EXAMINATION OF EXISTING TOOLS AND DATA FOR HIGHWAY SAFETY MANAGEMENT IN OKLAHOMA

By

ROHIT GHOSH

Bachelor of Engineering in Civil (Construction)

Engineering

Jadavpur University

Kolkata, India

2013

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
December, 2015

EXAMINATION OF EXISTING TOOLS AND DATA

FOR HIGHWAY SAFETY MANAGEMENT IN

OKLAHOMA

Thesis Approved:

Dr. Joshua Q. Li

Thesis Adviser

Dr. Kelvin C.P. Wang

Dr. Stephen A. Cross

Name: ROHIT GHOSH

Date of Degree: DECEMBER, 2015

Title of Study: EXAMINATION OF EXISTING TOOLS AND DATA FOR HIGHWAY SAFETY MANAGEMENT IN OKLAHOMA

Major Field: CIVIL ENGINEERING

Abstract: As an integral component of transportation asset management, Federal, state and local agencies spend considerable amount of resources on roadway safety management to reduce crashes and fatalities. Currently, most DOTs are collecting roadway safety inventory data on a periodic basis for their Safety Management Systems and several safety management tools such as Highway Safety Manual (HSM), Safety Analyst and Interactive Highway Safety Design Model (IHSDM) have been developed to assist in the safety management process. In this study, a comprehensive literature review on national and state efforts of safety management was conducted and the programs being undertaken to improve roadway safety in Oklahoma were summarized. Available tools for safety management, their data needs and their applications were overviewed. Thereafter, an analysis of the goodness-of-fit of the crash prediction model in HSM and IHSDM were evaluated with historical Oklahoma crash data on rural and urban roadway segments. Subsequently, rigorous statistical analysis was performed with the Poisson regression model using ten years of Oklahoma crash data obtained from the Fatality Analysis and Reporting System (FARS), Highway Performance Monitoring System (HPMS) and the Oklahoma Pavement Management System (PMS) databases to investigate the impact and significance of various roadway factors in Oklahoma crashes. Lastly, Analytic Hierarchy Process (AHP) was employed to rank roadway variables in order of their importance to roadway safety by assigning weights to them. It is anticipated that this research will assist Oklahoma Department of Transportation (ODOT) in evaluating future use of tools for assisting safety management efforts in Oklahoma and also to collect and store data for the roadway elements that have significant impact on Oklahoma crash rates.

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CHAPTER I

INTRODUCTION

1.1 Background

In the U.S. traffic crashes result in, an average of, 6 million fatalities and injuries and $250 billion of medical, emergency, social, economic, and damage costs every year as estimated by the National Highway Traffic Safety Administration [Blincoe et al., 2002]. The Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) [FHWA, 1991] required each state DOT to establish a Safety Management System (SMS) for enforcement and management of safety in the state. A Highway Safety Management System was defined as a systematic process designed to assist decision makers in selecting effective strategies to improve the efficiency and safety of the transportation system. The SMS aimed at consideration and implementation of all opportunities to improve highway safety in all phases of highway planning, design, construction, maintenance, and operation. The inception of SAFETEA-LU [FHWA, 2005] was a major step in promoting safety management on a network level. The act addressed the 4 E's (Engineering, Education, Enforcement and Emergency) in developing highway safety strategies. Most recently, the Moving Ahead for Progress in the 21st century (MAP-21) [FHWA, 2012] was signed into law by the legislation in 2012.

One of the major components of MAP-21 was to promote safety in transportation and several new programs aimed at reducing crash rates have been funded by this law. In the last decade, many research efforts have been devoted to evaluating the effects of roadway factors (roadway geometrics, intersection characteristics, roadside characteristics, pavement surface characteristics, traffic elements and traffic control features) on crash rates. The Tri-Level Study performed in Indiana [Treat et al. 1979] placed roadway factors as the second most important parameter influencing crash rates behind driver factors. Miller and Zaloshnja (2008) evaluated roadway conditions to account for 31.4% of the total 19.65 million crashes in the U.S in 2006.

1.2 Problem Statement and Research Objectives

In the recent past significant efforts have been made to strengthen roadway safety management in the U.S. and reduce fatality and injury rates due to accidents. Some of the prominent national programs such as the AASHTO Strategic Highway Safety Plan, Highway Safety Improvement Program and Model Inventory of Roadway Elements focused on identification of safety improvement areas and allocating funds for associated programs. In Oklahoma, the Oklahoma Strategic Highway Safety Plan [Oklahoma Department of Transportation, 2007] was developed to address safety management in the state, and specifically to reduce the high fatality rate in the state. In the first phase, the programs under SHSP eligible for federal funding were:

- Widening of existing pavements and shoulders
- Installation of high friction surfaces at high-crash roadway stretches
- Installation of rumble strips and warning devices to keep drivers from leaving the driving lane

- Installation of skid-resistant surfaces at high-crash intersections and junctions
- Upgradation of safety measures for bicyclists and pedestrians including installation and upgradation of signs
- Reduction of railroad grade crossing hazards
- Enforcement of traffic laws at rail-highway grade crossings
- Reduction of roadside hazards
- Improvement of signage and pavement markings on high-crash roads
- Installation of priority control system at signalized intersections for emergency vehicles
- Implementing better methodologies in crash data collection and research
- Improving and enforcing traffic activities in work zones
- Installation of guardrail and barriers at high-crash locations
- Traffic operation enforcements on high-risk rural roads

Despite of the significant amount of efforts made, Oklahoma recorded 678 traffic fatalities in 2013 and the fatality rate in Oklahoma in 2013 per 100 million vehicle miles of travel (VMT) was 1.41 compared to the United States average fatality rate of 1.20. The Oklahoma fatality rate per 100 million VMT has been consistently higher than the U.S national average in the last decade (shown in Fig 1).

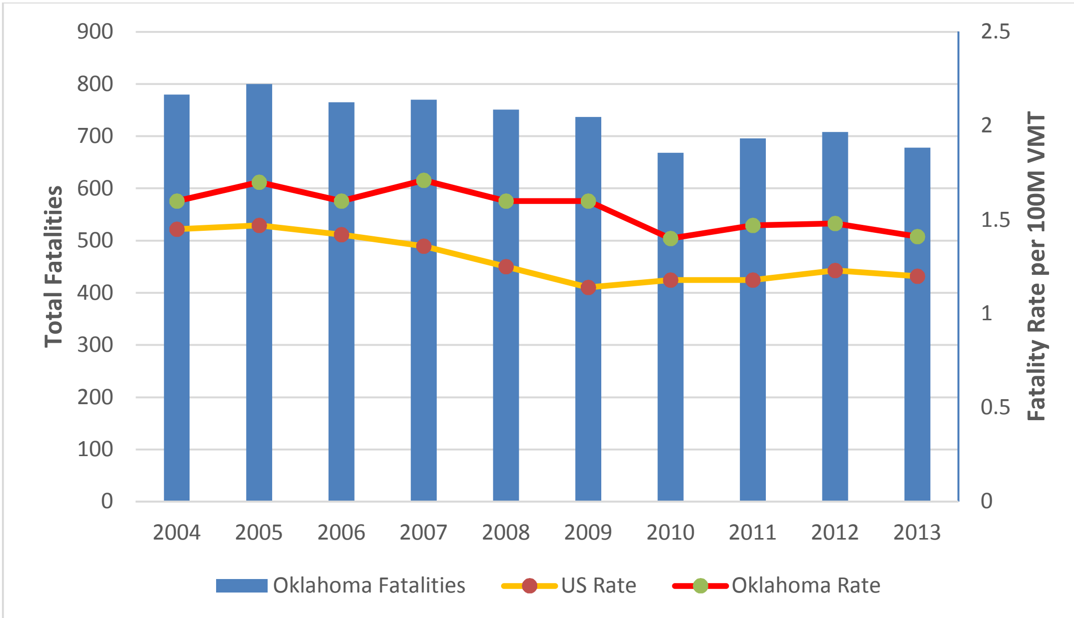

Figure 1. Roadway Fatality Trend in Oklahoma [FARS, 2013]

Currently, very few state transportation agencies use nationally developed tools such as the Highway Safety Manual (HSM), Interactive Highway Safety Design Model (IHSDM) and Safety Analyst in their state's safety management process. The roadway safety management process employed by such safety tools involves diagnosing roadway networks for identifying factors contributing to crashes and selecting countermeasures to reduce crashes, based on their benefit-cost parameters and overall effectiveness. It is anticipated that employing and locally calibrating such tools will streamline the safety management efforts in Oklahoma resulting in saving of public money and resources spent on safety management. Moreover, ODOT collects and stores roadway inventory data for assisting in safety management and it is necessary to collect data for those elements that have tangible impact on roadway crash rates in Oklahoma. In addition, establishing future programs under the Oklahoma SHSP and allocating funds & resources requires a good knowledge of the relationship between roadway elements and crash rates in Oklahoma. As such, there have been very few research studies that have investigated into the roadway factors having influence on vehicular crashes in Oklahoma.

To address the aforementioned limitations, the objectives of this thesis are given as follows:

- Examine the current tools used for highway safety management including Highway Safety Manual (HSM), Safety Analyst and Interactive Highway Safety Design Model (IHSDM) and their data requirements;
- Evaluate the goodness-of-fit of the crash prediction models of the tools with Oklahoma conditions using historical Oklahoma crash data and the possibility of implementation of such tools for safety management in the state;
- Conduct rigorous statistical regression analyses using ten years of Oklahoma crash data to identify the influential roadway parameters contributing to Oklahoma crash rates; this would reinforce the available data and resources for identifying specific safety treatments to lower crashes on Oklahoma roads;
- Implement Analytic Hierarchy Process (AHP) to rank and prioritize roadway elements in Oklahoma in order of their importance to roadway safety, which can assist agencies make decisions for safety management;

1.3 Organization of Thesis

Chapter I provides the background of roadway safety management, the problem statement and the objectives of this study;

Chapter II presents a literature review of national and state efforts in safety management, the emphasis areas and programs being undertaken to improve roadway safety in Oklahoma and the evolution of statistical crash prediction models;

Chapter III provides a summary of the major tools for safety management, their data needs and their application in roadway safety management. An analysis of the goodness-of-fit of the crash prediction model in these tools is conducted using Oklahoma data;

Chapter IV provides a summary of the data elements used in the Poisson regression analysis, the data sources and a short summary of the relationship of the predictor variable to roadway safety;

Chapter V presents a statistical summary of the input variables used in regression followed by the results of the regression analysis performed using ten years of Oklahoma data to correlate roadway variables with crash rates. A multivariate data analysis is implemented to rank the variables in order of their relationship with safety;

Chapter VI presents the key conclusion of this study and provides recommendations;

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

In this chapter, a review of the literature on national and state efforts of highway safety management is presented. The Oklahoma Strategic Highway Safety Plan along with its emphasis areas and the programs eligible for federal funding are discussed. Lastly, a review of literature is presented on the various statistical regression models used in crash prediction and their applicability in the present study is evaluated.

2.2 National and State Efforts of Highway Safety Management

2.2.1 Highway Safety Improvement Program

The Highway Safety Improvement Program (HSIP) [FHWA, 2005] was established under the Safe, Accountable, Flexible, Efficient Transportation Equity Act (SAFETEA-LU) initiated by the FHWA in 2005. In the first phase of the program, focus was on the 'Railway-Highway Crossings Program', the 'Hazard Elimination Program' and the 'High Risk Rural Roads Program'. The HSIP was incorporated into the Moving Ahead for Progress in the 21st century (MAP-21) bill as a Federal-funded program in 2012.

The MAP-21 requires each state must maintain a safety data system that is capable of performing analyses and meeting strategic and performance goals in the state's Strategic Highway Safety Plan and Highway Safety Improvement Program. In MAP-21, safety management is considered an integral part of transportation asset management and a framework has to be established for managing safety assets on public roads. The new law also requires states to use their safety data systems to identify fatalities and serious injuries on all public roads by location, and as such, they should have the capability to link crash, roadway and traffic data by geo-referencing.

2.2.2 AASHTO Strategic Highway Safety Plan (SHSP)

The AASHTO Standing Committee for Highway Traffic Safety (SCOHTS), the National Highway Traffic Safety Administration (NHTSA) and the Federal Highway Administration (FHWA) jointly created the Strategic Highway Safety Plan [AASHTO, 2005] to promote research in transportation safety. The plan identified 22 specific areas of highway safety which needed attention and they were categorized under the following emphasis areas: (1) Drivers (2) Special users (3) Vehicles (4) Highways (5) Emergency Medical Services and (6) Management. The aim of the SHSP was to reduce the annual highway crash fatality rate to 1.0 fatality per 100 million vehicle miles travelled.

2.2.3 NCHRP 500-Series Guidelines

The National Cooperative Highway Research Program (NCHRP) developed a series of safety guides [Transportation Research Board, 2003] to aid state and local agencies in reducing crashes and fatalities in vulnerable areas. The guides follow the emphasis areas outlined in the AASHTO Strategic Highway Safety Plan. Each guide comprises a brief introduction, a general description of the problem, the strategies/countermeasures developed to address the problem, and a model implementation process. Specifically, Volumes 3, 6, 7, 12, 13, 17 and 23 deal with mitigating crashes due to specific roadway factors and they are discussed hereby.

Volume 3 focused on reduction of vehicle collisions with trees and roadside objects and underlined the importance of enforcing guidelines for prevention of placing trees in hazardous locations, delineating trees in hazardous locations and modifying roadside clear zones in the vicinity of trees.

Volume 4 formulated strategies to reduce head-on collisions by preventing vehicles from encroaching into the opposite lane and minimizing the likelihood of it crashing into an oncoming vehicle.

Volumes 5 and 12 addressed intersection collisions and discussed the advantages and disadvantages of: improved management of access near unsignalized intersections by implementing driveway closures, reduction of the severity of intersection collisions through geometric design improvements such as providing left turn lanes and bypass lanes at intersections, improved availability of gaps in traffic by implementing an automated real-time system to intimate drivers of the suitability of available gaps and implementing safety measures such as improving drainage and providing skid resistant surfaces at intersections.

Volume 6 addressed run-of-the road collisions and discussed advantages and disadvantages of installing rumble strips, edgeline profile markings, safer side slopes and high friction pavement surfaces to keep vehicles from encroaching on the roadside.

Volume 7 addressed crashes on horizontal curves and discussed advantages and disadvantages of reducing the likelihood of vehicle departure on horizontal curves by providing electronic warning signs to alert drivers of steep curves, preventing edge drop-off, increasing superelevation, installing centerline rumble strips & high friction shoulder surfaces, curve delineation and increasing sight distance.

Volume 13 addressed crashes involving heavy trucks and discussed advantages and disadvantages of reducing fatigue related crashes by increasing efficiency of use of existing parking spaces and adding more parking spaces, reducing truck-vehicle proximity by enhancing road sharing and improving maintenance of heavy trucks by increasing truck maintenance programs.

Volume 17 addressed work zone crashes and discussed advantages and disadvantages of decreasing the number, duration, and impact of work zones by implementing roadway closures and nighttime road work, improving traffic control devices in work zones by implementing ITS strategies and improving visibility of work zone traffic control devices, and improving work zone design practices by establishing strong design guidelines and improving work zone safety for pedestrians, bicyclists, motorcyclists and truckers.

Volume 23 addressed speeding-related crashes and discussed advantages and disadvantages of enforcing fixed and variable speed limits, implementing safe traffic management programs, implementing automated speed enforcement, improving speed limit and speed warning signage, using combination of geometric elements to control speeds, implementing safe speed transitions by providing adequate elements, designing appropriate change & clearance intervals at signalized intersections among other strategies.

2.2.4 Model Inventory of Roadway Elements (MIRE)

The Model Inventory of Roadway Elements [FHWA, 2010] is a "recommended listing and data dictionary of roadway, traffic and driver history data" in addition to historical crash data which is critical to safety management of highways. It was created to enhance traffic and roadway data inventories and support information systems for safety programs. The next generation of highway safety tools such as the Highway Safety Manual (HSM), the Interactive Highway Safety Design Model (IHSDM), the Safety Analyst and AASHTO's NCHRP Series 500 Data and Analysis Guide have been designed for the highest level of accuracy involving heavy computations and hence data requirements of all these tools are tremendous. All state DOTs and highway agencies also require traffic, roadway and driver information for implementing countermeasures to reduce crashes on their highways and formulate strategies for the same. The need for a comprehensive database of elements integral to highway safety management led to FHWA's creation of MIRE. The version 1.0 of MIRE includes approximately 202 data elements with standardized coding for each element. The elements are divided into three categories: roadway segments, roadway alignment and roadway junctions. Each element is associated with a list of attributes for coding, a priority rank and a description of how the element is linked with the HPMS and other safety tools. Elements are ranked as 'critical' for the ones that are necessary for States to implement standard safety management or for those used in safety analysis tools as input data. Elements are ranked as 'value added' for those which are beneficial but not critical to safety analysis tools [MIRE Version 1.0 Report, 2010]. The detailed list of data elements in MIRE version 1.0 are provided in Appendix A.

2.2.5 MIRE Based Management Information System (MIS)

The next step after setting up the MIRE data element dictionary is to build a Management Information System (MIS) [FHWA, 2013] to identify improved means of collecting MIRE data elements and integrating MIRE data into the Information System. In order to develop MIRE into a production level software for highway safety management the conversion of MIRE from a listing of variables into a full-fledged management information system (MIS) capable of collecting, supporting and maintaining MIRE data is of utmost importance. Recently, FHWA initiated a Lead Agency Program to test the feasibility of collecting MIRE data. The objective of the study was to evaluate the feasibility of state DOTs to maintain and operate the MIRE MIS for safety management in the state. The New Hampshire Department of Transportation (NHDOT) and the Washington State Department of Transportation (WSDOT) were chosen as Lead Agencies to participate in the MIRE MIS effort [MIRE MIS Lead Agency Report, 2013]. The objective of the proposed MIS system would include: 1) Exploring data collection mechanisms 2) Efficiency in data handling and storage 3) Developing a data file structure 4) Integrating MIRE data with historical crash and other data types, and 5) Performance monitoring of MIRE data quality and MIS performance. In the first phase, NHDOT and WSDOT provided a list of the elements to be included in the intersection inventory. The major challenge in the first phase was to determine existing and future data needs, review roadway data collection methods and develop a node layer and model to populate the intersection inventory.

2.3 Oklahoma Safety Statistics and Related Programs

Oklahoma has 115,851 miles of public roadway of which 18,774 miles are urban and 97,077 miles are rural. Fig 2 shows that the crash locations in Oklahoma in 2013 are evenly distributed throughout all geographic areas in the state except the panhandle. The data obtained from FARS and the Oklahoma Highway Safety Office (OSHO) have shown that rural crashes have historically constituted three-fourths of total fatalities in Oklahoma. Traditionally, allocation of funds have been concentrated more on rural roadways in Oklahoma.

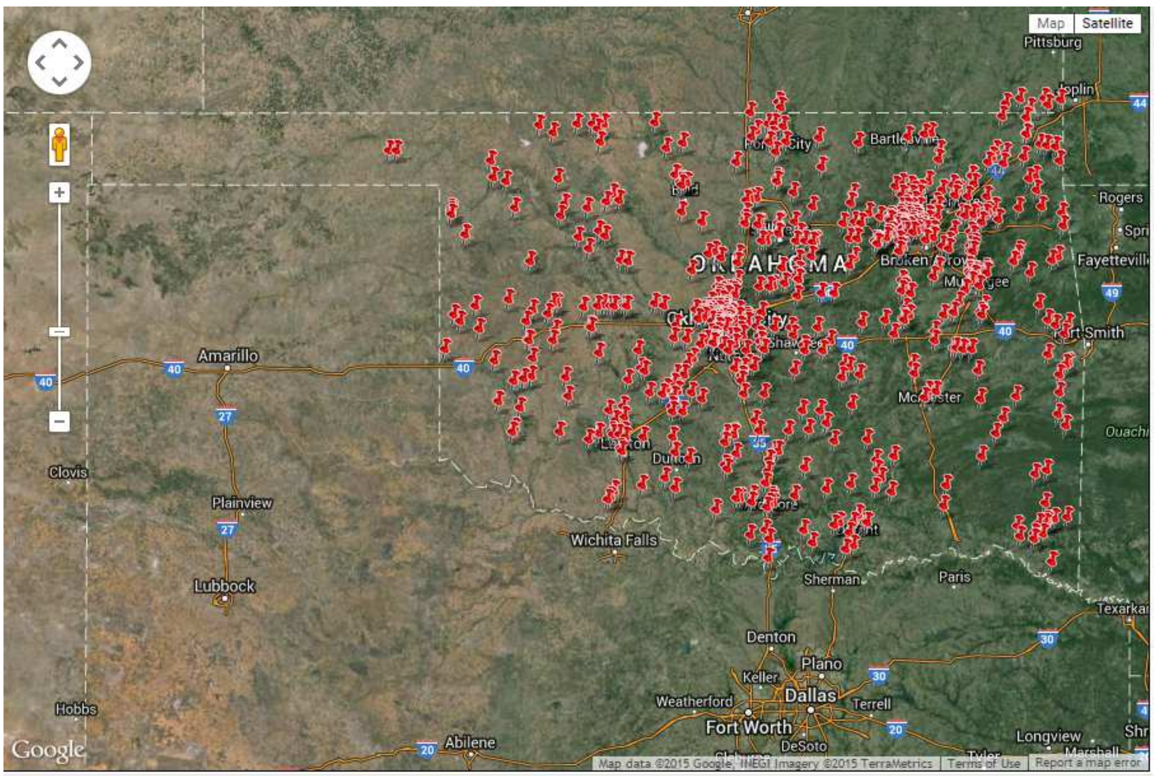

Figure 2. Oklahoma Traffic Crashes in 2013 [FARS, 2013]

Fig 3 and Fig 4 show speeding related fatalities and failure-to yield fatalities in Oklahoma. The number of unsafe speed crashes went from 8,768 in 2005 to 9420 in 2013, comprising about 23 percent of total fatalities. There were 144 fatal unsafe speed crashes and 3864 unsafe speed injury crashes resulting in 155 fatalities and 5698 persons injured in 2013. Similarly, there were 77 fatalities and 7006 injuries due to failure to yield crashes resulting in about 11.6 percent of all fatalities [FARS, 2013]. Many programs have been supported by ODOT to reduce speeding-related fatalities along the lines of Volume 23 in the NCHRP Report 500.

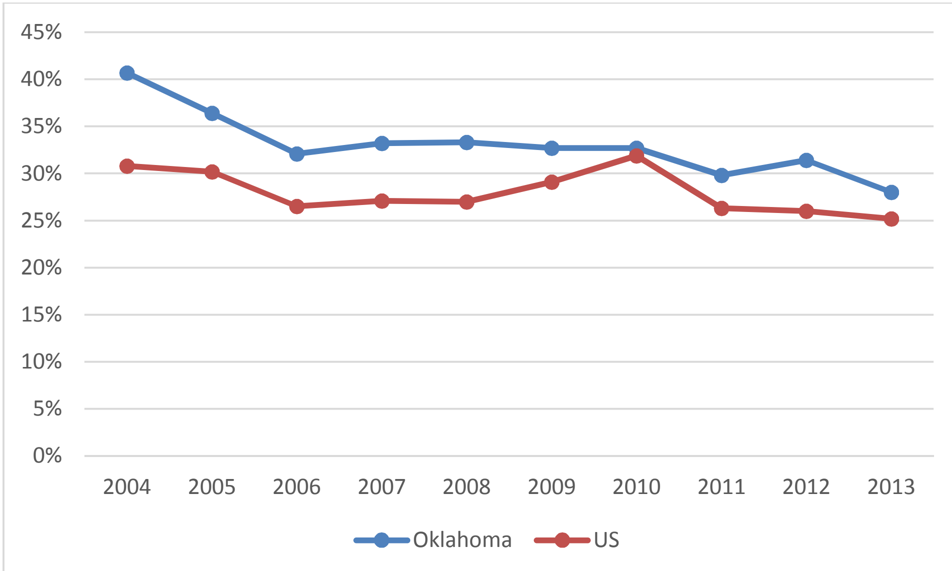

Figure 3. Speeding Related Fatalities as Percent of Total Fatalities [FARS, 2013]

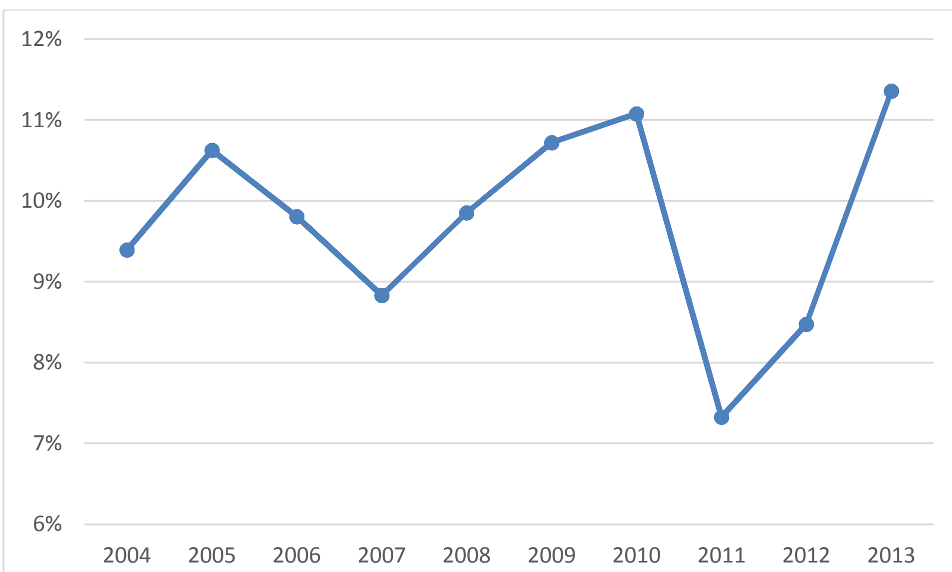

Figure 4. Oklahoma Failure to Yield-Related Fatalities as Percent of Total Fatalities [FARS, 2013]

Fig 5 shows fatal intersection crash statistics in Oklahoma. Fatal intersection related crashes accounted for an average of one-fifth of all crashes in Oklahoma. However, the percentage has been lower than the national average in the last decade. Fig 6 shows number of fatal intersection crashes with control device in Oklahoma. Uncontrolled intersections recorded the highest number of crashes followed by stop sign intersections and intersections without any traffic control device. Fig 7 shows the percentage of intersection crashes on rural highways have been significantly higher than urban highways.

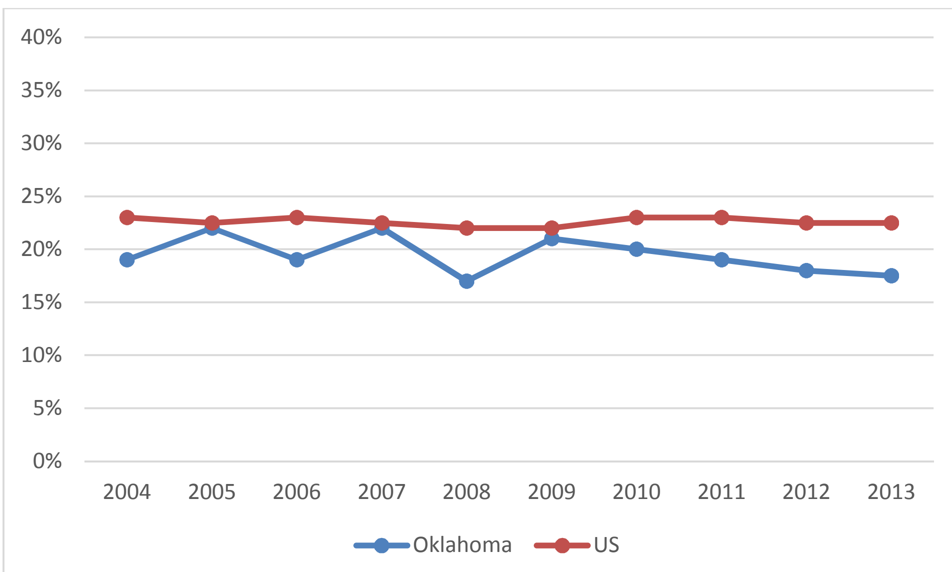

Figure 5. Fatal Intersection Crashes as Percent of Total Fatal Crashes [FARS, 2013]

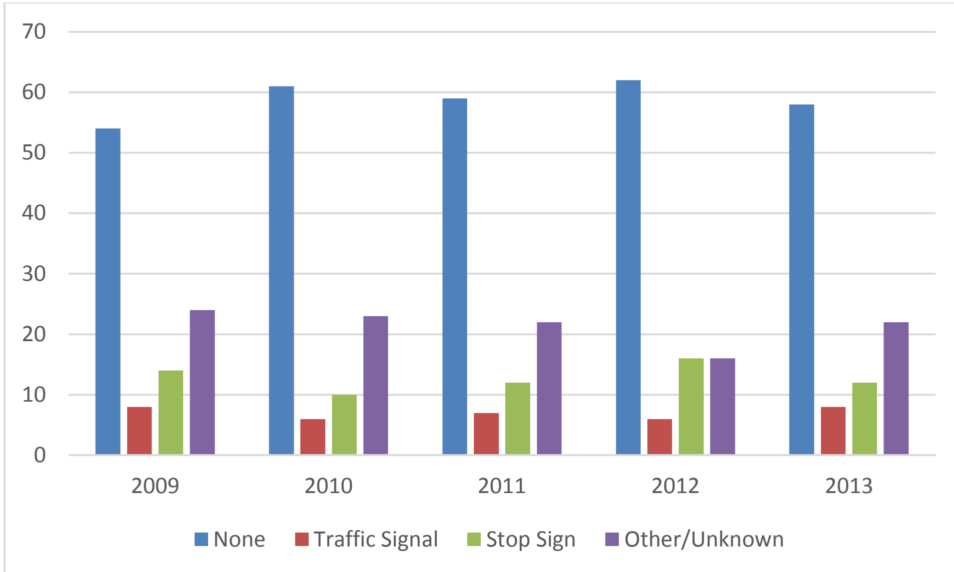

Figure 6. Oklahoma Fatal Intersection Crashes by Traffic Control Device [FARS, 2013]

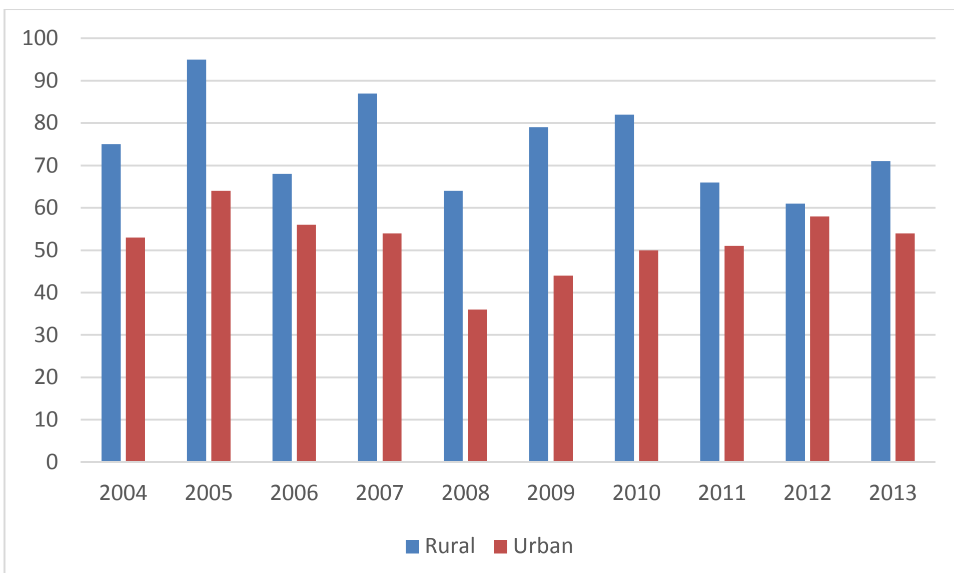

Figure 7. Oklahoma Rural versus Urban Fatal Intersection Crashes [FARS, 2013]

The following programs have been supported by ODOT in the past to increase intersection safety:

- Prioritization of low volume rural intersections
- Implementation of ITS technologies at high crash intersections
- Development of an access management policy supported by design guidelines
- Promoting public awareness regarding dangers and right-of-way at unsignalized intersections

Also, efforts have been made by ODOT to retrofit existing signals with retroreflective backplates for reducing intersection crashes. An effort to link the highest ranked intersections in the state through GIS mapping is underway. Fig 8 and Fig 9 show the roadway departure crash statistics in Oklahoma. Roadway departure crashes typically involve crossover, lane change, run-of-the road crashes, head-on collisions and roadside crashes. Several countermeasure programs have been implemented by ODOT in the last decade to reduce departure crashes such as implementation of enhanced pavement markings, centerlines, rumble strips, roadway signage and pavement/shoulder widening.

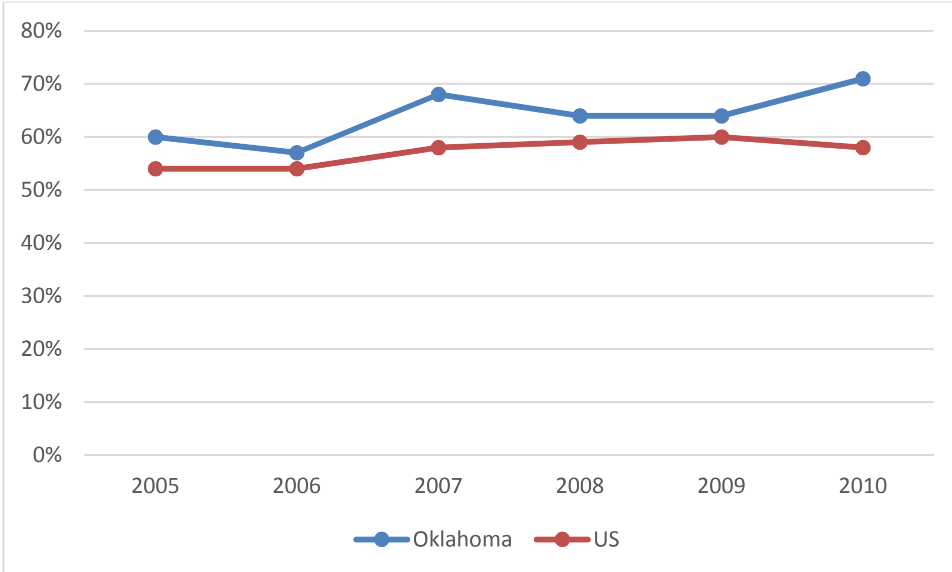

Figure 8. Oklahoma Roadway Departure Fatalities as Percent of Total Fatalities [FARS, 2013]

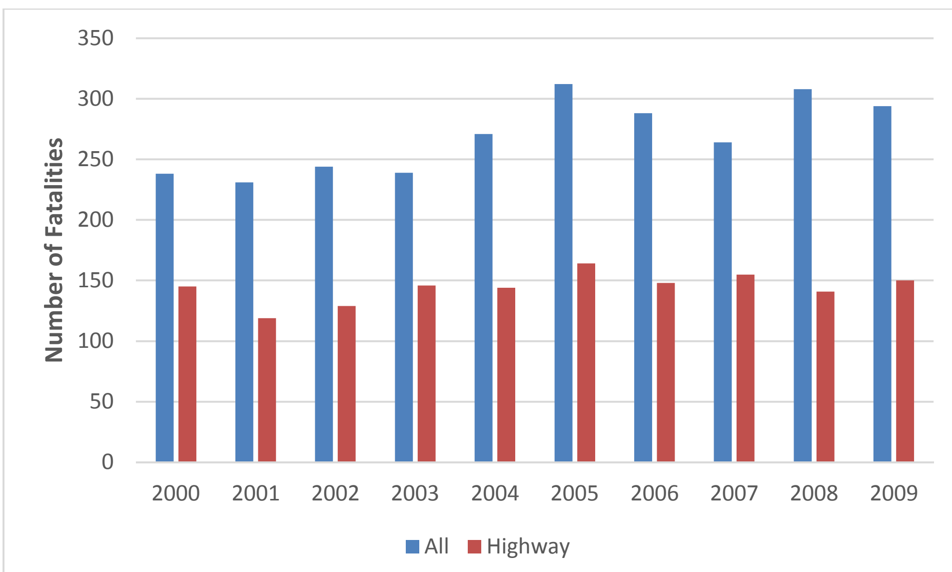

Figure 9. Oklahoma Roadway Departure Fatal Crashes [FARS, 2013]

The existing programs and strategies in Oklahoma that are being undertaken to reduce roadway crashes are [Oklahoma Strategic Highway Safety Plan, 2007]:

Table 1. Current Safety Improvement Programs in Oklahoma

Category	Current Strategy
Pavement Marking	Improving centerline and edgeline
	Installing Thermoplastic Pavement Markings
	High Friction Surface Treatments
	Pavement Preservation Programs
Roadway Improvement	Installing Rumble Strips
	Installing Cable Barriers
	Installing Guardrails and Median Barriers
	Paving and Widening shoulders
	Improving Sight Distances
Traffic Signs	Improving Night Inventory of Signs
	Installing Solar-Powered Flashing Light System
	Linking High Ranked Intersections through GIS
	Improving Intersection Lighting
	Installing Warning and Advisory Speed Signs
Roadside Improvement	Tree Removal
	Modifying Side Slopes

2.4 Crash Prediction Models

In the last few decades numerous accident-prediction-models have been developed to evaluate the impact of multiple roadway variables, including traffic, roadway signage, pavement surface, geometrics and roadside conditions on a standard crash indicating factor such as the crash frequency (crashes per year) or crash rate (crashes per million vehicle-kilometers). Such models are heavily used in commercial tools and software used in safety management and are relied upon by decision makers for making investments in safety.

2.4.1 Linear Regression Model

Okamoto (1989) and Miaou (1993) were among the first to use linear regression models for crash prediction. However, over time, it has been widely accepted by researchers that linear regression models are unsuitable to depict crash data because they lack the necessary distributional properties to model the discreteness and randomness of crash events and they rely only on normal distribution parameters (Miao et al., 1994). Also, linear models have not been found suitable for crash modeling since the error parameters of crash data are not typically normally distributed which is inherent in linear modeling (Jovanis et al., 1985).

2.4.2 Bayesian Regression Model

Persaud et al., (1999), Hauer et al., (2002), Miaou and Song, (2005), Ozbay and Noyan, (2006) first used Empirical Bayes method for crash prediction. To support traditional Bayesian models, many researchers have used techniques such as Markov Chain Monte Carlo simulation including Gibbs sampler and M-H algorithm for crash prediction Analysis (Hastings et al., 1970, Tanner and Wong. 1987, Gelfand and Smith. 1990).

2.4.3 Negative Binomial (NB) Regression Model

Dahir and Gramling (1990, FHWA 1990) used Poisson and NB regression to evaluate that 13.5 percent of fatal crashes and 18.8 percent of all crashes occur on wet pavement surfaces.

Knuiman et al. (1993) used Negative Binomial regression to investigate the effect of median width of four-lane roads on crash rates. The results showed a negative correlation between median width and crash rates and a reduction in roadway crossover accidents with increased median width.

Shankar et al. (1996) also used the Negative Binomial approach to investigate the effect of roadway geometrics and environmental factors. Their results showed that the density of horizontal curves (curves per mile) played an important role in the number of overturning crashes and that precipitation or snowfall increased crash rates on curves.

Streff and Kostyniuk (1997) used NB regression to estimate crash relationship with functional class, number of lanes and speed limit. They estimated two-lane rural collector and local frontage roads with speed limit of 55 mph to have the highest crash incidence rates.

Abdel-Aty and Essam Radwan (2000) used the NB model with AADT, horizontal curvature, section length, number of lanes, shoulder and median widths as predictor variables. Results showed that crash frequency increased with AADT, horizontal curvature and section length and decreased with lane, shoulder and median width.

Anastasopoulos, Tarko, and Mannering (2008) estimated several significant influences of pavement conditions, highway geometrics, and annual average daily traffic (AADT) on accident rates using NB regression analysis.

Chan, Huang and Richards (2010) used NB models to correlate between pavement surface condition and crash rates with Rut Depth, IRI and PSR as the indicator variables. The objectives of the study was to integrate the results with the Pavement Management System

(PMS) for safety management in Tennessee. The PSR model was seen to show a better goodness-of-fit result than IRI and RD.

2.4.4 Poisson Regression Model

The Poisson model has been used in several crash studies; Miaou (1994), Miaou, Hu, Wright, Rathi, and Davis (1992), and Miaou and Lum (1993) implemented Poisson regression to estimate truck crash rates with traffic and geometric characteristics of roads as generalized linear model variables to validate a relationship between truck accidents and geometric designs of roads.

Persaud and Dzbik (1993) initiated the Poisson GLM in their study of the relationship between AADT and hourly traffic volume (VH) with crash rates on multilane freeways. Results showed a positive correlation between crash rate and traffic volume on freeways with four or more lanes.

Miaou et al. (1994) proposed that AADT per lane, horizontal curvature, and mean absolute grade or vertical alignment had significant impact on truck crash rates.

Saccomanno, Grossi, Greco, and Mehmood (2001) developed a Poisson model to estimate expected crash frequency along homogeneous segments of highway sections in southern Italy using crash and road geometric data from 1993 to 1999. Since the AADT was uniform for entire road sections, length of road segments was used to measure crash vulnerability and the study found that the length of the section, number of private driveways, number of major intersections, and the change in 85th percentile speed from the previous road section showed greatest correlation with crash frequency.

Ossiander and Cummings (2002) used Poisson regression to analyze the relationship between fatal crash rates and posted speed limits. The results of their study showed a 110% increase in fatal crash rates after the speed limit was increased from 55 mph to 65 mph.

Ma et al. (2006) used a benefit-cost analysis to evaluate the effectiveness of a speed limit increase from 55 mph to 65 mph on highway safety. From Poisson regression analysis it was reported a 10 mph speed limit increase would increase the injury crash rates by 11.3%. This would mean more injury costs, medical, insurance and emergency costs, lost productivity and property damage costs. On the other hand, reduction in travel time due to such an increase in speed limit would translate to huge economic savings. The study estimated the Benefit-Cost ratio to be 2.3.

Caliendo et al. (2007) used Poisson for modeling crash with pavement surface conditions in Italy. Their results showed that wet pavement surface, after rainfall event, increased chances of crash by 132% for tangents and 270% for curves.

Recently, there has been an effort to analyze traffic crash data from the FARS database for state highways in Oklahoma (Comer et al., 2012) using Poisson and Negative Binomial regression models.

2.4.5 Zero Inflated Regression Models

In addition to Poisson and Negative Binomial models, Zero-inflated regression models (Mullahy, 1986; Lambert, 1992 and Greene, 1994) have also been used for crash modeling. These models are suitable when several observations have zero probability of experiencing a crash. Miaou (1994) compared Poisson, Poisson-gamma, and Zero-inflated models for modeling truck crash rates and found ZI models to perform better when the data had high overdispersion.

2.4.6 Selection of Model for Regression Analysis

Among the available statistical models, the Poisson regression model was chosen for regression analysis in the present study as it was most aptly-suited to model crash data because the dependent variable, number of crashes, can be considered as a variable with properties that are Poisson-distributed in a given space-time confinement, and hence they are well accepted for modeling discrete and rare events such as crash occurrence. The structure of the Poisson model is discussed briefly in Chapter IV.

CHAPTER III

TOOLS FOR HIGHWAY SAFETY MANAGEMENT

3.1 Introduction

In this chapter, three nationally developed safety management tools namely Highway Safety Manual (HSM), Interactive Highway Safety Design Model (IHSDM) and Safety Analyst are reviewed along with their individual components, data needs and their role in safety management. Thereafter, a case study is conducted to evaluate the goodness-of-fit of the crash prediction model of HSM and IHSDM with historical Oklahoma crash data. The results of this study will be useful for future implementation and local calibration of the nationally developed tools in Oklahoma's safety management process.

3.2 Safety Analyst

AASHTOWare Safety Analyst [AASHTO, 2012] is a state-of the art tool for comprehensive analysis and management of highway safety. It was developed by FHWA through a Transportation-Pooled-Fund study in collaboration with state and local agencies. It is a suite of tools that includes all the facets of roadway safety management process together with the inclusion of the Empirical Bayes technique for determining traffic safety.

It uses new effective measures and statistical methodologies to implement network screening analyses using numerous measures or indices of the potential for safety improvement, based on expected crash frequency or excess crash frequency and on assessment of the overrepresentation of specific crash types. Safety Analyst comprises sis discrete modules that are used to analyze safety performance of specific sites, propose appropriate countermeasures, quantify their expected benefits and costs, and estimate their effectiveness:

- The *Network Screening Module* helps identify potential sites for safety improvement. It employs the Empirical Bayes (EB) algorithm to estimate sites with higher-than-expected crash frequencies that pose safety threats using regression-to the-mean bias parameter.
- The *Diagnosis Module* assists users in understanding the nature of problems at specific sites by using collision diagrams to generate crash patterns and assessing whether these patterns represent higher-than-expected frequencies of particular collision types.
- The *Countermeasure Selection Module* aids in the selection of the appropriate countermeasures based on the crash patterns identified by the diagnosis module.
- The *Economic Appraisal Module* performs three types of economic appraisals of proposed countermeasures: cost-effectiveness, benefit-cost ratio, and net present value analyses. The sites are ranked using the *Priority Ranking Module* based on the results of the economic appraisals.
- The *Countermeasure Evaluation Module* evaluates the effectiveness of the countermeasures by comparing before and after results.

Safety Analyst requires four broad categories of input data: Roadway Segment Characteristics, Intersection Characteristics, Ramp Characteristics, and Crash data**.** Figure 10 provides a detailed description of all the input data elements:

Roadway Segment Characteristics Data	Intersection Characteristics Data	Ramp Characteristics Data	Crash Data
• Segment number • Segment location (in a form that is linkable to crash locations) • Segment length (mi) • Area type (rural/urban) • Number of through traffic lanes (by direction of travel) • Median type (divided/undivided) • Access control (freeway/non-freeway) • Two-way vs. one-way operation • Traffic volume (AADT)	• Intersection number • Intersection location (in a form that is linkable to crash locations) • Area type (rural/urban) • Number of intersection legs • Type on intersection traffic control • Major-road traffic volume (AADT) • Minor-road traffic volume (AADT)	• Ramp number • Ramp location (in a form that is linkable to crash locations) • Area type (rural/urban) • Ramp length (mi) • Ramp type (on-ramp/off-ramp/freeway-to-freeway ramp) • Ramp configuration (diamond/loop/directional etc.) • Ramp traffic volume (AADT)	• Crash location • Date • Collision type • Severity • Relationship to junction • Maneuvers by involved vehicles (straight ahead/left turn/right turn/etc.)

Figure 10. Safety Analyst Data Requirements

Safety Analyst is equipped with a Data Management Tool, Analytical Tool, and Implemented Countermeasure Tool to perform the complete roadway safety management process. Crash location mapping is conducted on one of the four location reference systems: Route/County/Milepost, Route/Milepost, Section/County/Distance, or Section/Distance [Khanal and Paz, 2014]. Recently, a visualization system was developed for Safety Analyst at the University of Nevada Las Vegas [Khanal and Paz, 2014]. The visualization system sought to utilize the spatial component of the output data of Safety Analyst using ArcGIS and Google Maps and it was equipped with multiple GIS functions including zoom in, zoom out, pan, and select sites that added to its graphical display feature. The visualization system was rated high in terms of effectiveness and usability.

3.3 Highway Safety Manual

The Highway Safety Manual [AASHTO, 2010] is a state-of-the-art highway safety tool that is primarily used for site-specific safety analysis. It is useful in identifying sites which need safety improvement, evaluating safety conditions, identifying potential remedies, and prioritizing and scheduling treatment strategies (3). Roadway safety incorporates an analytical data-driven methodology for quantifying the potential effects of decisions made in planning, design, operations and maintenance on future crashes using statistical computations. The HSM has evolved from a tool capable of conducting “descriptive analyses” to a tool capable of carrying out “predictive analyses” by calculating expected number and severity of crashes at sites with similar geometric and operational characteristics for existing conditions, future conditions and/or roadway design alternatives. The HSM is divided into the following four parts:

- Part A (Introduction, Human Factors, and Fundamentals) emphasizes the purpose and scope of the HSM and implementing the HSM for planning, design, operations, and maintenance activities. The fundamentals of the HSM processes and tools are described. Chapter 3 (Fundamentals) provides basic information needed to apply the crash prediction method and crash modification factors. The chapters in Part A are: Introduction and Overview, Human Factors and Fundamentals.
- Part B (Roadway Safety Management Process) includes a holistic view of the roadway safety management process. The components of Part B include Network Screening, Diagnosis, Countermeasure Selection, Economic Appraisal,

Prioritization of Projects and Safety Effectiveness Evaluation.

- Part C (Predictive Method) comprises the Crash Prediction Model. It includes a predictive method for analyzing average crash frequencies of a network or site using Safety Performance Functions (SPFs) for Rural Two-Lane, Rural Multilane and Urban and Suburban Arterial roadway classes.
- Part D (Crash Modification Factors) includes a methodology for incorporating Crash Modification Factors (CMFs) to quantify the reduction in crash frequency as a result of implementation of countermeasures on roadway segments, intersections, interchanges and special facilities.

3.4 Interactive Highway Safety Design Model

The Interactive Highway Safety Design Model (IHSDM) [FHWA, 2009] is a suite of software analysis tools developed by Federal Highway Administration (FHWA) to evaluate safety and operational effects of geometric design decisions on highways. It can be used as a support tool which estimates the impact of design decisions on safety throughout the road project, from the feasibility studies to the final inspection. Each module of IHSDM evaluates an existing or proposed geometric design from a different perspective and estimates measures describing one aspect of the expected safety and operational performance of the design. The suite of IHSDM tools includes the following evaluation modules:

- Policy Review Module (PRM) - The Policy Review Module checks a design relative to the range of values for critical dimensions recommended in AASHTO design policy.

- Crash Prediction Module (CPM) - The Crash Prediction Module provides estimates of expected crash frequency and severity.
- Design Consistency Module (DCM) - The Design Consistency Module estimates expected operating speeds and measures of operating-speed consistency.
- Intersection Review Module (IRM) - The Intersection Review Module leads users through a systematic review of intersection design elements relative to their likely safety and operational performance.
- Traffic Analysis Module (TAM) - The Traffic Analysis Module estimates measures of traffic operations used in highway capacity and quality of service evaluations.

Similar to Safety Analyst the crash prediction model in HSM and IHSDM also has intensive data requirements. The following table summarizes the list of data items required to run the crash prediction analysis:

Table 2. Data Requirements for HSM and IHSDM's CPM

Data Element	Attributes
Station (ft.)	Starting and Ending
Functional Class	2-Lane Rural, 4-Lane Rural, Urban Multilane
Evaluation Time	Start and End Year
Empirical Bayes Crash History Evaluation	Site Specific, Whole Project
Crash History	Severity, Year, Type, Location and Relation to Junction
Lane	Begin and End Width, Centerline Offset, Superelevation, Cross Slope
Surface	Material Type, Construction Date
Shoulder	Start and End Cross Slope, Start and End Width, Material Type, Presence of Rumble Strips
Roadside	Start and End Cross Slope, Roadside Hazard Rating
Traffic	AADT for Start and End Year

3.5 Description of the Crash Prediction Model in HSM and IHSDM

The Crash Prediction Model used in the HSM and IHSDM was created by Harwood et al. This model was initially developed to predict collisions on two-lane rural highways. It estimated the expected future frequency and severity of crashes for existing geometric design and traffic characteristics. The model was created by using negative binomial regression using data taken from Minnesota and Washington. To enhance the initial model, a calibration method was derived by Harwood et al. which contained two levels for which calibration could be performed. The Crash Prediction Module in the new beta version of the IHSDM implements the Highway Safety Manual (HSM) Part C predictive methods for evaluating rural 2-lane highways, rural multilane highways, urban/suburban arterials and urban freeways. The present version of IHSDM is embedded with the Empirical-Bayes based regression for site-specific and whole project analysis that allows the user to enter historical crash data based on the type and severity of crash. The software is incorporated with the Route/Milepost Linear Referencing System whereby a milepost value is assigned along the route of a particular facility. For example, the location of a roadway segment is provided with name or route number and its numeric begin and end milepost value. The figures shown below provide information on the crash prediction procedure.

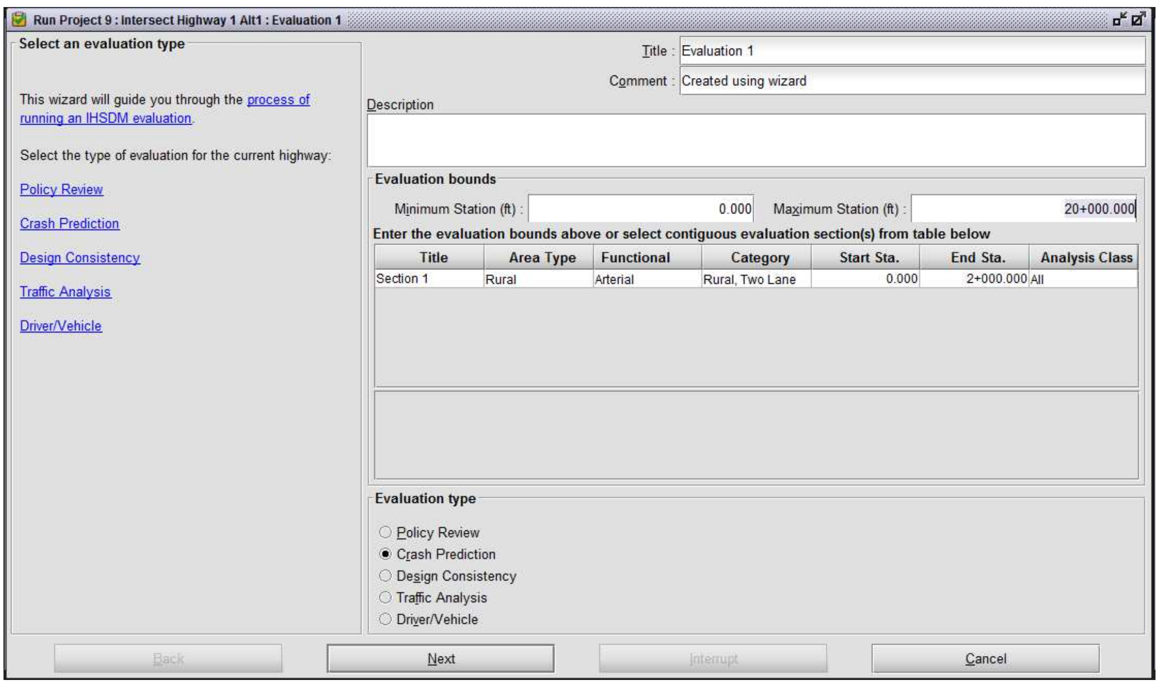

Figure 11. IHSDM Evaluation Type [FHWA, 2011]

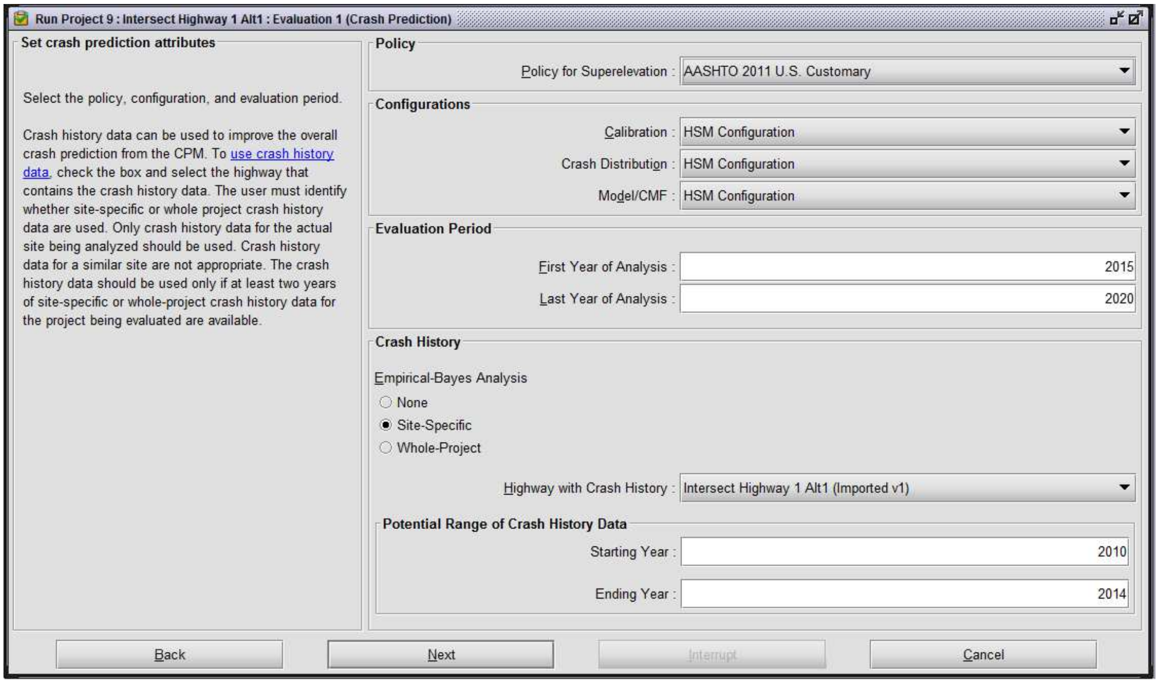

Figure 12. IHSDM Crash History Analysis [FHWA, 2011]

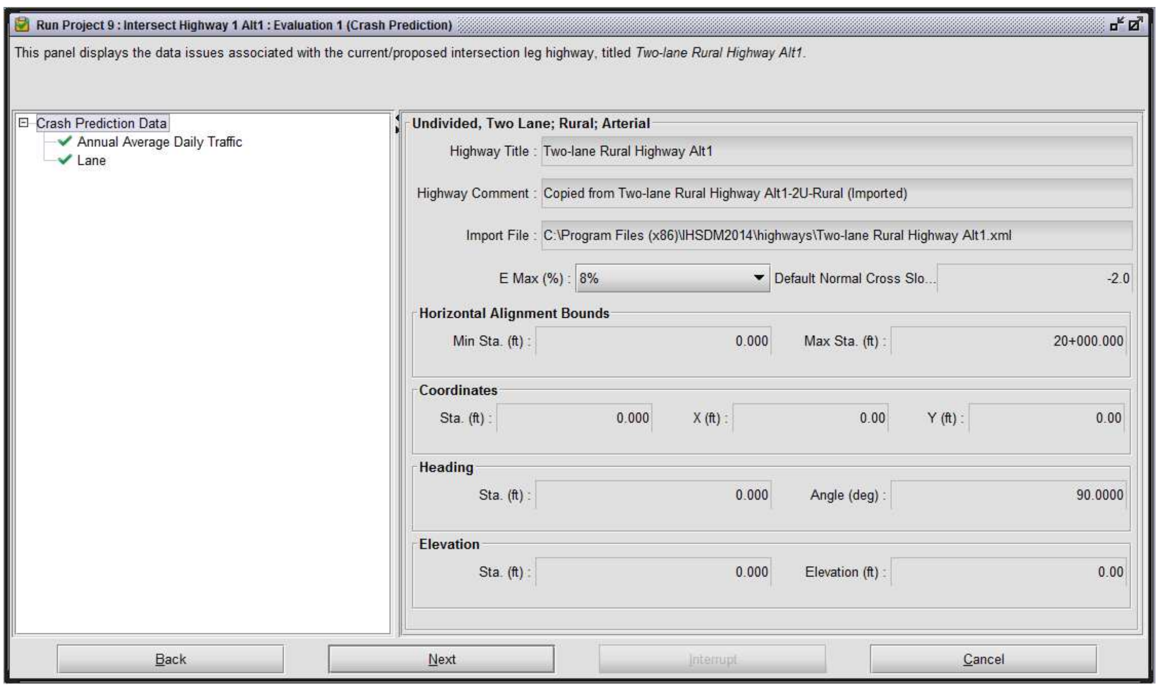

Figure 13. IHSDM Input Data [FHWA, 2011]

First Year of Analysis	2015
Last Year of Analysis	2020
Evaluated Length (mi)	0.3788
Average Future Road AADT (vpd)	500
Expected Crashes	
Total Crashes	3.69
Fatal and Injury Crashes	1.48
Fatal and Serious Injury Crashes	0.80
Property-Damage-Only Crashes	2.22
Percent of Total Expected Crashes	
Percent Fatal and Injury Crashes (%)	40
Percent Fatal and Serious Injury Crashes (%)	22
Percent Property-Damage-Only Crashes (%)	60
Expected Crash Rate	
Crash Rate (crashes/mi/yr)	1.6249
Fatal and Injury Crash Rate (crashes/mi/yr)	0.6499
Fatal and Serious Injury Crash Rate (crashes/mi/yr)	0.3501
Property-Damage-Only Crash Rate (crashes/mi/yr)	0.9750
Expected Travel Crash Rate	
Total Travel (million veh-mi)	0.41
Travel Crash Rate (crashes/million veh-mi)	8.90
Travel Fatal and Injury Crash Rate (crashes/million veh-mi)	3.56
Travel Fatal and Serious Injury Crash Rate (crashes/million veh-mi)	1.92
Travel Property-Damage-Only Crash Rate (crashes/million veh-mi)	5.34

Figure 14. IHSDM Expected Crash Rate Summary [FHWA, 2011]

Intersection Name/Cross Road	Start Location	End Location	Length (mi)	Expected No. Crashes for Evaluation Period	Crash Rate (crashes/mi/yr)	Travel Crash Rate (crashes/million veh-mi)
	0.000	32.808	0.0062	0.092	2.4760	0.97
	32.808	273.307	0.0455	1.959	7.1683	2.81
	273.307	601.391	0.0621	0.923	2.4760	0.97
	601.391	1+155.538	0.1050	2.152	3.4180	1.34
	1+155.538	1+640.420	0.0918	1.364	2.4760	0.97
	1+640.420	1+778.904	0.0262	0.429	2.7236	1.07
	1+778.904	1+886.260	0.0203	0.445	3.6491	1.43
	1+886.260	2+283.481	0.0752	1.229	2.7236	1.07
	2+283.481	2+512.523	0.0434	0.958	3.6824	1.44
	2+512.523	2+874.898	0.0686	1.472	3.5758	1.40
	2+874.898	2+952.756	0.0147	0.241	2.7236	1.07
	2+952.756	3+301.391	0.0660	0.981	2.4760	0.97
	3+301.391	3+703.461	0.0761	1.519	3.3254	1.30
	3+703.461	3+994.938	0.0552	1.068	3.2256	1.26
	3+994.938	4+265.092	0.0512	0.760	2.4760	0.97
	4+265.092	4+507.470	0.0459	0.791	2.8722	1.12
	4+507.470	4+564.731	0.0108	0.993	15.2673	5.98

Figure 15. IHSDM Expected Crash Rate by Segment [FHWA, 2011]

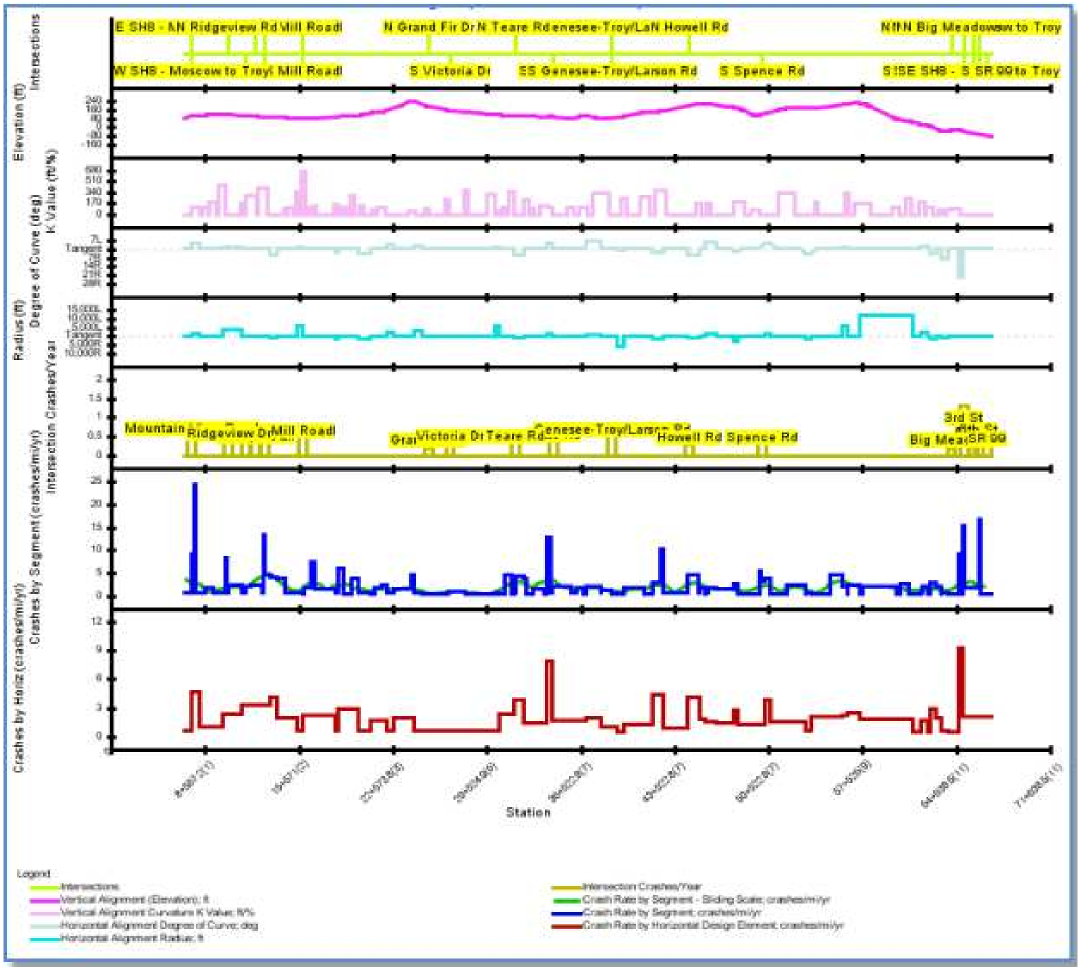

Figure 16. IHSDM Expected Crash Prediction Summary [FHWA, 2011]

3.6 Case Study of HSM/IHSDM's Crash Prediction Model using Oklahoma Data

3.6.1 Methodology

In this study the Crash Prediction Model of IHSDM and HSM was applied to rural and urban highways in Oklahoma to evaluate the capability of the model to fit the observed crash history in a typical Oklahoma context. IHSDM has a built-in Empirical-Bayes calibration method which utilizes previous collision history and has the predicted number of collisions conform more to the historical values. The crash prediction model used in the present study was not calibrated. Test segment data including the test segment length, start and end stations, the analysis period (years), superelevation, cross slope, AADT, lane width, shoulder width, horizontal & vertical alignment, design speed limit, driveway density, roadside hazard rating were obtained from the HPMS database, the Oklahoma Traffic Count Information System & AADT Maps Database using Linear Referencing System. For some of the data items IHSDM default values were used as no specific data was available.

In the present study, the crash prediction model was evaluated using three tests of goodness-of-fit namely the mean prediction bias (MPB), the mean absolute deviation (MAD), and linear regression (R^2). The mean prediction bias (MPB) test provides a measure of the goodness-of-fit of the model by comparing the overall difference between the test data and the actual historical data, as well as indicating the direction of the output from the historical data. A low MPB value indicates the model performs well in comparison to the historical data, whereas a high MPB value indicates poor conformance. Positive MPB rates show the model over-predicts the number of collisions, while negative MPB rates show the model under-predicts. MPB is calculated using the following formula:

$$MPB = \frac{\sum_{i=1}^{n}(Y'_i - Y_i)}{n}$$

Where,

Y'_i = predicted crash rate of the i^{th} segment,

Y_i = actual crash rate of the i^{th} segment,

n = number of segments

The mean absolute deviation (MAD) provides a similar goodness-of-fit comparison as the MPB test does; however, the MAD model uses an absolute format to give the average difference in prediction of the model, therefore negative and positive differences in prediction do not cancel each other out. Like the MPB, values closer to 0 show that the model performs well when compared to historical data whereas higher values indicate weak conformity. MAD is calculated using the following formula:

$$MAD = \frac{\sum_{i=1}^{n} |Y'_i - Y_i|}{n}$$

Where,

Y'_i = predicted crash rate of the ith segment,

Y_i = actual crash rate of the ith segment,

n = number of samples

Lastly, linear regression can be used to establish a direct linear relationship between the model output and the observed collision data when plotted against one another. The model is represented as:

$$Y = b.X + a$$

Where,

Y = predicted number of collisions

X = historical number of collisions,

a = y-intercept and b = slope of the linear line

An intercept close to 0 and a slope close to 1 highlights a strong fit between the model and the empirical data. The R^2 coefficient is a significant indicator of goodness-of-fit in a linear regression. It always takes a value between 0 and 1 wherein higher the value greater is the goodness-of-fit. For each analysis scenario, the figure contained two lines. First, the 45-degree line was plotted that would occur if the model results perfectly fitted the actual crash frequencies and secondly, the best fit regression line was plotted.

3.6.2 Case Study Sites

Three sites were examined using the IHSDM software: a rural 2-lane highway, a rural 4-lane highway and an urban arterial highway. The sites were randomly chosen from different geographical areas in the state that had high crash rates in the last three years (greater than 1.5 crash/mile/year). In addition, the three sites had different roadway terrains, lane & shoulder width, horizontal & vertical alignment, cross slope, superelevation, and roadside hazard rating essential to maintain diversity in analysis and to reduce bias. For crash analysis, the each of the three highway locations was divided into 25 sections, each section having a length of 2000 ft. The first section had a beginning milepoint of 0+00.00 and ending milepoint of 20+00.00 adhering to the linear referencing system used in IHSDM 10.1.0 for section identification of crash locations. Historical crash data in Oklahoma was obtained from the Fatality Analysis and Reporting System (FARS) database and compared to the IHSDM predicted output. Table 3 summarizes the three crash locations.

Table 3. Summary of the 3 Locations Used in Case Study

	Location 1	**Location 2**	**Location 3**
Route Name	US Highway 259	Oklahoma SH-20	Interstate 44
Reference GPS Coordinates	34.373075° N, -94.739780° W	36.307441° N, -95.526063° W	36.08882778° N, -96.0210638° W
County Name, FIPS Code	McCurtain county, 89	Rogers, 131	Tulsa/Creek, 89
Highway Functional Class	2-Lane Rural Principal Arterial	4-Lane Rural Arterial	4-Lane Urban Principal Arterial
Analysis Period	2011 to 2013	2011 to 2013	2011 to 2013
Beginning Milepoint	0+00.0	0+00.0	0+00.0
Ending Milepoint	500+00.0	500+00.0	500+00.0
AADT	2200 VPD from 0+00 to 280+00 and 1400 VPD from 280+00 to 500+00	11000 VPD from 0+00 to 130+00 and 12500 VPD from 130+00 to 500+00	38500 VPD from 0+00 to 175+00, 41500 VPD from 175+00 to 410+00 and 43000 VPD from 410+00 to 500+00
Length of each segment	2000 ft.	2000 ft.	2000 ft.

3.6.3 Results

IHSDM crash simulations were run for each of the 25 contiguous segments on the three locations. The results of the analysis are shown below:

Table 4. IHSDM CPM Results for 2-Lane Rural Highway

	Actual (crash/mi/yr)	IHSDM Model Results (crash/mi/yr)		
		2011	2012	2013
Average of all segments	2.273	2.748	2.802	2.805
MPB	-	0.502	0.506	0.528
MAD	-	0.765	0.776	0.784
R^2	-	0.4473	0.4482	0.4482

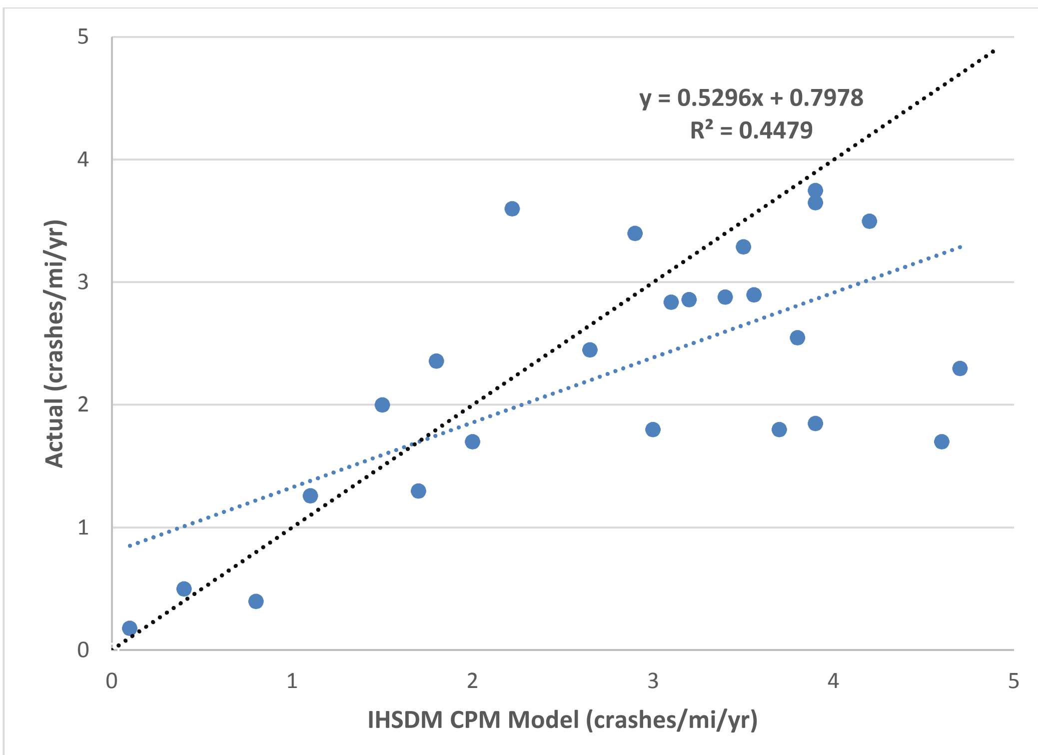

Figure 17. IHSDM Crash Prediction for 2-Lane Rural Highway

Table 5. IHSDM CPM Results for 4-Lane Rural Highway

	Actual (crash/mi/yr)	IHSDM Model Results (crash/mi/yr)		
		2011	**2012**	**2013**
Average of all segments	1.969	2.189	2.158	2.055
MPB	-	0.166	0.165	0.164
MAD	-	0.428	0.420	0.412
R^2	-	0.4515	0.4424	0.4402

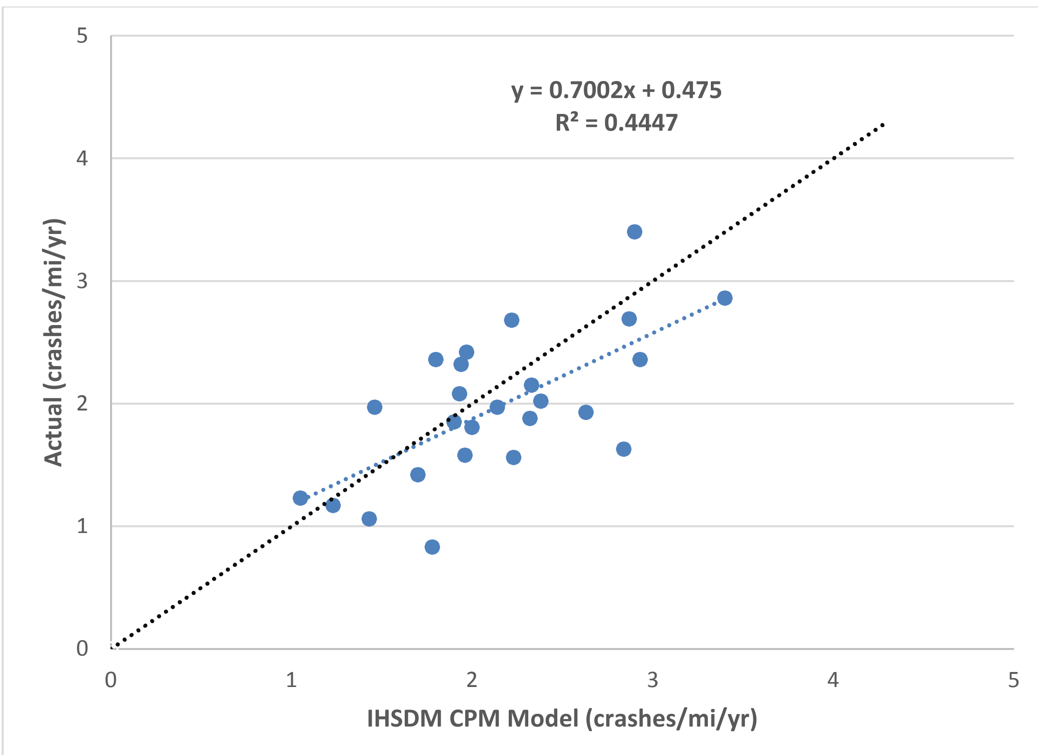

Figure 18. IHSDM Crash Prediction for 4-Lane Rural Highway

Table 6. IHSDM CPM Results for Urban Arterial Highway

	Actual (crash/mi/yr)	IHSDM Model Results (crash/mi/yr)		
		2011	2012	2013
Average of all segments	1.835	1.935	1.926	1.938
MPB	-	0.098	0.093	0.106
MAD	-	0.394	0.378	0.401
R^2	-	0.7131	0.7039	0.7214

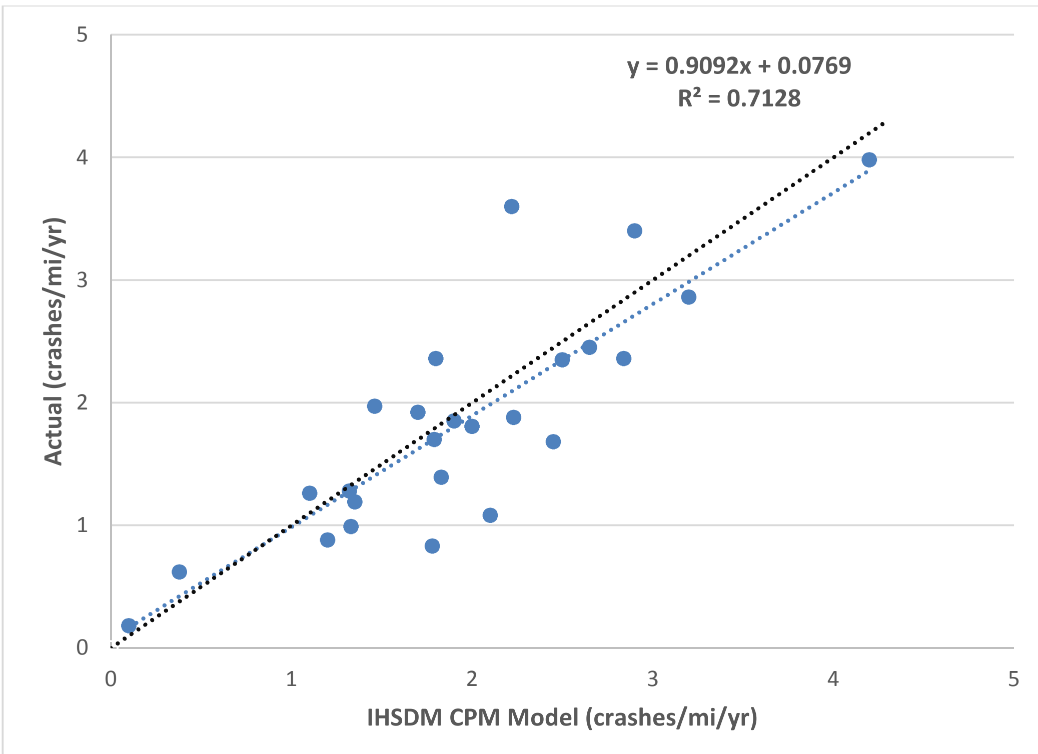

Figure 19. IHSDM Crash Prediction for Urban Arterial Highway

3.6.4 Summary

In this chapter the crash prediction model of the IHSDM and HSM was tested using Oklahoma crash data. Three locations were selected for the study. The model seemed to perform best for the urban highway with an R^2 value of 0.7128 compared to 0.4479 for two lane rural highway and 0.4447 for four lane rural highway. The model was stable with a difference between the actual collisions (crash/mi/yr) and predicted collisions (crash/mi/yr) of 5.34% for urban highway as opposed to 22.52 % for two lane rural highway and 8.38% for four lane rural highway. The MPB values for the urban highway were low and ranged from 0.093 to 0.106 indicating a good model fit however the MAD values were on the higher side ranging from 0.378 to 0.401 indicating a weaker reflection of the actual scenario. For two lane rural highway the MPB values were seen to be ranging from 0.502 to 0.508 and MAD values were seen to be ranging from 0.765 to 0.784 showing a weak prediction model fit with the observed data. A similar pattern was observed for four lane rural highway with MPB values ranging from 0.164 to 0.166 and MAD values ranging from 0.412 to 0.428 but since the values were lower than the two lane rural highway model values the four lane rural highway model showed a better fit with observed data. Overall, all the three models tended to overestimate the crash rates on Oklahoma highways. It is suggested that calibration of the crash prediction model of the software is required if it is used for safety management in Oklahoma.

There have been studies in recent years that have produced low goodness-of-fit and recommended calibration. Najjar and Mandavilli (2009) used Artificial Neural Networks (ANN) to identify relationships between highway features and safety on two-lane rural roads, rural expressways and rural freeways in Kansas using the IHSDM CPM. The rural two-lane model produced a coefficient of determination factor (R^2) of 0.4655 and the R^2 value for the total crash rate ANN model was 0.1728. Donnell *et al.* tested the IHSDM collision prediction model on two highway segments in the state of Pennsylvania over three geographic areas: county, district and state. The study found there was a large variation between the actual and estimated collision data. Marleau and Hildebrand (2010) analyzed the accuracy of the crash prediction model for two lane rural highways in Canada. The results of the study showed that calibration of the model to local conditions improved the R^2 statistic, however the overall model performed poorly with R^2 values ranging from 0.001 to 0.255.

CHAPTER IV

STATISTICAL ANALYSIS OF OKLAHOMA CRASH DATA

4.1 Introduction

In this chapter, the structure of the Poisson model is reviewed and its suitability in modeling traffic crashes is discussed. Subsequently, the data sources and the roadway data elements used in the Poisson regression analysis are listed and discussed.

4.2 Poisson Regression for Crash Analysis and Prediction

The Poisson regression model is also known as a “count model” as it estimates finite values of the dependent variable which is usually a discrete, non-negative integer in the form of crashes or fatalities. The response variable for the Poisson model is a discrete count variable exhibiting a Poisson distribution, and it is based on the assumption that the logarithm of its expected value can be modeled by a linear combination of unknown parameters [Miaou et.al, 1994; Lord et.al, 2006]. Poisson regression models are generalized linear models (glm) with the logarithm as the link function. However, a setback of using Poisson regression is that the variance of the dataset is restrained to be equal to the mean. This is true only in case of data isodispersion.

It has been seen that in most real time scenarios of modeling discrete events there is always either overdispersion (variance greater than mean) or underdispersion (variance less than mean) [Lord et.al, 2006; Lord and Mannering, 2010] . However, this drawback is outweighed by the numerous advantages of using Poisson regression in modeling discrete data. The Poisson model used in the present study to map crash events is represented as below:

$$P(y_i) = \frac{e^{(-\lambda_i)}\, {\lambda_i}^{y_i}}{y_i!}$$

And,

$$E\,(Y_i) = Var\,(Y_i) = \lambda_i$$

Where

$P(y_i)$ = Probability of roadway segment i experiencing y_i crashes per time period (year);

λ_i = Poisson parameter for segment i (equal to the segment's expected mean number of crashes per year)

The Poisson parameter λ_i is extracted from a linear regression consisting of multiple explanatory (independent) variables (X_j) representing highway attributes. It can be represented as:

$$\lambda_i = \exp\ (\beta_0 + \sum_{j=1}^{n} \beta_j\, x_j)$$

Where

β_0 = Intercept of the model

β_j = Coefficients to be estimated;

x_j = Explanatory variables;

The slope coefficient β in the above equation is used to evaluate direction and magnitude of each independent variable x_j on the number of crashes [Lord and Mannering, 2010]. It is evaluated by maximizing the likelihood function. Negative slope values for β (values less than 1 in exponential form) indicate a variable lowers the risk of crashes relative to other variables and positive values (values greater than 1 in exponential form) indicate the variable raises the risk. For the present study, Poisson regression has been used to analyze ten years of crash data on public roads in Oklahoma and correlate them with existing roadway geometry, traffic, junction, and pavement surface conditions. The major source of data for this study were the Fatality Analysis and Reporting System (FARS) database and the Highway Performance Monitoring System (HPMS) database. The state code of "40" was used to identify the state of Oklahoma. The counties were identified based on their FIPS code; there were a total of 77 counties in Oklahoma that reported crash incidents between 2004 and 2013. The models and estimators have been evaluated based on their (1) estimated regression parameters (2) associated z-statistics, (3) overall goodness-of-fit (Pearson's Chi-squared (χ^2) test).

4.3 Crash Data from FARS Database

4.3.1 Introduction to FARS

The Fatality Analysis and Reporting System [NHTSA (Revised Version), 2012] is a comprehensive national database of all roadway traffic crashes and fatalities in all 50 states of the United States for the last 20 years. The FARS program was created by the National Highway Traffic Safety Administration (NHSTA) to collect data for analyzing traffic safety information from previous crashes to identify highway safety emphasis areas and estimate countermeasures aimed at reducing fatalities, injuries and property damage resulting from motor vehicle crashes and identifying problem areas in particular locations. The FARS dataset includes descriptions, coded in standard format, of each fatal or injury crash involving a motor vehicle occurring on a public road in the US. Each crash has more than 100 coded data elements that categorize the crash, the vehicles and drivers, the people involved and pre-crash roadway and environmental conditions. This huge amount of collision data can be used in the statistical analysis of crashes, leading to a conclusive understanding of the plausible reasons for crashes in a specific geographic area. The geographic location information available in the FARS database includes the latitude, longitude, milepoint, and trafficway identifier fields. The latitude and longitude fields contain the GPS coordinates of the collision, the trafficway identifier represents the roadway on which the crash occurred and the milepoint field stores the mile point of the crash location on the roadway stretch with respect to a state boundary. For the purpose of the present study 10 years of crash data from 2004 to 2013 was analyzed for Poisson regression analysis. A summary of the number of crashes and fatalities from 2004 to 2013 is presented in Table 7. It can be noted that, despite all the safety efforts in Oklahoma, the number of crashes in any year has never decreased by more than 5 % from its preceding year except for 2006. Also, the number of fatalities have steadily increased since 2010.

Table 7. Oklahoma Crashes and Fatalities

Year	Crashes	Fatalities	Percent Increase or Decrease in crashes from Last Year
2013	621	1517	-3.42 %
2012	643	1439	5.58 %
2011	609	1428	-1.14 %
2010	616	1391	-4.64 %
2009	646	1521	-3.87 %
2008	672	1671	3.54 %
2007	649	1705	-2.99 %
2006	669	1744	-5.91 %
2005	711	1784	7.08 %
2004	664	1762	-

4.3.2 Selection of Explanatory Variables

For the present study, only roadway variables which were considered to have an effect on the occurrence of Oklahoma crashes were chosen for statistical regression analysis. The variables obtained from the FARS database were categorical and each variable was coded into distinct categories. The list of variables included in the Poisson model are given below and a detailed description of the FARS codes of each element and its categories are provided in Appendix B.

- Relation to Junction: This data element is coded in two fields based on the location of the "first harmful event of the crash". It identifies the vehicle's crash location with respect to presence in an interchange area and with respect to its proximity to junction components.
- Vehicle Wander from Trafficway: This element indicates whether the location of the vehicle at the time of crash was within or outside the trafficway at the time of the 'First Harmful Event'. It is a measure of traffic wander from its wheel path due

to curves, low visibility, or driver inattention leading to a roadway departure crash.

- Roadway Functional Class: This element identifies the functional classification of the roadway on which the crash occurred.
- Route Signing: This element identifies the route signing of the roadway on which the crash occurred.
- Type of Intersection: This element identifies and categorizes different intersection types.
- Work Zone: This data element identifies whether the crash is a “Work Zone Accident” as defined in ANSI D16.1, 7th Edition. If the crash qualifies as a "Work Zone Accident" then its type is categorized.
- Roadway Alignment: This element identifies the roadway alignment at the time of the vehicle’s critical pre-crash event.
- Roadway Grade: This element identifies the roadway grade at the time of the vehicle’s critical pre-crash event.
- Roadway Surface Condition: This element identifies the roadway surface condition at the time of the vehicle’s critical pre-crash event.
- Roadway Surface Type: This element identifies the roadway surface type at the time of the vehicle’s critical pre-crash event.
- Speed Limit: This element identifies the speed limit at the time of the vehicle’s critical pre-crash event.
- Total Lanes in Roadway: This element identifies the number of travel lanes at the time of the vehicle’s critical pre-crash event.
- Traffic Control Device: This element identifies the operational traffic controls in

the vehicle's environment at the time of the vehicle's critical pre-crash event.

- Trafficway Description: This element identifies the trafficway flow type at the time of the vehicle’s critical pre-crash event.

4.4 Roadway Data from HPMS Database

4.4.1 Introduction to HPMS

The Highway Performance Monitoring System [FHWA (revised version), 2014] is a nationally maintained highway information system that comprises data on the “extent, condition, use, performance, and operating characteristics of the nation's highways”. The HPMS contains critical inventory data of all public roads and each state is required to annually furnish roadway data following the specifications in the HPMS Field Manual to FHWA to be eligible for Federal-aid highway funds. In order to support the data geospatially each State's Geographic Information System (GIS) based spatial data is attached to the HPMS data in the form of an ESRI GIS shape file, which contains a Linear Referencing System (LRS) for reporting the State's road network in the HPMS. The state’s roadway characteristics are organized by geographical location on the roadways using Oklahoma’s control section/milepoint location system. While the location information in the FARS database consists of latitude/longitude based GPS coordinates, the HPMS is geographically referenced using the state code of “40”, the subsequent county FIPS code, Route ID, Section ID and milepoint. In this study, effort was taken to ensure that the locations were identified to the closest possible effect while matching the FARS and HPMS databases geospatially.

4.4.2 Selection of Explanatory Variables

Only the variables which had a high incidence rate and which are intrinsically tied to roadway safety were chosen for regression. The variables obtained from the HPMS database were divided into continuous and categorical. The following continuous data components were included [HPMS Field Manual, 2014]:

- Annual Average Daily Traffic (vehicle/day): The AADT value obtained represents average annual daily traffic volume on the roadway where the crash occurred. If the AADT data cannot be reported for any segment, a standard sample or donut sample AADT is reported in its place in the HPMS. AADT is adjusted with day of week, seasonal, axle correction and growth factors if the AADT is not extrapolated from current year counts. AADTs on NHS, Interstate, and Principal Arterials are based on a minimum of 48-hour traffic counts taken on a three-year cycle.
- Percent Peak Single-Unit Trucks and Buses (%): It provides the peak hour single-unit truck and bus volume as a percentage of the total AADT. The coding of this item is based on truck classification data in conformance to FHWA's Traffic Monitoring Guide for truck classes 4 through 7. The data collection is based on traffic counts taken on a minimum three-year cycle. The percent of peak single-unit trucks and buses is calculated by dividing the number of single-unit trucks and buses during the hour with the highest total volume (the peak hour) by the AADT.
- Percent Peak Combination Trucks (%): It provides the peak hour combination truck volume as a percentage of total AADT. The coding of this item is based on truck classification data in conformance to FHWA's Traffic Monitoring Guide for truck classes 8 through 13. The data collection is based on traffic counts taken on a

minimum three-year cycle. The percent of combination trucks is calculated by dividing the number of combination trucks during the hour with the highest total volume (the peak hour) by the AADT.

- Volume/Service Flow Ratio (VSF): It is defined in the HPMS as the ratio of the actual peak hour flow rate in vehicles per hour to the maximum hourly rate of flow at which vehicles can travel under prevailing roadway, traffic, and control conditions. It reflects peak hour congestion for a sample section. For traffic planning purpose, a VSF value greater than 0.80 indicates a congested roadway segment. The VSF value is used in transportation investment to estimate needed capacity improvements and for congestion delay analysis.
- Lane Width (ft.): It is a measure of existing lane width on a roadway section. Lane width is coded based on where the pavement/shoulder surface changes, or according to the pavement lane striping if the shoulder and pavement surface are the same, or according to traffic use and State/local design guidelines if no striping or only centerline striping is present.

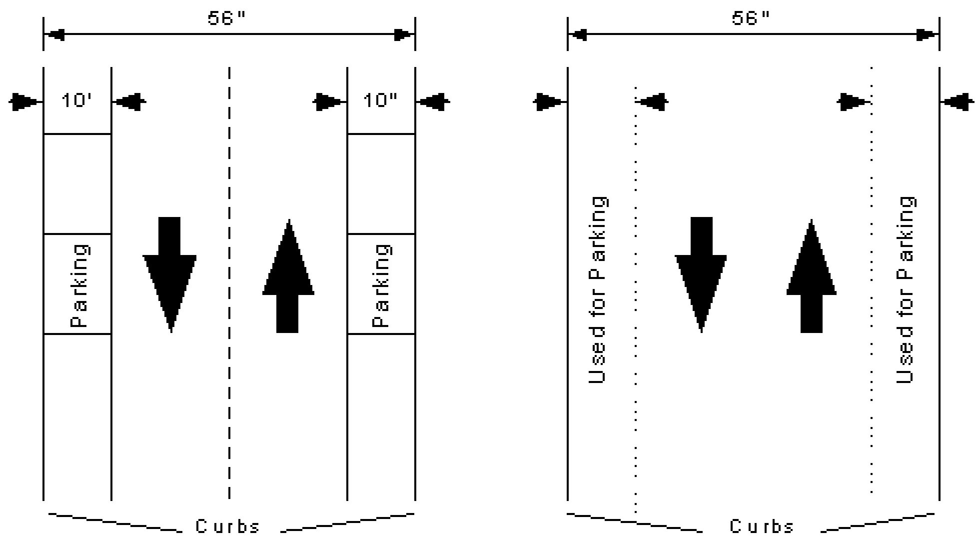

Figure 20. Typical Lane Profile [HPMS, 2014]

- Median Width (ft.): This item is a measure of existing median width on sample roadway sections. It is also used in transportation planning to analyze traffic capacity and to select roadway design type.

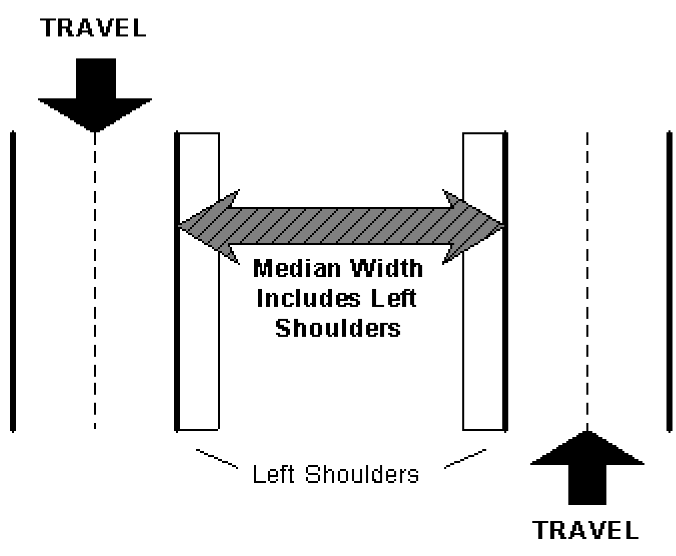

Figure 21. Typical Median Profile [HPMS, 2014]

- Shoulder Width (ft.): The shoulder width is coded into two separate items right (outside) shoulder width and left (inside) shoulder width. In the present study, only the right shoulder width was considered as previous research showed that left shoulder width had little impact on crashes.

The following categorical data components were included from the HPMS database for the regression analysis:

- Median Type: This item characterizes the type of median on the roadway section. Turning lanes or bays are not considered medians unless they are cut into an existing median at intersections or entrance drives.
- Shoulder Type: This item characterizes the type of shoulder on the roadway section. If the shoulder type changes back and forth along the length of the section, the predominant type is coded. If left and right shoulder types differ on a divided facility, the right shoulder type is coded as the predominant type.

4.5 Data from Oklahoma Pavement Management System Database

The following data elements were obtained from the Oklahoma PMS database:

- International Roughness Index (inch/mile): The IRI data is coded into the PMS based on the AASHTO Standard Practice for Determination of International Roughness Index for Quantifying Roughness of Pavements, AASHTO R 43-07. It requires that the longitudinal profile be measured following ASTM E 950 for estimating IRI. Roughness is reported in the units of inches/miles. Roughness data is reported for all sections in a route and IRI data is collected on a maximum of 2-year cycle. To maintain accuracy in data, IRI sections reported are not greater than 0.10 mile in length.
- Present Serviceability Rating (PSR): It provides information on pavement condition on selected roadway sections. The PSR is a score based on the rating of

the pavement ride quality by a panel of observers. This information is correlated to various pavement performance measures such as cracking, rutting, patching, faulting etc. and the final output is in the form of a score from 0 to 5. It is used in as a tool for investment decisions for estimating pavement deterioration, section deficiencies and identifying needed preservation/improvements. Present Serviceability Rating (PSR) is correlated to pavement surface characteristics using the following equation [AASHO Road Test Report, 1962]:

$$PSR = 5.03 - 1.91 \log(1 + SV) - 1.38RD^2 - 0.01\sqrt{C + P}$$

Where,

SV = slope variance, RD = Rut Depth, C = cracking (ft^2/1000 ft^2), P = Patching (ft^2/1000 ft^2)

- Rut Depth (in.): It is defined as a "longitudinal surface depression in the wheel path and it may have associated transverse displacement." The average rut depth data is collected on a two-year cycle for PMS reporting purpose.

CHAPTER V

RESULTS

5.1 Poisson Model Summary and Results

The roadway variables from FARS and HPMS databases were categorized as categorical and continuous variables based on their attributes and roadway inventory database requirements. Table 8 summarizes the dataset used for this research. The number of sub-categories for each categorical variable is also given. The R Statistical Software was used to perform the detailed regression analysis. R contains the built in function glm () to model generalized linear models including Poisson regression [Chambers and Hastie, 1992]. The Poisson model was denoted using the keyword “Poisson” and a predictor was represented as a categorical variable by using the keyword “factor”.

Table 8. Summary of Roadway Variables

Variable	Type	Number	Data Source
Relation to Junction: Specific Location	Categorical	6	FARS
Relation to Junction: Within Intersection?	Categorical	2	FARS
Wander from Trafficway	Categorical	7	FARS
Roadway Functional Class	Categorical	12	FARS
Route Signing	Categorical	7	FARS
Intersection Type	Categorical	6	FARS
Work Zone	Categorical	5	FARS
Roadway Alignment	Categorical	3	FARS
Roadway Grade	Categorical	6	FARS
Surface Condition	Categorical	8	FARS
Surface Type	Categorical	10	FARS
Speed Limit	Categorical	12	FARS
Traffic Lanes	Categorical	7	FARS
Control Device	Categorical	11	FARS
Traffic Description	Categorical	7	FARS
Median Type	Categorical	4	HPMS
Shoulder Type	Categorical	6	HPMS
AADT	Continuous/Ratio	1	HPMS
% Single Unit Buses and Trucks	Continuous/Ratio	1	HPMS
% Multiple Unit Trucks	Continuous/Ratio	1	HPMS
IRI	Continuous/Ratio	1	Oklahoma PMS
PSR	Continuous/Ratio	1	Oklahoma PMS
Rut Depth	Continuous/Ratio	1	Oklahoma PMS
VSF	Continuous/Ratio	1	HPMS
Lane Width	Continuous/Ratio	1	HPMS
Median Width	Continuous/Ratio	1	HPMS
Shoulder Width	Continuous/Ratio	1	HPMS

A detailed summary of descriptive statistics of the categorical variables at Oklahoma crash locations are provided in Appendix B and Appendix C. Table 9 provides descriptive statistics on the 10 year summary of the continuous variables at Oklahoma crash locations used in this study. A total of 27 predictor variables were selected for regression analysis of which 17 were categorical variables and 10 were continuous variables. The data obtained from HPMS and Oklahoma PMS databases, were reported to the nearest 0.1 mile of the FARS crash locations.

Table 9. Continuous Variable Summary at Oklahoma Crash Locations

Parameter	Minimum	Median	Mean	Maximum	Standard Deviation	Coefficient of Variation
AADT (vehicle/day)	810	6900	9668	48200	5922	0.612
Single-Unit Trucks and Buses (%)	0	2.8	3.28	17	3.88	1.18
Combination Trucks (%)	0	5	7.68	38	8.07	1.05
IRI (in/mi)	45	126	118	373	26	0.22
PSR	1.6	3.08	3.17	5	0.93	0.293
Rut Depth (in)	0	0.1446	0.1482	0.8946	0.0599	0.404
VSF Ratio	0	0.32	0.41	1.57	0.30	0.731
Lane Width (ft.)	8	11	11.3	18	2.04	0.18
Median Width (ft.)	0	0	3.5	42	9.78	2.8
Shoulder Width (ft.)	0	3.2	4.8	12.5	3.09	0.64

The following goodness-of-fit statistics were used to test the model:

- Deviance: The deviance of the model is expressed as:

$$Deviance = 2\sum_{i=1}^{n}\{ y_i \; ln\left(\frac{y_i}{\mu_i}\right) - (y_i - \mu_i)\}$$

- Degrees of Freedom: The degrees of freedom of the model is given as:

$$DF = n - p$$

- Log Likelihood: The likelihood-ratio is estimated by taking the ratio of the maximum value of the likelihood function under the constraint of the null hypothesis to the maximum without that constraint. The smaller the log-likelihood ratio the better the model fit. The likelihood function is expressed as:

$$L = \sum_{i=1}^{n} y_i \, ln\,(\mu_i) - \mu_i - \ln(y_i\,!)$$

The log-likelihood is expressed as:

$$D = -2ln\left[\frac{L_{Null\ Hypothesis}}{L_{Saturated}}\right]$$

If the model fits perfectly, the likelihood would be 1, and -2 times the log likelihood would be 0.

- Akaike Information Criterion: AIC is given as:

$$AIC = -2.\ln(L) + 2.p$$

- Pearson chi-square residual (goodness of fit statistic): The chi-square residual is given as [Agresti, 2007]:

$$\chi^2 = \sum_{i=1}^{n} \frac{y_i - \mu_i}{\sqrt{\mu_i}}$$

Where,

y_i = observed crash count

μ_i = expected crash count

n = total number of observations

L = Likelihood function

p = total number of estimated parameters

After running the Poisson regression on the ten year crash data the next step was to check whether the model fit the data well and to identify overdispersion or underdispersion. Table 10 summarizes the results of the Poisson regression analysis of the ten year Oklahoma crash data. The chi-squared goodness of fit test was conducted. The scaled Deviance/DF ratio was used to measure dispersion of the data. As a rule of thumb, any generalized linear model (such as Poisson, Negative Binomial, Gamma, Zero Inflated etc.) fits well with the data if the scaled Deviance/DF ratio is about 1. Also, generally, if the size of the raw deviance exceeds twice the number of degrees of freedom it indicates poor fit. Scaling factors are applied to account for missing, latent or incomplete parameters in the input dataset that amplify the data dispersion. Miao et al. (1992) noted that overdispersion in Poisson models occur when not all the relevant predictor variables are included in the model. However, in the present study, no scaling factor was used.

The data was seen to fit well with the model, however there seemed to be an overdispersion, which indicated the variance was higher than the mean. The chi-square test of the likelihood ratio was seen to be significant to $\alpha = 0.001$. The model had a fairly small Akaike

Information Criterion (AIC) value and log-likelihood ratio indicating minimal loss of information on the population dataset.

Table 10. Poisson Regression Summary and Results

Poisson Model Parameter	Degrees of Freedom (DF)	Value	Value/DF
Number of Observations	-	6500	-
Model Intercept		0.0374	
Deviance	694	784.2	1.129
Scaled Deviance	694	784.2	1.129
Chi-Square	694	823.8	1.187
Scaled Chi-Square	694	823.8	1.187
AIC	-	1276	-
Log Likelihood	-	-96.6	-

The regression results including coefficients, Z-scores and 95 % confidence interval limits are tabulated below. The regression coefficient output was in the form of log count and positive raw coefficient values for categorical variables (less than 1 on numeric scale) indicate that the variable lowers the risk of crash or it acts as a countermeasure and variables with negative regression coefficient (greater than 1 on numeric scale) indicates the variable increases crash possibility. A simple interpretation of the Poisson regression coefficients is that if a variable has a positive coefficient it signifies for a unit increase in its value the crash count is expected to increase given all other variables in the model are kept constant. Coefficients for ratio variables can be evaluated in the similar way. Prediction modeling was used to evaluate expected crash probabilities as a function of independent roadway variables (both categorical and continuous) based on the empirical results obtained from the ten year crash history. The equations for calculating 95 % confidence lower & upper limits and the Z-value are given below:

$$\text{LL at 95 \% CI (m)} = \text{coef(m)} - (1.96 * \text{SE})$$

$$\text{UL at 95 \% CI (m)} = \text{coef(m)} + (1.96 * \text{SE})$$

$$\text{Z value (m)} = \frac{\text{Coefficient(m)}}{\text{Standard Error (m)}}$$

5.2 Regression Analysis Results of Categorical Roadway Predictor Variables

The categorical variables obtained from FARS and HPMS were divided into mutually exclusive and non-overlapping categories. The significance of the variables were evaluated using the Null Hypothesis test. Pr. (>|Z|) or the p-value is the area under the normal distribution curve for the given z-value for a two-tail null hypothesis test. A variable is considered statistically significant to the model if its p-value < 0.001. In other words, if the p-value is low enough then the null hypothesis that a variable has a zero coefficient in the model can be rejected. The p-value is computed from the Z-value using the following equation:

$$\text{Pr.}(> Z) = \ 2 * NORMDIST(-|Z|)$$

5.2.1 Relation to Junction

Results are shown in Table 11 and Table 12. Intersection locations and entrance/exit ramps exhibited positive relationship with crash rates. Railway-grade crossing, median crossover and driveway access areas were found to be insignificant to crash rates (p < 0.001). Based on estimated coefficients, crash rates would be expected to be 37 % higher at intersections than non-intersections and 6 % higher at exit/entrance ramps than non-intersections.

Previously, Lu et al, (2006) analyzed predictability of crashes in Wisconsin as a consequence of median crossovers using logistic regression and concluded that it was an insignificant determinant of crashes. Similarly, Hu et al, (2006) estimated that presence of railway-highway crossing grades only marginally affect crash rates whereas AADT and climate exposure were more significant predictors of crash rates. Similarly, non-interchange areas correlated negatively with crash rates compared to interchange areas implying that all other factors remaining constant, roadway segments near interchange areas had a 22 % more likelihood to encounter a crash than a non-interchange zone.

Table 11. Relation to Junction: Specific Location Results

Parameter	**Estimated Regression Coefficient**	**Standard Error**	**Z-Value**	**Pr. (>|Z|)**	**Lower Limit for 95% confidence interval**	**Upper Limit for 95% confidence interval**
Non-Junction*	0.0101	0.003	3.309	0.0009	0.004	0.016
Intersection*	0.3264	0.097	3.352	0.0008	0.136	0.517
Entrance/Exit Ramp*	0.0178	0.005	3.307	0.0009	0.007	0.028
Railway Grade Crossing	0.0034	0.001	2.452	0.0142	0.001	0.006
Crossover-Related	0.0182	0.008	2.386	0.0170	0.003	0.033
Driveway Access	0.1906	0.057	3.057	0.0022	0.078	0.303

Note: * signifies the variable is significant to the model ($p < 0.001$)

Table 12. Relation to Junction: Within Interchange? Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
No*	-0.0387	0.011	-3.392	0.0007	-0.061	-0.016
Yes*	0.1536	0.046	3.306	0.0009	0.063	0.245

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.2 Wander from Trafficway

Results are shown in Table 13. Vehicle wander to roadside demonstrated maximum positive impact on roadway crashes, which is logical as hazards increase many times outside the roadway zone. The parameter 'Roadside Hazard Rating' is an important element in MIRE and the IHSDM Crash Prediction Module. It is a numeric score that gives the roadside hazard condition of a roadway segment. Vehicle wander towards median showed a negative impact on crashes. Vehicle wander towards shoulder showed a positive relationship on crash rates but a lower coefficient than vehicle wander to roadside. Crashes outside trafficway, crashes in parking zone and gore crashes were found to be insignificant variables. Estimated coefficients showed that compared to the roadway, crashes would increase 16 % on shoulders and 38 % on roadside and decrease 6 % on medians.

Table 13. Wander from Trafficway Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
On Roadway	-0.0020	0.001	-3.138	0.0017	-0.003	-0.001
On Shoulder*	0.0848	0.025	3.396	0.0007	0.036	0.134
On Median*	-0.0416	-0.013	3.318	0.0009	-0.017	-0.066
On Roadside*	0.1956	0.056	3.478	0.0005	0.085	0.306
Outside Trafficway	-0.0182	0.006	-3.262	0.0011	-0.029	-0.007
In Parking Lane/Zone	-0.0346	0.011	-3.057	0.0022	-0.057	-0.012
Gore	0.0176	0.005	3.274	0.0011	0.007	0.028

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.3 Roadway Functional Class

Results are shown in Table 14. The functional classes Rural Principal Arterial – Interstate, Rural Minor Collector, Urban Principal Arterial – Interstate, Urban Principal Arterial – Freeways/Expressways, Urban Minor Arterial and Urban Collector exhibited a negative relation with crashes. Among the rural functional classes, Rural Major Collector roadways were seen to have the highest positive regression coefficient followed by Rural Minor Arterial and Rural Principal Arterial – Other. Among the urban functional classes, Urban Local Road or Street was seen to have the highest positive relation to crashes followed by Urban Principal Arterial – Other.

Table 14. Roadway Functional Class Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Rural-Principal Arterial – Interstate*	-0.0040	0.001	-3.6	0.0003	-0.006	-0.002
Rural-Principal Arterial – Other*	0.0034	0.001	3.685	0.0002	0.002	0.005
Rural-Minor Arterial*	0.0040	0.001	3.724	0.0002	0.002	0.006
Rural-Major Collector*	0.0050	0.001	3.766	0.0002	0.002	0.008
Rural-Minor Collector*	-0.0274	0.009	-3.423	0.0006	-0.045	-0.010
Rural-Local Road or Street*	0.0010	0.000	3.699	0.0002	0.000	0.002
Urban-Principal Arterial - Interstate	-0.0080	0.003	-3.118	0.0018	-0.013	-0.003
Urban-Principal Arterial - Other (Freeways or Expressways)	-0.0016	0.001	-3.106	0.0019	-0.003	-0.001
Urban-Other Principal Arterial	0.0010	0.000	3.005	0.0027	0.000	0.002
Urban-Minor Arterial*	-0.0182	0.005	-3.342	0.0008	-0.029	-0.008
Urban-Collector*	-0.0274	0.008	-3.586	0.0003	-0.042	-0.012
Urban-Local Road or Street*	0.0030	0.001	3.646	0.0003	0.001	0.005

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.4 Route Signing

Results are shown in Table 15. State highways in Oklahoma were seen to have the highest positive impact on crashes followed by U.S highways, meaning all other variables kept constant, a vehicle was 16% more likely to encounter a crash on a state highway and 12% on a U.S highway than an Interstate highway. County roads also correlated positively;

although less than U.S highways. Interstate highways exhibited a negative relationship with crash rates. Local Street Frontage Roads was found to be significant crash predictors but Local Street Municipality was not.

Table 15. Route Signing Results

Parameter	**Estimated Regression Coefficient**	**Standard Error**	**Z-Value**	**Pr. (>|Z|)**	**Lower Limit for 95% confidence interval**	**Upper Limit for 95% confidence interval**
Interstate	-0.0080	0.003	-3.722	0.0002	-0.013	-0.003
U.S. Highway*	0.0797	0.024	3.332	0.0009	0.033	0.127
State Highway*	0.1310	0.036	3.608	0.0003	0.060	0.202
County Road*	0.0630	0.019	3.339	0.0008	0.026	0.100
Local Street - Municipality	0.0020	0.001	3.084	0.0020	0.001	0.003
Local Street - Frontage Road*	-0.0111	0.004	-3.334	0.0009	-0.018	-0.004
Other	-0.0555	0.022	-2.496	0.0126	-0.099	-0.012

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.5 Intersection Type

Results are shown in Table 16. Four-way intersections and T-intersections showed the highest positive correlation to vehicle crash rates in terms of regression coefficients. Four way intersections and T-intersections on low-volume rural roads would be expected to have the highest probability of crashes. Based on estimated results, four way intersections would be expected to have 4% higher crash rates than non-intersections and T-intersections would be expected to have 2% more crash rates than non-intersections. Also, Y-intersections, roundabouts and intersections with five or more legs exhibited no significance with crash rates.

Table 16. Intersection Type Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Not an Intersection*	0.2351	0.066	3.550	0.0004	0.105	0.365
Four-Way Intersection*	0.2822	0.080	3.537	0.0004	0.126	0.439
T-Intersection*	0.2531	0.068	3.724	0.0002	0.120	0.386
Y-Intersection	-0.0020	0.001	-3.259	0.0011	-0.003	-0.001
Roundabout	-0.0040	0.001	-3.097	0.0020	-0.007	-0.001
Five-Point, or More	-0.0080	0.002	-3.224	0.0013	-0.013	-0.003

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.6 Work Zone

Results are shown in Table 17. Construction work zones and maintenance work zones exhibited positive coefficients whereas utility work zones and other work zones of unknown nature showed a negative relation with crash rates. Based on estimated regression coefficients, construction work zones would increase the crash rate by 4.5% and maintenance work zones by 3.9% compared to no-work zones. Utility work zones would be expected to reduce crash rates by 14% and other work zone types would be expected to reduce crash rates by 10% compared to no-work zones.

Table 17. Work Zone Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
None*	0.1380	0.042	3.312	0.0009	0.056	0.220
Construction*	0.1807	0.053	3.423	0.0006	0.077	0.284
Maintenance*	-0.0587	0.017	-3.388	0.0007	-0.093	-0.025
Utility*	-0.0060	0.002	-3.32	0.0009	-0.010	-0.002
Work Zone, Type Unknown*	0.0910	0.027	3.345	0.0008	0.038	0.144

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.7 Roadway Alignment

Results are shown in Table 18. Horizontal curvature indicated a positive relationship with crash frequencies in Oklahoma. Both right curves and left curves showed positive regression coefficients with right curves having a slightly higher coefficient than left curves. Right curves would be expected to increase crash rates by 35% and left curves would be expected to increase crash rates by 14% compared to straight segments. The results are in agreement with previous literature (Mohamedshah et al. 1993, Miaou 1994, Schneider et al. 2009) that also proved a positive relationship. Again, there have been studies in the past (Daniel et al. 2002, Milton and Mannering 1998) showing a significant negative correlation of horizontal curvature with crash rates. Typically, horizontal curves in Oklahoma have low curvature values (not more than 3.5% per 100 ft. of arc) and hence it should not pose a significant threat to safety. Since, in the present study, the length of the section could not be accurately determined, the steepness of the curves were unknown and so it was difficult to ascertain the effect of curvature on crash rates.

Table 18. Roadway Alignment Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Straight*	-0.0253	0.006	-3.986	0.0001	-0.038	-0.013
Curve-Right*	0.2738	0.072	3.784	0.0002	0.132	0.416
Curve-Left*	0.0630	0.017	3.706	0.0002	0.030	0.096

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.8 Roadway Grade

Results are shown in Table 19. In the present analysis, uphill and downhill roadway profiles exhibited a positive correlation with vehicle crashes in Oklahoma. An uphill road profile would be expected to increase crash rates by 15% and a downhill road profile would be expected to increase crash rates by 26% compared to level roads. Historically, absolute values of vertical grade in Oklahoma have been seen to be within 4% for major highways (HPMS, 2010). Hillcrest and sag (bottom) road profiles showed a negative correlation with crash rates. Hillcrest profiles would be expected to reduce crash rates by 1.4% and sag (bottom) profiles would be expected to reduce crash rates by 0.9 % compared to level roads. In the past, some studies have indicated a negative relationship between absolute vertical grade and crash rates (Daniel et.al, 2002).

Table 19. Roadway Grade Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Level*	0.0020	0.001	3.633	0.0003	0.001	0.003
Grade, Unknown Slope*	-0.0060	0.002	-3.957	0.0001	-0.009	-0.003
Hillcrest*	-0.0030	0.001	-3.613	0.0003	-0.005	-0.001
Sag (Bottom)*	-0.0010	0.000	-3.426	0.0006	-0.002	0.000
Uphill*	0.1398	0.033	4.180	0.0000	0.074	0.205
Downhill*	0.2151	0.055	3.886	0.0001	0.107	0.324

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.9 Surface Condition

Results are shown in Table 20. All pavement surface conditions exhibited a positive relation with crashes except oil and mud. However, there were very few crashes on oil and mud surfaces and so the population dataset being so small, the results might be erroneous. Sandy surfaces were seen to be most vulnerable to crashes; sand would be expected to increase crash rates by 16% compared to dry surfaces. Wet, snow and icy surfaces would be expected to increase crash rates by 8%, 10%, and 12% respectively compared to dry surfaces. Surfaces with water (moving or standing) would be expected to reduce crash rates by 1.75% compared to dry surfaces. The findings were in sync with previous studies including Shankar and Mannering (1996), Ulfarsson and Mannering (2004) among others.

Table 20. Surface Condition Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Dry*	0.0797	0.022	3.582	0.0003	0.036	0.123
Wet*	0.1638	0.047	3.506	0.0005	0.072	0.255
Snow*	-0.0848	0.023	-3.618	0.0003	-0.131	-0.039
Ice/Frost*	0.1956	0.054	3.626	0.0003	0.090	0.301
Sand*	0.2021	0.055	3.705	0.0002	0.095	0.309
Water (Standing, Moving)*	0.0751	0.022	3.349	0.0008	0.031	0.119
Oil*	-0.0131	0.004	-3.342	0.0008	-0.021	-0.005
Mud*	-0.0010	0.0003	-3.478	0.0005	-0.002	0.000

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.10 Surface Type

Results are shown in Table 21. Asphalt surfaces showed the maximum positive correlation with Oklahoma crashes followed by JPCP surfaces whereas CRCP, AC overlay, bonded and unbonded PCC overlay, brick, slag and dirt roadway surfaces were seen to have a negative correlation with crashes. Compared to asphalt/bituminous pavement surfaces, JPCP surfaces would be expected to reduce crash rates by 12%, CRCP surfaces by 22%, AC overlay surfaces by 24%, unbonded PCC overlay surfaces by 25%, bonded PCC overlay surfaces by 27%, gravel surfaces by 19% and dirt surfaces by 18%.

Table 21. Surface Type Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Concrete (JPCP)*	0.1128	0.024	4.682	0.0000	0.066	0.160
Concrete (JRCP)*	NA	NA	NA	NA	NA	NA
Concrete (CRCP)*	-0.0034	0.001	-4.237	0.0000	-0.005	-0.002
Bituminous, Asphalt or RAP*	0.2386	0.066	3.612	0.0003	0.109	0.368
AC overlay*	-0.0090	0.002	-3.872	0.0001	-0.014	-0.004
Unbonded PCC overlay*	-0.0130	0.004	-3.38	0.0007	-0.021	-0.005
Bonded PCC overlay*	-0.0146	0.005	-3.346	0.0008	-0.024	-0.006
Brick or Block	-0.0084	0.003	-3.032	0.0024	-0.014	-0.003
Slag, Gravel or Stone*	-0.0008	0.000	-3.544	0.0004	-0.001	0.000
Dirt*	-0.0003	0.000	-3.355	0.0008	0.000	0.000

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.11 Speed Limit

Results are shown in Table 22. Posted speed limit of 45 mph showed the maximum positive impact on crashes which is logical as most crashes occurred on state highways having speed limit of 45 mph. Speed limit of 65 mph also showed a significant positive relation with crashes followed by speed limits 55 mph and 70 mph. All other speed limits exhibited negative coefficients, with 75 mph showing the maximum negative impact on crashes. Compared to 45 mph, a posted speed limit of 25 mph, 35 mph, 40 mph, 50 mph, 55 mph, 60 mph, 65 mph, 70 mph and 75 mph is likely to decrease crash rates by 21%, 22%, 23%, 6%, 26%, 1.5%, and 10 % and 22% while other roadway factors were uniform. 30 mph and 50 mph speed limits were found to be insignificant predictors of crash rates. The National Highway System Designation Act of 1995 allowed states freedom to increase interstate maximum speed limits from 55 mph to 65 mph, 70 mph, and 75 mph. Recently, Kockelman and Bottom (2006) had found that a speed limit increase from 55 to 65 mph resulted in a 3% increase in crash rate and a speed limit increases from 65 to 75 mph resulted in lowering of crash rates (less than 3%). The results from the present study coincided with these results.

Table 22. Speed Limit Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Speedlimit0	-0.0377	0.015	-2.483	0.0130	-0.067	-0.008
Speedlimit25*	-0.0161	0.005	-3.346	0.0008	-0.026	-0.007
Speedlimit30	-0.0091	0.003	-3.059	0.0022	-0.015	-0.003
Speedlimit35*	-0.0192	0.005	-3.893	0.0001	-0.029	-0.010
Speedlimit40*	-0.0212	0.006	-3.38	0.0007	-0.034	-0.009
Speedlimit45*	0.1939	0.047	4.164	0.0000	0.103	0.285
Speedlimit50	-0.0119	0.004	-3.155	0.0016	-0.019	-0.004
Speedlimit55*	0.1380	0.034	4.106	0.0000	0.072	0.204
Speedlimit60*	-0.0471	0.012	-3.976	0.0001	-0.070	-0.024
Speedlimit65*	0.1798	0.046	3.934	0.0001	0.090	0.269
Speedlimit70*	0.0779	0.021	3.778	0.0002	0.037	0.118
Speedlimit75*	-0.0193	-0.005	3.519	0.0004	-0.009	-0.030

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.12 Number of Traffic Lanes

Results are shown in Table 23. Only two lane and four lane roadways showed positive correlation with crashes. It could be inferred that two lane state highways in Oklahoma (AADT<8000) would be most prone to crashes. Six lane roads showed the maximum negative correlation with crashes. Compared to two lane roadways, single lane, four lane and six lane roadways would be expected to increase crash probability by 16%, 5% and 18% respectively. Three lane roadways exhibited a high p-value and hence were insignificant predictors of crash rates.

Table 23. Number of Traffic Lanes Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Trafficlanes0	-0.0171	0.006	-2.84	0.0045	-0.029	-0.005
Trafficlanes1	-0.0305	0.009	-3.267	0.0011	-0.049	-0.012
Trafficlanes2*	0.1363	0.036	3.814	0.0001	0.066	0.206
Trafficlanes3	-0.0153	0.005	-3.126	0.0018	-0.025	-0.006
Trafficlanes4*	0.0797	0.023	3.443	0.0006	0.034	0.125
Trafficlanes6*	-0.0481	0.013	-3.646	0.0003	-0.074	-0.022

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.13 Control Device

Results are shown in Table 24. Uncontrolled/unsignalized intersections were seen to have the maximum positive impact on crashes, which is expected. However, railway crossing device also showed a high positive impact despite there being few railway crossing crashes in Oklahoma in the last 10 years. Control signal with pedestrian control was found to be an insignificant predictor. Compared to uncontrolled intersections, traffic control signals without pedestrian signal, traffic control signal with pedestrian signal and traffic control signal of unknown color would be expected to reduce crash rates by 24%, 28%, and 27% respectively. Also, stop signs, school signs and warning signs would be expected to reduce crashes by 20%, 23% and 18% and respectively. Presence of yield signs were found to be insignificant.

Table 24. Control Device Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Uncontrolled and Unsignalized*	0.2515	0.075	3.367	0.0008	0.105	0.398
Traffic Control Signal without Pedestrian Signal*	-0.0212	0.006	-3.704	0.0002	-0.032	-0.010
Traffic Control Signal with Pedestrian Signal	-0.0302	0.011	-2.872	0.0041	-0.051	-0.010
Traffic Control Signal (on colors) not known whether or not Pedestrian Signal*	-0.0429	0.011	-3.882	0.0001	-0.065	-0.021
Stop Sign*	0.0276	0.007	3.963	0.0001	0.014	0.041
Yield Sign	-0.0141	0.005	-3.005	0.0027	-0.023	-0.005
School Zone Sign/Device	-0.0381	0.013	-2.904	0.0037	-0.064	-0.012
Other Regulatory Sign*	0.0450	0.012	3.834	0.0001	0.022	0.068
Warning Sign*	0.0658	0.018	3.622	0.0003	0.030	0.101
Person	-0.0284	0.011	-2.645	0.0082	-0.049	-0.007
Railway Crossing Device*	0.0898	0.024	3.685	0.0002	0.042	0.138

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.14 Trafficway Description

Results are shown in Table 25. Two way undivided roadways with (and without) continuous left-turn lane expressed the highest positive impact on crash rates. Two way roadways with unprotected (painted) median also showed a positive impact on crashes. Two way roads with unprotected (painted) median would be expected to result in 3.5% less crashes compared with two way undivided roads. Two way divided roadways with positive median barrier and one way roadways showed a negative relationship with crashes. They would be expected to reduce crash rates by 18% and 24% respectively. However, other results have also been seen in the past. Squires and Parsonson (1989) found that for four lane roadways raised medians had lower crash rates than painted medians and continuous left turn lane roads and for six lane roads the opposite was observed.

Table 25. Trafficway Description Results

Parameter	**Estimated Regression Coefficient**	**Standard Error**	**Z-Value**	**Pr. (>|Z|)**	**Lower Limit for 95% confidence interval**	**Upper Limit for 95% confidence interval**
Non-Trafficway or Driveway Access	-0.0202	0.007	-3.016	0.0026	-0.033	-0.007
Two-Way, Not Divided*	0.1638	0.045	3.658	0.0003	0.076	0.252
Two-Way, Divided, Unprotected (Painted > 4 Feet) Median*	0.1354	0.039	3.478	0.0005	0.059	0.212
Two-Way, Divided, Positive Median Barrier*	-0.0346	0.010	-3.420	0.0006	-0.054	-0.015
One-Way Trafficway*	-0.0758	0.020	-3.872	0.0001	-0.114	-0.037
Two-Way, Not Divided With a Continuous Left-Turn Lane*	0.1790	0.048	3.762	0.0002	0.086	0.272
Entrance/Exit Ramp	-0.0182	0.004	-3.021	0.0026	-0.027	-0.010

Note: * signifies the variable is significant to the model (p < 0.001)

5.2.15 Median Type

Results are shown in Table 26. Curbed medians and positive barrier medians were seen to have a negative impact and unprotected medians had a positive impact on crashes. It is validated from the results that curbed medians are the safest median type. From the obtained results, unprotected/painted medians, positive barrier medians and curbed medians would be expected to reduce crashes by 5%, 16% and 21% respectively.

Table 26. Median Type Results

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
Curbed*	-0.0151	0.004	-3.629	0.0003	-0.023	-0.007
Positive Barrier*	-0.0101	0.003	-3.444	0.0006	-0.016	-0.004
Unprotected*	0.1450	0.043	3.363	0.0008	0.060	0.229
None*	0.1948	0.052	3.782	0.0002	0.094	0.296

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.2.16 Shoulder Type

Results are shown in Table 27. Among all the shoulder types, stabilized shoulders and combination shoulders showed negative correlation with Oklahoma crashes. Stabilized shoulders showed the maximum negative correlation with crash rates. Earth shoulders and barrier curbs exhibited a positive regression output implying they are vulnerable to crashes. Based on estimated results, stabilized shoulders and combination shoulders would be likely to reduce crash rates by 8% and 5% respectively compared to no shoulders. The negative correlation with crashes for stabilized shoulders could also be attributed to the presence of rumble strips. Surfaced shoulders, earth shoulders and barrier curbs would be likely to increase crash rates by 1%, 6% and 18% respectively compared to no shoulders.

Table 27. Shoulder Type Results

Parameter	**Estimated Regression Coefficient**	**Standard Error**	**Z-Value**	**Pr. (>|Z|)**	**Lower Limit for 95% confidence interval**	**Upper Limit for 95% confidence interval**
None: No shoulders or curbs exist*	0.0080	0.002	3.587	0.0003	0.004	0.012
Surfaced shoulder exists (bituminous concrete or Portland cement concrete surface)*	0.0090	0.002	4.632	0.0000	0.005	0.013
Stabilized shoulder exists (stabilized gravel or other granular material with or without admixture)*	-0.0481	0.012	-3.905	0.0001	-0.072	-0.024
Combination shoulder exists (shoulder width has two or more surface types)	-0.0387	0.013	-2.988	0.0028	-0.064	-0.013
Earth shoulder exists*	0.0602	0.017	3.470	0.0005	0.026	0.094
Barrier curb exists; no shoulders in front of curb*	0.1689	0.041	4.082	0.0000	0.088	0.250

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.3 Significance of Categorical Variables in the Crash Prediction Model

To evaluate the significance of each categorical variable as a whole, dummy coding was performed. The reference model was constructed with all the variables in the model and a dummy model was created by excluding one level of a categorical variable and its categories. ANOVA tests were run on these models and the significance of the variable was evaluated by observing the deviation of the mean coefficients in the dummy model from the coefficients in the reference model. If the coefficients changed slightly or no change was observed, it implied that the variable was not significant to the model. The ANOVA analysis was implemented by conducting Likelihood Ratio Test on the reference and dummy models. In other words, the reference model m_0 consisting of all the categorical predictors and a dummy model m_1 formed by excluding a single categorical predictor X_i were evaluated by running the ANOVA test as anova (m_1, m_0) to evaluate the importance of X_i in the model [Allen, 1997; Cohen & Cohen, 1983; Keppel & Zedeck, 1989]. The probability of observing a difference on addition or removal of a variable with a given number of degrees of freedom is represented by Pr (>Chi). The p-values are interpreted for different significant levels (α). Generally, p-values greater than 0.05 indicate that the predictor is redundant or insignificant, p-lower than 0.05 indicate that a predictor is moderately significant and p-values lower than 0.001 indicate it is extremely significant. Table 28 summarizes the results:

Table 28. Result of ANOVA Test on Categorical Variables

Model Variable	Resid.Df	Resid.Dev	Df	Pr(>Chi)
Reference Model	*694*	*784*	-	-
Relation to Junction: Specific Location′	699	814	-5	0.074
Relation to Junction: Within Interchange? **	696	827	-2	$2.4*e^{-7}$
Vehicle Wander from Trafficway ***	700	836	-6	$5.8*e^{-11}$
Roadway Functional Class*	702	823	-8	0.033
Route Signing′	699	828	-5	0.087
Intersection Type**	698	841	-4	$6.8*e^{-7}$
Work Zone**	698	832	-4	$3.1*e^{-7}$
Roadway Alignment**	698	829	-4	$2.6*e^{-7}$
Roadway Grade***	696	828	-2	$2.1*e^{-11}$
Surface Condition*	700	833	-6	$8.1*e^{-6}$
Surface Type*	705	831	-11	$8.3*e^{-6}$
Speed Limit′	702	834	-8	0.084
Number of Traffic Lanes***	696	840	-2	$9.4*e^{-11}$
Control Device**	699	821	-5	$3.4*e^{-6}$
Traffic Description**	698	828	-4	$1.9*e^{-6}$
Median Type**	698	831	-4	$2.9*e^{-6}$
Shoulder Type**	698	826	-4	$3*e^{-6}$

Significance Codes: 0 * 0.001 ** 0.01 * 0.05 ′ 0.1 1**

From the evaluation of categorical variables it was seen that vehicle wander from trafficway, roadway grade and number of traffic lanes were the most significant variables in the model ($\alpha < 0.001$). Hence, it could be said that these variables are the most sensitive predictors of crash rates in Oklahoma. Route signing, speed limit and specific location of vehicle with relation to junction were seen to exhibit $0.05 < \alpha < 0.1$ thereby implying that they are redundant predictors of crash rates. Functional class, surface condition and surface type ($0.01 < \alpha < 0.05$) were moderately significant and the remaining variables in the model were in the significance range of $0.001 < \alpha < 0.01$.

5.4 Regression Analysis Results of Continuous Roadway Predictor Variables

The analysis results for the continuous variables are summarized in Table 29. For each continuous predictor the best fit curve of the expected crash rate is provided. As an example, Figure 22 is provided showing the crash rate with IRI distribution for different surface types. The remaining figures are provided in Appendix D. Among the numeric/ratio variables, AADT, PSR, VSF and Median Width were found to have a negative impact on crash rates. Percentage of single unit and combination trucks, IRI, Rut Depth, Lane Width and Shoulder Width exhibited a positive relationship with crash rates.

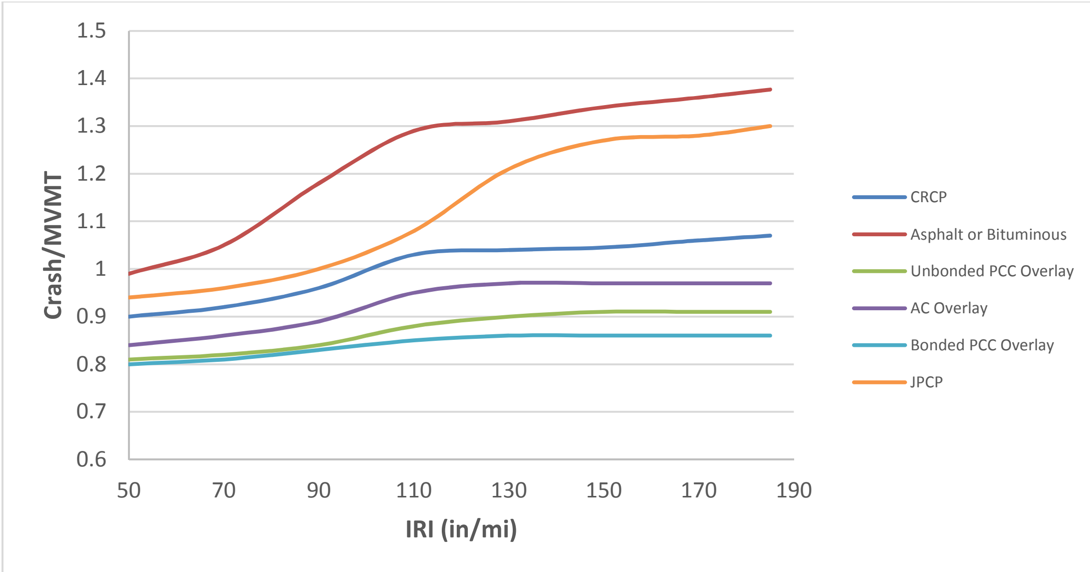

Figure 22. IRI Crash Rate with Surface Type

5.4.1 Annual Average Daily Traffic (AADT)

Crash probability showed a decrease with increase of AADT and AADT values < 10000 vehicle/day was found to produce the maximum crashes on 'Rural Major Collector', 'Rural Principal Arterial' and 'Urban Minor Arterial' roadways in Oklahoma. A low p-value (0.0001) suggested that AADT is a significant predictor of crashes.

5.4.2 Percentage of Trucks

Crash probability increased with both single unit trucks and combination trucks and based on estimated results, single unit trucks (Classes 4 through 7) would be likely to cause 5% more crashes than combination trucks (Classes 8 through 13) on the same roadway. A higher coefficient and a lower p-value signified that single unit buses and trucks is a more influential parameter in Oklahoma for determining crash rates than combination (heavy commercial) trucks.

5.4.3 International Roughness Index (IRI)

IRI showed a minor positive impact on crash rates. Crash rates showed a noticeable jump from IRI values > 110 in/mi. But since it had a p-value > 0.001, it may not be considered as a sensitive predictor of crashes.

5.4.4 Present Serviceability Rating (PSR)

A strong negative relationship was seen with PSR and crash rates showed a sharp decrease with PSR values > 2. Based on the observed coefficients and p-value, PSR exhibited the strongest inverse relationship with crash rates.

5.4.5 Rutting

Rutting was also found to be a significant factor at Oklahoma crash locations and a positive relation was found between rut depth and crash probability. Rutting was only confined to AC and AC overlay surfaces. Rut depths of the range 0.6 inch to 0.8 inch were found to be most significant.

5.4.6 Volume Service Flow Ratio (VSF)

Volume Service Flow ratio was found to exhibit a similar trend as AADT because congestion is intrinsically tied to AADT. Crash probability was found to negatively correlate with VSF and a low p-value suggested it is a significant predictor. The results suggested congestion cannot be considered as a contributing factor in Oklahoma crashes.

5.4.7 Lane Width

Lane width was found to be a significant predictor exhibiting a positive impact on Oklahoma crash rates with most of the crashes recorded on lane widths 7.5 ft. – 13 ft. The results seem counter-intuitive as wider lanes provide more room for vehicles to maneuver and avert head-on collisions.

5.4.8 Median Width

Median width was the variable with the smallest influence on crash rates. It exhibited a very low coefficient and a high p-value thereby suggesting it has very little impact on Oklahoma crashes.

5.4.9 Shoulder Width

Shoulder width was found to exhibit a minor positive impact on Oklahoma crash rates but a low coefficient and a high p-value signified it is not a significant predictor. The range of outside shoulder widths at Oklahoma crash locations was found to be uniformly distributed from 0 ft. to 12.5 ft. Again, the result seemed contradictory to popular opinion that wider shoulders increase safety.

Table 29. Continuous Variable Results Summary

Parameter	Estimated Regression Coefficient	Standard Error	Z-Value	Pr. (>|Z|)	Lower Limit for 95% confidence interval	Upper Limit for 95% confidence interval
AADT*	-0.0640	0.012	-5.188	0.0000	-0.088	-0.040
% Single Unit* Trucks and Buses	0.0602	0.010	5.769	0.0000	0.040	0.081
% Combination Trucks*	0.0188	0.005	4.016	0.0000	0.010	0.028
IRI	0.0009	0.000	3.115	0.0018	0.000	0.001
PSR*	-0.1325	0.032	-4.109	0.0000	-0.196	-0.069
Rut Depth*	0.0494	0.012	4.166	0.0000	0.026	0.073
VSF*	-0.0877	0.023	-3.765	0.0002	-0.133	-0.042
Lane Width*	0.0695	0.020	3.458	0.0005	0.030	0.109
Median Width	-0.0004	0.000	-3.055	0.0023	-0.001	0.000
Shoulder Width	0.0010	0.000	3.052	0.0023	0.000	0.002

Note: * signifies the variable is significant to the model ($p < 0.001$)

5.5 Analysis of Roadway Elements Using Analytic Hierarchy Process (AHP)

Statistical analysis of crash data provide rigorous inference on the importance of each predictor on the roadway safety in terms of crashes and fatalities. However, on some occasions, challenges remain on the interpretation of such statistical results. Moreover, often, decision makers do not consider statistical results on the grounds that they are empirical and might be biased. In this section, Analytical Hierarchy Process (AHP), a multivariate decision making tool, is employed to provide a more straightforward illustration of such relationships. AHP is a decision making tool (Saaty, 1980) that involves developing pairwise comparisons of critical elements in a model to assist in complex decision making. AHP has been used as a tool in the past for infrastructure asset management (Smith and Tighe, 2006) and in pavement maintenance prioritization (Farhan et al. 2009). Farah et al. (2006) used AHP to develop an Infrastructure Coefficient for two lane rural highway elements to predict contribution of individual elements in the total crash probability.

The objective of running the AHP survey on the roadway variables was to have an idea of the areas considered important by transportation experts for safety management in Oklahoma. A framework was developed consisting of three levels. Level 1 is the goal of ranking and prioritizing variables having significant impact on Oklahoma roadway crashes. Level 2 is formed of several broad generic roadway categories based on their attributes with regard to roadway safety under which the roadway variables are bracketed. These are: Roadway Segment Descriptor, Roadway Junction Descriptor, Geometry/Cross Section Descriptor, roadway segment condition, roadway traffic descriptor. The categories are created in conjunction with the input data format of MIRE, Safety Analyst and HSM/IHSDM. In Level 3 the roadway variables obtained from FARS, HPMS and PMS databases are decomposed into the aforementioned categories based on their characteristics. Figure 23 provides the entire framework used for AHP in the present study.

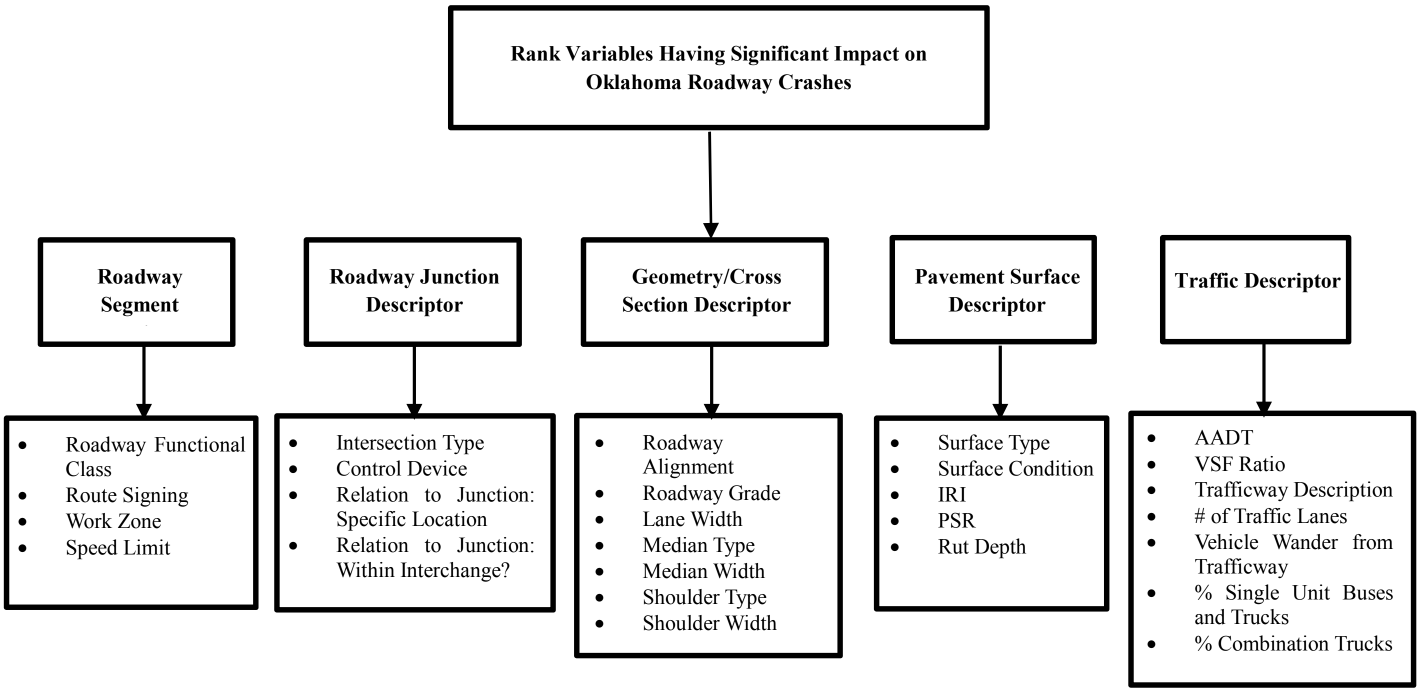

Figure 23. Distribution of Roadway Variables into Levels and Categories for AHP

Pairwise comparison matrix was developed for Level 2 and Level 3 factors using the Analytic Hierarchy Process (AHP). Surveyors were asked to compare two elements in terms of how important each factor is considered towards crash attenuation, which could be judged by the amount of resources allocated and investments made for each. This was done by attributing each element in Level 2 and Level 3 with a weighting factor. The idea was to construct the pairwise comparison matrix and subsequently calculate its eigenvector which represents the relative weight of each factor using the following equation:

$$\bar{A}\bar{W} = \lambda\,\bar{W}$$

Where,

$\bar{A}$ is the binary importance matrix, $\bar{W}$ is the vector of weights of objectives, and λ is the eigenvalue. The criteria was used to develop the pairwise matrix (Saaty et al, 1991) is shown in Table 30:

Table 30. AHP Pairwise Comparison Guideline

Scale	Degree of Preference
1	Equally preferred
3	Moderately preferred
5	Strongly or essentially preferred
7	Very strongly preferred
9	Extremely preferred
2,4,6,8	Values for inverse comparison

For example, if roadway grade: roadway alignment has a score 7:1 it means that roadway grade is "very strongly preferred" to roadway alignment for implementing safety countermeasures. The consistency of the pairwise comparison matrix was evaluated using the parameters Consistency Index (C.I.) and Consistency Ratio (C.R.) as defined below (Saaty, 1980):

$$C.I. = \frac{\lambda_{max} - n}{n - 1}$$

$$C.R. = \frac{C.I.}{R.I.}$$

Where,

n is the number of factors in concern, and *R.I.* is random index provided by Saaty (1980). In general, a *C.R.* value less than 0.1 is acceptable or else the pairs have to be re-compared using more consistent judgment.

Several graduate students and faculty with substantial transportation engineering experience were provided with the Level 2 and Level 3 matrix spreadsheets and they were requested to assign scores to the elements based on their subjective evaluation following the criteria stated in Table 4.2. Thereafter, the data was analyzed using the following steps:

1. First, the pairwise comparison matrix was developed for Level 2 categories. Experts were asked to fill the upper triangular matrix and the lower triangular matrix was formed by taking the reciprocals of those elements.

Table 31. Level 2 Pairwise Matrix

	Roadway Segment Descriptor	**Roadway Junction Descriptor**	**Geometry/Cross Section Descriptor**	**Pavement Surface Descriptor**	**Traffic Descriptor**
Roadway Segment Descriptor	**1.00**	0.20	0.20	0.33	0.20
Roadway Junction Descriptor	5.00	**1.00**	1.00	3.00	1.00
Geometry/Cross Section Descriptor	5.00	1.00	**1.00**	3.00	1.00
Pavement Surface Descriptor	3.00	0.33	0.33	**1.00**	0.33
Traffic Descriptor	5.00	1.00	1.00	3.00	**1.00**

2. The next step was to obtain the eigenvectors of the matrix elements. The matrix was normalized by first totaling all the numbers in each column and then dividing each entry in that column by the sum to yield the normalized score of that element. The sum of the normalized scores in each column was equal to 1. The weighting factor for each element was calculated by taking the average of the normalized scores in that row.

Table 32. Level 2 Normalized Eigenvectors

	Roadway Segment Descriptor	Roadway Junction Descriptor	Geometry/Cross Section Descriptor	Pavement Surface Descriptor	Traffic Descriptor	Eigenvector
Roadway Segment Descriptor	0.053	0.057	0.057	0.032	0.057	0.051
Roadway Junction Descriptor	0.263	0.283	0.283	0.290	0.283	0.281
Geometry/Cross Section Descriptor	0.263	0.283	0.283	0.290	0.283	0.281
Pavement Surface Descriptor	0.158	0.093	0.093	0.097	0.093	0.107
Traffic Descriptor	0.263	0.283	0.283	0.290	0.283	0.281

3. The consistency ratio was calculated using the maximum eigenvalue and the number of factors.

Table 33. Level 2 Summary

Max Eigenvalue	5.05
Number of Factors	5
Consistency Index	0.0089
Random Index	1.12
Consistency Ratio	0.0079
CR < 0.1?	Yes

4. Steps 1 through 3 were repeated for the Level 3 factors of each category. In total, there were five pairwise matrix formed in Level 3. The eigenvectors of Level 3 were multiplied to the eigenvectors of their Level 2 category to obtain the normalized AHP weight of each variable. Table 24 shows the normalized score summary.

Table 34. Statewide Normalized Score Summary

Level 2 Category	Level 3 Variable	Statewide Normalized Score
Roadway Segment Descriptor	Roadway Functional Class	0.008
	Route Signing	0.003
	Work Zone	0.031
	Speed Limit	0.008
Roadway Junction Descriptor	Intersection Type	0.019
	Relation to Junction: Specific Location	0.043
	Relation to Junction: Within Interchange?	0.109
	Control Device	0.109
Geometry/Cross Section Descriptor	Roadway Alignment	0.066
	Roadway Grade	0.024
	Lane Width	0.066
	Median Type	0.024
	Median Width	0.011
	Shoulder Type	0.024
	Shoulder Width	0.066
Pavement Surface Descriptor	Surface Type	0.004
	Surface Condition	0.064
	IRI	0.022
	PSR	0.010
	Rut Depth	0.010
Traffic Descriptor	AADT	0.028
	VSF Ratio	0.048
	Trafficway Description	0.016
	# of Traffic Lanes	0.086
	Vehicle Wander from Trafficway	0.086
	% Single Unit Buses and Trucks	0.009
	% Combination Trucks	0.007

Figure 24 shows the normalized score of all the predictors used in the AHP analysis. Only the top two variables showed more than 80 percent in weight and the top eight variables were seen to have more than 50 percent in weights. The criteria CR < 0.1 was found consistent in all the pairwise matrices formed.

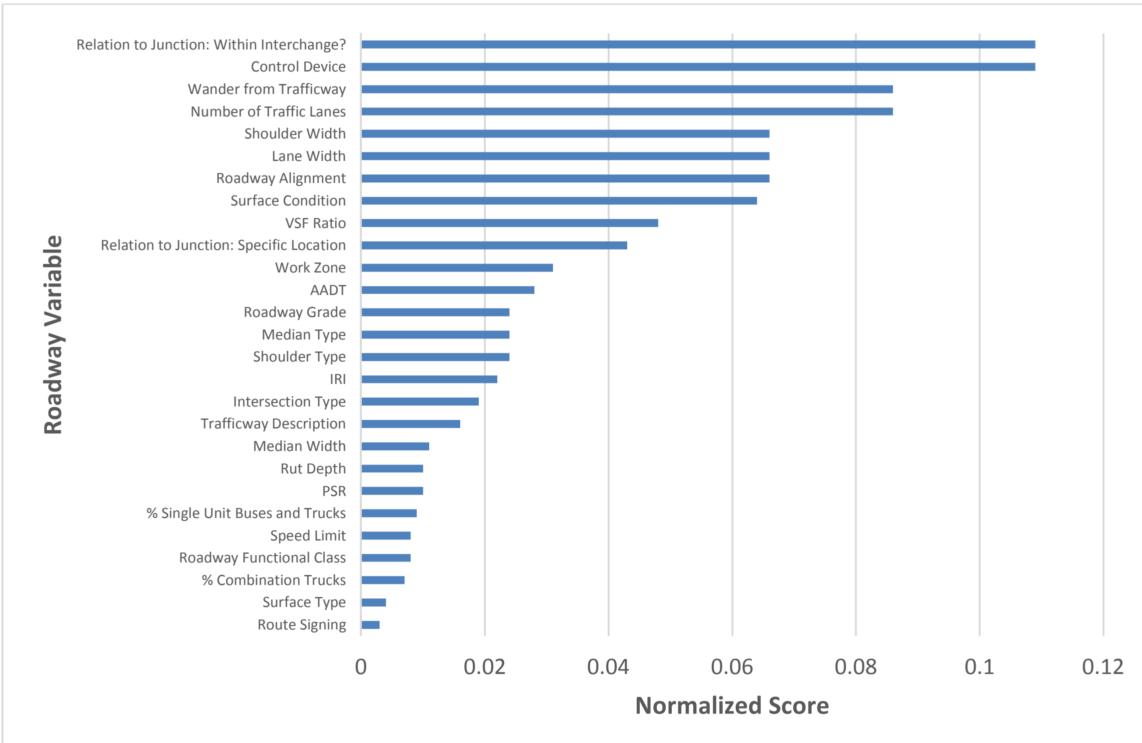

Figure 24. Ranking of Roadway Elements on their normalized score

5.6 Discussion

The results obtained from the AHP results were analyzed to screen out the most influential roadway areas where safety improvement measures could be undertaken.

- For junction safety, interchange locations were seen to be considered important. It is therefore suggested that effective countermeasures be implemented at interchanges such as providing low speed ramps, installing signs and markings for smooth merging of vehicle into oncoming traffic and providing reflective markings for nighttime vision.

- 'Vehicle wander from trafficway' at the time of crash was found to be an extremely significant parameter from the survey results and strategies such as installation of rumble strips, night-visible pavement markings, construction of high friction surfaces such as AC course, improved driver awareness and reduced alcohol impaired driving would help drivers keep the vehicle on the driving lane and prevent run off the road crashes.
- Likewise, control device and work zones had relatively high normalized scores which means they are considered important for safety improvements. Recent research has focused on the applicability of lightweight crash-worthy control devices. For work zones, the following strategies have been proven reducers of crashes: controlling large truck movement at work zones, using bright and reflective signs near work zones, enforcing alternating one-way traffic operations, partial lane closures, and enforcing low speeds at work zones by creating detours.
- Geometric parameters such as alignment, grade, median type, shoulder type, lane width, and shoulder width had moderate normalized scores. Some of the geometric safety improvements implemented by ODOT in recent years are: application of median cable barriers, improving edgeline stripping & shoulder rumble strips and rehabilitating existing guardrails.
- Percentage of single unit and combination trucks on roadways was not highly rated thereby suggesting that large truck presence is not considered an important safety area. However, some strategies have been implemented by ODOT for safety

enhancement on routes with large trucks such as innovative road signage for truck sharing, preventing overturning of trucks by geometric improvements and others.

- Surface type, rut depth and PSR had low normalized scores which is indicative that pavement surface parameters are not considered important in safety management. Among all the pavement surface parameters, IRI had the highest score implying the importance of roughness in safety management. However, high friction surface treatments and rehabilitation measures for low PSR roads have proved to be beneficial for Oklahoma roads in recent years and it is an important area in the Oklahoma SHSP.
- A comparison of the survey results with the significance results obtained from the statistical regression results revealed that some roadway factors were commonly regarded as important such as wander from trafficway and number of traffic lanes. Similarly, route signing, functional class, speed limit and surface type were commonly found to be unimportant parameters. Some dissimilarities were also noted. Roadway grade, % single unit trucks, rut depth and PSR, although not ranked high by surveyors, were found statistically significant predictors of crashes. 'Relation to Junction: Specific Location', surface condition, IRI and shoulder width were found statistically insignificant parameters despite being ranked high by surveyors.

CHAPTER VI

CONCLUSION AND RECOMMENDATIONS

The present study has been conducted to analyze roadway safety conditions in Oklahoma and the factors that affect it. The roadway safety management process is a critical component of transportation asset management which consists of network screening of sites which need safety improvements, diagnosing appropriate countermeasures, conducting benefit-cost analysis of individual countermeasure strategies and evaluating the overall effectiveness of strategies.

- The crash prediction module of HSM/IHSDM was evaluated for two lane rural, four lane rural and multilane urban highway segments in Oklahoma. The expected crash rates (crash/year/mi) were compared with actual observed crash rates in the state. Goodness-of-fit results showed urban highways performed better than rural highways and calibration of the model was required for Oklahoma crash prediction, especially for rural roadway segments.
- Rigorous Poisson regression analysis was performed using ten years of Oklahoma crash data obtained from the Fatality Analysis and Reporting System (FARS) and Highway Performance Monitoring System (HPMS) databases.

- The input data variables were classified as categorical and continuous for conducting Poisson regression. Output variables were evaluated in terms of their estimated model coefficients, Z-statistics and null hypothesis significance test results.
- Analytic Hierarchy Process, a multivariate decision-making tool, was used to rank the roadway variables by assigning specific weights to each element. Two levels of analysis were conducted and the Level 3 values of discrete elements were multiplied with the Level 2 infrastructure category values. Engineering judgement was used to rate pairwise variables based on their importance to roadway safety.

The regression results revealed profound positive relationship of crash rates with some roadway factors such as: rural major collector & rural minor arterial functional classes and state highways, 45 and 65 mph speed limit, vehicle wander to roadside, 4-way and T-intersections, construction work zones, right and left curves, uphill and downhill roadway grades, sandy/icy/wet surfaces, JPCP and asphalt surfaces, two and four lanes with, uncontrolled intersections and stop signs, two way undivided lanes and painted medians, surfaced shoulders & barrier curbs, % single unit and combination trucks, rut depth and lane width.

Many roadway factors were seen to exhibit a negative relationship with crash rates such as: rural principal arterial – Interstate functional class, Interstate highways, vehicle wander to median, maintenance and utility work zones, hillcrest and sag vertical curves, snowy and oily surfaces, AC overlay & concrete overlay (bonded and unbonded), speed limits of 40 mph & 60 mph, six lanes, traffic control signal without pedestrian sign and yield sign, one way trafficway, positive barrier & curbed medians, stabilized shoulders, AADT, PSR and VSF.

The roadway factors which were found to be insignificant to Oklahoma crashes (as they failed to pass the null hypothesis test at α=0.001) are: railway grade crossings and median crossover areas, urban arterial functional class, interstate highways in Oklahoma, Y-Intersections, speed limits of 30 mph and 50 mph, one and three lanes, traffic control signal with pedestrian sign, exit/entrance ramps, combination shoulders, IRI, median and shoulder width.

The results obtained in this study were in good agreement with past research but some dissimilarities were also observed. For instance, shoulder width showed a positive relationship with crash rate, against the opinion that wider shoulders increase safety. Also, lane width was found to exhibit a positive coefficient which is in contrary to several previous studies.

A few roadway elements could not be included in this study as the network level data was not available. For instance, absolute friction values expressed as Skid Number, pavement macro-texture and micro-texture have been critical indicators of crash rates. Many research studies have investigated their effect on crash rates. Cross slope and roadside hazard rating, which are integral elements in MIRE, have also served as useful indicator variables. In addition, weather and climate information at crash locations provide useful insight on their effect on crash rates but such information was not included in the present study to avoid complexity. This study would have been more accurate if some of these variables were considered in the regression modeling.

This study, also, did not categorize crashes into different types such as fatal, injury, incapacitating/non- incapacitating, property damage only etc. based on their severity. Such a classification would be more realistic in modeling the effect of roadway elements on crash rates with varied severity levels.

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APPENDICES

A. Model Inventory of Roadway Elements 1.0 Data Items

Table A.1: MIRE Version 1.0 Elements [FHWA MIRE Version 1.0 Report]

Element Name	Attributes	Priority
County Name	County name	Critical
County Code	Census defined County FIPS code	Critical
Highway District	Numeric district number	Critical
Type of Governmental Ownership	Type of ownership or agency	Critical
Specific Governmental Ownership	City name or equivalent entity	Critical
City/Local Jurisdiction Name	City name or equivalent entity	Critical
City/Local Jurisdiction Urban Code	Census urban code	Critical
Route Number	Signed numeric value for the roadway segment	Critical
Route/Street Name	Alphanumeric route or street name	Critical
Begin Point Segment Descriptor	Linear Reference System (e.g. milepoint) or spatial data system (e.g. latitude/longitude)	Critical
End Point Segment Descriptor	Linear Reference System (e.g. milepoint) or spatial data system (e.g. latitude/longitude)	Critical
Segment Identifier	Derived from other elements	Critical
Segment Length	Miles	Critical
Route Signing	Type of route signing	Critical
Route Signing Qualifier	Descriptive qualifier	Critical
Coinciding Route Indicator	Primary or Minor	Critical
Coinciding Route-Minor Route Information	Signed coinciding minor route number	Value Added
Direction of Inventory	For divided roads inventoried in each direction	Critical
Functional Class	The functional class	Critical
Rural/Urban Designation	Rural (population < 5,000) Urban (population > 5,000)	Critical
Federal Aid/Route Type	Federal-aid/National Highway System (NHS) route type	Critical
Access Control	Full, Partial and No Access Control	Critical
Surface Type	The surface type	Critical
Total Paved Surface Width	Feet	Critical
Surface Friction	Measured skid number	Critical

Surface Friction Date	Date surface friction was last measured or assigned	Critical
Pavement Roughness/Condition	International Roughness Index (IRI)	Value Added Preferred
Pavement Roughness Date	Date pavement roughness (IRI) was collected	Value Added Preferred
Pavement Condition	Present Serviceability Rating (PSR)	Value Added Alternative
Pavement Condition (PSR) Date	Date PSR was last assigned	Value Added Alternative
Number of Through Lanes	Total number of through lanes on the segment	Critical
Outside Through Lane Width	Width of the outside (curb) through lane	Critical
Inside Through Lane Width	Predominant inside lane width	Critical
Cross Slope	Cross slope for each lane starting with the leftmost lane	
Auxiliary Lane Presence/Type	Climbing lane, Passing lane, Exclusive continuous right turn lane, Other	Critical
Auxiliary Lane Length	Auxiliary Lane Length	Critical
HOV Lane Presence/Type	No HOV lanes, Has exclusive HOV lanes, Normal through lanes used as HOV at specified times, Shoulder/parking lanes used as HOV at specified times	Value Added
HOV Lanes	Maximum number of HOV lanes	Critical
Reversible Lanes	Number of reversible lanes	Value Added
Presence/Type of Bicycle Facility	Presence and type of bicycle facility	Critical
Width of Bicycle Facility	Width of Bicycle Facility	Width of Bicycle Facility
Number of Peak Period Through Lanes	Number of through lanes in peak period in the peak direction	Value Added
Right Shoulder Type	Right Shoulder Type	Critical
Right Shoulder Total Width	Total width of the right shoulder including both paved and unpaved parts	Critical
Right Paved Shoulder Width	Width of paved portion of right shoulder	Critical
Right Shoulder Rumble Strip Presence/Type	Presence and type of rumble strips on right shoulder	Critical
Left Shoulder Type	Shoulder type on left side of roadway	Critical
Left Shoulder Total Width	Width of left (outside) shoulder	Critical
Left Paved Shoulder Width	Width of the paved portion of left (outside) shoulder	Critical
Left Shoulder Rumble Strip Presence/Type	Presence and type of rumble strips on the left shoulder	Critical
Sidewalk Presence	Presence of a paved sidewalk	Critical
Curb Presence	Presence of curb along segment	Critical
Curb Type	Type of curb on the segment	Value Added
Median Type	Type of median on the segment	Critical
Median Width	Width of the median including inside shoulders	Critical
Median Barrier Presence/Type	Presence and type of median barrier	Critical
Median (Inner) Paved Shoulder Width	Width of the paved shoulder on the median (inner) side	Critical
Median Shoulder Rumble Strip Presence/Type	Presence and type of median shoulder rumble strip	Critical

Median Sideslope	Sideslope in the median adjacent to the median shoulder	Critical Preferred
Median Sideslope Width	Width of the median sideslope adjacent to the median shoulder	Critical
Median Crossover/Left Turn Lane Type	Presence and type of crossover/left turn bay in the median	Critical
Roadside Clear zone Width	Average roadside clearzone width	Critical Preferred
Right Sideslope	Sideslope on right side of roadway	Critical Preferred
Right Sideslope Width	Width of sideslope on right side of roadway	Critical Preferred
Left Sideslope	Sideslope on left side of roadway	Critical Preferred
Left Sideslope Width	Width of sideslope on left side of roadway	Critical Preferred
Roadside Rating	Rating of the safety of the roadside from 1 to 7	Critical Alternative
Major Commercial Driveway Count	Count of commercial driveways in segment serving 50 or more parking spaces	Critical
Minor Commercial Driveway Count	Count of commercial driveways in segment serving fewer than 50 parking spaces	Critical
Major Residential Driveway Count	Count of residential driveways in segment serving 50 or more parking spaces	Critical
Minor Residential Driveway Count	Count of residential driveways in segment serving fewer than 50 parking spaces	Critical
Major Industrial/Institutional Driveway Count	Count of industrial/institutional driveways in segment serving 50 or more parking spaces	Critical
Minor Industrial/Institutional Driveway Count	Count of industrial/institutional driveways in segment serving fewer than 50 parking spaces	Critical
Other Driveway Count	Count of ―other‖ driveways in segment	Critical
Terrain Type	Terrain Type for segment	Critical Alternative
Number of Signalized Intersections in Segment	Number of at-grade intersections with a signal	Critical
Number of Stop-Controlled Intersections in Segment	Number of at-grade intersections with a stop sign	Critical
Number of Uncontrolled/Other Intersections in Segment	Number of at-grade intersections without a control	Critical
Annual Average Daily Traffic (AADT)	Vehicles per day	Critical
AADT Year	AADT Year	Critical
AADT Annual Escalation Percentage	Expected annual percent growth in AADT	Value Added
Percent Single Unit Trucks or Single Truck AADT	Percentage combination truck (Classes 4-7)	Critical Preferred
Percent Combination Trucks or Combination Truck AADT	Percentage combination truck (Classes 8-13)	Critical Preferred
Percentage Trucks or Truck AADT	Percentage Trucks or Truck AADT	Critical Alternative
Total Daily Two-Way Pedestrian Count/Exposure	Total daily pedestrian flow along roadway in both directions	Value Added
Bicycle Count/Exposure	Total daily bicycle flow in both directions	Value Added

Motorcycle Count or Percentage	Daily motorcycle count or percentage of AADT	Critical
Hourly Traffic Volumes (or Peak and Off-Peak AADT)	Hourly Traffic Volumes	Value Added
K-Factor	30th highest hourly volume for a year, as a percentage of the AADT	Value Added
Directional Factor	Proportion of peak hour traffic in the predominant direction of flow	Value Added
One/Two-Way Operations	Whether the segment operates as a one- or two-way roadway	Critical
Speed Limit	Regulatory speed limit	Critical
Truck Speed Limit	Regulatory speed limit for trucks	Value Added
Nighttime Speed Limit	Regulatory speed limit for nighttime vehicles	Value Added
85th Percentile Speed	Traffic speed exceeded by 15 percent of the vehicles	Value Added
Mean Speed	Average of all observed vehicle speeds in the segment	Value Added
School Zone Indicator	Indication of school zone	Critical
On-Street Parking Presence	Time-based parking restrictions	Critical
On-Street Parking Type	Type of on-street parking	Critical
Roadway Lighting	Type of roadway lighting	Critical
Toll Facility	Presence and type of toll facility	Critical
Edgeline Presence/Width	Presence and width of edgeline	Critical
Centerline Presence/Width	Presence and width of centerline	Critical
Centerline Rumble Strip Presence/Type	Presence and type of centerline rumble strips	Critical
Passing Zone Percentage	Percent of segment length striped for passing	Critical
Bridge Numbers for Bridges in Segment	Bridge numbers from bridge file for bridges in segment	Critical
Curve Identifiers and Linkage Elements	Elements needed to define location of each curve record	Critical
Curve Feature Type	Type of horizontal alignment feature	Critical
Horizontal Curve Degree or Radius	Degree or radius of curve	Critical
Horizontal Curve Length	Length of curve including spiral	Critical
Curve Superelevation	Superelevation rate or percent	Critical
Horizontal Transition/Spiral Curve Presence	Presence and type of transition from tangent to curve and curve to tangent	Critical
Horizontal Curve Intersection/Deflection Angle	Angle between the two intersecting tangents	Critical
Horizontal Curve Direction	Direction of curve	Critical
Grade Identifiers and Linkage Elements	Elements needed to define location of each vertical feature	Critical
Vertical Alignment Feature Type	Type of vertical alignment feature	Critical
Percent of Gradient	Percent of gradient	Critical
Grade Length	Grade length	Critical
Vertical Curve Length	Vertical curve length	Critical
Unique Junction Identifier	Unique junction identifier	Critical
Type of Intersection/Junction	Type of intersection/junction	Critical
Location Identifier for Road 1 Crossing Point	Location of the center of the junction on the first intersecting route	Critical

Location Identifier for Road 2 Crossing Point	Location of the center of the junction on the second intersecting route	Critical
Location Identifier for Additional Road Crossing Points	Location of the center of the junction on the third and additional intersecting route	Critical
Intersection/Junction Number of Legs	Number of legs entering an at-grade intersection	Critical
Intersection/Junction Geometry	type of geometric configuration	Critical
School Zone Indicator	School Zone Indicator	Critical
Railroad Crossing Number	Railroad Crossing Number	Critical
Intersecting Angle	Smallest angle between any two legs of the intersection	Critical
Intersection/Junction Offset Distance	Offset distance between the centerlines of the intersection legs	Critical
Intersection/Junction Traffic Control	Traffic control at intersection	Critical
Signalization Presence/Type	Presence and type of signalization at intersection	Value added
Intersection/Junction Lighting	Presence of lighting at intersection	Critical
Circular Intersection - Number of Circulatory Lanes	Number of circulatory lanes in circular intersection	Critical
Circular Intersection - Circulatory Lane Width	Width of the roadway between the central island and outer edge of the circulatory lane in a circular intersection	Value added
Circular Intersection—Inscribed Diameter	Distance between the outer edges of the circulatory roadway of a circular intersection	Critical
Circular Intersection—Bicycle Facility	Presence and type of bicycle facility at circular intersection	Value added
Intersection Identifier for this Approach	Unique numeric identifier assigned to the intersection	Critical
Unique Approach Identifier	Unique intersection approach identifier	Critical
Approach AADT	Vehicles per day	Critical
Approach AADT Year	Year of AADT	Critical
Approach Mode	Approach mode	Critical
Approach Directional Flow	Indication of one-way or two-way flow	Critical
Number of Approach Through Lanes	Number of through lanes on approach	Critical
Left Turn Lane Type	Type of left turn lane	Critical
Number of Exclusive Left Turn Lanes	Number of exclusive left turn lanes	Critical
Amount of Left Turn Lane Offset	Amount of offset between conventional left turn lane and opposing approach	Critical
Right Turn Channelization	Right turn channelization	Critical
Traffic Control of Exclusive Right Turn Lanes	Traffic control of exclusive right turn lanes	Critical
Number of Exclusive Right Turn Lanes	Number of exclusive right turn lanes	Critical
Length of Exclusive Left Turn Lane	Storage length of exclusive left turn lanes	Value added
Length of Exclusive Right Turn Lanes	Storage length of exclusive right turn lanes	Value added
Median Type at Intersection	Median type at intersection	Critical
Approach Traffic Control	Traffic control present on approach	Critical
Approach Left Turn Protection	Presence and type of left turn approach protection	Critical
Signal Progression	Signal progression on approach	Critical
Crosswalk Presence/Type	Presence and type of crosswalk	Critical

Pedestrian Signalization Type	Type of pedestrian signalization	Critical
Pedestrian Signal Special Features	Special features for pedestrian signals	Value added
Crossing Pedestrian Count/Exposure	Estimate of average daily pedestrian flow crossing approach	Critical
Left/Right Turn Prohibitions	Signed left or right turn prohibitions	Critical
Right Turn-On-Red Prohibitions	Prohibition of right turns-on-red	Critical
Left Turn Counts/Percent	Estimate of average daily left turns or percent of total approach traffic turning left	Value added
Year of Left Turn Counts/Percent	Year of estimate	Value added
Right Turn Counts/Percent	Estimate of average daily right turns or percent of total approach traffic turning right	Value added
Year of Right Turn Counts/Percent	Year of estimate	Value added
Transverse Rumble Strip Presence	Presence of transverse rumble strips	Value added
Circular Intersection—Entry Width	Full width of entry on approach where it meets the inscribed circle	Critical
Circular Intersection—Number of Entry Lanes	Number of entry lanes into circular intersection	Critical
Circular Intersection— Presence/Type of Exclusive Right Turn Lane	Presence and type of exclusive right turn lanes	Critical
Circular Intersection—Entry Radius	Minimum radius of curvature of the curb on the right side of the entry	Value added
Circular Intersection—Exit Width	Width of exit on approach where it meets the inscribed circle	Critical
Circular Intersection—Number of Exit Lanes	Number of exit lanes from roundabout	Critical
Circular Intersection—Exit Radius	Minimum radius of curvature of the curb on the left side of approach	Value added
Circular Intersection—Pedestrian Facility	Type of facility for pedestrians crossing approach	Critical
Circular Intersection—Crosswalk Location (Distance From Yield Line)	Location of marked pedestrian crosswalk line	Value added
Circular Intersection—Island Width	Width of raised or painted island separating entry and exit legs	Value added
Unique Interchange Identifier	Unique identifier for each interchange	Critical
Location Identifier for Road 1 Crossing Point	Location of midpoint of interchange on first intersecting route	Critical
Location Identifier for Road 2 Crossing Point	Location of midpoint of interchange on second intersecting route	Critical
Location Identifier for Additional Road Crossing Points	Location of midpoint of interchange on third and additional intersecting route	Critical
Interchange Type	Interchange type	Critical
Interchange Lighting	Interchange lighting type	Critical
Interchange Entering Volume	Sum of entering volumes for all routes entering interchange	Critical
Interchange Identifier for this Ramp	Interchange identifier for ramp	Critical
Unique Ramp Identifier	Unique numeric ramp identifier	Critical

Ramp Length	Length of ramp	Critical
Ramp Acceleration Lane Length	Length of acceleration lane	Critical
Ramp Deceleration Lane Length	Length of deceleration lane	Critical
Ramp Number of Lanes	Maximum number of lanes on ramp	Critical
Ramp AADT	AADT on ramp	Critical
Year of Ramp AADT	Year of AADT on ramp	Critical
Ramp Metering	Presence and type of any metering of traffic on ramp	Critical
Ramp Advisory Speed Limit	Advisory speed limit on ramp	Critical
Roadway Type at Beginning Ramp Terminal	Type of roadway intersecting with the ramp at the beginning terminal	Critical
Roadway Feature at Beginning Ramp Terminal	Feature found at the beginning terminal of the ramp	Critical
Location Identifier For Roadway at Beginning Ramp Terminal	Location on the roadway at the beginning ramp terminal	Critical
Location of Beginning Ramp Terminal Relative to Mainline Flow	Side of the roadway flow intersected by the ramp	Critical
Roadway Type at Ending Ramp Terminal	Type of roadway intersecting with the ramp at the ending terminal	Critical
Roadway Feature at Ending Ramp Terminal	Feature found at the ending terminal of the ramp	Critical
Location Identifier for Roadway at Ending Ramp Terminal	Location on the roadway at the ending ramp terminal	Critical
Location of Ending Ramp Terminal Relative to Mainline Flow	Side of the roadway flow intersected by the ramp	Critical

B. FARS Categorical Elements, Codes and 10 Year Oklahoma Crash Summary

Table B.1 Relation to Junction: Specific Location

Element Value	Specific Location	10 Year Crash Count	Percentage
1	Non-Junction	4268	65.66 %
2	Intersection	1600	24.61 %
5	Entrance/Exit Ramp	142	2.19 %
6	Railway Grade Crossing	40	0.62 %
7	Crossover-Related	23	0.35 %
8	Driveway Access	427	6.57 %

Table B.2 Relation to Junction: Within Interchange Area?

Element Value	Within Interchange	10 Year Crash Count	Percentage
0	No	6090	93.69 %
1	Yes	410	6.31 %

Table B.3 Vehicle Wander from Trafficway

Element Value	Wander from Trafficway	10 Year Crash Count	Percentage
1	On Roadway	3900	60 %
2	On Shoulder	145	2.23 %
3	On Median	269	4.14 %
4	On Roadside	2027	31.18 %
5	Outside Trafficway	94	1.45 %
7	In Parking Lane/Zone	23	0.35 %
8	Gore	42	0.65 %

Table B.4 Roadway Functional Class

Element Value	Roadway Functional Class	10 Year Crash Count	Percentage
1	Rural-Principal Arterial - Interstate	426	6.55 %
2	Rural-Principal Arterial - Other	911	14.02 %
3	Rural-Minor Arterial	897	13.80 %
4	Rural-Major Collector	1674	25.75 %
5	Rural-Minor Collector	48	0.74 %
6	Rural-Local Road or Street	556	8.55 %
11	Urban-Principal Arterial - Interstate	334	5.14 %
12	Urban-Principal Arterial - Other (Freeways or Expressways)	141	2.17 %
13	Urban-Other Principal Arterial	668	10.28 %
14	Urban-Minor Arterial	352	5.42 %
15	Urban-Collector	78	1.20 %
16	Urban-Local Road or Street	415	6.38 %

Table B.5 Route Signing

Element Value	Route Signing	10 Year Crash Count	Percentage
1	Interstate	722	11.11 %
2	U.S. Highway	1668	25.66 %
3	State Highway	1703	26.20 %
4	County Road	1027	15.80 %
6	Local Street - Municipality	1278	19.66 %
7	Local Street - Frontage Road	14	0.22 %
8	Other	88	1.35 %

Table B.6 Type of Intersection

Element Value	Type of Intersection	10 Year Crash Count	Percentage
1	Not an Intersection	4712	72.49 %
2	Four-Way Intersection	1286	19.78 %
3	T-Intersection	377	5.80 %
4	Y-Intersection	65	1.00 %
6	Roundabout	21	0.32 %
7	Five-Point, or More	39	0.60%

Table B.7 Work Zone

Element Value	Work Zone	10 Year Crash Count	Percentage
0	None	5874	90.37 %
1	Construction	256	3.94 %
2	Maintenance	62	0.95 %
3	Utility	49	0.75 %
4	Work Zone, Type Unknown	259	3.98 %

Table B.8 Roadway Alignment

Element Value	Roadway Alignment	10 Year Crash Count	Percentage
1	Straight	4985	76.69 %
2	Curve-Right	688	10.58 %
3	Curve-Left	827	12.72 %

Table B.9 Roadway Grade

Element Value	Roadway Grade	10 Year Crash Count	Percentage
1	Level	4232	65.11%
2	Grade, Unknown Slope	78	1.20 %
3	Hillcrest	157	2.42 %
4	Sag (Bottom)	59	0.91 %
5	Uphill	862	13.26 %
6	Downhill	1112	17.11 %

Table B.10 Roadway Surface Condition

Element Value	Roadway Surface Condition	10 Year Crash Count	Percentage
1	Dry	5690	87.54 %
2	Wet	569	8.75 %
3	Snow	42	0.65 %
4	Ice/Frost	94	1.45 %
5	Sand	68	1.04 %
6	Water (Standing, Moving)	11	0.17 %
7	Oil	18	0.28 %
10	Mud	8	0.12 %

Table B.11 Roadway Surface Type

Element Value	Roadway Surface Type	10 Year Crash Count	Percentage
1	Concrete (JPCP)	1025	15.77 %
2	Concrete (JRCP)	0	0.00 %
3	Concrete (CRCP)	262	4.03 %
4	Bituminous, Asphalt or RAP	4575	70.38 %
5	AC overlay	184	2.83 %
6	Unbonded PCC overlay	68	1.05 %
7	Bonded PCC overlay	29	0.45 %
8	Brick or Block	14	0.22 %
9	Slag, Gravel or Stone	211	3.25 %
10	Dirt	132	2.03 %

Table B.12 Speed Limit

Element Value	Speed Limit (mph)	10 Year Crash Count	Percentage
00	No Statutory Limit/Non-Trafficway or Driveway Access	18	0.28 %
25	Actual Speed Limit	165	2.54 %
30	Actual Speed Limit	133	2.05 %
35	Actual Speed Limit	306	4.71 %
40	Actual Speed Limit	586	9.02 %
45	Actual Speed Limit	1208	18.58 %
50	Actual Speed Limit	166	2.55 %
55	Actual Speed Limit	835	12.86 %
60	Actual Speed Limit	226	3.48 %
65	Actual Speed Limit	2147	33.03 %
70	Actual Speed Limit	506	7.78 %
75	Actual Speed Limit	204	3.14 %

Table B.13 Total Lanes in Roadway

Element Value	Total Lanes	10 Year Crash Count	Percentage
0	Non-Trafficway or Driveway Access	49	0.75 %
1	One lane	106	1.63 %
2	Two lanes	4933	75.89 %
3	Three lanes	285	4.38 %
4	Four lanes	1094	16.83 %
6	Six lanes	33	0.51 %
7	Seven or more lanes	0	0.00 %

Table B.14 Control Device

Element Value	Total Lanes	10 Year Crash Count	Percentage
0	Uncontrolled and Unsignalized	3896	59.4 %
1	Traffic Control Signal without Pedestrian Signal	32	0.49 %
2	Traffic Control Signal with Pedestrian Signal	17	0.26 %
3	Traffic Control Signal (on colors) not known whether or not Pedestrian Signal	286	4.40 %
20	Stop Sign	467	7.18 %
21	Yield Sign	88	1.35 %
23	School Zone Sign/Device	20	0.31 %
28	Other Regulatory Sign	1487	22.88 %
40	Warning Sign	148	2.28 %
50	Person	5	0.08 %
65	Railway Crossing Device	54	0.82 %

Table B.15 Trafficway Description

Element Value	Total Lanes	10 Year Crash Count	Percentage
0	Non-Trafficway or Driveway Access	28	0.43 %
1	Two-Way, Not Divided	4413	67.89 %
2	Two-Way, Divided, Unprotected (Painted > 4 Feet) Median	1124	17.29 %
3	Two-Way, Divided, Positive Median Barrier	786	12.09 %
4	One-Way Trafficway	30	0.46 %
5	Two-Way, Not Divided With a Continuous Left-Turn Lane	93	1.43%
6	Entrance/Exit Ramp	26	0.40 %

C. HPMS Categorical Elements, Codes and 10 Year Oklahoma Crash Summary

Table C.1 HPMS Median Type Descriptors

Element Value	Median Type	10 Year Crash Count	Percentage
1	Curbed	312	4.80 %
2	Positive Barrier	591	9.09 %
3	Unprotected	2178	33.51 %
4	None	3419	52.60 %

Table C.2 HPMS Shoulder Type Descriptors

Element Value	Shoulder Type	10 Year Crash Count	Percentage
1	None: No shoulders or curbs exist	1128	17.35 %
2	Surfaced shoulder exists (bituminous concrete or Portland cement concrete surface)	1491	22.94 %
3	Stabilized shoulder exists (stabilized gravel or other granular material with or without admixture)	128	1.97 %
4	Combination shoulder exists (shoulder width has two or more surface types)	384	5.91 %
5	Earth shoulder exists	1329	20.45 %
6	Barrier curb exists; no shoulders in front of curb	2040	31.38 %

D. Best Fit Curves of Poisson Regression Results

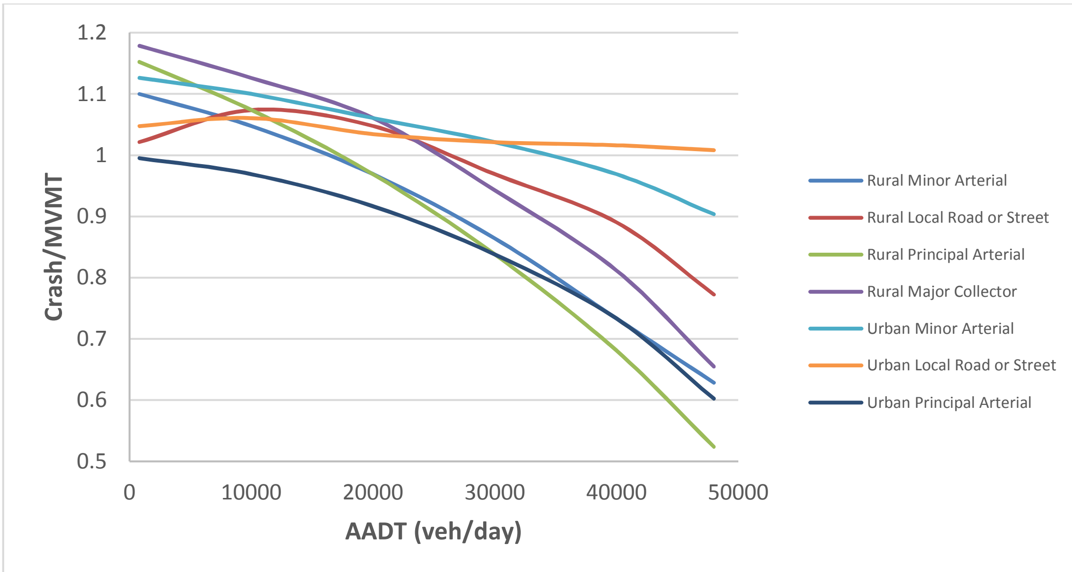

Fig D.1 AADT Crash Rate with Functional Class

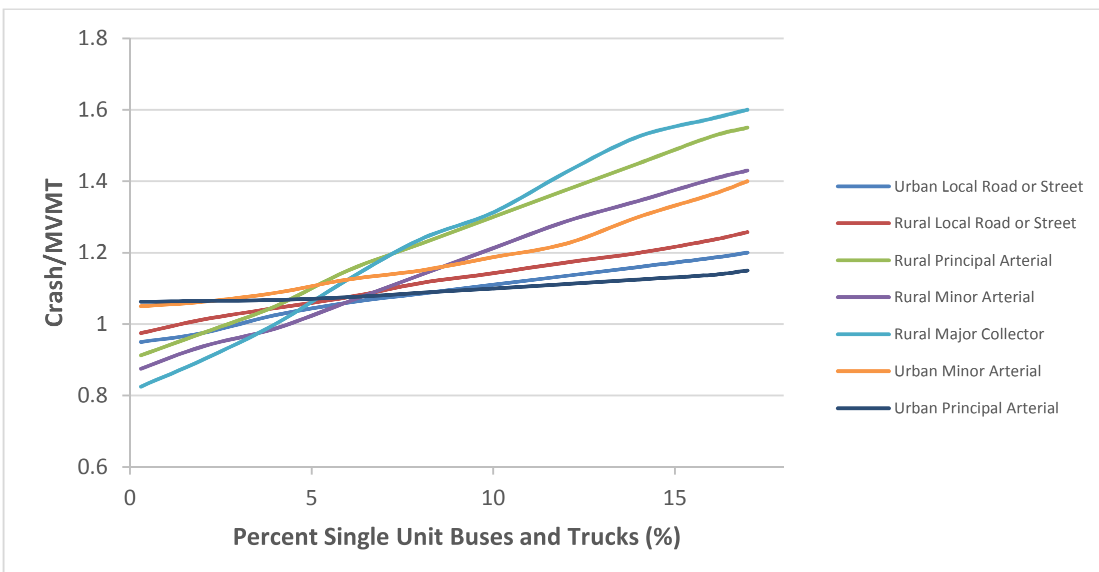

Fig D.2 Single Unit Buses and Trucks (%) Crash Rate with Functional Class

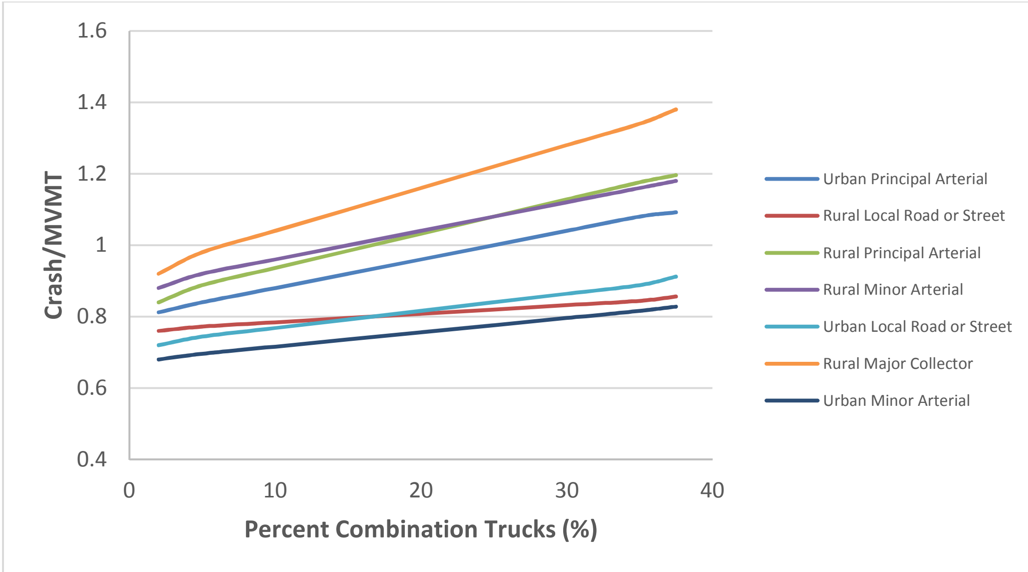

Fig D.3 Combination Trucks (%) Crash Rate with Functional Class

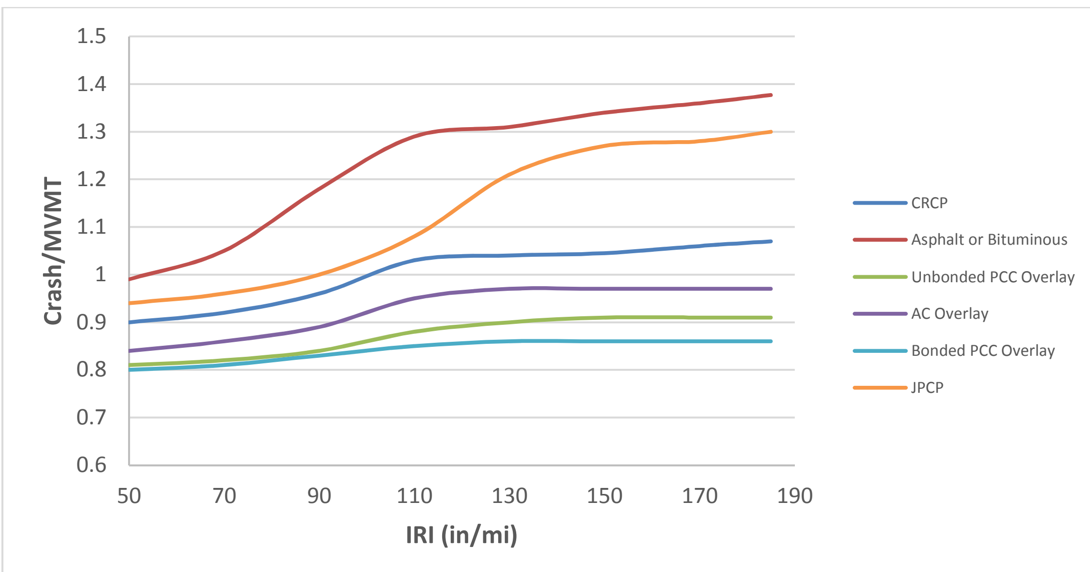

Fig D.4 IRI Crash Rate with Surface Type

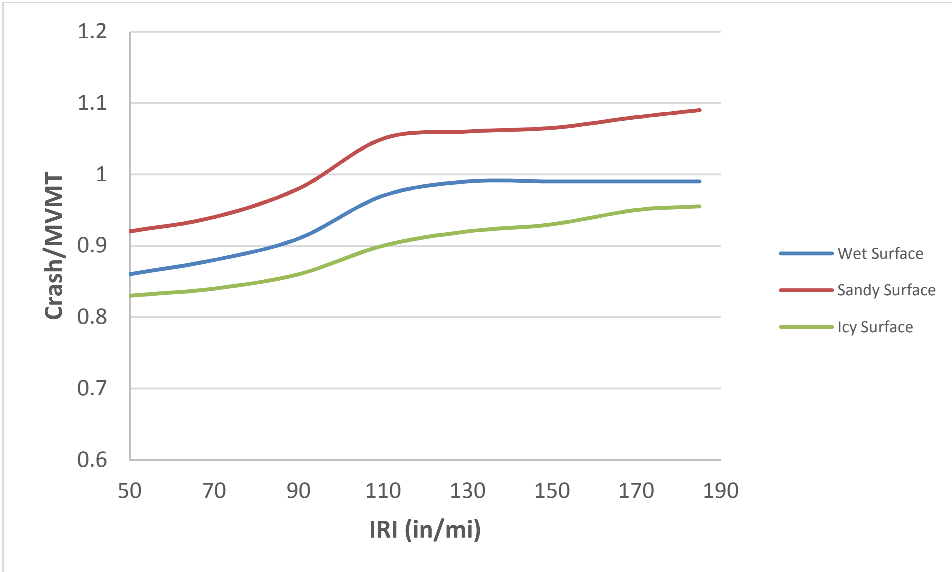

Fig D.5 IRI Crash Rate with Surface Condition

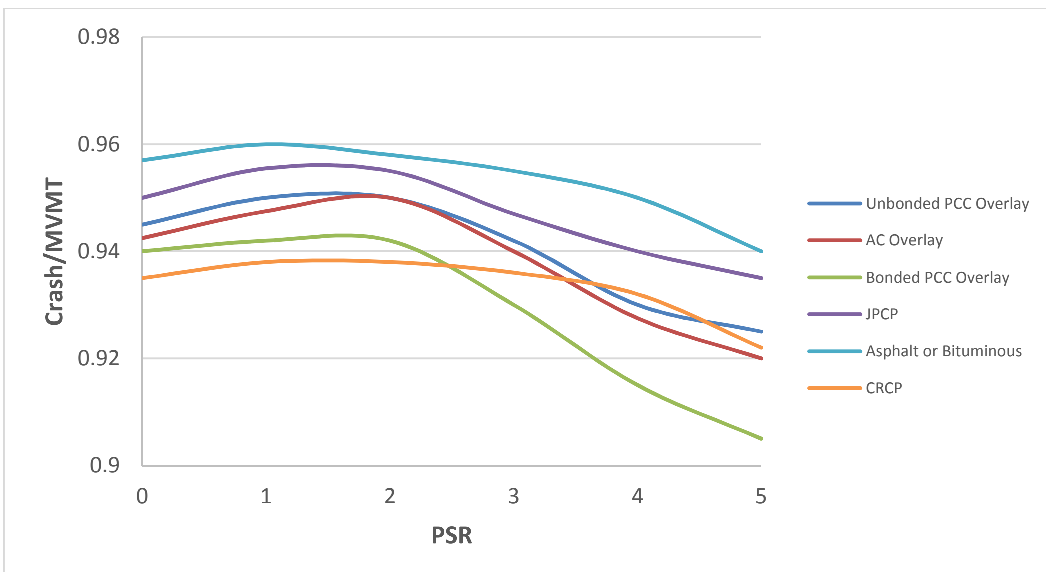

Fig D.6 PSR Crash Rate with Surface Type

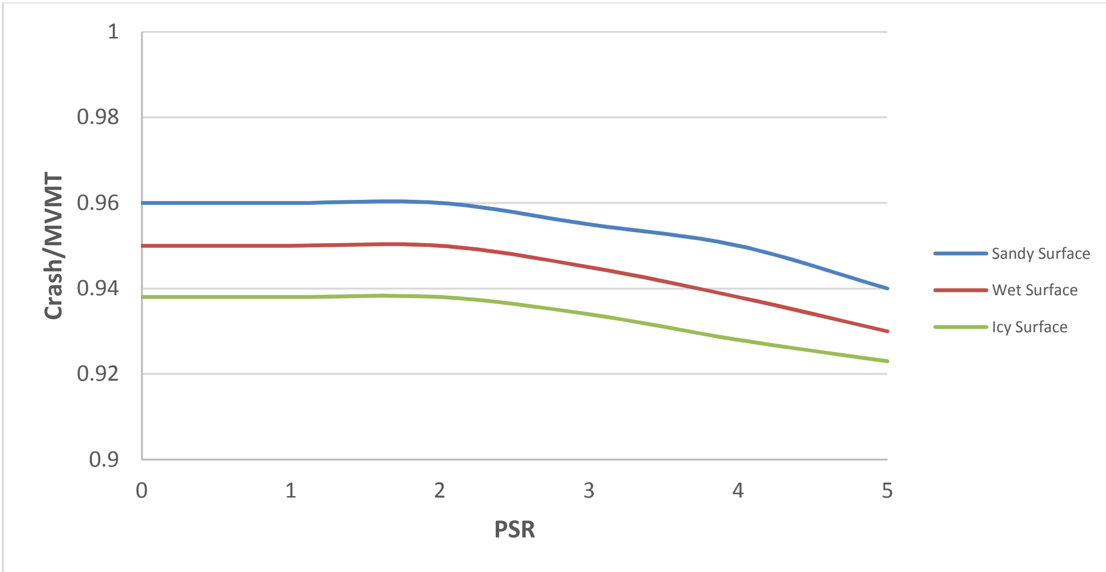

Fig D.7 PSR Crash Rate with Surface Condition

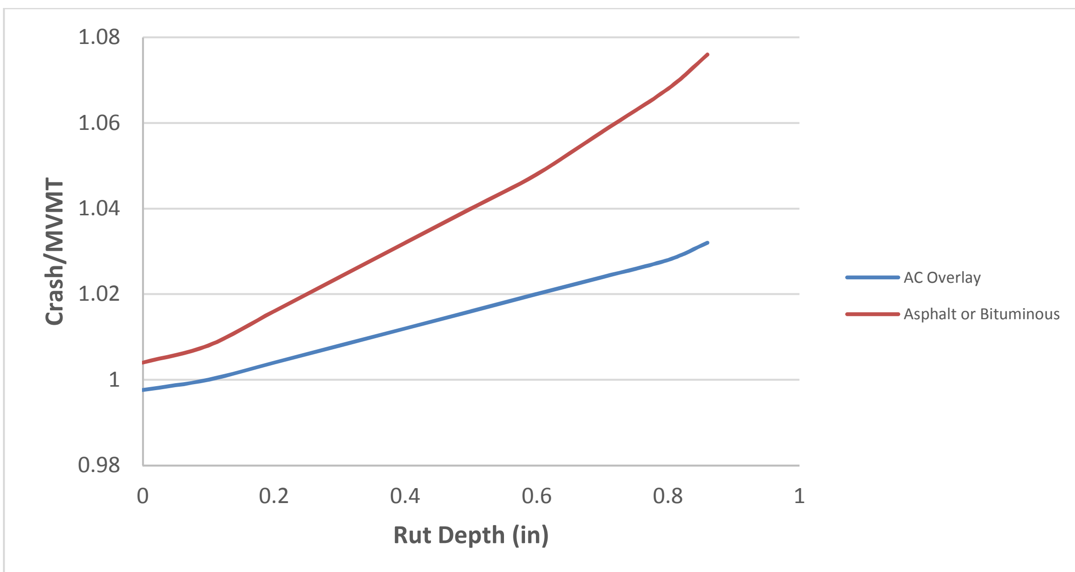

Fig D.8 Rut Depth Crash Rate with Surface Type

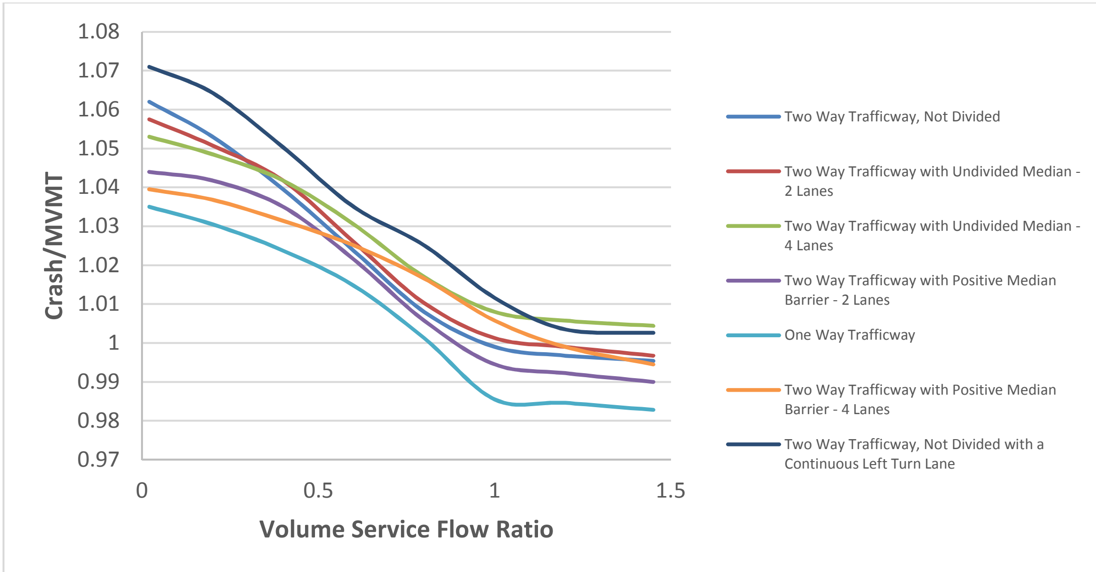

Fig D.9 VSF Crash Rate with Trafficway Type

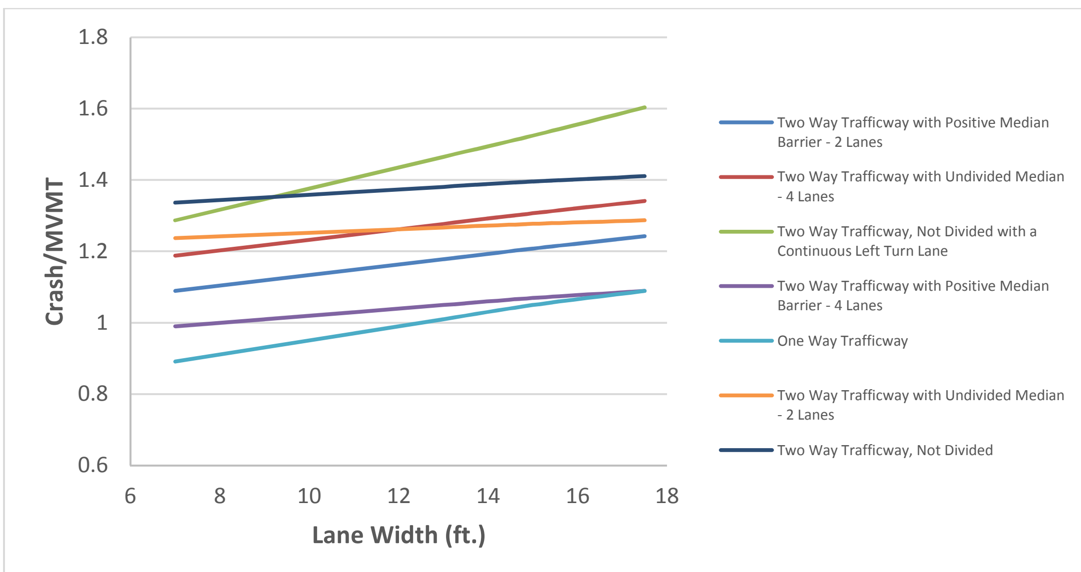

Fig D.10 Lane Width Crash Rate with Trafficway Type

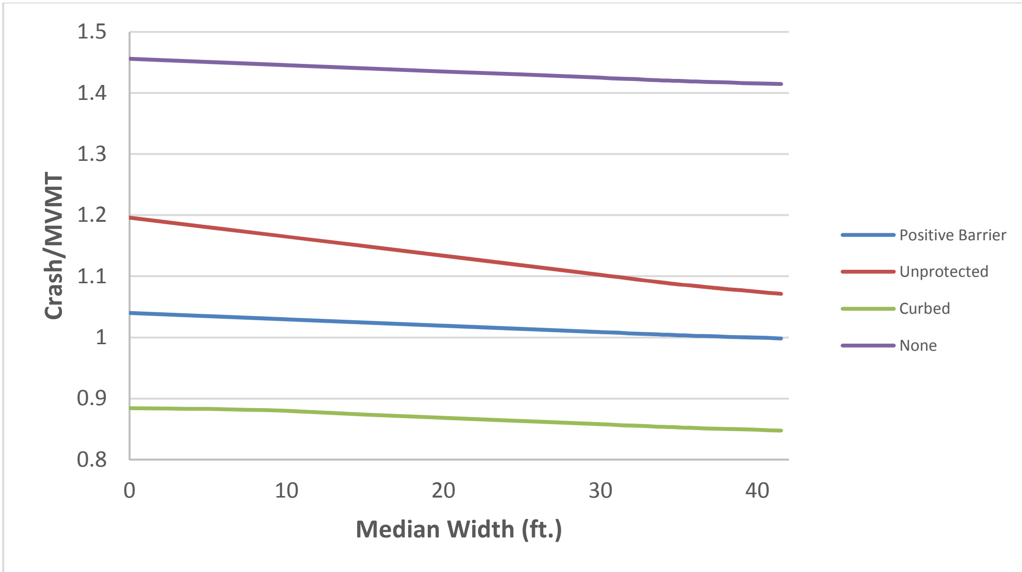

Fig D.11 Median Width Crash Rate with Median Type

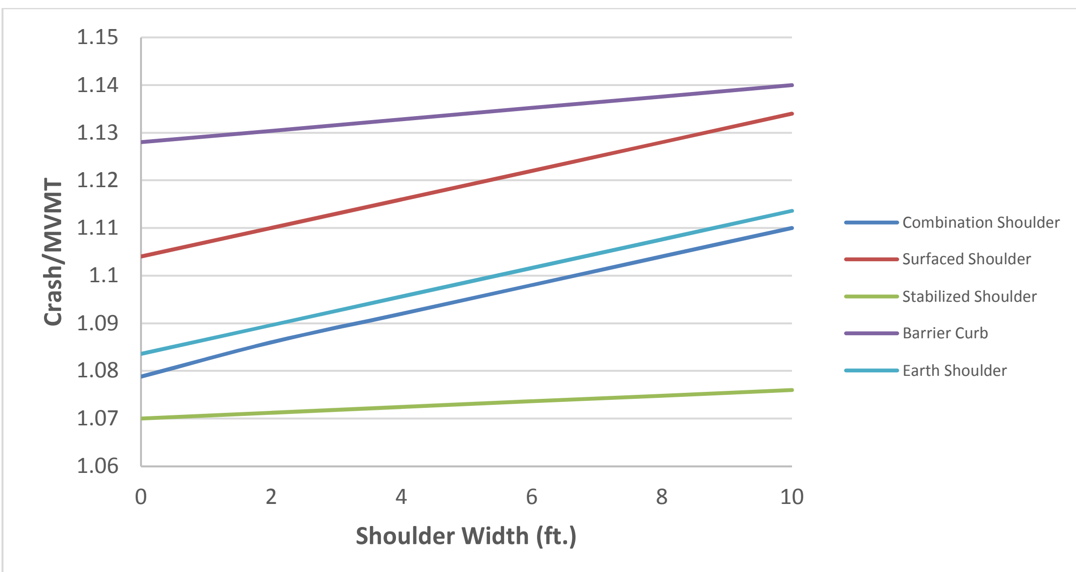

Fig D.12 Shoulder Width Crash Rate with Shoulder Type

VITA

ROHIT GHOSH

Candidate for the Degree of

Master of Science

Thesis: EXAMINATION OF EXISTING TOOLS AND DATA FOR HIGHWAY SAFETY MANAGEMENT IN OKLAHOMA

Major Field: CIVIL ENGINEERING

Biographical:

Education:

Completed the requirements for the Master of Science in Civil Engineering at Oklahoma State University, Stillwater, Oklahoma in December, 2015.

Completed the requirements for the Bachelor of Science in Civil (Construction) Engineering at Jadavpur University, Kolkata, India in June, 2013.

Experience:

Graduate Research Assistant, August 2013-Present
Dr. Kelvin Wang, OSU Department of Civil Engineering, Stillwater, OK

Research projects involved:

- Traffic, materials, climate and soil data preparation and development of the Prep-ME software for the new Pavement-ME
- Distress Condition survey of ODOT Interstate highway and bridge network and data preparation
- Automated distress survey of airport infrastructure and preparation of AutoCAD drawings