USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No. 051WY02

Using Detector Data to Identify and Examine Crashes and Incidents on Freeways

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DISCLAIMER

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TECHNICAL SUMMARY

NEXTRANS Project No. 051WY02 Final Report, September 2010

Using Detector Data to Identify and Examine Crashes and Incidents on Freeways

Introduction

Traffic incidents, such as crashes and vehicular breakdowns, result in reductions in roadway capacity and are the primary cause of non-recurrent congestion in urban areas. In addition to contributing to congestion and delay, incidents adversely affect the safety of other motorists, as well as first responders. To address these issues, transportation agencies have initiated incident management programs aimed at detecting and responding to incidents in order to restore freeways to full capacity by clearing the incident scene as soon as possible. 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 patrols. In the Detroit metropolitan area, the Michigan Department of Transportation (MDOT) operates a Freeway Courtesy Patrol (FCP) program as part of its freeway incident management program from the Michigan Intelligent Transportation Systems (MITS) Center in downtown Detroit. As a part of its operations, the MITS Center maintains a series of databases that detail freeway operations, as well as the activities of the FCP. However, to date these databases have been maintained independently of one another and no research has examined the interrelationships between freeway operations and the services of the FCP. This report details the activities from the first year of a two-year study aimed at analyzing operations and incident response on the Detroit freeway network.

Findings

The first year of this study assesses the data maintained by the MITS Center and involves the development of a software interface that is used to combine data from roadside traffic detectors and an MDOT FCP call database. In addition to linking these independent data sources, preliminary data analyses were conducted and a methodology was developed in order to identify factors influencing the frequency of incidents, as well as the response time of FCP responders and the associated incident clearance time. Further data will be collected to allow for a determination of how traffic flow, roadway geometry, and incident-specific factors may impact both the frequency of incidents and the resultant clearance time.

Recommendations

The activities conducted during the first year of this study have led to the development of a comprehensive database that will allow for a broad examination of freeway operations in metro Detroit. Numerous freeway segments will be examined to determine how site-specific factors impact incident frequency and duration and how these impacts vary across locations. Specific tasks during year two will include: the development of incident prediction models for various freeway segments based on location-specific factors; an examination of factors affecting clearance times for incidents responded to by the FCP and an assessment of the transferability of these impacts across segments; and further evaluation of the efficacy of using traffic flow data, aggregated into five-minute intervals, in order to identify the occurrence of traffic crashes or other incidents. Collectively, these activities will provide an assessment of freeway operations on Detroit freeways and highlight areas of opportunity for MDOT and other road agencies to clear incidents in a more effective manner.

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CHAPTER 1. INTRODUCTION

1.1 Background

Traffic incidents are the primary cause of non-recurrent congestion in urban areas. Incidents are generally described as any planned or unplanned event affecting traffic flow (Sethi, 1994). These events result in the reduction of the traffic flow, thus affecting the roadway capacity either directly by lane closure or indirectly by motorists slowing down to look at the incident (Giuliano, 1988). These events include traffic crashes, vehicle breakdowns, 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 to drivers directly involved (TRB, 1994). 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). Capacity reduction due to incidents have been found to be higher than those due to physical reductions in roadway space (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., 2005). In response to the growing and adverse impacts of incidents, 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 (Khattak and Rouphail, 2004). Incident management is broadly described as a coordinated and well-planned approach for restoring traffic to its normal operation as quickly as possible after an incident has occurred (Carvell et al., 1997). 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 patrols (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. 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. The FCP is 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). 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.

1.2 Research Objectives

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 report details the activity from the first year of a two-year study aimed at analyzing operations on the Detroit freeway network, including inputs related to the occurrence of incidents. The first year of this study aims to assess the data maintained by the MITS Center and to develop an interface that can be used to combine data from these various sources. These data include traffic flow information obtained from roadside microwave sensors, as well as data related to FCP operations and DMSs 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 response time of FCP responders and incident clearance time. Further data is collected to allow for a determination of what factors may impact the frequency of incidents on particular freeway segments.

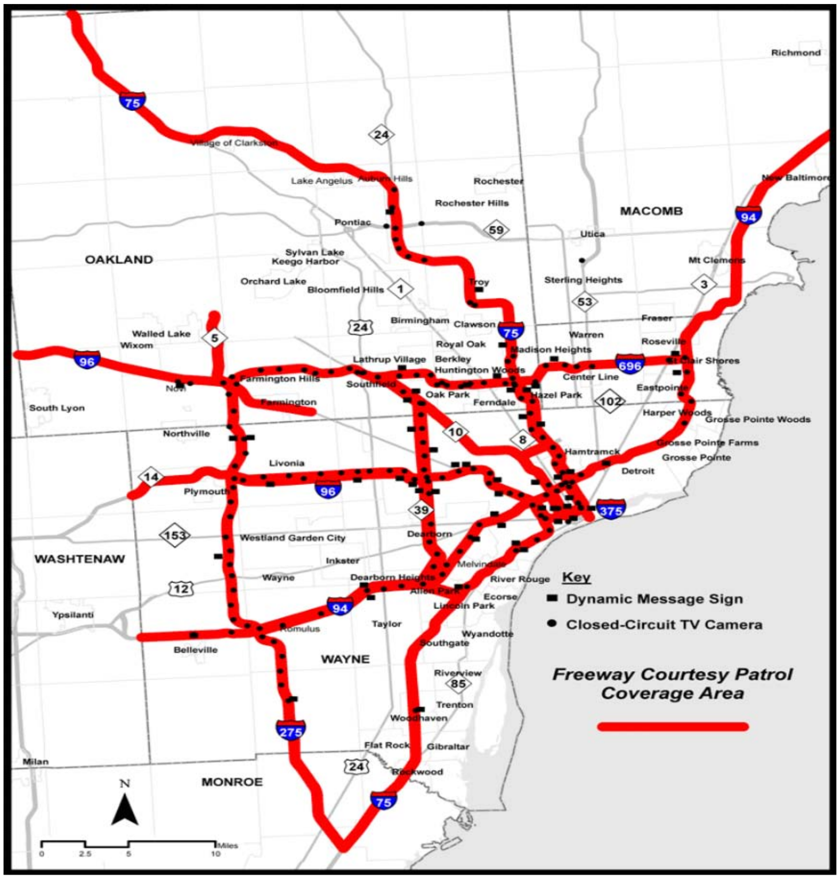


Figure 1.1. Freeway Courtesy Patrol (FCP) Coverage Area (MDOT, 2010a)

In 2009, the FCP responded to 5,342 incidents, of which 725 (14 percent) resulted in freeway lane or interchange closures. During 2008, the average time taken by FCP responders to clear an incident was approximately 12.5 minutes (SEMCOG, 2009).

1.3 Organization of the research

Having outlined the importance of this research and the study objectives, the remainder of the research is organized as follows. Chapter 2 provides a literature review of previous research in the area of freeway safety and operations. Chapter 3 describes the assessment of data from various sources and subsequent data preparation procedures, as wel as details of how these sources were combined through the development of a software interface. In Chapter 4, results of some preliminary analyses are presented. Chapter 5 discusses how the results of this research will be expanded as a part of subsequent activities during the second year of this project.

CHAPTER 2. 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 segments 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 section 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) evaluated 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 type, 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 number of explanatory variables. This study did not consider the incident types separately, rather they categorized ten different incident types 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. (2005) 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 segment as it relates to roadway geometry, traffic volumes, and other characteristics. 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). In the field of transportation engineering, hazard-based duration models have been applied for the analysis of traffic crashes (Jovanis and Chang, 1989; Chang and Jovanis, 1990; Mannering, 1993), trip-making decisions (Mannering and Hamed, 1990; Hamed and Mannering, 1993; Bhat, 1996a, 1996b; Bhat et al., 2004), vehicle ownership (Mannering and Winston, 1991; Gilbert, 1992; De Jong, 1996; Yamamoto and Kitamura, 2000), as well as incident durations (Jones et al., 1991; Nam, 1997; Nam and Mannering, 2000, Stathopoulos and Karlaftis, 2002; Chung, 2010).

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 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 both incident frequency and clearance time. 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 COLLECTION, ASSESSMENT, AND INTEGRATION

The primary objective for the first year of this two-year study was to assess the data that is being inventoried by the Michigan Department of Transportation (MDOT) Michigan Intelligent Transportation Systems (MITS) Center for its use in examining traffic operations on the Southeastern Michigan freeway network. A software interface was developed in order to integrate some of these separate databases for subsequent data analysis activities. Three general types of data were obtained: traffic flow data from roadside sensors collected by Traffic.com, Freeway Courtesy Patrol (FCP) operational data maintained by the MITS Center, and Dynamic Message Sign data, also 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 monitor 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.

3.1 Traffic.com 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 sidefire 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 (I-75, I-94, I-275 and I-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"

3.2 MDOT Detector Data

In addition to the sensors owned and maintained by Traffic.com, MDOT maintains a series of sensors along the freeway network. While these data are also available through Traffic.com, the data are very sparse and of generally poor quality. 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.

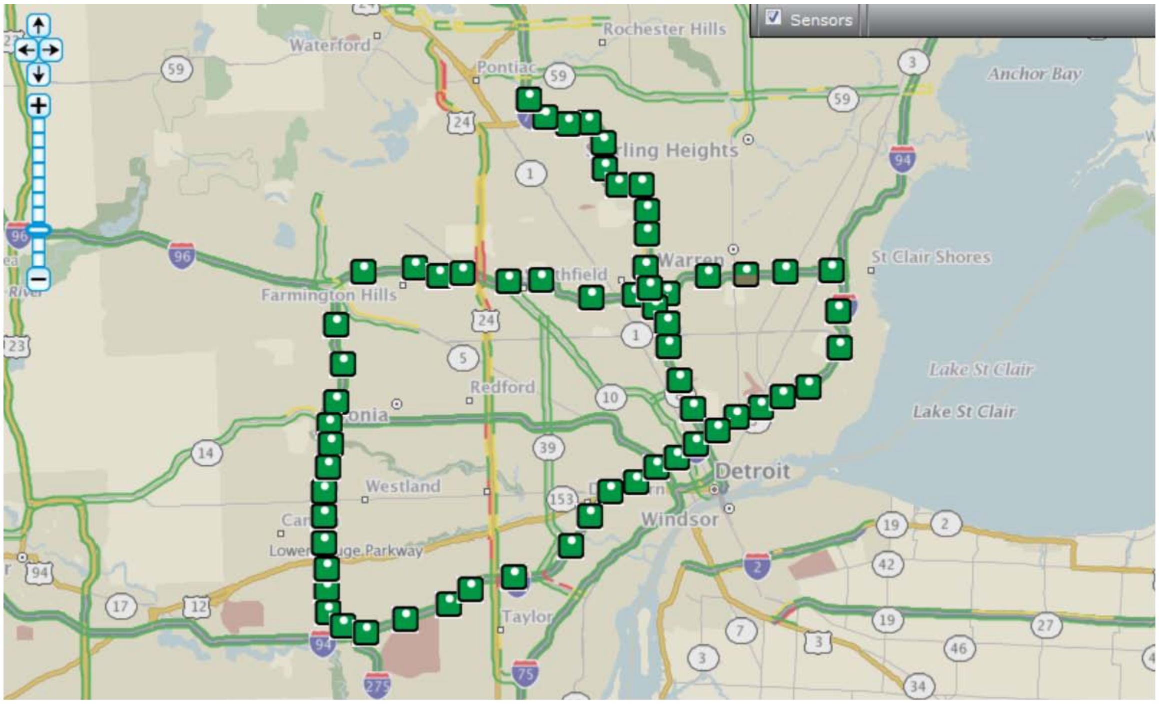


Figure 3.1. Location of Traffic.com Maintained Sensors (Traffic.com, 2010)

3.3 Freeway Courtesy Patrol (FCP) data

Incident-related data for 2009 were 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

3.4 Dynamic message sign data

Dynamic (changeable) message sign data were also extracted from archived records obtained from MITS center. These records provide users with the specific information/messages that were disseminated to the motorists by MITS center personnel on any particular day on a specific sign for every 15 minutes intervals along freeway routes. There are total of 41 dynamic message signs for the four local freeway corridors (I-75, I-94, I-275 and I-696). While these data do not include specific location information (i.e., GPS coordinates or mile markers), mile point information for these 41 signs were found using Google Earth. Table 3.3 provides the name and descriptions of variables present in the DMS database. While these data could not be linked directly to the detector and FCP data, though such information may be used on a limited basis during year two activities.

Table 3.3. List of Variables Included In The DMS Database

Name	Description
Location	Location of DMS sign
MSG1	Message displayed on the first line
MSG2	Message displayed on the second line
MSG3	Message displayed on the third line
TYPE	Type of message displayed
DATETIME	Date and time of message displayed

3.5 Development of of software interface

While the previously described data provide rich source of information that can be utilized to examine freeway operations in metro Detroit. 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 principal task of the first year of this research was to develop a software interface program to combine the Traffic.com sensor data and MDOT FCP data into a single integrated database. The software interface, shown in Figure 3.2, allows users to extract traffic flow data during the time of incidents from the 110 active sensors maintained by Traffic.com along four local freeways (I-75, I-94, I-275 and I-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. Mile markers of such incidents were found manually as part of this research. For a particular segment 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.

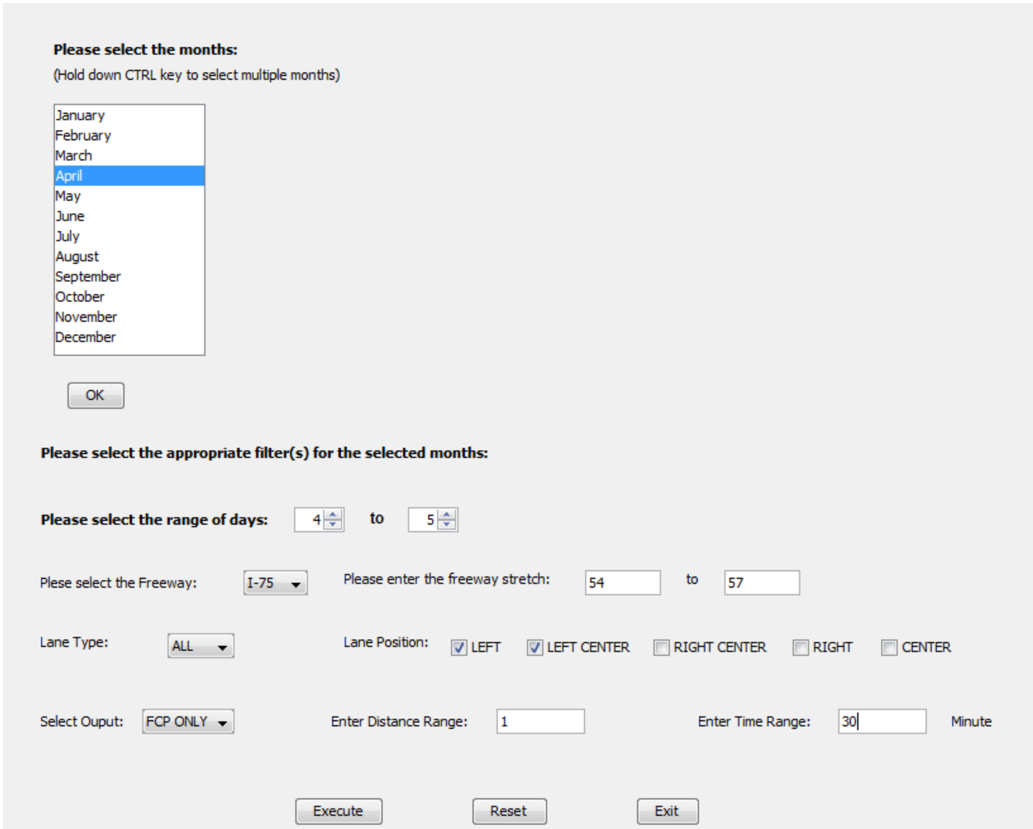


Figure 3.2. Screenshot of Software Interface

The FCP database provides the users several timestamps related to a 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. This activity and other preliminary work conducted during year one is detailed in Chapter 4.

CHAPTER 4. PRELIMINARY ANALYSES

After developing the software interface program, several preliminary analyses were conducted to determine the possible applications and limitations of the data, as well as to lay the foundation for subsequent activities to be conducted during the second year of this project. This preliminary work included:

- Preparation of a sample database for preliminary analyses;
- Identification/Estimation of incident occurrence, response, and clearance times; and
- Development of a preliminary incident clearance model.

4.1 Preparation of a sample database for preliminary analyses

Due to the large volume of data available for the Detroit freeway network, sample data were extracted for a section of Interstate 75 (I-75) in southeastern Michigan north of the City of Detroit for preliminary analyses. These data were 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 was 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 segment yielded a data set of 1,549 incidents, of which 62 cases were removed from the dataset because of incomplete information. The final analysis dataset includes the FCP data for each of the remaining 1,487 incidents, as well as weather-related information obtained from Weather Underground. Table 4.1 provides summary information related to these incidents.

Table 4.1. Summary Statistics of Freeway Incidents

Variable	Number (percentage)	Variable	Number (percentage)
Day of Week		*Area of Roadway Affected*	
Weekend	299 (20.11%)	Shoulder only	1330 (89.44%)
Weekday	1188 (79.89%)	Exactly one travel lane	135 (9.08%)
Number of Vehicles Involved		More than one travel lane	22 (1.48%)
One Vehicle	1427 (95.97%)	*Service type*	
Multiple vehicles	60 (4.03%)	Abandoned vehicle	436 (29.32%)
Weather		Flat tire	194 (13.05%)
Clear	1324 (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/unknown	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 data were combined with the related traffic flow data from Traffic.com in order to conduct some preliminary investigations.

4.2 Identification/Estimation 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 4.1 and 4.2. These figures show the plot of vehicular speed, traffic volume and detection zone occupancy with respect to the time of day for two incidents. For these two particular incidents traffic flow data were obtained from the nearest downstream sensor using the software interface. The first incident (Figure 4.1), 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 4.1. Conversely, the approximate occurrence time of the second incident (Figure 4.2), which is a traffic crash, can be detected by the drastic change in the profile of traffic flow characteristics. The FCP database confirms that the response team arrived on the scene at 15:00 PM and the incident was cleared at approximately 15:48 PM. Figure 4.2 shows a sudden change in traffic volume and mean speed at approximately 2:50 PM and again at 3:50 pm. During the second year of this project, further analysis will focus on crash identification as non-crash involved incidents cannot be detected with reasonable confidence using the available data.

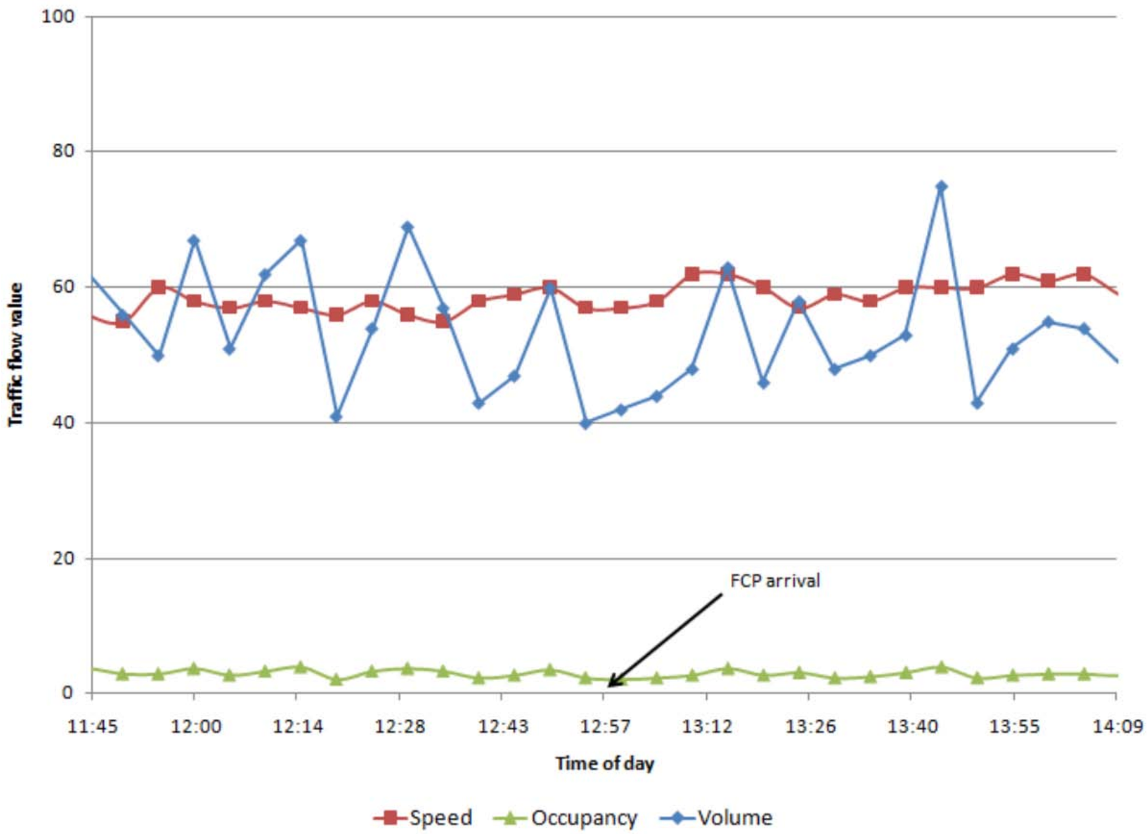


Figure 4.1. Traffic Flow Profile With Respect to Time of Day for Incident#1

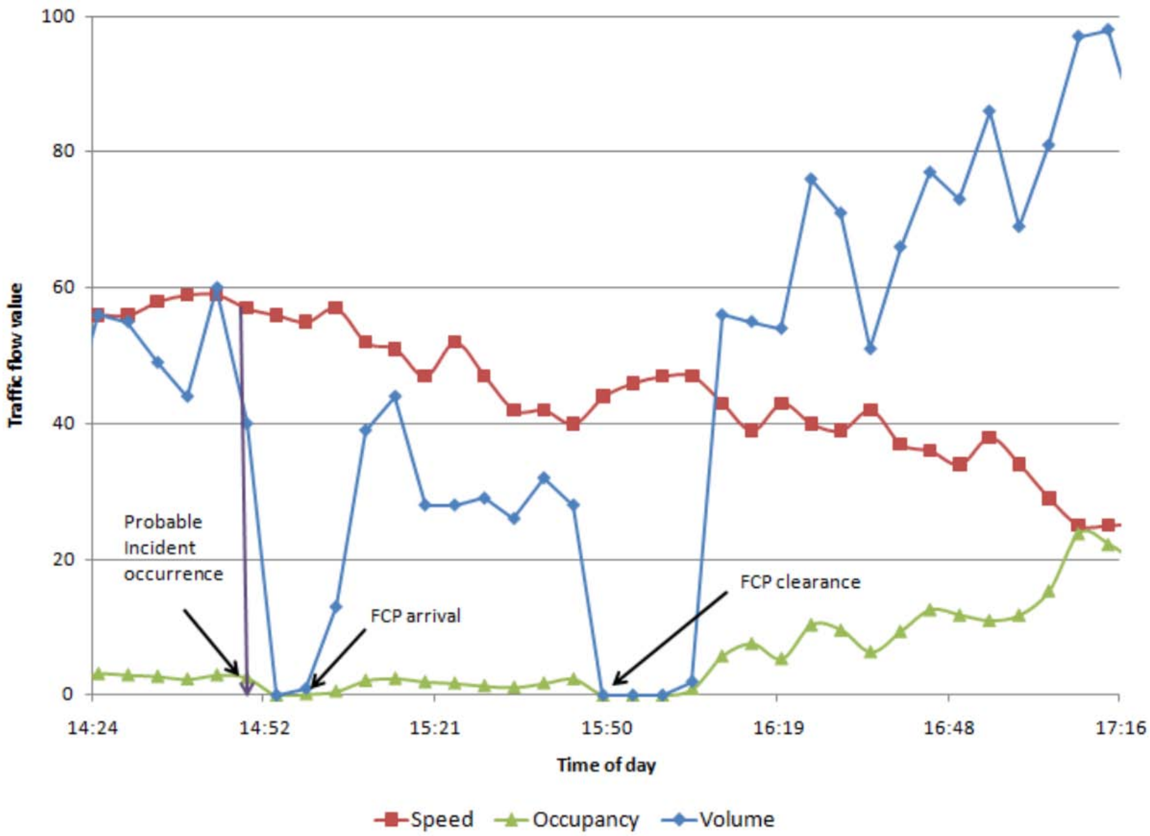
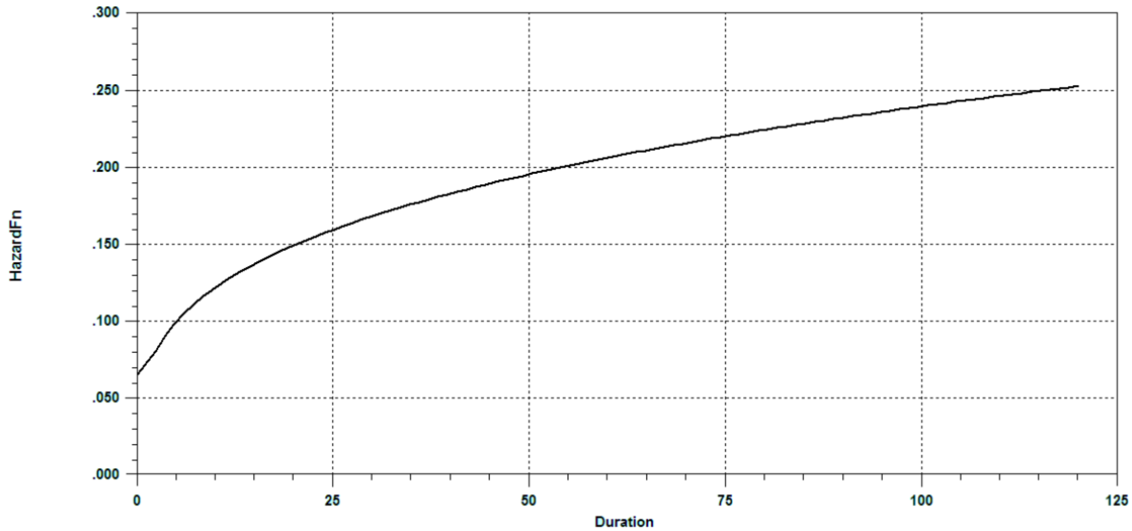


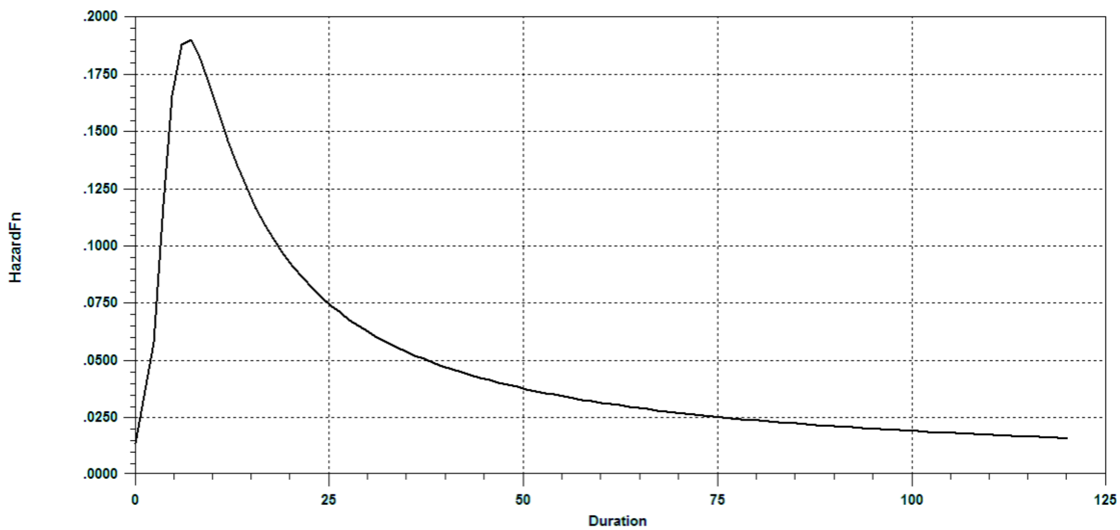
Figure 4.2. Traffic Flow Profile With Respect to Time of Day for Incident#2

4.3 Development of a preliminary incident clearance model

Additional preliminary work focused on examining the time required to clear incidents along the study segment of I-75 by developing four hazard duration models, each with a different assumption regarding the underlying distribution for the hazard function. The distributions compared included the Weibull, both with and without heterogeneity effects, as well as the log-normal and log-logistic distributions. Likelihood ratio statistics (Nam and Mannering, 2000; Washington et al., 2003) were compared to select the model that provides the best fit. LIMDEP Version 8 software was used for the analysis process because of its capability to analyze duration data utilizing various parametric approaches (Greene, 2002). Figure 4.4 presents a plot of each of these four hazard functions versus incident duration. From visual inspection, it is apparent that the Weibull distribution does not provide a particularly good fit for the data as the hazard function is shown to be monotonically increasing, which indicates that as incident duration increases, the likelihood of the incident continuing over the following time period also increases continuously. However, when introducing heterogeneity effects based upon the gamma distribution, the distribution appears more reasonable. The hazard function peaks at between 7 and 8 minutes, after which the likelihood of the incident being cleared increases monotonically. However, in order to determine which of the four distributions provides the best statistical fit, the likelihood ratio statistics for each model are compared. Results for each of the four models are presented in Table 4.2, including parameter estimates and log-likelihood values. These results show the model which uses a Weibull distribution with heterogeneity performs the best (log-likelihood of -1583.7), followed by the models with the log-logistic (log-likelihood of -1599.3), log-normal (log-likelihood of -1615.1), and Weibull distribution without heterogeneity effects (log-likelihood of -1814.6).

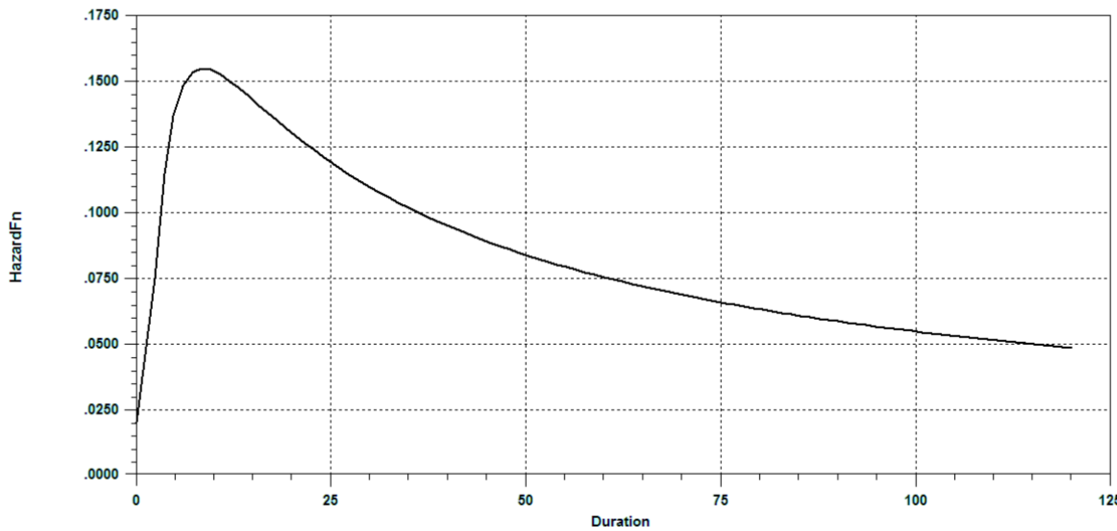


Hazard Distribution Function for Weibull Distribution (no heterogeneity effects)

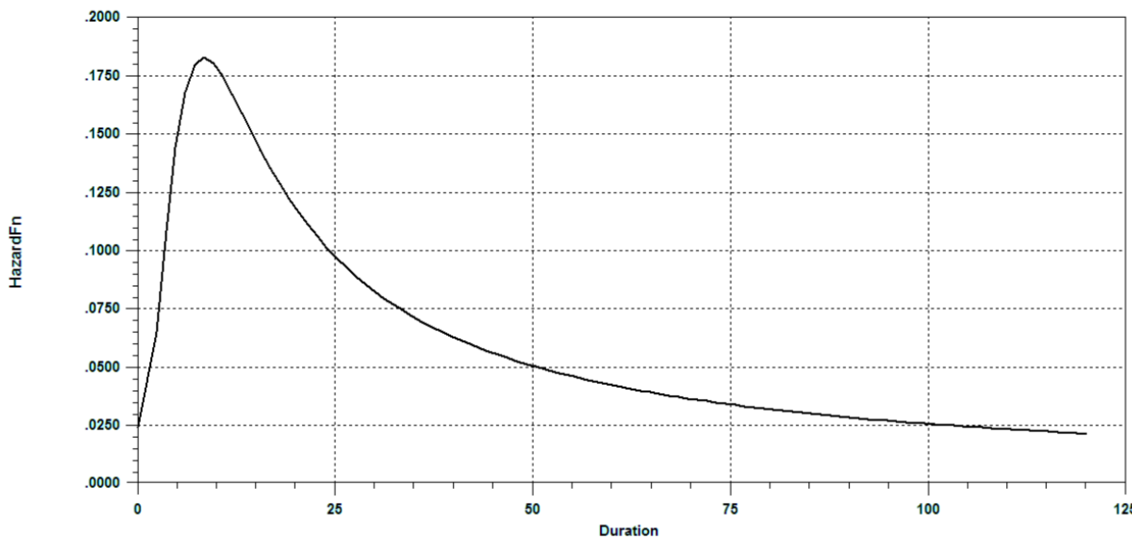


Hazard Distribution Function for Weibull Distribution with Gamma Heterogeneity

Figure 4.3. Comparison of Models with Various Hazard Distributions



Hazard Distribution Function for Log-Normal Distribution



Hazard Distribution Function for Log-Logistic Distribution

Figure 4.4. Comparison of Models with Various Hazard Distributions (Continued)

Table 4.2. Survival Model Estimation Results

Variable	Weibull	Weibull with heterogeneity	Log-normal	Log-logistic
Constant	3.494 (25.584)	3.022 (24.648)	3.108 (25.062)	3.212 (26.754)
Weekday first shift	-.280 (-4.511)	-.275 (-3.249)	-.283 (-3.275)	-.307 (-3.536)
Weekend	-.282 (-8.392)	-.349 (-7.536)	-.329 (-6.606)	-.360 (-7.734)
One vehicle	-.998 (-8.177)	-1.114 (-10.718)	-1.036 (-9.462)	-1.122(-10.785)
Inside shoulder	.132 (2.249)	.129 (2.252)	.137 (2.120)	.141 (2.270)
Only shoulder	-.260 (-3.219)	-.243 (-3.717)	-.245 (-3.681)	-.301 (-4.397)
Service tire	.570 (10.678)	.893 (14.329)	.807 (10.012)	.836 (12.546)
Service mechanical	.404 (5.059)	.574 (8.999)	.539 (7.193)	.572 (8.543)
Service debris	-.805 (-6.502)	-.565 (-5.624)	-.631 (-5.633)	-.6317 (-5.954)
Service traffic	.384 (3.566)	.288 (2.786)	.344 (3.223)	.375 (3.664)
Towing service	.492 (7.497)	.335 (5.587)	.424 (6.786)	.418 (6.837)
Service transportation	1.060 (4.207)	1.357 (7.460)	1.282 (5.025)	1.325 (6.396)
Service cell phone	-1.212 (-1.988)	-.743 (-2.921)	-.880 (-2.136)	-.828 (-2.687)
Service gone-on-arrival	-2.106 (-3.117)	-1.605 (-2.593)	-1.735 (-2.174)	-1.714 (-3.018)
σ (Distribution parameter)	.772 (51.706)	.311 (22.638)	.717 (58.784)	.396 (44.689)
θ (Heterogeneity)	-	1.722 (11.129)	-	-
P	1.295	3.216	1.395	2.525
λ	.095	.160	.138	.141
Log-likelihood at convergence	-1814.638	-1583.726	-1615.109	-1599.289

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

To gain further insight as to the effects of key covariates, the impacts of each of the model parameters are examined by calculating elasticities. These elasticities were 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 4.3, show that the impacts of specific parameters are relatively consistent among the four models with some exception. A discussion of the findings follows, based upon the results of the hazard model assuming a Weibull hazard distribution with heterogeneity.

Though the incident response times have been shown to be longer at night and during the weekends due to decreased staffing levels, incidents occurring during these time periods tended to be cleared 24.0 percent early during the weekday midnight shift and 29.5 percent early during the weekend. The magnitude of the incident was also a significant determinant of its duration. Single-vehicle incidents cleared 67.2 percent sooner than multi-vehicle incidents. As expected, the incident location also had a pronounced impact, as well. Incidents that occurred on the shoulders only tended to clear 21.6 percent sooner than incidents on lanes, while incidents occurring on the inside shoulder tended to last 13.8 percent longer than incident blocking other locations.

Incident duration was also shown to various substantially based upon the type of incident that necessitated the FCP call. As expected, incidents that required minor service tended to result in lesser delays. For example, the removal of debris generally took 43.2 percent less time than typical incidents. Similarly, allowing motorists to use a cell phone reduced delay by 52.4 percent. The types of incidents that required the longest clearance times were those that required work to be conducted outside of the vehicle or assist in managing traffic during closures. Flat tires took the longest time to service, 144.2 percent longer on average, followed by mechanical service (77.5 percent increase) and towing the vehicle (39.8 percent increase). When the FCP was tasked with managing traffic, operators were on the scene 33.4 percent longer. When operators were required to provide transportation to stranded motorists, nearly three-fold increases were experienced. In addition to demonstrating the efficacy of hazard duration models in examining incident duration, these findings highlight factors associated with increased incident clearance that may be addressed by subsequent policies by the MDOT and the FCP.

Table 4.3. Survival Model Variable Elasticities

Variable	Weibull	Weibull with heterogeneity	Log-normal	Log-logistic
Weekday first shift	24.4%	24.0%	24.6%	26.4%
Weekend	24.6%	29.5%	28.0%	30.2%
One vehicle	63.1%	67.2%	64.5%	67.4%
Inside shoulder	-14.1%	-13.8%	-14.7%	-15.1%
Only shoulder	22.9%	21.6%	21.7%	26.0%
Service tire	-76.8%	-144.2%	-124.1%	-130.7%
Service mechanical	-49.8%	-77.5%	-71.4%	-77.2%
Service debris	55.3%	43.2%	46.8%	46.8%
Service traffic	-46.8%	-33.4%	-41.1%	-45.5%
Towing service	-63.6%	-39.8%	-52.8%	-51.9%
Service transportation	-188.6%	-288.5%	-260.4%	-276.2%
Service cell phone	70.2%	52.4%	58.5%	56.3%
Service gone-on-arrival	87.8%	79.9%	82.4%	82.0%

Incident clearance is a critical element 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. Subsequent research during year two will examine how these results may transfer to other freeway segments in southeastern Michigan. Additional factors, such as roadway geometry, will be considered as a part of subsequent models.

CHAPTER 5. DIRECTIONS FOR FUTURE RESEARCH

The activities conducted during the first year of this study have led to the development of a comprehensive database that will allow for a broad examination of freeway operations in metro Detroit. Numerous freeway segments will be examined to determine how site-specific factors impact incident frequency and duration and how these impacts vary across locations.

During 2009, the Detroit metro area experienced approximately 51,407 incidents that were responded to by the MDOT Freeway Courtesy Patrol (FCP). After removal of those incidents with incomplete information, this number is reduced to 48,116. Table 5.1 shows the frequency of incidents by type.

Table 5.1. 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 5.2 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 5.2. Incident Frequency And Percentages On Different Freeways

Freeways	Number of incidents	Percentage
I-275	3,829	8.0%
I-373	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 (I-75, I-94, I-275 and I-696) where Traffic.com maintains sensors experienced a total of 32,578 of these incidents. These incidents will be the emphasis during year two of this research. Preliminary work has involved the development of a methodology that can be used to identify the factors affecting the frequency of an incident on various segments of freeways, and examine the factors impacting the incident response and clearance time. Statistical models will be developed to examine freeway operations in Detroit metro area using larger-scale data. Each freeway will be divided into finite-length segments and these segments will be examined to determine how site-specific variables (e.g., number of lanes, lane widths, 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 and clearance times and how these impacts vary across freeway segments. Specific tasks during year two will include:

- Development of incident prediction models for various freeway segments based on location-specific factors, including traffic flow characteristics and roadway geometry;

- Examination of factors affecting the clearance times for incidents responded to by the FCP and an assessment of the transferability of these impacts across segments.
- Further evaluation of the efficacy of using traffic flow data, aggregated into five-minute intervals, in order to identify the occurrence of traffic crashes or other incidents.

Collectively, these activities will provide for an assessment of operations on Detroit freeways and highlight areas of opportunity for MDOT and other road agencies to clear incidents in a more effective manner in the future.

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