Incorporating Crash Severity and Continuous Improvement of SHIFT

Report Number: KTC-23-16

DOI: https://doi.org/10.13023/ktc.rr.2023.16

Kentucky Transportation Center
College of Engineering, University of Kentucky, Lexington, Kentucky

in cooperation with
Kentucky Transportation Cabinet
Commonwealth of Kentucky

The Kentucky Transportation Center is committed to a policy of providing equal opportunities for al persons in recruitment, appointment, promotion, payment, training, and other employment and education practices without regard for economic, or social status and will not discriminate on the basis of race, color, ethnic origin, national origin, creed, religion, political belief, sex, sexual orientation, marital status or age.

Kentucky Transportation Center
College of Engineering, University of Kentucky, Lexington, Kentucky

in cooperation with
Kentucky Transportation Cabinet
Commonwealth of Kentucky

Kentucky
Transportation Center

Kentucky Transportation Center • University of Kentucky
176 Raymond Building • Lexington, KY 40506 • 859.257.6898 • www.ktc.uky.edu

University of
Kentucky

Research Report
KTC-23-16

Incorporating Crash Severity and Continuous Improvement of SHIFT

Reginald Souleyrette, Ph.D., P.E.
Program Manager

Riana Tanzen
Graduate Research Assistant

and

Teng (Alex) Wang, Ph.D., P.E.
Research Engineer

Kentucky Transportation Center
College of Engineering
University of Kentucky
Lexington, Kentucky

In Cooperation With
Kentucky Transportation Cabinet
Commonwealth of Kentucky

April 2023

<table>
<tr><td colspan="2">1. Report No.
KTC-23-16</td><td colspan="2">2. Government Accession No.</td><td colspan="2">3. Recipient's Catalog No</td></tr>
<tr><td colspan="4" rowspan="2">4. Title and Subtitle
Incorporating Crash Severity and Continuous improvement of SHIFT</td><td colspan="2">5. Report Date
April 2023</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="4">7. Author(s):
Reginald Souleyrette, Riana Tanzen, and Teng Wang</td><td colspan="2">8. Performing Organization Report No.
KTC-23-16</td></tr>
<tr><td colspan="4" rowspan="2">9. Performing Organization Name and Address
Kentucky Transportation Center
College of Engineering
University of Kentucky
Lexington, KY 40506-0281</td><td colspan="2">10. Work Unit No. (TRAIS)</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
SPR 21-603</td></tr>
<tr><td colspan="4" rowspan="2">12. Sponsoring Agency Name and Address
Kentucky Transportation Cabinet
State Office Building
Frankfort, KY 40622</td><td colspan="2">13. Type of Report and Period Covered</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code</td></tr>
<tr><td colspan="6">15. Supplementary Notes</td></tr>
<tr><td colspan="6">16. Abstract
The Strategic Highway Investment Formula for Tomorrow (SHIFT) is the Kentucky Transportation Cabinet's data-informed approach for comparing capital improvement projects and prioritizing limited transportation funds. SHIFT 2022 incorporates advancements in methods and flexibility. This project revises the SHIFT crash data safety metric. The crash data safety metric from the previous version of SHIFT was excess expected crashes (EECs). It is computed using the total number of crashes of all severities. Locations with a higher proportion of severe (fatal and injury) crashes received the same weight as locations with an equal number of property damage only crashes. This project redefines the SHIFT crash data safety metric, increasing the weight of serious (KAB) crashes while still accounting for the potential to reduce less serious crashes. It also attends to the five-year and ultimate goals of Kentucky's Strategic Highway Safety Plan by developing a metric sensitive to these policy goals. The five-year goal is represented by a new definition of EEC (the difference between expected crashes, the Empirical Bayes estimate, and the number of systemwide crashes when the goal is achieved). The ultimate goal is represented by the potential to reduce crashes on all road sections to zero, which is the EB estimate itself.</td></tr>
<tr><td colspan="4">17. Key Words
highway safety, severity, SHIFT</td><td colspan="2">18. Distribution Statement
Unlimited</td></tr>
<tr><td>19. Security Classification (report)
Unclassified</td><td colspan="2">20. Security Classification (this page)
Unclassified</td><td colspan="2">21. No. of Pages
38</td><td>19. Security Classification (report)</td></tr>
</table>

Table of Contents

Chapter 1 Introduction 1
1.1 Background 1
1.2 Kentucky's Situation 1
Chapter 2 Literature Review 3
2.1 High Crash Locations (Site Rankings) 3
2.2 Crash Severity 4
2.3 The Highway Safety Manual 7
2.3.2 Empirical Bayes (EB) Estimate 8
2.3.3 Excess Expected Crashes (EEC) 9
Chapter 3 Methodology Overview 11
3.1 Roadway and Intersection Data 11
3.2 Segmentation and Categorization 12
3.3 Crash Data 12
3.4 SPF Development 13
3.5 EB Estimates and EEC 15
Chapter 4 Project Prioritization 17
4.1 Methods for Project-Level EB estimate and EEC 17
4.1.1 Summation Method 17
4.1.2 Average Theta Method 19
4.1.3 Correlation Coefficient (ρ) Method 20
4.1.4 Summary of Results 21
4.2 Proposed Methods for Project Prioritization 21
4.2.1 Base Ranking Method: Ranking Based on EECs of the Total Crashes (Uses Base Condition for SPFs) 22
4.2.2 Method 1 (No Base Condition): Ranking Based on EECs of Total Crashes (No Base Conditions for SPFs) 22
4.2.3 Method 2 (Considering Crash Severity): Ranking Based on the Combined Score of EECs of KAB and CO 23
4.2.4 Method 3: Ranking Based on Combined Score of EB and EEC 25
4.2.5 Method 4 (Goal-Driven Method): Ranking Based on EEC_{alt} of Total Crashes 26
4.2.6 Comparing Ranking Methods 28
Chapter 5 Recommendations and Implementation 29
Chapter 6 References 31

List of Figures

Figure 2.1 Visual Representation of EB Estimate and EEC 10
Figure 3.1 Study Methodology 11
Figure 3.2 SPFs Developed 15
Figure 3.3 Flow Chart for EEC Calculation 16
Figure 4.1 Project Example 17
Figure 4.2 Visualization of Five Cases 18
Figure 4.3 Comparison of Ranking By Method 1 and Base Method 23
Figure 4.4 Comparison of Ranking By Method 2 and Base Method 25
Figure 4.5 Comparison of Ranking By Method 3 and Base Method 26
Figure 4.6 Graphical representation of EEC_{alt} 27
Figure 4.7 Comparison of Ranking By Method 4 and Base Method 28

List of Tables

Table 2.1 Site Ranking Metrics 5
Table 3.1 Characteristics of the Roadway Networks and Number of Crashes By Severity........ 12
Table 3.2 Base Conditions Used for SPF Development........ 14
Table 4.1 Descriptions and Equations of Final Metric Calculation 18
Table 4.2 Sample Calculation for Summation Method on Project-Level $N_{EB(KAB)}$ and EEC_{KAB} 19
Table 4.3 Sample Calculation for Average Theta Method on Project-Level $N_{EB(KAB)}$ and EEC_{KAB} 20
Table 4.4 Sample Calculation for Correlation Coefficient Method (ρ = 0 and 1) on Project-Level $N_{EB(KAB)}$ and EEC_{KAB} 21
Table 4.5 Summary of Project-Level $N_{EB(KAB)}$ and EEC_{KAB} From Three Methods........ 21
Table 4.6 Differences in Ranking Between Method 1 and Base Method........ 23
Table 4.7 Frequency and Cost of Crashes by Severity 24
Table 4.8 Weighted Average Crash Cost by Crash Groups 24
Table 4.9 Differences in Ranking Between Method 2 and Base Method........ 24
Table 4.10 Differences in Ranking Between Method 3 and Base Method........ 26
Table 4.11 Differences in Ranking Between Method 4 and Base Method........ 27
Table 4.12 Summary of Ranking Method Differences........ 28
Table 5.1 Weights for Metrics to Calculate Project Ranking Metric (R) 29
Table 5.2 Example of Project Ranking Metrics R and S 29
Table 5.3 Regression Parameters for SHIFT 2022........ 30

Chapter 1 Introduction

The Strategic Highway Investment Formula for Tomorrow (SHIFT) is the Kentucky Transportation Cabinet's data-informed approach for comparing capital improvement projects and prioritizing limited transportation funds. SHIFT 2022 incorporates advancements in methods and flexibility. This project revises the SHIFT crash data safety metric.

1.1 Background

Highway safety management aims to reduce the frequency and severity of crashes within the constraints of available resources. Allocating limited resources to realize the maximum benefits from appropriate countermeasures requires that transportation professionals identify and prioritize sites hazardous to safety. Ineffective safety project prioritization can distribute funds to locations with less potential for improvement while unsafe sites may remain untreated. Before the release of the *Highway Safety Manual* (HSM), transportation professionals used several metrics (i.e., crash frequency, crash rate, crash cost, or a combination of these) to identify and prioritize high-crash locations [1]. These metrics, however, are limited by several methodological weaknesses, in particular regression-to-the-mean bias (RTM). RTM occurs when the average observed crash rates over a few years are overly influenced by a single year with an unusually high or low number of crashes [2].

Published in 2010 by AASHTO, the HSM provides comprehensive guidelines for evaluating highway safety improvements and facilitates decision making based on safety performance [3]. This manual outlines a methodologically sophisticated analytical procedure for detecting and prioritizing high-risk locations and selecting appropriate countermeasures. Nonetheless, AASHTO has released only one edition of the HSM, and the need for improvement persists.

The HSM introduced safety performance functions (SPF), crash prediction models that correlate predicted crash frequency with traffic volume and geometric features of a roadway network with similar characteristics [4]. The HSM also facilitates the Empirical Bayes (EB) method, which provides a more realistic measure of a site's safety performance by combining predicted crashes with historical crashes. The EB method accommodates overdispersion and compensates for the random fluctuation commonly observed in crash data by estimating the magnitude of the expected crashes and thus corrects the RTM bias in the estimation [5, 6]. In addition, the manual illustrates several safety performance measures (e.g., average crash frequency, crash rate, equivalent property damage only crashes, excess proportion of crash types, excess predicted crash frequency, excess expected crash frequency) for ranking potential sites. While most of the performance measures do not account for RTM, one of the most widely used metrics, *Excess Expected Average Crash Frequency*, is free from this bias. This index is the difference between the estimate obtained from the EB method and SPF-predicted crash counts [3]. Many states, including Virginia, Illinois, and Ohio, have implemented this method for ranking sites, defining the term as *Potential for Safety Improvement* (PSI) [7, 8]. In Kentucky, this index is referred to as *Excess Expected Crashes* (EEC), and this term is used in this report.

1.2 Kentucky's Situation

One of the limitations of the previous (SHIFT 2020) crash data–based safety metric, EEC, was its basis on total crashes, with equal weights assigned to all crashes, regardless of severity. Intuitively, sites with a higher proportion of severe crashes should receive higher priority than a location with an equal proportion of less severe or no-injury crashes. Furthermore, EEC is calculated by taking the difference between expected (EB) and predicted (SPF) crashes. This relative difference represents the *likely* potential for reducing crashes, but only the potential to reduce crashes at a particular location to the average of similar facilities. Of course, it is theoretically possible to reduce crashes at any location to zero (however unlikely). Two sites with the same difference between expected and predicted crashes can receive equal importance even though one might have higher projected crashes and thus a higher likelihood or further reduction (the lower crash site cannot be reduced to below zero).

This study aimed to improve the SHIFT safety project ranking technique by addressing crash severity as well as possible reduction potential in the final ranking metric. The study also developed a method for calculating the goal-driven EEC, which represents the potential for reaching a systemwide average crash experience when safety goals are met. Lastly, the study integrated and implemented these metric components for ranking at the project level.

Chapter 2 Literature Review

Before the HSM was published, safety practitioners used various methods (e.g., crash frequency method, equivalent property damage only (EPDO) crash frequency method, crash rate or critical rate method, crash cost method, rate quality control method) to rank sites. Some transportation agencies used individual metrics, while some used a combination of metrics, which led to a somewhat arbitrary ranking of hazardous sites or networks [9]. However, these methods were limited to addressing several issues. For example, one of the most commonly used ranking criteria was crash frequency, which does not consider the effects of crash exposure. This leads to a bias toward locations with higher traffic volumes and longer segment lengths [10]. Although the crash rate method was introduced to account for traffic exposure, it assumes a linear relationship between the number of crashes and traffic flow [11]. Moreover, the EPDO method assigns weighting factors to crashes by severity relative to the property damage only (PDO) crash cost. This may overemphasize locations with a low frequency of severe crashes [3]. Additionally, none of these methods consider the random fluctuation in crash counts, resulting in RTM [12]. In another method, a typical predicted value was compared to observed crashes which might be misleading for safety analysis if the historic crashes are unusually high or low.

2.1 High Crash Locations (Site Rankings)

Several studies [13–17], along with the HSM, recommend the use of the EB method, which compensates for random fluctuations in crash data. EB estimates can be used to identify high-risk locations by ranking them by the order of magnitude or by taking the difference between the EB estimate and output of the predictive models (known as the potential for safety improvement, PSI; accident reduction potential, ARP; excess expected crashes, EEC) [18,19].

To compare the performances of different site ranking methods, Cheng and Washington [20] developed four new evaluation tests and applied them to select the most appropriate method — crash frequency method, crash rate method, ARP method, and the EB method. The study showed that based on the quantitative evaluation tests, the EB method is the most consistent and reliable method for identifying hazardous locations [20]. While this study used data from Arizona, similar research was performed by Montella [17]. The result is consistent with the previous study, where the EB method outperformed the other competing methods [17].

Persaud et al. proposed an approach to rank sites based on their potential for safety improvement [21]. The concept of this parameter was introduced by Jorgensen and McGuigan, who termed it the potential accident reduction [22, 23]. However, the definition was a bit different from the conventional PSI concept as it took the difference between observed crash frequencies and EB estimates. The potential of this index was limited by the random fluctuations in crash counts, specifically for the short-term crash history. Tarko et al. addressed this limitation by suggesting a confidence level that could be used as an indicator of real safety problems [24]. Later, in several studies, Persaud et al. validated the PSI concept showing that the method is conceptually sound and has advantages over other alternative ranking methods [21, 25].

After the HSM was published, several states adopted its safety evaluation procedure for high-risk site selection. In Virginia, Garber et al. [7] published a report on the development of SPFs for total crashes and combined fatal plus injury crashes. A total of 139,635 sites were evaluated, where each site was a segment of a rural or urban two-lane road without an intersection. The results indicated that as a site prioritization criterion, PSI shows more potential than crash rates.

Tegge et. al [8] developed Illinois-specific SPFs to predict crash frequency for 12 types of segments and eight types of intersection peer groups. From the SPFs, predicted and EB expected crashes were estimated for fatal crashes, fatal plus injury crashes, and type A and B injury crashes. Site-specific analysis based on PSI treated each segment and intersection as a separate entity. Apart from calculating PSI for each peer group of crashes, they computed weighted average PSIs, showing the relative significance of each severity (weighs of 25 for fatal PSIs, 5 for Type A PSIs, and 1 for Type B PSIs) [8].

Souleyrette et al. [26] developed SPFs for total crashes using Kentucky-specific data, where models were estimated for eight roadway types, 36 classes of intersections, and ramps. The study prioritized 1,274 safety projects, where each project contained different combinations of elements (road segment, intersection, and ramps). The project prioritization was based on the summation of the EEC of each element that falls inside a project, and projects with higher EEC values received higher priority.

From the above literature, it is clear that disagreement exists over which criteria (the EB estimate or PSI) should be used to identify and rank high-risk locations. Cheng et al. [27] attempted to resolve this disagreement by proposing a methodology that combines rankings estimated from both criteria. Furthermore, they illustrate the estimation of confidence levels representing the uncertainties associated with computed values. Results showed the proposed method is more efficient than the other hotspot prioritization methods.

2.2 Crash Severity

A number of studies [13, 28, 29] have acknowledged that equally weighting all crashes is an unrealistic assumption and that the severity of the crashes needs to be taken into account in hotspot ranking. One of the most common ways of integrating crash frequency and severity is the EPDO method. This method assigns weighting factors to all crashes relative to the PDO crash cost and develops a single combined frequency. Washington et al. [30] proposed a combination of EPDO crashes and a quantile regression technique to identify hotspots. However, this method is significantly driven by the weights of fatal and injury crashes. Montella [17] evaluated the effectiveness of seven hotspot identification methods, including the EPDO method. Results showed that the performance of this method was second-worst overall.

Bandyopadhyaya and Mitra [31] proposed a frequency severity index (I_{FS}), which is a combination of total and fatal crash frequency. This study tested the efficacy of three severity-based metrics (fatal crash frequency, EPDO, and I_{FS}) along with the traditional crash frequency method. I_{FS} performed the second-worst among the four techniques according to their consistency testing.

Qu and Meng [13] proposed using a societal risk-based method for ranking hazardous sites. They introduced a new indicator that determines societal costs of crash types based on the probability of crash severities. This metric was integrated into a simple ranking and EB method for hotspot identification. Based on consistency tests, the study found that the frequency-based method outperformed the societal risk based method. A similar study conducted by Costa et al. [29] reached a contradictory finding. Their consistency analysis showed that the societal crash-based method is more consistent than traditional frequency based approaches. Table 1 summarizes the previous studies and the parameters used for site ranking.

Table 2.1 Site Ranking Metrics

Study	Facility Type	Study Area	Crash Data Period (Years)	Site Ranking Metric
Rudy [33]; Morin [34]; Higle and Witkowski [35]	Highway segment	USA	—	Crash rates
Jorgensen [23]	—	—	—	Difference between observed and expected crashes divided by the square root of the expected crashes
Deacon et al. [35]	Rural highway	Computerized crash data	2	Crash frequency
Laughland et al. [36]	—	—	—	Combination of crash frequency and crash rate
Hakkert and Mahalel [37]	Intersections	Israel	15	Crash frequency exceeding threshold level of significance
McGuigan [22]	Junctions and links	Scotland	5	Difference between observed and expected crashes
Maher and Mountain [38]	Artificially generated dataset			Crash frequency and difference between observed and expected crashes
Persaud [14]	Road segment	Ontario, Canada	6	EB estimate
Hauer [15]	Rail-highway grade crossing	USA	5	EB estimate
Heydecker and Wu [39]	—	—	—	The proportion of crashes using the EB approach
Stokes and Mutabazi [40]	Provided historical perspective of the development of rate-quality control method			Crash rate and rate quality control
Hauer [41]	—	—	—	Crash frequency and rate
Tarko et al. [42]	—	—	—	Difference between overall crash rate and minimum crash rate

Study	Facility Type	Study Area	Crash Data Period (Years)	Site Ranking Metric
Persaud et al. [43]	Rural two-lane roads, intersections	Ontario, Canada	6	PSI
Tarko and Kanodia [44]	Rural two-lane roads	Indiana, USA	3	An index of crash frequency and an index of crash cost
Miaou and Song [16]	Urban intersection, rural two-lane roads	Toronto, Canada; Texas, USA	6;1	EB estimate
Cheng and Washington [45]	Road segment, intersection	Artificially generated dataset		EB estimate and confidence interval technique (with some caveats)
Miranda-Moreno et al. [46]	Highway-railway intersection	Canada	5	Marginal and posterior mean* of accident frequency
El-Basyouny and Sayed [47]	Arterials	Vancouver and Richmond, Canada	3	Relative risk (ratio between the EB estimate and the predicted accident frequency as obtained from the prediction model) and PSI
Cheng and Washington [20]	Principal arterials	Arizona, USA	3	Crash frequency, crash rates, ARP, and EB estimate*
Lord and Park [48]	Intersections	California, USA	5	EB estimate
Elvik [49]	Road segments	Norway	8	EB estimate
Montella [17]	Roadway segment	Italy	5	Crash frequency, EPDO crash frequency, crash rate, proportion method, EB estimate of total crashes* and EB estimate of severe crashes.
Garber et al. [7]	Roadway segment	Virginia, USA	5	PSI

Study	Facility Type	Study Area	Crash Data Period (Years)	Site Ranking Metric
Tegge et al. [8]	Roadway segment, intersections	Illinois, USA	5	PSI
Cheng et al. [27]	Intersection	Artificially generated dataset		Combination of EB estimate, ARP and, confidence levels
Wang et al. [50]	Roadway segment	London, England	5	Total crash cost rate
Park et al. [51]	Rural multilane road segment	California and Texas, USA	5 to 10	The conditional mean of crash frequency and posterior expected ranks
Yu et al. [11]	Road segment	UK	10	Crash frequency, crash rate, EB estimate*, ARP, local spatial autocorrelation index, Kernel density (a simplified version of EB)*
Qu and Meng [13]	On-ramps and off-ramps	Singapore	3	Societal risk-based method (proposed) and EB estimate*
Costa et al. [29]	Road segment	Australia	5	Societal cost based on crash type and severity (proposed index)*, EB estimate, and simple ranking
Ohio Department of Transportation [52]	Roadway segment, intersection	Ohio, USA	3	PSI
Souleyrette et al. [26]	Roadway, Intersections	Kentucky, USA	5	EEC (also known as PSI)

* This metric outperformed the other metrics.
Note: The definition of ARP, PSI, and EEC are the same, but the terminology varies from study to study.

2.3 The Highway Safety Manual

The HSM outlies a methodologically sophisticated analytical procedure for safety performance evaluation by considering many of the limitations of conventional methods. The manual works as a guide for identifying and ranking sites with potential for safety improvements in addition to selecting appropriate countermeasures. The HSM includes four parts: Part A (Introduction, Human Factors, and Fundamentals), Part B (Roadway Safety Management Process), Part C (Predictive Method), and Part D (Crash Modification Factors). Focused on the predictive method, Part C describes a structured methodology for estimating the expected average crash frequency of roadway network, site, or facility and demonstrates the technique to use it for ranking sites with promise. The basic components of the predictive method are predictive models (SPFs), the EB method, and safety performance measures (e.g., EEC).

2.3.1 Safety Performance Functions (SPFs)

SPFs are developed based on regression modeling of observed crash data over a number of years at sites with similar characteristics. They develop mathematical equations to estimate the predicted crash frequency for a specific roadway type (e.g., rural, urban) and geographic space (e.g., roadway segment, intersection, ramp, any other special facility). Statistical distributions are used to estimate SPF regression parameters. Many studies propose using the Poisson distribution to fit the observed crash data for predicting crash frequency [53, 54]. Miaou and Lum [55] showed the Poisson distribution is more appropriate when the variance in the crash data is equal to the mean. However, crash data are characterized by overdispersion because of the random nature of crash frequencies. Recent practices including, those in the HSM, show that a negative binomial (NB) distribution is better suited to model crash data since it is capable of handling overdispersion, where the variance is greater than the mean [56 – 58]. This distribution is also known as Poisson-Gamma distribution since it has the characteristics of both Poisson distribution (for crash frequency) and the Gamma distribution (variation of crash count exceeds the mean) [59].

Using NB regression, several functional forms can be used to develop SPFs. The HSM recommends a mathematical form where both segment length and traffic volume are treated as offsets to predict the response crashes [3]. Where the HSM assumed a linear relationship between crashes and traffic volume, most recent studies found an exponential relationship between crashes and traffic count, and segment length is kept as a simple multiplier. The most commonly used functional form and the variance of the prediction are expressed as follows [3, 4, 60]:

$$\mathrm{N_{SPF}} = \mathrm{e}^{\alpha} * \mathrm{L} * \mathrm{AADT}^{\beta} \qquad \text{Eq. 1}$$

$$\mathrm{Variance} = \mathrm{N_{SPF}} + \mathrm{k} * \mathrm{N_{SPF}^2} \qquad \text{Eq. 2}$$

where:
N_{SPF} = The predicted number of crashes by SPF
L= Length of a segment
AADT = Average Annual Daily Traffic
α = Regression parameter for intercept
β = Regression parameter for AADT
k = overdispersion parameter

The NB model converges to the Poisson model when the overdispersion parameter equals zero. Some studies [60, 61] prefer to use the inverse of the overdispersion parameter rather than the overdispersion parameter. The term is referred to as theta ($\boldsymbol{\theta}$) or the inverse dispersion parameter (k), where k = 1/$\boldsymbol{\theta}$.

2.3.2 Empirical Bayes (EB) Estimate

The EB technique is a state-of-the-art method for evaluating safety performance. According to Hauer et al. [15], this method increases the accuracy of the estimate when the usual estimate is too imprecise to be useful. This method accounts for RTM by estimating the magnitude of the expected crashes and generates a more accurate estimate of the long-term mean at a site. The statistical reliability of the expected crash frequency improves when the EB method shifts the expected crashes toward the observed crashes using the SPF-predicted crash frequency. To combine the two estimates (historical and SPF-predicted crashes) the EB method uses a weight factor. It is a function of the SPF overdispersion parameter and depends on the SPF's variance. An SPF shows poor correlation when developed from very dispersed crash data. In this case, the weight factor places more importance on the observed crash data than the predicted crash frequency. Conversely, when the data used for model development have little dispersion, the reliability of predicted crashes increases, and therefore, it receives more weight than the observed crashes [3]. The formulas for EB expected crashes and the weight factor are as follows [61]:

$$N_{EB} = w * N_{SPF} + (1 - w) * N_{observed} \qquad \text{Eq. 3}$$

$$w = \frac{1}{1 + \frac{N_{SPF}/L}{\theta}} \qquad \text{Eq. 4}$$

where:
N_{EB} = Expected average crash frequency by EB method
N_{SPF} = Predicted average crash frequency using SPFs
w = weight factor, 0≤w≤1
$N_{observed}$ = Historical crash frequency
θ = Inverse overdispersion parameter (theta)
L = roadway segment length (L = 1 for intersections)

2.3.3 Excess Expected Crashes (EEC)

The idea of EEC is introduced to deal with one of the limitations of using the EB estimate as a site ranking metric. The SPF-predicted and EB-estimated crashes are dependent on AADT — as AADT increases, the values increase. A site might rank higher in the prioritization process due to having higher AADT, and the true potential for safety improvement becomes secondary. However, when EEC is used to compare sites with varying AADT, it shows how much the EB-estimated crashes exceed the SPF predictions. Therefore, the natural increase in crash count resulting from increasing AADT cannot significantly influence the ranking [8].

The difference between EB-expected crashes and SPF-predicted crashes is defined as EEC (See Equation 5). EEC measures the number of crashes occurring at a site more or less than expected for sites with similar characteristics [19].

$$EEC = N_{EB} - N_{SPF} \qquad \text{Eq. 5}$$

The value of EEC can be positive or negative. Positive EEC indicates that more crashes are occurring than expected at a site and, therefore, it has the potential for improvements. A higher value indicates more vulnerability. On the other hand, a negative EEC represents that fewer crashes are occurring than expected and so are comparatively safer sites. Figure 2.1 is a visual representation of the relationship between SPF-predicted crashes, observed crashes, EB-expected crashes, and EEC.

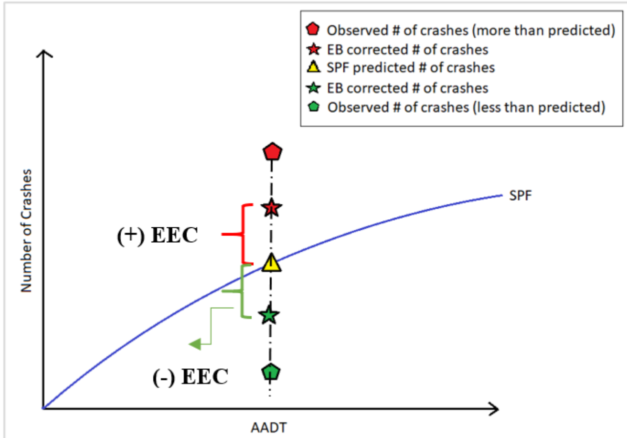


Figure 2.1 Visual Representation of EB Estimate and EEC

When EEC represents how much expected crashes surpass the predicted crashes, it does not consider the severity of crashes in general. The HSM demonstrates two ways to incorporate crash severity in the calculation of excess crashes.

2.3.3.1 EEC By Severity Distribution

In this method, predicted crashes for fatal plus injury crashes (FI), and PDO crashes are estimated using SPFs developed from corresponding crash groups. Another recommendation is to use the default crash severity distributions provided by the HSM on predicted total crashes. The EB-expected crashes are computed, and the excess from each crash group is summed to estimate the final EEC. The formula of EEC is:

$$\text{EEC (by severity distribution)} = \left(\mathrm{N_{EB(F,I)}} - \mathrm{N_{SPF(F,I)}}\right) + \left(\mathrm{N_{EB(PDO)}} - \mathrm{N_{SPF(PDO)}}\right) \qquad \text{Eq. 6}$$

Although this method uses predicted and expected crashes from two crash severity groups for EEC estimation, it gives equal weight to the excess of fatal plus injury crashes and PDO crashes.

2.3.3.2 EEC By Severity Cost

Another method is demonstrated in the HSM where excess fatal plus injury and PDO crashes are weighted using crash cost for severity (CC). The formula is:

$$\text{EEC (by severity cost)} = \left(\mathrm{N_{EB(F,I)}} - \mathrm{N_{SPF(F,I)}}\right) * \mathrm{CC_{F,I}} + \left(\mathrm{N_{EB(PDO)}} - \mathrm{N_{SPF(PDO)}}\right) * \mathrm{CC_{PDO}} \qquad \text{Eq. 7}$$

One limitation of this method is that the discrepancy between the crash cost of fatal and injury crashes and PDO crashes is very prominent. Thus, this method may overemphasize sites with a small number of severe crashes.

Chapter 3 Methodology Overview

The next two chapters describe the research methodology. First, a brief description of the data and an overview of the data preparation process are provided. This is followed by the SPF development process and the estimation of SPF-predicted crashes, EB-estimated crashes, and EEC. The next chapter is divided into two parts, which address the goals of the study: methods for project-level EB estimate and EEC, and method for project prioritization. The outline of the methodology is shown in Figure 3.1.

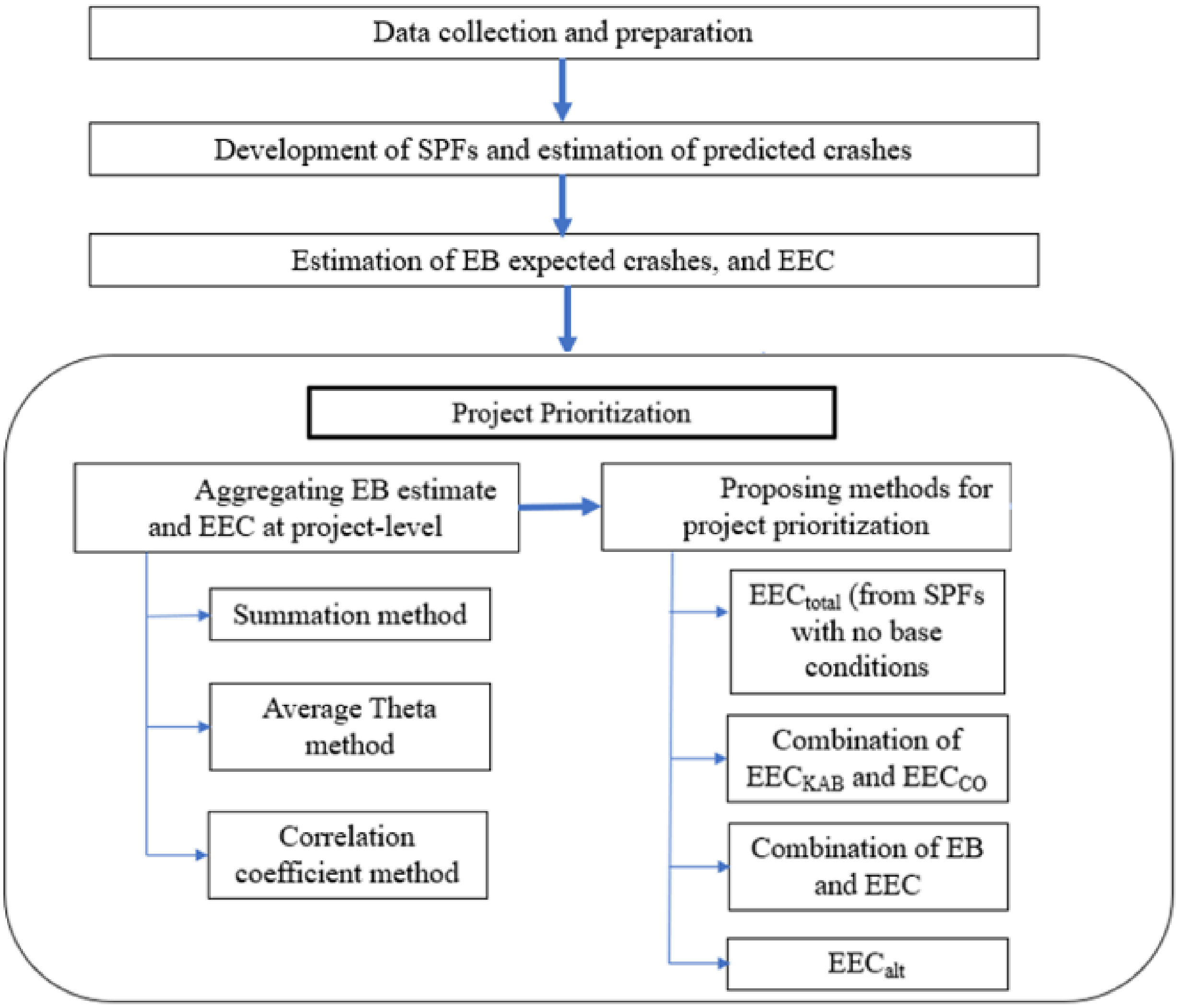


Figure 3.1 Study Methodology

3.1 Roadway and Intersection Data

In Kentucky, the road centerline network and highway information system (HIS) data[1] are collected and maintained by the Kentucky Transportation Cabinet (KYTC). Data (traffic flow, functional classification, various roadway features including information on lanes, shoulders, median, vertical, and horizontal curves) for all state-maintained roads

[1] https://transportation.ky.gov/Planning/Pages/Centerlines.aspx

were obtained from this database in shapefile format. A dataset with all the intersection approaches was collected from a database maintained by the Kentucky Transportation Center (KTC). Critical information includes the locations of intersections on the routes, traffic control type, and geometric configuration.

3.2 Segmentation and Categorization

Processing and organizing the datasets is necessary to form a comprehensive dataset usable for SPF development and further evaluation. A key aspect of the SPF development process is ensuring homogeneity of roadway elements (road segment or intersection); this can be achieved through homogenous segmentation. It enables the segregation of observed crashes within the bounds of a consistent combination of geometric features and reflects the underlying pattern with greater reliability [57]. Segmentation splits the intersections and produces a set of roadway segments of varying lengths and fixed beginning and ending mile points where traffic volumes and key roadway features remain constant. Following HSM guidelines, features such as functional class, average annual daily traffic (AADT), number of lanes, lane width, shoulder width, horizontal curves, vertical curves, median type, and intersection approaches have been used to make the segments homogenous.

Based on functional class, number of lanes, and median type, the dataset was categorized into 10 groups so that similar segments and intersections could be modeled together. Intersections in Kentucky are categorized into 36 classes based on their geometric configuration and control type. The study included the following categories:

1. Rural two-lane (R2L)
2. Rural intersections and parkways (RIP)
3. Rural multilane, divided (RMD)
4. Rural multilane, undivided (RMU)
5. Urban two-lane (U2L)
6. Urban intersections and parkways (UIP)
7. Urban multilane, divided (UMD)
8. Urban multilane, undivided (UMU)
9. Intersections (36 classes)
10. Ramps

3.3 Crash Data

To develop and test the methodology, crash data from SHIFT 2020 were compiled for five years (2013 – 2017). Kentucky crash reports use a five-point scale (KABCO) to classify injury severity, where K= fatal, A = incapacitating injury, B = non-incapacitating injury, C = possible injury, and O = no injury/PDO [62]. The crashes were linked to corresponding segments, intersections, and ramps. A segment was assigned all the crashes that occurred between the starting and the ending mile points. If a crash occurred exactly at any mile point, it was assigned to the segment with the lower endpoint. Table 3.1 presents selected road characteristics by roadway class as well as crash frequency totals by severity and roadway class.

Table 3.1 Characteristics of the Roadway Networks and Number of Crashes By Severity

	R2L	RIP	RMD	RMU	U2L	UIP	UMD	UMU	Intersections	Ramps
Number of segments	278186	1184	1962	347	24709	476	4269	4100	69077	2450
Total miles	21004.8	1008.4	613.8	52.2	2133.03	233.7	546.2	310.1	-	593.3

	R2L	RIP	RMD	RMU	U2L	UIP	UMD	UMU	Intersections	Ramps
AADT (min)	2	4546	72	270	9	5099	1239	1514	10	35
AADT (max)	22380	91932	44967	31200	48500	210707	73365	73365	449673	118983
Crashes										
K	1281	101	55	8	224	59	79	102	792	17
A	3358	267	113	34	956	277	385	439	3689	129
B	8117	838	370	59	3458	1044	1524	1739	13649	450
C	12227	1147	588	107	5651	1379	2729	2860	22188	826
O	69322	10522	3764	988	48313	13429	25610	28897	172061	10646
Note: Intersection AADT data are the traffic count on the major roads.										

3.4 SPF Development

SPFs should be calibrated for each roadway type, intersections, and ramps [63]. In this study, SPFs were developed using the most common functional form [61], as shown in Equation 8, for the roadway classes and ramps. For intersections, Equation 9 was used, where $AADT_{Major}$ and $AADT_{Minor}$ are the AADT of the major and minor roads, respectively, and α, β_1, and β_2 are the regression parameters. SPF-R, a script in RStudio[2] was used to develop the models for this study.

$$N_{SPF}(\text{segment or ramp}) = e^{\alpha} * L * AADT^{\beta} * AF_1 * AF_2 * \ldots. \qquad \text{Eq. 8}$$

$$N_{SPF}(\text{intersection}) = e^{\alpha} * AADT_{Major}^{\beta 1} * AADT_{Minor}^{\beta 2} \qquad \text{Eq. 9}$$

The development and application of the SPFs are influenced by the size of the dataset. It was not possible to develop individual SPFs for each crash severity level, especially for K or KA-only crashes because the sample size was too small for every roadway type (See Table 3.1). To develop statistically meaningful models for all roadway types, intersections, and ramps, SPFs were developed for the following combinations of crash severity level:

KAB: More severe crashes
CO: Less severe crashes
KABCO: Total crashes

SPFs can be considered as statistical base models for any roadway network, preferably developed with specified base conditions. Base conditions are typically the most frequently encountered geometric attributes and may include features such as lane width, shoulder width, median width, and horizontal and vertical curves. Crash modification factors (CMF) are used when a segment's geometric attributes do not match the base conditions used to develop the models [3]. In Kentucky, CMFs are referred to as adjustment factors (AFs) when used for this purpose. Although there are several resources for AFs (i.e., the HSM and CMF Clearinghouse) there remain several roadway features for which AFs are not yet available yet. The absence of AFs limits the application of SPFs. When SPFs are

[2] http://github.com/irkgreen/SPF-R

modeled without any base condition and use the entire dataset, no AF is required to adjust predicted crashes. In this study, all SPFs were developed in two ways: using specific base conditions, and without using base conditions.

For each of the eight roadway types, multiple iterations were performed with total crashes and various sets of base conditions. Quality of fit was investigated using cumulative residual (CURE) plots, which reflect the functional form of a particular explanatory variable (in this case, AADT). Additionally, several other goodness-of-fit measures (i.e., modified R^2, CURE deviation percentage (CDP), maximum absolute CURE deviation (MACD), and theta) were used to compare the performance of multiple models and make the best choice. Since adjustment factors were not available for the base attributes of the SPFs for urban two-lane roads, and rural and urban interstates and parkways, the final models did not use any filters. Once base conditions were finalized, the same geometric features were used for the modeling of KAB and CO crashes. Additionally, 36 separate SPFs were developed for each of the intersection classes. Since each group is already homogenous, no base conditions were needed for the intersections. Figure 3.2 shows all the combinations for which SPFs have been developed and summarizes base conditions as well as the regression parameters for each model.

Table 3.2 Base Conditions Used for SPF Development

Roadway Type	Base Conditions
R2L	Lane Width = 9 ft; Shoulder Width = 3 ft; Horizontal Curve = Class A[3]; Vertical Curve = Class A[4]
RIP	-
RMD	Shoulder Width = 10 ft
RMU	Lane Width = 12 ft
U2L	-
UIP	-
UMD	Median Width > 20ft
UMU	Lane Width = 12 ft

[3] Grade Class Description (Percentage): A=0-0.4; B=0.5-2.4; C=2.5-4.4; D=4.5-6.4; E=6.5-8.4; F=8.5 or higher
[4] Curve Class Description (Degrees): A =0-3.4; B=3.5-5.4; C=5.5-8.4; D=8.5-13.9; E=14-27.9; F=28 or higher

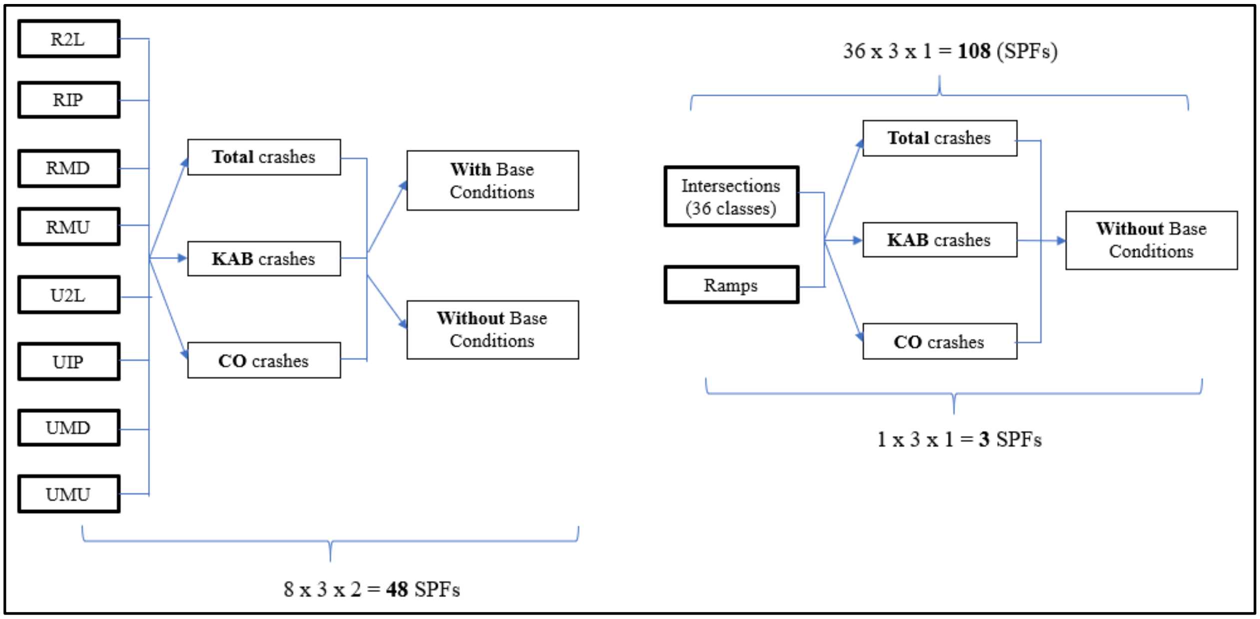


Figure 3.2 SPFs Developed

3.5 EB Estimates and EEC

Based on the SPF and the overdispersion parameter, the EB method combines the crash history of a roadway network with the predicted crash frequency. Equations 3 and 4 were used to calculate the EB-expected total as well as KAB and CO crashes for every roadway segment, intersection, and ramp. To evaluate a site's likely potential for reducing crashes, EECs (EEC_{total}, EEC_{KAB}, and EEC_{CO}) were calculated using Equation 5. Figure 3.3 illustrate the process used to calculate EECs.

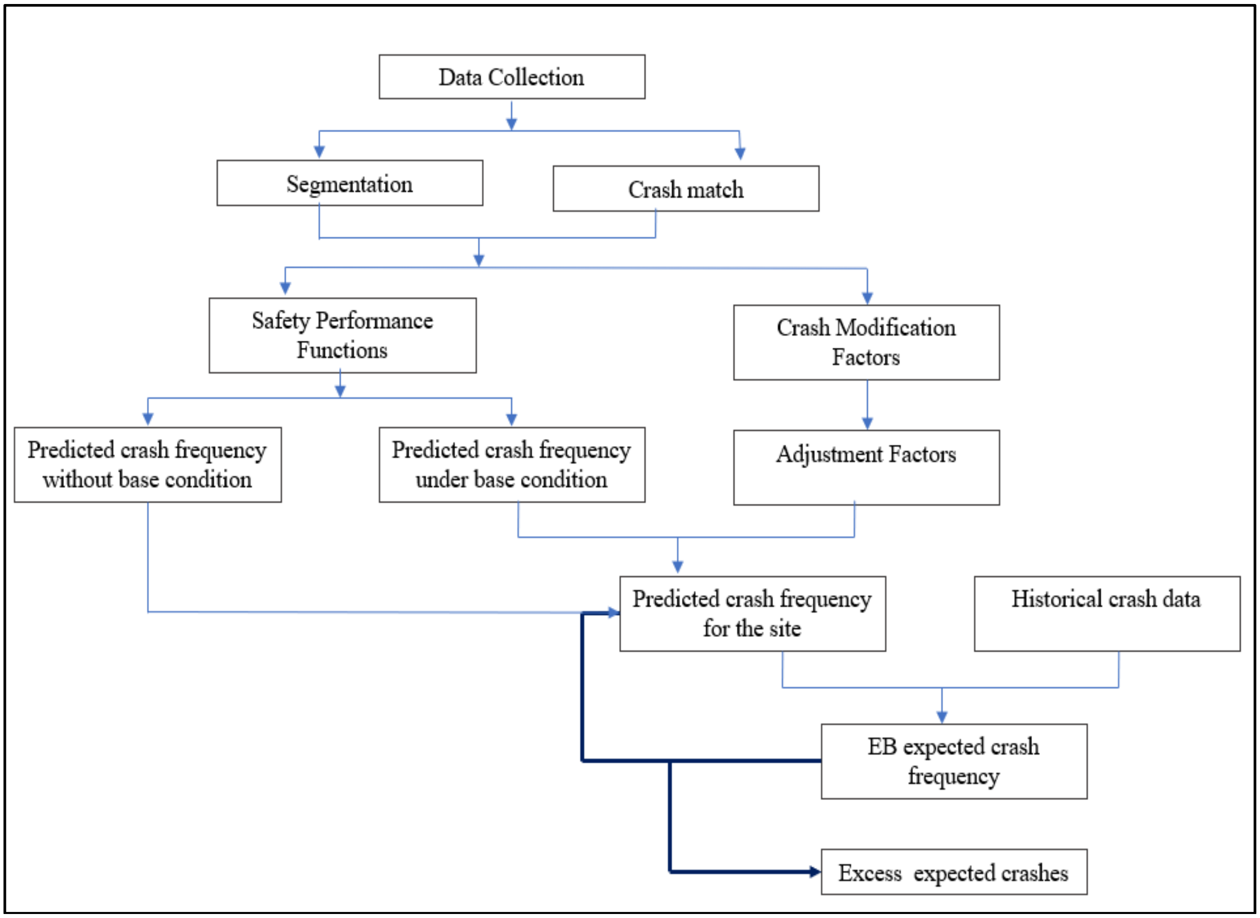


Figure 3.3 Flow Chart for EEC Calculation

Chapter 4 Project Prioritization

The ultimate goal of highway safety management is to reduce the number and severity of crashes by implementing highway safety improvement projects. In SHIFT, a project is defined as the combination of contiguous roadway elements (i.e., roadway segments, intersections, or ramps). A hypothetical example of a project is illustrated in Figure 4.1, where a project comprises two routes (with multiple segments) and one intersection. Today, EEC (or its equivalent) is widely used as a ranking criterion. To address some shortcomings in using EEC with total crashes, as mentioned above, this project adds additional components. However, no literature could be found on aggregating ranking criteria.

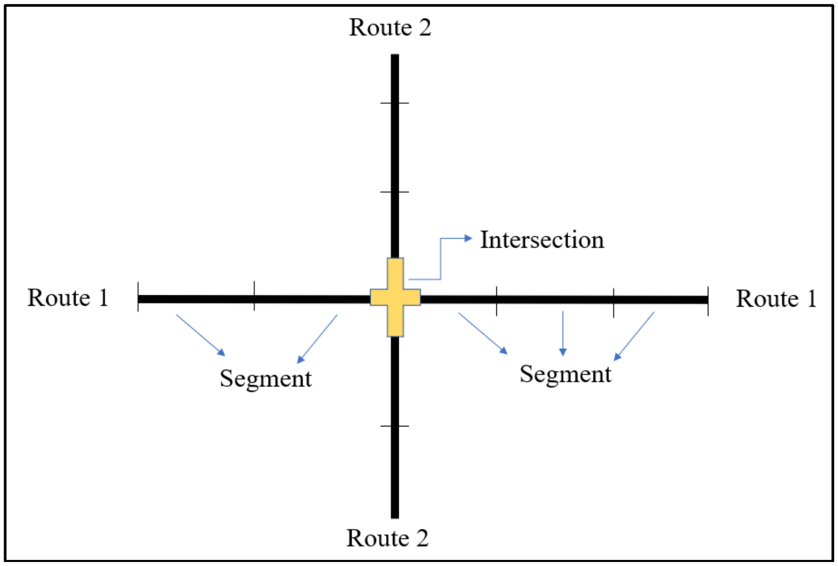


Figure 4.1 Project Example

This section proposes two steps for project prioritization: (a) prioritization criteria and (b) methods for combining prioritization metrics.

4.1 Methods for Project-Level EB estimate and EEC

Calculating each prioritization metric (i.e., EB estimate and EEC at the project level) is necessary before integrating them into the final ranking analysis. This section shows three methods for aggregating the metrics of each element (road segment, intersection, and ramps) that comprises a project.

4.1.1 Summation Method

This following is a modified version of the technique provided in the HSM [3]. The final safety metric for a project is calculated by summing all the roadway networks the project contains:

$$\text{Final metric (project level)} = \sum X_{\text{Segments}} + \sum X_{\text{Intersections}} + \sum X_{\text{Ramps}} \qquad \text{Eq. 10}$$

where:

X = $N_{EB\ (total)}$, $N_{EB\ (KAB)}$, $N_{EB\ (CO)}$, EEC_{total}, EEC_{KAB} or EEC_{CO}.

During the segmentation process, each segment is assigned beginning and ending mile points. Calculating metrics at the project level is straightforward if the beginning and ending mile points coincide with those of the project's first and last roadway segments. It becomes more complex when either the starting point, ending point, or both mile points do not match segment beginning or ending mile points. In these cases, it is necessary to calculate the weighted metric over the project length. There are five possible scenarios (Figure 4.2).

Sample calculations for project-level EB estimates and EEC of KAP crashes ($NEB_{(KAB)}$ and EECKAB) are shown in Table 4.2. Estimates are given for one project that is a combination of two routes: 056-KY-1065-000. Table 4.1 summarizes equations for calculating the final metric of a project's segments for all five cases.

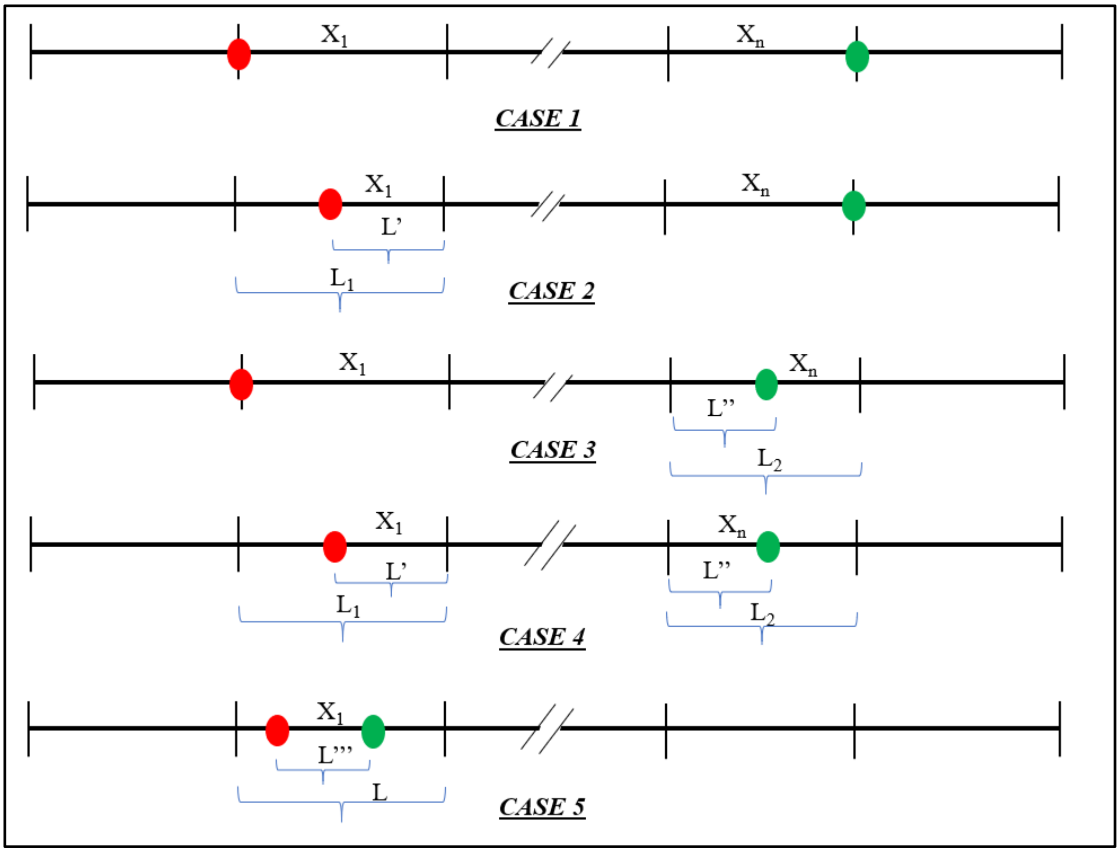


Figure 4.2 Visualization of Five Cases
(Red and green dots refer to the beginning and ending mile points of a project, respectively.)

Sample calculations for project-level EB estimates and EEC of KAB crashes ($N_{EB(KAB)}$ and EEC_{KAB}) are shown in Table 4.2. The estimates are shown for one project which is a combination of two routes: 056-KY-1065-000 (beginning mile point: 6.06 and ending mile point: 6.16) and 056-KY-0061-000 (beginning mile point: 3.95 and ending mile point: 4.01). These sections consist of three segments and two intersections.

Table 4.1 Descriptions and Equations of Final Metric Calculation

Cases	Description	Equation
Case 1	The beginning and ending mile points of the project coincide with those of the segments.	$\text{Final X} = X_1 + \cdots + X_n$
Case 2	Only the beginning mile point falls inside a segment.	$\text{Final X} = \frac{L'}{L_1} * X_1 + \cdots + X_n$

Cases	Description	Equation
Case 3	Only the ending mile point falls inside a segment.	$\text{Final X} = X_1 + \cdots + \frac{L''}{L_2} * X_n$
Case 4	Both the beginning and ending mile points fall inside two different segments	$\text{Final X} = \frac{L'}{L_1} * X_1 + \cdots + \frac{L''}{L_2} * X_n$
Case 5	Both the beginning and ending mile points fall inside the same segment	$\text{Final X} = \frac{L'''}{L} * X_1$

Table 4.2 Sample Calculation for Summation Method on Project-Level $N_{EB(KAB)}$ and EEC_{KAB}

Summation Method				
Project: 056-KY-1065 -000 (MP 6.06-MP 6.16) and 056-KY-0061 -000 (MP 3.95- MP 4.01)				
Elements	$N_{EB(KAB)}$	**$N_{EB(KAB)}$ (Project)**	EEC_{KAB}	**EEC_{KAB} (Project)**
Segment 1	1.48		1.31	
Intersection 1	1.58		1.06	
Segment 2	0.01	**11.01**	-0.02	**4.69**
Intersection 2	7.91		2.45	
Segment 3	0.03		-0.11	

4.1.2 Average Theta Method

With this method the EB estimate and EEC are not computed for each element of a project. Instead, an EB estimate for the entire project is computed using an average overdispersion parameter (theta) and a weighting factor calculated from theta. Hauer [61] demonstrated a case that included only two intersections and took the simple mean of the two overdispersion parameters. However, for a project with roadway segments and intersections combined, taking a simple mean would be problematic. As an alternative, theta can be weighted using exposure (e.g., length or vehicle miles travelled (VMT)). Although these exposures are relevant to road segments, they are not valid parameters for intersections as length is not meaningful for an intersection. Therefore, site risk may be used to weight the parameters. Site risk can be quantified as SPF-predicted crashes (N_{SPF}). N_{SPF} considers length for segments but not for intersections, so it can be used to calculate a weighted average theta (θ_{avg}) for a project (see Equation 11). Equation 12 can be used to calculate an average weight factor (w_{avg}), which can further be used to compute a project's EB estimate and EEC (from Equations 3 and 5).

$$\text{Average Theta } (\theta_{avg}) = \frac{\sum_{i=1}^{n}(N_{SPF} * \theta)}{\sum_{i=1}^{n} N_{SPF}} \qquad \text{Eq. 11}$$

$$w_{avg} = \frac{1}{1 + \frac{\sum_{i=1}^{n} N_{SPF}}{\theta_{avg}}} \qquad \text{Eq. 12}$$

Table 4.3 provides a sample calculation using the average theta method for project-level EB estimates and EEC of KAB crashes ($N_{EB(KAB)}$ and EEC_{KAB}) for the same project shown in Table 4.2.

Table 4.3 Sample Calculation for Average Theta Method on Project-Level $N_{EB(KAB)}$ and EEC_{KAB}

Average Theta Method						
Project: 056-KY-1065 -000 (MP 6.06-MP 6.16) and 056-KY-0061 -000 (MP 3.95- MP 4.01)						
Elements	$N_{SPF\ (KAB)}$	KAB crashes	θ_{KAB}	θ_{avg}	**$N_{EB(KAB)}$ (Project)**	**EEC_{KAB} (Project)**
Segment 1	0.17	2	0.95	2.20	**13.09**	**6.76**
Intersection 1	0.52	3	0.70			
Segment 2	0.03	0	0.95			
Intersection 2	5.46	9	2.43			
Segment 3	0.14	0	0.95			
Total	6.33	14				

4.1.3 Correlation Coefficient (ρ) Method

None of the above-mentioned methods considers the correlation between two elements (road segment to segment or segment to intersection), which is a problem as statistical methods assume independence of observations. Along with the average theta method, Hauer outlined another technique to directly compute the EB estimate of a combination of entities [61]. In it, the weighting factor can be computed using the following formula:

$$w = \frac{1}{1 + \frac{\sum_{i=1}^{n} N_{SPF,i}^{2} / \theta_i + 2\sum_{i=1}^{n}\sum_{j=i+1}^{n} \rho_{i,j}\sqrt{\frac{1}{\theta_i\theta_j}N_{SPF,i}N_{SPF,j}}}{\sum_{i=1}^{n} N_{SPF,i}}} \qquad \text{Eq. 13}$$

where:

$N_{SPF,1}$, $N_{SPF,2}$, ….. , $N_{SPF,n}$ = SPF predicted crashes ($N_{predicted}$) of the entities in a project
$\theta_1, \theta_2, \ldots, \theta_n$ = The overdispersion parameters
$\rho_{i,j}$ = the correlation coefficient between N_i and N_j

If a project consists of more than one entity, each pair should get a separate ρ based on their correlation. The Hauer study does not provide direction on estimating correlation coefficient pairs. It calculates only the two extreme cases where ALL elements are statistically independent ($\rho_{i,j} = 0$) and where ALL elements are perfectly correlated ($\rho_{i,j} = 1$). The weighting factors for these cases are noted as w_0 and w_1, respectively, and the formulas are expressed in Equations 14 and 15. The EB estimate and EEC are calculated as before.

$$w_0 = \frac{1}{1 + \frac{\sum_{i=1}^{n} N_{SPF,i}^{2} / \theta_i}{\sum_{i=1}^{n} N_{SPF,i}}} \qquad \text{Eq. 14}$$

$$w_1 = \frac{1}{1 + \frac{\left(\sum_{i=1}^{n} \sqrt{N_{SPF,i}^{2} / \theta_i}\right)^2}{\sum_{i=1}^{n} N_{SPF,i}}} \qquad \text{Eq. 15}$$

Along with ρ = 0 and 1, this study tries to evaluate the estimates for three other correlation coefficients between 0 and 1 — ρ = 0.25, 0.5 and 0.75. For simplification, we assumed that every pair of entities inside a project has the same correlation coefficient (not a totally justifiable assumption).

For this method, sample calculations for project-level EB estimates, as well as EEC for KAB crashes ($N_{EB(KAB)}$ and EEC_{KAB}), are shown in Table 4.4. Estimates are shown for the extremes — ρ = 0 and ρ = 1. This analysis used the same project data as used to generate Table 4.2 and Table 4.3.

Table 4.4 Sample Calculation for Correlation Coefficient Method (ρ = 0 and 1) on Project-Level $N_{EB(KAB)}$ and EEC_{KAB}

Correlation Coefficient Method							
Project: 056-KY-1065 -000 (MP 6.06-MP 6.16) and 056-KY-0061 -000 (MP 3.95- MP 4.01)							
Elements	$N_{SPF\ (KAB)}$	KAB crashes	θ_{KAB}	ρ	w	**$N_{EB(KAB)}$ (Project)**	**EEC_{KAB} (Project)**
Segment 1	0.17	2	0.95				
Intersection 1	0.52	3	0.70	0	0.33	**11.45**	**5.13**
Segment 2	0.03	0	0.95				
Intersection 2	5.46	9	2.43				
Segment 3	0.14	0	0.95	1	0.24	**12.16**	**5.84**
Total	6.33	14					

4.1.4 Summary of Results

Table 4.5 summarizes project-level $N_{EB(KAB)}$ and EEC_{KAB} computed using the three methods. For this project, the summation method provided the lowest values of $N_{EB(KAB)}$ and EEC_{KAB}, and the average theta method returned the highest. With the correlation coefficient method, estimates increased with an increase in ρ, indicating a monotonic relationship. Additionally, none of the values from the summation or average theta method is in the range of the values yielded by the correlation coefficient method. Before making a final choice, further evaluation is needed to assess the methods.

Table 4.5 Summary of Project-Level $N_{EB(KAB)}$ and EEC_{KAB} From Three Methods

Project: 056-KY-1065 -000 (MP 6.06-MP 6.16) and 056-KY-0061 -000 (MP 3.95- MP 4.01)							
Project-Level Score	**Summation Method**	**Average Theta Method**	**Correlation Coefficient Method**				
			ρ = 0	**ρ = 0.25**	**ρ = 0.5**	**ρ = 0.75**	**ρ = 1**
$N_{EB(KAB)}$	11.01	13.09	11.45	11.68	11.87	12.03	12.16
EEC_{KAB}	4.69	6.76	5.13	5.35	5.54	5.7	5.84

4.2 Proposed Methods for Project Prioritization

This study evaluates four methods for safety data–based project prioritization and compares rankings with the base ranking method used in SHIFT 2020. The proposed methods are described below.

4.2.1 Base Ranking Method: Ranking Based on EECs of the Total Crashes (Uses Base Condition for SPFs)

This method uses SPFs developed from total crash counts, where crashes of different severities are combined, and determines the ranking of each project based on EEC_{total}. The project-level EEC is estimated by summing EECs for all the roadway segments, intersections, and ramps that fall inside the project. Since the EECs represent the surplus of expected crashes for all severities, all crashes receive equal weight regardless of severity [26].

4.2.2 Method 1 (No Base Condition): Ranking Based on EECs of Total Crashes (No Base Conditions for SPFs)

According to the HSM's recommendation, SPFs should be developed for specific base conditions which are generally the most common geometric attributes of any roadway class. Including base conditions accounts for omitted variable bias (OVB) that occurs when a regression model leaves out one or more variables critical to the model. One of the key aspects of using base conditions for model development is the requirement of AFs. They are needed to adjust the predicted crashes of roadway networks whose geometric features differ from the base conditions. Application of the SPF becomes limited when appropriate AFs are not available. Although there are several sources for AFs (e.g., CMF Clearinghouse, the HSM), AFs for several geometric attributes have not been estimated yet. The scarcity is even greater for multilane roadways, including interstates and parkways.

This study recommends developing SPFs without constraints on geometric features. When the entire dataset is used for model development, no AFs are needed to adjust predicted crashes. Ultimately, EB estimates and EEC can be calculated from these SPF-predicted crashes. The idea is to evaluate the tradeoff between using more reliable SPFs (requiring more AFs) and less reliable SPFs (requiring no AFs) for site and project rankings. As the project ranking metric, this method uses EEC for total crashes calculated from SPFs without base conditions.

Differences in ranking using the Base Method and Method 1 are presented in Figure 4.3. Figure 4.3 (i) shows all 1,274 projects from SHIFT 2020 and Figure 4.3 (ii) shows the top 100 projects ranked. Table 4.6 indicates 41.4% projects ranked within 10 positions and 16.4% within 20 positions.

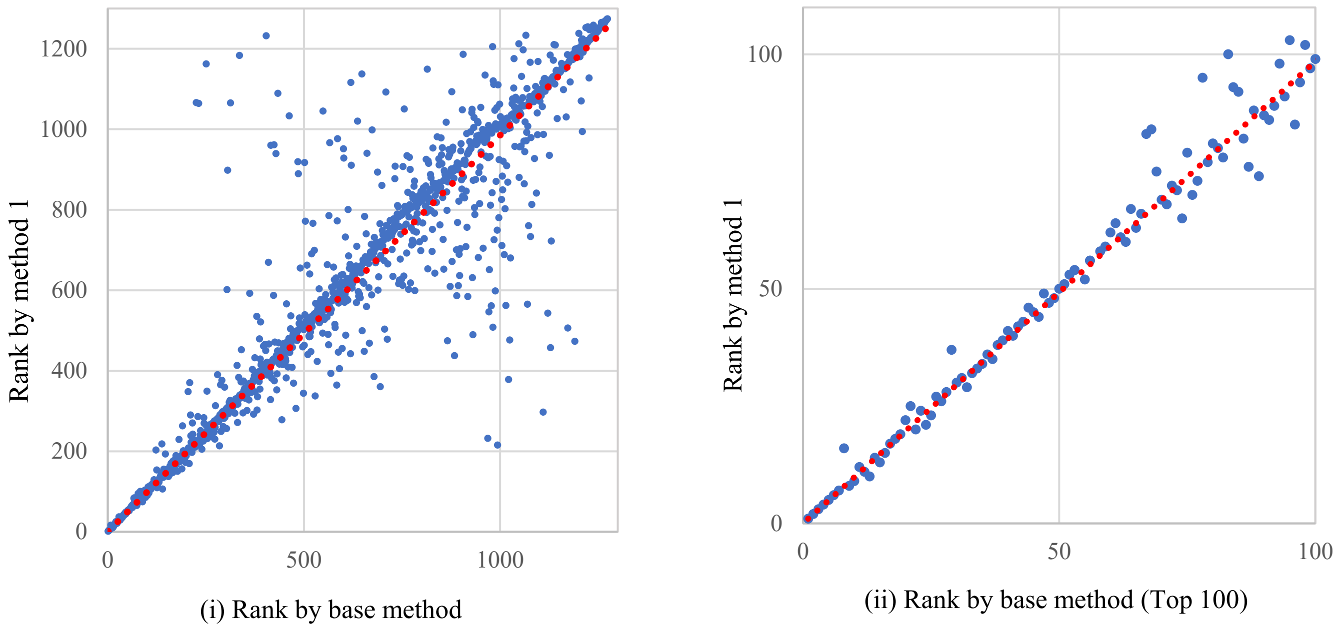


Figure 4.3 Comparison of Ranking By Method 1 and Base Method

Table 4.6 Differences in Ranking Between Method 1 and Base Method

Ranking Difference	Number of projects	%
Within 10 positions	528	41.4
Within 20 positions	209	16.4
Within 50 positions	230	18.1
Within 100 positions	122	9.6
Beyond 100 positions	185	14.5
Total	1274	100

4.2.3 Method 2 (Considering Crash Severity): Ranking Based on the Combined Score of EECs of KAB and CO

This method develops SPFs using two crash severity categories — KAB and CO. EEC_{KAB} and EEC_{co} indicate excess expected KAB and CO crashes, respectively. These two metrics can be combined using the weights a and b (where, a + b = 1). Ranks from EEC_{KAB} and EEC_{CO} are weighted to create a project ranking metric (R_1). The equation for R_1 is below:

$$R_1 = a * \ Rank_{EEC_{KAB}} + b * \ Rank_{EEC_{CO}} \qquad \text{Eq. 16}$$

Table 4.7 summarizes the cost of crashes by severity for Kentucky. The weighted average crash cost for KAB crashes is $652,612 and $81,187 for CO crashes. Weights a and b for Equation 16 are thus computed as 0.89 for KAB crashes and 0.11 for CO crashes.

Table 4.7 Frequency and Cost of Crashes by Severity

Severity	Cost Per Crash	Number of Crashes	Total Cost
K	$9,281,571	732	$6,794,109,972
A	$537,913	2736	$1,471,729,968
B	$162,885	12257	$1,996,481,445
C	$102,957	359020	$36,963,622,140
O	$9,689	109313	$1,059,133,657

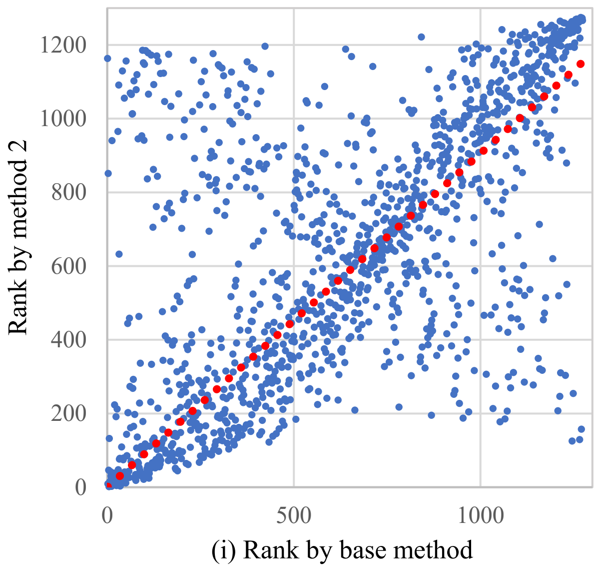
Table 4.8 Weighted Average Crash Cost by Crash Groups

Severity	Weighted Average Cost	Ratio
KAB	$652,612	**0.89**
CO	$81,187	**0.11**
Total	$733,799	1.00

Figure 4.4 illustrates the differences between the rankings generated using the Base Method and Method 2. There are more significant differences between the ranks. Table 4.9 shows that rankings for roughly 73% of projects differ by more than 50 positions.

Table 4.9 Differences in Ranking Between Method 2 and Base Method

Ranking Difference	Number of projects	%
Within 10 positions	95	7.5
Within 20 positions	75	5.9
Within 50 positions	178	14.0
Within 100 positions	252	19.8
Beyond 100 positions	674	52.9
Total	1274	100



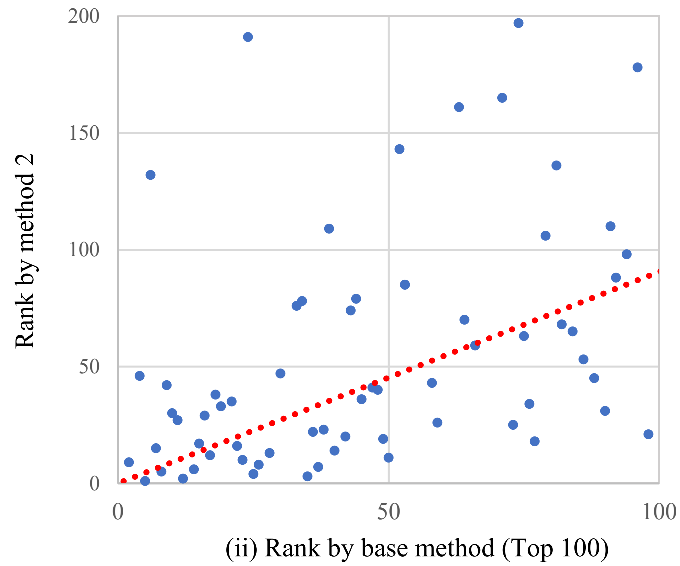


Figure 4.4 Comparison of Ranking By Method 2 and Base Method

4.2.4 Method 3: Ranking Based on Combined Score of EB and EEC

EEC gauges how crash performance at a site compares to the average site for that roadway type and AADT. It does not explicitly reflect the magnitude of the overall number of crashes occurring or expected to occur at that site. For a project, EEC represents the resulting improvement if the crash experience could be reduced to the average level. Of course, crashes at a particular site may be further reduced with countermeasures not represented in the base comparison.

The EB estimate, on the other hand, forecasts future crashes at the site and is biased toward sites with higher AADT. It does not account for natural growth in crash frequencies caused by increasing AADT [8]. However, the EB estimate does represent the theoretical maximum reduction in crashes that might be experienced at a site.

Since both criteria are critical, this method ranks each project by combining the ranks of sites by both EB estimate and EEC. These two metrics can be weighted by m and n, respectively, where m + n =1 (Equation 17), to calculate a ranking metric, R_2. In this study, the EB estimate, and EEC were equally weighted — 50% on each metric.

$$R_2 = m * \mathrm{Rank}_{N_{EB(Total)}} + n * \mathrm{Rank}_{EEC_{Total}} \qquad \text{Eq. 17}$$

Figure 4.5 illustrates the differences between the rankings generated using the Base Method and Method 3. While Figure 4.5 (i) and (ii) show a degree of positive correlation between rankings, there are clearly significant differences produced by the proposed method. This indicates there would be significant differences in the safety ranking of SHIFT 2020 projects had this propose metric been deployed.

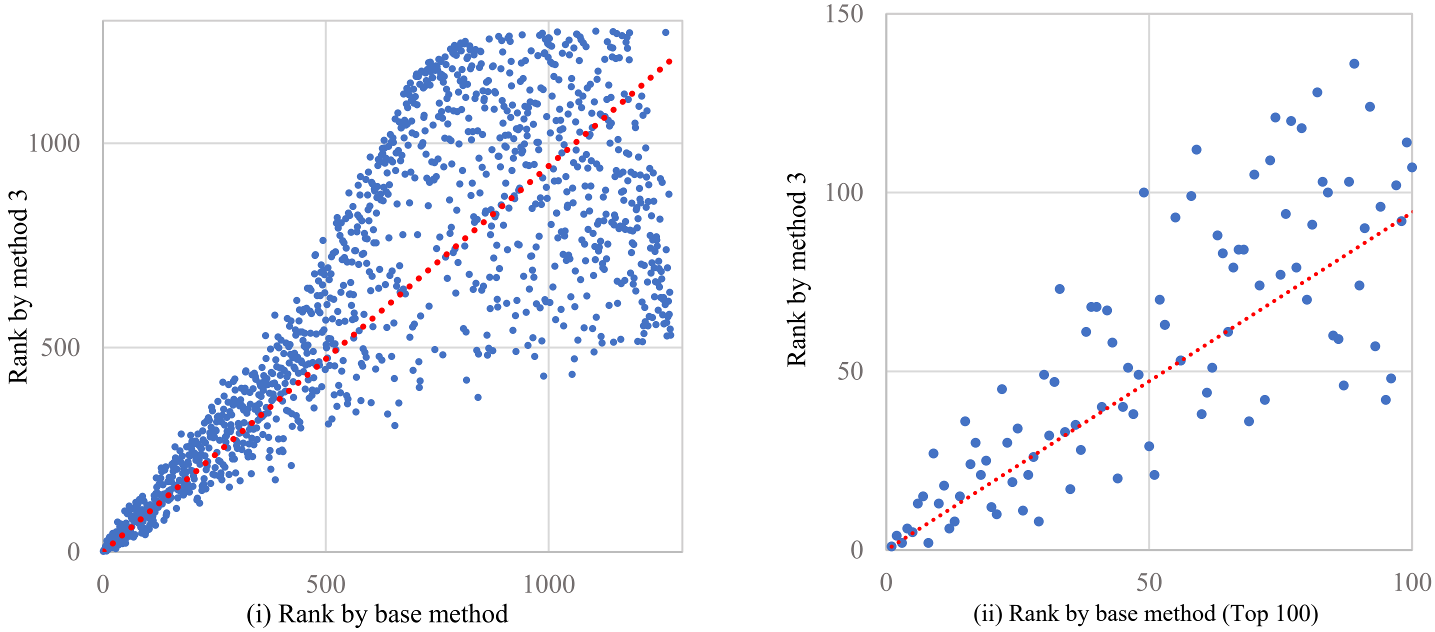


Figure 4.5 Comparison of Ranking By Method 3 and Base Method

Table 4.10 further quantifies differences — 53.5% of projects had rankings that differed by more than 100 positions.

Table 4.10 Differences in Ranking Between Method 3 and Base Method

Ranking Difference	Number of Projects	%
Within 10 positions	112	8.8
Within 20 positions	77	6.0
Within 50 positions	198	15.5
Within 100 positions	206	16.2
Beyond 100 positions	682	53.5
Total	1274	100

4.2.5 Method 4 (Goal-Driven Method): Ranking Based on EEC_{alt} of Total Crashes

Each state is required to develop a comprehensive Strategic Highway Safety Plan (SHSP) to implement effective safety improvement measures. The Kentucky SHSP defines safety goals for the plan timeline (five years) as well as restating the overall objective of vision zero.

To make progress toward fulfilling SHSP goals, this method proposes a project ranking criteria which is a modified version of EEC and terms it Alternate EEC or EEC_{alt}. EEC_{alt} is a goal-driven metric that considers that projects on average would need to reduce crashes below the average of similar facilities (reducing only above-average projects to average would not be enough to achieve the SHSP goal). To implement this metric, SPF-predicted crashes are modified by multiplying by the ratio of SHSP goal for fatalities to the current fatality level. The Kentucky 2020 – 2024 SHSP goal is to go from approximately 750 fatal crashes per year on average to less than 500 by 2024. These numbers produce a ratio of 2:3 with which to multiply SPFs to compute EEC_{alt}. The equation for EEC_{alt} is given below and graphically depicted in Figure 4.6.

$$\mathrm{EEC_{alt}} = \mathrm{N_{EB(Total)}} - \left(\frac{\text{SHSP fatalities goal}}{\text{Current fatal crashes}}\right) * \mathrm{N_{SPF(Total)}} \qquad \text{Eq. 18}$$

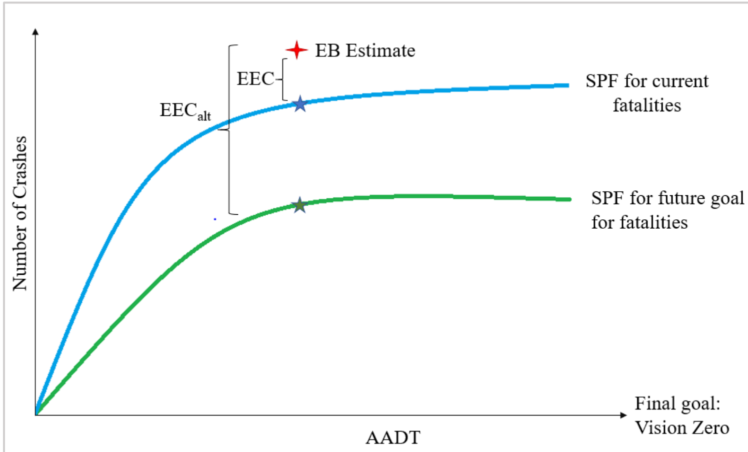
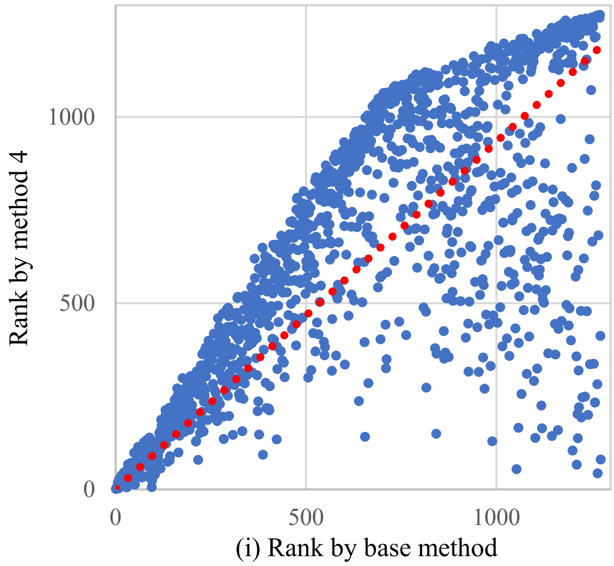


Figure 4.6 Graphical representation of $\mathrm{EEC_{alt}}$

Figure 4.7 (i) and (ii) represent the differences in rankings from the Base Method and Method 4 for all 1,274 projects and the top 100 projects, respectively. Differences in the rankings are significant for this method as well. There is a prominent sharp bend in the plot of Figure 4.7 (i), and the bend mainly occurs when the EECs trend negative. More research is required to see if this bend is meaningful and significant. Additionally, Table 4.11 shows that about 75% of the projects changed ranks by more than 50 positions.

Table 4.11 Differences in Ranking Between Method 4 and Base Method

Ranking Difference	Number of Projects	%
Within 10 positions	97	7.6
Within 20 positions	66	5.2
Within 50 positions	172	13.5
Within 100 positions	218	17.1
Beyond 100 positions	721	56.6
Total	1274	100



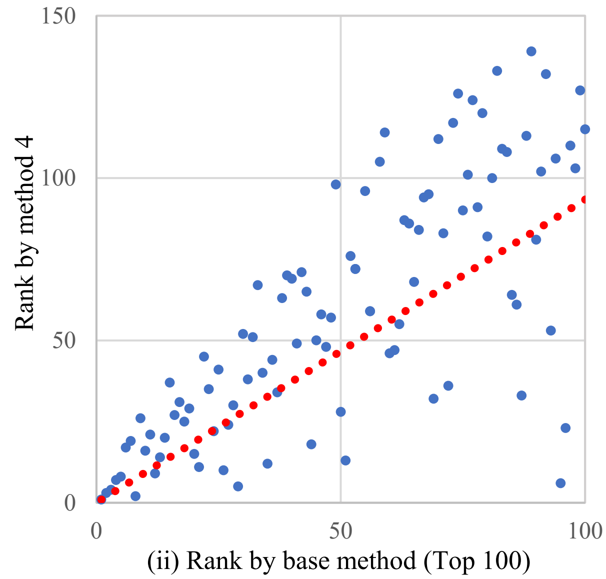


Figure 4.7 Comparison of Ranking By Method 4 and Base Method

4.2.6 Comparing Ranking Methods

Based on the analysis above, Table 4.12 summarizes differences in ranking methods.

Table 4.12 Summary of Ranking Method Differences

Methods	Description	Significant Difference in Ranking?*
0	EEC_{total} (with base conditions for SPFs)	N/A
1	EEC_{total} (no base condition for SPFs)	No
2	Combination of EEC_{KAB} and EEC_{CO}	Yes
3	Combination of EB_{total} and EEC_{total}	Yes
4	$EEC_{alt\ (total)}$	Yes

*Compared to the Base Method.

Chapter 5 Recommendations and Implementation

We recommend that KYTC use a combination of the four proposed ranking methods (see bullet points below). Table 5.1 provides a summary, and the formula is shown in Equation 19.

- Use generic base conditions for SPF development (i.e., no adjustment factors).
- Use 89 percent to weight rankings based on KAB crash metrics and 11 percent to weight rankings based on CO metrics.
- Use EEC_{alt} instead of EEC for both KAB and CO to make the metric goal-driven.
- Lacking information on which is most important for policy at this time, weight EB and EEC_{alt} equally.
- Calculate a crash data-based safety ranking score (R) using Equation 19. The final ranking is based on this metric.

Table 5.1 Weights for Metrics to Calculate Project Ranking Metric (R)

Project Ranking Metric (R)				
Metric	Rank by $N_{EB(KAB)}$	Rank by $EEC_{alt(KAB)}$	Rank by $N_{EB(CO)}$	Rank by $EEC_{alt(CO)}$
Weight	44.5%	44.5%	5.5%	5.5%

$$R = 0.445 * \text{Rank}\,[N_{EB(KAB)}] + 0.445 * \text{Rank}\,[EEC_{alt(KAB)}] + 0.055 * \text{Rank}\,[N_{EB(CO)}] + 0.055 * \text{Rank}[EEC_{alt(CO)}] \quad \text{Eq. 20}$$

An idiosyncrasy of the proposed method (R) is the seemingly disproportionate influence of negative EEC_{alt} on the rankings, specifically if $EEC_{alt(KAB)}$ is positive but $EEC_{alt(CO)}$ is negative. An example project where this is the case is shown in Table 5.2. This project was highly ranked for both KAB metrics, which indicates it has the potential to reduce fatal and serious injury crashes. However, it was ranked lower due to its negative $EEC_{alt(CO)}$ rank (1,175), which decreased the overall ranking to #62.

A recommended solution is to weight the values of each metric score instead of the ranks themselves to develop project ranking metric (S). Final project rankings would therefore be based on S (Equation 20). For this example, the overall rank is increased from #62 to #6.

$$S = 0.445 * N_{EB(KAB)} + 0.445 * EEC_{alt(KAB)} + 0.055 * N_{EB(CO)} + 0.055 * EEC_{alt(CO)} \quad \text{Eq. 20}$$

Table 5.2 Example of Project Ranking Metrics R and S

	Scores	Metric Ranks	Project Ranking Metric (R)	Overall Rank By R	Project Ranking Metric (S)	Overall Rank By S
$N_{EB(KAB)}$ (44.5%)	209.55	1	80.02	68	174.92	6
$EEC_{alt(KAB)}$ (44.5%)	28.68	21				
$N_{EB(CO)}$ (5.5%)	1354.23	6				
$EEC_{alt(CO)}$ (5.5%)	-101.42	1271				

SPFs were developed using no base conditions for each road class and intersection type using 2015 – 2019 Kentucky crash data. Regression parameters from the calibration of roadway types are given in Table 5.3. The recommended new safety metric (S) was applied to over 1,200 projects for SHIFT 2022 and submitted to KYTC on June 29, 2021.

Table 5.3 Regression Parameters for SHIFT 2022

	KAB	CO
R2L		
Theta	1.500	1.835
Alpha	-5.274	-4.410
Beta	0.684	0.817
RIP		
Theta	3.260	2.706
Alpha	-9.764	-7.924
Beta	0.983	1.025
RMD		
Theta	0.937	1.126
Alpha	-9.296	-5.697
Beta	0.992	0.845
RMU		
Theta	1.415	0.914
Alpha	-5.425	-3.281
Beta	0.668	0.711
U2L		
Theta	1.569	1.220
Alpha	-5.824	-3.978
Beta	0.774	0.841
UIP		
Theta	2.249	1.712
Alpha	-13.585	-10.619
Beta	1.363	1.314
UMD		
Theta	1.171	0.771
Alpha	-9.750	-7.453
Beta	1.102	1.156
UMU		
Theta	0.924	0.908
Alpha	-6.220	-4.509
Beta	0.840	0.937

Chapter 6 References

[1] A.-V. Jonathan, K.-F. (Ken) Wu, and E. T. Donnell, “A multivariate spatial crash frequency model for identifying sites with promise based on crash types,” *Accid. Anal. Prev.*, vol. 87, pp. 8–16, Feb. 2016, doi: 10.1016/j.aap.2015.11.006.

[2] A. L. Carriquiry, M. Pawlovich, and others, “From empirical Bayes to full Bayes: methods for analyzing traffic safety data.,” 2004.

[3] AASHTHO, “Highway Safety Manual, First Edition,” American Association of State Highway and Transportation Officials, Washington, D.C., 2010.

[4] R. Srinivasan and K. Bauer, “Safety Performance Function Development Guide: Developing Jurisdiction-Specific SPFs,” Federal Highway Administration Office of Safety, Final Report FHWA-SA-14-005, Sep. 2013.

[5] B. Persaud and C. Lyon, “Safety performance assessment of freeway interchanges, ramps, and ramp terminals,” *Transp. Assoc. Can.*, 2006.

[6] Y. Zou, J. E. Ash, B.-J. Park, D. Lord, and L. Wu, “Empirical Bayes estimates of finite mixture of negative binomial regression models and its application to highway safety,” *J. Appl. Stat.*, vol. 45, no. 9, pp. 1652–1669, 2018.

[7] N. J. Garber, P. R. Haas, and C. Gosse, “Development of safety performance functions for two-lane roads maintained by the virginia department of transportation,” 2010.

[8] R. A. Tegge, J.-H. Jo, and Y. Ouyang, “Development and Application of Safety Performance Functions for Illinois,” Illinois Department of Transportation, Technical Report FHWA-ICT-10-066, Mar. 2010. [Online]. Available: https://core.ac.uk/download/pdf/18618779.pdf?fbclid=IwAR1IXDoyMIswH0NV0I2Nthq2O4lpUX91Q2q3nTJJhhpSx_VpPYt12-AKRKY.

[9] K.-F. Wu, S. C. Himes, and M. T. Pietrucha, “Evaluation of effectiveness of the federal highway safety improvement program,” *Transp. Res. Rec.*, vol. 2318, no. 1, pp. 23–34, 2012.

[10] R. Tanzen, “The Relationship between Roadway Homogeneity and Network Coverage for Network Screening,” 2020.

[11] H. Yu, P. Liu, J. Chen, and H. Wang, “Comparative analysis of the spatial analysis methods for hotspot identification,” *Accid. Anal. Prev.*, vol. 66, pp. 80–88, May 2014, doi: 10.1016/j.aap.2014.01.017.

[12] E. Hauer, *Observational before/after studies in road safety. estimating the effect of highway and traffic engineering measures on road safety*. 1997.

[13] X. Qu and Q. Meng, “A note on hotspot identification for urban expressways,” *Saf. Sci.*, vol. 66, pp. 87–91, Jul. 2014, doi: 10.1016/j.ssci.2014.02.006.

[14] B. N. Persaud, “Blackspot identification and treatment evaluation,” 1990.

[15] E. Hauer, “Empirical bayes approach to the estimation of ‘unsafety’: The multivariate regression method,” *Accid. Anal. Prev.*, vol. 24, no. 5, pp. 457–477, Oct. 1992, doi: 10.1016/0001-4575(92)90056-O.

[16] S.-P. Miaou and J. J. Song, “Bayesian ranking of sites for engineering safety improvements: Decision parameter, treatability concept, statistical criterion, and spatial dependence,” *Accid. Anal. Prev.*, vol. 37, no. 4, pp. 699–720, Jul. 2005, doi: 10.1016/j.aap.2005.03.012.

[17] A. Montella, “A comparative analysis of hotspot identification methods,” *Accid. Anal. Prev.*, vol. 42, no. 2, pp. 571–581, Mar. 2010, doi: 10.1016/j.aap.2009.09.025.

[18] D. Lord and P. Y.-J. Park, “Investigating the effects of the fixed and varying dispersion parameters of Poisson-gamma models on empirical Bayes estimates,” *Accid. Anal. Prev.*, vol. 40, no. 4, pp. 1441–1457, Jul. 2008, doi: 10.1016/j.aap.2008.03.014.

[19] C. Blackden, E. Green, R. Souleyrette, and W. Staats, “Automating Safety Performance Function Development to Improve Regression Models,” 2018.

[20] W. Cheng and S. Washington, “New Criteria for Evaluating Methods of Identifying Hot Spots,” *Transp. Res. Rec.*, vol. 2083, no. 1, pp. 76–85, Jan. 2008, doi: 10.3141/2083-09.

[21] B. Persaud, W. Cook, and A. Kazakov, “DEMONSTRATION OF NEW APPROACHES FOR IDENTIFYING HAZARDOUS LOCATIONS AND PRIORITIZING SAFETY TREATMENT,” presented at the Traffic Safety on Two ContinentsPTRC Education and Research Services Limited, 1998, Accessed: Apr. 15, 2021. [Online]. Available: https://trid.trb.org/view/504575.

[22] D. McGuigan, “The use of relationships between road accidents and traffic flow in" black-spot" identification,” *Traffic Eng. Control*, vol. 22, no. HS-032 669, 1981.

[23] N. Jorgensen, “Statistical detection of accident blackspots,” *OTA-PIARC 11th Study Week Transp. Saf.*, 1972.

[24] A. P. Tarko, K. C. Sinha, and O. Farooq, “Methodology for Identifying Highway Safety Problem Areas,” *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1542, no. 1, pp. 49–53, Jan. 1996, doi: 10.1177/0361198196154200108.

[25] B. Persaud, C. Lyon, and T. Nguyen, “Empirical Bayes Procedure for Ranking Sites for Safety Investigation by Potential for Safety Improvement,” *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1665, no. 1, pp. 7–12, Jan. 1999, doi: 10.3141/1665-02.

[26] R. R. Souleyrette, R. Tanzen, W. N. Staats, E. R. Green, and M. Chen, “Safety Analysis for SHIFT Implementation,” 2019.

[27] W. Cheng, X. Wang, and K. Anderson, “How to Identify Hazardous Locations in Roadway Network,” in *ICCTP 2010*, Beijing, China, Jul. 2010, pp. 1632–1644, doi: 10.1061/41127(382)178.

[28] A. S. Abdulhafedh, “Crash severity modeling in transportation systems,” Thesis, University of Missouri--Columbia, 2016.

[29] S. D. Costa, X. Qu, and P. M. Parajuli, “A Crash Severity-Based Black Spot Identification Model,” *J. Transp. Saf. Secur.*, vol. 7, no. 3, pp. 268–277, Jul. 2015, doi: 10.1080/19439962.2014.911230.

[30] S. Washington, Md. M. Haque, J. Oh, and D. Lee, “Applying quantile regression for modeling equivalent property damage only crashes to identify accident blackspots,” *Accid. Anal. Prev.*, vol. 66, pp. 136–146, May 2014, doi: 10.1016/j.aap.2014.01.007.

[31] P. D. R. Bandyopadhyaya, Scholar, A. Professor, and S. Mitra, *Comparative Analysis of Hotspot Identification Methods in the Presence of Limited Information*. .

[32] B. M. Rudy, “OPERATIONAL ROUTE ANALYSIS,” *Traffic Q.*, vol. 16, no. 3, Jul. 1962, Accessed: Apr. 15, 2021. [Online]. Available: https://trid.trb.org/view/709382.

[33] D. A. Morin, “Application of statistical concepts to accident data,” 1967.

[34] J. L. Higle and J. M. Witkowski, “Bayesian identification of hazardous locations (with discussion and closure),” *Transp. Res. Rec.*, vol. 1185, pp. 24–36, 1988.

[35] J. A. Deacon, C. V. Zegeer, and R. C. Deen, “Identification of Hazardous Rural Highway Locations,” p. 28.

[36] J. Laughland, L. Haefner, J. Hall, and D. Clough, “NCHRP Report 162: methods for evaluating highway safety improvements,” *Wash. DC Natl. Res. Counc.*, 1975.

[37] A. S. Hakkert and D. Mahalel, “Estimating the number of accidents at intersections from a knowledge of the traffic flows on the approaches,” *Accid. Anal. Prev.*, vol. 10, no. 1, pp. 69–79, Mar. 1978, doi: 10.1016/0001-4575(78)90009-X.

[38] M. J. Maher and L. J. Mountain, “The identification of accident blackspots: A comparison of current methods,” *Accid. Anal. Prev.*, vol. 20, no. 2, pp. 143–151, Apr. 1988, doi: 10.1016/0001-4575(88)90031-0.

[39] B. Heydecker and J. Wu, “Using the information in road accident records,” Jan. 1991.

[40] R. W. Stokes and M. I. Mutabazi, “Rate-Quality Control Method of Identifying Hazardous Road Locations,” *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1542, no. 1, pp. 44–48, Jan. 1996, doi: 10.1177/0361198196154200107.

[41] E. Hauer, “Identification of Sites with Promise,” *Transp. Res. Rec.*, vol. 1542, no. 1, pp. 54–60, Jan. 1996, doi: 10.1177/0361198196154200109.

[42] A. P. Tarko, J. V. Weiss, and K. C. Sinha, “An advanced method of identifying hazardous locations,” *IATSS Res.*, vol. 20, no. HS-042 343, 1996.

[43] B. Persaud, C. Lyon, and T. Nguyen, “Empirical Bayes Procedure for Ranking Sites for Safety Investigation by Potential for Safety Improvement,” *Transp. Res. Rec.*, vol. 1665, no. 1, pp. 7–12, Jan. 1999, doi: 10.3141/1665-02.

[44] A. P. Tarko and M. Kanodia, “Effective and Fair Identification of Hazardous Locations,” *Transp. Res. Rec.*, vol. 1897, no. 1, pp. 64–70, Jan. 2004, doi: 10.3141/1897-09.

[45] W. Cheng and S. P. Washington, “Experimental evaluation of hotspot identification methods,” *Accid. Anal. Prev.*, vol. 37, no. 5, pp. 870–881, Sep. 2005, doi: 10.1016/j.aap.2005.04.015.

[46] L. F. Miranda-Moreno, L. Fu, F. F. Saccomanno, and A. Labbe, “Alternative risk models for ranking locations for safety improvement,” *Transp. Res. Rec.*, vol. 1908, no. 1, pp. 1–8, 2005.

[47] K. El-Basyouny and T. Sayed, “Comparison of Two Negative Binomial Regression Techniques in Developing Accident Prediction Models,” *Transp. Res. Rec.*, vol. 1950, no. 1, pp. 9–16, Jan. 2006, doi: 10.1177/0361198106195000102.

[48] D. Lord and P. Y.-J. Park, “Investigating the effects of the fixed and varying dispersion parameters of Poisson-gamma models on empirical Bayes estimates,” *Accid. Anal. Prev.*, vol. 40, no. 4, pp. 1441–1457, Jul. 2008, doi: 10.1016/j.aap.2008.03.014.

[49] R. Elvik, “The predictive validity of empirical Bayes estimates of road safety,” *Accid. Anal. Prev.*, vol. 40, no. 6, pp. 1964–1969, Nov. 2008, doi: 10.1016/j.aap.2008.07.007.

[50] C. Wang, M. A. Quddus, and S. G. Ison, “Predicting accident frequency at their severity levels and its application in site ranking using a two-stage mixed multivariate model,” *Accid. Anal. Prev.*, vol. 43, no. 6, pp. 1979–1990, Nov. 2011, doi: 10.1016/j.aap.2011.05.016.

[51] B.-J. Park, D. Lord, and C. Lee, “Finite mixture modeling for vehicle crash data with application to hotspot identification,” *Accid. Anal. Prev.*, vol. 71, pp. 319–326, Oct. 2014, doi: 10.1016/j.aap.2014.05.030.

[52] “Safety Analysis Guidelines,” Ohio Department of Transportation, Dec. 2018.

[53] A. Nicholson and Y.-D. Wong, “Are accidents poisson distributed? A statistical test,” *Accid. Anal. Prev.*, vol. 25, no. 1, pp. 91–97, 1993.

[54] P. P. Jovanis and H.-L. Chang, “Modeling the relationship of accidents to miles traveled,” *Transp. Res. Rec.*, vol. 1068, pp. 42–51, 1986.

[55] S.-P. Miaou and H. Lum, “Modeling vehicle accidents and highway geometric design relationships,” *Accid. Anal. Prev.*, vol. 25, no. 6, pp. 689–709, 1993.

[56] Y. Zhang, Z. Ye, and D. Lord, “Estimating dispersion parameter of negative binomial distribution for analysis of crash data: bootstrapped maximum likelihood method,” *Transp. Res. Rec.*, vol. 2019, no. 1, pp. 15–21, 2007.

[57] B. Hariharan, “Functional Form and Heterogeneity on Safety Performance Function Estimation,” Dissertation, The Pennsylvania State University, 2015.

[58] T. Gates *et al.*, “Safety Performance Functions for Rural Road Segments and Rural Intersections in Michigan,” Michigan. Dept. of Transportation. Research Administration, Technical Report SPR-1645, 2018.

[59] M. Ahmed and R. Chalise, “Calibration of the Highway Safety Manual’s Safety Performance Functions for Rural Two-Lane Highways with Regional Considerations for the Rocky Mountains and Plain Regions,” MPC 18-344, 2018.

[60] E. Green, “Segmentation Strategies for Road Safety Analysis,” Dissertation, University of Kentucky, 2018.

[61] E. Hauer, D. W. Harwood, F. M. Council, and M. S. Griffith, “Estimating safety by the empirical Bayes method: a tutorial,” *Transp. Res. Rec.*, vol. 1784, no. 1, pp. 126–131, 2002.

[62] C. Burch, L. Cook, and P. Dischinger, “A Comparison of KABCO and AIS Injury Severity Metrics Using CODES Linked Data,” *Traffic Inj. Prev.*, vol. 15, no. 6, pp. 627–630, Aug. 2014, doi: 10.1080/15389588.2013.854348.

[63] F. Xie, K. Gladhill, K. K. Dixon, and C. M. Monsere, “Calibration of Highway Safety Manual Predictive Models for Oregon State Highways,” *Transp. Res. Rec.*, vol. 2241, no. 1, pp. 19–28, Jan. 2011, doi: 10.3141/2241-03.