Final Report VTRC 11-R4

Virginia Transportation Research Council

research report

A Planning-Level Methodology for Identifying High-Crash Sections of Virginia's Primary System

http://www.virginiadot.org/vtrc/main/online_reports/pdf/11-r4.pdf

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Standard Title Page - Report on Federally Funded Project

1. Report No.: FHWA/VTRC 11-R4	2. Government Accession No.:	3. Recipient's Catalog No.:
4. Title and Subtitle: A Planning-Level Methodology for Identifying High-Crash Sections of Virginia's Primary System		5. Report Date: August 2010 6. Performing Organization Code:
7. Author(s): Ajmal Hamidi, Michael D. Fontaine, Ph.D., and Michael J. Demetsky, Ph.D.		8. Performing Organization Report No.: VTRC 11-R4
9. Performing Organization and Address: Virginia Transportation Research Council 530 Edgemont Road Charlottesville, VA 22903		10. Work Unit No. (TRAIS): 11. Contract or Grant No.: 91268
12. Sponsoring Agencies' Name and Address: Virginia Department of Transportation 1401 E. Broad Street Richmond, VA 23219	Federal Highway Administration 400 North 8th Street, Room 750 Richmond, VA 23219-4825	13. Type of Report and Period Covered: Final 14. Sponsoring Agency Code:
15. Supplementary Notes:		

16. Abstract:

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The purpose of this study was to develop an SPF-based methodology to conduct more intermediate-scale safety analyses. VDOT's Traffic Engineering Division indicated that such a methodology would be useful for corridor screening and planning-level applications. The scope of the study was limited to the following roadway types in Virginia's primary system: rural two-lane, rural multilane divided, rural multilane undivided, urban two-lane, urban multilane divided, and urban multilane undivided. For each type, roadway inventory data, traffic volume data, and crash data from 2003 through 2007 were compiled and integrated into a database.

This study then took an approach that diverged from that of other SPF research to develop intermediate-scale SPFs. Instead of crashes at intersections and on roadway segments being separated, intersection and segment crashes were combined and mapped onto the appropriate roadway inventory links. In addition, site aggregation was performed to combine similar, adjacent roadway links into longer aggregated sites. SPFs were then generated from these aggregated sites through regression analysis. A site prioritization demonstration was then performed using the aggregate SPFs and aggregate sites to create lists of sites with the highest potential for safety improvement. Finally, a comparison of these lists and those generated by the critical rate method produced quantitative evidence of the advantage of the developed SPF-based methodology over the traditionally used critical rate method. Once implemented, the methodology developed in this study should enable VDOT to conduct corridor screening and planning-level analyses in a more effective and cost-efficient manner.

17 Key Words: Safety performance functions, safety analysis, potential for safety improvement, crash data, crash modeling		18. Distribution Statement: No restrictions. This document is available to the public through NTIS, Springfield, VA 22161.	
19. Security Classif. (of this report): Unclassified	20. Security Classif. (of this page): Unclassified	21. No. of Pages: 61	22. Price:

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

FINAL REPORT

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In Cooperation with the U.S. Department of Transportation
Federal Highway Administration

Virginia Transportation Research Council
(A partnership of the Virginia Department of Transportation
and the University of Virginia since 1948)

Charlottesville, Virginia

August 2010
VTRC 11-R4

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ABSTRACT

The Virginia Department of Transportation (VDOT) has been developing safety performance functions (SPFs) as a way to identify sites with a potential for safety improvement more effectively. An SPF estimates the expected safety performance of a roadway as a function of its characteristics. Using SPFs, VDOT can identify which roads have a significantly higher number of crashes than would be expected based on site conditions. Other VDOT studies have developed SPFs with a microscopic perspective that separately examine individual intersections or discrete roadway segments.

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INTRODUCTION

In the Commonwealth of Virginia's Strategic Highway Safety Plan, Virginia stated its vision of making its surface transportation system the safest in the nation by 2025 (Surface Transportation Safety Executive Committee, 2006). Achieving such an ambitious goal requires considerable reductions in the raw number of motor vehicle crashes, especially those that result in injuries or fatalities. Reducing crashes will in turn require an effective means of identifying potentially problematic locations so that appropriate countermeasures can be put in place. Traditionally, the Virginia Department of Transportation (VDOT) has used a crash rate–based identification methodology for its highway safety management programs such as the Highway Safety Improvement Program. Specifically, VDOT has employed the critical rate method, which compares the crash rate of a particular site and the crash rates of similar sites, to identify high-crash locations. The crash rates are adjusted for exposure, which is measured in vehicle miles traveled (VMT) for roadway segments and number of entering vehicles for intersections. Although reliance on crash rates has been a long-standing practice in Virginia, this methodology has inherent limitations, which have prompted the development of alternative approaches.

There is an overarching problem with a crash rate–based methodology for identifying problematic locations. An underlying assumption in this methodology is that there is a linear relationship between crash counts and traffic volume. However, recent research has cast doubt on the validity of this assumption. As Qin et al. (2005) and Hauer (1995) pointed out, the relationship between crash counts and traffic volume tends to be nonlinear. Although the exact relationship varies depending on facility type, geographic region, and other factors, what is almost universally true is that the relationship is not perfectly linear. Often, but not always, the relationship resembles a logarithmic curve such that the slope of the curve tends to flatten out as traffic volume increases. Given this knowledge, it is apparent that a crash rate–based methodology with its linear assumption has a systematic bias.

Another drawback of a crash rate–based methodology relates to its instability at low traffic volumes. Since crash rates normalize crash counts for exposure, small changes in crash counts on low-volume roads can cause dramatic fluctuations in crash rates. A crash rate–based methodology can incorrectly interpret slight changes in crash count at such sites to be significant when they are, in actuality, random variations in crash occurrence.

There is also a more general problem with a crash rate–based methodology. Such a methodology is potentially ill equipped to identify locations with a high raw number of crashes since many sites with a large crash count do not necessarily have a high crash rate. In this methodology, a site with a large number of crashes may be overlooked for potential treatments if it has a sufficiently high level of exposure.

An emerging method that addresses many of the limitations of crash rate–based methodologies is the use of safety performance functions (SPFs). An SPF predicts the safety performance of a road as a function of its characteristics. As with the critical rate method, roads can be stratified into high-level categories (e.g., multilane divided primaries), and separate SPFs can be developed for each category through regression. The general premise of many SPF-based methodologies is that high-crash locations may be identified by comparing the recently observed safety record of a particular site to the expected safety performance using an appropriate SPF. Use of SPFs offers the opportunity to identify locations in need of safety improvement more effectively than crash rate–based approaches, thereby ensuring more effective use of limited state funds to improve safety.

This emerging trend has prompted VDOT's Traffic Engineering Division (TED) and the Virginia Transportation Research Council (VTRC) to pursue a program of research to develop SPFs for Virginia roads. Such studies have been conducted to develop SPFs for discrete, isolated roadway segments and intersections (Garber and Rivera, 2010; Garber et al., 2010). No studies, however, have developed and applied an SPF-based methodology to analyze intermediate-length sections of Virginia's roads. VDOT's TED indicated the need for a planning-level methodology that could identify 2- to 3-mi sections of roadway for further, localized analysis. A robust methodology would support a number of VDOT's programs, such as the Highway Safety Corridor Program, the Highway Safety Improvement Program, and the Strategically Targeted Affordable Roadway Solutions Program, and a variety of statewide and regional planning applications.

It is important to note how the microscopic SPFs developed in other Virginia-specific studies may not be well tailored to support some highway safety management programs and applications. Garber et al. (2010) developed urban and rural two-lane roadway segment SPFs for primary and secondary roads in Virginia. In a separate study, Garber and Rivera (2010) developed SPFs for rural and urban intersections with varying traffic control types (i.e., signalized versus unsignalized) and numbers of approach legs. In both studies, an attempt was made to segregate intersection-related crashes from segment-related crashes because of the differing characteristics of intersection and segment crashes (Garber et al., 2010). Therefore, the

SPFs developed by Garber et al. (2010) are intended strictly for discrete two-lane roadway segments because crash data deemed to be intersection related were not included in the regression analysis. A threshold value of 0.03 mi (158.4 ft) was selected so that any crash occurring within a 0.03-mi radius of an intersection was deemed to be intersection related and thus excluded (Garber et al., 2010). Conversely, the intersection SPFs developed by Garber and Rivera (2010) used crash data from within only a 0.03-mi radius of intersections. This procedural assumption contributes to the microscopic, localized nature of the SPFs developed in both studies.

It can be argued that such a modeling approach is inappropriate for corridor and planning-level analyses. No single threshold value can be selected that correctly distinguishes all intersection-related crashes from segment-related crashes for every site. For example, if the left-turn bay storage on a leg of an intersection is 200 ft and a queue builds on the turn lane extending into a through lane, a rear-end collision between a vehicle in the queue and a vehicle traveling on the through lane would be incorrectly designated a segment-related crash. Numerous other crash scenarios may also be incorrectly designated intersection related or segment related. In addition, by partitioning the roadway system in this way, each site becomes an isolated, discrete roadway entity. For roadway segments, this may cause lengths to become very short (e.g., 0.01 mi). In these situations, a number of these sites would have to be grouped together in order to conduct a meaningful corridor analysis. In order to characterize accurately a highway corridor, any and all intersections must also be modeled separately. Thus, the sites that were disaggregated into roadway entities to construct segment and intersection SPFs must be aggregated back together in some way for corridor analysis.

Given the limitations of existing SPF-based approaches in identifying corridors, there is a need for a planning-level SPF-based methodology for identifying high-crash locations. Such a safety analysis methodology could benefit VDOT in three areas: intermediate-scale analyses necessary for corridor screening programs; analysis of alternatives during the project development process; and incorporation of safety into the planning process.

PURPOSE AND SCOPE

The purpose of this study was to develop a methodology that would enable VDOT to conduct planning-level safety analyses to identify sections of the primary system with a higher than expected crash frequency. Such a capability would support a variety of safety programs in Virginia and facilitate more effective investment of available highway safety funds. Since safety performance modeling plays a crucial role in this safety analysis methodology, appropriate SPFs must be developed and calibrated to Virginia's conditions.

The objectives of the study were as follows:

- Devise a site aggregation procedure to combine the disaggregate sites into aggregate sites.

- Develop a set of SPFs for different roadway types first from the disaggregate sites and then from the aggregate sites.

- Evaluate and compare the goodness of fit (GOF) of the SPFs developed using appropriate statistical measures.

- Demonstrate site prioritization using the aggregate SPFs and aggregate sites, and compare the results relative to those of the critical crash rate–based method.

The scope of the study was limited to primary roads in Virginia with no control of access. More precisely, the study addressed the following six roadway types in the primary system: rural two-lane, rural multilane divided, rural multilane undivided, urban two-lane, urban multilane divided, and urban multilane undivided. Freeways were not assessed. The primary system was selected for analysis since it contains a diverse set of roads and offers the opportunity to examine the methodology across a broad range of roadway configurations and traffic conditions. SPFs were also developed for two levels of crash severity: all crashes and severe (fatal and injury) crashes.

METHODS

The following tasks were undertaken to achieve the study objectives.

1. Select an SPF model form.
2. Prepare the data.
3. Stratify the data.
4. Aggregate the sites.
5. Assign the data to estimation and validation data sets.
6. Develop SPFs.
7. Assess GOF.
8. Demonstrate site prioritization.

Selection of an SPF Model Form

The main purpose of this study was to produce a planning-level methodology for identifying high-crash roadway sections. Since SPFs would be the basis of this methodology, the first task was to identify and select the most appropriate SPF model form for this purpose. The literature was reviewed to identify candidate model forms that could be adapted to a macroscopic analysis of corridors. In doing so, four criteria were considered in evaluating the suitability of the candidate models.

1. *Feasibility of meeting the data requirements of the candidate model.* Since an explicit parameter of this study was to use data commonly available in existing VDOT databases, this criterion was of paramount importance.

2. *Versatility of the model form in terms of the areas of application.* Since the study had to address six specific roadway types and two severity levels, candidate models that best covered these required areas were sought.

3. *Quality of model fit demonstrated by each candidate SPF.*

4. *Ease of implementation for VDOT.* Regardless of model fit, versatility, and feasibility of development, the SPFs generated would not be highly useful if they could not easily be applied by VDOT for highway safety management. Ease of implementation was assessed by comparing the capabilities of analytical software tools available to TED to support the deployment of each candidate SPF model. Specifically, the feasibility of integrating the SPFs into the existing SafetyAnalyst tool being used by TED was assessed.

Preparation of Data

Prior to the development of SPFs, it was necessary to develop a database that could be used for model construction. A database was assembled that contained roadway cross-section data, traffic volume data, and crash data for the 5-year period 2003 through 2007. Each data element was originally in a separate database, so integrating the elements into one database was a major initial task. The VDOT Highway and Traffic Records Information System (HTRIS) contains a roadway inventory database that includes cross-section data. The VDOT Traffic Monitoring System (TMS) database consists of traffic volume data on each link. The VDOT crash database, also maintained in HTRIS, contained the required crash data. All three data sources had to be combined into an integrated database that could be used for model construction.

This task was divided into two major stages. First, the HTRIS roadway inventory links were joined to the TMS traffic links. Second, the resulting combined roadway inventory and traffic dataset was joined to the crash data. At this point, it is important to note the way intersection crashes were mapped to the roadway inventory system in this study. A crash that occurred in an intersection was mapped to either the major road or the minor road but not to both. This determination was made using the VDOT crash database. Every crash record in the VDOT crash database assigns the crash to a specific route number. If the route number belonged to the major road, the crash count was mapped onto the major road (and vice versa). This approach was taken to avoid double counting crashes and facilitate site aggregation. In contrast, the intersection models developed in microscopic SPF studies incorporated the crash data and traffic volume data from both the major road and the minor road.

Stratification of Data

The next task was to stratify the primary system into appropriate divisions that warranted their own SPF. Since Virginia's primary roads vary tremendously in terms of geometric and traffic conditions, it was essential to distinguish among different roadway types when SPFs were generated. Since the results of this study were intended to be incorporated into SafetyAnalyst, the roadway types used by this software were used to stratify the data. After a review of the roadway types included in SafetyAnalyst, the following six categories were selected for this study:

1. rural two-lane
2. rural multilane divided (no control of access)
3. rural multilane undivided
4. urban two-lane
5. urban multilane divided (no control of access)
6. urban multilane undivided.

As shown in Table 1, the database was stratified into these roadway types using three data fields from the roadway inventory database: functional classification, number of lanes, and facility type. The functional classification field separated the rural and urban sites, as shown in Table 2. The number of lanes separated the two-lane and multilane sites. The facility type data field separated the divided multilane highways and the undivided highways and filtered out sites with full or partial control of access, as shown in Table 3.

Table 1. Data Fields Used to Define Roadway Types

SPF Category	Functional Classification	No. of Lanes	Facility Type
Rural two-lane	2, 3, 4, 5 or 6	2	0
Rural multilane divided	2, 3, 4, 5 or 6	>2	1
Rural multilane undivided	2, 3, 4, 5 or 6	>2	0
Urban two-lane	E, F, G, H, I, or J	2	0
Urban multilane divided	E, F, G, H, I, or J	>2	1
Urban multilane undivided	E, F, G, H, I, or J	>2	0

SPF = safety performance function.

Table 2. Codes and Descriptions for Functional Classification Data Field

Functional Classification	Description
0	Unknown functional class
1	Rural interstate
2	Rural other principal arterial
3	Rural minor arterial
4	Rural major collector
5	Rural minor collector
6	Rural local
A	Urban interstate
B	Urban freeways and expressways; Connecting links of rural principal arterial
C	Urban freeways and expressways; Connecting links of rural minor arterial
D	Urban freeways and expressways; Other
E	Urban other principal arterials; Connecting links of other rural principal arterial
F	Urban other principal arterials; Connecting links of rural minor arterial
G	Urban other principal arterials; Other
H	Urban minor arterial
I	Urban collector
J	Urban local

Table 3. Codes and Descriptions of Facility Type Data Field

Facility Type	Description
0	Two-way, non-divided
1	Divided, no control of access
2	Divided, partial control of access
3	Divided, full control of access
4	One-way, part of a one-way system
5	Two-way, part of a one-way system
6	One-way couplet
7	Transition
A	One-way structure (bridge, tunnel, causeway, etc.)
B	Two-way structure (bridge, tunnel, causeway, etc.)

Further, since geography can influence geometric and traffic conditions, geographic differences had to be taken into account. A separate SPF was developed for each roadway type in distinct geographic regions in addition to statewide models. Using VDOT districts was one means of defining distinct geographic regions. Figure 1 illustrates these districts. If they were used to subdivide the data, however, the sample sizes of specific roadway types would be prohibitively small in some cases. Therefore, an alternative geographic sorting scheme was developed through consultation between VTRC and TED. In this alternative, the nine VDOT districts were divided into three major geographical regions that were essentially based on aggregations of the VDOT operations regions in use at the time. It was determined that the regions produced sufficiently large sample sizes while preserving some information regarding the distinct geographic variations found in Virginia. This same approach toward geographic stratification of data was taken by Garber and Rivera (2010). Table 4 shows how these three regions were defined using VDOT operations regions, districts, and maintenance jurisdictions.

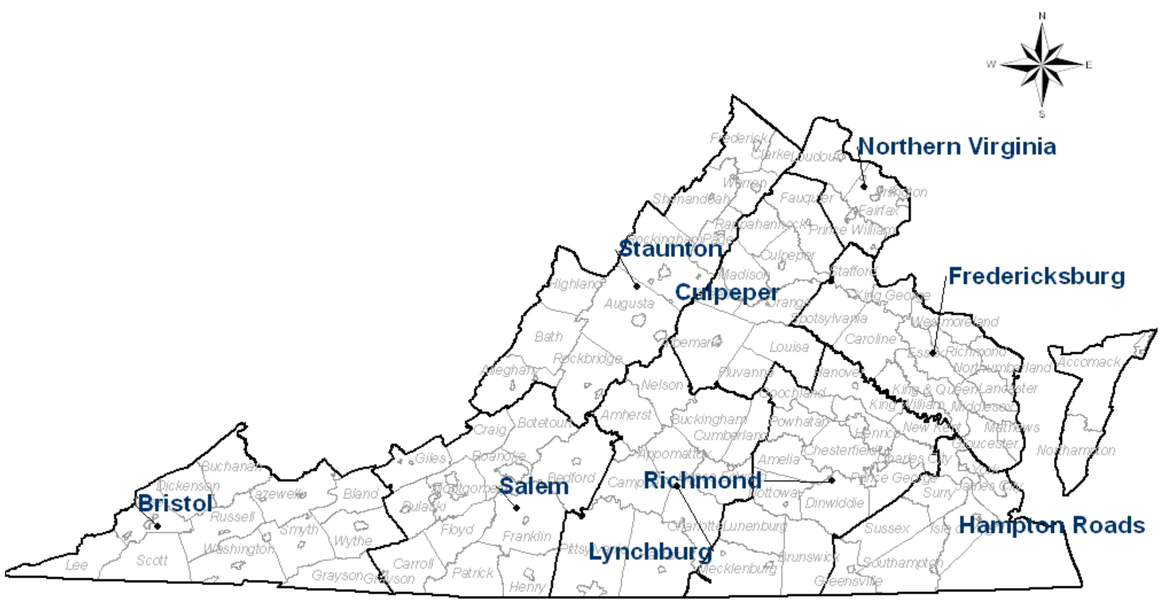

Figure 1. VDOT Construction Districts

Table 4. Composition of the Three Major Geographic Regions for Study

SPF Regions	North	West		Central/East	
Operations regions	Northern	Northwest	Southwest	Central	Eastern
Districts	Northern Virginia	Staunton	Bristol Salem Lynchburg	Richmond	Hampton Roads
Additional maintenance jurisdictions (if applicable)	Fauquier Stafford Rappahannock Culpeper Madison Orange Spotsylvania King George	Greene Albemarle Fluvanna Louisa		Lancaster Northumberland Richmond Westmoreland Essex Caroline King and Queen King William	Matthews Middlesex Gloucester

SPF = safety performance function.

One potential limitation of these specific geographic regions relates to what is classified as rural versus urban in different parts of the state. This problem is probably most pronounced in the North region. In that case, rural two-lane roads from heavily urbanized areas (such as those in Northern Virginia) are grouped with rural two-lane roads in rural areas (such as those in Madison County). Even though the roads in both areas have rural functional classifications, roadside characteristics and design may be different. The SPFs in this study were developed using the operational regions in place at the time of the study, but there may be bias in the rural SPF classifications toward identifying locations in more urbanized counties because of the way the counties were grouped. Since the SPFs were developed as functions of volume, however, the modeling process can address this to some extent.

Aggregation of Sites

The integrated database of disaggregate sites developed in the last task was not well designed to meet the goal of developing planning-level SPFs directly. This database contained a high proportion of short links, including numerous links only 0.01 mi long. These extremely short links were often located between two nearby intersections. Such sites would, in essence, reflect the crash characteristics of intersections as opposed to roadway segments. They would also be likely to have tremendous variability in terms of crash occurrence because of the higher number of conflict points at intersections relative to roadway segments. Even if certain short links did not display the crash characteristics of intersections, they would be problematic in another sense. Shorter links tend to have lower exposure since exposure is a function of segment length and average annual daily traffic (AADT). As Lord et al. (2004) showed, low exposure on heterogeneous sites is sometimes the reason excess zeros are observed in crash data. Thus, in an effort to give the methodology a macroscopic perspective, improve model fit, and reduce the occurrence of excess zeroes, the concept of site aggregation was explored.

Site aggregation, as defined in this study, is simply the combining of geographically adjacent links that are identical with respect to geometric and traffic characteristics. The roadway inventory currently terminates links at every intersection or whenever any of a host of data fields representing roadway characteristics changes. Many of these roadway characteristics were relevant to SPF generation such as the number of lanes, functional classification, facility type, access control, and traffic volume. Other roadway characteristics were not directly relevant such as whether the roadway base type was crushed gravel or crushed stone. With site aggregation, only adjacent links with equivalent, relevant roadway characteristics were combined. Through this process, numerous links would be aggregated upward in size, thereby increasing the average link length of the entire database and removing a large portion of short links.

Factors for terminating link aggregation had to be identified. During the data stratification step, six distinct road types were identified that warranted their own SPFs. These categories were defined by three attributes: rural/urban designation, number of lanes, and facility type. In addition, traffic volume was an essential variable and needed to be included. Another critical factor in the aggregation process was geographic proximity and continuity. This merely meant that two road links had to be immediately adjacent (i.e., end mile post of the prior link equaled the start mile post of the following link) in order for the two links to be aggregated into one link. In this way, five factors for the site aggregation process were selected:

1. rural versus urban designation
2. number of lanes
3. facility type (divided versus undivided)
4. traffic volume
5. geographic proximity and continuity.

After these factors were selected, two possible approaches to perform the aggregation process were identified. The first approach, called *Tier 1 aggregation* in this study, was to terminate aggregation whenever there was a change in any of these factors. For example, if the number of lanes on a rural divided route changed from three to four, the aggregation of links would terminate. The second approach, called *Tier 2 aggregation*, was to terminate aggregation only when a change in one of these factors altered the road type classification of the link. In this case, a change in the number of lanes on an urban undivided route from three to four would not terminate aggregation because the link would still remain classified as a rural multilane undivided road. However, a change in the number of lanes from two to three would terminate the aggregation since the road type classification would change from urban two-lane to urban multilane undivided.

Tier 1 and 2 aggregation also differed with respect to rural versus urban designation. The rural or urban designation for each link was determined using the functional classification data field. For instance, urban principal arterials, urban minor arterials, urban major collectors, urban minor collectors, and urban local road links were all designated urban. Likewise, rural principal arterials, rural minor arterials, rural major collectors, rural minor collectors, and rural local road links were all designated rural. As was the case for the number of lanes data field, Tier 1 and 2 aggregation would use the functional classification data field differently. In Tier 1 aggregation, aggregation would terminate after any change in the functional classification data field. In Tier 2 aggregation, a change in functional classification would terminate aggregation only if the rural versus urban designation was changed. For example, Tier 2 aggregation would combine a rural principal arterial two-lane link to an adjacent rural minor arterial two-lane link and Tier 1 aggregation would not. As a consequence, Tier 2 aggregation was more intensive than Tier 1 aggregation because the criteria for terminating aggregation were less restrictive.

Assignment of Data to Estimation and Validation Datasets

Prior to the development of SPFs, the integrated database in its disaggregated and aggregated forms had to be separated into estimation and validation sample datasets. SPFs would be generated through regression analysis of the estimation samples. The validation samples would be reserved to test the predictive performance of the SPFs using multiple GOF measures. Data were assigned to the estimation and validation samples by random sampling in SAS 9.1.3 (SAS Institute, Inc., 2006). The sampling parameters were set so that 70% of a particular dataset would be assigned to form an estimation sample and the remaining 30% would be assigned to form a validation sample.

It was important for the estimation samples and corresponding validation samples to be as similar as possible in terms of traffic volume, total crash count frequency, and fatal + injury (FI) crash count frequency. To ensure that the validation samples were representative of the corresponding estimation samples with respect to these three variables, several nonparametric statistical tests were run in SAS to compare the distributions of the validation set and of the corresponding estimation set. SAS has a built-in subprogram for nonparametric tests that included the following: Wilcoxon test for two-sample data; Kruskal-Wallis test; median two-sample test; median one-way; Kolmogorov-Smirnov two-sample test; Cramér von Mises; and Kuiper for two-sample test (more information on nonparametric tests is provided by Hayek et al. [1999]). Whenever the two-sided *p*-value of a Wilcoxon, Kruskall-Wallis, median, Kolmogorov-Smirnov, or Kuiper test was less than 0.20, the random sampling was repeated.

This approach for separating data into estimation and validation datasets was rather conservative compared to statistical conventions for hypothesis testing. The null hypothesis in each of these nonparametric tests was that the distributions of the estimation and validation sets were not statistically different in terms of AADT or crash frequency. In this situation, a type I error would be to judge that two datasets were statistically different when they were not. A Type II error would be to judge that two datasets were not statistically different when they were. In this context, the researchers were far more concerned with avoiding a Type II error than a Type I error. The consequence of a Type I error was merely that the researchers repeated a random sampling unnecessarily. The consequence of a type II error was that the researchers had incorrectly decided that the validation and estimation sets were properly assigned when they had not been. This error, in turn, could reduce the accuracy of the regression analysis because of over-fitting models and impact the GOF analysis. Therefore, it was more important to reduce the probability of committing a Type II error, known as β, than it was to reduce the probability of a type I error, known as α. In order to do so, it was critical to maximize the power, $(1- \beta)$, of these nonparametric tests. As Hauer (1996) pointed out, "when the sample size is fixed, the price of a decrease in the probability of Type II error is an increase in the probability to make a Type I error." In other words, one must increase α in order to decrease β assuming a fixed sample size.

Hence, a relatively high value was set for α, 0.2, compared to statistical conventions in hypothesis testing (typically 0.05) in order to help ensure that the estimation and validation sets had been assigned properly.

Development of SPFs

The next step was to perform regression analyses on the estimation datasets to develop the SPFs. Simple linear regression could not be used because it assumes that the dependent variable, crash count data in this case, follows a normal distribution. As Hauer (1997) and others have explained, assuming that crash count data are normally distributed is not usually valid. Generalized linear modeling (GLM) is an extension of traditional linear modeling that is not subject to this normal distribution requirement. GLMs can assume that the dependent variable follows any member of "a wider class of distributions called the exponential family of distributions" (Dobson and Barnett, 2008). Since crash count data are commonly modeled using a negative binomial or Poisson-gamma distribution (Geedipally et al., 2009), GLMs were more appropriate than traditional linear models for this study.

GLM, however, also requires an assumption that is questionable for this study. GLMs assume that the dependent variables are independent random variables and thus uncorrelated (Dobson and Barnett, 2008). Since this study compiled longitudinal data, this assumption might not have held true. To be more specific, 5 years of crash and traffic data were gathered for each site in the database. Using a GLM in this context would mean assuming that a particular site's crash count in one year is uncorrelated to its crash count in another year. This, of course, would have been a dubious assumption. Not taking the data correlation into account could have rendered the entire modeling process invalid. Fortunately, there was an alternative. One way to handle longitudinal data or any repeated measures data is through generalized estimating equations (GEEs) (Dobson and Barnett, 2008). GEEs are similar to GLMs except that they explicitly model the correlation structure of the data (Dobson and Barnett, 2008).

The SAS 9.1.3 software package was used in this study since it has the capability to invoke GEEs to model the data. Specifically, the GENMOD procedure in SAS was used. This program required the specification of a probability distribution for the dependent variable and a link function. The negative binomial distribution and a logarithmic link were assumed. The program also required that the user input a model, i.e., a formula relating the response variables as a function of explanatory variables. The response variable was simply the number of crashes per year at a site. AADT was the only explanatory variable. Since no regression parameters were to be estimated for the segment length variable, the segment length was specified as an offset variable in the model. It is important to emphasize that each site had 5 years of AADT values and crash counts and that these values were not averaged as would be done in a cross-sectional study. As a consequence, this analysis was using panel data (repeated measures data). Incorporating all of these specifications, the model took the form of Equation 1, which is the SafetyAnalyst SPF model form:

$$k = e^{a} \times AADT^{b} \times SL \qquad \text{[Eq. 1]}$$

where

k = number of crashes per year at a site
a, b = regression parameters
AADT = average annual daily traffic (veh/day)
SL = segment length (mi).

In the GENMOD procedure, SAS first constructed a GLM based on Equation 1 to obtain initial estimates for the regression parameters a and b and their standard errors and an estimate for the negative binomial dispersion parameter. Then the procedure accounted for correlation in the crash data by refining the estimates for a and b through the use of a GEE. In this way, an SPF was constructed for every dataset in the disaggregate database, Tier 1 aggregated database, and Tier 2 aggregated database. For the disaggregate database, there were 48 SPF combinations based on the four factors shown in Table 5. For the aggregate databases, there were 20 SPF combinations based on the factors shown in Table 6. Note that all 24 possible aggregate SPF combinations were not produced because the results for Tier 1 and 2 aggregation were identical in some cases. In addition, regional models were not developed using aggregated data because of small regional sample sizes. In all, 68 SPFs were generated for testing.

Table 5. Factors Used to Define Disaggregate Safety Performance Functions

Region	Rural/Urban	Facility Type	Crash Severity
1. Statewide	1. Rural	1. Two-lane	1. Total
2. North	2. Urban	2. Multilane divided	2. Fatal + Injury
3. West		3. Multilane undivided	
4. East/Central			

Table 6. Factors Used to Define Aggregate Safety Performance Functions

Aggregation Level	Region	Rural/Urban	Facility Type	Crash Severity
1. Tier 1 aggregation	1. Statewide	1. Rural	1. Two-lane	1. Total
2. Tier 2 aggregation		2. Urban	2. Multilane divided	2. Fatal + Injury
			3. Multilane undivided	

Assessment of Goodness of Fit

Model fit for the SPFs generated in this study was assessed with the following five GOF statistics: mean prediction bias (MPB) (see Equation 2); mean absolute deviation (MAD) (see Equation 3); mean squared prediction error (MSPE) (see Equation 4); coefficient of determination (R^2) (see Equations 5 through 7); and the Freeman-Tukey R^2 coefficient of determination (R^2_{FT}) (see Equations 8 through 11). The exact formulas used for these GOF statistics follow:

$$MPB = \frac{\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)}{n} \quad \text{[Eq. 2]}$$

$$MAD = \frac{\sum_{i=1}^{n} \left| \hat{Y}_i - Y_i \right|}{n} \quad \text{[Eq. 3]}$$

$$MSPE = \frac{\sum_{i=1}^{n} \left(\hat{Y}_i - Y_i \right)^2}{n} \quad \text{[Eq. 4]}$$

$$R^2 = \frac{SS_{total} - SS_{error}}{SS_{total}} = 1 - \frac{SS_{error}}{SS_{total}} \quad \text{[Eq. 5]}$$

$$SS_{error} = (\hat{Y}_i - Y_i)^2 \quad \text{[Eq. 6]}$$

$$SS_{total} = (\bar{Y} - Y_i)^2 \quad \text{[Eq. 7]}$$

$$R_{FT}{}^2 = \frac{\sum_{i=1}^{n} (f_i - \bar{f})^2 - \sum_{i=1}^{n} \hat{e}_i}{\sum_{i=1}^{n} (f_i - \bar{f})^2} = 1 - \frac{\sum_{i}^{n} \hat{e}_i{}^2}{\sum_{i=1}^{n} (f_i - \bar{f})^2} \quad \text{[Eq. 8]}$$

$$f_i = \sqrt{Y_i} + \sqrt{Y_i + 1} \quad \text{[Eq. 9]}$$

$$\bar{f} = \frac{\sqrt{Y_i} + \sqrt{Y_i + 1}}{n} \quad \text{[Eq. 10]}$$

$$\hat{e}_i = \sqrt{Y_i} + \sqrt{Y_i + 1} - \sqrt{4\hat{Y}_i + 1} \quad \text{[Eq. 11]}$$

where

Y_i = number of crashes observed at site *i*

$\hat{Y}_i$ = number of crashes predicted for site i by SPF

n = sample size of dataset.

With the exception of the Freeman-Tukey R^2, the statistics shown earlier are commonly used to study model fit. Freeman and Tukey (1950) developed the variance stabilizing transformation for the Poisson distribution shown in Equation 9. Fridstrøm et al. (1995) applied this transformation when developing generalized regression models for crash data from Denmark, Finland, Norway, and Sweden. They used Equation 8 as a GOF measure when this transformation was used. This statistic was also used by the developers of SafetyAnalyst to represent the GOF of their negative binomial regression models.

All five GOF statistics were first computed using each generated SPF and its corresponding estimation dataset. The resulting GOF measures indicated how well each SPF fit the data from which it was generated. The GOF statistics were then computed again using the corresponding validation dataset. The resulting GOF measures indicated how well each SPF fit data not used in its development. By comparing the GOF measures of the estimation set to those of the validation set, one could also determine if the model demonstrated an overfitting problem. If the GOF measures of the estimation set were significantly better than those of the validation set, the model may have been over-fit to the estimation data.

Although five GOF statistics were computed, the model fit analysis relied most heavily on the Freeman-Tukey R^2. The reason was that the segment-based SPFs in SafetyAnalyst served as a baseline for comparison when evaluating this study's SPFs. By combining intersection crashes with segment crashes, it was known a priori that the SPFs in this study would suffer in terms of model fit when compared to the segment-based SPFs in SafetyAnalyst. Therefore, comparing the model fit of the SPFs from this study to the model fit of SafetyAnalyst's segment-based SPFs provided valuable insights. For instance, this comparison was first performed using this study's disaggregate SPFs. By judging the level of deterioration in model fit of the disaggregate SPFs relative to SafetyAnalyst's segment-based SPFs, one could assess how much combining segment and crash data worsened model fit. In another instance, the Freeman-Tukey R^2 values provided information regarding geographic differences. Comparing the model fit of SafetyAnalyst's segment-based SPFs to this study's regional disaggregate SPFs would help gauge if geographic distinctions were significant and to what extent. Further, this Freeman-Tukey R^2 statistic was also useful in assessing the model fit of the aggregate SPFs. The Freeman-Tukey R^2 statistic provided a standard metric to compare this study's aggregate SPFs and disaggregate SPFs and SafetyAnalyst's segment-based SPFs.

Demonstration of Site Prioritization

The next step was to demonstrate how the aggregate SPFs developed in this study could be applied to identify roadway sections on the primary system with potential safety problems. To do so, a network screening procedure had to be formulated that was based on safety performance modeling as opposed to crash rates. SafetyAnalyst already had such a methodology in its network screening module for roadway segments: the sliding window approach.

In the SafetyAnalyst sliding window approach, a window with a user-specified length would move incrementally along contiguous roadway segments such that the current window location would overlap the previous one (Federal Highway Administration [FHWA], 2006). The roadway segments contained in the window would be grouped as a single site so long as they were contiguous and homogenous (e.g., equal AADTs). If the combined length of contiguous, homogenous segments was less than the user-specified length of the window at a particular location, the window would become as long as possible without violating these two constraints (FHWA, 2006).

At each window location, a site's potential for safety improvement (PSI) would be computed (FHWA, 2006). The PSI could be measured as either the expected accident frequency or the excess accident frequency: “the expected accident frequency that is in excess of what is considered normal for that type of site” (FHWA, 2006). Both frequencies would be calculated using the empirical Bayes (EB) method. Once the window traversed the entire roadway system, a site list would be generated by ranking the sites from the highest PSI to the lowest.

Using the SafetyAnalyst software would have been an ideal way to apply the SPFs developed in this study to perform site prioritization. However, doing so would have required extensive data preparation and formatting to make all Virginia primary system data compatible with SafetyAnalyst. Time constraints made this option impossible. Therefore, the site prioritization demonstration was performed outside the SafetyAnalyst software.

This study could not replicate the sliding window approach exactly because significant programming would have been required to mimic SafetyAnalyst’s moving window technique. Nonetheless, this study sought to follow the technique closely using MS Excel. First, Tier 1 aggregated site data were used to simulate the moving window. Site aggregation had an effect similar to the moving window because both combined similar, contiguous roadway links. In contrast to the moving window technique, site aggregation had neither a maximum user-specified length nor the same overlapping effect as the moving window technique.

At the outset of prioritization, crash data from the aggregated sites and uncalibrated aggregate SPFs for each model were available. The next step was to calibrate the aggregate SPFs using the observed crash data. To do so, five calibration factors had to be computed for every roadway category’s SPF (i.e., one calibration factor for every year). A yearly calibration factor was computed for each roadway category by dividing the number of crashes observed in a given year for that entire category by of the number of crashes predicted by the appropriate uncalibrated SPF. These yearly calibration factors were then applied to each uncalibrated SPF to produce yearly calibrated SPFs. Equation 12 shows the form of these yearly calibrated SPFs.

Afterward, yearly correction factors were calculated for each site by dividing the number of crashes predicted by the yearly calibrated SPF in a particular year by the number of crashes predicted by the yearly calibrated SPF for the base year of 2003 (see Equation 13). The EB weight was then calculated for each site using Equation 14. Then, the EB-adjusted number of expected crashes for 2003 was computed for each site using Equation 15. The yearly correction factor for the last year, 2007, was then applied to obtain the EB-adjusted expected number of crashes for 2007 (see Equation 16). The excess crash frequency for each site was then calculated using Equation 17. These values represented the PSI for each site for total crashes.

$$k_{y(TOT)} = c_{yTOT} \times e^{a} \times AADT^{b} \times SL \qquad \text{[Eq. 12]}$$

$$C_{y(TOT)} = \frac{k_{y(TOT)}}{k_{1(TOT)}} \qquad \text{[Eq. 13]}$$

$$w_{TOT} = \frac{1}{1 + d_{TOT} \sum_{y=1}^{Y} k_{y(TOT)}} \qquad \text{[Eq. 14]}$$

$$X_{1(TOT)} = w_{TOT} k_{1(TOT)} + (1 - w_{TOT}) \frac{\sum_{y=1}^{Y} K_{y(TOT)}}{\sum_{y=1}^{Y} C_{y(TOT)}} \qquad \text{[Eq. 15]}$$

$$X_{Y(TOT)} = X_{1(TOT)} C_{Y(TOT)} \qquad \text{[Eq. 16]}$$

$$Excess_{Y(TOT)} = X_{Y(TOT)} - k_{Y(TOT)} \qquad \text{[Eq. 17]}$$

where

c_{yTOT} = calibration factor for total crashes for year y
C_{yTOT} = yearly correction factor
k_{yTOT} = expected number of crashes at a site during year y (from adjusted SPF)
k_{1TOT} = expected number of crashes at a site during year 1 (from adjusted SPF)
K_{yTOT} = observed number of crashes at a site during year y
a, b = regression parameters
AADT = average annual daily traffic (vehicles per day)
SL = segment length (mi)
w_{TOT} = EB weight
X_y = EB-adjusted number estimated number of crashes for year y
$X_{1(TOT)}$ = EB-adjusted number estimated number of crashes for year 1.

Had the SafetyAnalyst approach been followed, the next step would have been to divide the excess crash frequency of each site by the length of its respective sliding window to express the excess frequency on a per mile basis (FHWA, 2006). However, for the purposes of this study, it was uncertain whether this normalization step was appropriate. With the normalization, PSI would be presented on a per mile basis. Without the normalization, PSI would be presented on a per site basis. Instead of assuming which form would be more meaningful, both options were explored. First, site lists were created so that each list comprised 5% of the centerline mileage of each roadway category and contained sites with the highest PSI per site. Similarly, site lists were created containing sites with the highest PSI per mile. Thus, the result was two alternative prioritized site lists for each roadway category. The alternative site lists were then analyzed to identify similarities and differences.

The last major task in this study was to compare these SPF-based site prioritization methods with the critical rate method currently used by VDOT. For this objective, the critical rate method was applied to the Tier 1 aggregated database of the primary system. The critical rate was computed for each site in each roadway category using Equation 18. The actual crash rate was then calculated for each site. Tier 1 aggregated sites were then ranked by the ratio of the actual crash rate to critical rate. Lists were then generated with the top 5% of these sites for each roadway type. These crash rate-derived site lists were compared to the normalized and non-normalized SPF-derived site lists. The comparison was performed by calculating the total PSI for each top 5% list along with the overall average PSI per site in each list.

$$CR = AVR + \frac{0.5}{TB} + TF\sqrt{\frac{AVR}{TB}} \qquad \text{[Eq. 18]}$$

where

CR = critical crash rate, per 100 million VMT
AVR = average crash rate in each district for each facility type per 100 million VMT
TB = traffic base at site, per 100 million VMT
TF = test factor (1.96 assumed for a 95% confidence level).

The purpose of this was to compare differences between the site lists generated from SPF-based prioritization methods and the critical rate method. More specifically, this comparison was intended to show which method more effectively identified sites with a high PSI.

RESULTS AND DISCUSSION

SPF Model Form

A literature review was conducted to identify candidate SPF models that could be adopted for intermediate-length analysis of roadway sections. Literature on estimating the safety performance of transportation facilities dates back more than two decades and covers a range of facility types. In one of the earliest examples, Hauer et al. (1988) investigated the safety performance of signalized intersections. Additional research on estimating the safety performance of intersections was conducted by Kulmala (1995) and Poch and Mannering (1996). Although numerous sources of research regarding the estimation of safety performance were found, most of the literature was not directly relevant to the scope and context of this study. For the purposes of this study, three major sources of SPF research were found to be especially useful. In contrast to many other sources, these three studies provided a wealth of information regarding the safety performance modeling of roadway segments and represented some of the most recent research in this area. Moreover, each source had implementation software. This factor was an extremely important consideration for this study because the results of this research need to be implemented by TED. The SPFs in each of these three sources were examined carefully to assess their suitability for this study.

FHWA sponsored two of the three studies. One developed the software suite known as the Interactive Highway Safety Design Model (IHSDM), and the other created the software package known as SafetyAnalyst. Neither software is solely designed to model safety performance, but both have a component in their software suite with that capability. The third study is a joint study between the Transportation Research Board and the American Association of State and Highway Transportation Officials (AASHTO) to compose the *Highway Safety Manual* (HSM) (AASHTO, 2010). Like the IHSDM and SafetyAnalyst, the HSM provides a means of estimating the expected safety performance of road segments. The IHSDM is the designated software for the implementation of the HSM.

It is important to note that at the very beginning of this study, TED expressed a strong preference for receiving SPF research that was compatible with SafetyAnalyst since TED plans to use this program heavily in the future. As a consequence, the outcome of any subsequent comparative analyses of these SPF sources was largely predetermined. Nonetheless, the three sources were compared to learn about the different SPF modeling approaches.

The IHSDM, SafetyAnalyst, and the HSM each developed a set of road segment SPFs and formulated a methodology to adapt their SPFs for use by other agencies. The methodologies have differing areas of application, regression models, calibration requirements, and model fit. The regression models assumed by each differ mainly in terms of variables selected for inclusion into their general model form. The calibration requirements for adapting each source's SPFs also vary in terms of data intensity and complexity.

IHSDM SPFs

The IHSDM was developed to support detailed analyses of specific design alternatives. As a result, it assumes that detailed data on a roadway is available and the models are very data intensive. In the initial release of the IHSDM, SPFs were developed only for rural two-lane highways (Turner-Fairbank Highway Research Center, 2008). Its SPF model is shown in Equation 19, and the meaning of each variable is given in Table 7 (Harwood et al., 2000). If baseline conditions are assumed for all variables other than exposure, Equation 19 reduces to a baseline SPF model, i.e., Equation 20. Accident modification factors (AMFs) can then be applied to the baseline SPF model for certain roadway features that reflect local conditions (Harwood et al., 2000). At a minimum, the IHSDM calibration procedure requires reliable traffic volume and crash record data. Although it is not necessary, the calibration procedure can be improved if roadway width, shoulder width, vertical curvature, horizontal curvature, and access point data are available. When the calibration factors and AMFs are included in the baseline model, the resulting SPF model is Equation 21.

The model fit of the IHSDM SPF is summarized in Table 8 (Harwood et al., 2000), and Equation 22 illustrates how the GOF statistic R_{LR}^2 is computed. The IHSDM SPF was data intensive and required many elements that are not commonly available in VDOT databases. The data requirements of this model, coupled with the fact that models exist only for rural two-lane highways, made it difficult to adopt the IHSDM model form for this study.

Table 7. Definition of Variables in the IHSDM Safety Performance Function Model

N_{br}	Predicted number of total accidents per year on a particular roadway segment
EXPO	Exposure in million VMT per year = (ADT)(365)(L)(10^{-6})
ADT	Average daily traffic volume (veh/day) on roadway segment
L	Length of roadway segment (mi)
STATE	Location of roadway segment (0 in Minnesota, 1 in Washington)
LW	Lane width (ft); average lane width if the two directions of travel differ
SW	Shoulder width (ft); average shoulder width if the two directions of travel differ
RHR	Roadside hazard rating; this measure takes integer values from 1 to 7 and represents the average level of hazard in the roadside environment along the roadway segment
DD	Driveway density (driveways per mile) on the roadway segment
W_{hi}	Weight factor for the i^{th} horizontal curve in the roadway segment; the proportion of the total roadway segment length represented by the portion of the i^{th} horizontal curve that lies within the segment. (The weights, WH_i, must sum to 1.0.)
DEG_i	Degree of curvature for the i^{th} horizontal curve in the roadway segment (degrees per 100 ft)
WV_j	Weight factor for the j^{th} crest vertical curve in the roadway segment; the proportion of the total roadway segment length represented by the portion of the j^{th} crest vertical curve that lies within the segment. (The weights, WV_j, must sum to 1.0.)
V_j	Crest vertical curve grade rate for the j^{th} crest vertical curve within the roadway segment in percent change in grade per 31 m (100 ft) = $\lvert g_{j2}-g_{j1}\rvert/l_j$
g_{jl}, g_{j2}	Roadway grades at the beginning and end of the j^{th} vertical curve (%)
l_j	Length of the j^{th} vertical curve (in hundreds of feet)
WG_k	Weight factor for the k^{th} straight grade segment; the proportion of the total roadway segment length represented by the portion of the k^{th} straight grade segment that lies within the segment. (The weights, WG_k, must sum to 1.0.)
GR_k	Absolute value of grade for the k^{th} straight grade on the segment (%)

IHSDM = Interactive Highway Safety Design Model.
Source: Harwood, D.W., Council, F.M., Hauer, E., Hughes, W.E., and Vogt, A. *Prediction of the Expected Safety Performance of Rural Two-Lane Highways*. FHWA-RD-99-207. Federal Highway Administration, Washington, DC, 2000.

Table 8. Model Fit of the IHSDM Two-Lane Road Segment Safety Performance Function

Goodness of Fit	
R^2	R_{LR}^2
0.6547	0.8291

IHSDM = Interactive Highway Safety Design Model.
Source: Harwood, D.W., Council, F.M., Hauer, E., Hughes, W.E., and Vogt, A. *Prediction of the Expected Safety Performance of Rural Two-Lane Highways*. FHWA-RD-99-207. Federal Highway Administration, Washington, DC, 2000.

$$N_{br} = EXPO \times \exp(0.6409 + 0.1388STATE - 0.0846LW - 0.0591SW + 0.0668RHR + 0.0084DD) \times (\sum WH_i \exp(0.0450DEG_i)) (\sum WV_j \exp(0.4652 V_j))(\sum WG_k \exp(0.1048GR_k)) \quad \text{[Eq. 19]}$$

$$N_{br} = (ADT)(L)(365)(10^{-6}) \exp(-0.4865) \quad \text{[Eq. 20]}$$

$$N_{rs} = N_{br} \times C_r (AMF_{1r} \cdot AMF_{2r} \cdots AMF_{nr})$$ [Eq. 21]

$$R_{LR}^2 = 1 - k/k_{max}$$ [Eq. 22]

where

N_{rs} = predicted number of total accidents per year on a segment after calibration for the state and adjustment for local conditions
N_{br} = predicted number of total accidents per year on a particular roadway segment assuming base conditions
ADT = average daily traffic (veh/day)
L = segment length (mi)
C_r = calibration factor developed for use by a particular highway agency
AMF_{1r}, …AMF_{nr} = accident modification factors for various roadway features
k = overdispersion parameter of a regression model
k_{max} = overdispersion parameter in a model with no covariates.

Subsequent expansions to the IHSDM have added models that cover rural multilane, urban arterial, and suburban arterial roads. Those models are identical with those adopted by the HSM (AASHTO, 2010), which are discussed later.

SafetyAnalyst SPFs

In contrast to the IHSDM, SafetyAnalyst was developed to support a broader analysis of safety across an agency's roadway network. It is intended to identify sites with promise for crash reductions through engineering interventions and for prioritization of sites. As a result, SafetyAnalyst developed SPF models that are applicable to a wide range of roadway types. Table 9 summarizes all possible road segment types for which models were developed. Equation 23 shows the SPF model form selected for use by SafetyAnalyst (FHWA, 2006). Table 10 shows Freeman-Tukey R^2 values for the SafetyAnalyst SPF models relevant to this study alongside the specific models adopted by SafetyAnalyst for use in the software (FHWA, 2006). Table 10 also shows that model fits are generally better for rural segments than for urban segments.

Table 9. Roadway Types Covered by SafetyAnalyst's Safety Performance Functions

Rural	Urban
Two-lane	Two-lane arterial
Multilane undivided	Multilane undivided arterial
Multilane divided	Multilane divided arterial
Freeway with 4 lanes	One-way arterial
Freeways with 6 or more lanes	Freeways with 4 lanes
Freeways within interchange area with 4 lanes	Freeways with 6 lanes
Freeways within interchange area with more than 6 lanes	Freeways with 8 or more lanes
	Freeways within interchanges with 4 lanes
	Freeways within interchanges with 6 lanes
	Freeways within interchange with 8 or more lanes

Source: Federal Highway Administration. *SafetyAnalyst User's Manual.* Turner-Fairbank Highway Research Center, McLean, VA, 2006.

$$\kappa = e^{\alpha} \times ADT^{\beta 1} \times SL \quad \text{[Eq. 23]}$$

where

ADT = average daily traffic (veh/day)
SL= segment length (mi)
α = intercept
β_1 = coefficient of ADT.

Table 10. Freeman-Tukey Values for SafetyAnalyst's Segment-Based Safety Performance Functions

Site Description	State	Crash Severity	Safety Performance Function	R_{FT}^2
Rural two-lane	Ohio	Total	$\kappa = e^{-3.63} \times AADT^{0.53} \times SL$	0.725
		FI	$\kappa = e^{-4.86} \times AADT^{0.53} \times SL$	0.599
Rural multilane undivided arterials	North Carolina	Total	$\kappa = e^{-3.17} \times AADT^{0.49} \times SL$	0.465
		FI	$\kappa = e^{-4.20} \times AADT^{0.50} \times SL$	0.459
Rural multilane divided arterials	Minnesota	Total	$\kappa = e^{-5.05} \times AADT^{0.66} \times SL$	0.498
		FI	$\kappa = e^{-7.46} \times AADT^{0.72} \times SL$	0.372
Urban two-lane	Ohio	Total	$\kappa = e^{-7.16} \times AADT^{0.84} \times SL$	0.136
		FI	$\kappa = e^{-8.84} \times AADT^{0.89} \times SL$	0.140
Urban multilane undivided arterials	Washington	Total	$\kappa = e^{-10.24} \times AADT^{1.29} \times SL$	0.235
		FI	$\kappa = e^{-12.07} \times AADT^{1.39} \times SL$	0.258
Urban multilane divided arterials	Ohio	Total	$\kappa = e^{-11.85} \times AADT^{1.34} \times SL$	0.014
		FI	$\kappa = e^{-14.87} \times AADT^{1.52} \times SL$	0.022

FI = Fatal + Injury.
Source: Federal Highway Administration. *SafetyAnalyst User's Manual.* Turner-Fairbank Highway Research Center, McLean, VA, 2006.

The SafetyAnalyst SPFs have several distinct advantages. Distinct models do exist in SafetyAnalyst for every roadway type to be modeled in this study. The SPF model form is also simple and can be used with easily obtainable data elements. The disadvantage of the SafetyAnalyst SPFs is that they do not include many roadway attributes that could play a strong role in safety. For example, no consideration of roadway geometry, cross section, or speed is included.

HSM SPFs

The HSM (AASHTO, 2010) developed SPFs for the following roadway types: non-limited access urban and suburban arterial highways, rural two-lane highways, and nonlimited-access rural multilane highways (Lord et al., 2008). The SPFs for urban and suburban arterial multi-vehicle and single-vehicle crashes are given in Equations 24 and 25 (Harwood et al., 2007). Assuming baseline conditions, Equations 24 and 25 become Equation 26. For rural two-lane highways, the HSM uses the IHSDM's SPF model. Assuming baseline conditions and no covariates, the HSM's SPF models for rural multilane highways also take the form of Equation 26 (Lord et al., 2008). If covariates are included in the rural multilane SPFs, lane width, shoulder width, intersection density, and horizontal curve density are added to the regression model as independent variables and coefficients are estimated for each. With respect to the calibration of the model, a general procedure has not yet been published. When including the AMFs and calibration factor, the HSM SPF model takes the form of Equation 27.

$$N_{brmv} = \exp\,(a + b\ \ln ADT + \ln L + c\ SW + d\ OSP) \quad \text{[Eq. 24]}$$

$$N_{brsv} = \exp\,(a + b\ \ln ADT + \ln L + c\ SW + d\ OSP + e\ RHR) \quad \text{[Eq. 25]}$$

$$N_{base} = \exp\,(a + b\ \ln ADT + \ln L) \quad \text{[Eq. 26]}$$

$$N = N_{base} \times C\ (AMF_1 AMF_2 ... AMF_n) \quad \text{[Eq. 27]}$$

where

N_{brmv} = predicted number of multi-vehicle accidents per year for a segment
N_{brsv} = predicted number of single-vehicle accidents per year for a segment
N_{base} = predicted number of vehicle accidents per year assuming base conditions
N = predicted number of vehicle accidents per year with calibration and AMFs
ADT = average daily traffic volume (veh/day) for roadway segment
L = length of roadway segment (mi)
SW = shoulder width (ft)
OSP = availability of on-street parking (dummy variable)
RHR = Roadside Hazard Rating (scale of 1 to 7)
a,…,d = regression coefficients determined by model fitting
C = calibration factor.

The HSM models offer an intermediate alternative to the IHSDM and SafetyAnalyst. Data requirements are more intensive than in SafetyAnalyst, and individual models are not available for all roadway types of interest in this study. The models do incorporate consideration of certain roadway characteristics that could impact safety that are not included in SafetyAnalyst.

Assessment of Models

After evaluation of the IHSDM, SafetyAnalyst, and the HSM candidate SPF models based on the four criteria described earlier, the SPF model form from SafetyAnalyst was deemed most appropriate for this study. With regard to the first criterion, the feasibility of meeting data requirements, this candidate was clearly superior. Alternative model forms were far more data intensive since they required data on a number of roadway characteristics, which often were not in existing VDOT databases.

As for the second criterion of versatility, SafetyAnalyst again performed better than the alternatives. SafetyAnalyst had applied the same SPF model form successfully to all the roadway types and severity levels required for this study. Further, the SafetyAnalyst model form was not restricted to particular functional classifications as were the urban and suburban arterial models. Its applications extended to collectors and local roads as well as arterials.

With regard to the third criterion, the evaluation results were far less definitive. Multiple factors complicated the comparative analysis of model fit. The difficulty in evaluating candidates in terms of model fit was due, in part, to differences in how roadway types were defined. In many cases, one-to-one comparisons of model fit could not be made among the various candidates. Even when they could be made, there was another difficulty. Different sources of SPFs used different metrics to assess model fit. For example, SafetyAnalyst relied on the Freeman-Tukey R^2 measure whereas other models may have used the Pearson correlation coefficient (Pearson R^2), MSPE, or other metrics. Therefore, no SPF source was judged superior with respect to this criterion because of the lack of consistent comparative data.

The evaluation results based on the fourth criterion, ease of implementation, were more clear and decisive. Once again, the SafetyAnalyst SPF model form proved to be superior. The deployment potential for alternative models seemed quite limited compared to that of SafetyAnalyst. SafetyAnalyst software was capable of applying its SPF model form to analyze all six roadway types addressed in this study as well as a host of others. Selecting the SafetyAnalyst model form for this study could, therefore, simplify the integration of the study's results with those of future studies for other roadway types in Virginia (e.g., expressways). Although SPF coefficients could be changed in the SafetyAnalyst software, the underlying model form cannot currently be altered. This made it impossible to apply model forms that differed from the default SafetyAnalyst model form in the software.

Overall, SafetyAnalyst's regression model proved most suitable to this study based on this multifaceted evaluation. Not only did it require the least amount of input data, it also demonstrated high versatility and ease of implementation while producing an acceptable model fit. For these reasons, the SafetyAnalyst model form was selected, and all SPFs developed in this study take the form of the regression models in SafetyAnalyst as expressed in Equation 23.

Data Preparation

There were two stages to the data preparation step. First, the HTRIS roadway inventory had to be linked to the TMS AADT data. Second, the resulting HTRIS-TMS database had to be linked with the VDOT crash data.

Linking of HTRIS Roadway Inventory to TMS AADT Data

The first stage of this integration process presented multiple challenges. First, some links did not have any corresponding AADT information. Since AADT was a critical variable for the model, links without AADT information were deleted. Fortunately, this problem affected only about 2.3% of the primary road links in the roadway inventory database. There was also another variation of this problem. In some cases, AADT data on a link existed in some years but not in others. For example, AADT data may have existed for 2003, 2004, and 2007 but not for 2005 and 2006. This problem affected 2.7% of the roadway inventory links. Each instance of this problem was treated differently. If traffic volume data were missing from either 2003 or 2007, the corresponding HTRIS link was deleted. If 1 or 2 years of traffic data were missing from 2004, 2005, or 2006, AADT values were linearly interpolated for the missing values using the existing three or four AADT values. This occurrence was rare. If more than 2 years of traffic data were missing, the corresponding HTRIS link was deleted.

Yet another problem was encountered when combining the HTRIS and TMS data. In the case of some HTRIS links, there were drastic fluctuations in the corresponding TMS traffic volume data at some time during the 5-year period under consideration. To be more specific, any change of 50% in AADT or more from one year to the next was deemed a drastic fluctuation. Such large changes raised suspicions regarding the accuracy of the traffic volume data. As a consequence, these particular roadway segments were analyzed to determine the cause of the fluctuations. A minority of these cases was found to be related to construction activity in which land development in the vicinity of the roadway explained the fluctuations. Since the remaining portion had inexplicable, large changes in traffic volume, they were deleted. After these and other minor issues were addressed, a database had been produced that joined the TMS traffic links to the HTRIS roadway inventory links.

Linking Resulting HTRIS-TMS Database with VDOT Crash Data

The second stage in the construction of an integrated database was to join the VDOT crash data to the combined HTRIS-TMS database. The integrated database needed to derive two bits of information from the crash database: the annual crash counts for each HTRIS link, and the annual FI crash counts for each HTRIS link. This process presented its own set of problems. One problem was that a small portion of the crash data was invalid or unreliable. The other problem was that crash data were missing for some parts of the primary system.

Invalid or unreliable crash data were identified by comparing data fields common to the crash database and the HTRIS database and checking for inconsistencies. Slightly more than 1% of the crash records over the 5-year period had an inconsistency with the HTRIS database in one or more data fields. The most common form of inconsistency was in the facility type data field. For example, a crash record might have indicated that the crash occurred on a divided roadway segment and the HTRIS database indicated the segment was undivided or vice versa. In instances of this nature, the crash data from these flawed crash records were not included in the final integrated database.

The crash database was also tested for completeness. It was during this data quality test that a second problem was discovered with the crash database. When crash data were queried by one particular field, i.e., government level of control, a section of the primary system was found to be missing virtually all crash data. This portion of the primary system was known as urban extensions–primary routes. These roads are technically within the limits of municipalities; however, their maintenance is provided by VDOT through mutual agreements (VDOT, 2007). Since they are in the jurisdiction of municipalities, no location data were associated with any crash reports for these areas. Urban extensions comprise approximately 1,000 mi of the roughly 8,000 centerline miles of primary system and more than 6,000 of its roughly 30,000 HTRIS links. Although removing this section of the primary system from the study significantly reduced the sample size of data available for SPF generation, there was no recourse since crashes could not be located. All other deletions described earlier, cumulatively, had removed an additional 1,700 HTRIS links, meaning that the resulting database contained 22,217 HTRIS links. At this point, an integrated database had been produced for the primary system with all geometric, traffic volume, and crash data necessary to generate SPFs.

Stratification of Data

As described earlier, the Virginia primary system was stratified by roadway type and geographic region. Before geographical divisions were considered, the entire statewide database was stratified by roadway type. Table 11 summarizes the resulting sample sizes of roadway inventory, traffic volume, and crash data for each of the six major roadway types examined in this study. Geographic divisions were then imposed to create the three major geographic regions defined earlier: North, West, and East/Central. Tables 12, 13, and 14 show the resulting sample sizes of roadway inventory, traffic volume, and crash data for those three geographic regions.

Table 11. Data Sample Sizes by Roadway Type in Entire State

Region	Rural/ Urban	Class	No. of Centerline Miles	No. of HTRIS Roadway Inventory Links	No. of TMS AADT Links	No. of Crashes 2003-2007	No. of Fatal + Injury Crashes 2003-2007
State	Rural	Two-lane	4579.48	11587	1611	39302	16249
		Multilane divided	1311.58	3932	643	25292	10353
		Multilane undivided	256.01	1039	239	4176	1687
	Urban	Two-lane	261.66	1572	215	8005	3051
		Multilane divided	398.02	3186	432	54015	18745
		Multilane undivided	105.51	901	146	12039	4614
	Total		6912.26	22217	3286	142829	54699

HTRIS = Highway Traffic Records Information System; TMS = Traffic Monitoring System; AADT = annual average daily traffic.

Table 12. Data Sample Sizes by Roadway Type for North Region

Region	Rural/ Urban	Class	No. of Centerline Miles	No. of HTRIS Roadway Inventory Links	No. of TMS AADT Links	No. of Crashes 2003-2007	No. of Fatal + Injury Crashes 2003-2007
North	Rural	Two-lane	399.24	1019	141	6729	2457
		Multilane divided	166.02	475	76	5273	1840
		Multilane undivided	7.49	28	7	236	83
	Urban	Two-lane	53.64	323	42	2418	840
		Multilane divided	142.5	1310	141	24821	8824
		Multilane undivided	45.33	425	47	7838	3072
	Total		814.22	3580	454	47315	17116

HTRIS = Highway Traffic Records Information System; TMS = Traffic Monitoring System; AADT = annual average daily traffic.

Table 13. Data Sample Sizes by Roadway Type for West Region

Region	Rural/ Urban	Class	No. of Centerline Miles	No. of HTRIS Roadway Inventory Links	No. of TMS AADT Links	No. of Crashes 2003-2007	No. of Fatal + Injury Crashes 2003-2007
West	Rural	Two-lane	2996.46	7458	1023	24385	10254
		Multilane divided	677.25	2150	330	12563	5335
		Multilane undivided	131.52	550	135	2064	833
	Urban	Two-lane	86.01	507	91	2173	884
		Multilane divided	99.54	699	129	7950	2699
		Multilane undivided	25.59	199	45	1379	470
	Total		4016.37	11563	1753	50514	20475

HTRIS = Highway Traffic Records Information System; TMS = Traffic Monitoring System; AADT = annual average daily traffic.

Table 14. Data Sample Sizes by Roadway Type for East/Central Region

Region	Rural/ Urban	Class	No. of Centerline Miles	No. of HTRIS Roadway Inventory Links	No. of TMS AADT Links	No. of Crashes 2003-2007	No. of Fatal + Injury Crashes 2003-2007
East/ Central	Rural	Two-lane	1183.78	3110	447	8188	3538
		Multilane divided	468.31	1307	237	7456	3178
		Multilane undivided	117	461	97	1876	771
	Urban	Two-lane	122.01	742	82	3414	1327
		Multilane divided	155.98	1177	162	21244	7222
		Multilane undivided	34.59	277	54	2822	1072
	Total		2081.67	7074	1079	45000	17108

HTRIS = Highway Traffic Records Information System; TMS = Traffic Monitoring System; AADT = annual average daily traffic.

A notable finding of site stratification was that the roadway types in certain geographic regions had extremely limited sample sizes. The most extreme example was the rural multilane undivided roadway type in the North region. With only 28 total sites covering 7.49 mi of roadway, the sample size of data for this category was extremely small. This finding was important because of its implications with regard to SPF model construction. Such a small sample size of data would make the regression analysis unstable and cast doubt on the validity of any SPF model produced from that regional data.

Site Aggregation

Before examining the results of site aggregation, it is important to note that site aggregation was performed only on a statewide basis. Aggregating regional data produced sample sizes that were unacceptably small for some roadway classes. Prior to presentation of the overall, general effects of site aggregation on the data, an illustration is provided to show how site aggregation affects a particular stretch of highway. Table 15 shows how Tier 1 and 2 aggregations combine disaggregate links for U.S. 29 in the Northern Virginia District. The functional classification data field ensures that rural and urban sites are not aggregated together. For Tier 1 aggregation, the lane data field terminates aggregation when the number of lanes changes. For Tier 2 aggregation, this data field terminates aggregation only when a two-lane site becomes a multilane site or vice versa. The facility data field terminates aggregation whenever a divided site becomes undivided or vice versa and also filters out any sites with full or partial control of access. The AADT data field determines whether aggregation should be terminated based on traffic volume. Finally, a combination of data fields (route prefix, route number, route suffix, start mile post, and end mile post) checks for geographic proximity and continuity. The results in Table 15 clearly show that the aggregation process results in many short links being combined into a homogeneous longer link.

Table 15. Demonstration of Site Aggregation[a]

Route Prefix	Route No.	Start MP	End MP	Functional Classification	No. of Lanes	Facility Type	2007 AADT	No. of 2007 Fatal + Injury Crashes	No. of 2007 Total Crashes
Disaggregate Sites									
US	29	224.81	225.08	E	3	1	18087	1	3
US	29	225.08	225.1	E	4	1	18087	0	0
US	29	225.1	225.13	E	4	1	18087	0	1
US	29	225.13	225.6	E	4	1	18087	2	3
US	29	225.6	225.65	E	4	1	18087	0	0
US	29	225.65	225.72	E	4	1	18087	0	1
US	29	225.72	225.83	E	4	1	18087	1	3
US	29	225.83	225.85	E	4	1	18087	0	0
US	29	225.85	226.13	E	4	1	18087	0	2
US	29	226.13	226.41	E	4	1	18087	0	1
US	29	226.41	226.43	E	4	1	18087	0	0
US	29	226.43	226.46	E	4	1	18087	0	0
US	29	226.46	226.5	E	4	1	18087	0	1
US	29	226.5	226.62	E	4	1	18087	0	1
US	29	226.62	226.76	E	4	1	18087	1	2
US	29	226.76	226.79	E	4	1	18087	1	3
US	29	226.79	226.95	E	4	1	18087	0	1
US	29	226.95	227	E	4	1	18087	0	0
US	29	227	227.23	E	4	1	18087	0	2
After Tier 1 Aggregation									
US	29	224.81	225.08	E	3	1	18087	1	3
US	29	225.08	227.23	E	4	1	18087	7	32
After Tier 2 Aggregation									
US	29	224.81	227.23	E	Multi	1	18087	8	35

MP = mile post, AADT = annual average daily traffic.
[a]Functional classification and facility type codes are defined in Tables 2 and 3, respectively.

Table 16 summarizes the effects of Tier 1 and 2 aggregation on the six roadway types. It shows that the number of sites prior to site aggregation was simply the number of disaggregate roadway inventory links. Site aggregation combined the disaggregate roadway inventory links whenever possible in accordance with the rules outlined earlier to produce sites that were fewer in number but greater in length. Both Tier 1 and 2 aggregations greatly reduced the number of sites. As expected, Tier 2 aggregation produced a higher level of aggregation. As may be seen, the number of aggregated sites is always greater than the number of TMS AADT links, with changes in AADT terminating aggregation as explained earlier. Therefore, under no circumstance could the aggregation process combine links to produce fewer sites than there were distinct TMS AADT links.

Table 17 provides additional information on the impact of the aggregation process. Since aggregation decreased the number of sites without affecting the total number of centerline miles in the system, the average lengths of the aggregated sites were generally far greater than those of the disaggregated sites. Table 17 shows that aggregation always increased the mean site length for each roadway type. Aggregation did not, however, eliminate all extremely short links since the minimum site length of every road type remained unchanged. Table 17 also shows that the differences between Tier 1 and 2 aggregations were minor in some cases and nonexistent in others. Specifically, in the case of the rural and urban two-lane categories, Tier 1 and 2 aggregation produced identical outcomes.

Table 16. Number of Sites by Different Aggregation Levels

Roadway Type	No. of Centerline Miles	No. of TMS AADT Links	No. of Sites		
			Pre-Aggregation	Tier 1 Aggregation	Tier 2 Aggregation
Rural two-lane	4579.48	1611	11587	1698	Same as Tier 1
Rural multilane divided	1311.58	643	3932	761	697
Rural multilane undivided	256.01	239	1039	295	281
Urban two-lane	261.66	215	1572	231	Same as Tier 1
Urban multilane divided	398.02	432	3186	615	462
Urban multilane undivided	105.51	146	901	180	167
Total	6912.26	3286	22217	3780	3536

TMS = Traffic Monitoring System, AADT = annual average daily traffic.

Table 17. Effect of Aggregation on Site Lengths

Roadway Type	Pre-Aggregation Lengths (mi)			Tier 1 Lengths (mi)			Tier 2 Lengths (mi)		
	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	Mean
Rural two-lane	0.01	10.35	0.4	0.01	12.7	2.7	Same as Tier 1		
Rural multilane divided	0.01	3.29	0.33	0.01	9.6	1.72	0.01	9.6	1.88
Rural multilane undivided	0.01	3.83	0.25	0.01	6.29	0.87	0.01	6.29	0.91
Urban two-lane	0.01	2.34	0.17	0.01	5.73	1.13	Same as Tier 1		
Urban multilane divided	0.01	1.74	0.12	0.01	7.07	0.65	0.01	7.26	0.86
Urban multilane undivided	0.01	2.08	0.12	0.01	3.07	0.59	0.01	3.07	0.63

Table 18 reveals another significant effect of site aggregation. The table shows the negative binomial dispersion parameters for every statewide dataset before and after site aggregation. The dispersion parameters for the aggregated sites are consistently lower than those for the disaggregate sites. Since the variance of a negative binomial distribution is a function of its negative binomial dispersion parameter and its mean, the lower dispersion parameters indicate that site aggregation substantially reduced the variance of every dataset. This result is not surprising in light of the assertions put forth by Lord et al. (2005). They claimed that overdispersion, characterized by excess zeros, may be caused by "sites with a combination of low exposure, high heterogeneity" and "analyses with small time or spatial scales." It is not unreasonable to assume that site aggregation mitigated the effects of both of these factors by increasing the site exposure levels and the spatial scale of analysis. It is also noteworthy to compare the Tier 1 and 2 dispersion parameters. In five of eight cases, the Tier 2 dispersion parameters actually were slightly higher. In the three other cases, however, the Tier 2 dispersion parameters were lower. This result indicates that the additional aggregation that occurred with the Tier 2 approach relative to the Tier 1 approach had a negligible to slightly negative effect. It also suggests that the Tier 2 approach of combining multilane links and combining links with different functional classifications may not have been appropriate. Links may have been combined when they should not have been, increasing the variance of the category's crash data.

Table 18. Negative Binomial Dispersion Parameter by Site Aggregation Level

Model				Dispersion Parameter		
Region	**Rural/ Urban**	**Class**	**Crash Type**	**Pre-Aggregation**	**Tier 1 Aggregation**	**Tier 2 Aggregation**
State	Rural	Two-lane	Total	0.5498	0.19	Same as Tier 1
			FI	0.5204	0.1767	
		Multilane divided	Total	0.8451	0.3095	0.3156
			FI	0.8602	0.1843	0.1946
		Multilane undivided	Total	1.1617	0.4373	0.3688
			FI	1.1307	0.2984	0.3228
	Urban	Two-lane	Total	1.0419	0.3749	Same as Tier 1
			FI	0.9393	0.282	
		Multilane divided	Total	1.2956	0.8014	0.728
			FI	1.4103	0.6399	0.5526
		Multilane undivided	Total	1.3506	0.6446	0.6564
			FI	1.3018	0.5289	0.5407

FI = Fatal + Injury.

Data Assignment to Estimation and Validation Datasets

As described earlier, random sampling was used in SAS to divide every dataset into an estimation set (consisting of 70% of the data) and a validation set (consisting of 30% of the data). To help ensure that the estimation datasets and their corresponding validation datasets were similar with respect to traffic volume and crash occurrence, nonparametric tests were performed using a 0.20 significance level. Whenever the two-sided *p*-value for a nonparametric test was below 0.20, the random sampling was repeated.

There were, however, two exceptions to this rule in the regional datasets. In the North region urban multilane undivided disaggregate dataset, the highest two-sided p-value from repeated random samplings for the Kuiper test on traffic volume was 0.1991. The other nonparametric tests for this random sampling produced *p*-values higher than 0.40. Such high *p*-values in all the other nonparametric tests strongly contradicted the Kuiper test results. Further, the Kuiper test results could have been due to the low sample size because this regional dataset covered a relatively small number of centerline miles of roadway (see Table 12). Therefore, this exception was allowed. In the East urban multilane undivided disaggregate dataset, the highest two-sided *p*-value from repeated random samplings for the Kuiper test on traffic volume was 0.0947. This exception was permitted for the same reasons that the previous exception was allowed. The two anomalies in the regional disaggregate database notwithstanding, the separation of data into estimation and validation datasets proceeded smoothly. This result was crucial because improper assignment of data into estimation and validation datasets would have adversely impacted the regression analysis and GOF evaluation.

SPF Development Using Disaggregate Data

Through the use of GEEs in SAS, SPFs were first generated for the disaggregate data. As stated earlier, each of these SPFs took the SafetyAnalyst SPF model form shown in Equation 28. More precisely, SPFs were generated using the estimation datasets in the disaggregate database. SAS provided an estimate for the two regression parameters required for the selected model form as well as the standard error of each estimated parameter. An SPF was generated for each of the six major roadway types based on statewide data, and Table 19 shows the regression parameters and standard errors for the resulting statewide models. Afterward, SPFs were generated for each of the three geographic regions defined earlier. Tables 20, 21, and 22 show the estimated regression parameters and standard errors for the North, West, and East/Central regions, respectively. The four tables also indicate the number of sites in the estimation and validation datasets.

$$\kappa = e^{a} \times ADT^{b} \times SL \qquad \text{[Eq. 28]}$$

where

κ = predicted number of accidents at a site per year
a = intercept
b = coefficient of ADT
ADT = average daily traffic of a site (veh/day)
SL = segment length (mi).

Figures 2 through 5 graphically illustrate a few representative SPF models. In every graph, each regional SPF curve extends only to the maximum AADT observed in its regional database. For example, the SPF for the West region in Figure 2 extends only to an AADT of 25,482 because that was the maximum AADT for rural two-lane roads in the West region. Although not shown in any of the tables, the *p*-value for all regression parameters in this study was 0.0001. This result indicated that the AADT and the intercept were statistically significant factors in every dataset.

Table 19. Safety Performance Functions Based on Statewide Disaggregate Data

Model Definition				GEE Parameter Estimates		Standard Error		No. of Sites in Estimation and Validation Sets	
Region	Rural/ Urban	Class	Crash Type	a	b	a	b	70%	30%
State	Rural	Two-lane	Total	-6.2083	0.8467	0.1429	0.0178	8111	3476
			FI	-6.4065	0.7606	0.162	0.0199	8111	3476
		Multilane divided	Total	-7.1042	0.9198	0.4737	0.0505	2753	1179
			FI	-7.9927	0.9108	0.5322	0.0563	2753	1179
		Multilane undivided	Total	-7.7241	1.0140	0.6188	0.0691	728	311
			FI	-9.3341	1.0838	0.7503	0.0831	728	311
	Urban	Two-lane	Total	-6.0865	0.8916	0.4617	0.0511	1101	471
			FI	-6.7668	0.8525	0.6099	0.0665	1101	471
		Multilane divided	Total	-6.5292	0.9764	0.5803	0.0564	2231	955
			FI	-7.7037	0.9834	0.5801	0.0561	2231	955
		Multilane undivided	Total	-7.0440	1.0517	1.0829	0.1075	631	270
			FI	-9.0901	1.1513	1.0433	0.1036	631	270

GEE = generalized estimating equation**,** FI = Fatal + Injury.

Table 20. Safety Performance Functions for Disaggregate Data in North Region

Model Definition				GEE Parameter Estimates		Standard Error		No. of Sites in Estimation and Validation Sets	
Region	Rural/ Urban	Class	Crash Type	a	b	a	b	70%	30%
North	Rural	Two-lane	Total	-5.6955	0.8012	0.4674	0.0536	714	305
			FI	-6.7320	0.7985	0.7985	0.0674	714	305
		Multilane divided	Total	-7.3780	0.9639	1.3230	0.1359	333	142
			FI	-8.9210	1.0080	1.3455	0.1381	333	142
		Multilane undivided	Total	-8.1492	1.0813	5.7970	0.6204	20	8
			FI	-18.8528	2.1077	9.8954	1.0641	20	8
	Urban	Two-lane	Total	-3.5915	0.6364	1.6057	0.1699	227	96
			FI	-4.4427	0.6032	1.9616	0.2051	227	96
		Multilane divided	Total	-4.0876	0.7446	0.8828	0.0836	917	393
			FI	-5.9680	0.8218	0.8480	0.0801	917	393
		Multilane undivided	Total	-5.2604	0.8917	1.6787	0.1615	298	127
			FI	-6.0055	0.8659	1.6329	0.1570	298	127

GEE = generalized estimating equation**,** FI = Fatal + Injury.

Table 21. Safety Performance Functions Based on Disaggregate Data in West Region

Model Definition				GEE Parameter Estimates		Standard Error		No. of Sites in Estimation and Validation Sets	
Region	**Rural/ Urban**	**Class**	**Crash Type**	**a**	**b**	**a**	**b**	**70%**	**30%**
West	Rural	Two-lane	Total	-5.7263	0.7897	0.1441	0.0180	5221	2237
			FI	-6.0939	0.7254	0.1792	0.0222	5221	2237
		Multilane divided	Total	-6.2931	0.8303	0.5528	0.0592	1505	645
			FI	-7.3899	0.8501	0.5977	0.0637	1505	645
		Multilane undivided	Total	-7.8172	1.0162	0.8018	0.0904	385	165
			FI	-9.4295	1.0903	0.9774	0.1101	385	165
	Urban	Two-lane	Total	-7.4098	1.0203	1.0070	0.1126	355	152
			FI	-7.0529	0.8749	1.1469	0.1278	355	152
		Multilane divided	Total	-10.8995	1.3839	1.8127	0.1829	490	209
			FI	-11.1035	1.2899	1.6861	0.1693	490	209
		Multilane undivided	Total	-1.2804	0.4054	3.3666	0.3475	140	59
			FI	-2.1954	0.3816	3.0053	0.3125	140	59

GEE = generalized estimating equations, FI = Fatal + Injury.

Table 22. Safety Performance Functions Based on Disaggregate Data in East/Central Region

Model Definition				GEE Parameter Estimates		Standard Error		No. of Sites in Estimation and Validation Sets	
Region	**Rural/ Urban**	**Class**	**Crash Type**	**a**	**b**	**a**	**b**	**70%**	**30%**
East/ Central	Rural	Two-lane	Total	-6.5402	0.8629	0.3188	0.0397	2177	933
			FI	-7.2420	0.8401	0.3736	0.0462	2177	933
		Multilane divided	Total	-7.1249	0.9156	0.8798	0.0948	915	392
			FI	-8.3447	0.945	1.1448	0.1220	915	392
		Multilane undivided	Total	-7.6245	1.0001	0.7888	0.0868	323	138
			FI	-9.3673	1.0785	1.0904	0.1183	323	138
	Urban	Two-lane	Total	-5.9634	0.8865	0.6695	0.0764	520	222
			FI	-7.6633	0.9602	0.8532	0.0959	520	222
		Multilane divided	Total	-4.7940	0.8160	1.3150	0.1293	824	353
			FI	-6.1242	0.8374	1.1179	0.1093	824	353
		Multilane undivided	Total	-4.3246	0.7718	2.0186	0.2054	194	83
			FI	-5.2591	0.7626	2.1668	0.2200	194	83

GEE = generalized estimating equations, FI = Fatal + Injury.

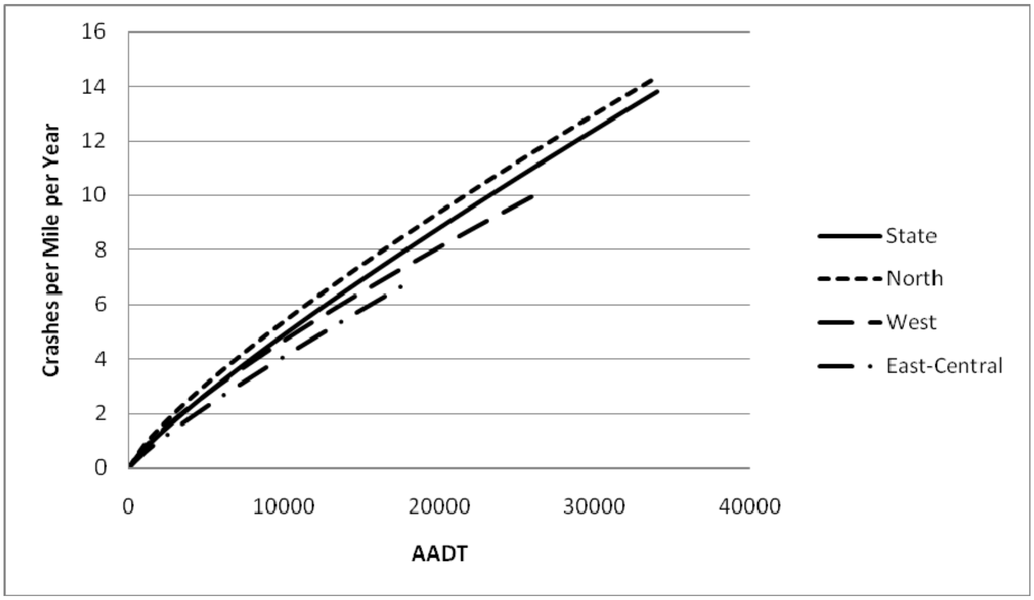

Figure 2. Rural Two-Lane Total Crashes Safety Performance Functions for Different Regions. AADT = average annual daily traffic.

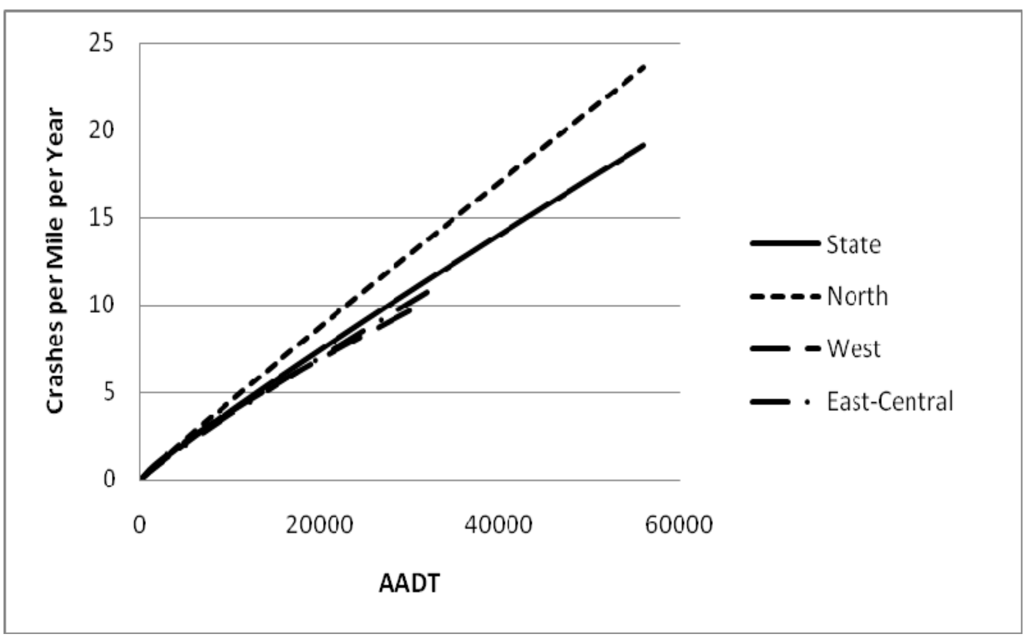

Figure 3. Disaggregate Rural Multilane Divided Total Crashes Safety Performance Functions for Different Regions. AADT = average annual daily traffic.

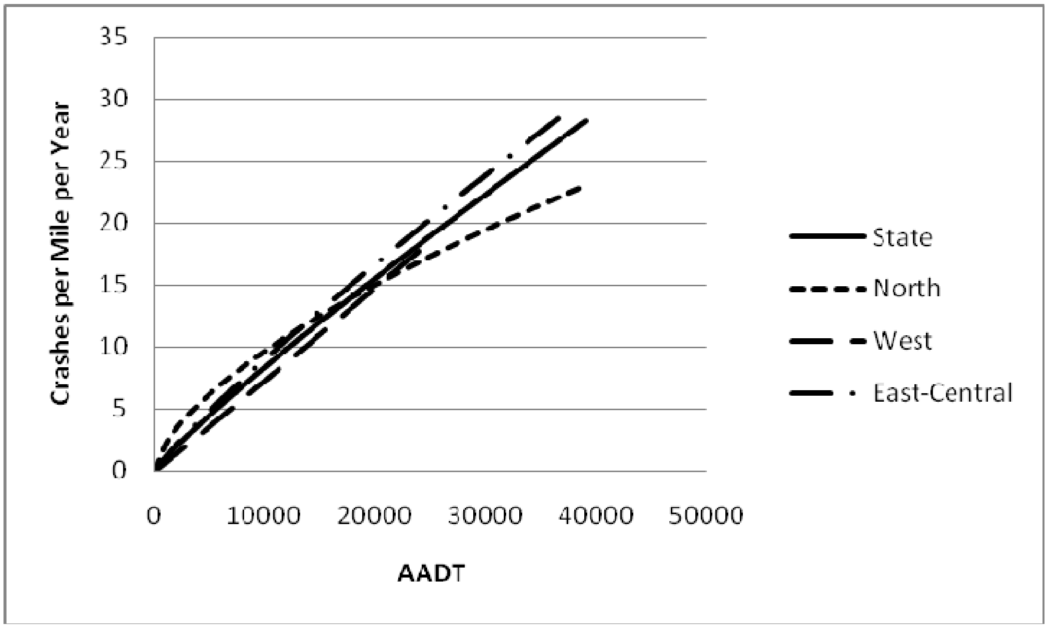

Figure 4. Urban Two-lane Total Crashes Safety Performance Functions for Different Regions. AADT = average annual daily traffic.

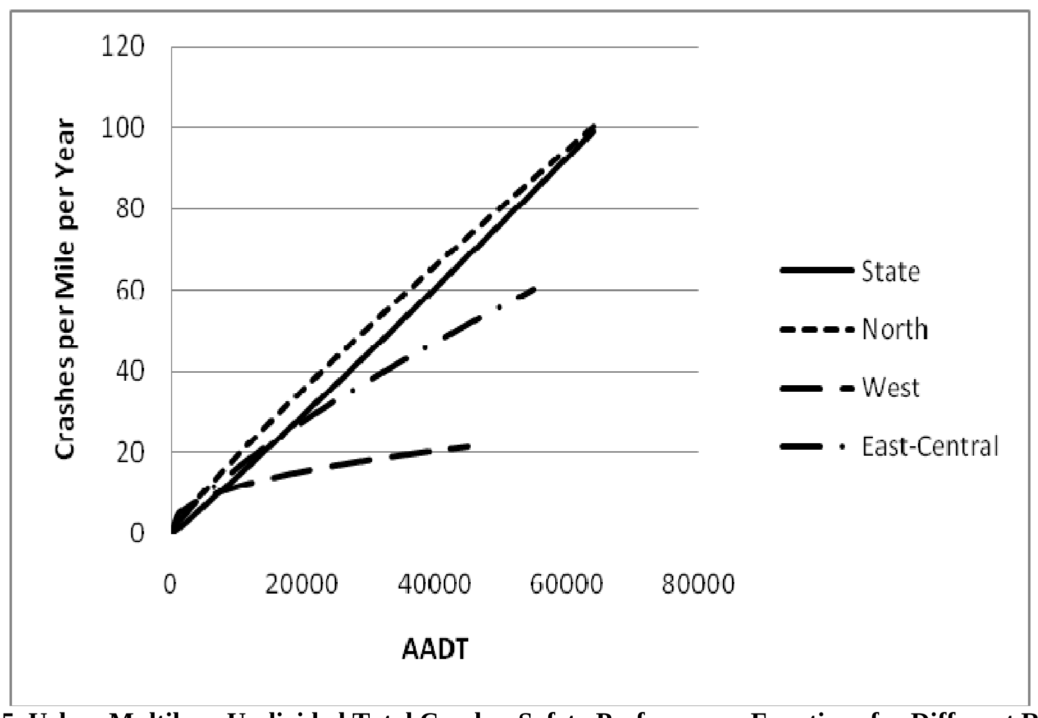

Figure 5. Urban Multilane Undivided Total Crashes Safety Performance Functions for Different Regions. AADT = average annual daily traffic.

When visually comparing the regional SPFs, one can identify a few trends. Perhaps the most conspicuous is the distinct shape of the West region SPF relative to the other urban multilane undivided total crashes SPFs (see Figure 5). This region's SPF resembles a square root function whereas the SPFs of other regions have an almost linear or logarithmic function. It is also noteworthy that the North region SPF curve is generally slightly higher than that of the statewide SPFs in many cases. For example, its SPF is clearly and consistently higher in the rural two-lane, rural multilane divided, and urban multilane undivided categories. In the urban two-lane categories, it differs in another way from the others. Whereas the others have a nearly linear relationship between traffic flow and crash frequency, the SPF curve for the North region flattens out as the traffic volume increases (see Figure 4).

It is interesting to observe the trends with respect to the regression parameter b across different regions. In the North and East/Central regions, the parameter is consistently below 1 for all urban cases. This suggests that crash frequency levels off as AADT increases in those highly urbanized areas. For the West region, the parameter fluctuates from well above 1 for the urban multilane divided to well below 1 for the urban multilane undivided case. This indicates that the relationships between traffic volume and crash frequency in urban multilane divided primaries and urban multilane undivided primaries are different in the West region.

All these apparent trends may not be statistically meaningful because the standard errors of the regression estimates have not yet been considered. One way to do so would be to plot the 95% confidence intervals for the regression parameter estimates for the statewide models and then ascertain if the parameter estimates of the regional models fall within the confidence intervals. Doing so indicates that regional models were significantly different from the statewide models in the following SPF categories:

- West region in the rural two-lane total crashes category
- East/Central region in the rural two-lane FI crashes category
- North and West regions in the urban two-lane total crashes category
- North region in the urban two-lane FI crashes category
- all three regions in the urban multilane divided total crashes category
- West and East/Central regions in the urban multilane divided FI crashes category
- West and East/Central in the urban multilane undivided total crashes category
- all three regions in the urban multilane undivided FI crashes category.

None of the other regional models had parameter estimates that were significantly different from those of the corresponding statewide model. Of the 36 regional models, only 15 were significantly different from their corresponding statewide models. Based on this standard error analysis, the general trends regarding the parameter b and the visual evaluation of the graphs described earlier cannot be dismissed and may indeed be statistically meaningful.