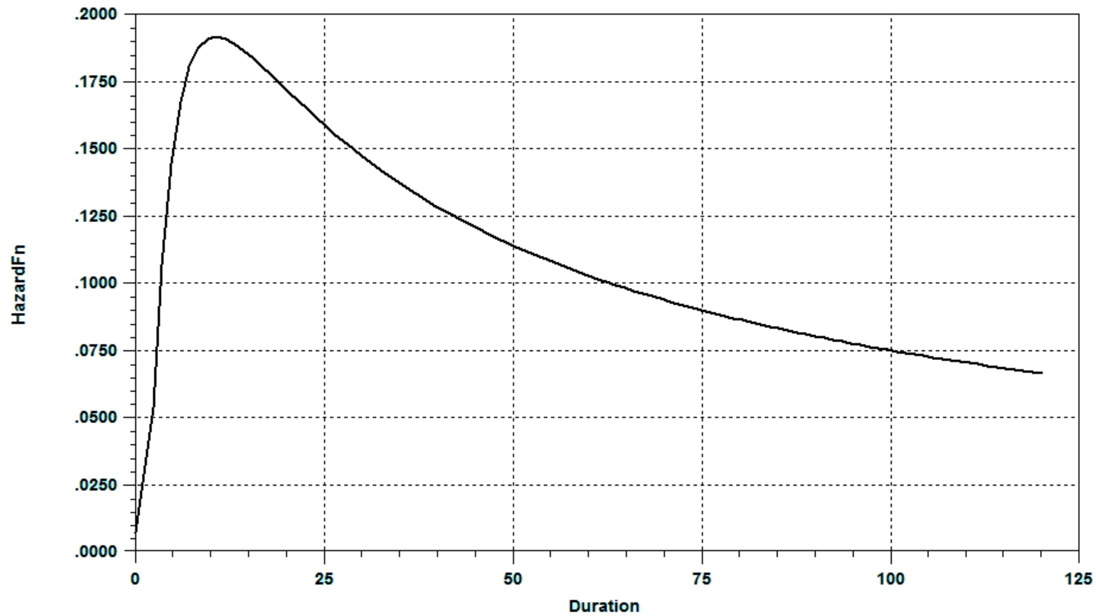

Figure 5.3. Hazard Distribution Function for Log-normal Distribution I

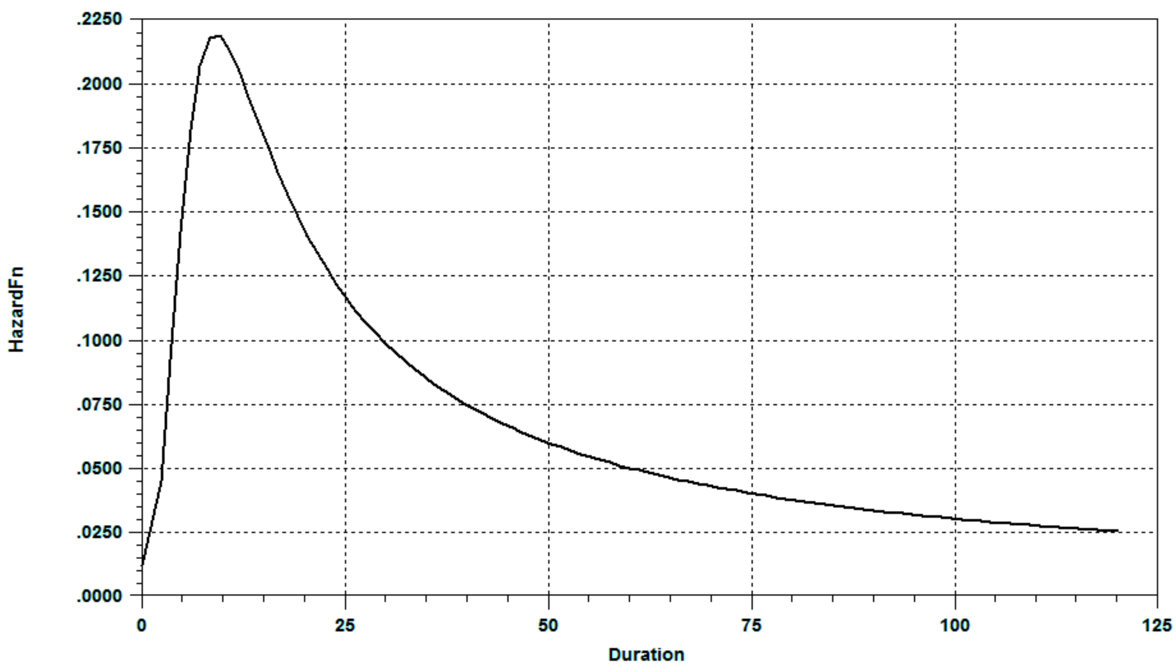

Figure 5.4. Hazard Distribution Function for Log-logistic Distribution I

Results for each of the four preliminary incident clearance duration models are presented in Table 5.1 and Table 5.2, including parameter estimates, log-likelihood values and other particular model outputs. A negative sign of the coefficients in Table 5.1 signifies an increase in the hazard function (i.e., a decrease in incident duration) and a positive coefficient indicates a decrease in the hazard function (i.e., an increase in duration). In general, the effects of most factors are found to be consistent for each of the four parametric models. Specifically, it is found that incidents are likely to have shorter clearance duration during weekday nighttime hours, on weekends, or when only a single vehicle is involved in the incident or a single lane of traffic is affected. In comparison to incidents requiring multiple services and incidents where victims were transported by FCP operators, all other service types are found to be associated with shorter clearance duration.

Table 5.1. Survival Model Estimation Results for Preliminary Incident Duration Time

Variable[a]	**Weibull**	**Weibull with heterogeneity**	**Log-normal**	**Log-logistic**
Constant	3.859(36.163)	3.572(34.539)	3.535(32.999)	3.607(35.135)
Weekday first shift (10 pm - 6 am)	-0.358(-4.488)	-0.216(-2.898)	-0.236(-2.877)	-0.225(-2.983)
Weekend	-0.322(-9.229)	-0.279(-6.897)	-0.268(-6.028)	-0.282(-6.984)
One vehicle	-0.583(-5.995)	-0.660(-6.845)	-0.593(-5.946)	-0.654(-6.686)
Single lane	-0.117(-2.051)	-0.095(-1.496)	-0.096(-1.548)	-0.105(-1.649)
Service abandoned vehicle	-1.471(-30.545)	-1.375(-25.156)	-1.364(-22.862)	-1.391(-25.340)
Service tire	-0.363(-7.297)	-0.306(-4.727)	-0.298(-4.077)	-0.323(-4.939)
Service gas	-1.094(-14.191)	-0.952(-11.888)	-0.966(-11.150)	-0.970(-12.004)
Service mechanical	-0.536(-8.869)	-0.589(-9.032)	-0.571(-8.305)	-0.584(-8.900)
Service debris	-1.436(-16.117)	-1.436(-15.784)	-1.441(-15.662)	-1.429(-15.655)
Service traffic	-0.153(-1.593)	-0.300(-3.094)	-0.311(-3.034)	-0.266(-2.716)
Towing service	-0.400(-7.201)	-0.799(-12.604)	-0.693(-11.167)	-0.763(-12.145)
Service stand by	-0.452(-4.126)	-0.725(-6.483)	-0.649(-5.830)	-0.704(-6.282)
Service cell phone	-2.198(-5.357)	-1.908(-8.070)	-1.956(-6.577)	-1.937(-7.734)
Service gone-on-arrival	-3.063(-7.886)	-2.809(-7.005)	-2.814(-5.161)	-2.839(-7.339)
Service direction	-1.611(-9.107)	-1.468(-10.730)	-1.470(-8.411)	-1.478(-10.641)
Service declined	-1.399(-23.961)	-1.412(-21.799)	-1.403(-20.335)	-1.413(-21.618)
Other services	-1.165(-14.661)	-1.574(-19.224)	-1.548(-20.776)	-1.490(-18.336)
σ (Distribution parameter)	0.596(51.771)	1.211(9.555)	0.607(60.250)	0.334(45.952)
θ (Heterogeneity)	-	0.310(23.189)	-	-
P (Scale parameter)	1.677	3.221	1.648	2.991
λ (Shift parameter)	.102	.143	.138	.138
Log-likelihood at convergence	-1,472.690	-1,348.731	-1,366.844	-1,350.161
Number of parameters	19	20	19	19

Note: Parameter estimates are provided for each model formulation, followed by t-statistics in parentheses.

[a] Dependent variable is log of incident clearance time in minutes

Table 5.2 provides duration model output information obtained by using Limdep Version 9 for each of the four types of distribution considered in the present study. In order to determine which of the four distributions provides the best statistical fit, the likelihood ratio statistics as described in the previous chapter (Section 4.4.3) for each model are computed and then compared (Washington et al., 2003). The model that provides the highest level of significance for this statistic is chosen as the best one. The results show that the model which uses a Weibull distribution performs the best as it provides the highest level of significance (likelihood ratio statistic of 1158.992), followed by the models with the log-logistic (likelihood ratio statistic of 1126.278), Weibull distribution with gamma heterogeneity effects (likelihood ratio statistic of 1118.732) and log-normal (likelihood ratio statistic of 1053.684). The Weibull model showed a positive duration dependence (P=1.68) indicating an increasing hazard (Table 5.11), which indicates that the probability of an incident being cleared in the immediate future increases over time.

Table 5.2. Selection of Best Preliminary Incident Clearance Time Model

Variable[a]	**Weibull**	**Weibull with heterogeneity**	**Log-normal**	**Log-logistic**
Initial log-likelihood	-2,052.186	-1,908.097	-1,893.686	-1,913.300
Log-likelihood at convergence	-1,472.690	-1,348.731	-1,366.844	-1,350.161
Likelihood ratio statistics	1,158.992	1,118.732	1,053.684	1,126.278
Degrees of freedom	17	17	17	17
Akaike information criterion	2.006	1.841	1.864	1.841
Bayesian information criterion	2.074	1.912	1.932	1.909
Number of parameters	19	20	19	19

[a] Dependent variable is log of incident response time in minutes

5.1.1.2 Elasticity calculations

To gain further insight as to the effects of key covariates, the impacts of each of the model parameters are examined by calculating elasticities as described in the previous chapter (Section 4.9). These elasticities are determined by examining changes in the average duration resulting from changing the value of each binary indicator variable from zero to one. These results, summarized in Table 5.3, show that the impacts of specific parameters are relatively consistent with some exceptions among the four models.

Table 5.3. Variable Elasticities for Preliminary Incident Duration Model

Variable	**Weibull**	**Weibull with gamma heterogeneity**	**Log-normal**	**Log-logistic**
Weekday first shift (10 pm – 6 am)	30.09%	19.43%	21.02%	20.15%
Weekend	27.53%	24.35%	23.51%	24.57%
One vehicle	44.18%	48.31%	44.73%	48.00%
Single lane	11.04%	9.06%	9.15%	9.97%
Service abandoned vehicle	77.03%	74.72%	74.44%	75.12%
Service tire	30.44%	26.36%	25.77%	27.60%
Service gas	66.51%	61.40%	61.94%	62.09%
Service mechanical	41.49%	44.51%	43.50%	44.23%
Service debris	76.21%	76.21%	76.33%	76.05%
Service traffic	14.19%	25.92%	26.73%	23.36%
Towing service	32.97%	55.02%	49.99%	53.37%
Service stand by	36.36%	51.57%	47.74%	50.54%
Service cell phone	88.90%	85.16%	85.86%	85.59%
Service gone-on-arrival	95.33%	93.97%	94.00%	94.15%
Service direction	80.03%	76.96%	77.01%	77.19%
Service declined	80.03%	76.96%	77.01%	77.19%
Other services	68.81%	79.28%	78.73%	77.46%

5.1.2 Larger incident clearance duration model

After developing preliminary incident duration models using incident database for a certain stretch of Interstate 75, a comprehensive database consisting of incident data along with traffic flow information and site-specific geometrical features are utilized to develop larger incident clearance duration models. Both fully parametric models and semiparametric models are developed along with the elasticities for different parameters.

5.1.2.1 Fully parametric models

Similar to the preliminary analysis of incident duration along a certain stretch of I-75 just outside the City of Detroit, four hazard based duration models (the hazard function is assumed to follow Weibull distribution, with and without heterogeneity effects, log-normal and log-logistic distributions, respectively) are developed to examine the time required to clear incidents along the sections of four local freeways (I-75, I-94 and I-96). This study identifies the factors responsible for influencing the incident clearance time, which is helpful for the quick clearance practice. The likelihood ratio statistics are compared to select the best model. Table 5.4 and Table 5.5 provide the model results for all the four parametric models considered in the study

Once again, four figures (Figure 5.5, 5.6, 5.7 and 5.8) present plots of each of these four hazard functions against incident duration. The log-logistic hazard function implies that if P>1, the hazard increases from zero to a maximum at an inflection point, $t = [(P-1)^{1/P}/\lambda]$, and decreases toward zero thereafter. The results of the present study (Table 5.4) show the value of P and λ are 2.999 and 0.154, respectively, which determines an inflection point of 8.18 minute. It can be interpreted as the hazard is increasing until 8.18 minutes and decreasing toward zero afterwards, implying that the incidents with clearance time longer than 8.18 minutes are challenging as they become less and less likely to end soon (Nam and Mannering, 2000).

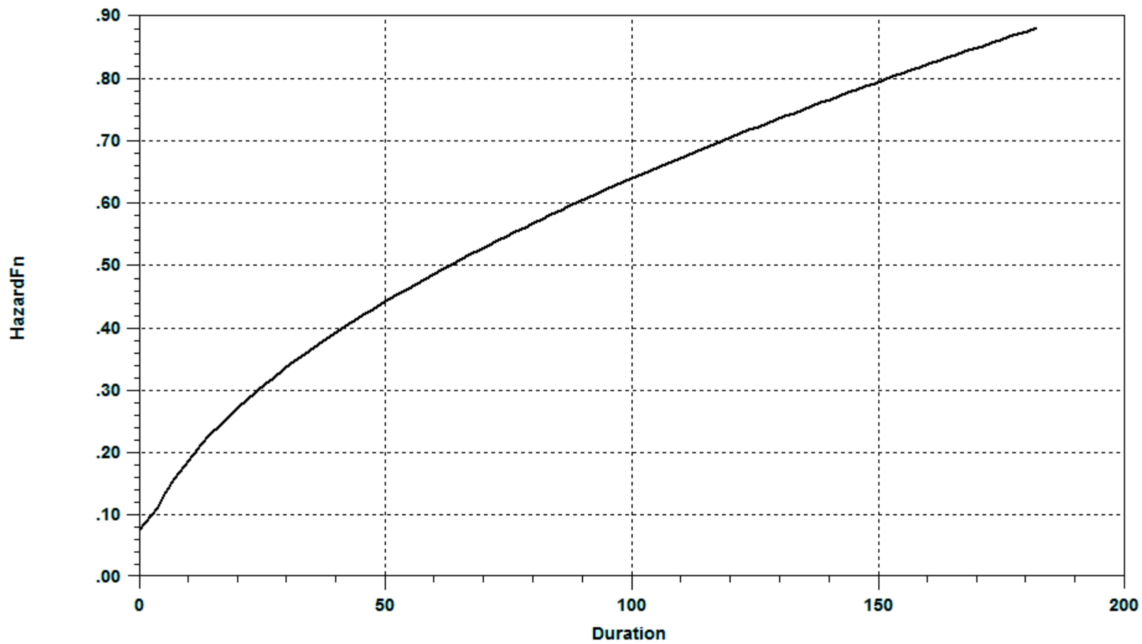

Figure 5.5. Hazard Distribution Function for Weibull Distribution II (No Heterogeneity Effects)

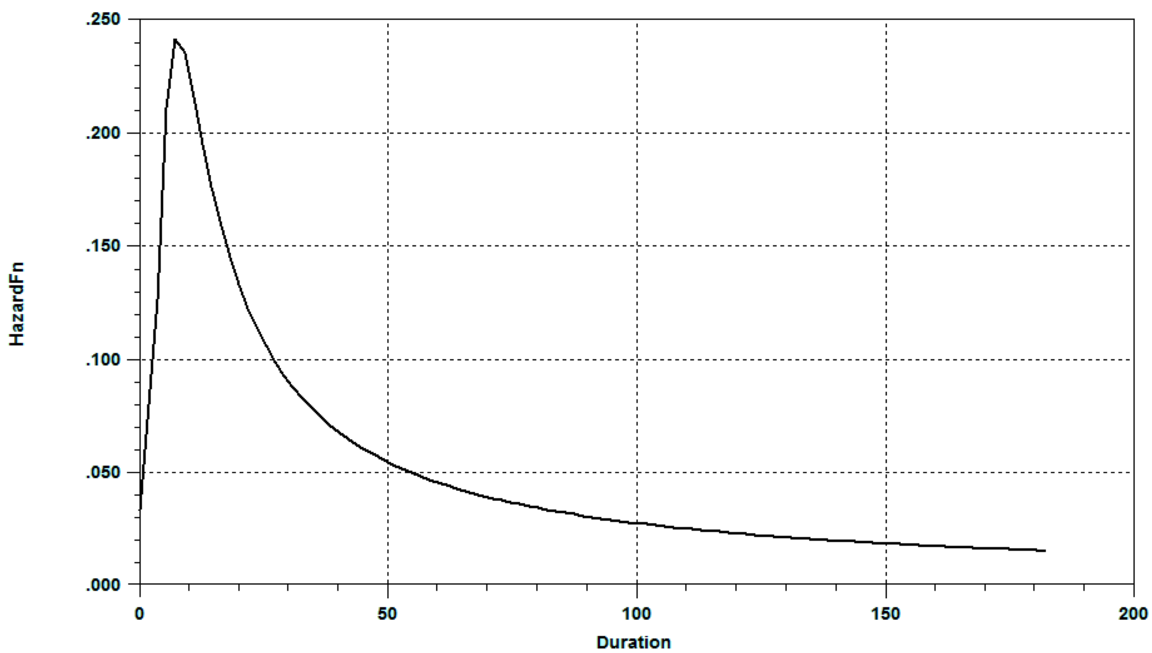

Figure 5.6. Hazard Distribution Function for Weibull Distribution with Gamma Heterogeneity II

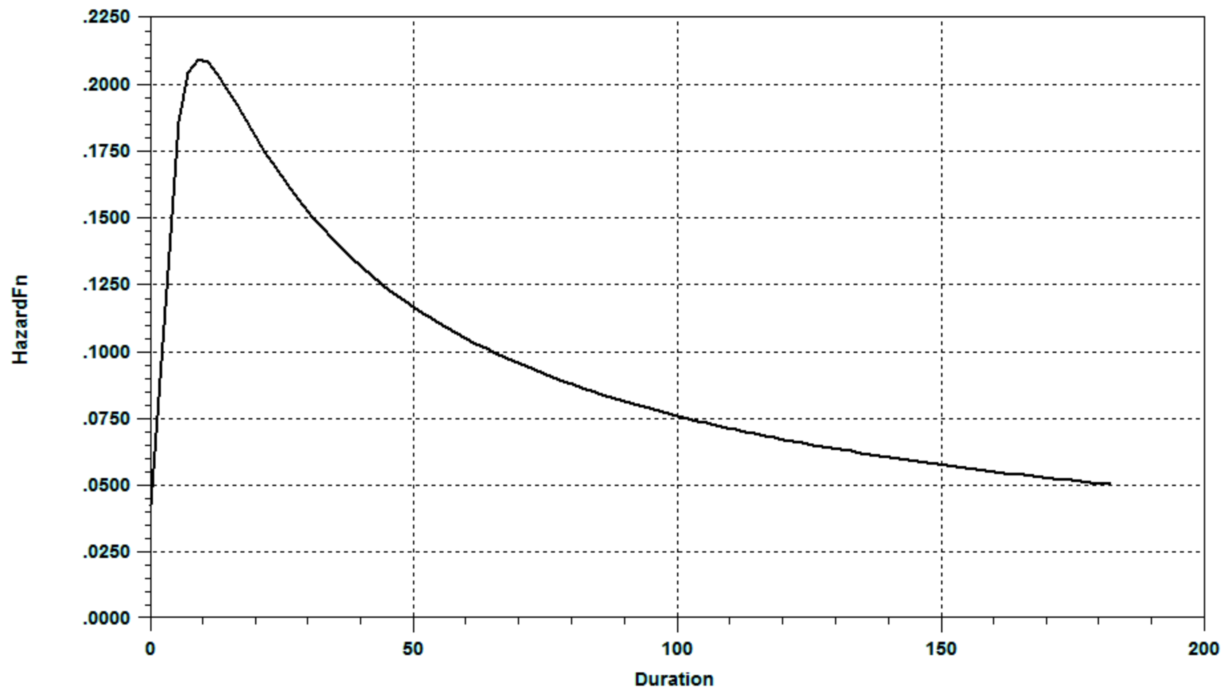

Figure 5.7. Hazard Distribution Function for Log-normal Distribution II

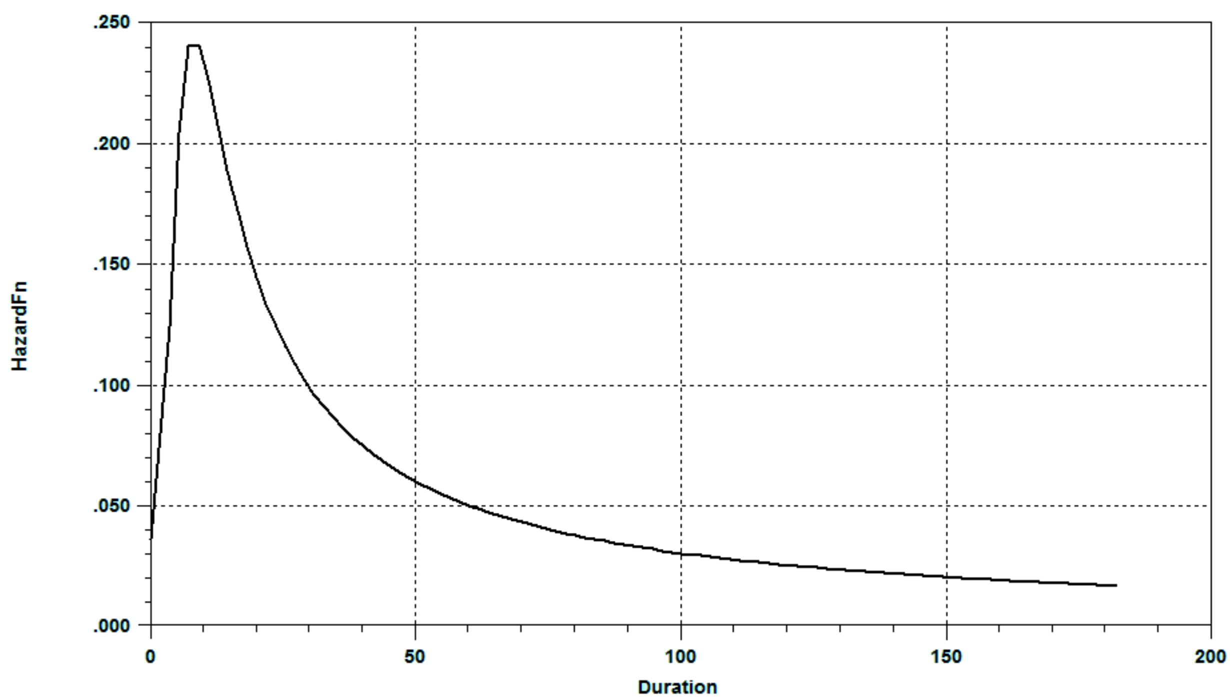

Figure 5.8. Hazard Distribution Function for Log-logistic Distribution II

Table 5.4. Survival Model Estimation Results for Larger Incident Clearance Time

Variable	**Weibull**	**Weibull with gamma heterogeneity**	**Log-normal**	**Log-logistic**
Constant	1.234(34.082)	0.969(15.917)	1.038(17.755)	0.973(16.332)
Weekday first shift	-0.121(-13.095)	-0.120(-8.243)	-0.117(-7.708)	-0.123(-8.403)
Weekend	-0.180(-31.267)	-0.234(-26.026)	-0.211(-22.358)	-0.235(-26.059)
Winter	0.035(7.018)	0.053(7.974)	0.053(7.513)	0.053(7.868)
Interstate 75 (I-75)	0.168(33.585)	0.103(14.190)	0.113(14.627)	0.109(14.958)
Interstate 275 (I-275)	0.007(0.929)	-0.030(-2.660)	-0.015(-1.220)	-0.027(-2.457)
Tangent section	-0.026(-5.445)	-0.030(-4.433)	-0.029(-4.026)	-0.030(-4.330)
No exit ramp	0.027(4.499)	0.027(3.117)	0.027(2.964)	0.027(3.045)
One vehicle	-0.220(-7.777)	-0.493(-16.546)	-0.436(-14.467)	-0.472(-15.662)
Inside shoulder	0.073(7.583)	0.049(4.101)	0.056(4.585)	0.053(4.423)
Only shoulder	-0.457(-26.522)	-0.372(-13.710)	-0.382(-15.067)	-0.377(-13.862)
Single lane	-0.311(-19.313)	-0.322(-11.835)	-0.327(-12.787)	-0.321(-11.774)
Service abandoned vehicles	0.924(71.931)	1.197(25.899)	1.092(25.084)	1.194(27.037)
Service tire	2.088(138.070)	2.380(50.838)	2.279(51.200)	2.376(53.072)
Service gas	1.404(100.795)	1.674(35.232)	1.575(34.690)	1.668(36.654)
Service mechanical	1.918(120.464)	2.062(43.564)	1.980(44.124)	2.071(45.696)
Service debris	0.781(45.091)	1.004(20.695)	0.908(19.674)	1.005(21.566)
Service traffic	2.414(127.755)	2.317(47.073)	2.258(48.928)	2.350(49.699)
Service FCP towing	2.235(144.144)	2.152(45.334)	2.096(47.125)	2.186(48.139)
Service non-FCP towing	1.894(101.508)	1.684(34.224)	1.664(36.295)	1.719(36.435)
Service stand-by	2.094(104.074)	1.968(39.800)	1.940(41.751)	1.999(42.117)
Service transportation	2.640(74.338)	2.825(49.643)	2.731(47.992)	2.831(51.092)
Service cell phone	1.065(32.994)	1.056(14.813)	1.028(15.407)	1.060(15.317)
Service direction	0.950(38.921)	1.166(21.481)	1.066(19.768)	1.169(22.168)
Service declined	1.057(79.566)	1.206(25.734)	1.112(25.120)	1.210(26.986)
Other services	1.415(87.212)	1.233(25.465)	1.147(25.550)	1.266(27.297)
Multiple services	2.560(176.075)	2.603(55.955)	2.508(57.456)	2.623(59.020)
Difference between 85^{th} and 15^{th} percentile speed > 7mph	0.040(7.360)	0.021(2.936)	0.024(3.184)	0.022(3.081)
85^{th} percentile speed ≤ 70	0.042(6.532)	0.036(4.021)	0.034(3.572)	0.037(4.151)
σ (Distribution parameter)	0.650(393.436)	0.314(115.475)	0.613(321.243)	0.334(223.390)
θ (Heterogeneity)	-	1.178(51.014)	-	-
P (Scale parameter)	1.538	3.190	1.632	2.999
λ (Shift parameter)	0.113	0.159	0.153	0.154
Number of parameters	30	31	30	30
Log-likelihood at convergence	-34,099.790	-29,547.510	-30,272.240	-29,577.990
Number of observation	32,574	32,574	32,574	32,574

Note: Parameter estimates are provided for each model formulation, followed by t-statistics in parentheses.

[a] Dependent variable is log of incident clearance time in minutes

Table 5.5 provides the essential information which is useful to decide the best incident clearance duration model among four developed models. Once again, likelihood ratio statistics are computed and evaluated to decide on the best model. It is observed from the likelihood ratio statistics that the model of log-logistic distribution performs the best among all four parametric models as it gives the highest level of significance (likelihood ratio statistics of 24,379.24), followed by the models with Weibull distribution with gamma heterogeneity effects (likelihood ratio statistics of 23,936.96), Weibull distribution without gamma heterogeneity (likelihood ratio statistics of 22,858.74), and the log-normal distribution (likelihood ratio statistics of 22,317.44).

Table 5.5. Selection of Best Incident Clearance Duration Model

Variable	**Weibull**	**Weibull with gamma heterogeneity**	**Log-normal**	**Log-logistic**
Initial log-likelihood	-45,599.990	-41,636.210	-41,557.210	-41,885.360
Log-likelihood at convergence	-34,099.790	-29,547.510	-30,272.240	-29,577.990
Likelihood ratio statistic	23,000.400	24,177.400	22,569.940	24,614.740
Degrees of freedom	30	31	30	30
Akaike information criterion	2.096	1.816	1.861	1.818
Bayesian information criterion	2.103	1.824	1.868	1.826
Number of observations	32,574	32,574	32,574	32,574

Table 5.4 provides the coefficients of various factors affecting the incident clearance duration along with their t-statistics. It is evident that coefficients are consistent again for all the four parametric models similar to the preliminary incident clearance models. All the variables were found to be significant with 95 percent for model assuming log-logistic distribution. A discussion of the significant variables affecting the incident clearance is provided. Elasticity values of the factors are

presented in Table 5.6 and also discussed to evaluate the impacts of the parameters. The discussion is based upon the results of the hazard model assuming a log-logistic distribution.

Table 5.6. Variable Elasticities for Larger Incident Clearance Duration Model

Variable	**Weibull**	**Weibull with gamma heterogeneity**	**Log-normal**	**Log-logistic**
Weekday first shift (10 pm -6 am)	11.40%	11.31%	11.04%	11.57%
Weekend	16.47%	20.86%	19.02%	20.94%
Winter	-3.56%	-5.44%	-5.44%	-5.44%
Interstate 75 (I-75)	-18.29%	-10.85%	-11.96%	-11.52%
Interstate 275 (I-275)	-0.70%	2.96%	1.49%	2.66%
Tangent section	2.57%	2.96%	2.86%	2.96%
No exit ramp	-2.74%	-2.74%	-2.74%	-2.74%
One vehicle	19.75%	38.92%	35.34%	37.62%
Inside shoulder	-7.57%	-5.02%	-5.76%	-5.44%
Only shoulder	36.68%	31.06%	31.75%	31.41%
Single lane	26.73%	27.53%	27.89%	27.46%
Service abandoned vehicles	-151.93%	-231.02%	-198.02%	-230.03%
Service tire	-706.88%	-980.49%	-876.69%	-976.18%
Service gas	-307.15%	-433.35%	-383.07%	-430.16%
Service mechanical	-580.73%	-686.17%	-624.27%	-693.28%
Service debris	-118.37%	-172.92%	-147.94%	-173.19%
Service traffic	-1017.86%	-914.52%	-856.39%	-948.56%
Service FCP towing	-834.65%	-760.20%	-713.36%	-789.95%
Service non-FCP towing	-564.59%	-438.71%	-428.04%	-457.89%
Service stand-by	-711.73%	-615.63%	-595.88%	-638.17%
Service transportation	-1301.32%	-1586.09%	-1434.82%	-1596.24%
Service cell phone	-190.08%	-187.48%	-179.55%	-188.64%
Service direction	-158.57%	-220.91%	-190.37%	-221.88%
Service declined	-187.77%	-234.01%	-204.04%	-235.35%
Other services	-311.65%	-243.15%	-214.87%	-254.66%
Multiple services	-1193.58%	-1250.42%	-1128.03%	-1277.70%
Difference between 85^{th} and 15^{th} percentile speed > 7mph	-4.08%	-2.12%	-2.43%	-2.22%
85^{th} percentile speed ≤ 70 mph	-4.29%	-3.67%	-3.46%	-3.77%

Time of Incident Clearance

Weekday first shift hours

It is observed from Table 5.4 that incidents have shorter clearance time during weekday first shift hours (10 pm to 6 am) which may be due to light traffic conditions during this time period. It is easier for the FCP operators to clear the incidents as soon as possible when fewer vehicles travel on roadways. Incidents tended to be cleared 11.6 percent sooner during the weekday midnight shift.

Weekends

Incident clearance times are likely to be shorter during weekends (Saturdays and Sundays). This is probably due to lower number of vehicular traffic the FCP operators are exposed to in the process of incident clearance. Incidents tended to be cleared 21.0 percent faster during on weekend days compared to weekdays.

Winter Season

Incidents tended to take longer to clear during the winter season, which is likely due to the effects of inclement weather deterring the clearance process. Incidents in winter season experienced 5.4 percent more time for the incident clearance process than other seasons.

Incident Location

Interstate 75 and Interstate 275

Incidents on Interstate 75 tend to have longer clearance times compared to Interstate 94 and Interstate 696, which may be due to the exposure of FCP responders and victim motorists to heavy traffic condition on Interstate 75. On the contrary, Interstate 275 is associated with shorter incident clearance duration due to lower traffic volumes on that corridor. While incidents on Interstate 75 tended to have 11.5 percent longer clearance times, incidents on Interstate 275 tended to experience 2.7 percent shorter clearance times.

Exit ramps

Incidents occurring on freeway sections with no exit ramps are likely to be associated with longer clearance times. Exit ramps help other non-involved motorists to take alternative routes and thus result in quick clearance of incidents by the FCP operators. Freeway sections with no exit ramps are likely to take 2.7 percent more clearance times.

Tangent sections

Incidents occurring on tangent sections with no horizontal curvatures are likely to have shorter clearance times. It may be due to enough available sight distance for the motorists to notice the incident well ahead of time and their subsequent cautious driving to avoid the possible conflict resulting in secondary incidents. All of these facts help the

FCP operators clear the incident in an effective way. Incidents on tangent freeway sections are likely to experience about 3.0 percent less delay in the clearance process.

Incident characteristics

One vehicle

Incidents involving only one vehicle are likely to have shorter clearance duration. Involvement of only one vehicle makes the clearance process easier for the incident responders compared to incidents involving multiple vehicles. Single-vehicle incidents tended to clear 37.6 percent sooner compared to multi-vehicle incidents.

Single lane

Incidents blocking only one lane on freeways are likely to have shorter incident clearance times as such incidents do not as much of a hazard for FCP operators by minimizing their exposure to the adjacent passing traffic. Incidents involving only one lane are likely to be cleared 27.5 percent faster.

Roadway Shoulder

In case of incidents affecting only the roadway shoulders, non-involved motorists can use all freeways lanes, reducing potential traffic conflicts that may delay incident clearance. On the other hand, incidents blocking the left shoulder are likely to take additional time for the clearance activity due to the proximity of incident location to the left lane with fast moving traffic. Incidents blocking only the shoulder cleared 31.4 percent sooner while incidents on the left shoulder cleared 5.4 percent later.

FCP service types

FCP operators respond to various types of incidents, including abandoned vehicles, flat tires, motorists running out of gas, mechanical failure, removal of debris from roadways, providing traffic control at the incident scene, towing damaged vehicles from the roadway (both FCP related and non-FCP related), providing stand-by service for emergency response, providing motorists with cell phones or directions, as well as multiple types of services. Incidents with multiple services requirement generally are of higher severity (for example, the clearance process of a crash involves multiple services like Police, EMS, Tow truck, etc in addition to the FCP operator). Additionally, incidents where transportation was provided to the victim motorists and/or passengers, as well as occupants, took significant longer to clear the incidents as these scenarios could refer to either severe incidents resulting in completely non-drivable condition of the vehicles or vehicle breakdown cases due to mechanical failure of the vehicles or running out-of-gas circumstances. These situations are associated with higher clearance duration due to longer waiting time for the incident victims. Incidents where no victim motorists were found when FCP operators arrive on the incident site or incidents were cleared before the FCP arrival (termed as service gone-on-arrival scenarios in the present dataset) generally are of lower severity compared to other incidents requiring different type of services. That is the major reason behind the particular finding of all types of FCP services associated with longer clearance time compared to gone-on-arrivals situations. Removal of debris from roadway, offering fuel to run out-of-gas vehicles, helping stranded motorists by providing direction scenarios were cleared 173.2 percent, 430.2 percent and 221.9 percent slower, respectively, than incidents where involved motorists left the incident scene before the FCP responders arrived on site. Similarly, offering involved motorists with a cell phone tended to increase the incident clearance duration by 188.6 percent. Incidents requiring service to the abandoned vehicles and incidents involving denial of FCP service by motorists were cleared 230.0 percent and 235.4 percent sooner, respectively. The incidents requiring service for the flat tire, mechanical failure, managing the traffic, towing of broken vehicles as well as the incidents requiring stand by situations took longer clearance time (in the range of 600-900 percent) compared to gone-on-arrival scenarios. Providing other types of services by the FCP operators are likely to increase the incident clearance duration by 254.7 percent. Incidents where transportation was offered to the involved motorists experienced 1596.2 percent more time in the clearance process.

Traffic characteristics

85th percentile speed, 15th percentile speed

Differences between the 85th percentile and 15th percentile speeds of more than 7 mph and when the 85th percentile speeds were less than or equal to 70 mph are found to be associated with longer clearance times. As differences between 85th percentile and 15th percentile speeds are increased, this condition is indicative of stop-and-go traffic due to the presence of high traffic volumes, which result in additional time for the FCP operator to clear the incident. Similarly, 85th percentile speed of 70 mph or less also indicates high traffic volume situations which disrupt the clearance process of the incident. Freeway sections with the differences of 85th percentile speed and 15th percentile speed more than 7 miles per hour and 85th percentile speed less than or equal to 70 miles per hour tended to experience 2.2 percent and 3.7 percent more time, respectively, during incident clearance.

5.1.2.2 Semiparametric model

The estimation results for the Cox proportional hazard model of incident clearance time duration utilizing comprehensive database for four freeways in southeastern Michigan region are presented in Table 5.7. A negative coefficient in semiparametric models for clearance duration analysis signifies increase in the clearance duration, whereas a positive coefficient indicates reduction in clearance time. Once again, the results obtained from the semiparametric model are found to be consistent with the parametric model results obtained using parametric approach.

Table 5.7. Semiparametric Model Estimation Results for Incident Clearance Time

Variable[a]	**Coefficient (t-statistics)**
Weekday first shift (10 pm – 6 am)	0.202(8.461)
Weekend	0.313(20.765)
Winter	-0.061(-5.253)
Interstate 75 (I-75)	-0.218(-17.112)
Interstate 275 (I-275)	0.018(0.974)
One vehicle	0.326(5.845)
Inside shoulder	-0.078(-3.676)
Only shoulder	0.557(10.320)
Single lane	0.421(8.006)
Service abandoned vehicles	-1.392(-20.379)
Service tire	-3.028(-43.535)
Service gas	-2.103(-29.939)
Service mechanical	-2.761(-38.721)
Service debris	-1.219(-16.455)
Service traffic	-3.231(-41.152)
Service FCP towing	-3.075(-42.038)
Service non-FCP towing	-2.627(-33.665)
Service stand-by	-2.893(-36.892)
Service transportation	-3.596(-39.597)
Service cell phone	-1.585(-14.168)
Service direction	-1.447(-17.249)
Service declined	-1.559(-22.313)
Other services	-2.041(-26.942)
Multiple services	-3.457(-49.185)
Difference between 85^{th} and 15^{th} percentile speed > 7mph	-0.047(-3.875)
85^{th} percentile speed ≤ 70 mph	-0.066(-4.278)
Tangent section	0.038(3.270)
No exit ramp	-0.033(-2.232)
Restricted log likelihood	-307,959.800
Log likelihood function	-299,457.800
Number of observations	32,574

[a] Dependent variable is log of incident clearance time in minutes

5.2 Results of response time duration model

As discussed in the previous chapter, incident response time duration models are developed utilizing incident data for four local freeways in Detroit metro area. In addition to incident data, various site related information as well as traffic flow data are included in the models.

5.2.1 Fully parametric model

Survival analysis is conducted to analyze the response time of the FCP responders for the four local freeways (I-75, I-275, I-94 and I-96) in southeastern Michigan region. Once again, Weibull distribution, with and without heterogeneity effects, log-normal and log-logistic distributions are assumed as underlying distribution for the hazard function. Table 5.8 and Table 5.9 provide the model results for all the four parametric models considered in the study.

Table 5.8. Fully Parametric Model Estimation Results for Incident Response Time

Variable[a]	Weibull	Weibull with heterogeneity	Log-normal	Log-logistic
Constant	2.691(113.832)	2.563(82.480)	2.294(71.362	2.356(76.070)
Weekend	.189(6.675)	.223(7.382)	.269(8.000)	.263(8.314)
Weekday second shift (6 am – 2 pm)	-.159(-8.032)	-.149(-6.041)	-.091(-3.219)	-.106(-3.986)
May	-.113(-3.046)	-.106(-2.488)	-.093(-1.928)	-.092(-2.003)
Interstate 94 (I-94)	-.075(-3.738)	-.076(-3.214)	-.065(-2.452)	-.061(-2.433)
Section with at least one entrance	-.116(-4.820)	-.098(-3.358)	-.099(-3.015)	-.104(-3.273)
σ (Distribution parameter)	.625(97.285)	.526(47.746)	.733(90.636)	.402(69.934)
θ (Heterogeneity)	-	.250(8.330)	-	-
P (Scale parameter)	1.600	1.900	1.364	2.484
λ (Shift parameter)	.078	.087	.110	.105
Number of parameters	7	8	7	7
Log-likelihood at convergence	-3,872.731	-3,816.532	-3,995.178	-3,938.651
Number of observations	3,604	3,604	3,604	3,604

[a] Dependent variable is log of incident response time in minutes

Table 5.9 provides the necessary information about all four parametric model distributions which is helpful to choose the best duration model among all. Once again, likelihood ratio statistics are evaluated to select the best model. It is observed from the likelihood ratio statistics that the model of Weibull distribution without heterogeneity effects performs the best among all as it provides the highest level of significance (likelihood ratio statistics of 177.042), followed by the models with Weibull distribution with gamma heterogeneity (likelihood ratio statistics of 175.854), log-logistic distribution (likelihood ratio statistics of 143.958) and the log-normal distribution (likelihood ratio statistics of 125.134). Though the difference of the likelihood ratio statistics is very small for Weibull distribution without and with gamma heterogeneity, Weibull distribution without gamma heterogeneity was chosen as the best model because of the nonsignificance of heterogeneity term associated with Weibull distribution with gamma heterogeneity. T-statistic of the heterogeneity effect term for Weibull distribution with gamma heterogeneity indicates that it plays marginally significant role (t-statistic=0.250). It implies that survivor function in the response process is relatively homogeneous across incident observations (Nam, 1997). The Weibull model showed a positive duration dependence (P=1.6) indicating an increasing hazard (Table 5.11). This means that the longer the incident response time has lasted, the more likely that the incident is going to end soon.

Table 5.9. Selection of Best Incident Response Time Model

Variable[a]	**Weibull**	**Weibull with heterogeneity**	**Log-normal**	**Log-logistic**
Initial log-likelihood	-3,961.252	-3,904.459	-4,057.745	-
Log-likelihood at convergence	-3,872.731	-3,816.532	-3,995.178	-
Likelihood ratio statistics	177.042	175.854	125.134	143.958
Degrees of freedom	7	8	7	7
Number of observations	3,604	3,604	3,604	3,604
Akaike information criterion	2.100	1.823	1.868	1.825
Bayesian information criterion	2.107	1.831	1.876	1.833

[a] Dependent variable is log of incident response time in minutes

Table 5.8 provides the coefficients of various factors significant at 95 percent confidence interval affecting the response time duration along with their t-statistics. It is observed that coefficients are consistent again for all the four parametric models similar to the incident clearance models. A discussion of the significant variables affecting the incident clearance is provided. Elasticity values are again calculated (Table 5.10) and discussed based upon the results of the hazard model assuming a Weibull distribution to examine the impacts of the parameters.

Time of incidents

Weekends

From Table 5.8, it is observed that incidents occurring on the weekends have longer response times. This could be due to the lower number of assigned FCP operators during the weekend days compared to typical weekdays. Incidents occurring during weekend days tended to experience 20.8 percent more response time as compared to incidents on weekdays.

Weekday second shift hours

Incidents those occurred during weekday second shift hours (6 am to 2 pm) are likely to have shorter response times. Morning and early afternoon hours experience relatively less traffic volume on the four freeways compared to the afternoon and evening hours (2 pm to 10 pm). At the same time, more number of FCP operators are allotted on freeways compared to nighttime and early morning hours (from 10 pm to 6 am) making weekday second shift hours (6 am to 2 pm) less likely to have longer response time. Incidents on weekday second shift hours (6 am to 2 pm) are likely to be responded 14.7 percent early than other shifts.

Month of May

Weather condition is generally good during the month of May and rarely bad weather condition is experienced, thus making the incidents likely to have shorter response time in May. The month of May also tended to have responded 10.7 percent early than other months of the year.

Incident locations

Interstate 94

Incidents that occurred on the Interstate 94 (I-94) show negative correlation with response duration. The probable reason behind it could be due to higher number of assigned FCP operators on Interstate 94 corridor, being it one of the most important and busy corridors in Detroit freeway network. This makes incidents on this freeway likely to be associated with shorter response duration. Incidents on Interstate 94 are likely to get a response from the FCP operators 7.23 percent early in comparison to other freeways.

Presence of entrance ramp

Incidents on freeway sections with at least one entrance ramp have shorter response times due to relatively less time taken by of FCP operators to arrive on the incident scene using the entrance ramp(s). Incident that occurred on freeway sections with at least one entrance ramp is found to be responded about 11 percent early compared to sections with no entrance ramps.

Table 5.10. Variable Elasticities for Incident Response Duration Model

Variable[a]	Weibull	Weibull with gamma heterogeneity	Log-normal	Log-logistic
Weekend	-20.80%	-24.98%	-30.87%	-30.08%
Section with at least one entrance ramp	10.95%	9.34%	9.43%	9.88%
Weekday second shift (6 am – 2 pm)	14.70%	13.84%	8.70%	10.06%
Interstate 94 (I-94)	7.23%	7.32%	6.29%	5.92%
May	10.68%	10.06%	8.88%	8.79%

[a] Dependent variable is log of incident response time in minutes

5.3.2 Semiparametric model

It is observed from Table 5.11 that the results obtained from the semiparametric model are consistent with the parametric model results obtained earlier.

Table 5.11. Semiparametric Model Estimation Results for Incident Response Time

Variable[a]	Coefficient (t-statistics)
Weekend	-0.292(-6.472)
Weekday second shift (6 am – 2 pm)	0.237(6.211)
May	0.157(2.449)
Interstate 94 (I-94)	0.115(3.216)
Section with at least one entrance ramp	0.146(3.247)
Restricted log likelihood	-26,112.690
Log likelihood at convergence	-26,037.600
Number of observations	3,604

[a] Dependent variable is log of incident response time in minutes

5.3 Results of spatial transferability

To check the spatial stability of the developed models, likelihood ratio test is performed to check the stability of coefficients over various locations (different freeways in Detroit metro area). This test checks the difference between the transferred model and the model estimated from the entire set of application context data. The null hypothesis is that the coefficients of the transferred model do not deviate significantly from the coefficients estimated from the entire set of application context data. Both the developed incident clearance time and response time duration models are checked for the spatial satiability using the likelihood ratio test described in previous chapter (Section 4.7). It is already found that assumption of log-logistic distribution for the hazard function performs the best for clearance time duration model, whereas Weibull distribution exhibits the best performance for response time duration model. Table 5.12 and Table 5.13 summarizes the results of likelihood ratio test for incident clearance time duration model assuming log-logistic distribution and response time model with the assumption of Weibull distribution, respectively, for the underlying hazard functions.

Table 5.12. Results of Spatial Transferability Test for Clearance Duration Model

Models	**Log likelihood at convergence**
Clearance time model (Log-logistic distribution)	
Interstate 75	-10,400.770
Interstate 275	-3,237.309
Interstate 94	-11,348.900
Interstate 696	-4,269.522
Summation of all individual Freeway model	-29,256.501
Overall model	-29,577.990
X^2	321.489
Degrees of freedom	82
p-value	0.000

Table 5.13. Results of Spatial Transferability Test for Response Duration Model

Models	**Log likelihood at convergence**
Response time model (Weibull distribution)	
Interstate 75	-1,190.220
Interstate 275	-521.774
Interstate 94	-1,354.550
Interstate 696	-781.332
Summation of all individual Freeway model	-3,847.876
Overall model	-3,872.731
X^2	49.71
Degrees of freedom	12
p-value	0.000

It is observed from Table 5.12 and Table 5.13 that the assumption of transferability of effects across freeways can be rejected with a confidence level of more than 99 percent. The test results show that the parameter effects vary over the freeways in the Detroit metro area and thus it can be concluded that spatial instability is present for both response and clearance duration models. The source of this instability is possibly due to varying traffic conditions and change in geometrical features along various freeways, as well as different incident characteristics and subsequent types of services provided by the FCP operators on various freeways.

To provide insight on factors responsible for the spatial instability of the developed models, separate models have been developed for each of the four individual freeways considered in the study. Table 5.14 provides the coefficients of different variables along with their t-statistics for clearance duration models assuming log-logistic distribution. It is evident from Table 5.14 that coefficients of some of the variables are not consistent over models for different freeways. For example, winter season is more likely to be associated with longer clearance times for incidents on Interstate 75, Interstate 275 and Interstate 94, but less likely to be associated with longer clearance duration on Interstate 696. Similarly, incidents blocking left shoulder on Interstate 275 are found to less likely associated with longer clearance times, whereas incidents on other three interstates involving left shoulder are more likely associated with longer clearance times. Similar type of inconsistency exists in case of incidents on sections where difference of 85^{th} and 15^{th} percentile speed is more than 7 miles per hours, incidents on sections with 85^{th} percentile less than or equal to 70 miles per hour, incidents on tangent sections, as well as in case of incidents on sections with no exit ramps. Those variables with coefficients which exhibited opposite signs for particular freeway(s) were found to be statistically insignificant for those freeways where the effects were found to be in the opposite direction. For example, inside or left shoulder variable is not significant for Interstate 275 and Interstate 696. In addition to that some variables which are significant for all the freeway models found to have varying effect of significance on the clearance duration time of incidents for certain freeways. For example, the weekday first shift hour variable is significant for all the four freeway models, but it has different value of t-statistics for various freeway models indicating varying effect on the incident clearance time.

Table 5.14. Estimation Result of Variable Coefficients for Clearance Duration Models

Variables	Log-logistics Distribution for Hazard Function			
	Interstate 75	**Interstate 275**	**Interstate 94**	**Interstate 696**
Constant	1.146(10.522)	0.831(4.408)	1.004(10.835)	0.735(5.583)
Weekday first shift (10 pm-6 am)	-0.213(-7.240)	-0.120(-2.815)	-0.045(-2.132)	-0.162(-4.677)
Weekend	-0.320(-19.447)	-0.264(-10.104)	-0.163(-11.884)	-0.238(-10.745)
Winter	0.030(2.371)	0.128(7.031)	0.070(6.676)	-0.007(-0.423)
One vehicle	-0.514(-9.495)	-0.272(-3.355)	-0.512(-9.514)	-0.330(-5.742)
Inside shoulder	0.065(2.868)	-0.025(-0.915)	0.086(4.542)	0.039(1.326)
Only shoulder	-0.475(-9.894)	-0.392(-4.217)	-0.335(-7.292)	-0.243(-4.330)
Single lane	-0.375(-7.836)	-0.362(-3.934)	-0.288(-6.270)	-0.217(-3.753)
Service abandoned vehicles	1.299(15.777)	1.059(7.160)	1.132(17.592)	1.222(12.165)
Service tire	2.397(28.663)	2.298(15.435)	2.377(36.394)	2.368(23.255)
Service gas	1.733(20.466)	1.618(10.705)	1.634(24.546)	1.645(15.781)
Service mechanical	2.104(24.813)	2.115(14.064)	2.029(30.801)	2.066(19.910)
Service debris	1.030(11.897)	0.842(5.513)	0.965(14.099)	1.171(10.874)
Service traffic	2.353(26.723)	2.348(14.724)	2.277(32.831)	2.510(23.418)
Service FCP towing	2.297(27.165)	2.110(13.968)	2.099(31.673)	2.190(21.000)
Service non-FCP towing	1.861(21.012)	1.724(11.293)	1.562(22.380)	1.796(16.789)
Service stand-by	2.207(24.355)	2.368(14.889)	1.917(27.975)	1.682(15.593)
Service transportation	2.963(28.870)	2.720(15.105)	2.750(33.733)	2.818(22.105)
Service cell phone	0.959(6.840)	2.268(8.256)	1.034(10.138)	1.117(7.636)
Service direction	1.288(12.647)	1.184(7.372)	1.084(14.168)	1.041(8.059)
Service declined	1.263(15.052)	1.137(7.605)	1.191(18.290)	1.187(11.610)
Other services	1.315(15.209)	1.500(9.734)	1.244(18.335)	1.034(9.735)
Multiple services	2.560(30.792)	2.737(18.405)	2.591(40.110)	2.767(27.380)
Difference between 85^{th} and 15^{th} percentile speed > 7mph	0.068(5.016)	0.052(2.571)	-0.014(-1.306)	-0.015(-0.703)
85^{th} percentile speed ≤ 70 mph	0.057(3.427)	-0.004(-0.215)	0.036(2.270)	0.059(2.116)
Tangent section	-0.024(-1.876)	-0.039(-1.933)	-0.034(-3.072)	0.000(0.015)
No exit ramp	0.062(3.558)	0.012(0.589)	0.057(3.113)	-0.028(-1.600)
σ (Distribution parameter)	0.355(123.655)	0.313(76.249)	0.322(142.780)	0.314(90.923)
P (Scale parameter)	2.813	3.191	3.109	3.186
λ (Shift parameter)	0.142	0.165	0.161	0.155
Number of parameters	28	28	28	28
Initial log-likelihood	-13,943.680	-4,961.093	-16,449.010	-6,424.096
Log likelihood at convergence	-10,400.770	-3,237.309	-11,348.900	-4,269.522
Number of observations	10,760	3,828	12,981	5,005

[a] Dependent variable is log of incident clearance time in minutes

Table 5.15 provides the coefficients of different variables along with their t-statistics for response time duration models assuming Weibull distribution. It is found that incidents on freeway sections with at least one entrance ramp are less likely to be associated with longer response time for all freeways except Interstate 94, where it is not found to be significant. Additionally some significant variables found to have varying effect of significance on the response time duration time for certain freeways. For example, weekend variable has different values of t-statistics for various freeway models indicating varying effect on the incident response time.

Table 5.15. Estimation Result of Variable Coefficients for Response Duration Models

Variables	**Weibull Distribution for Hazard Function**			
	Interstate 75	**Interstate 275**	**Interstate 94**	**Interstate 696**
Constant	2.734(45.304)	2.774(61.407)	2.520(31.053)	2.698(60.691)
Weekend	0.253(4.573)	0.095(1.145)	0.135(2.787)	0.249(4.589)
Section with at least one entrance ramp	-0.221(-4.136)	-0.055(-1.015)	0.002(0.020)	-0.140(-3.216)
Weekday second shift (6 am -2 pm)	-0.050(-1.134)	-0.350(-6.148)	-0.174(-5.470)	-0.191(-3.794)
May	-0.204(-2.833)	-0.171(-1.644)	-0.055(-0.753)	-0.121(-1.403)
σ (Distribution parameter)	0.666(44.075)	0.589(29.045)	0.618(65.514)	0.579(36.864)
P (Scale parameter)	1.502	1.697	1.617	1.728
λ (Shift parameter)	0.077	0.074	0.083	0.076
Number of parameters	6	6	6	
Initial log-likelihood	-1,212.992	-545.692	-1,375.367	-810.065
Log likelihood at convergence	-1,190.218	-521.774	-1,354.552	-781.332
Number of observations	1047	504	1280	773

[a] Dependent variable is log of incident response time in minutes

5.4 Results of count data model

As discussed in the previous chapter (Section 4.8), count data models are developed using incident data for four local freeways (Interstate 75, Interstate 275, Interstate 94 and Interstate 696) in Detroit freeway network. Variables related to time and location of incident occurrence along with various site specific characteristics and traffic flow information have been included in the models.

5.4.1 Poisson and negative binomial models

The study area of Detroit freeway network is divided into fixed length (one mile long) sections to analyze the effects of highway geometrics and traffic flow characteristics along with other factors on incident frequency per month basis. Table 5.16 and Table 5.17 summarize the estimation results of the Poisson and negative binomial regression models, respectively. Twelve variables are found to be statistically significant in determining incident likelihood. For both the tables (Table 5.16 and Table 5.17), the variables with a positive sign indicate that they can significantly increase the likelihood of incidents. On the contrary, variables with a negative sign imply that they can significantly reduce the incident likelihood. It is observed from Table 5.17 that the dispersion parameter, α, is significantly different from zero, confirming the suitability of the negative binomial model compared to the Poisson model for the present study. Additionally, higher pseudo R-square value support the appropriateness of negative binomial model in comparison to the Poisson regression model.

Table 5.16 and Table 5.17 provides the coefficients of various factors significant at 95% confidence level affecting the incident frequency along with their t-statistics for the Poisson and negative binomial models, respectively. As negative binomial model is found to be the more suitable model, a discussion of the significant variables affecting the incident frequency in negative binomial model is provided. The impacts of each of the model parameters are explored by calculating elasticities. These calculated elasticity values in Table 5.18 show that the impacts of specific parameters are relatively consistent among the two models with one exception. As negative binomial model was found to be more suitable than the Poisson model, the impacts of model parameters are studied based upon the results of the negative binomial model.

Table 5.16. Poisson Estimation Results

Variable	**Estimated Coefficient**	**t-statistics**
Constant	1.954	97.104
Winter	-0.164	-14.381
Interstate-75 (I-75) north bound	-0.146	-9.154
Interstate -275 (I-75) north bound	-0.252	-10.185
Interstate-94 (I-94) east bound	0.277	17.934
Less than four lanes	0.067	3.945
Minimum radius>1,850 ft	-0.162	-9.593
Maximum radius>2,700 ft	-0.160	-8.261
No entrance or exit ramp	-0.753	-56.82
Tangent section	-0.156	-11.525
Peak hour volume more than 4,500 vph	0.247	17.632
85^{th} percentile speed>70 mph	0.114	6.97
15^{th} percentile speed>55 mph	0.497	34.625
Number of observations	5,064	
Number of parameters	13	
Restricted log likelihood	-23,295.51	
Log likelihood at convergence	-18,342.58	
Akaike information criterion	7.249	
Bayesian information criterion	7.266	
McFadden Pseudo R^2	21.26%	

Table 5.17. Negative Binomial Estimation Results

Variable	Estimated Coefficient	t-statistics
Constant	2.166	38.295
Winter	-0.161	-5.784
Interstate-75 (I-75) north bound	-0.214	-6.118
Interstate -275 (I-75) north bound	-0.182	-3.429
Interstate-94 (I-94) east bound	0.340	7.088
Less than four lanes	-0.134	-2.787
Minimum radius>1,850 ft	-0.221	-5.102
Maximum radius>2,700 ft	-0.187	-4.161
No entrance or exit ramp	-0.824	-28.502
Tangent section	-0.201	-5.45
Peak hour volume more than 4500	0.236	5.078
85^{th} percentile speed>70 mph	0.181	3.257
15^{th} percentile speed>55 mph	0.513	12.42
α (Dispersion coefficient)	0.690	36.353
Number of observations	5,064	
Number of parameters	14	
Restricted log likelihood	-18,342.58	
Log likelihood at convergence	-14,033.36	
Akaike information criterion	5.548	
Bayesian information criterion	5.566	
McFadden Pseudo R^2	23.49%	

Time of incidents

Winter season

The winter season is less likely to experience incidents compared to other seasons of the year. During the winter months specifically saying during the months of December, January, February and March, motorists tend to drive more watchfully. In addition, it has been found that motorists check their vehicles on a regular basis before starting their journey as well as repair any small problems of their vehicles without further delay to stay away from the possible vehicle breakdown situations and as a consequence of that to avoid seeking help from others while standing outside in inclement weather condition. All of these reasons combined probably resulted in lower incident frequency. Incident frequencies are found to be 17.5 percent lower in the months of winter season than others.

Table 5.18. Variable Elasticities for Incident Frequency Model

Variables	Poisson	NB
Winter	-17.87%	-17.51%
Interstate-75 (I-75) north bound	-15.76%	-23.84%
Interstate -275 (I-75) north bound	-28.67%	-19.93%
Interstate-94 (I-94) east bound	24.22%	28.80%
Less than four lanes	6.50%	-14.35%
Minimum radius>1,850 ft	-17.59%	-24.75%
Maximum radius>2,700 ft	-17.33%	-20.52%
No entrance or exit ramp	-112.34%	-127.87%
Tangent section	-16.94%	-22.24%
Peak hour volume more than 4500 vph	21.86%	20.98%
85^{th} percentile speed>70 mph	10.79%	16.52%
15^{th} percentile speed>55 mph	39.17%	40.14%

Location of incidents

Interstate 94, Interstate 75 and Interstate 275

Interstate 94 (I-94) is likely to experience more number of incidents in the eastbound direction in comparison to westbound direction. Eastbound I-94 is exposed to higher traffic conditions than westbound direction resulting in higher incident frequency. Northbound direction on Interstate 75 (I-75) and Interstate 275 (I-275) are likely to have less incident frequencies than southbound direction. Northbound directions of Interstate 75 and Interstate 275 have lower traffic than southbound direction which is more likely to result in lower incident frequency. Northbound direction of Interstate 75 and Interstate 275 are tended to have 23.8 percent and 19.9 percent lower number of incidents, respectively, than the southbound direction. On the other hand, eastbound direction of Interstate 94 experienced 28.8 percent more incidents than westbound direction.

Number of lanes

Freeway sections with less than four lanes are found to be less likely to experience incidents. Four lanes on freeways are generally present on the sections near the exit and entrance ramp locations which are associated with increased likelihood of incident occurrence. Freeway sections with less than four lanes tended to have 14.4 percent lower number of incidents.

Maximum and minimum radii of horizontal curve

Sections with minimum radii of horizontal curves greater than 1,850 feet and maximum radii of horizontal curves greater than 2,700 feet are less likely to have incidents. Higher radii of horizontal curves form favorable driving condition for motorists due to absence of sharp turns and ensure less control of the vehicle steering and thus minimize the chances of incident occurrence. Sections with minimum radius greater than 1850 ft and maximum radius of 2,700 ft are likely to experience 24.8 percent and 20.5 percent less number of incidents, respectively.

Entrance and exit ramp

Freeway sections with no entrance and exit ramps are less likely to experience incidents due to the absence of traffic conflict situations which are generally formed due to merging, diverging or weaving movement of traffic on freeways in the vicinity of entrance or exit ramps. Freeway sections with no entrance or exit ramps have a tendency to experience 127.9 percent less number of incidents.

Tangent section

Tangent sections with no horizontal curvatures are less likely to experience incidents compared to sections with horizontal curves. Absence of horizontal curves on freeway sections allows more comfortable driving condition (least control over steering) to the motorists which results in lower incident frequencies. Freeway tangent sections are likely to experience 22.2 percent less number of incidents.

Traffic characteristics

Peak hour volume

Sections with higher peak hour traffic volume are more likely to experience incidents compared to sections with lower peak hour traffic volume. Probability of incident occurrence increases with increase in traffic volume, consequently raising the incident frequency. Sections with peak hour traffic volume of 4,500 vehicles per hour are likely to experience about 21.0 percent more incidents.

85th percentile speed, 15th percentile speed

Freeway sections having 85th percentile speed over 70 mph and 15th percentile speed over 55 mph are likely to experience higher frequency of incidents. Both of these variables indicate high speed of vehicles on those freeway sections. Chances of incident occurrence increase with the increment in speed, which results in higher incident frequency on the sections with higher vehicular speed. Freeway sections with 85th percentile speed over 70 miles per hour and 15th percentile speed of 55 miles per hour tended to have 16.5 percent and 40.0 percent more incidents, respectively.

Chapter 6 Conclusions and Research Contributions

This research aimed to assess freeway operations in metropolitan Detroit, with particular emphasis on the impacts of traffic incidents. A software interface program was developed to combine traffic flow data (e.g., volume, speed, and occupancy) with incident response data provided by the Michigan Department of Transportation (MDOT) Freeway Courtesy Patrol (FCP). A framework was developed to analyze the effects of traffic incidents and the resultant congestion, as well as to identify important factors that impact the frequency of incidents and the time required by FCP operators to respond to and clear incidents. This framework was tested on data for a sample freeway segment and then applied more broadly across four major freeways in southeastern Michigan.

The research began with a comprehensive review of past work related to incident modeling, with a focus on studies related to incident frequency and duration. An assessment was conducted of the data currently collected and maintained by the MDOT Michigan Intelligent Transportation Systems (MITS) Center. This included traffic flow data collected by both MDOT in-pavement loop detectors, as well as Traffic.com data collected through microwave side-fire detectors. The traffic flow data obtained from Traffic.com was integrated with FCP incident response data in order to create a rich database that was subsequently used to assess the interrelationships between traffic, roadway geometry, and incident response data. The MDOT traffic flow database could not be integrated due to data limitations and similar limitations were found in regard to the dynamic message sign data that is maintained by the MITS Center.

6.1 Research Findings, Contributions, and Conclusions

One of the initial tasks of the research was to examine whether the traffic flow data provided through Traffic.com could be used to identify the occurrence of incidents in near real-time by detecting changes in traffic flow parameters over time. While differences could be detected through a manual review of the location-specific detector data for severe incidents (e.g., crashes), the traffic flow data generally did not provide sufficient precision in order to identify incident in an automated fashion, due in part to the fact that the data were aggregated into 5-minute intervals.

This study is first of its kind because of the novel application of count data model for incidents. Both Poisson model and negative binomial regression models were developed in order to model the frequency of freeway incidents and compared to identify factors affecting incident occurrence. The negative binomial modeling structure was shown to outperform the Poisson model due to the presence of overdispersion in the incident count data. The month of year and direction of travel were also shown to impact incidents on a per-mile basis. Incident occurrence is less frequent for the winter months due to more careful driving and more frequent checking up process of the vehicles by the motorists. Northbound direction of Interstate 75 and Interstate 275 were observed to experience lower number of incidents than southbound direction which may be due to lower congestion in the northbound direction during high-activity periods. For similar reason, eastbound direction of Interstate 94 was observed to experience higher number of incidents in comparison to westbound direction. The roadway geometry factors that were shown to be significant determinants of incident occurrence included horizontal curvature (presence of curves, as well as maximum and minimum horizontal radii), number of lanes, and presence of entrance and exit ramps. Freeway sections with three or fewer lanes were observed to have lower incident frequency. Additionally, minimum and maximum radii of horizontal curves more than 1,850 feet and 2,700 feet, respectively, were associated with lower number of incident frequency. Freeway sections with no merging/weaving movements due to the absence of entrance or exit ramps were associated with lower frequency of incident occurrences. Tangent sections with no horizontal curves have been found to experience less number of incidents. Various geometric and traffic factors were found to affect the number of incidents experienced on a particular one-mile freeway segment during the study period. Among the traffic flow data, travel speeds (85th percentile and 15th percentile) and variability in traffic volumes (e.g., peak hour factor) were found to significantly impact incident frequency. Incident occurrences are more frequent with higher speeds. The freeway sections where average 85th percentile speed was found to be more than 70 mile per hours, were associated with higher number of incidents. Similar situations of higher incident occurrences were observed for freeway sections with average 15th percentile speed of more than 55 miles per hour. Incident frequency is more for sections with peak hour traffic volume of 4,500 vehicles per hour or higher.

Survival analyses were conducted in order to identify those characteristics that impacted both the response time of FCP operators, as well as the time required by FCP personnel to clear the incident scene. Various model formulations were examined, with the results demonstrating that the Weibull distribution provided the best fit to the incident response data while the log-logistic distribution provided a better fit for the incident clearance data in comparison to other parametric models.

Incident response rates varied based upon the day of week, month of the year, and time of day (during weekdays), as well as whether entrance ramps were present near the incident location. Incidents during weekends were observed to be associated with longer response time due to lower staffing level. Because of higher number of staffs, incidents were responded faster during the weekday second shift hours (6 am to 2 pm). Incident response times were shorter for incidents on Interstate 94 (I-94) in comparison to the other three freeways under examination. Incidents that occurred on freeway sections with at least one entrance ramp had shorter response time. Shorter response times were observed for the incidents occurring in the month of May due to clear weather conditions.

Clearance times varied based upon the day of week and time of day (during weekdays). Shorter clearance times were observed for the incidents that occurred during the weekends due to lower number of vehicular traffic movements which result in minimum exposure of the involved motorist and incident responders to the other passing traffic. Inclement weather conditions during the winter months were responsible for longer clearance durations of incidents. Incident clearance times were higher along Interstate 75 (I-75) and lower on Interstate 275 (I-275). Interstate 75 experience greater congestion compared to other freeways, whereas Interstate 275 is exposed to least congestion among all the freeways considered in this study. As expected, clearance times varied substantially based upon the type of incident that necessitated the FCP response, the number of vehicles involved, and whether a lane or shoulder was blocked by the occurrence of the incident. Incidents that necessitate involvement of multiple services from various agencies associated with the incident management program and incidents requiring the transportation of involved motorists by the FCP operators were found to have longer clearance duration periods. Incidents involving single vehicle and incidents blocking only one lane had shorter clearance times, whereas incidents blocking left shoulder took longer time for the clearance procedure. Traffic conditions (85^{th} percentile speed and difference between the 15^{th} and 85^{th} percentile speeds) and the presence of exit ramps and horizontal curves were also found to affect clearance duration. Incidents on freeway sections with no exit ramps took longer times for the clearance process due to greater congestion. Incidents on tangent freeway sections experienced shorter clearance times due to the availability of enough sight distance for the other non-involved motorists in advance and their subsequent decisions of cautious driving near the incident sites or taking exit ramp(s) to avoid the incident scene.

The framework developed as a part of this research identified several important factors that influence frequency of incidents, as well as FCP response time and the time required by responders to clear such incidents. By identifying freeway segments and operating conditions that are most prone to incidents, MDOT may be able to find avenues for improving their incident management process.

From an analytical standpoint, the framework developed over the course of this research showed that hazard-based duration models provide an appropriate tool for assessing incident durations. Such duration models can be used by MDOT to more efficiently manage incident response and clearance process. Additionally, these models may be used in the future to assess changes in incident management performance over time or to estimate the potential impacts of policy changes. Similarly, the count data models were able to identify the effects of various traffic and geometric conditions on incident frequency and the results of this analysis can be used by MDOT to optimize staffing and logistics for FCP operations.

The framework also provides suitability of developing different modeling structures for incident response and clearance durations. Test of spatial transferability reveals that impacts of most of the significant factors were consistent across freeways, but freeway specific models are more appropriate as geometrical features, traffic conditions as well as nature of incidents and consequent services provided by FCP vary significantly across freeways. The findings from the crash frequency and duration models would not only benefit the MITS Center, but may also provide insight to other communities and metropolitan areas throughout the country with similar traffic management centers (TMC) and present potential opportunities for improving the efficiency of their operation.

6.2 Future research directions

This research creates a starting point for future initiatives aimed at investigating freeway operations and safety. The analytical framework can be expanded or supplemented in order to conduct further investigations. For example, if more detailed sensor data become available, it may be possible to identify incidents or potential incidents based upon changes in traffic flow parameters. Data collected in 30-second or 1-minute intervals would also increase the precision of the incident response and clearance models. Furthermore, it would allow for an examination of overall incident duration from the time the incident first occurs until the freeway is restored to its pre-incident capacity.

Another potential extension of this research would be to examine the effects of dynamic message signs (DMS) on freeway operations. While the MITS Center maintains a database of the messages displayed on the DMS across the freeway network, this data is not in a format by which it can be easily linked to the incident and traffic flow data. If these data sources can be linked, information could be disseminated in a more optimal manner to road users regarding incidents, including potential detour routes. The existing incident database can also be enhanced in order to provide richer information through which other research questions can be analyzed. Other data that may be of value include additional geometric characteristics (e.g., number of vertical curves, maximum and minimum grade) and site-specific weather information.

From a methodological point of view, there are alternatives in assessing freeway operations, including analyzing homogeneous freeway sections as opposed to sections of equal length for the incident count models. The duration models were found to vary across locations, but examining their transferability over time is also warranted. Both fully parametric and semiparametric models can be developed using pooled data over a number of years. Other parametric and non-parametric forms of the hazard function can also be assumed and checked for spatial and temporal transferability. The models developed as a part of this research can also be applied in other areas to determine how impacts may differ based upon regional or agency-specific factors. Additional research can be conducted to develop more flexible statistical models by accounting for heterogeneity effects within and across freeways.

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ABSTRACT

EXAMINATION OF FACTORS AFFECTING THE FREQUENCY, RESPONSE TIME, AND CLEARANCE TIME OF INCIDENTS ON FREEWAYS

by

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December 2010

Advisor: Dr. Peter Tarmo Savolainen

Major: Civil Engineering (Transportation)

Degree: Doctor of Philosophy

Traffic incidents are the primary cause of non-recurrent congestion in urban areas, resulting in reductions in roadway capacity and significant safety hazards to other motorists, as well as first responders. Many communities have initiated incident management programs that detect and respond to incidents and restore freeways to full capacity by clearing the incident scene as soon as possible. In the Detroit metro area, the Michigan Department of Transportation (MDOT) operates a Freeway Courtesy Patrol (FCP) program as part of its larger freeway incident management program from the Michigan Intelligent Transportation Systems (MITS) Center in downtown Detroit. The MITS Center maintains a series of databases that detail freeway operations, as well as the activities of the FCP. However, these databases are independent of one another and no research has concurrently examined the interrelationships between freeway operations and the services provided by the MITS Center. This study aims at analyzing operations on the Detroit freeway network.

This study assesses the data maintained by the MITS Center and involves the development of a software interface that was used to combine data from these various sources. These data include traffic flow information obtained from side-fire sensors, as well as data related to FCP operations in the Detroit freeway network. In addition to linking these independent data sources, preliminary data analyses are conducted in order to identify important factors influencing the incident clearance time. A comprehensive database along with traffic flow characteristics is prepared and statistical analyses are conducted to identify important factors that impact the frequency and duration of incidents on various freeway sections in Detroit metro area. It allows the consideration of the effect of various site-specific variables across different locations as well as the transferability of developed models. Consequently, this assessment highlights different areas of opportunity, uncovers the underlying strong and weak areas of existing MDOT freeway incident management program and offers important directions for the possible improvement that can collectively result in the development of better freeway traffic operations in Detroit metro area.

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