

DEVELOPING A NETWORK SCREENING
METHOD FOR LOW VOLUME ROADS

by

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DEDICATION

To the Almighty, my parents, family, friends and well-wishers who believed in me and my capabilities. To those who directly and indirectly motivated me to reach for my dreams. Also, to those who dreams of achieving something.

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ABSTRACT

Crash occurrences on rural low-volume roads (LVRs) are usually more severe in nature. This is mostly because of higher speeds and outdated infrastructure designs. Therefore, safety management programs for these roads are equally as important as their urban and high-volume counterparts. Network screening is an important aspect of safety management programs. However, traditional network screening methods based on historical crash data may not provide accurate results for LVRs. This is because of the sporadic nature of crash occurrence and the lower volumes. Therefore, the purpose of this research is to develop a suitable network screening method for LVRs. The literature review of this research identified a few existing network screening methods. A state-of-practice survey was also carried out in order to understand the LVR safety management practices across the United States. Then the identified methods were assessed for their suitability for LVRs. The method using a combination of crash frequency, severity and rate, and the Empirical Bayes (EB) method scored the highest. However, the EB method was selected for further analysis as it is not entirely dependent on historical crash experience and it incorporates risk factors. Actual LVR data from Oregon was used to analyze the EB method. This analysis indicated that the safety performance functions (SPFs) of the EB method overestimates the predicted crash numbers. This overestimation is mostly due to the high accident modification factors (AMF) for sharp horizontal curves. Finally, an alternative method was proposed. Two multiple linear regression models for estimating expected crashes mostly using risk factor categories were developed. The risk factor data were categorized using Classification and Regression Tree (CART) analysis. Both models have R square values of more than 0.90.

CHAPTER ONE

INTRODUCTION

Background

Traffic crashes (or accidents) have been causing fatalities and injuries since the beginning of motorized mobility. According to the World Health Organization (WHO), road injuries are one of the top ten causes of human fatalities (WHO, 2019). Therefore, significant efforts are invested to reduce these numbers. These efforts can adhere to improvements of highway infrastructure, vehicle technologies and enforcement of traffic laws.

Safety management programs, generally funded by governments, are formal efforts of reducing fatal and injurious crashes. These programs use data-driven approaches to improve traffic safety conditions of the highway infrastructure. Multiple safety related projects are administered under these safety programs. One of the major tasks of any safety project is to identify sites that would return the most benefits against any safety improvements. The benefits are usually in terms of reduced fatal and injurious crashes. Generally, methods for identifying locations that would return the most safety benefits are known as network screening.

Crash history (crash frequency, severity and rate) is the most commonly used network screening approach. These methods are based on the rationale that, sites that have experienced higher number of crashes are in most need of safety improvements. However, researchers have found that crash history alone is not the sole indicator of risks. Roadway

and traffic factors were found to have a strong correlation with crash risk (Bendigeri et al., 2011; Ewan et al., 2016; Gross et al., 2011; Gross and Jovanis, 2007; FHWA, 2009; Findley et al., 2012). Geometric or traffic variables that have strong correlation with crash occurrence are known as risk factors. Many network screening methods that incorporate these risk factors were proposed and many are also applied in real life network screening.

Network Screening on Low Volume Roads

Highways that has less than 1000 vehicles travelling on it each day and are mostly located in a rural setting, are defined as rural low volume roads (LVRs). Though there are no formal cutoff traffic volume value for LVRs, many studies have used the cutoff average daily traffic (ADT) of 1000 vehicles per day (vpd) (Ewan et al., 2016; FHWA, 2009; Gross et al., 2011). Therefore, this thesis has also used the same cutoff.

In 2018, about 50 percent of fatal crashes occurred on rural roads, even though only 19 percent of the US population resided in rural areas (NHTSA, 2018). This indicates that crashes on LVRs are generally more severe in nature. This is mostly because of outdated infrastructure designs and higher speeds. This statistic also highlights the importance of safety management on LVRs.

Network screening on LVRs are generally different than their higher volume counterparts. This is because of the sporadic nature of the crash occurrence which is caused by lower traffic volumes. Therefore, commonly used crash history-based methods would not be suitable in most cases. For instance, if crash frequency is used, sites along low-volume roads would not rank high on the list because low volumes normally result in a few sporadic crashes. On the other hand, when crash rate is used, these sites are going to show

high crash rates with small number of crashes, only because of their lower volumes. Also, crash history-based methods does not incorporate the risk factors that contribute to the crash risks at a site. Including risk factors allows to consider the outdated infrastructure designs in the screening process. Ideally, a good LVR network screening method should use risk factors along with crash history to correctly identify sites at risk.

Objectives

The main purpose of this research is to identify a suitable network screening method for LVRs. The main purpose is divided into four distinct objectives. The first is to identify different existing network screening methods. The second objective is to get an idea about the current LVR safety management practices across the United States. The third is to assess the identified network screening methods for their suitability for LVRs. A set of criteria, addressing the practical aspects of LVR network screening was developed for this assessment. The fourth objective is to analyze the Empirical Bayes (EB) method (one of the high scoring methods) using actual LVR data. This analysis would identify potential sources of inaccuracies and its challenges when it is being applied to an actual LVR network. Finally, the fifth objective is to develop a simple and accurate network screening method for LVRs. The new method is a simple alternative to the EB method that tried to mitigate the major challenges of applying the EB method on LVRs.

Outline

This thesis has seven chapters. The first chapter is the introduction which presents the background, objectives and the outline for this thesis. The second chapter is the

literature review chapter which presents existing network screening methods identified from a comprehensive literature search. The third chapter discusses the results from a state-of-practice survey that was carried out in order to understand current LVR safety management practices across the United States. The fourth chapter presents an assessment of the identified screening methods. The criteria used for the assessment, the process of assigning weights to each criterion, the scoring process and a discussion of the results, are presented in this chapter.

The fifth chapter presents the analysis of the Empirical Bayes (EB) method using actual LVR data. This chapter first discusses about the potential benefits and challenges of the Empirical Bayes method. Then it presents the different investigations that were carried out, and the findings from these investigations. The sixth chapter presents the newly developed method. The process of how the method was developed along with a discussion of its benefits and challenges are discussed as well. Finally, the last chapter summarizes the results and presents the major findings from this research.

CHAPTER TWO

LITERATURE REVIEW

The main purpose of a network screening process is to correctly identify sites that are in need of safety improvement. Over time, several network screening methods were developed, proposed and implemented. This chapter presents the results of a state-of-the-art literature review, that identified many of these methods. These methods were classified into four broad classes. The different methods under each of these classes are discussed in the following sections.

Methods Based on Historical Crash Experience

The first class of network screening methods use historical crash experience such as crash frequencies, severities, crash types, and/or crash rates (the latter require the use of traffic exposure data). First, methods that uses historic crash data alone are presented, followed by other methods that use crash data along with other information (such as traffic or roadway characteristics).

Methods using Crash Data Alone

Crash Frequency/Density Method: Crash frequency methods use the number of crashes for each site in the network. These sites could be a spot location (e.g. intersection, bridge, highway-rail crossing, etc.) or a roadway segment. Crash frequency could also be established for specific crash types, such as run-of-the-road crashes, pedestrian crashes, etc. The sites are then ranked in a descending order. When crash frequency at a location is

greater than a pre-determined critical value, that location is considered a “high crash location.” The critical frequency values are either calculated using average crash frequency at similar sites (and their standard deviations) or by choosing a considerably high number for that particular type of location (Pawlovich, 2007; Southeast Michigan Council of Governments [SEMCOG], 1997; National Cooperative Highway Research Program [NCHRP], 1986; NCHRP, 2000).

The crash density method calculates the number of crashes per mile for roadway segments. A segment can be defined as the minimum length of roadway having consistent characteristics. Similarly, the segments are ranked in descending order and segments having a crash density greater than a pre-determined critical density are considered as “high crash locations.” The critical density is calculated in a similar fashion as described in the frequency method (Pawlovich, 2007; SEMCOG, 1997; NCHRP, 1986; NCHRP, 2000).

An illustrative approach to the crash frequency/density method is the spot map method. The spot map method develops a map showing crashes on the network, thus identifying crash clusters at spot locations and on segments of the road network. The map is then used to identify those locations or segments having the greatest numbers of total crashes or total crashes of a specific type. This is a simple and easy method more suitable for small areas and areas having lower number of crashes (Pawlovich, 2007; SEMCOG, 1997). It only provides rough estimates of high crash locations and fails to provide a list of those locations.

Crash Severity Methods: Crash injury severity is also incorporated in network screening. One method for assessing crash injury severity utilizes the ratio of fatal crashes

to total number of crashes in identifying sites for further consideration. Fatal crash rates, fatal plus injury crash rates, and total crash rates may also be used. Crash severity methods incorporate injury severity in a few ways, including frequency/density of severe crashes, rate of severe crashes and ratio of severe crashes. In this method, severe crashes are assigned more weight than other crashes. Generally, the results for each site are compared to a system-wide average for similar roadways. The idea behind this method is to allow agencies to devote more resources to locations with a greater potential for severe crashes.

The equivalent property damage only (EPDO) method and the relative severity index (RSI) are two types of crash severity methods. The EPDO method provides a weight to fatal and injury crashes against a baseline of property-damage-only (PDO) crashes. The EPDO for a site (or segment) is calculated using the weights and the frequency of fatal, injury and PDO crashes. The EPDO rate for a site is calculated using traffic exposure data (Pawlovich, 2007; SEMCOG, 1997; NCHRP, 1986; NCHRP, 2000). The RSI method incorporates the weighted average cost of crashes at the site or segment. The RSI is calculated using frequencies and estimated crash costs for fatal, injury and property damage crashes (Pawlovich, 2007; SEMCOG, 1997; NCHRP, 1986; NCHRP, 2000).

A combination of crash frequency and crash severity is sometimes used for network screenings. This method incorporates both concentration criteria and severity criteria. To meet the concentration criteria, the site crash frequency/density must exceed a predetermined critical value. To meet the severity criteria, the EPDO rate for the site must also exceed a predetermined cut-off value. If both criteria are met, the site is considered a

candidate for safety improvement measures. Critical rates for total crash frequencies, fatal crash frequencies, etc. are used to determine the cut-off values (Pawlovich, 2007).

Methods using Crash Data in Conjunction with Other Data

The Crash Rate Method: The crash rate method incorporates traffic exposure with crash history in the network screening process. Crash rates are expressed for highway segments as the number of crashes per million vehicle miles travelled, and for spot locations as the number of crashes per million vehicles entering. Similar to the crash frequency methods, a critical crash rate has to be established, with locations higher than the critical value classified as “high-crash locations.” A common practice is to use a critical value that is twice as high as the system-wide mean crash rate (Pawlovich, 2007; SEMCOG, 1997). The crash rate method often uses total crashes in calculating rates, however, rates for specific crash type (e.g. single-vehicle crashes) and severity levels (e.g. fatal crashes) are also used.

The Frequency-Rate Method: The frequency-rate method combines the results from crash frequency-density methods and the crash rate method. In this method, the crash frequencies and densities, as well as crash rates are calculated for point locations and roadway segments. Critical values are established for crash frequencies or densities as well as for crash rates both for point locations and roadway segments independently. Consequently, locations having both frequency/density value and crash rate value greater than the pre-specified critical values are considered “high crash locations” (Pawlovich, 2007; SEMCOG, 1997; NCHRP, 1986; NCHRP, 2000).

The Quality Control Method: The quality control method uses similar principles as that of the frequency and rate methods. This method involves comparing crash frequencies/densities or rates with pre-determined values for sites of similar characteristics. There are two types of quality control: number quality control and rate quality control.

The number quality control compares the actual frequency/density for each site with the critical frequency/density. A test is applied to determine the statistical significance of a site's crash frequency/density when compared to the mean crash frequency/density for similar sites. The statistical test assumes crashes have a Poisson distribution, and uses a probability constant that adjusts the critical value as per the level of confidence requirements. The rate quality control method follows the same principle but uses crash rates instead of frequency/density. The final step of this method includes the calculation of a safety index. The safety index is the ratio of observed frequency/density or crash rate to the critical frequency/density or crash rate. The sites are then ranked by the safety index (Pawlovich, 2007; SEMCOG, 1997; NCHRP, 2000).

Deacon et al. (1975) developed an effective procedure for identifying hazardous rural highway locations based on accident statistics. The procedure utilized multiple indicators of accident experience which included the number of fatal accidents, the total number of accidents, the number of effective-property-damage-only accidents, and the accident rate. Critical levels of these four indicators are expected to vary from state to state depending on the nature of the local safety improvement program as well as local traffic and roadway conditions and prevailing attitudes toward highway safety. Critical accident rates are established using quality control procedures.

Index Methods: Index methods combine crash severity indices with other methods. There are three main index methods: the weighted rank method, the crash probability index method (CPI) and the Iowa method.

The weighted rank method (Pawlovich, 2007; SEMCOG, 1997; NCHRP, 2000) combines results from other methods. For example, ranks based on the crash frequency/density, crash rate and crash severity methods are generated. Then using a weighting factor, the combined rank based on the individual ranks are calculated.

The crash probability index (CPI) combines the results from the crash rate, crash frequency and casualty ratio (CR) methods. Casualty Ratio is the ratio of fatal and all types of injury crashes to the total number of crashes at a given site or segment. This method reduces misleading results that arise from either high or low traffic volume at a site, while also incorporating the severity of the crashes. When any of the results exceed their critical values, penalty points are assigned. The CPI value for a site is the sum of all the penalty points. Sites with higher CPI values receive higher priority. The penalty points for each of the criteria (rate, frequency and CR) can be subjectively assigned based on how much importance an agency puts on each of the methods. The critical value for the rate and frequency is set using the same principle as that of crash rate and crash frequency/density methods. The critical value for CR can be determined by using the regional CR. The regional CR can also be in terms of facility and intersection type in conjunction with traffic exposure (AADT) (Pawlovich, 2007; SEMCOG, 1997). Both the weighted rank method and the CPI method allows retention of some of the benefits of the different methods while also minimizing the disadvantages of each method. For example, using the crash frequency

and the crash rate together helps to address the inaccuracy of the crash frequency method that arises due to very low or high volumes.

In Iowa, a method similar to the weighted rank methods are used. Three rank lists are developed: frequency rank, severity rank and rate rank. The original Iowa method requires identification of sites with at least eight total crashes, four injury crashes and one fatality. The selected sites are first sorted by descending frequency of crashes (frequency rank). Then the locations are sorted by a severity rank. The severity ranks are developed using the principle of loss of value. Each crash severity (Fatal, injury, property damage only, etc.) is assigned a monetary value. The loss value at a site is calculated based on the frequency of each crash severity and the respective monetary value. Finally, using the traffic exposure data, crash rates are calculated, and the sites are ranked according to the crash rates. The three ranks are then combined to create a composite rank factor which is used to prioritize the sites in a descending order (Pawlovich, 2007; Estochen, 1999; Iowa Department of Transportation Office of Traffic and Safety [IDOT TAS], n.d.)

The newer Iowa method uses a similar approach with focus on intersections. Crashes on road segments within a certain proximity of an intersection are considered as intersection related crashes. The frequency and rate rankings are developed in the same way as the original method. The injury severity ranking is developed by multiplying the frequency of each injury severity by specific weights. A normalization process of the ranks is carried out for each of the methods. This helps to reduce the impact of very large numbers, when the ranks are combined. This is done by dividing each of the frequency, rate and severity values by their respective maximum values. For example, the maximum

crash frequency in the frequency-based ranking is 5000. Another site has a frequency of 3000. Therefore, the normalized value for the second site would come out as 3/5. Finally, a weighted sum of the ranks of the measures is calculated. The weights are assigned based on the importance the agency puts on the individual ranks (Pawlovich, 2007).

Methods Based on Crash/Risk Predictions

These methods generally use predicted crash numbers/risk for network screening. Generally, mathematical models are used to predict the number of crashes for a site and/or segment. These models are developed based on the relationship between crash occurrence and various roadway and traffic variables. This section will first discuss about a few models that predicts crash numbers using the relationships between crash occurrence and geometric and traffic variables. Then this section will proceed to explain about predictions based on surrogate measures.

Methods using crash/risk prediction models

Zhong et al (2011) developed crash prediction models for rural roads of Wyoming using both the Negative Binomial Regression (NBR) and Poisson regression method. The model used historical crash rate (number of crashes per unit length), traffic volume, and speed. The study found that NBR fits the over dispersed data more accurately. The study showed statistically similar crash rates for both gravel and paved road surfaces. The study also correlated higher crash rates with high traffic volumes in conjunction with high speeds. However, only 36 effective observations were used for this investigation.

Using data from rural two-lane highways of Pennsylvania, Agüero-Valverde et al (2016) developed a methodology using crash type for identifying Sites With Promise (SWiPs). Full Bayes multivariate crash frequency model with spatial correlation to estimate crash frequency according to crash types was used. AADT at a particular time and segment length was used to predict the number of crashes. The study also compared univariate model, univariate spatial model, a multivariate Poisson lognormal model (MVPLN), and a MVPLN spatial model and found that MVPLN spatial model had a better fit of the data.

Schultz et al. (2016) developed a crash prediction model using the following variables: average daily traffic (AADT), segment length, speed limit, number of lanes, percent trucks, VMT, and the interaction between speed limit and number of lanes. About 100,000 iterations were performed on each segment to obtain posterior predictive distributions of the number of crashes that is expected to occur. The actual number of crashes were compared to the posterior predictive distribution to assign a percentile to each segment. The percentile was determined by where the actual number of crashes fell on the predicted distribution and was assigned a number between 0 and 1. The higher the percentile, the greater chance the segment is a hot spot that needs to be analyzed for safety improvements.

A Canadian study (de Leur and Sayed, 2002) developed a Road Safety Risk Index (RSRI) utilizing concepts related to the traffic conflict observation technique and drive-through safety reviews. Well-defined and quantifiable characteristics of road features are studied and scored while completing a drive-through review. These scores are then

combined to produce an overall road safety risk, by combining three components of risk: the exposure of road users to road features, the probability of becoming involved in a collision, and the resulting consequences should a collision occur.

Ewan et al. (2015) developed a risk index to identify locations along Oregon's low-volume rural roads that deserve further consideration. The crash risk index was developed using three major elements: geometric features, crash history and traffic exposure. Weights, which show the contribution of geometric and roadside features, crash history, and traffic exposure elements in the overall crash risk index, are assigned to each of these elements.

The International Road Assessment Program (iRAP) (2009) developed a methodology for network screening and for prioritizing locations for safety investments. The methodology involved inspection of the desired road either by driving and recording potential risk factors along a highway or by using video log data routinely acquired by highway agencies. The methodology introduced Road Protection Score (RPS) which is a function of likelihood, severity, crash type, and type of road users. The RPS for a site is the sum of the individual RPS of different crash types. For example, car occupant RPS is the sum of run-off RPS, head-on RPS and intersection RPS. The likelihood factor is the connection of a certain risk factor with the likelihood of death due to a certain type of crash. The severity factor is determined from the speed and the presence of roadside objects. For example, steep embankments have a potential to increase the severity of roadside crashes. The crash-type calibration factors are based on the analysis of the fatality proportions associated with each crash type along generic type of roads. Finally, a star rating is

provided for different ranges of RPS. The higher the rating, the better the safety score, with one star being the least performing score and 5 star being the highest performing score.

Methods Using Surrogate Safety Measures

According to a FHWA study (Gettman et al., 2008), surrogate safety measures are “*measures other than actual crash frequencies*” that are helpful to assess safety needs without waiting for a statistically significant number of crashes to actually occur. Many methods for identifying candidate sites for safety improvements using surrogate safety measures have been proposed and/or used. This section discusses a few of these methods.

Speed and speed variation are identified as potential surrogate measures by many studies (Lee et al., 2002; Lee et al., 2006; Kwon et al., 2011). Studies have linked higher speeds with higher crash rates (Nilsson, 2004; Finch et al., 1994; Baruya, 1998). It was also found that speed is a major determinant of crash severity (Aarts and van Schagen, 2006). Speed and speed variations are also used by many studies to determine crash potential (Stipanica and Miranda-Moreno, 2015). Siddiqui and Al-Kaisy (2017) has also used speed and speed variation as part of their investigation in assessing safety effects of a variable speed limit system.

A study from New Zealand (Harris et al., 2015) developed a method to identify curves on rural highways with higher level of risk using speed. Using the Austroads (the Australian transportation agency) operating speed model, the methodology calculated speeds along road sections based on the geometric features of the road. The method then compared the calculated speed with the horizontal curve radius in order to assess the design limitations of the curve. A new Geographic Information Systems (GIS) model was

developed. The model identified the curves, predicted the operating speeds along road corridors and assessed curve risk using approach speeds and radius. However, the operating speed prediction was based only on the observations of passenger car drivers and therefore, the results of the speed prediction could only refer to the predicted speed of passenger cars.

Stipancica et al. (2018) examined whether vehicle braking, and accelerating maneuvers could be used as surrogate safety measure. GPS data was collected from smartphones of people who regularly drive to explore their braking and acceleration as potential surrogate measures through correlation with historical collision frequency and severity across different facility types. Data was collected from Quebec City, Canada in 2014. The sample for this study contained over 4000 drivers and 21,000 trips. Hard braking and accelerating events were extracted and compared to historical crash data using Spearman's correlation coefficient and pairwise Kolmogorov-Smirnov tests. Both braking and accelerating showed positive correlation with crash frequency on highway segments, and stronger correlations were found at intersections. Locations with more braking and accelerating also tended to have more collisions. Though this study did not propose an identification and screening method for these maneuvers, the proposed surrogate measures can potentially be utilized for identification of candidate sites for safety improvements at the network level.

Methods Using Both Crash History and Prediction Models

The previous sections of this chapter presented screening methods that uses historical crash experience followed by methods that uses crash/risk prediction. The benefit of using predictive methods is that, geometric properties that have a correlation with crash

occurrence can be included in the screening method. Moreover, if reliable historical crash data is available, actual crash history along with predicted crash numbers can be used for a more accurate network screening. This section of the chapter will discuss about those network screening methods.

Empirical Bayes Method

One example of the methods using both crash history and crash prediction is the well-known Empirical Bayes (EB) method. This method determines the expected number of crashes using the actual number of crashes (crash history) along with the predicted number of crashes. The predicted crash numbers are obtained with safety performance functions (crash prediction models). The Highway Safety Manual (HSM) recommends the use of Empirical Bayes method in assessing safety performance at sites for which the observed crash frequency is available (AASHTO, 2010). The HSM prediction models are mathematical models developed using data from a large number of similar sites. The HSM models use traffic exposure as the main variable. The HSM refers to these models as the Safety Performance Functions (SPFs). These models were developed using data from sites with specific geometric features, traffic control, etc. For sites with different geometric features and/or traffic control, adjustment to the predicted crash numbers are required. Adjustment factors used for this purpose are called the accident modification factors (AMFs). A calibration factor may also be used to account for regional and local variations.

Other Methods

A study from Kentucky (Hummer et al., 1999) compared the collision-based method and an inventory-based method to identify candidate locations for safety improvements on rural roads. At that time, Tennessee DOT used the collision-based methods to identify those locations (the traditional hotspot identification methods). For the inventory-based methods, a seven-step process was developed. Three of the seven steps involve identifying sites for further consideration. Those three steps are: selection of suitable segments of highways on which the analysis is to be performed, breaking down those segments into distinct locations (such as bridges, curves, straight segments, etc.) and applying crash prediction models to calculate the predicted number of crashes for the segments. Then using both results, sites that are good candidates for safety improvement projects were ranked. In order to identify the effectiveness of each methods, a survey was designed and sent to safety experts. As a part of the questionnaire, photographs of the sites were included. The experts were asked to rank those sites and their results were compared with the results of the two methods. The comparison indicated that both methods have the potential to perform equally well in identifying candidate safety improvement sites, and the study recommended using the inventory method to compliment the collision-based method.

Šenk et al. (2012) proposed a method that uses reported crash numbers and predicted crash numbers in order to find the accident potential for a site. Secondary rural roads data from South Moravian region of Czech Republic was used. Crash was predicted using a model with geometric and traffic data. The difference between reported and

predicted crashes over length gave the accident potential value. Any site with positive accident potential was identified as at-risk site.

Ossenbruggen (1987) developed a probability-based method to identify hazardous sections. The expected number of crashes for a spot was identified using an equation connecting the Average Daily Traffic (ADT) and the probability of a harmful event taking place. The probability is calculated using two main variables; the probability of an individual being killed in a single motor vehicle trip and the mean number of trips made by an individual in a lifetime. The expected numbers of fatal and injury crashes are calculated by their respective equations. Sites with expected number of crashes less than the actual number of fatal and injury crashes, are identified as hazardous.

Tarko et al (2004) proposed two crash screening methods for ranking hazardous locations. One of the methods is based on the difference between expected and true crash numbers and the other is based on crash cost. The two proposed methods are index of crash frequency and index of crash cost.

The index of crash frequency (ICF) measures the difference between the estimates of the expected crashes and the typical numbers of crashes. The difference is then divided by the standard deviation of the difference estimate. Locations having an ICF value greater than 2 are considered as high crash locations. The higher the ICF value, the higher the chance of the location having higher number of crashes. This is so because it compares a location to a typical location of the same type having the same exposure. This study did not use the Empirical Bayes method, as the aim was to identify sites that had “*anomalies*

in crash frequencies that might indicate a need for road improvements". The study also stated that the index method has already been used in Indiana for several years.

The second method compares the total cost of reported crashes with the typical cost. For this method, crashes are divided into two main categories, namely; injury or fatality crashes and property damage- only crashes. The authors claim that this method *"incorporates crash severity through average crash costs"*.

Non-Mathematical Methods of Network Screening

Sometimes accurate and reliable crash data are unavailable for many LVRs. For such situations, few methods have been developed that are simple and only requires the presence/absence of risk factors for screening the network.

One well-known method is the FHWA Systemic Safety Project Selection tool. This network screening and prioritization process uses site-specific crash information (including type and severity), considers common factors contributing to the focus crash type, traffic volumes and geometric features of the road (FHWA, 2013). Special focus is also placed on the severity of crashes. Risk factors are determined based on the analysis of crash and roadway data. Roadway and traffic attributes shown to have a correlation to a particular crash type are known as risk factors. Locations having one or more of these risk factors are scored with "1" or an asterisk. After reviewing the locations, the risk factors are reassessed for their usefulness in identification of safety improvement locations in the whole system. Any risk factor that is present in every location of the network is discarded. Finally, the locations are ranked based on the presence of risk factors. Higher number of risk factors indicate higher potential for a particular crash type and therefore has higher priority.

Kentucky (KYTC, 2012), Minnesota (MnDOT, 2014), New York (Richard et al., 2013) and Thurston County in Washington (The Thurston County Public Works Department, 2013) have all reported using the systematic safety project tool.

Both the Minnesota County Roadway Safety Plan (CRSP) and North Dakota Department of Transportation employ a star approach to identify at-risk locations. The approach identifies risk factors for the network and any site having the identified risk factors receives a star. If any site has more than a pre-determined number of stars, it is identified as an at-risk site.

CHAPTER THREE

SAFETY MANAGEMENT PRACTICES FOR LVRs

Before developing a new network screening method for LVRs, this research tried to understand the existing safety management practices for LVRs. For this purpose, a state-of-practice survey was conducted. This chapter presents the methodology and the results of this survey.

Survey Methodology

The survey questionnaire consisted of two major parts. The first part contained seven questions about identifying sites for low-volume roads that are owned and operated by the state's transportation department (state DOT). These questions addressed issues such as the use of specific screening methods, whether cost effectiveness is considered in the process, access to various types of data, and the level of agency's satisfaction with the site selection process. The second part of the questionnaire consists of ten questions and focused on site identification for non-state-owned local roads. The questions in this section inquired about whether or not the leadership of the safety programs for non-state-owned low-volume roads (LVRs) is different from that of other state-owned roads, local agency involvement and its level, safety fund allocation for non-state-owned local roads and site identification methods, besides other relevant aspects.

The survey was created and managed using Qualtrics survey software. The survey was sent via email to safety personnel at state DOTs of all the 50 states. Thirty-two (32) agencies responded resulting in a response rate of 64 percent. The responding states are

shown on the map in Figure 1. However, one respondent submitted the survey without completing the questionnaire, and as such, this response was excluded from further consideration and analysis. A copy of the questionnaire is provided in appendix A at the end of the report.

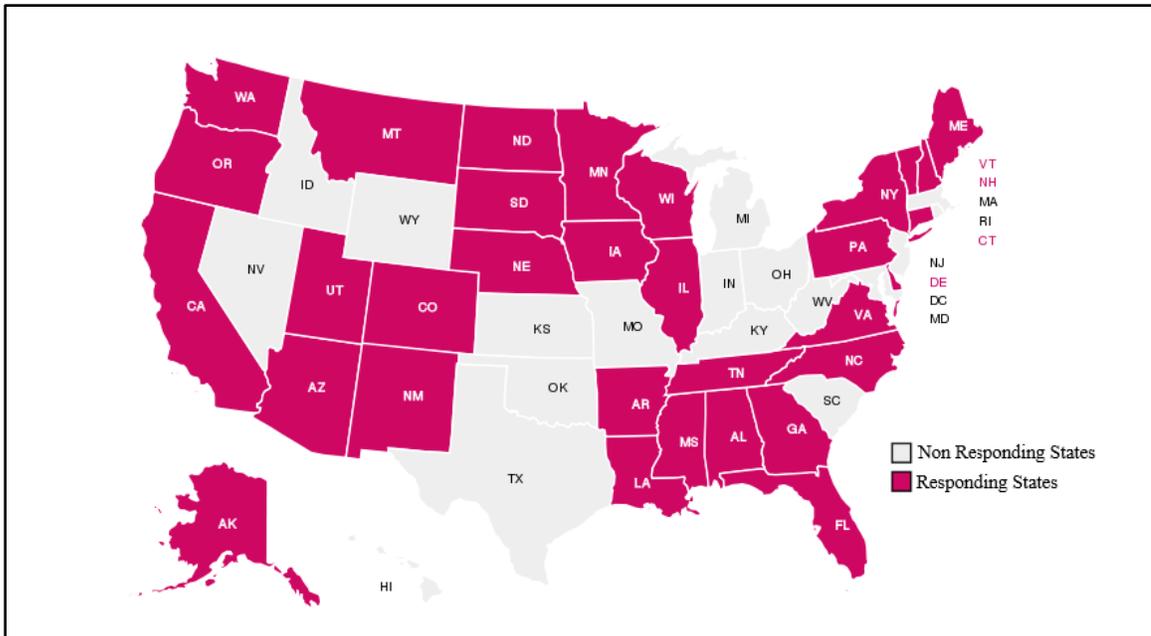


Figure 1. Map showing Survey Responding States.

Survey Results

Safety Improvement Programs for State-Owned Low Volume Roads

As discussed earlier, the survey was divided into two parts. The first part consisted of questions that focused specifically on state-owned local roads. The results from the analysis of the responses from this part are discussed in the following paragraphs.

Before inquiring about the different methods of how safety concerns on low-volume roads are addressed, a question about the percentage of low-volume roads in each

state was asked. The question asked, “*what percentage of roadways in the state has a volume of less than 1000 vehicles per day (vpd)*”. The responses are illustrated in Figure 2.

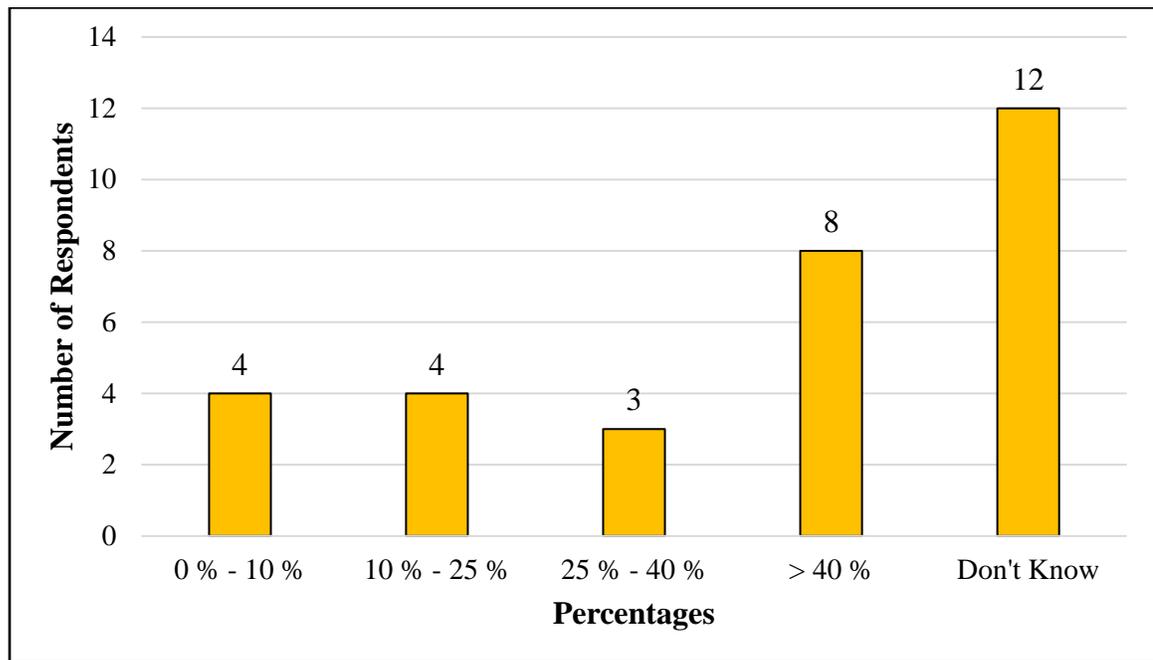


Figure 2. Percentage of Roads having an AADT of less than 1000 vpd.

Eight out of 31 states (around 25%) reported that more than 40 percent of their roads have AADT of less than 1000 vehicles per day. Four out of 31 (about 13 percent) of them reported a percentage between 10 and 25 and a similar number of states reported a percentage less than 10. Only three out of 31 states (less than 10%) reported a percentage between 25 and 40. However, it is important to note that 12 out of 31 respondents (around 38 percent) reported of not knowing the percentage of low-volume roads in their states. This might be because most states do not classify their roads based on daily volumes. Another possible reason is that many of the low-volume roads are in remote rural areas and therefore it is likely that traffic counts on these roads are not readily available.

Moving on, to understand how states manage safety projects for LVRs, the survey inquired about “*whether the agencies has a different method for selecting sites for local roads than well-travelled roads*”. This information is important because traditional methods for site identification for well-travelled roads may not work well for low-volume roads.

More than 80 percent of respondents (25 out of 31) reported having a different method for their local roads, while only about 19 percent of respondents (6 out of 31) reported using the same method/process. This is consistent with the general understanding that methods for well-travelled roads may not work well for LVRs and therefore most of the responding states use separate methods.

The next question in the survey asked agencies about “*the different site identification methods*.” Figure 3 shows the number of times different methods were reported to be used for site identification on state-owned local roads. Results show that crash severity is the most often reported method (21 times) followed by FHWA systemic approach (15 times) and the combination of the crash frequencies and crash rates (15 times). Crash rate method alone is the least used method (8 times). Eleven states reported using different methods other than the usual standard methods. Out of those methods, around seven (out of eleven) responses are related to the use of predictive methods outlined in the Highway Safety Manual (HSM).

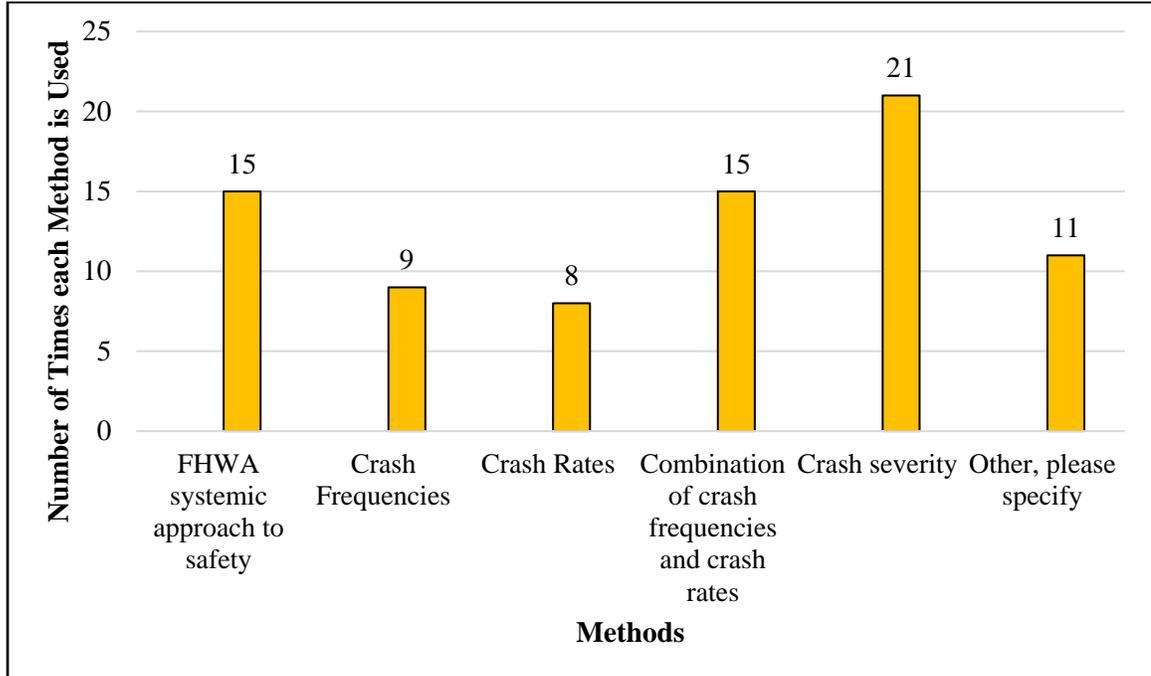


Figure 3. Frequency of Use of the Different Site Identification Methods.

Many of the respondents reported using the traditional network screening methods along with the FHWA systemic approach for site identification of state-owned local roads. Specifically, 15 out of 31 responding agencies (48 percent) reported using the FHWA systemic approach in combination with one or more network screening methods. These numbers suggest that the systemic approach is gaining popularity and is being used alongside with the traditional network screening approaches for safety improvements on local roads.

The following question in the survey queried agencies about “*how cost effectiveness is used for site identification.*” Table 1 summarizes the responses to this question.

Seventeen out of 31 responding agencies (55 percent) reported using cost effectiveness for both ranking sites on local roads as well as for comparing different site-specific safety improvement alternatives. Only 7 agencies (22 percent) use cost effectiveness for site-specific comparative analyses and another 6 agencies (19 percent) use it for ranking sites at the network level (network screening). Use of cost effectiveness for both network screening and countermeasure identification was expected in most of the cases as it ensures maximum potential benefits on safety investments.

Table 1. Use of Cost Effectiveness in Safety Management on State-Owned LVRs

How Cost Effectiveness is Used	Number of Responses
Rank safety improvement sites at the network level	6
Compare alternative safety countermeasures at specific sites	7
For both ranking sites and comparing alternatives	17
Not used	1

To gather information on potential challenges and difficulties in managing safety on low-volume roads, agencies were asked about their level of satisfaction with the methods they reported using on state-owned LVRs. The question used a scale of 1 to 10 with 1 being “not satisfied” and 10 “extremely satisfied.” The responses to this question are summarized in Table 2.

The responses varied in a range from 4 to 10. Eighteen out of 31 (About 58 percent) reported a satisfaction level of 8 or higher indicating high level of satisfaction with their LVRs methods. Ten out of 31 agencies (around 32%) reported a score of 6 or 7 indicating agencies are somewhat satisfied with the methods used. The remaining three agencies (around 10%) scored 4 or 5 on the scale, which reflect a lower level of satisfaction with the

methods used. The responses reveal that majority of the agencies are satisfied with their methods of identifying safety improvement sites on LVRs.

Table 2. Agencies' Level of Satisfaction with their state-owned LVR Methods.

Level of Satisfaction	Number of responding agencies
1	0
2	0
3	0
4	1
5	2
6	5
7	5
8	14
9	3
10	1

To effectively manage safety on LVRs, access to crash, traffic, roadway, and roadside data is critical. A question about the type of data that is readily available to safety personnel at the network level was therefore included in the survey. The responses are summarized in Table 3.

Seven out of 31 agencies (around 22 percent) reported having access to all data, i.e. crash, traffic, roadway and roadside data. Fourteen agencies (around 45 percent) reported of having access to all data except roadside features. The remaining 9 agencies don't have access to any roadway or roadside data: 7 agencies have access to crash and traffic data and two agencies have access to crash data only. Those numbers show that around two

thirds of the responding agencies have access to most of the data needed to analyze safety at the network level.

Table 3. Access to Different Data Types.

Combination of Different Data Types	Number of Times Each Combination of Data Is Easily Accessible
Detailed Crash Data	2
Crash & Traffic	7
Crash, Traffic & Roadway	14
All	7
Crash, Roadway & Roadside	1

Safety Improvement Programs for Non-state-owned Low Volume Roads

The second part of the survey focused on safety programs and practices for non-state-owned local roads. The findings from the responses from this part are discussed in the following paragraphs.

To understand how safety in non-state-owned local roads are managed by agencies, the survey asked agencies whether the HSIP program leader for non-state-owned roadways is different from the individual leading the program for state-owned roadways.

Around 90 percent (28 out of 31) of the responding agencies reported of not having a separate HSIP leader for non-state-owned local roads. The remaining 10 percent (3 agencies) confirmed that different leaders are assigned to safety programs on state-owned and non-state-owned local roads. This is somewhat expected partly because fewer crashes usually occur on low-volume roads, and thus may not constitute a priority for many agencies. Further, assigning a different leader and team for non-state-owned roads would require more resources and administrative costs.

For more effective safety improvement programs on low-volume roads, input from local agencies is always important. To understand the extent of involvement of local agencies, a question about involvement of local agencies was included in the survey. Approximately, 90 percent of the respondents (28 out of 31) reported of involving local agencies in the site identification process, while only about 10 percent (3 out of 31 respondents) reported of no involvement from the local agencies. These numbers suggest that most programs rely on input from local agencies in identifying safety improvement sites on local roads.

To gain a better understanding of how agencies manage safety on non-state-owned local roads, agencies were asked about the way agencies allocate funds for safety improvements on these roads. Specifically, a question regarding the process in determining how much funding is allocated to safety projects on non-state-owned local roads was included in the survey. Most of the responses were descriptive responses and the results are codified and summarized in Figure 4.

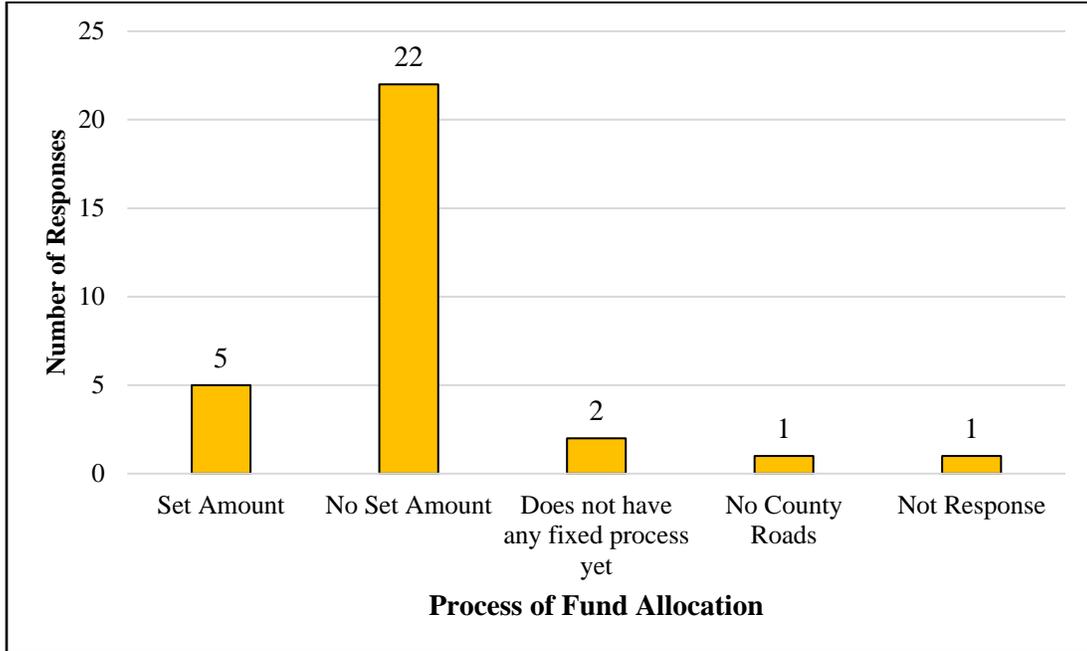


Figure 4. Number of States Using the Different fund Allocation Methods.

It can be observed that about 70 percent (22 out of 31) of the respondents do not set aside a certain amount of funds for non-state-owned local roads. This figure clearly shows that only five states have a process where they set aside a specific amount of safety funds for these roads. This indicates that those states already have a systematic procedure/process for allocating safety funds to non-state-owned local roads. Most respondents (24 out of 31) indicated that they don't use a set amount or don't have an established process for allocating funds to non-state-owned local roads. This is somewhat expected, as most highway agencies rely heavily on cost-effectiveness in selecting sites for safety improvements, an approach that has an inherent bias against low-volume roads in general including the non-state-owned local roads. The state of North Carolina reported of not having any significant number of non-state-owned roads and therefore, does not have any separate fund allocation methods for them.

One of the most important aspect of any safety program is site identification. Therefore, a question about how safety improvement sites are identified on non-state-owned local roads was included in the survey. The frequency of using different methods in the responses is illustrated in Figure 5. In answering this question, respondents had the option to choose more than one method in their answers. Fifteen agencies reported that they include non-state-owned local roads in their statewide hotspot network screening. Another 13 agencies indicated they perform network screening within local jurisdiction. Further, crash experience at sporadic sites, perception at individual sites by law enforcement or the public were reported in 21, 17, and 8 responses respectively. Seven of the responding states reported using methods other than those included in this question. Out of those methods, 2 of them reported of using a systemic approach, 3 of them has reported of working on the development of a process, 1 of them reported of including non-state owned LVRs into a statewide screening and 1 of them have reported of developing local road clusters.

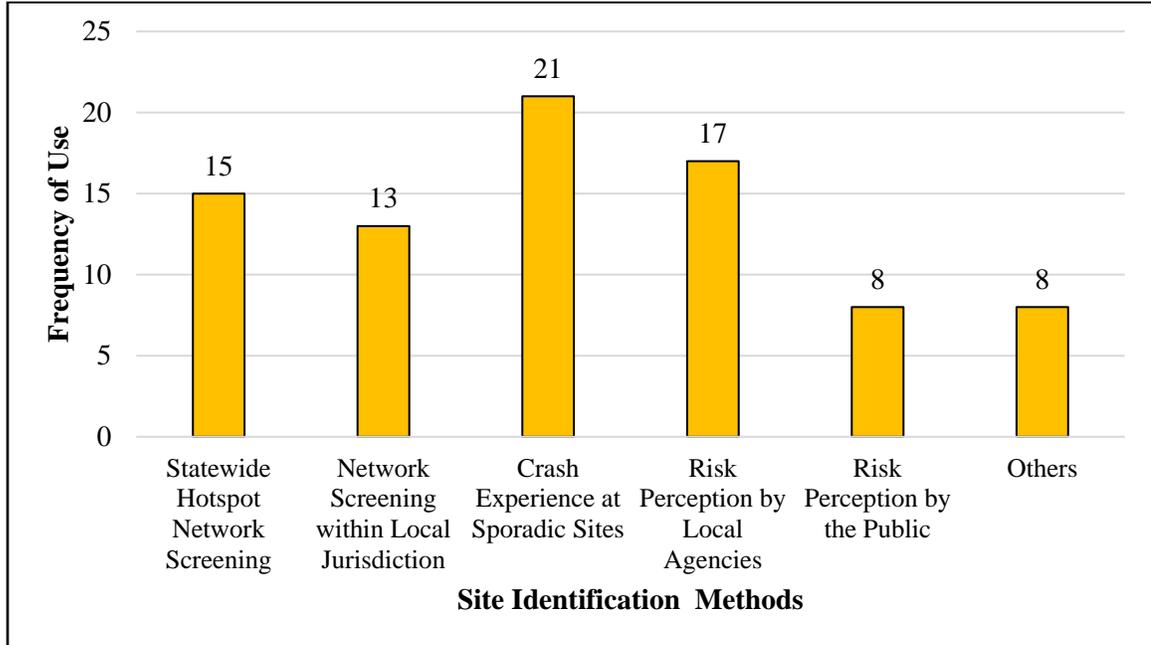


Figure 5. Frequency of Different Site Identification Methods for Non-state Local Roads.

For any data-driven safety analysis, access to crash, roadway and traffic data is critical. To understand how the different agencies, handle non-state-owned local roads, a question about which entity conducts traffic and roadway data collection for non-state-owned local roads was included. The summary of the responses is provided in Table 4.

Table 4. Entities Conducting Roadway and Traffic Data Collection for Non-State-Owned Local Roads.

State DOT	3
Local Agency	9
Both	16
Others	3

As shown in this table, around half of the responding agencies reported that both the state DOT and the local agencies conduct the traffic and roadway data collection needed for safety improvement sites. Nine responding agencies indicated that local agencies are

responsible for collecting traffic and roadway data, while only three agencies indicated that data collection is undertaken only by the state DOT.

To understand the selection process of safety improvement sites on non-state-owned local roads, a question about the criteria used for justifying the selection of safety improvement sites was included in the survey. Figure 6 shows the frequency of the different criteria used in agency responses. In answering this question, agencies can select more than one criterion from the list of criteria provided. Consistent with expectation, cost effectiveness is the criterion most frequently used in selecting safety improvement sites (reported by around 80% of the agencies). Crash severity was reported in 12 responses while the combination of crash frequency and rate was reported in 10 responses. Crash frequency and crash rate were reported in 8 and 5 responses respectively.

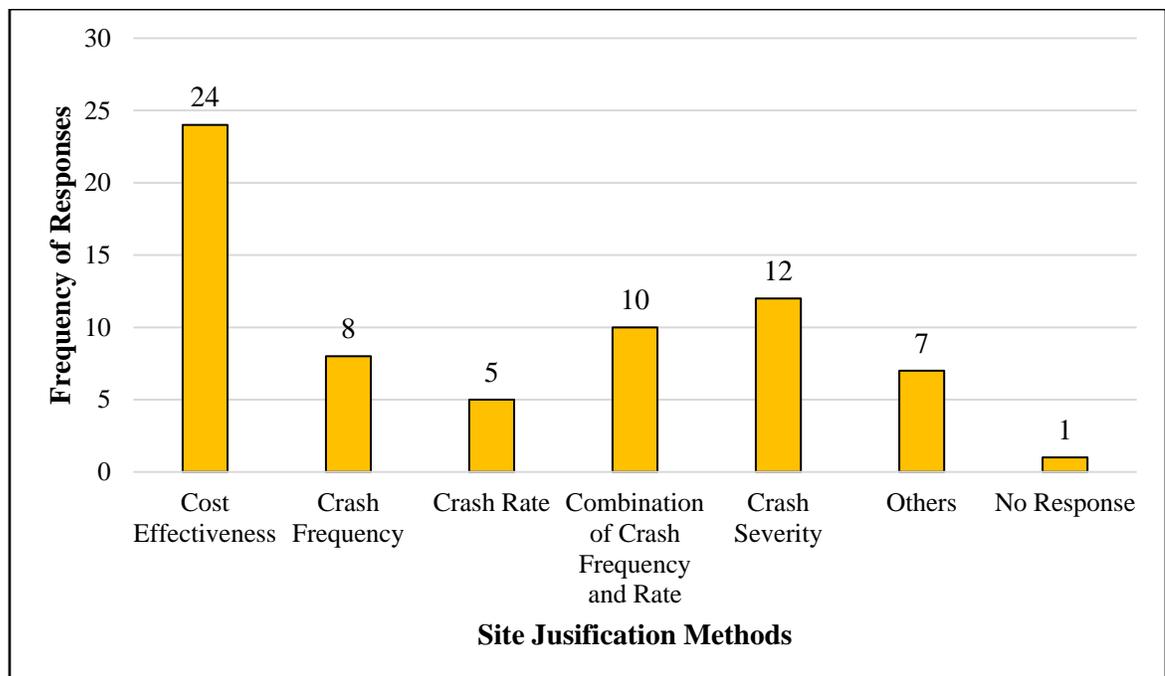


Figure 6. Frequency of Different Site Justification Methods for Non-state Local Roads.

Another question in the survey asked agencies whether the selection of safety improvement sites on non-state-owned local roads is performed separately from the state-owned roadways. About 55 percent (17 out of 31) of the responding agencies select safety improvement sites on non-state-owned local roads together with state-owned local roads, while the remaining 45 percent (14 out of 31) of the responding agencies select them separately.

The FHWA systemic approach to safety evaluates risk across an entire roadway system and implements low-cost safety countermeasures throughout the roadway network. Given the lower crash densities on local and low-volume roads, and the associated difficulty in using crash data alone for identifying safety improvement sites, systemic safety improvements become even more important in managing safety on low-volume roads. To understand the extent of its application on non-state-owned local roads, highway agencies were asked about the percentage of safety improvement funds allocated to systemic improvements. The responses are shown in Figure 7.

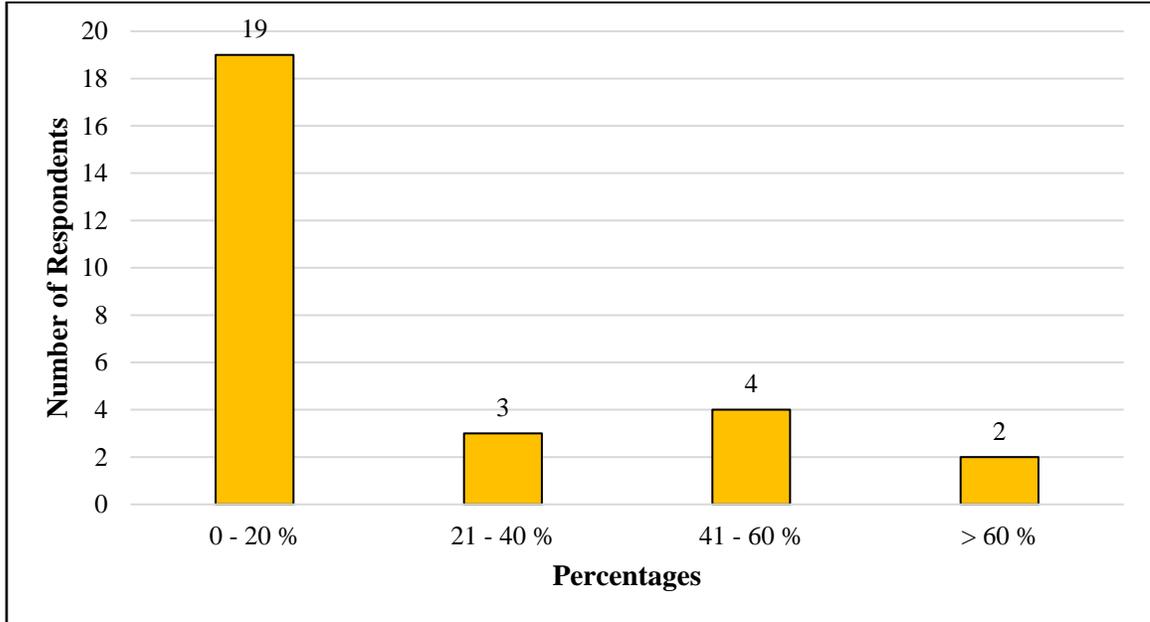


Figure 7. Safety Funds for Systemic Improvements for Non-state Local Roads.

More than two thirds of the responding agencies (19 out of 28) reported allocating less than 20 percent of the funds for systemic improvements, while only about 7 percent (2 out of 28) of the responding agencies reported allocating more than 60 percent. Seven agencies (25%) reported allocating 20 to 60 percent of total safety improvement funds to systemic improvements. Three agencies did not answer to this question.

Many of the non-state-owned low-volume local roads are unpaved, and therefore, a question was included in the survey on whether agencies include unpaved roads in the selection of safety improvement project sites. About 61 percent (19 out of 31) of the responding agencies reported of not including non-state-owned unpaved roads in their projects while only about 39 percent (12 out of 31) of the agencies includes them. This is somewhat expected because these roads mostly serve very low traffic volumes and as such does not represent a priority for most highway agencies.

Key Findings from the Survey

A state of practice survey was conducted in order to learn about state agency practices on different aspects related to safety improvement programs on low-volume local roads. The survey was sent to safety personnel in all 50 states and 32 of the states responded to the survey. The major findings from this state of practice survey are:

- About 80 percent of the agencies have a separate method for selecting sites on low volume roads (LVRs) than the one used for conventional roads.
- Crash severity is the most frequently used criterion for identification of potential safety improvement sites on LVRs.
- Around 48 percent of the responding agencies reported using the FHWA systemic approach in combination with one or more network screening criteria.
- More than half of the responding agencies (55%) reported using cost effectiveness both in ranking sites at the network level as well as in comparing specific safety improvements at individual sites.
- Around two thirds of the responding agencies reported of having access to crash, traffic and roadway data for low-volume local roads. However, only 23 percent of those agencies reported of having access to roadside data as well.
- About 90 of the responding agencies reported having the same personnel leading the safety improvement program for state-owned and non-state-owned local roads. About 90 percent of the responding agencies also reported of involving local agencies in identifying safety improvement sites on non-state-owned local roads.

- Majority of the responding agencies (70 percent) reported of not allocating a set amount of funds for safety projects on non-state-owned local roads.
- Crash experience at sporadic sites was the most frequently reported method for identifying safety improvement sites on non-state-owned local roads.
- About 52 percent of the respondents reported that data for non-state-owned local roads are collected by both the state and the local agency.
- Cost effectiveness was the most frequently reported criterion (around 80 percent) in justifying safety improvement projects on non-state-owned local roads.
- More than half of the responding agencies (55 percent) reported of using one process for identifying safety improvement sites on state-owned and non-state-owned local roads.
- More than two thirds of the responding agencies allocate less than 20 percent of total safety funds to systemic improvements on non-state-owned local roads.
- Unpaved roads are not involved in safety improvement programs on non-state-owned local roads for 61 percent of the responding agencies.

CHAPTER FOUR

ASSESSING NETWORK SCREENING METHODS

Different network screening methods for LVRs were identified on the literature review chapter. Different methods used different approaches and required different data and resources. Therefore, it was essential to assess these methods for their suitability for LVRs. This chapter presents such an assessment and discusses the results obtained from it.

Assessment Criteria

A set of assessment criteria were selected for assessing the methods. These criteria assessed the methods based on aspects like economic effectiveness, sensitivity, ease of implementation etc. The seven criteria are discussed in the following subsections.

Sensitivity to Level of Risk

For the purpose of this research, level of risk is defined as the likelihood of a crash taking place at a site when it is used by motorists. Risk factors are defined as roadway, roadside, traffic and environmental properties that have a strong correlation with crash occurrence. Basically, this criterion assessed whether risk factors were incorporated in the network screening process.

Sensitivity to Economic Effectiveness

Economic effectiveness, often used in the form of benefit-cost ratio, is based on the premise that a site that is expected to yield higher monetary return on safety investment is more deserving to receive safety funds. Sites with higher crash frequencies and higher

number of severe crashes tend to yield greater benefits upon implementing safety countermeasures. This criterion assessed a screening method for its incorporation of economic effectiveness.

Precision

This criterion is used to assess whether a network screening method can respond to small and subtle changes of any factor related to the level of risk or crash occurrence at a site. A less precise screening method might lead to discarding potential at-risk sites, as the method may not be able to accurately assess the risk due to subtle differences in magnitude of a risk-related feature.

Previous Performance Record

Only when a screening method is applied and validated, a full understanding of the strengths and limitations of that method is achieved. The record of a method being used in practice with satisfactory results is often associated with the practicality of the method and the merits perceived by users. This criterion assessed a method using the number of times it has been used.

Ease of Understanding

This criterion refers to how intuitive or easy to comprehend a network screening method is to the practitioner. Most LVRs are owned and operated by local agencies. These agencies usually do not have resource to implement sophisticated screening methods. Therefore, a screening method that is easier to understand is important.

Ease of Implementation

As discussed, most LVRs are owned and managed by local agencies. Therefore, a suitability of a method is also dependent on the practicality of a method. This criterion is related to the practicality of the method. This criterion assessed a method based on its need of accurate data and trained personnel for implementation.

Resource Requirement

This criterion refers to the resources needed when implementing a prospective network screening method, which primarily involve agency personnel as well as other costs involved in acquiring the data, including staff time.

Assessment of Screening Methods

The assessment methodology developed and used in this task aims at removing much of the subjectivity of the assessment criteria by following a systematic quantitative approach in expressing the level of a method meeting certain criteria. The method consists of three key elements: developing a scoring scheme for criteria, assigning weights to criteria, and preparing the final assessment matrix. Each of these elements is discussed in detail in the following sections.

Developing a Scoring Scheme for Assessment Criteria

In this step, numerical scores were assigned to the evaluation criteria based on the level a particular method meets those criteria. The scoring scheme developed is shown in Table 5. A four-level score (1 to 4) was assigned to level of risk representing sites lacking risk factors, those with traffic properties, geometric properties, and those with both traffic

and geometric properties involving risk in an ascending order. Cost effectiveness was assigned three levels (1 to 3) with the lowest level for methods overlooking frequency and severity of crashes, middle level for methods considering either frequency or severity of crashes, and the higher level for methods considering both crash frequency and severity in screening the network. Precision was assigned three levels: presence of a feature, a range of values for a feature, and an exact value for that feature with scores increasing with the level of precision. Previous performance record was assigned four levels based on three factors: 1) whether the method was used by agencies, 2) the number of agencies using the method, and 3) any reported evaluation or validation of the respective method. Methods that are proposed in the literature but haven't moved yet into practice are assigned the lowest level. Methods that have been used by one or two highway agencies, but no validation is reported are assigned level 2. Level 3 is assigned for methods used by one or two agencies with reported validation, or methods that are used by three or more agencies without a reported validation. The highest level (level 4) is assigned for methods that are used by three or more agencies with validation or evaluation of the method reported in the literature. Ease of understanding is assigned only two levels: level 1 for complicated methods that may be difficult to understand and level 2 for methods that are intuitive and easy to understand. Ease of implementation is assigned three levels, with the lowest level (level 1) representing methods that are difficult to implement, highest level (level 3) for methods that are easy to implement, and the middle level (level 2) for methods that fall in between the previous two categories. Finally, the resource requirements criterion is

assigned two levels, level 1 for methods requiring significant resources and level 2 for methods requiring average resources.

Assigning Weights to Assessment Criteria

Different criteria bear different significance in assessing the merits of a screening method. Therefore, it was important to develop a quantitative approach where relative weights are assigned to the assessment criteria. The procedure outlined in this section is intended to quantify a process that is inherently subjective. To simplify comparisons across multiple criteria, the problem was reduced to conducting pairwise comparisons between pairs of variables using a matrix covering all pair combinations, as shown in Table 6. In this table, green cells are for relative weights assigned to criteria in the column headings, while blue cells are for weights assigned to criteria shown in the row headings. In pairwise comparisons, weights are assigned to the two variables based on their relative importance (the total weight 10 is split between the two variables, with a minimum weight of 1 and a maximum weight of 9). The weights assigned to each criterion while comparing to all other criteria are then summed to find the total weight which is an indicator of the level of significance of that criterion. Lastly, the total weight is normalized by dividing by the highest possible weight (63 is the highest possible weight for the matrix shown in Table 6) and converted to a suitable scale (a scale of 0-10 is used for this assessment).

Table 5. Scoring Scheme for Assessment Criteria

Criteria	Scores	Score Categories	
Level of Risk	1-4	No risk factors	1
		Risk - Traffic properties	2
		Risk - Geometric properties	3
		Risk - Traffic & geometric properties	4
Economic Effectiveness	1-3	No frequency, no severity	1
		Only frequency	2
		Only severity	2
		Crash frequency and severity	3
Precision	1-3	Existence of attributes	1
		Range of values of attributes	2
		Exact values of attributes	3
Previous Performance Record	1-4	Proposed methods	1
		Used by 1 or 2 agencies without any validation	2
		Used by 1 or 2 agencies with validation	3
		Used by 3 or more agencies without validation	3
		Used by 3 or more agencies with validation	4
Ease of Understanding	1-2	Difficult to understand	1
		Easy to understand	2
Ease of Implementation	1-3	Difficult to implement	1
		Somewhat easy to implement	2
		Easy to implement	3
Resource Requirements	1-2	Significant resources	1
		Average resources	2

Table 6. Pairwise Comparison Results and the Relative Weights Assigned to Criteria.

	Level of Risk	Cost Effectiveness	Precision	Previous Performance Record	Ease of Understanding	Ease of Implementation	Resource Requirements	Total Weight	Normalized Weight (out of 10)
Level of Risk	5	4	8	7	8	8	8	48	7.6
	5	6	2	3	2	2	2		
Cost Effectiveness	6	5	9	8	9	9	9	55	8.7
	4	5	1	2	1	1	1		
Precision	2	1	5	3	5	5	5	26	4.1
	8	9	5	7	5	5	5		
Previous Performance Record	3	2	7	5	7	7	7	38	6.0
	7	8	3	5	3	3	3		
Ease of Understanding	2	1	5	3	5	5	5	26	4.1
	8	9	5	7	5	5	5		
Ease of Implementation	2	1	5	3	5	5	5	26	4.1
	8	9	5	7	5	5	5		
Resource Requirements	2	1	5	3	5	5	5	26	4.1
	8	9	5	7	5	5	5		
Total Weight	48	55	26	38	26	26	26		
Normalized Weight	7.6	8.7	4.1	6.0	4.1	4.1	4.1		

While the process outlined above largely simplifies the problem at hand (comparison across multiple criteria), pair-wise comparisons could still be difficult and may yield inconsistent results in the absence of any guiding rules. These guiding rules regarding the significance of different criteria are important for accurate and consistent evaluation results. It should be noted that, the guiding rules reflects the priorities and perspective of this particular project. In this assessment, the following set of rules to guide the pairwise comparisons in the assessment process was developed.

1. Cost effectiveness is the most important among all other criteria reported in this project earlier. This is in line with the fact that most highway agencies use cost effectiveness in selecting and justifying safety improvement projects.
2. The inherent level of risk to any specific site in the network is the second most important criterion after cost effectiveness and above all other criteria.
3. Previous performance record is more important than other criteria, namely; precision, ease of implementation, ease of understanding and resource requirements.

Using these guiding principles and conducting the respective pairwise comparisons, the overall weights assigned to different criteria are shown in Table 6. The minimum and maximum weights are found to be 4.1 and 8.7 on a scale of 10.

Assessment Matrix

The scoring scheme and relative weights developed in the previous steps are used in establishing the assessment matrix and ranking of the network screening methods. The assessment is accomplished using the following steps:

1. All methods are scored using the scoring scheme developed earlier in the process and normalized using a common scale of 0 to 10.

2. The normalized scores are then multiplied by the weights of their respective criteria discussed previously (shown in Table 6) resulting in a weighted score for each assessment criterion.
3. Finally, the weighted scores for the various criteria are summed to yield the overall score for each method included in the assessment.

Table 7 shows the assessment matrix using the steps discussed above.

Table 7. Assessment Matrix for the Different Methods.

	Assessment Criteria																										Overall Score		
	(1) Level of Risk				(2) Economic Effectiveness				(3) Precision				(4) Previous Performance Record				(5) Ease of Understanding				(6) Ease of Implementation				(7) Resource Requirements				
	Actual Score	Normalized Score	Weights	Weighted Score	Actual Score	Normalized Score	Weights	Weighted Score	Actual Score	Normalized Score	Weights	Weighted Score	Actual Score	Normalized Score	Weights	Weighted Score	Actual Score	Normalized Score	Weights	Weighted Score	Actual Score	Normalized Score	Weights	Weighted Score	Actual Score	Normalized Score		Weights	Weighted Score
	4	10	7.6		3	10	8.7		3	10	4.1		4	10	6		2	10	4.1		3	10	4.1		2	10		4.1	
Methods Using Only Historical Data																													
Crash Frequency Methods	1	2.5	7.6	19	2	6.7	8.7	58	3	10	4.1	41	2	5	6.0	30	2	10	4.1	41	3	10	4.1	41	2	10	4.1	41	272.49
Crash Frequency and Severity Methods	1	2.5	7.6	19	3	10	8.7	87	3	10	4.1	41	3	7.5	6.0	45	2	10	4.1	41	3	10	4.1	41	2	10	4.1	41	316.67
Crash Rate Methods	2	5	7.6	38	2	6.7	8.7	58	3	10	4.1	41	2	5	6.0	30	2	10	4.1	41	3	10	4.1	41	2	10	4.1	41	291.53
Crash Frequency and Rate Methods	2	5	7.6	38	2	6.7	8.7	58	3	10	4.1	41	3	7.5	6.0	45	2	10	4.1	41	3	10	4.1	41	2	10	4.1	41	306.61
Crash Frequency, Rate and Severity Methods	2	5	7.6	38	3	10	8.7	87	3	10	4.1	41	3	7.5	6.0	45	2	10	4.1	41	2	6.67	4.1	28	2	10	4.1	41	321.96
Methods Using Prediction Only																													
Using only Traffic Characteristics	2	5	7.6	38	2	6.7	8.7	58	3	10	4.1	41	1	2.5	6.0	15	2	10	4.1	41	2	6.67	4.1	28	2	10	4.1	41	262.70
Using only Geometric Characteristics	3	7.5	7.6	57	2	6.7	8.7	58	3	10	4.1	41	1	2.5	6.0	15	2	10	4.1	41	2	6.67	4.1	28	2	10	4.1	41	281.75
Using Traffic and Geometric Characteristics	4	10	7.6	76	2	6.7	8.7	58	3	10	4.1	41	2	5	6.0	30	2	10	4.1	41	2	6.67	4.1	28	2	10	4.1	41	315.87
Using Surrogate Safety Measures	2	5	7.6	38	1	3.3	8.7	29	2	6.7	4.1	28	2	5	6.0	30	1	5	4.1	21	1	3.33	4.1	14	1	5	4.1	21	179.89
Comb. of Historical and Prediction Methods																													
Empirical Bayes	4	10	7.6	76	3	10	8.7	87	3	10	4.1	41	4	10	6.0	60	1	5	4.1	21	1	3.33	4.1	14	1	5	4.1	21	320.11
Index Methods	4	10	7.6	76	3	10	8.7	87	3	10	4.1	41	3	7.5	6.0	45	1	5	4.1	21	1	3.33	4.1	14	1	5	4.1	21	305.03
Other Methods																													
FHWA Systemic Approach to Safety	3	7.5	7.6	57	1	3.3	8.7	29	2	6.7	4.1	28	4	10	6.0	60	2	10	4.1	41	3	10	4.1	41	2	10	4.1	41	297.88

Assessment Results

It is observed from the matrix that the overall scores for different methods roughly ranged between 180 and 320. Only two methods scored greater than 320: methods using crash frequency, rate, and severity (321.96) and the Empirical Bayes method (320.11). These two scores are very close, and for all practical reasons, they can be considered comparable. A careful examination of the assessment matrix revealed that the Empirical Bayes scored very high on all criteria except the last three criteria in the matrix which are assigned lower weights (i.e. less significant criteria). On the other hand, the conventional frequency, rate and severity methods scored lower on criteria 1 and 4 (level of risk and previous performance record) and higher on the last three criteria. Methods using surrogate safety measures scored lower than all other methods included in the matrix, which is somewhat expected. Another important observation is that the FHWA systemic approach to safety scored right in the middle compared to other methods. Nonetheless, this method could have scored higher than all other methods if the cost effectiveness criterion was assessed more objectively. Specifically, this method scored lowest on cost effectiveness due to the way the scoring scheme was developed (no crash frequency nor severity is used). However, it is well known that systemic improvements consist of low-cost countermeasures that are often associated with relatively high benefit-cost ratios.

CHAPTER FIVE

EMPIRICAL EXAMINATION OF THE EMPIRICAL BAYES

The assessment on the previous chapter found that the method that uses a combination of the conventional crash frequency, rate and severity methods, and the Empirical Bayes (EB) method have scored the highest. However, only the EB method was chosen for further analysis. This is because crash risk on LVRs are generally linked to other factors along with historical crash experience. Furthermore, low volumes on LVRs can make screening based entirely on historical crash experience inaccurate. The EB method incorporates these risk factors as well as the historical crash experience. By doing so, the EB method incorporates the risk presented by outdated geometric designs in the screening process. Therefore, in terms of accuracy, EB can be the better option for LVRs. This chapter discusses the potential advantages and disadvantages of the EB method. Then this chapter presents the analyses that were carried out on the EB method using actual LVR data.

Advantages and Disadvantages of the Empirical Bayes Method

Network screening using the EB method can be expected to be appropriate for LVRs because it includes geometric features for screening along with crash history into consideration. Furthermore, based on the results of the method assessments, the EB method was one of the two highest scoring methods. The EB method incorporates almost all risk factors related to crash occurrences, incorporates both crash frequency and severity and uses precise values of different variables. On the other hand, it scored relatively low in

ease of understanding, ease of implementation and resource requirements. These criteria penalized the EB method because it requires significant mathematical understanding, trained personnel and extensive resources for implementation. These might present a significant challenge to many local agencies that does not have access to significant budgets to support these requirements.

Analyses of the Empirical Bayes

This section discusses about different empirical analyses that were carried out on the EB method. The following subsections discusses about the data used for these analyses, followed by the results from these analyses.

Data Description

State owned LVR data from Oregon were used for these analyses. A total of 871.3 miles of LVR data were collected. Out of these 871.3 miles, 848.85 miles were of roads with volume of less than 1000 vehicles per day (vpd) and the remaining 22.45 miles were of roads with volume of greater than a 1000 vpd but less than 2500 vpd. Data for roads of more than 1000 vpd were included in order to understand the trend of the EB method for volumes greater than a 1000 vpd. Roadway and traffic data along with 10 years of observed crash data for every 0.05 mile segments were collected. The 0.05 mile resolution was selected because this increment allowed video log processing to be comprehensive and fast, and reduced the possibilities of missing any attributes of interest. No major intersections were included in the dataset. Intersection segments along with one 0.05 mile segment both

before and after the intersection were excluded from the dataset. All the segments were for two lane roads with a posted speed limit of 55 mph.

Oregon Department of Transportation (ODOT) online databases and video logs were used to identify and compile exposure, geometric and crash data. AADT, lane type and width, shoulder type and width, degree of curvature for horizontal curve and the presence of spiral curve, type of vertical curve and percent grade were collected from online databases. The video logs were used to collect the driveway density, side slope rating and fixed objects near the roadway rating. Fixed objects and side slopes data were collected categorically. This is because it was not possible to have exact information about those features from the video logs.

Predicted Crash Numbers from the Empirical Bayes Method

Using the exposure and the geometric data, number of crashes were predicted for each of the 0.05 mile segment for 10 years. At first the exposure was used to calculate the predicted number of crashes for each 0.05 mile segment using the safety performance function (SPF) for rural two-lane highways. Equation 1 shows the safety performance function for crash prediction under the base conditions.

$$N_{spf} = AADT \times L \times 365 \times e^{(-0.312)} \dots \dots \dots (1)$$

Where, N_{spf} = Total predicted crash frequency under base conditions,

AADT = Average annual daily traffic volumes (vehicles per day),

L = Length of roadway segments in miles = 0.05 miles

The base conditions for this safety performance function are provided in Figure 8.

▪ Lane width (LW)	12 feet
▪ Shoulder width (SW)	6 feet
▪ Shoulder type	Paved
▪ Roadside hazard rating (RHR)	3
▪ Driveway density (DD)	5 driveways per mile
▪ Horizontal curvature	None
▪ Vertical curvature	None
▪ Centerline rumble strips	None
▪ Passing lanes	None
▪ Two-way left-turn lanes	None
▪ Lighting	None
▪ Automated speed enforcement	None
▪ Grade Level	0% (see note below)

Figure 8. Base Conditions for safety performance function for rural two-lane two-way highways (Source: AASHTO, 2010).

Based on the collected geometric feature data and their difference from the base conditions, suitable accident modification factors were calculated. These accident modification factors were then used to adjust the predicted crash numbers as per equation 2.

$$N_{predicted} = N_{spf} \times (AMF_1 \times AMF_2 \times \dots \dots \dots AMF_n) \dots \dots \dots (2)$$

Where, $N_{predicted}$ = Predicted average crash frequency for the particular year,

N_{spf} = Total predicted crash frequency under base conditions,

AMF_n = Accident modification factors different risk factors

The predicted crash numbers obtained from equation 2 are only for one year.

However, to find the predicted crash numbers for 10 years, $N_{predicted}$ is multiplied with 10.

This step is done assuming that no significant change in the surrounding land use and roadway properties had occurred on these highways during this 10-year period. This assumption was necessary because all the highways under investigation were rural two-lane two-way highways and most of the 0.05 mile segments did not have significant number of observed crashes for one year. Hence, 10 years of observed crash data were collected so that significant crash numbers were available for any statistical analysis and because of this, 10 years of predicted crash numbers were also needed.

Following the calculation for the 10 year predicted crash numbers, the EB weight for predicted crash numbers were calculated. The weight is calculated by equation 3.

$$w = \frac{1}{1 + k \times (N_{\text{predicted for 10 years}})} \dots \dots \dots (3)$$

Where, w = Weight for 10 year predicted crash numbers,

k = Overdispersion parameter associated with the specific SPF = $\frac{0.236}{L} = \frac{0.236}{0.05} = 4.720$,

$N_{\text{predicted for 10 years}}$ = Predicted number of crashes for 10 years

In order to understand how volume, effects the weight that the EB method assigns to predicted crash numbers, a weight versus volume scatter plot is generated with a best fitting line through the data points. This plot is shown in Figure 9.

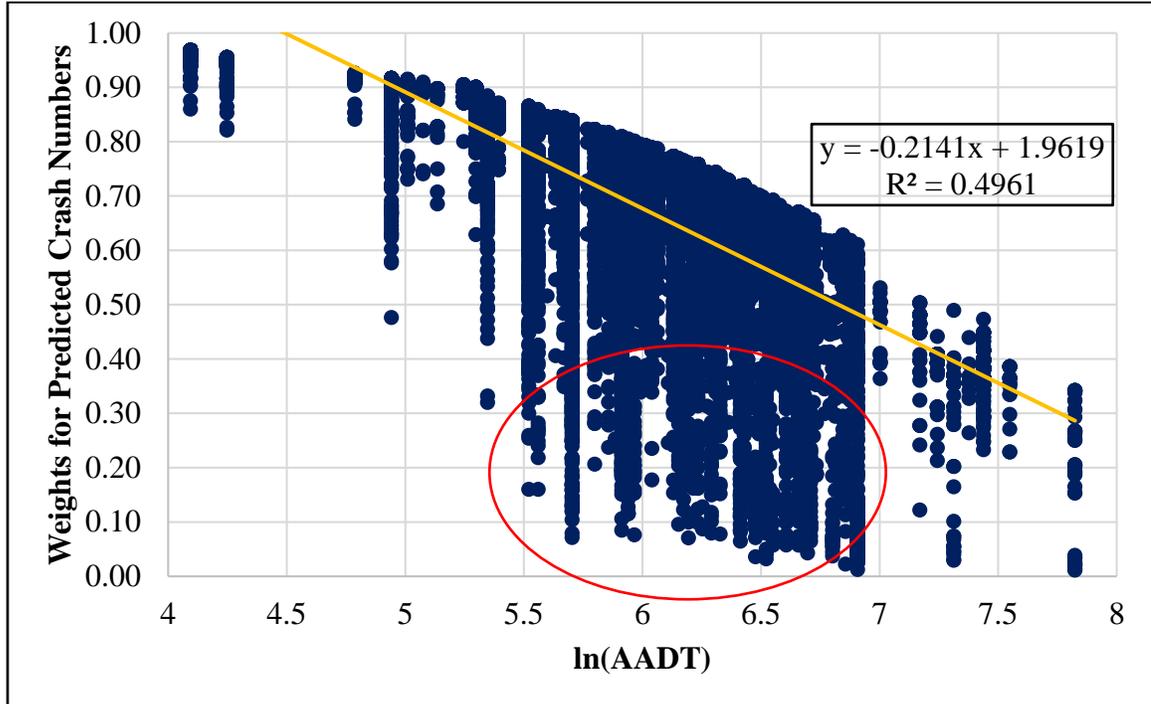


Figure 9. Weights for Predicted Crash Number versus AADT.

It can be observed from Figure 9 that weights for predicted crash number have a negative logarithmic relationship with volume. With increase of volumes, the weights decrease. The HSM predicted crash numbers are calculated mostly based on geometric properties i.e. risk factors. Therefore, this analysis reveals that for lower volumes, the EB method relies more on risk factors for calculating the expected crash numbers while for higher volumes it relies more on observed crash numbers.

Based on the scatterplot, an equation describing the relationship between weights for predicted crashes and volume is derived. The equation along with its R squared value is also shown in Figure 9. This equation only has a R square of 0.4961. The R square value indicates that volume only explains about 50 percent of the variability of the weights for predicted crashes. Looking closely at the scatter, it can be understood that the points

marked with the red oval are the farthest from the equation. In order to understand the reason behind this dispersion, a more detailed investigation of those points was necessary.

Overestimation of Predicted Crash Numbers

To understand why the points identified in Figure 9 are so far from the fitted relationship, this report analyzed the weight calculation equation presented in equation 3. According to that equation, weights for predicted crash numbers are mainly dependent on two factors. They are the overdispersion factor and the 10-year predicted crash numbers itself. For our data, the overdispersion factor, k was constant. Therefore, the only variable that influenced the weight was the predicted crash number itself. Increases of the predicted crash numbers are going to decrease the weights. It can be observed that most of the points within the red circle in Figure 9 have a volume of less than 1000 vpd and have lower weights than the others within the same volume range. This observation indicates the possibilities of high predicted crash numbers which in turn was decreasing the weights.

To analyze this, observed and predicted crash numbers were plotted against volume. This plot is shown in Figure 10. It can be observed from the figure that for most of the cases, the predicted crash numbers are much higher than the observed crash numbers. The maximum 10-year observed crash is around 6 while predicted is around 20. This indicates a possibility of overestimation of the predicted crash numbers.

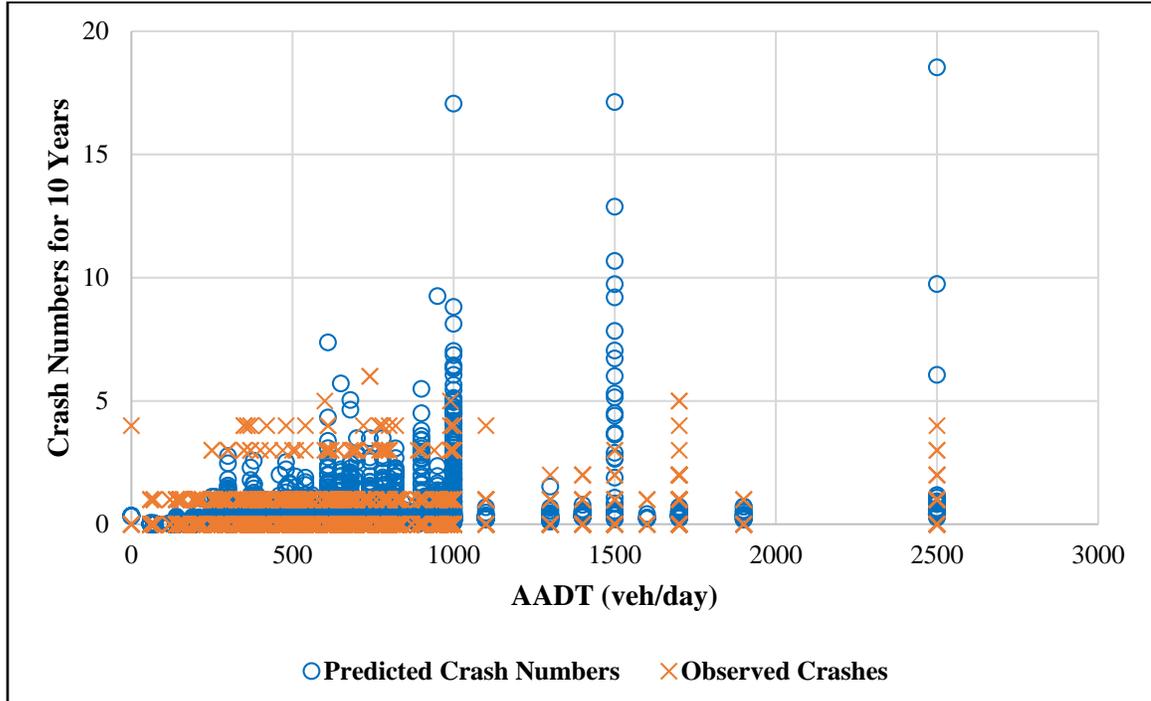


Figure 10. Observed and Predicted Crash numbers against Volume.

Overestimation due to Accident Modification Factors

This subsection of the chapter discusses about a potential reason for which the predicted crash numbers were overestimated.

It is observed from equation 2 that the predicted crash numbers under base conditions were adjusted with applicable accident modification factors (AMFs). For our data, these AMFs were for lane width, shoulder width, horizontal curvature along with the presence or absence of spiral curve, vertical grade, driveway density, side slope rating and fixed object rating. After investigating each of the AMFs, it was discovered that the AMF due to horizontal curve had the longest range, and this long range of this AMF can be the reason for the overestimation of the predicted crash numbers.

Therefore, to understand how sharpness of the horizontal curves influence the AMF for horizontal curves, an AMF versus degree of horizontal curvature scatter was generated. This plot is shown in Figure 11. A general trend that is observed from this plot is that as the degree of curvature increases, the AMF values also increases. This gives the general idea that sharper horizontal curves tend to have higher AMF values. It is also observed that increases in the degree of curvature increases the variability of the AMF values.

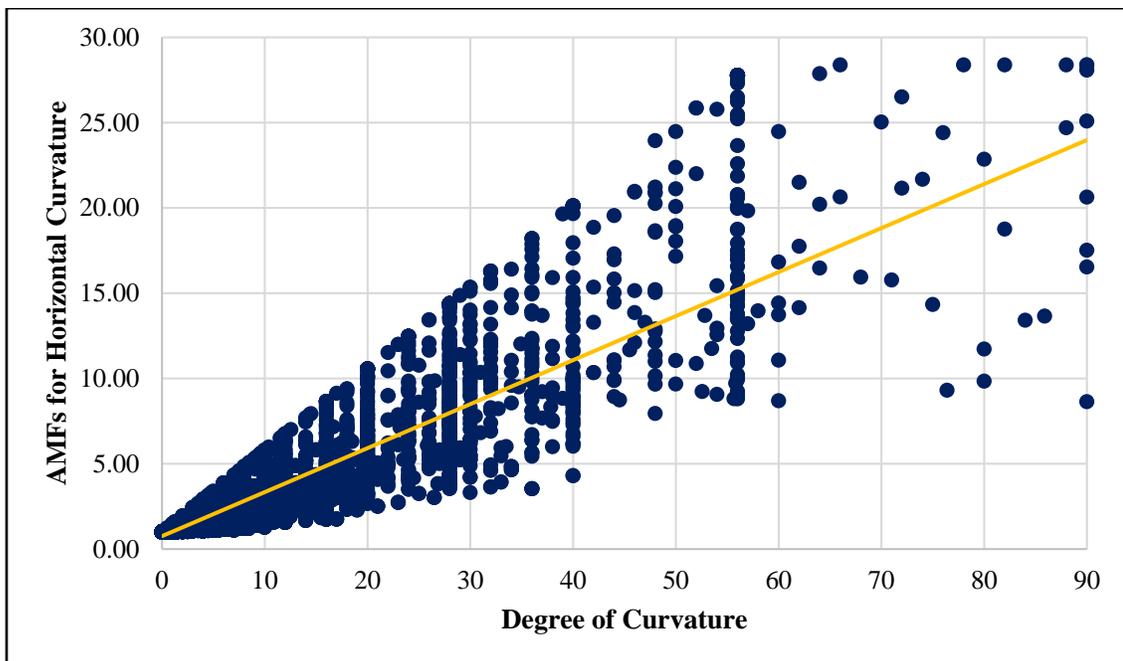


Figure 11. Accident Modification Factor for Horizontal Curve versus their Degree of Curvature.

Using Classification and Regression Tree (CART) analysis, the weights for predicted crash numbers were split into two groups based on the effect of the degree of curvature. The open source statistical package R was used for running this analysis. The output from this analysis is shown in Figure 12.

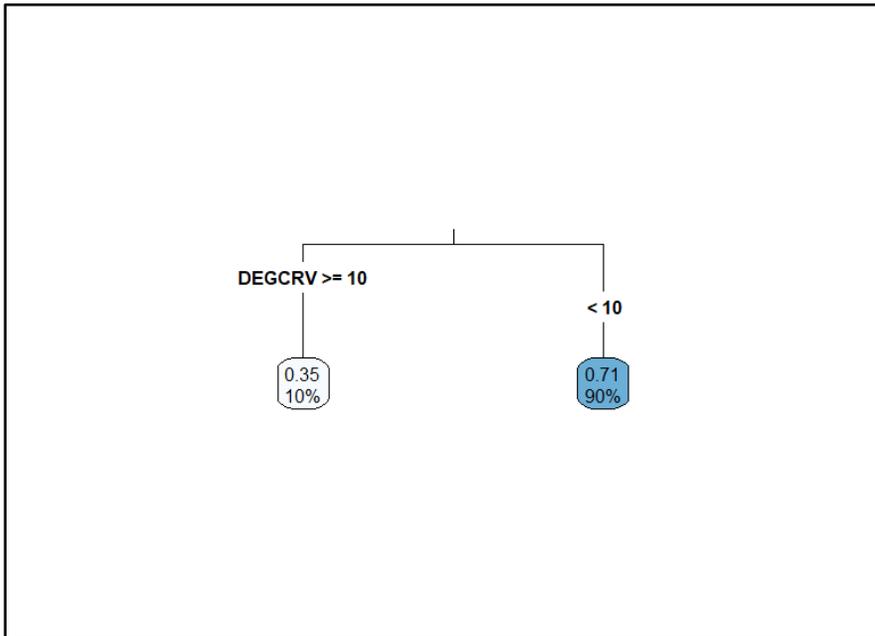


Figure 12. Split of Weights for Predicted Crashes based on Degree of Curvature.

It can be seen in Figure 12 that about 10 percent of the segments have a horizontal curve with a degree of curvature of more than or equal to 10 degrees while about 90 percent of the segments have degree of curvature of less than 10 degrees. Based on this split, the data is classified into two groups. The first group contains segments with degrees of curvature of more than or equal to 10 degrees and were classified as “Sharp”. Segments that have degrees of curvatures of less than 10 degrees were classified as “Others”. Figure 13 shows the plot of weights for predicted crashes versus AADT with the “Sharp” segments identified with orange crosses and the “Others” segments identified with green dots. It can be observed from the figure that most of the points identified with a red oval in Figure 9 are from the “Sharp” segments. Furthermore, the graph shows the relationship between weights and AADT using all the data as well as using only the “Others” data. The relationship without the “Sharp” segments has a much better relationship ($R^2 = 0.73$) than

the one with all data ($R^2 = 0.50$). This indicates that the AMFs for sharper horizontal curve are mostly causing the overestimation of the predicted crash numbers which in turn is creating a weaker relationship between weights and AADT.

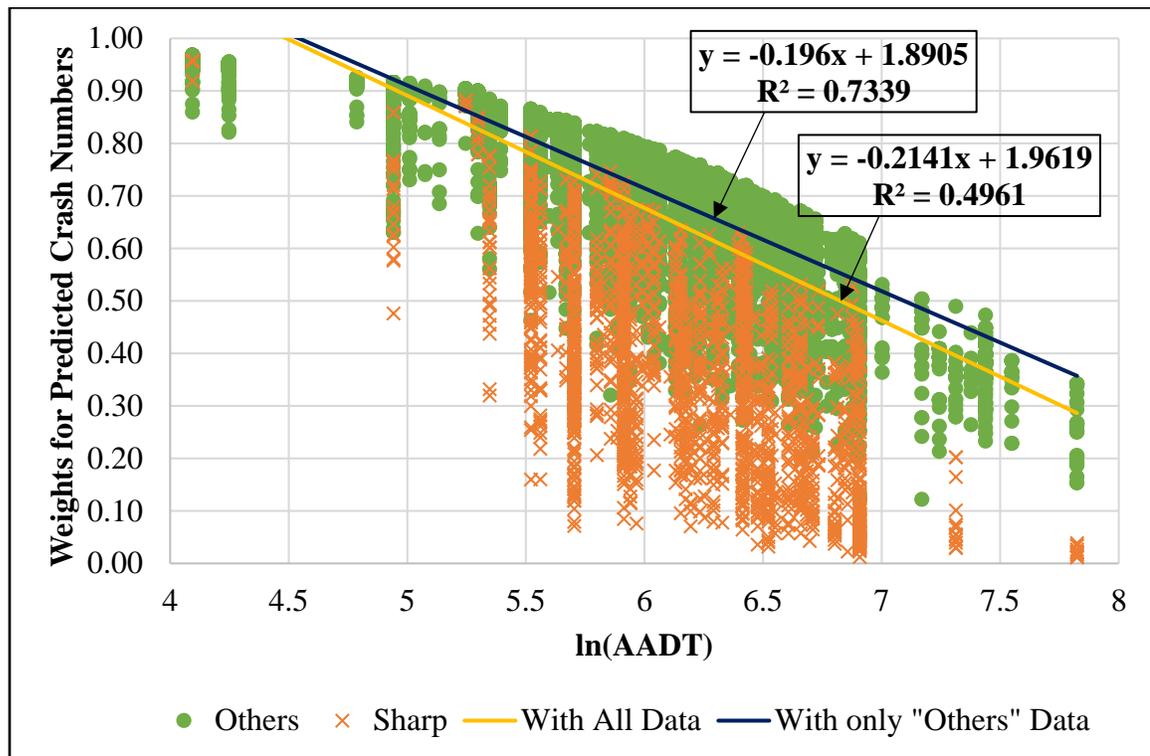


Figure 13. Weights for Predicted Crash Numbers versus AADT classified with Degree of Curvature.

Investigating a new Accident Modification Factor for Horizontal Curves

The previous section of this report has identified that AMFs for sharper horizontal curves caused the overestimation of the predicted crash numbers. Therefore, the research carried out a search for an updated AMF equation and came across one that is proposed by Wu et al. (2017). The new AMF was developed based on data from rural two-lane undivided highways of Texas. Only horizontal curves of less than 5000 feet were included in this study. For this purpose, any horizontal curve segments in our data having a radius

of greater than 5000 feet were assigned an AMF of 1. This study used a cross-sectional study to develop a new AMF equation for horizontal curves on rural two-lane undivided highways. The study also compared the prediction performance of the proposed AMF equation with the performance of HSM equation and found that their AMF equation performed better than the HSM equation.

The new AMF equation proposed by Wu et al. (2017) has the following form.

$$AMF = 196.4 \times R^{-0.65} \dots \dots \dots (4)$$

Where, AMF = Accident Modification Factor for horizontal curves,

R = Radius of Horizontal Curvature

This report then conducted the same analyses using the same data and Wu et al. (2017) AMF. The Wu et al. (2017) AMFs from the new equation were found to have a much smaller range than the HSM AMFs.

The weight for predicted crash numbers versus AADT with the Wu et al. (2017) AMF is shown in Figure 14. This AMF has a slightly better relationship between weights for predicted crashes and volume with a R square of about 0.51. However, a good number of points within the same region (marked with a red oval) are still present. The plot of observed and predicted crash numbers versus AADT, shown in Figure 15, indicates that the overestimation of the predicted crash numbers is smaller than the HSM horizontal curve AMF equation. The highest predicted crash number is around 10 whereas the highest observed crash number is 6. It is also observed that for volumes of less than 1000 vpd, the overestimation of the predicted crash numbers is lesser than that for volume of more than 1000 vpd.

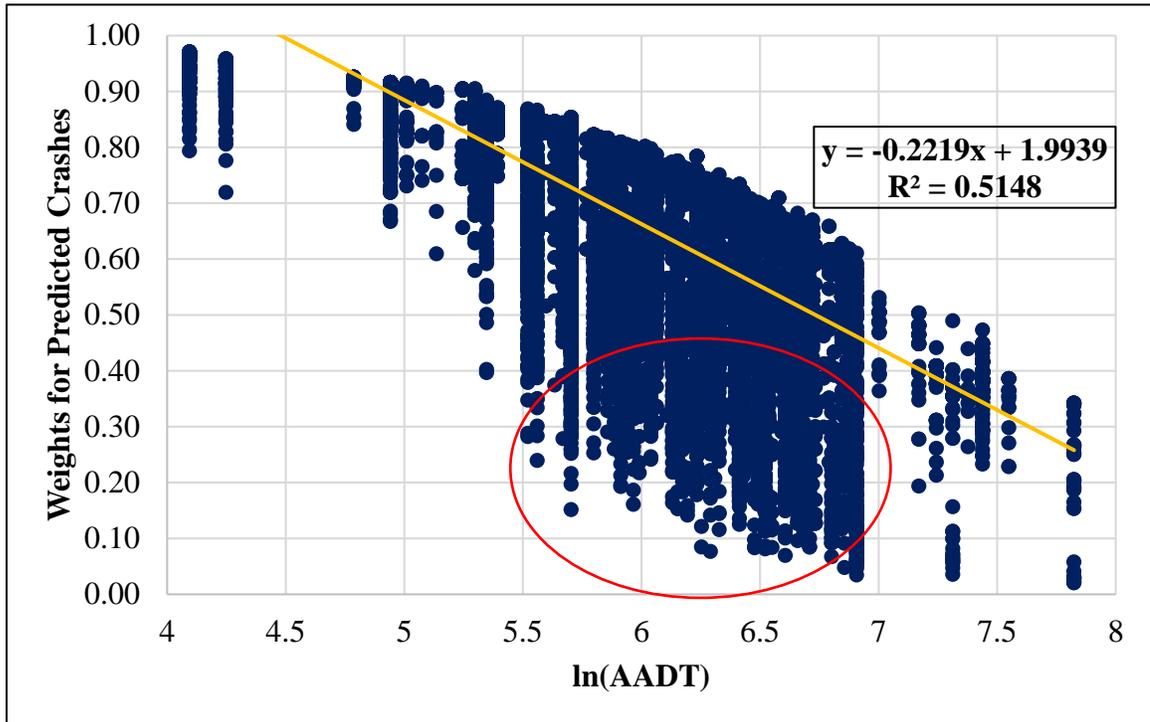


Figure 14. Weights for Predicted Crash Numbers versus AADT using Wu et al's (2017) AMF for Horizontal Curves.

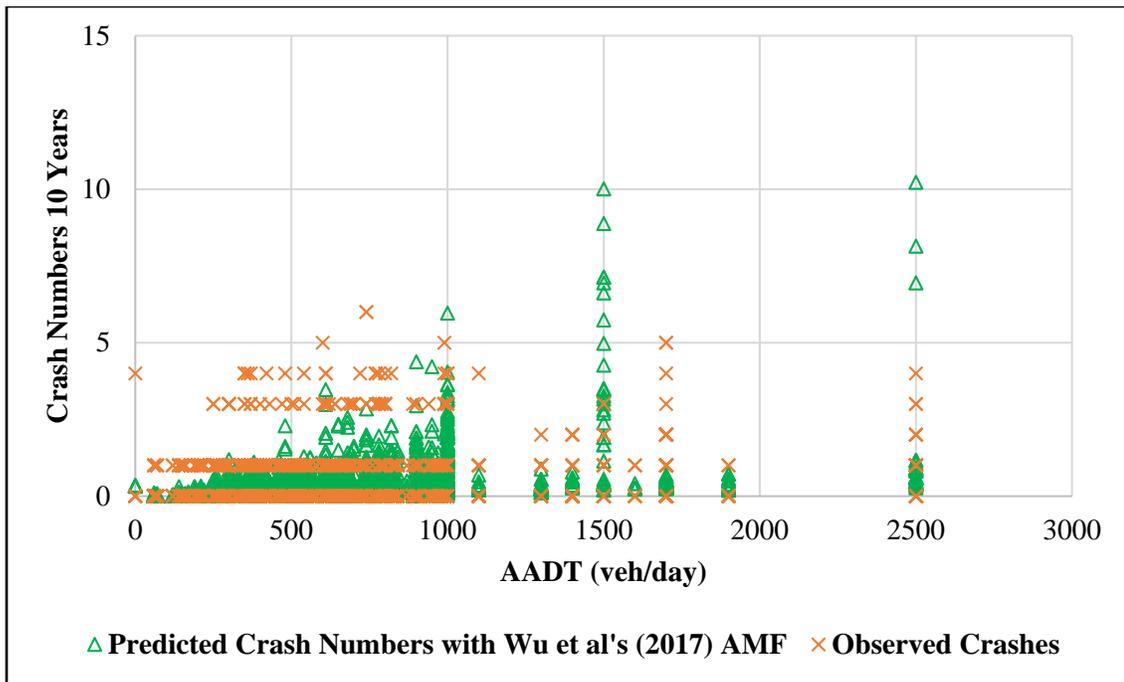


Figure 15. Observed and Predicted Crashes with Wu et al's (2017) AMF versus Volume.

Using CART analysis again, the data were split into two groups. Segments with curves with degree of curvature of greater than or equal to 4.3 degrees were grouped as the lower weight group. This group comprised of about 24 percent of the whole dataset while the higher weight group consisted of 76 percent of the dataset.

Subsequently, segments with degrees of curvature of greater than or equal to 4.3 degrees were grouped as “Sharp” and the remaining were grouped as “Others”. The weight for predicted crashes versus volume relationship along with the classified data is shown in Figure 17. Similar observations like those for using HSM’s AMF equation were observed. Most of the points identified with a red oval in Figure 14 falls under the “Sharp” group and a relationship without the “Sharp” data have a stronger relationship ($R^2 = 0.77$) than the relationship using all the data ($R^2 = 0.51$).

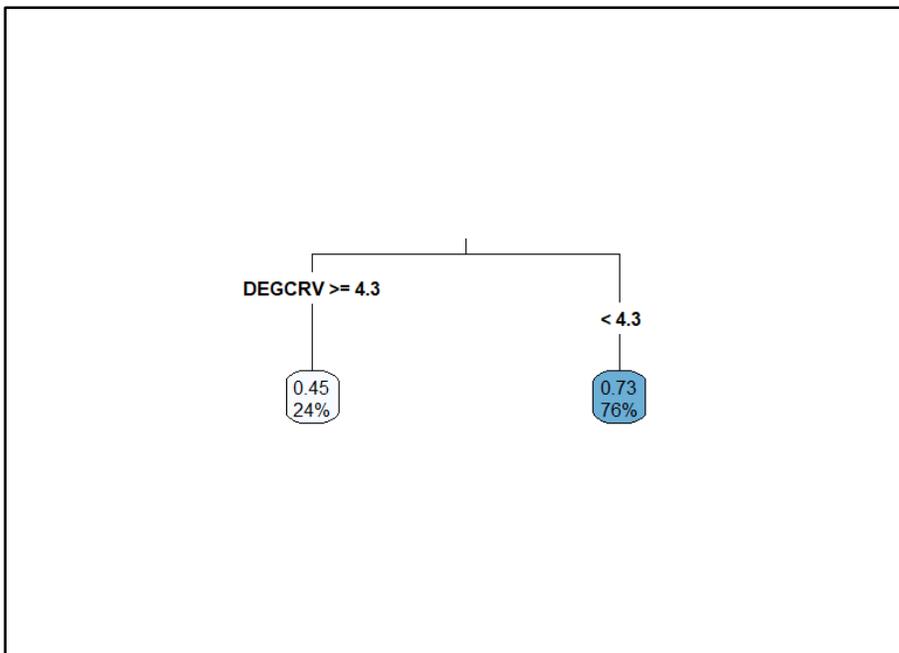


Figure 16. Split of the Weights for Predicted Crashes with Wu et al (2017) AMF based on Degree of Curvature.

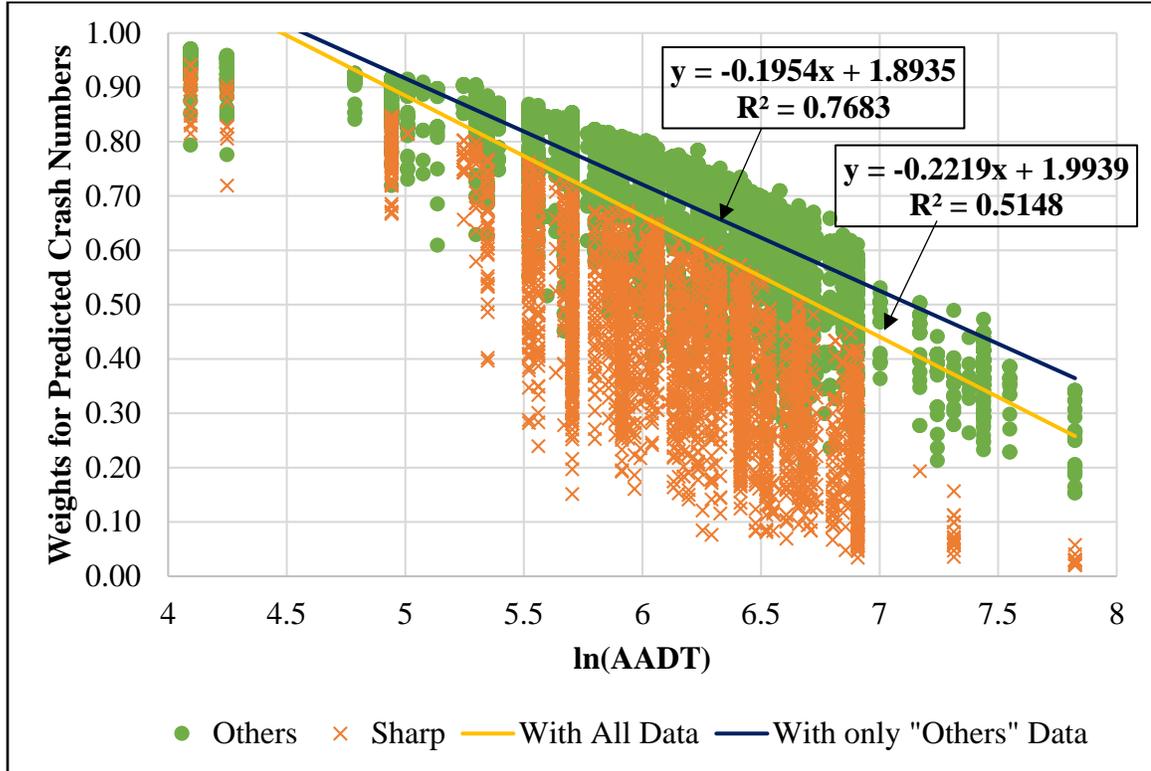


Figure 17. Weights for Predicted Crash Numbers with Wu et al's (2017) AMF versus AADT classified with Degree of Curvature.

Observations

The analyses in this chapter indicated that the weights for predicted crash numbers have a negative logarithmic relationship with volume. This observation indicates that at lower volumes, the EB method relies more on the predicted crash numbers for calculating the expected crash numbers. The weight and volume relationship had significant dispersion and most of it is caused by overestimation of the predicted crash numbers. The crash numbers were overestimated mostly because of high AMF values for sharp horizontal curves. A new AMF proposed by Wu et al. (2017) was also analyzed. Weight also had a negative logarithmic relationship with the volume. However, the dispersion was small in this case and so were the overestimations of the predicted crash numbers. AMFs for sharp horizontal curves were also found to have caused these overestimations.

CHAPTER SIX

DEVELOPING AN ALTERNATIVE METHOD

Earlier chapters of this thesis identified the Empirical Bayes (EB) method of the Highway Safety Manual (HSM) (AASHTO, 2010) as a good network screening method for rural low volume roads (LVRs). This thesis also discussed possible challenges of implementing the EB method for LVRs. One of the major disadvantages of the EB method is that it mostly requires precise data to operate. Local agencies (other than state department of transportation) might not have access to such data or neither the resources to collect the data themselves. In addition, the EB method also requires trained/skilled personnel to implement, which again, the local jurisdictions might not have access to. Based on these two major challenges, this project developed an alternative methodology for the EB method. This project tried to develop a method that is accurate, relatively easy to understand, and does not require extensive resources for implementation. This new method would predict the expected crash numbers from an EB network screening process by mostly using risk factors.

Classification of the Risk Factors

One of the challenges of the EB method, is the need of precise risk factor data. This study developed a method that overcomes this hurdle. For this purpose, the risk factors data were divided into categories. Instead of using the exact value of a risk factor variable, the category of the variable can be used in the screening process. The risk factors were

classified into few simple categories. The classification and regression tree (CART) analysis was used to develop these categories.

The same Oregon data were used for this exercise. Most of the variables were categorized based on how each of the variables affect the predicted crash numbers. The predicted crash numbers were obtained using safety performance function (SPF) and accident modification factors (AMF). The results of the CART analysis of the different variables are provided in the following subsections.

Lane Width

The output for the CART analysis of lane width and predicted crash numbers is presented in Figure 18.

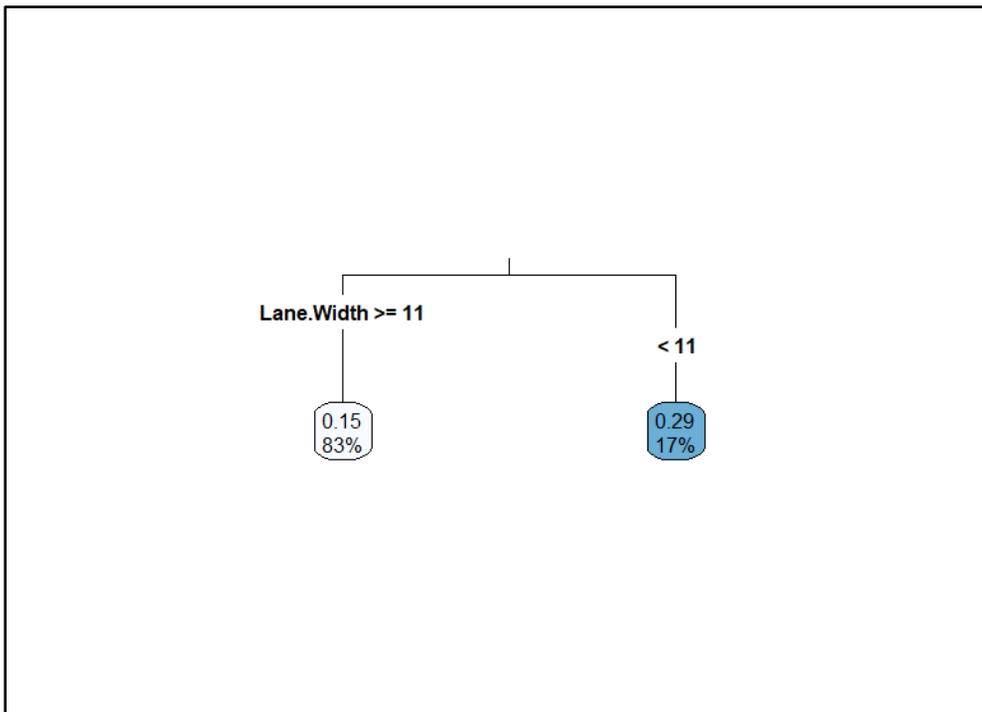


Figure 18. Classification of Lane Width based on Predicted Crash Numbers.

The CART output shows that lane width data based on predicted crashes are divided into two groups. The first group consists of lane widths greater than or equal to 11 feet. This group comprises 83 percent of the data and the predicted crash numbers for this group is 0.15. The second group comprises of lanes narrower than 11 feet. This group contains about 17 percent of the data and the predicted crash number for this group is 0.33, which is almost double the wider lane group. This indicates that wider lanes have lower predicted crash numbers.

Shoulder Width

The output for the CART analysis of lane width and predicted crash numbers is presented in Figure 19.

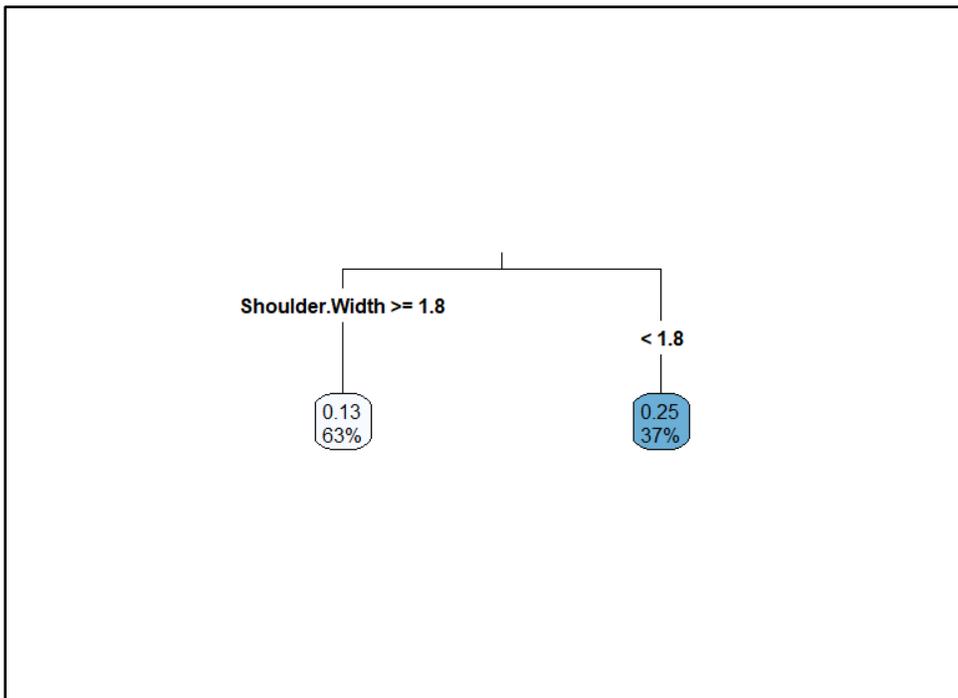


Figure 19. Classification of Shoulder Width based on Predicted Crash Numbers.

Similar to lane widths, wider shoulder widths (widths of greater than or equal to 1.8 feet) have lower predicted crash numbers whereas narrower ones (width of less than

1.8 feet) have higher predicted crash numbers. The wider group comprised of about 63 percent of the data while the narrower group comprises of only 37 percent of the data. This also indicates that wider shoulders have lower predicted crash numbers.

Degree of Curvature

The output for the CART analysis of degree of curvature and predicted crash numbers is presented in Figure 20. Based on the output, about 90 percent of the 0.05 mile segments in the data has a degree of curvature of less than 10 degrees and they correspond to a predicted crash number of 0.10. The next group has segments that have a degree of curvature greater than or equal to 10 degrees but less than 27 degrees. This group comprises of only 7 percent of the data and corresponds to a predicted crash number of 0.39. The third group contains segments with degree of curvature of greater than or equal to 27 degrees but less than 40 degrees. This group contains about 2 percent of the data and corresponds to a predicted crash number of 1.2. The fourth group contains segments with degree of curvature of greater than or equal to 40 degrees. This group comprises of about 1 percent of the data and corresponds to a predicted crash number of 2.3. This indicates that sharper horizontal curves have higher predicted crash numbers.

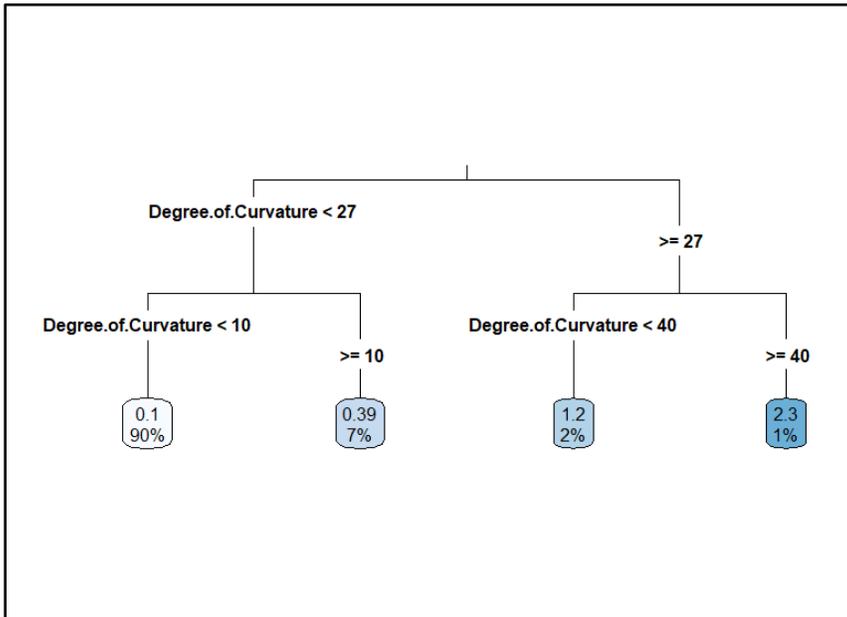


Figure 20. Classification of Degree of Curvature based on Predicted Crash Numbers.

Vertical Grade

The output of the CART analysis for the vertical grade of the segments and predicted crash numbers is shown in Figure 21. It can be observed from the output that the analysis groups 100 percent of the data under one group and all the data for vertical grade corresponds to a predicted crash number of 0.19. This indicates that vertical grade does not have a significant effect on the predicted crash numbers. Still, the vertical grade was included in the model building and for this purpose the presence or absence was used.

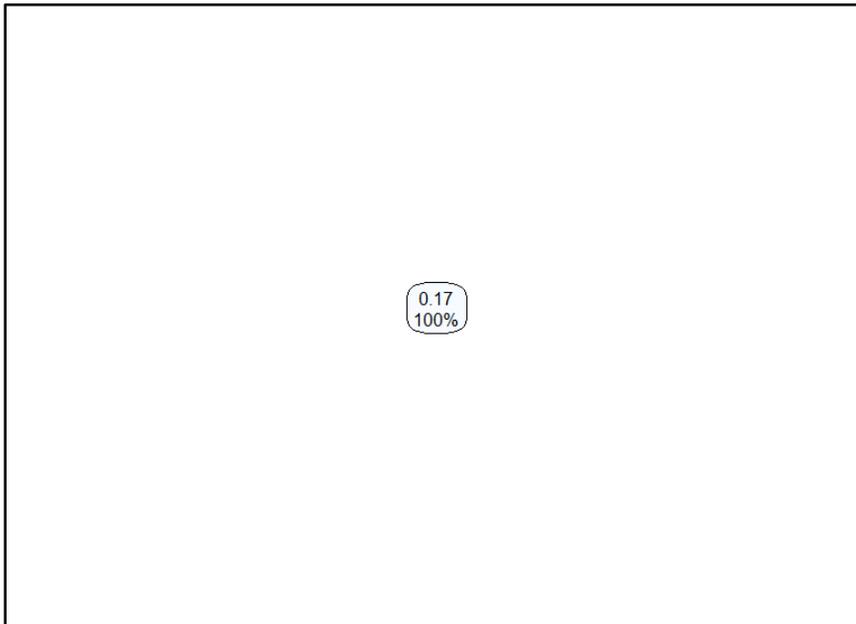


Figure 21. Classification of Vertical Grade with Predicted Crash Numbers.

Risk Factor Classes

Volume, driveway density, side slope and fixed object ratings were not classified with the help of CART analysis. Driveway density data are significantly easy to collect. One can simply use an updated map to find the number of driveways accessing a segment and hence precise driveway density data were used. Volume data is quite easy to collect as well using tube counters. Also, without any indication of the traffic level, it would not be possible to identify the volume category. Therefore, the precise volume data were used. The side slope and fixed object rating data were collected categorically from video logs. The same categories were used for developing the models as well. The risk factor categories and other variables used for developing the models, are presented in Table 8.

Table 8. Classification of different Risk Factor Variables for Network Screening.

Risk Factors	Approximate Ranges of Variables	Categories	Terms
Lane Width (LW)	LW < 11	1	Narrower
	LW ≥ 11	2	Wider
Shoulder Width (SW)	SW < 1.8 (~ 2 ft)	1	Narrower
	SW ≥ 1.8 (~2 ft)	2	Wider
Degree of Horizontal Curvature (DC)	DC = 0	0	Straight Segments
	DC < 10	1	Mild
	10 ≤ DC < 27	2	Moderate
	DC ≥ 27	3	Sharp
Vertical Curve Grade (VC)	VC = 0	0	Absent
	VC ≠ 0	1	Present
Driveway Density per mile (DD)	Use Actual Data		
Side Slope (SS)	Steep	1	Steep
	Moderate	2	Moderate
	Flat	3	Flat
Fixed Objects (FO)	Many	1	Many
	Some	2	Some
	Few	3	Few
Volume (V)	Use Actual Data		

Developing an Alternative Network Screening Method

Empirical Bayes (EB) method assigns weights to observed and predicted crash numbers and the weighted sum of these two numbers gives the expected crash numbers. The equation for calculating the weight for predicted crash numbers was presented earlier as equation 3. Equation 5 shows how expected crash number is calculated for a segment using the observed and predicted crash numbers and weights assigned to each of them.

$$N_{Expected} = w \times N_{predicted} + (1 - w)N_{observed} \dots \dots \dots (5)$$

Where, w = weight assigned for predicted crash numbers,

$N_{Expected}$ = weighted sum of predicted and observed crashes,

$N_{predicted}$ = predicted crash numbers based on exposure and risk factors,

$N_{observed}$ = observed crash numbers

The dataset used in this study collected the observed crash numbers and risk factor data. Using the risk factor data for their respective accident modification factors, and using equation 1 and 2, the predicted crash numbers for each of the 0.05 mile segments were calculated. Then the weight assigned to the predicted crash numbers of each of these segments were calculated. Finally, using the weights, the predicted crash numbers and the observed crash numbers, the expected crash numbers for each of the segments were calculated using equation 5.

On the next step of the analysis, all the risk factor variables were categorized using the classes defined in Table 8. Any segments that had any missing data were removed from the dataset. Finally, a regression model with expected crash numbers (exp) as the dependent variable was developed. After running multiple iterations and removing variables with insignificant coefficients and/or illogical relationships, the final model with the following form was developed.

$$\ln(Exp) = -0.88 LW - 0.27SW + 0.014DD + 0.0012V + 0.20DC - 0.30SS \\ - 0.22FO \dots \dots \dots (6)$$

The open source statistical software R was used for developing this model and the output for this model is shown in Figure 22. It is observed from the output, that the model in equation 6 has an adjusted R squared of about 0.91, which basically indicates that 91 percent of the variability of expected crash numbers can be explained by the categorized risk factors. This indicates an accurate model which can be used for predicting the EB method's expected crash numbers for segments using mostly risk factor categories. All the

variables in the model in equation 6 also have significant coefficients (α value of less than 0.05 for 95 percent confidence level). The model excludes vertical curvature because, for the available data, it has a counterintuitive relationship. The CART analysis in the previous section also indicated that vertical grade did not have any effect on the predicted crash numbers.

```

Call:
lm(formula = log(Exp) ~ 0 + LW + SW + DD + V + DC - VC + SS +
    FO - obs - Pred, data = riskfactorsnumcat)

Residuals:
    Min       1Q   Median       3Q      Max
-4.0791 -0.3452  0.0029  0.1969  3.5036

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
LW -8.839e-01  2.001e-02  -44.18  <2e-16 ***
SW -2.696e-01  1.656e-02  -16.28  <2e-16 ***
DD  1.442e-02  6.094e-04   23.66  <2e-16 ***
V   1.218e-03  2.991e-05   40.73  <2e-16 ***
DC  1.984e-01  8.127e-03   24.41  <2e-16 ***
SS -2.985e-01  1.138e-02  -26.23  <2e-16 ***
FO -2.191e-01  1.264e-02  -17.33  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8426 on 16805 degrees of freedom
(614 observations deleted due to missingness)
Multiple R-squared:  0.9136,    Adjusted R-squared:  0.9135
F-statistic: 2.537e+04 on 7 and 16805 DF,  p-value: < 2.2e-16

```

Figure 22. Regression Output for Expected Crash Numbers and Classified Risk Factors.

The model in equation 6 requires precise volume data for running a network screening analysis. Collection of volume data might still present a significant challenge to many local agencies that do not have the budget or expertise to collect the volume data. Hence another regression model without the volume variable was developed. Equation 7 shows the second model.

$$\ln(Exp) = -0.53 LW - 0.47 SW + 0.02DD + 0.26 DC - 0.26 SS - 0.20 FO \dots \dots \dots (7)$$

The output from R for this model is shown in Figure 23. It can be seen from the output, that the model has an adjusted R square of 0.905. This indicates that the new model still has an acceptable level of accuracy. Also, all the variables have significant coefficients (α value of less than 0.05 for 95 percent confidence level).

```

Call:
lm(formula = log(Exp) ~ 0 + LW + SW + DD - V + DC - VC + SS +
    FO - Obs - Pred, data = riskfactorsnumcat)

Residuals:
    Min       1Q   Median       3Q      Max
-4.2287 -0.4356 -0.0303  0.3117  3.6969

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
LW  -0.5290470    0.0188759  -28.03  <2e-16 ***
SW  -0.4675077    0.0165973  -28.17  <2e-16 ***
DD   0.0175508    0.0006336   27.70  <2e-16 ***
DC   0.2569175    0.0083839   30.64  <2e-16 ***
SS  -0.2538057    0.0118730  -21.38  <2e-16 ***
FO  -0.1986155    0.0132395  -15.00  <2e-16 ***
---
signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8832 on 16806 degrees of freedom
(614 observations deleted due to missingness)
Multiple R-squared:  0.905,    Adjusted R-squared:  0.905
F-statistic: 2.669e+04 on 6 and 16806 DF,  p-value: < 2.2e-16

```

Figure 23. Regression Output for Expected Crash Numbers and Classified Risk Factors without Volume.

Challenges of the Alternative Method

The alternative method proposed in this research has a simple procedure. It does not require extensive technical expertise for implementation and neither precise data. These models mostly require risk factor categories to predict the EB method's expected crash numbers for a segment. Both models had R squared values of more than 90 percent. This means that the risk factor classes can explain more than 90 percent of the variability of the EB expected crash numbers.

However, these types of models are usually data specific. Results from applying these models outside of Oregon might be slightly inaccurate. Therefore, calibration for local conditions would be needed for LVRs outside Oregon. LVRs outside of Oregon, might have some unique risk factors that influence the expected crash numbers. Since those risk factors were not included in these models, these models might give inaccurate results. Therefore, for LVRs outside of Oregon, redevelopment of these models might be needed to get the most accurate results. Also, these models were developed using only highway segment data and hence these models are not applicable for rural intersections. The effects of risk factors are different on intersections and hence these models would be inaccurate in predicting the intersection expected crash numbers.

CHAPTER SEVEN

CONCLUSIONS

This thesis studied network screening approaches for rural low volume roads (LVRs). For this study, LVRs were defined as roads having an average volume of less than 1000 vehicles per day (vpd). This research identified different network screening methods and assessed these methods for their suitability for LVRs. This research then carried out an empirical analysis of the Empirical Bayes (EB) method with actual LVR data. Finally, a new screening method for LVRs was developed.

The assessment task of this research identified the EB method as the most suitable network screening method for LVRs. This was logical because the EB method uses both observed and predicted crash numbers to find the expected crash numbers, which is then used for ranking. Most LVRs have outdated roadway designs which contribute to the crash risk of a site and the EB predicts crash numbers by using risk factors mostly. Therefore, the EB method incorporates the risk presented by the outdated roadway designs by incorporating these risk factors. This increases the chances of accurate network screening for LVRs. However, the FHWA systemic approach was ranked somewhere in the middle by the assessment. This was unexpected and the most probable reason for this outcome is that the economic effectiveness criterion used sensitivity to crash occurrence instead of benefit cost ratios. If benefit cost ratios were indeed used, then the FHWA screening method could have scored much higher.

The analyses of the EB method revealed that weights for predicted crash numbers has a negative logarithmic relationship with volume. Basically, an increase in volume

decreases the weight. This relationship indicates that at lower volumes EB relies more on predicted crash numbers than on observed crash numbers for calculating the expected crash numbers. As discussed earlier, predicted crash numbers are calculated mostly with risk factors. Therefore, it can be concluded that at lower volumes, EB relies more on risk factors than on actual observed crash numbers.

The analyses also identified that the weight-volume relationship had significant dispersion, which was caused by overestimation of the predicted crash numbers. It was found that sharper horizontal curves had higher AMF values. Also, increase in the sharpness of the horizontal curve increased the variability of the AMFs. These high AMF values were found to have caused the overestimation of the predicted crash numbers. The same analyses with an updated AMF indicated that both the dispersions of the weight-volume relationship and the overestimation of the predicted crash numbers were small. This indicates the need of a more detailed analysis of the accident modification factors to identify why they are overestimating the predicted crash numbers.

Finally, this research proposed a new network screening method for LVRs. The new method is a simple alternative to the EB method. This method predicts the EB expected crash numbers using mostly risk factors. Two prediction models were developed, and these models mostly use risk factor categories to predict the expected crash numbers. This would allow agencies to conduct network screening even if they do not have access to precise roadway data. Analysts can easily identify the categories of the risk factors and use those categories to predict the EB expected crash numbers. Furthermore, these prediction models have a simple structure. Therefore, extensive training and statistical understanding of an

analyst is not required for implementing the new method. This would make this method practical for small agencies, particularly those that do not have the budget to train and/or hire staff with extensive technical knowledge.

Both prediction models in the new method have adjusted R square values greater than 0.90. A logical answer for these high R square values can be found from the weight and volume relationship of the EB method. That analysis identified that at lower volumes the EB method relies more on risk factors than on actual observed crashes to calculate the expected crash numbers. Most of the data used for developing these models were for LVR segments that have volumes of less than 1000 vpd and therefore, these models with the risk factor categories were able to predict the expected crash numbers with such accuracy.

However, the prediction models proposed in the new method have some weaknesses. This type of models is usually very data specific. Therefore, if these models were to be used for LVRs outside of Oregon, they might give inaccurate results. Additionally, LVRs outside of Oregon might have some unique risk factors and as these risk factors were not incorporated in the models, the models would not be incorporating the effects of these risk factors. Therefore, these models would lose further accuracy in these cases. One way of mitigating this inaccuracy is by calibrating the models for local conditions. Another approach is to redevelop these models using local data. The second approach would require precise crash, traffic and geometric data for redeveloping the models.

Moreover, this research used only about 870 miles of LVR data for the different analyses out of which about 30 miles of data were dropped while developing the prediction

models. This was done because these 30 miles had some missing data and therefore could not be used for model building. A much larger sample should be used for developing these prediction models before introducing them in practice. A larger sample might make the models more accurate and reduce the chances of any misleading ranking.

For the dataset used in building the models, the vertical grades were found not to have a logical significant relationship with expected crashes. This might be because the data only had very few segments with steep grades. Therefore, a larger sample with a good number of segments with high vertical grade would verify whether the vertical grade indeed have any significant effect on the expected crashes or not. Other risk factor data like pavement type could also be included in the model development step. If they indeed have significant effect on crash occurrence, then they can be included in the models.

Also, the LVR data used for this research were only for state-owned LVRs. Therefore, these models might not provide fully accurate results for non-state-owned LVRs. Data from LVRs owned and operated by non-state-owned agencies should also be included in the larger sample and in the model development stage. Doing so would allow the models to be more universal and accurate for LVRs under different jurisdictions.

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APPENDIX

SURVEY QUESTIONNAIRE FOR THE STATE-OF-PRACTICE SURVEY

The purpose of this survey is to understand the state of practice in selecting highway safety improvement sites on rural low-volume roads (LVRs). Low-volume roads may be owned and operated by state DOTs or by local agencies such as counties, cities, and townships. For local agencies non-state owned local roads will be used to refer to low-volume roads under local jurisdictions.

The survey is divided in two parts. Part A is concerned with the agency practice in identifying sites for safety improvement projects on state-owned and operated low-volume roads. Part B includes questions about safety improvement projects on non-state owned local roads, i.e. roads that fall under local jurisdictions (primarily counties, townships and cities).

This survey should be completed by those in your agency who are involved in the safety improvement programs. Participation is voluntary, you can choose not to answer any question that you do not want to answer, and you can stop at any time. The survey has 17 questions in total and is expected to take approximately 15-20 minutes to complete. Thank you in advance for your participation.

Please enter your contact information: (We may wish to contact you if we need clarification or desire more information regarding a response)

NAME:

TITLE:

AGENCY:

PHONE:

EMAIL:

PART A - Identifying Sites for Safety Improvements – State-Owned LVRs

QA1. Defining low-volume roads (LVRs) as roads with AADT less than 1000 vehicles per day, how much do LVRs constitute of your highway network by length?

- 0% - 10%
- 10% - 25%
- 25% - 40%
- > 40%
- Don't know

QA2. Is your agency's method / process for selecting sites for safety improvements on state-owned LVRs different from that used on other state-owned roadways?

- Yes
- No

QA3. What is the method / process used for identifying safety improvement sites on state-owned LVRs? (check all that apply)

- FHWA systemic approach to safety
- Network screening using:
 - Crash frequencies
 - Crash rates
 - Combination of crash frequencies and crash rates
 - Crash severity (check if severity is accounted for by the method)
 - Other, please specify

QA4. In identifying sites for safety improvement on state-owned LVRs, cost-effectiveness (e.g. benefit-to-cost ratio) is used by the agency to (check all that apply):

- Rank safety improvement sites at the network level
- Comparing alternative safety countermeasures at specific sites

- Cost effectiveness is not used

QA5. On a scale of 1 to 10, how satisfied is your agency using this method / process on state-owned LVRs? (1 = not satisfied, 10 = extremely satisfied)

- 1 2 3 4 5 6 7 8 9 10

Q A6. Do safety personnel in your agency have ready access to the following low-volume road data at the network level? (check all that apply)

- Detailed crash data
- Traffic data (i.e. counts, vehicle class)
- Roadway geometry
- Roadside features

QA7. Please add any other information related to how your agency select sites for safety improvements on state-owned low-volume roads.

PART B - Identifying Sites for Safety Improvements – Non State Owned Local Roads

QB1. Is the HSIP program leader for non-state owned roadways (counties, townships, etc.) different from the staff member leading the program for state-owned roadways?

- Yes No

QB2. Are local agencies (counties, townships, etc.) involved in the identification of safety improvement project sites on local roads under their jurisdiction?

- Yes No

QB3. What is the process for determining how much funding is allocated to local (non-state owned and operated) safety projects?

- Past crash experience (e.g. proportion of crashes on non-state owned roads)
- Size of network by length (e.g. proportion of network consisting of non-state owned roads)
- Estimated vehicle miles of travel (e.g. proportion of travel on non-state owned roads)
- Other, please specify

QB4. From past experience, safety improvement sites on local roads (counties, townships, and cities) are identified based on (check all that apply):

- Statewide hotspot network screening
 - Network screening within local jurisdiction
 - Crash experience at sporadic (individual) sites
 - Risk perception by local agency staff or law enforcement
 - Risk perception by the public
-

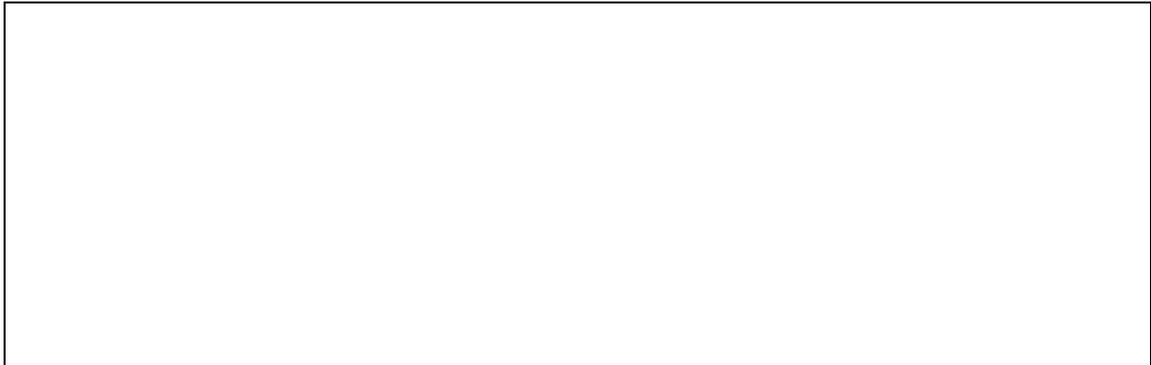
- Other, please specify

QB5. For sites on non-state owned local roads proposed by local agencies, traffic and roadway data collection is usually undertaken by:

- State DOT
- Respective local agency (county, township, etc.)
- Both (i.e. for some sites, local agencies provide data, and for others state DOT does)
- Other, please explain:

QB6. How is the selection of safety improvement sites (and their ranking) justified on non-state owned local roads?

- Cost effectiveness (e.g. benefit-to-cost ratio)
 - Crash frequency
 - Crash rate
 - Combination of crash frequency and rate
 - Crash severity (if severity is accounted for in the process)
 - Other, please explain:
-



QB7. Is the selection of safety improvement sites on non-state owned local roads performed separately from state-owned roadways, (i.e. the list of sites, rankings, etc. is done exclusively for non-state owned roadways)?

- Yes No

QA8. For non-state owned local roads, what is the percentage of safety improvement funds allocated to systemic safety improvements? (i.e. using the FHWA systemic approach to safety)

- 0% - 20%
 21% - 40%
 41% - 60%
 > 60%
 Don't know

QA9. Do safety improvement project sites involve unpaved non-state owned local roads?

- Yes No

QB10. Please provide any additional information on selecting sites for safety improvements on non-state owned local roadways that are not covered in the previous questions.

A large, empty rectangular box with a thin black border, intended for the respondent to provide additional information regarding the selection of sites for safety improvements on non-state owned local roadways.