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FINAL REPORT
HIGHWAY SAFETY MANUAL SAFETY PERFORMANCE FUNCTIONS & ROADWAY CALIBRATION FACTORS: ROADWAY SEGMENTS

PHASE 2, PART 1

Authored by:
Asad Khattak, Numan Ahmad, Amin Mohammadnazar, Iman MahdiNia, Behram Wali, Ramin Arvin

Research Agency:

University of Tennessee – Knoxville
Tennessee State University

TN TDOT Department of Transportation

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To enhance safety, the Tennessee Department of Transportation (TDOT) is in the process of adopting the Highway Safety Manual (HSM) as a resource to facilitate decision making based on the safety performance of its roadways. The predictive models which are known as Safety Performance Functions (SPFs) are used to forecast the expected crash frequency for various roadway facility types. The HSM (2010) recommends transportation agencies such as TDOT either to develop their own SPFs using local data or develop calibration factors for use with the HSM default SPFs to reflect local conditions. This is because the HSM default SPFs were developed using data from a subset of states. Geographical conditions in Tennessee may differ substantially from the factors used to develop the default SPFs in the HSM such as terrain, weather, animal populations, driver populations, crash reporting thresholds, and crash reporting practices. Therefore, this study undertakes the task of developing 1) Tennessee-specific calibration factors, and 2) estimating Tennessee-specific SPFs. The calibration factors and locally estimated SPFs presented in this report are ready for implementation in Tennessee. Part 1 of the report focuses on rural multilane segments and urban/suburban arterial segments (Part 2 focuses on relevant intersections). Given the availability of relevant data in E-TRIMS, TDOT is in a good position to adopt the HSM procedures and benefit from software applications that make it easier to use the HSM. In this regard, the AASHTO Safety Analyst tool is discussed in detail. An example demonstrates how the Safety Analyst can use calibration factors and locally calibrated SPFs to make predictions of crashes with and without countermeasures. At the end of the report, recommendations are provided for advancing safety analysis in Tennessee.</td></tr>
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NOTES

1. This report for Phase II is divided into two parts based on analyses conducted for road segments and intersections. Part 1 presents in detail the analyses for rural multilane highways including both four-lane divided (4D) and four-lane undivided (4U), and five types of urban and suburban arterials which include two-lane (2U), three-lane with two-way-left-turn lane, four-lane divided (4D), four-lane undivided (4U), and five-lane with a two-way left-turn lane (2WLTL) (5T) road segments conducted by the University of Tennessee, Knoxville (UTK) team. Part 2 presents in detail the analyses for rural multilane and urban and suburban intersections conducted by the Tennessee State University (TSU) team. To achieve project objectives, the teams have had close coordination during Phase II of the project.
2. The previous version of this report was updated because the data extraction in the previous version required segments with structures, e.g., bridges. TDOT staff provided guidance on how to conduct queries that relaxed the requirement of the structure. This resulted in the revision of the entire data extraction process, which was undertaken. The activities conducted in updating the Phase II report for segments can be summarized as follows:
    a. Re-extraction of crash and inventory data for seven types of roadways based on the query procedure provided by TDOT staff. These include rural multi-lane highways (2 types), and urban and suburban arterials (5 types).
    b. The new sample sizes of 4D and 4U segments of rural multilane used for analysis (after cleaning) are 271 and 81, respectively. While the new sample size of 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials finally used for analyses are 234, 80, 278, 80, and 304, respectively.
    c. Fully covering 3T and 4U Urban & Suburban Arterials (which were not covered before due to the query issue).
    d. Covering and analyzing all seven roadway types (as mentioned in the proposal) in the updated report.
3. The literature review is embedded in the appropriate sections of the report.

Executive Summary

To enhance safety on Tennessee roadways and calibrate the Highway Safety Manual (HSM) predictive models for TDOT use, this study is a collaboration between the University of Tennessee (focusing on segments) and Tennessee State University (focusing on intersections). The Tennessee Department of Transportation (TDOT) is in the process of adopting the HSM as a resource to facilitate decision making based on the safety performance of its roadways. The HSM will provide TDOT with quantitative information for decision making, presenting tools, and methodologies for consideration of safety across the range of highway activities. Key features in the 2010 HSM for use by TDOT are the crash Predictive Models for three facility types:

- Rural Two-Lane and Two-Way Roads
- Rural Multilane Highways
    - Four Lane Divided Segments
    - Four Lane Undivided Segments
- Urban and Suburban Arterials
    - Two-Lane Undivided (2U) Segments
    - Three Lane with Two-Way Left-Turn Lane (2WLTL) (3T) Segments
    - Four Lane Divided (4D) Segments
    - Four Lane Undivided (4U) Segments
    - Five Lane with Two-Way Left-Turn Lane (2WLTL) (5T) Segments

Part 1 of the Phase 2 report focuses on segments. The calibration results are summarized in the following Table.

Location	**Project Phase**	**Facility Type**	**Divided**	**Undivided**
Rural	Phase I	Two-lane Two-Way	NA	2.49
	Phase II	Four-lane (Multilane)	1.47	2.25
Urban and Suburban	Phase II	Two-lane (2U)	NA	4.71
	Phase II	Three-lane (3T)	NA	5.82
	Phase II	Four-lane (4D and 4U)	4.46	7.63
	Phase II	Five-lane (5T)	NA	3.57

This report documents in detail the activities undertaken in Phase 2 of the project to calibrate the HSM safety performance functions (SPFs) for rural multilane highways and urban and suburban arterial roads. Given the availability of data in E-TRIMS, TDOT is in a good position to calibrate HSM default SPFs to match local conditions in Tennessee. As such, a detailed crash rate and calibration factor analysis are conducted for rural multilane highways and urban and suburban arterial roads using five years (2013-2017) of crash, road inventory, and traffic data. In addition, considering the diverse geographical nature of Tennessee rural multilane highways and urban and suburban arterial road infrastructures, crash rates and calibration factors are calculated for all four regions in Tennessee collectively as well as for each of the four regions separately. Likewise, in order to capture the temporal variations, the analysis is conducted both using data for all five years (2013-2017) together as well as separate analysis is conducted for each of the five years.

Building on the aforementioned tasks, as an additional activity, an in-depth empirical analysis is conducted for developing Tennessee-specific SPFs considering different distribution assumptions, i.e., the Poisson and negative binomial distributions. Given the count nature of crashes, Tennessee-specific SPFs are developed using both the fixed-parameter Poisson and negative binomial models. Such analysis provides greater localization than is possible with calibration factors.

Despite the fact that jurisdiction-specific fixed-parameter SPFs (as compared to the HSM SPFs) can better represent local conditions at hand, traffic crash frequencies and associated factors (such as traffic volumes) can vary significantly across similar, or even identical, road geometry and conditions within the jurisdiction (i.e., Tennessee in this case) where a single SPF is estimated. Alternatively, this means that associations between crashes on rural multilane highways and/or urban and suburban arterial roads and associated factors can be heterogeneous (or varying), requiring further investigation. As a methodological advance, it is important to correct for heterogeneity in the modeled relationships that can arise from some observed and unobserved factors relating to road driver behavior, vehicle types, socioeconomic factors, traffic and pavement characteristics, road geometry, variations in police accident recording thresholds, and other time and space-related unobserved factors.

Overall, our analyses suggest that the number of observed crashes on two types of rural multilane highways (four-lane divided and undivided segments) and five types of urban and suburban arterials (i.e., 2U, 3T, 4D, 4U and 5T segments) were significantly higher than the predicted number of crashes by applying the HSM SPFs and modification factors (i.e., after accounting for local conditions), indicating a potential for safety improvements. Note that a calibration factor is the ratio of observed crashes to predicted crashes. The predicted crashes can be for base conditions (capturing exposure and standard road geometry) or adjusted conditions (capturing exposure and any deviations from standard road geometry, e.g., 10 ft lanes instead of standard 12 ft lanes). The predicted crashes used in this study are for adjusted conditions based on the HSM (2010) SPFs and crash modification factors that capture deviations from standard road geometry, i.e., they capture local conditions. After accounting for local roadway conditions, the adjusted calibration factors for 4D and 4U segments of rural multilane highways are found to be 1.47 and 2.25 respectively which indicate that the observed (actual) number of crashes on 4D and 4U segments of rural multilane highways are greater than those predicted by the HSM. The situations on various types of urban and suburban arterials (i.e., 2U, 3T, 4D, 4U, and 5T) in Tennessee show even greater improvement potential as observed crashes are substantially higher than predicted by the HSM (2010) even after adjusting for local conditions. Our analyses indicate that calibration factors for the HSM after accounting for local conditions on Tennessee roadways for 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials are found to be 4.71 (for 2U segments), 5.82 (3T), 4.46 (4D), 7.63 (4U), and 3.57 (5T). These adjusted calibration factors can be used for the analysis of safety by TDOT.

Besides calibration factors, the HSM equivalent to the fixed-parameter Poisson and negative binomial models are estimated for various roadway types that include 2 types of rural multilane and 5 types of urban and suburban arterial. These are based on the Tennessee crash and inventory data. Compared to the fixed-parameter Poisson, the fixed-parameter negative binomial model significantly improved the performance of the model. The negative binomial models improved the estimation/prediction performance for all the roadway types. The implications of the findings and recommendations are discussed in the report.

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1. INTRODUCTION & BACKGROUND

1.1. Synopsis of the problem

The Highway Safety Manual (HSM) published by the American Association of State Highway and Transportation Officials (AASHTO) serves as the main guideline for transportation agencies by providing scientific techniques to identify factors associated with road safety outcomes and the likelihood of crash occurrence (*1*). As the core tools provided in the HSM, Safety Performance Functions (SPFs) are used to estimate the expected crash frequencies at a particular facility. The crash predictive models which are known as SPFs are the statistical models used to estimate the expected crash frequency for a particular facility type with specified "base" conditions (*2*). Importantly, SPFs that accurately predict crashes are valuable to state departments of transportation as they identify areas with potential safety concerns.

Since crash occurrence/frequency and the associated under- and over-dispersion in crash data can vary significantly across jurisdictions, it is important to calibrate the HSM SPFs for specific jurisdictions (*3*). This need for calibrating the HSM SPFs to specific jurisdictions is clearly recognized by AASHTO due to variations in safety factors. Such factors include road geometry and conditions, environmental factors, geographic characteristics, crash characteristics, reporting thresholds, all of which can be unique to specific jurisdictions (*1*). As such, the 2010 HSM recommends local agencies, such as TDOT, to calibrate the HSM developed SPFs to reflect local conditions and/or develop their own SPFs using local data (*1*). In essence, calibration is the process of multiplying the HSM predictive models (SPFs) by a factor to account for Tennessee HSM users. Specifically, the calibration factors are the sum of observed crashes divided by the SPF predicted crashes for the sites of a particular facility type.

The calibration procedure of the HSM predictive models can account for the variations in safety factors associated with segments of any specific roadway class, and thus can facilitate more accurate crash predictions compared to the un-calibrated HSM predictive models. However, when enough data are available, the HSM permits transportation agencies to develop jurisdiction-specific SPFs. Building upon this, an in-depth empirical analysis is conducted for developing Tennessee-specific SPFs[1]. Specifically, given the count nature of crashes, Tennessee-specific SPFs were developed using the Poisson and negative binomial distributions used by researchers in different US states. Even though jurisdiction-specific SPFs (as compared to the HSM SPFs) can better represent local conditions at hand, traffic crash frequencies and associated factors (such as traffic volumes) can vary significantly across similar, or even identical, road geometry and conditions within the jurisdiction (such as Tennessee) where a single SPF is estimated. Alternatively, this means that associations between crashes on various rural multilane highways and urban and/or suburban arterial road segments and associated factors are generally heterogeneous (or varying). It is important to correct for heterogeneity in the modeled relationships that can arise from some observed and unobserved factors relating to road driver behavior, vehicle types, socioeconomic factors, traffic and pavement characteristics, road geometry, variations in police accident recording thresholds, and other time and space-related unobserved factors.

Keeping in view the aforementioned perspective, the key objectives of this study are to:

- Apply the HSM predictive models to various types of rural multilane highways and urban and suburban arterial road segments.
- By using detailed traffic, road inventory, and crash data, compute calibration factors for various

[1] In addition to the identified tasks in Phase 1 of the project, the comprehensive analysis of estimating TN-specific SPFs (which is important for better safety monitoring in Tennessee) is conducted as an additional task.

types of rural multilane highways and urban and suburban arterial road segments.
- While accounting for unobserved heterogeneity, develop new Tennessee-specific SPFs for various types of rural multilane highways and urban and suburban arterial road segments.

1.2. SCOPE

Different states have calibrated the HSM for various types of roadways using local data. This proposed study will, therefore, focus on Tennessee with the following scope of the study:

- To provide calibration factors for SPFs following HSM procedures. In addition to the calibration tasks, the objectives will be to develop Tennessee specific SPFs based on rigorous predictive modeling that can better reflect Tennessee roadway conditions, climate, terrain, population, and crash reporting methodologies. Data from the E-TRIMS will be used for the estimation of SPFs.
- To estimate the HSM SPFs for rural multilane highways and urban and suburban arterials.
- To review AASHTO's Safety Analyst Tool and explore implications for TDOT's current Hexagon "HSIP" tool to best meet TDOT needs.
- To make recommendations about integrating the HSM into TDOT's safety analysis process.

1.3. Deliverables

The project deliverables include:

- Applying predictive models for Rural Multilane Highways.
- Computing calibration factors for Rural Multilane Highway using predictive models.
- Developing Tennessee-specific SPFs for Rural Multilane Highways.
- Applying predictive models for Urban and Suburban Arterials.
- Computing calibration factors for Urban and Suburban Arterials.
- Developing Tennessee-specific SPFs for Urban and Suburban Arterials.
- Reviewing of AASHTO's Safety Analyst tool.
- Providing recommendations for integrating the HSM into TDOT's network screening process.
- Performing Technology Transfer, e.g., papers presented at the Transportation Research Board annual meeting.

2. METHODOLOGY/CONCEPTUAL FRAMEWORK

2.1. Time period for analysis

To meet the study objectives (in Phase II), we collected crash, traffic, and roadway geometric data for a five-year period (2013-2017) for various types of rural multilane highways and urban and suburban arterial road segments. This study analyzes two different types of rural multilane highways including four-lane divided (4D) and four-lane undivided (4U) road segments, and five different types (2U, 3T, 4D, 4U and 5T) of urban and suburban arterials. Since crash frequencies are random and rare events, it is better to express them as an average for multiple years. Moreover, considering multiple years of data for analysis accounts for regression to the mean philosophy as discussed by (*4*). Similarly, the HSM also recommends using data for a time period similar to the length of time which is planned to be used in practice (*1*). Given the aforementioned discussion, this study uses crash, traffic, and geometric data for a period of five years (2013-2017). For calibration factors analysis, we conduct these analyses for each year and the average of five years of data. For the development of Tennessee-specific SPFs, the average of five years of data was used in all subsequent model estimations (*3; 5*).

2.2. Data assembly

Substantial efforts went into manually extracting data from various sources of the Tennessee Department of Transportation (TDOT). Initially, a main query (i.e., selecting accurate functional classification, number of lanes, and presence of specific features (e.g., median, two-way-left-turn-lane separating opposite directional flow)) was run in E-TRIMS to extract all segments of rural multilane highways (4D and 4U) and urban and suburban arterials (2U, 3T, 4D, 4U, and 5T segments). All roadway segments belonging to a specific roadway class were identified and extracted from E-TRIMS. The selection of four-lane undivided (4U) segments (i.e., both rural multilane, and urban and suburban arterials) in E-TRIMS were challenging as there was no appropriate feature type option based on which we could extract simple 4U segments (i.e., where opposing traffic is separated via solid yellow line only). TDOT provided guidance on this, and we extracted 4U segments for each arterial (rural multilane, urban, and suburban). As a next step, shorter segments (i.e., segment length lesser than 0.10 mile) and those with route number issue (i.e., which were not extractable from the TDOT Image Viewer – the route number of such segments included only digit with no suffix like SR) were removed from the data. After this, random samples from the clean data of 4D rural multilane and all five types of urban and suburban arterials (2U, 3T, 4D, 4U, and 5T) were selected which represent diverse statewide geographical conditions. Importantly, the clean data for overall 4U segments of rural multilane were found to have a fewer number of segments therefore no random sample was selected for this specific class (Table 2).

As a next step, we collected five years (2013-2017) of crash data and roadway geometric data for each of the types of rural multilane highways and urban and suburban arterials. The data extraction procedure is discussed below in detail:

- The crash data, for each of the five years (2013-2017), were obtained from the police crash reports in TDOT's E-TRIMS (https://e-trims.tdot.tn.gov).
- Roadway geometric information of these roadways was extracted using TDOT's Image Viewer Software in E-TRIMS (https://e-trims.tdot.tn.gov). A significant amount of effort went into extracting data on the number of fixed objects per mile, the number of different driveways per mile (i.e., including residential, industrial, commercial, and other), and offset distance to fixed objects along the roadway segments of the three types of urban and suburban arterials as needed for calibration according to the HSM (2010) guidelines.
- Traffic data including average annual daily traffic (AADT) for each of the five years (2013-2017) were obtained using TDOT's traffic history application for each segment (https://www.tdot.tn.gov/APPLICATIONS/traffichistory).

- Finally, the three data files including crash, roadway geometric, and traffic files were merged using unique BLM, ELM, county, route name, sequence number, and station number associated with each roadway segment, respectively. Figure 1 summarizes the procedure followed while collecting and linking different data elements.

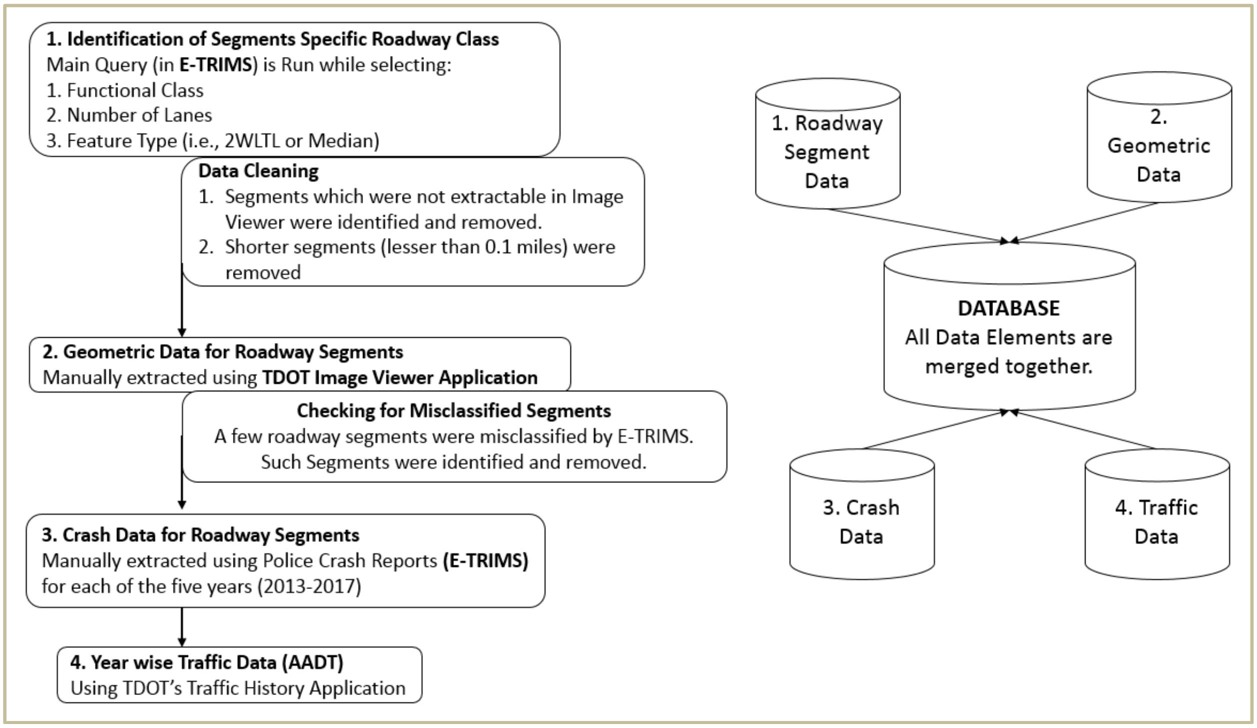

Figure 1. An Overview of Data Collection using TDOT's E-TRIMS and TDOT's Traffic History Application

The summary of data inclusion required for calibration analysis of different roadway types is shown in Table1. The overall number of segments for various roadway types (excluding four-lane undivided (4U) rural multilane, and urban and suburban arterials) in Tennessee were identified by running a main query in E-TRIMS and specifying the appropriate functional class (i.e., arterials), the number of lanes (i.e., four lanes), and feature type (i.e., two-way left-turn lane (2WLTL) or median). TDOT provided guidance in the identification of 4U segments for both rural multilane and urban and suburban arterials. Besides providing a sample query for retrieving the 4U segments, TDOT also provided an excel sheet including all 4U segments (both Rural and Urban) in Tennessee. For the sake of accuracy, we also ran the query suggested by TDOT for identifying 4U rural multilane highways and urban and suburban arterials by adding a query of urban classification (i.e., rural/urban) to separate the 4U rural multilane and 4U urban and suburban arterial segments. The following query was used to identify the 4U segments for both rural multilane and urban and suburban arterials:

- Road Segment: Functional Classification (Rural/Urban Arterials)
- Roadway Description: Route Like = SR (State Route)
- Roadway Description: Feature Type = Pavement
- Roadway Description: Feature Width ≥ 40 feet

The outcomes of this query are 4U segments and 4D segments with a pavement width greater than 40 feet. The duplicate log mile segments were then deleted, and the segments were checked in the TDOT

Image Viewer Application to exclude 4D segments from further analysis. The data collection for various types of rural multilane highways and urban and suburban arterials are discussed below.

Table 1. Data Inclusion Summary by Roadway Functional Class for Calibration and SPF

DATA ELEMENT	ROADWAY FUNCTIONAL CLASSIFICATION	
	RURAL MULTILANE	URBAN & SUBURBAN
Segment Length	E-TRIMS data	E-TRIMS data
Average Annual Daily Traffic (AADT) (for each year)	*Data extracted	* Data extracted
Lane Width	*Data extracted	Not required
Number of the Through Traffic Lanes	E-TRIMS data	E-TRIMS data
Presence of Median	E-TRIMS data	E-TRIMS data
Median Width	*Data extracted	Not required
Median Type	*Data extracted	Not required
Shoulder Width (inner and outer)	*Data extracted	Not required
Shoulder Type	**Optional	Not required
Presence of Lightning	E-TRIMS data	E-TRIMS data
Presence of Two-way-left-turn Lane	**Optional	*Data extracted
Presence of Centerline Rumble Strip	**Optional	Not required
Presence of Inner/Outer Rumble Strip	**Optional	Not required
Number of Driveways by Different Land Use	Not required	*Data extracted
Roadside Fixed Object Density	Not required	*Data extracted
Presence of On-street Parking	Not required	*Data extracted
Type of On-street Parking	Not required	*Data extracted

Notes: The green text highlight color indicates that information on a specific factor was available in TDOT's E-TRIMS database; the red text highlight color indicates that a specific factor was not required in the calibration as per the HSM (2010) criteria.
"*" indicates that additional data collection efforts were made to extract several geometric factors (mainly from TDOT's E-TRIMS Image Viewer Application) or year wise traffic (AADT) data (mainly from TDOT's Traffic History Application).
"**" indicates that data on these factors were not required for calibration analysis but were additionally extracted for SPF development.

2.2.1. Rural Multilane Highways

The E-TRIMS database showed a total of 2,065 (815.46 miles) and 142 (36.95 miles) segments of 4D and 4U rural multilane highways in Tennessee, respectively (Table 2). All segments of 4D and 4U rural multilane highways were extractable from the TDOT's Image Viewer Application using the route number (Table 2). However, a significant number of segments were found to be shorter than 0.1 miles and were therefore excluded from further analyses. A total of 933 (48.35 miles) and 61 (2.93 miles) segments of 4D and 4U rural multilane respectively were found to be less than 0.1 miles and were excluded (Table 2). Importantly, the resulting clean data on 4U rural multilane highways includes 81 segments (34.02 miles). Additionally, the clean data for 4D rural multilane highways includes 1,132 segments (767.11 miles) from which a random sample of 296 segments (186.959 miles) was selected. Finally, 271 4D and 81 4U segments of rural multilane highways with complete information were considered for analyses. It is important to mention that for 4U segments of rural multilane highways, we did not select a random sample, rather we considered the whole population for these roadway types in Tennessee. We also considered that the roadway segments for each facility type do not exceed the maximum allowable limit of AADT (vehs/day) as recommended by the HSM (2010) (Table 3).

Table 2. Data Collection Summary for 4D and 4U Segments of Rural Multilane Highways in Tennessee

Rural Multilane	All Segments		Shorter Segments		Clean Data		Random Sample	
	Number	Miles	Number	Miles	Number	Miles	Number	Miles
Four-lane Divided (4D)	2065	815.46	933	48.35	1132	767.11	296	186.96
Four-lane Undivided (4U)	142	36.95	61	2.93	81	34.02	---	---

Note: The 4U segments were selected while running the query suggested by the TDOT. The overall number of 4U segments (rural multilane, and urban and suburban arterials) are consistent with 4U segments (spreadsheet) by TDOT. Note that, we did not have any issue with 4D and 4U segments of rural multilane highways - we were able to extract all the segments for the two roadway types in E-TRIMS based on their route number (e.g., SR014)

Table 3. Maximum allowable AADT (vehicles per day) for Various Roadways (HSM, 2010)

Roadway Facility	Maximum Allowable AADT (Vehs/day)
Rural Multilane Divided (4D)	89,300
Rural Multilane Undivided (4U)	33,200
Two-lane Urban and Suburban (2U)	32,600
Three-lane (with 2WLTL) Urban and Suburban (3T)	32,900
Four-lane Divided Urban and Suburban (4D)	66,000
Four-lane Undivided Urban and Suburban (4U)	40,100
Five-lane (with 2WLTL) Urban and Suburban (5T)	53,800

The final sample of 4D rural multilane highways considered for analyses includes 44, 78, 41, 108 roadway segments from region 1 (Knoxville), region 2 (Chattanooga), region 3 (Nashville), and region 4 (Memphis), respectively (Figure 2). Similarly, the final dataset of 4U rural multilane highways considered for analyses include 20, 14, 19, and 28 roadway segments in region 1, 2, 3, and 4, respectively (Figure 3).

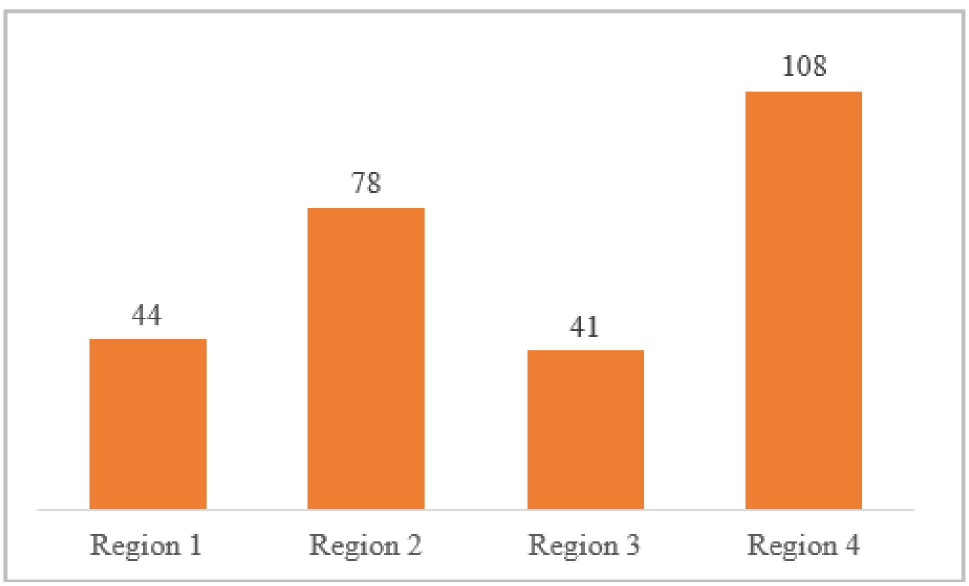

Figure 2. Distribution of 4D Segments of Rural Highway segments across Tennessee (N=271)

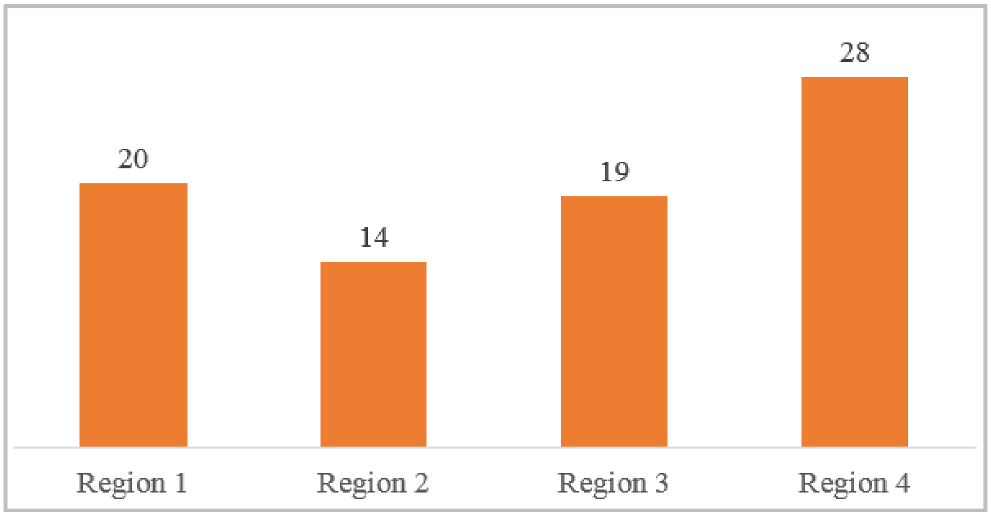

Figure 3. Distribution of 4U Segments of Rural Highway segments across Tennessee (N=81).

Note: The number of segments of 4U rural multilane highways meets the HSM's minimum sample size criteria (30+ segments), still the number of segments in some regions (i.e., Region 1, 2, and 3) have lower sample size than 30. Therefore, the region-wise calibration factors (please refer to Appendix C) should be used with caution due to fewer than 30 segments in these regions. Note that we did not select any random sample for this specific roadway type but rather used the population of segments which were 81 segments, after data cleaning.

2.2.2. Urban and Suburban Arterials

The E-TRIMS database shows that the total number of 2U, 3T, 4D, 4U, and 5T segments of suburban arterials in Tennessee are 7,085 (2165.15 miles), 1,659 (304.83 miles), 5,294 (853.13 miles), 737 (135.44 miles), and 3,208 (753.97 miles), respectively (Table 4). A significant number of segments belonging to each of these five roadway types of urban and suburban arterial were found to have a segment length of less than 0.1 mile (Table 4). Similarly, a significant number of segments belonging to the remaining four types of urban and suburban arterials were not extractable in TDOT's Image viewer in E-TRIMS (based on their route number) (Table 4). After excluding the shorter segments and those which were not extractable in E-TRIMS, we finally had 2,472 (1124.76 miles), 414 (117.73 miles), 1,735 (585.47 miles), 431 (120.35 miles), and 1,519 (523.934 miles) segments of 2U, 3T, 4D, 4U, and 5T urban and suburban arterials, respectively (Table 4). Next, a random sample of the clean data was selected for each of the five types of urban and suburban arterials (Table 4).

Table 4. Summary of Various Types of Urban and Suburban Arterials in Tennessee

Roadway Type	**Population**						**Random Sample**	
	All Segments		**Shorter Segments**		**Clean Data**			
	Number	Miles	Number	Miles	Number	Miles	Number	Miles
Two-lane (2U)	7,085	2165.15	2,413	117.91	2,472	1124.76	341	163.89
Three-lane (3T) with 2WLTL	1,659	304.83	709	36.32	414	117.73	81	25.81
Four-lane Divided (4D)	5,294	853.13	2,587	125.01	1,735	585.47	325	112.98
Four-lane Undivided (4U)	737	135.44	306	15.09	430	120.35	86	23.97
Five-lane (5T) with 2WLTL	3,208	753.97	851	41.29	1,519	523.93	317	105.78

Note: It should be noticed that 2,200 (992.48 miles), 536 (150.68 miles), 972 (142.65 miles), and 837 (188.75 miles) segments of 2U, 3T, 4D, and 5T urban and suburban arterials were not extractable in E-TRIMS (TDOT's Image Viewer

Application) due to their route numbers (i.e., their route numbers were just numbers and did not include any prefix like SR).

2.2.2.1. 2U Segments of Urban and Suburban Arterials

For the 2U urban and suburban arterials, a random sample of 341 segments (163.894 miles) was selected from the clean dataset (Table 4) following the standard statistical sampling procedure. While extracting the geometric data in the TDOT Image Viewer, we noticed that a significant number of segments in the random sample include a portion of other roadway types (i.e., 3T) hence we did not extract geometric data for such segments and were therefore excluded from further analysis. Finally, a clean sample comprising of 234 segments (125.19 miles) was selected for analyses which include 67, 38, 88, and 41 segments from region 1 (Knoxville), region 2 (Chattanooga), region 3 (Nashville), and region 4 (Memphis), respectively (Figure 4).

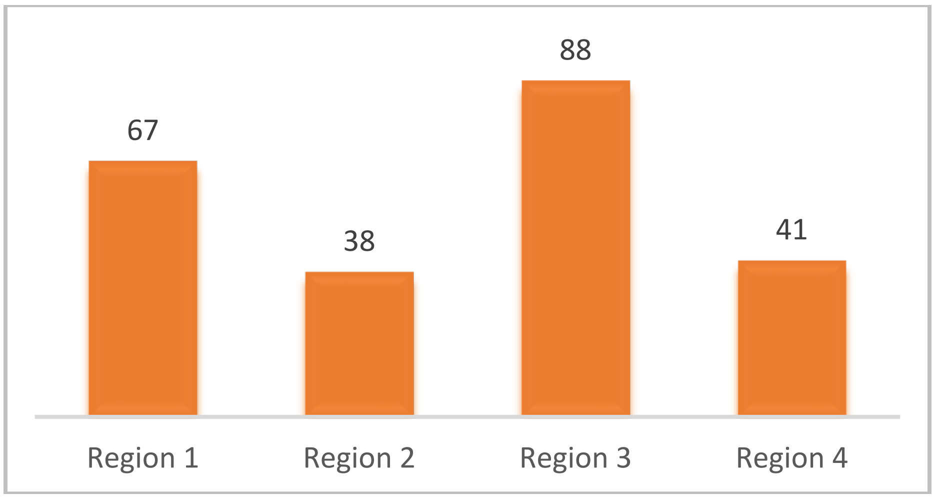

Figure 4. Distribution of randomly sampled 2U urban and suburban arterial segments across Tennessee (N=234)

2.2.2.2. 3T Segments of Urban and Suburban Arterials

For the 3T segments of urban and suburban arterials, a random sample of 86 segments (25.809 miles) was selected from a total of 414 segments (117.73 miles) which was finally reduced to 80 segments (24.24 miles). Hence, a total of 80 segments of 3T urban and suburban arterials are considered for final analyses. The random sample for 3T urban and suburban arterial is representative of the four regions in Tennessee as it includes 22, 16, 34, and 8 segments from region 1 (Knoxville), region 2 (Chattanooga), region 3 (Nashville), and region 4 (Memphis), respectively (Figure 5).

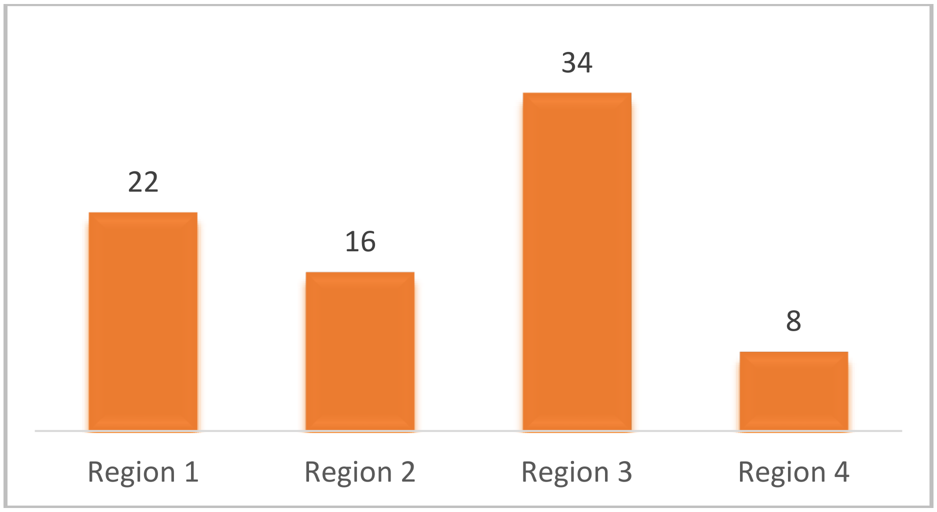

Figure 5. Distribution of randomly sampled 3T urban and suburban arterial segments across Tennessee (N=80)

Note: The random sample for 3T segments of urban and suburban arterials was selected using 90% of the confidence level criteria, which is in accordance with the HSM's minimum sample size criteria (30 segments). Note that the number of segments in some regions (i.e., Region 1, 2, and 4) is lower than 30 segments. Therefore, the region-wise calibration factors (please refer to Appendix C) should be used with caution due to the lower number of segments (i.e. less than 30 segments).

2.2.2.3. 4D Segments of Urban and Suburban Arterials

A random sample of 325 segments (112.981 miles) was reduced to 278 segments (100.803 miles) after the removal of segments with incomplete data or outliers based on certain attributes (e.g., median width). The final clean sample of 278 segments of 4D urban and/or suburban arterials is representative of the four regions in Tennessee as it includes 114, 41, 59, and 64 segments from region 1 (Knoxville), region 2 (Chattanooga), region 3 (Nashville), and region 4 (Memphis), respectively (Figure 6).

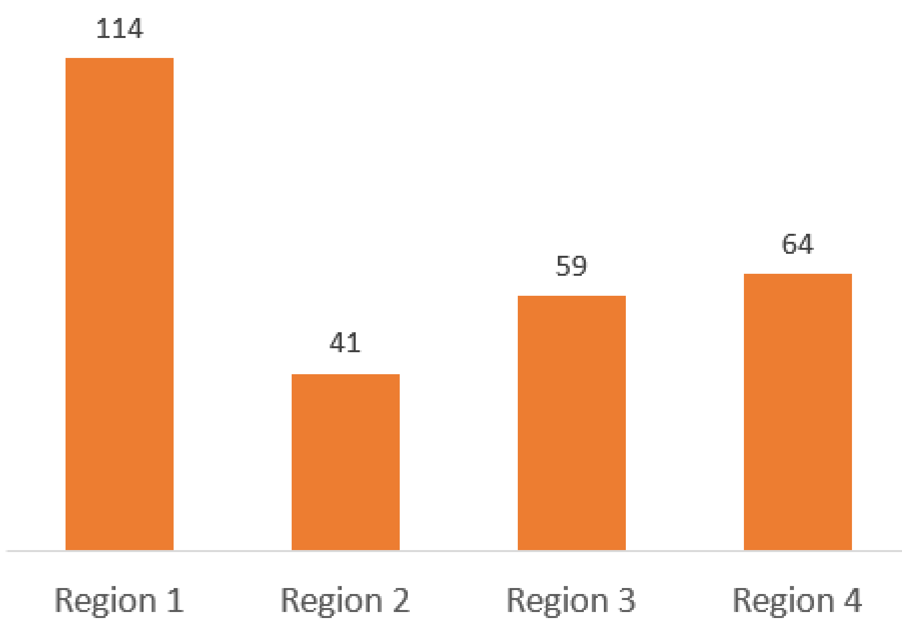

Figure 6. Distribution of randomly sampled 4D urban and suburban arterial segments across Tennessee (N=278)

2.2.2.4. 4U Segments of Urban and Suburban Arterials

In order to conduct the calibration analysis and SPFs development for the 4U segments of urban and suburban arterials, a random sample consisting of 86 segments was selected from the clean dataset (N = 430 comprising of 120.305 miles) after excluding segments less than 0.1 miles. We finally considered 80 segments (~ 19.63 miles) with complete data for analysis. Among these 80 segments, 14, 16, 20, and 30 segments are from region 1 (Knoxville), region 2 (Chattanooga), region 3 (Nashville), and region 4 (Memphis), respectively, indicating fair representation across Tennessee (Figure 7).

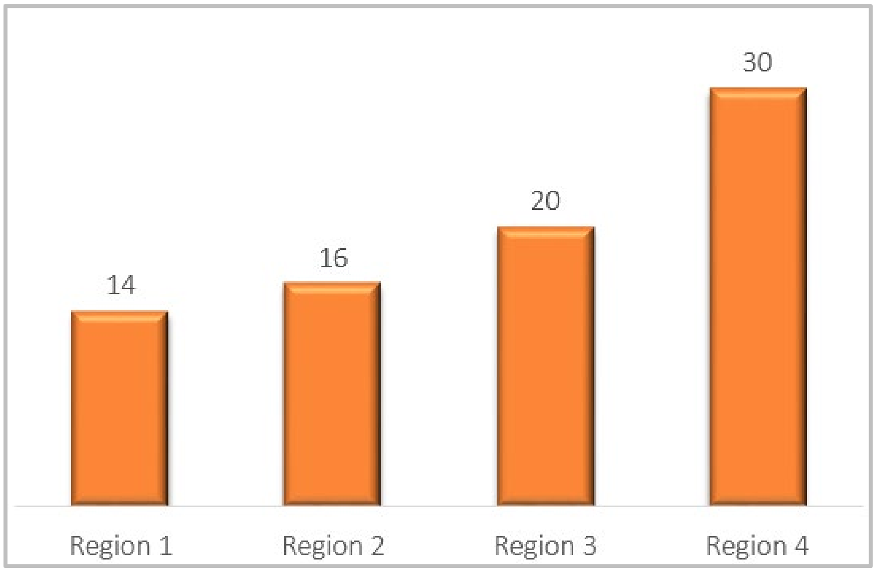

Figure 7. Distribution of randomly sampled 4U urban and suburban arterial segments across Tennessee (N=80)

Note: The random sample for 4U segments of urban and suburban arterials was selected using 90% of the confidence level criteria which is in accordance with the HSM's minimum sample size criteria (30 segments). Note that the number of segments in some regions (i.e., Region 1, 2, and 3) is lower than 30 segments. Therefore, the region-wise calibration factors (please refer to Appendix C) should be used with caution due to the lower number of segments (i.e. less than 30 segments).

2.2.2.5. 5T Segments of Urban and Suburban Arterials

Finally, a random sample of 317 segments (105.78 miles) of 5T urban and suburban arterials was selected from the clean data set (Table 4). Nonetheless, we considered 304 segments (103.269 miles) of 5T urban and suburban arterials after removing segments with incomplete data and/or outlying observations based on certain roadway attributes. Among these 304 segments, 87, 46, 119, and 52 segments are from region 1 (Knoxville), region 2 (Chattanooga), region 3 (Nashville), and region 4 (Memphis), respectively (Figure 8).

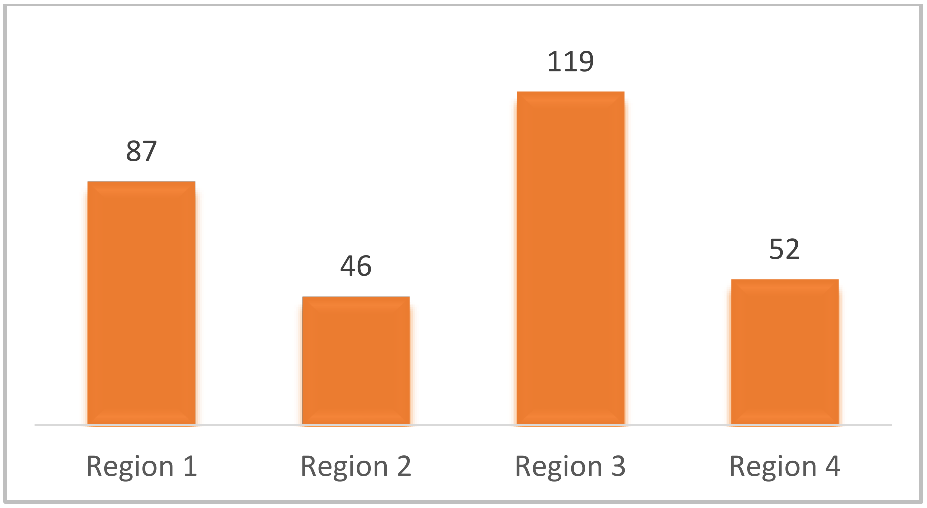

Figure 8. Distribution of randomly sampled 5T urban and suburban arterial segments across Tennessee (N=304)

The geometric data collected on variables for rural multilane highway segments as recommended by (*1*) include (Figure 9):

- Lane width
- Median width
- Median type
- Shoulder width (both inner and outer)
- Shoulder type (both inner and outer)
- Presence or absence of roadway lighting
- Presence or absence of rumble strips
- Presence or absence of automated speed enforcement

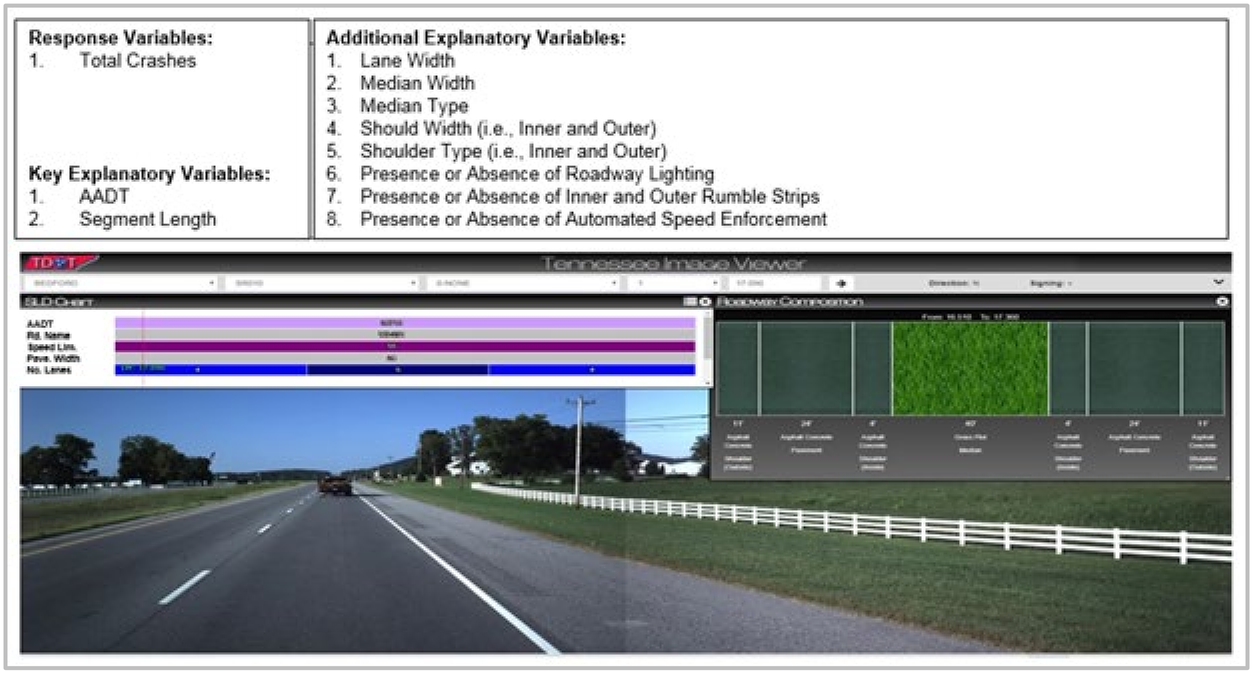

Figure 9. Illustration of TDOT's Image Viewer Software (E-TRIMS) for Manual Extraction of Key Roadway Geometric Data (Multilane Highways).

Also, we collected data on additional variables for urban and suburban arterials as recommended by the HSM (*1*) using TDOT's Image Viewer Software (E-TRIMS) including:

- Lane width
- Number of major driveways per mile (commercial, industrial, residential, and other)
- Number of minor driveways per mile (commercial, industrial, residential, and other)
- Length of on-street parking along a roadway segment
- Number of fixed objects along a roadway segment
- Offset to fixed objects along a roadway segment
- Median width (for 4D segments of urban and suburban arterials)
- Median type (for 4D segments of urban and suburban arterials)

2.3. Crash rates and calibration factor analysis

2.3.1. Crash Rates

Prior to conducting detailed empirical analyses of different types of rural multilane highways and urban and suburban arterials, we use crash rates as an effective "*first brush*" tool for quantifying the relative safety at specific locations on rural multilane highways and urban and suburban arterials. Crash rates are usually established while normalizing the total number of crashes by any exposure-related factor(s), like AADT or segment length. The key objective of this analysis is to compute and determine the safety of different roadway segments of rural multilane highways (4D and 4U) and urban and suburban arterials (2U, 3T, 4D, 4U, and 5T) in Tennessee and to determine how crash rates vary across different regions in Tennessee. Crash rates can be estimated using different measures of exposure like crash rates by segment length and crash rate by vehicle miles traveled (VMT) (*1*). We estimate the crash rates by both segment length and by VMT for various roadway segments of rural multilane and urban and suburban arterials in Tennessee.

The crash rates by VMT can be computed as follows (*6*):

$$R = \frac{C * 100{,}000{,}000}{V * 365 * N * L} \tag{1}$$

where:

R: Crash rate per VMT
C: Total crashes in the study period (five years)
V: Traffic volume using Annual Average Daily Volumes
N: Number of years of data
L: Length of the roadway segment (miles)

Similarly, crash rates per segment length can be computed as follows (*6*):

$$R = \frac{C}{N * L} \tag{2}$$

where:

R = Crash rate per mile of the segment
N = Number of years of data
L = Length of the roadway segment (miles)

2.3.2. Calibration Factor Analysis

2.3.2.1. Calibration Factor Analysis for Rural Multilane Highways

The HSM (2010) provides SPF for both 4D and 4U road segments of rural multilane highways and can be applied if the local conditions meet the specified base conditions as the HSM SPFs were developed based on data from selected states in the United States (HSM, 2010). Equation 3 represents the rural multilane highways SPF for roadway segments and can be applied when the base conditions (as documented in the HSM) meet the conditions of local jurisdictions to which the HSM SPF is applied. The HSM (2010) recommends applying the same SPF for both 4D and 4U segments of rural multilane highways. However, it is important to mention that the values of regression coefficients (*a* and *b*) in the equations are recommended by the HSM (2010).

$$N_{SPF} = e^{(a+b*ln(AADT)+ln(L))} \tag{3}$$

where:

N_{SPF}: Base predicted number of crashes in the study period
L: Length of roadway segment in miles
AADT: Average annual daily traffic on a road segment
a and *b* are the regression coefficients (i.e., for total crashes)

It should be noted that the recommended values by the HSM for *a* and *b* are -9.025 and 1.049 for 4D segments, while the recommended values of *a* and *b* for 4U segments of rural multilane highways are -9.653 and 1.176, respectively.

In case local conditions do not meet the base conditions, the HSM (2010) highly recommends calibrating the base conditions SPFs for the local conditions by computing several CMFs (HSM 2010). Hence, equation (4) can be applied to compute the adjusted predicted number of crashes on a roadway segment (HSM 2010). If the site-specific characteristics of rural multilane highways segments in Tennessee deviate from the HSM base conditions, the base predicted crash frequency (N_{SPF}) can be multiplied by CMFs for rural multilane highways road segments provided in the HSM[2] (*1*). The final jurisdiction-specific crashes can then be predicted as:

$$N = N_{SPF} \times CMF_1 \times CMF_2 \times CMF_3 \times \ldots . \times CMF_i \tag{4}$$

where:

N: Adjusted predicted crash frequency in a local jurisdiction
CMF_i: Crash modification factors for road segment features that deviate from the HSM base conditions (shown above)

2.3.2.2. Calibration Factor Analysis for Urban and Suburban Arterials

The predictive models applied for urban and suburban roadway segments are given below:

$$N_{Predicted\ rs} = C_r * (N_{br} + N_{pedestrians} + N_{bicyclists}) \tag{5}$$
$$N_{spf\ rs} = N_{brmv} + N_{brsv} + N_{brdwy} \tag{6}$$
$$N_{brmv} = e^{(a+b*ln(AADT)+ln(L))} \tag{7}$$
$$N_{brsv} = e^{(a+b*ln(AADT)+ln(L)} \tag{8}$$
$$N_{brdwy} = \Sigma total\ number\ of\ driveways\ n_i * N_i * \left(\frac{AADT}{15{,}000}\right)^{t} \tag{9}$$
$$N_{br} = N_{spf\ rs} * (CMF_1 + CMF_2 + CMF_3 + \ldots + CMF_n) \tag{10}$$
$$N_{pedestrians} = N_{br} * f_{pedestrians}) \tag{11}$$
$$N_{bicyclists} = N_{br} * f_{bicyclists}) \tag{12}$$

where:

N: predicted
Rs: predicted average crash frequency of a specific road segment
C_r : calibration factor for road segments developed for a specific geographical location
N_{br} : predicted average crash frequency of a specific road segment (excluding vehicle-pedestrian and vehicle-bicycle collisions)
$N_{pedestrians}$: predicted average crash frequency of vehicle-pedestrian collisions for a specific road segment
$N_{bicyclists}$: predicted average crash frequency of vehicle-bicycle collisions for a specific road segment
$N_{spf\ rs}$: predicted total average crash frequency for road segment base conditions (excluding vehicle-pedestrian and vehicle-bicycle collisions)
$CMF_1, \ldots, CMF_n$ = crash modification factors for road segments
N_{brmv} : predicted average crash frequency of multiple-vehicle non-driveway collisions for base conditions
N_{brsv}: predicted average crash frequency of single-vehicle crashes for base conditions
N_{brdwy}: predicted average crash frequency of multiple-vehicle driveway collisions for base conditions
L: length of roadway segment (miles)
AADT: average annual daily traffic volume (vehs/day) on the road segment

[2] A CMF of greater than one indicates an increase in predicted crash frequency attributable to the non-base jurisdiction specific conditions; a CMF less than one represents reduction in crash frequency related to the base conditions (*2*).

As mentioned earlier, the HSM (2010) SPFs are applicable for road segments that do not exceed the maximum AADT limit. The maximum AADT limit for 2U, 4D, and 5T road segments of urban and suburban arterials are 32600, 66000, and 53800 vehicles per day, respectively (HSM 2010).
While *a* and *b* are the regression coefficients (for total crashes) as given in Table 5:

Table 5. Regression Coefficients for Urban and Suburban Arterials SPFs (HSM 2010)

Road Type	For Multiple vehicle non-driveway collisions		For single-vehicle collisions	
	A	B	a	b
2U	-15.22	1.68	-5.47	0.56
3T	-12.40	1.41	-5.74	0.54
4U	-11.63	1.33	-7.99	0.81
4D	-12.43	1.36	-5.05	0.47
5T	-9.70	1.17	-4.82	0.54

After the predicted crash frequency (for local conditions) for rural multilane highways and urban and suburban arterials is calculated, the following equation is used to compute the calibration factor for these roadway facilities:

$$Cf = \frac{\sum Observed\ Crashes}{\sum Adjusted\ Predicted\ Crashes} = \frac{N_{observed}}{N} \tag{13}$$

where:

Cf: Calibration factor
$N_{observed}$: Observed crash frequency in the study period
N: Adjusted predicted crash frequency in the local jurisdiction

The calibration factor (*Cf*) in Eq. 13 can be multiplied with the HSM base conditions SPF of rural multilane highways (i.e., Eq. 3) and urban and suburban arterials (i.e., Eq. 6) for predicting rural multilane highways and urban and suburban arterials road segment crashes in Tennessee, accounting for differences in crash, traffic, and roadway specific characteristics between the HSM and the TN-specific data.

2.4. Tennessee-specific safety performance functions

In addition to calibrating the HSM SPFs for a specific roadway type of urban and suburban arterials or multilane highways, when enough data are available, it is recommended that users develop jurisdiction-specific SPFs (*1*). Developing state-specific SPFs can help in network screening and evaluation of engineering treatments, at a site and/or project level.

Typically, state-specific SPFs are estimated using only AADT information for each segment as such data are easily available (*7*). However, in this study, Tennessee-specific SPFs are estimated using detailed information about road segments, such as AADT, segment length, and roadway geometric characteristics (as shown in the Data Collection section) for various types of urban and suburban arterials and rural multilane highways. While considering the discrete non-negative nature of crashes, we apply fixed-parameter count data models considering different distributions, i.e., the Poisson and negative binomial. For a detailed discussion, please refer to Appendix A. While developing TN-specific SPFs, we apply both the Poisson and Negative binomial regression considering which are discussed in detail in the subsequent section.

In order to develop TN-specific SPFs, we consider the functional form (as shown in Equation 14 and 15) including all key correlates of the average five-year crash frequency using both the fixed-parameter the Poisson and fixed-parameter Negative Binomial regression techniques (*2; 5; 8; 9*):

$$ln\ (N_{TN-SPF})\ = \beta_o + \sum_{i=1}^{P} \beta_i X_i \tag{14}$$

A re-arrangement of Equation 14 then predicts the number of crashes for the study time period, as:

$$N_{TN-SPF} = exp^{[\beta_o + \sum_{i=1}^{P} \beta_i X_i]} \tag{15}$$

where X_i is a matrix of explanatory factors such as AADT, segment length, lane width, shoulder width, and other factors, and β_i is a column-vector of parameter estimates associated with each of the variables in matrix X_i. Model 1 refers to SPF based on the Poisson regression whereas model 2 refers to SPF based on negative binomial regression. This functional form is also widely used by researchers for modeling crash frequencies, and as such is also used in the current study (*5; 10-13*).

In summary, the following models are considered for various roadway types of rural multilane (i.e., 4D and 4U segments) and urban and suburban arterials (i.e., including 2U, 3T, 4D, 4U, and 5T segments), based on different count data distributional assumptions.

- Model 1: TN SPF the Fixed-Parameter Poisson SPF
- Model 2: TN SPF the Fixed-Parameter Negative Binomial SPF

2.4.1. Goodness of Fit Measures

The goodness of fit measures for a particular econometric model describes how well the estimated model fits the data at hand. In essence, it describes the discrepancies between the observed and predicted values of crashes. In this analysis, we use log-likelihood at convergence, McFadden R-squared, Akaike Information Criteria (*14*), and Bayesian Information Criteria (*15*) to compare and evaluate the statistical adequacy (fit) of all estimated models. For mathematical formulations of the aforementioned criteria, interested readers can refer to standard statistical texts (*14; 15*). A lower value of AIC and BIC indicates a relatively better model. As the number of estimated parameters affect AIC and BIC, it effectively discourages overfitting of crash data by penalizing the addition of undesirable parameters (*9*).

3. FINDINGS: DESCRIBING THE DATA

3.1. Descriptive Statistics

The descriptive statistics of key variables for different types of rural multilane highways and urban and suburban arterials are briefly discussed in the subsequent subsections. Importantly, the rural multilane highways include four-lane divided (4D) and four-lane undivided (4U) road segments. While the urban and suburban arterials include two-lane undivided (2U), three-lane including 2WLTL (3T), four-lane divided (4D), four-lane undivided (4U), and five-lane (5T) including 2WLTL road segments.

3.1.1. Descriptive Statistics - Rural Multilane Highways

Table 6 captures the summary statistics for the key variables for both 4D and 4U rural highways in Tennessee. The mean of five-year crashes (rounded to the nearest integer) for 4D and 4U segments of rural highways is 1.339 and 2.555 with standard deviations of 1.995 and 5.601, respectively, revealing over-dispersion in both the cases (Table 6).

The mean value for an average five years AADT (in 1000s) and segment length for 4D segments of multilane highways are 8.137 (in thousands) and 0.669 miles, respectively (Table 6). On 4U segments of rural multilane highways, the mean value of average five years AADT (in thousands) and segment length are 6.940 (in thousands) and 0.420 miles, respectively (Table 6). For other key variables, associated with 4D and 4U segments of rural multilane highways, which were used in the analyses, please refer to Table 6. The data were error checked by the authors for consistency.

Table 6. Descriptive statistics of key variables (4D and 4U Multilane Highways)

Variable	Obs.	Mean	Std. Dev.	Min	Max
	4D Segments of Rural Multilane Highways				
Average 5 Year Crashes (rounded to nearest integer)	271	1.339	1.995	0	18.00
Segment length (miles)	271	0.669	0.801	0.100	4.80
Average annual daily traffic (AADT) in 1000s	271	8.137	4.591	0.489	27.08
Inner shoulder width (in feet)	271	3.782	1.235	0	8.00
Speed limit (miles per hour)	271	56.60	8.350	30.00	70.00
	4U Segments of Rural Multilane Highways				
Average 5 Year Crashes (rounded to nearest integer)	81	2.555	5.601	0	39
Segment length (miles)	81	0.420	0.536	0.100	2.50
Average annual daily traffic (AADT) in 1000s	81	6.940	4.298	0.634	31.64
Presence of rumble strip along outer shoulder (1/0)	81	0.2712	0.447	0	1.00

3.1.2. Descriptive Statistics - Urban and Suburban Arterials

The descriptive statistics of key variables used in the development of Tennessee-specific SPFs for two-lane (2U), three-lane including 2WLTL (3T), four-lane divided (4D), four-lane undivided (4U), and five-lane including 2WLTL segments of urban and suburban arterials are presented in Table 7. Since the response variable considered in this study is the five-year average crash frequency (rounded to the nearest integer), summary statistics for the five-year average crash frequency are only presented for the sake of clarity and simplicity (Tables 7). Statistics reveal that the mean five-year average frequency (rounded to the nearest integer) on 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials is 4.128, 5.800, 5.471, 10.037, and 11.019, respectively (Table 7). The five-year average crashes indicate that the 5T, 4U, and 3T segments experience the most crashes among all five types of urban and suburban arterials (Table 7). This can be due to the existence of the shared left turning lane (2WLTL) or simple physically undivided traffic (i.e., on 4U segments) increasing crash risk as inappropriate gap selection by left-turning vehicles increases potential conflict for through traffic.

Based on the final datasets, the mean segment length of 2U, 3T, 4D, 4U, and 5T roadway segments of urban and suburban arterials are 0.532, 0.303, 0.363, 0.2454, and 0.339 miles, respectively (Table 7). Considering our final datasets, the mean AADT (in thousands of vehicles per day) on 2U, 3T, 4D, 4U, and 5T roadways segments of urban and suburban arterials is 7.410, 11.71, 20.041, 15.203, and 19.367, respectively (Table 7). Moreover, it can be seen that per the HSM (2010) guidelines, maximum values of AADT on 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials are found to be (in thousands of vehicles per day) 24.155, 26.473, 64.780, 36.981, and 51.644, respectively (Table 7). These maximum values of ADDT on each roadway type of urban and suburban arterials are within the range recommended by the HSM (2010) (for detail, please refer to Table 3). Descriptive statistics of other important key correlates of five-year crash frequency on each of the five types of urban and suburban arterials are presented in Table 7. It should be noted that we present the descriptive statistics of only key variables which showed a significant correlation with average five-year crash frequency on each roadway type of urban and suburban arterials (Table 7).

Table 7. Descriptive Statistics of Key Variables (Various Types of Urban and Suburban Arterials)

Variable	Obs.	Mean	Std. Dev.	Min	Max
2U Urban and Suburban Arterials					
Average 5 Year Crashes (rounded to nearest integer)	234	4.128	6.830	0	77
Segment length (miles)	234	0.532	0.483	0.100	3.145
Average annual daily traffic (AADT) in 1000s	234	7.410	3.868	1.288	24.15
Number of minor commercial driveways per mile	234	0.162	0.531	0	4.00
Number of major industrial/institutional driveways per mile	234	0.247	0.633	0	4.00
Speed limit (mile per hour)	234	41.410	8.385	25	55
3T Urban and Suburban Arterials					
Average 5 Year Crashes (rounded to nearest integer)	80	5.800	9.187	0	62.00
Segment length (miles)	80	0.303	0.281	0.100	1.703
Average annual daily traffic (AADT) in 1000s	80	11.71	5.915	0.969	26.473
Number of major commercial driveways per mile	80	0.162	0.462	0	3.00
Number of minor commercial driveways per mile	80	0.550	1.241	0	7.00
4D Urban and Suburban Arterials					
Average 5 Year Crashes (rounded to nearest integer)	278	5.471	9.854	0	130
Segment length (miles)	278	0.362	0.390	0.10	2.230
Average annual daily traffic (AADT) in 1000s	278	20.041	10.610	2.706	64.78
Number of major commercial driveways per mile	278	0.345	0.928	0	6
Median width (in feet)	278	27.687	14.113	2	70
Inner shoulder width (in feet)	278	2.622	2.086	0	9
Presence of rumble strips along inner shoulder (1/0)	278	0.273	0.446	0	1
4U Urban and Suburban Arterials					
Average 5 Year Crashes (rounded to nearest integer)	80	10.037	16.731	0	98
Average annual daily traffic (AADT) in 1000s	80	15.203	8.148	2.772	36.981
Segment length (miles)	80	0.245	0.162	0.1	0.955
Number of minor commercial driveways per mile	80	0.762	1.224	0	5
Number of major industrial/institutional driveways per mile	80	0.375	0.700	0	4
Speed limit (miles per hour)	80	38.625	6.559	30	55
5T Urban and Suburban Arterials					
Average 5 Year Crashes (rounded to nearest integer)	304	11.019	13.976	0	80
Segment length (miles)	304	0.3397	0.2788	0.10	1.809
Average annual daily traffic (AADT) in 1000s	304	19.367	8.948	3.475	51.64
Number of minor commercial driveways per mile	304	0.8651	1.6263	0	12
Number of major industrial/institutional driveways per mile	304	0.4605	0.9361	0	7
Number of minor industrial/institutional driveways per mile	304	1.2861	1.8438	0	11
Offset to roadside fixed objects (in feet)	304	14.266	8.1882	0	30

3.2. Crash rates by vehicles miles traveled (VMT) and segment length

3.2.1. Crash rates by VMT and segment length - Rural Multilane Highways

The crash rate for the entire state and each region (please refer to Appendix B) are computed using both VMT and segment length. Statistics reveal that the mean crash rate per 100 million VMT on 4U segments of rural multilane highways is 260.467, which is 2 times the crash rate (130.028) on 4D segments of rural multilane highways (Table 8). This indicates that the absence of physical media separating opposing traffic is important in reducing the chance of a crash (Table 8). Region 3 has the highest crash rate on 4D segments while Region 2 has the highest crash rate on 4U segments of the rural multilane highways in Tennessee (Table B1 in Appendix B). On the other hand, Region 2 (118.87 crash rate per 100 million VMT) was found to have the lowest crash rate on 4D segments while Region 3 (109.79 crash rate per 100 million VMT) was found to have the lowest crash rate on 4U segments of rural multilane highways in Tennessee (TABLE B1 in Appendix B).

Table 8. Crash Rates by VMT and Segment Length (Rural Multilane Highways)

Area	Crash Rate per 100 Million VMT					Crash Rate per mile of roadway per year				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Four Lane Divided (4D) (All Regions)	271	130.028	221.7824	0	1700.21	271	2.8722	4.0321	0	41.8181
Four Lane Undivided (4U) Rural Highways (All Regions)	81	260.467	419.6564	0	2591.16	81	6.0456	9.0053	0	57.5667

Notes: (*) The high maximum crash rates (as indicated by “max” column) are for very short segments i.e., $0.10\ miles$ with a low number of crashes, N is the sample size; Std. Dev. is the standard deviation.

3.2.2. Crash rates by VMT and segment length - Urban and Suburban Arterials

The crash rate per 100 million VMT and per mile of segment length per year for five different types of urban and suburban arterials including 2U, 3T, 4D, 4U, and 5T segments are summarized in Table 9. The crash rate for both overall Tennessee (Table 9) and each of the four regions (please refer to Table B.2 in Appendix B) are computed. Our analyses reveal that the highest crash rate (769.77) occurs on 4U segments of the urban and suburban arterials, followed by 3T and 5T segments where the value of crashes per 100 million VMT were 527.89 and 493.10, respectively (Table 9). Based on the computed crash rate for 4U road segments of urban and suburban arterials, Region 3 is found to be with the highest crash rate at 1049.45 crashes per 100 million VMT, while Region 1 shows the lowest crash rate (i.e., 498.59) for 4U segments (Table B.2 in Appendix B). Region 2 had the highest crash rate on 3T segments of urban and suburban arterials (709.74), while Region 1 has the lowest crash rate of 321.12 among the four regions in Tennessee of this arterial type (Table B.2 in Appendix B). Region 3 and Region 4 are respectively the high and low crash regions for 4D segments of urban and suburban arterials (Table B.2 in Appendix B). For 5T segments, Region 2 is noteworthy as the value of the crash rate per 100 million VMT is found to be 583.06, which is the highest across all the four regions (Table B.2 in Appendix B). For 2U segments of urban and suburban arterials, Region 1 and Region 4 are found to have the highest and lowest crash rate per 100 million VMT, respectively (Table B.2 in Appendix B).

Table 9. Crash Rates by VMT and Segment Length (Urban and Suburban Arterials)

Arterial type (All Regions)	Crash Rate per 100 million VMT					Crash Rate per mile of roadway per year				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Two Lanes Undivided (2U)	234	339.99	358.44	0	2597.76	234	9.36	13.63	0	105.71
Three Lanes (3T)	80	527.89	641.12	0	3884.28	80	22.74	32.85	0	221.11
Four Lanes Divided (4D)	278	312.99	564.35	0	4949.82	278	25.31	49.02	0	370
Four Lanes Undivided (4U)	80	769.77	1227.85	0	7528.29	80	43.47	76.42	0	515.78
Five Lanes (5T)	304	493.10	508.22	0	4119.67	304	38.80	50.43	0	445.61

4. FINDINGS: CALIBRATION FACTOR RESULTS FOR TENNESSEE

The procedures applied for computing the calibration factors for rural multilane highways and urban and suburban arterials are discussed in section 2.3.2.1. and 2.3.2.2., respectively. We calculated two types of calibration factors for each type of the rural multilane highways (4D and 4U segments) and urban and suburban arterials (2U, 3T, 4D, 4U, and 5T segments):

- *Base Calibration Factors (Cf_{base}):* We estimated the base conditions calibration factors (Cf_{base}) while applying the HSM SPF i.e., Eq. 3 for rural multilane highways and Eq. 6 for urban and suburban arterials mainly using AADT and segment length. We then calculated the mean calibration factor for each of the facility types by simply dividing their observed crashes over corresponding predicted crashes. It is important to mention that we consider all crash modification factors as 1, assuming that rural multilane highway segments meet the HSM (2010) base conditions.
- *Adjusted Calibration Factors (Cf_{adj}):* We estimated the adjusted calibration factors (Cf_{adj}) while applying the Equation 4 using AADT and segment length as well as incorporating the CMFs for cases when Tennessee-specific road geometry deviates from the HSM default values. A similar procedure was followed for urban and suburban arterials as discussed in section 2.3.2.2. We then calculated the mean calibration factors (Cf_{adj}) while dividing the observed crashes over the adjusted predicted number of crashes (Equation 13).

The calibration factors (for both case conditions and adjusted conditions) are estimated for the whole state (Tennessee including four regions) as well as separately for each of the four regions in Tennessee. While accounting for temporal variations, we estimated the calibration factors using five-year average crash data, as well as separately for each of the five years (2013-2017). The complete calibration procedure was conducted using statistical programming software STATA, and the codes are available from the authors. The detailed results (i.e., how calibration factors vary with time and space) for each of the roadway facilities are provided in Appendix C. In order to compare the calibration factors of each roadway type in Tennessee with other states, the overall state calibration factors are illustrated in the following figures.

4.1. Calibration factors results: Rural Multilane Highways

The adjusted calibration factor (Cf_{adj}) for 4D segments of rural multilane highways using five-year average crash data is 1.475, indicating that the actual crashes in Tennessee are at least 0.475 times higher than the predicted crashes computed after adjusting for the Tennessee-specific conditions (Table 10). The comparison of calibration factors (after accounting for the local adjustments) for 4D segments of rural multilane highways in Tennessee with other states is illustrated in Figure 10. It is noticeable that 4D segments of rural multilane highways have greater potential for improvement compared to other states (Figure 10). Moreover, the comparison of Cf_{base} and Cf_{adj} for the whole state of Tennessee and each of the four regions is illustrated in Figure 11 and Figure 12, respectively. Several insights can be drawn from the figures below:

- The average five-year calibration factor (assuming TN roadway segments meet the HSM base case conditions) is 1.445, with year-wise calibration factors ranging from 1.404 to 1.488 (Figure 11). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions is still greater than the national average (1.475) with year-wise calibration factors ranging between 1.433 and 1.519 (Figure 11). It was interesting to notice that even after accounting for TN-specific conditions, the Cf_{adj} was almost like the Cf_{base} which was unexpected as Cf_{adj} was expected to be lower than Cf_{base}.

- Region 3 appears to be the least risky with an average five-year calibration factor (Cf_{adj}) equaling 1.369, with yearly calibration factors varying between 1.192 and 1.615 (Figure 12).

Table 10. Summary of Calibration Factors in Tennessee for 4D Rural Multilane Highways

Calibration Factors (*Cf*)	Statewide (N = 271)	Region 1 (N = 44)	Region 2 (N = 78)	Region 3 (N = 41)	Region 4 (N = 108)
Base *Cf* (Cf_{base})	1.445	1.571	1.388	1.338	1.489
Modified *Cf* (Cf_{adj})	1.475	1.601	1.421	1.369	1.515

Notes: All reported calibration factors for Tennessee are the average of five years' calibration factors (See Appendix C for details).

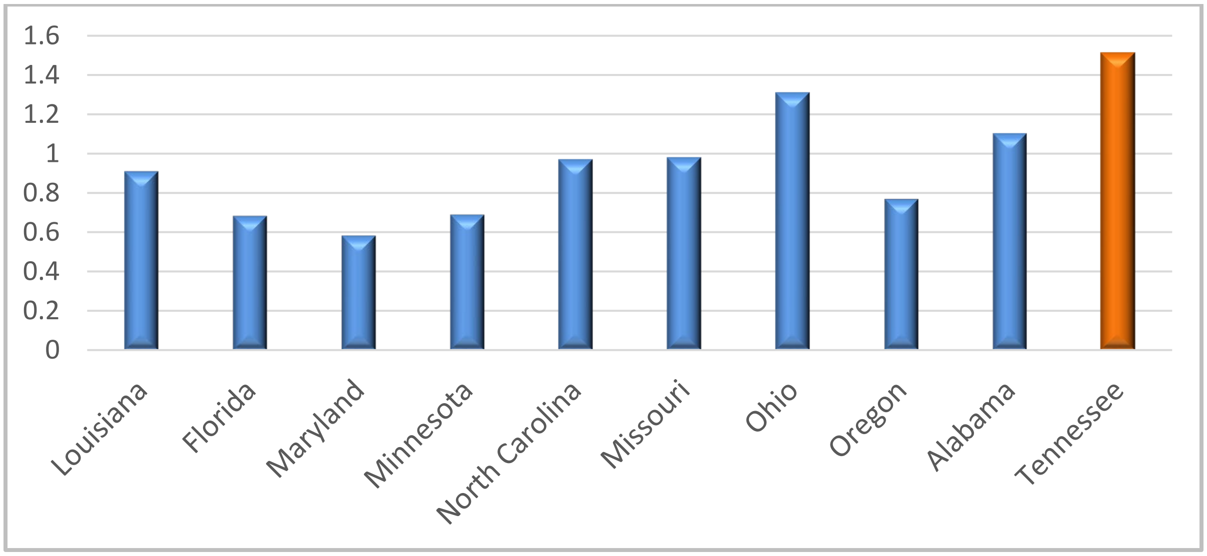

Figure 10. Comparison of Calibration Factor (*Cf*) for 4D segments of Rural Multilane Highways in Tennessee with Other States (*7; 16-23*)

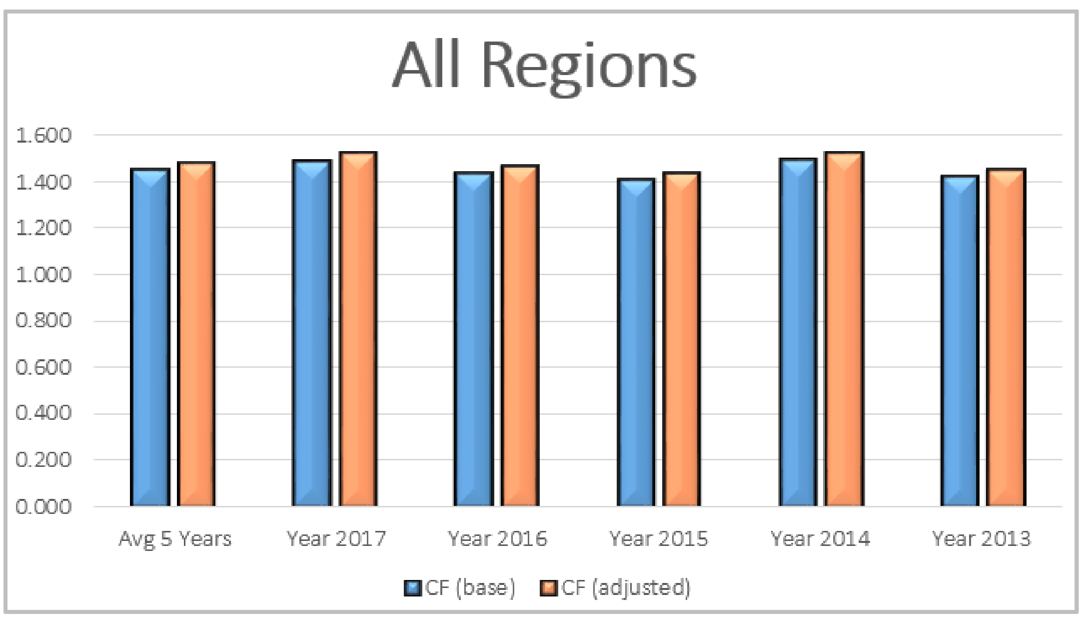

Figure 11. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) Calibration Factors for All Regions (4D Segments of Rural Multilane Highways)

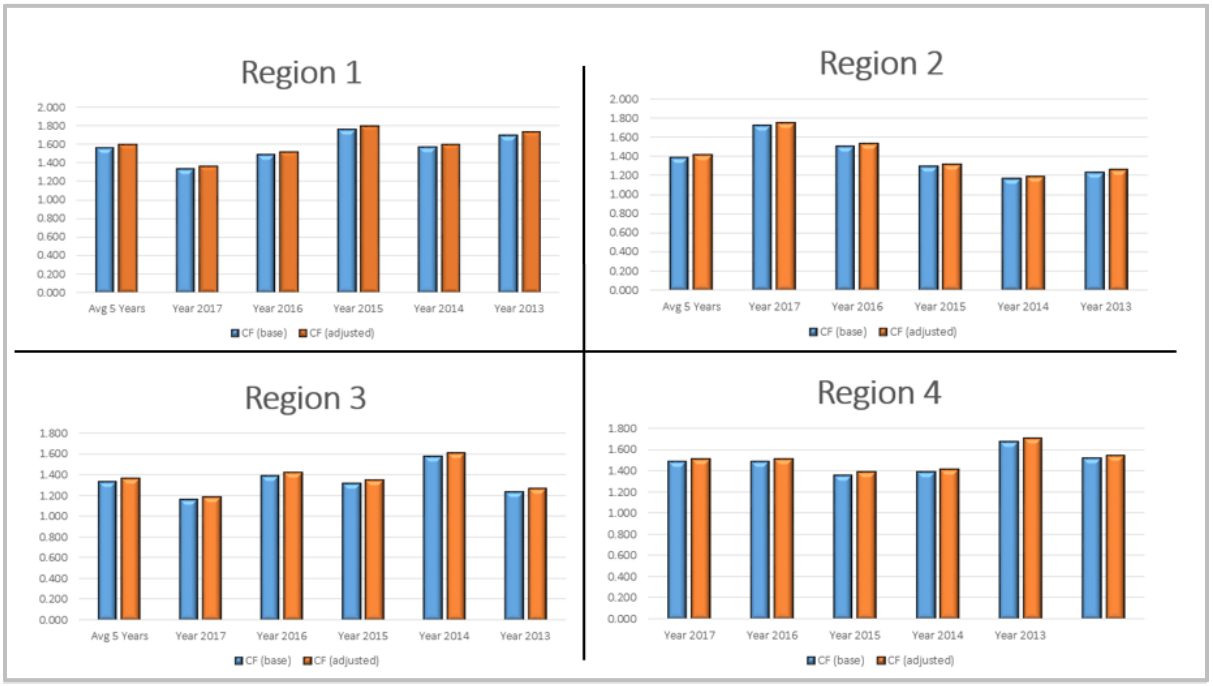

Figure 12. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) for Calibration Factors 4D Segments of Rural Multilane Highways: Region Comparison

Note: The scales (i.e., along Y-axis) for Cf_{base} and Cf_{adj} for various regions illustrated in Figure 12 are different depending on their calibration results and must be read carefully.

The calibration factor for 4U segments of rural multilane highways (for Tennessee as a whole and each of the four regions) while using five-year average crash data after accounting for TN-specific conditions are presented in Table 11. The comparison of calibration factors (after applying local adjustments) for 4U segments of rural multilane highways in Tennessee with other states is illustrated in Figure 13. Moreover, the comparison of Cf_{base} and Cf_{adj} for 4U segments of rural multilane highways for the whole state of Tennessee and each of the four regions is illustrated in Figure 14 and Figure 15 respectively.

- The average five-year calibration factor for the 4U rural multilane highways (assuming TN roadway segments meet the HSM base case conditions) is 2.309, with year-wise calibration factors ranging between 2.043 and 2.538 (Figure 14). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions is still greater than the national average (2.257) with year-wise calibration factors ranging between 1.996 and 2.482 (Figure 14). It is interesting to notice that even after accounting for TN-specific conditions, the Cf_{adj} was like the Cf_{base} which was expected otherwise (Cf_{adj} was expected to be lower than Cf_{base}).
- However, based on the average five-year Cf_{adj}, Region 1 and Region 3 are the riskiest and least risky regions, respectively (Figure 15).

Table 11. Summary of Calibration Factors in Tennessee for 4U Rural Multilane Highways

Calibration Factors (*Cf*)	**Statewide (N = 81)**	**Region 1 (N = 20)**	**Region 2 (N = 14)**	**Region 3 (N = 19)**	**Region 4 (N = 28)**
Base *Cf* (Cf_{base})	2.309	2.750	2.505	1.127	2.658
Modified *Cf* (Cf_{adj})	2.257	2.602	2.480	1.174	2.587

Notes: All reported calibration factors for Tennessee are average of five-year calibration factors (See Appendix C for details).

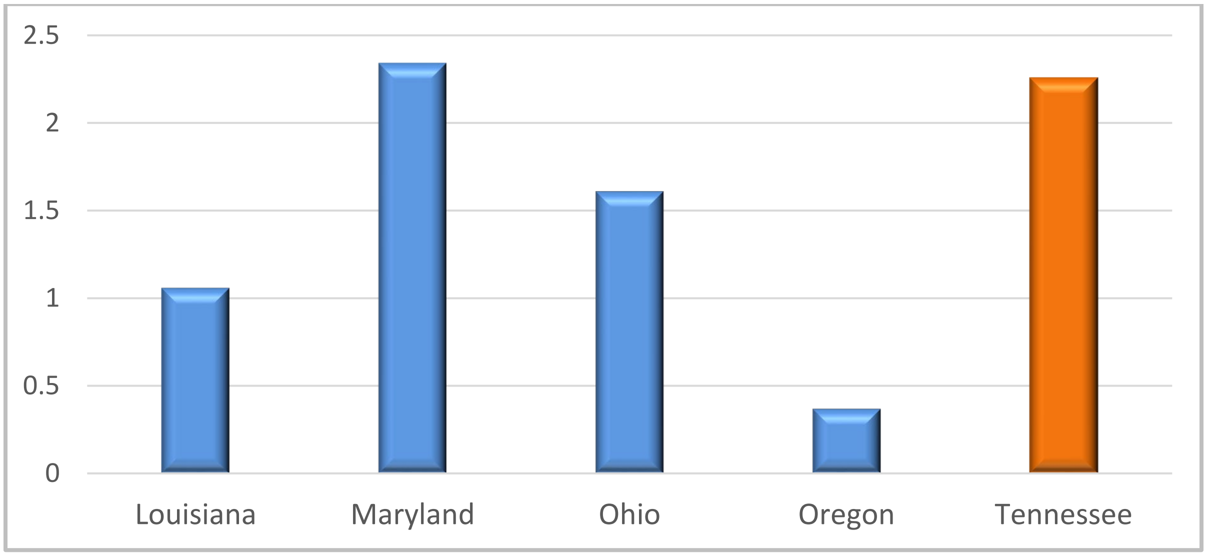

Figure 13. Comparison of Calibration Factor (Cf_{adj}) for 4U segments of Rural Multilane Highways in Tennessee with Other States (*16; 17; 19; 23*)

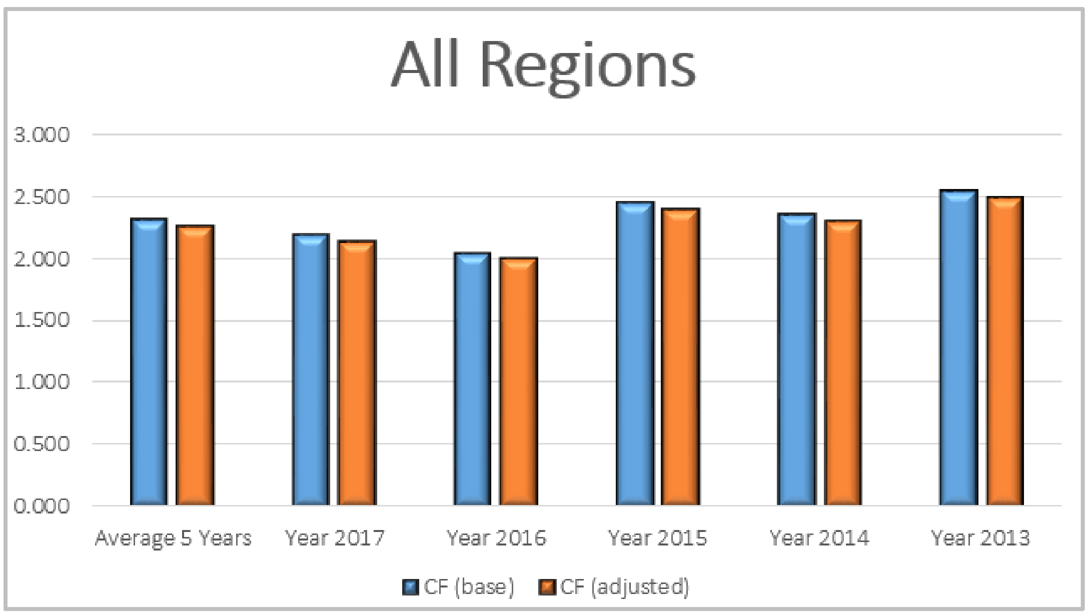

Figure 14. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) Calibration Factors for All Regions (4U Segments of Rural Multilane Highways)

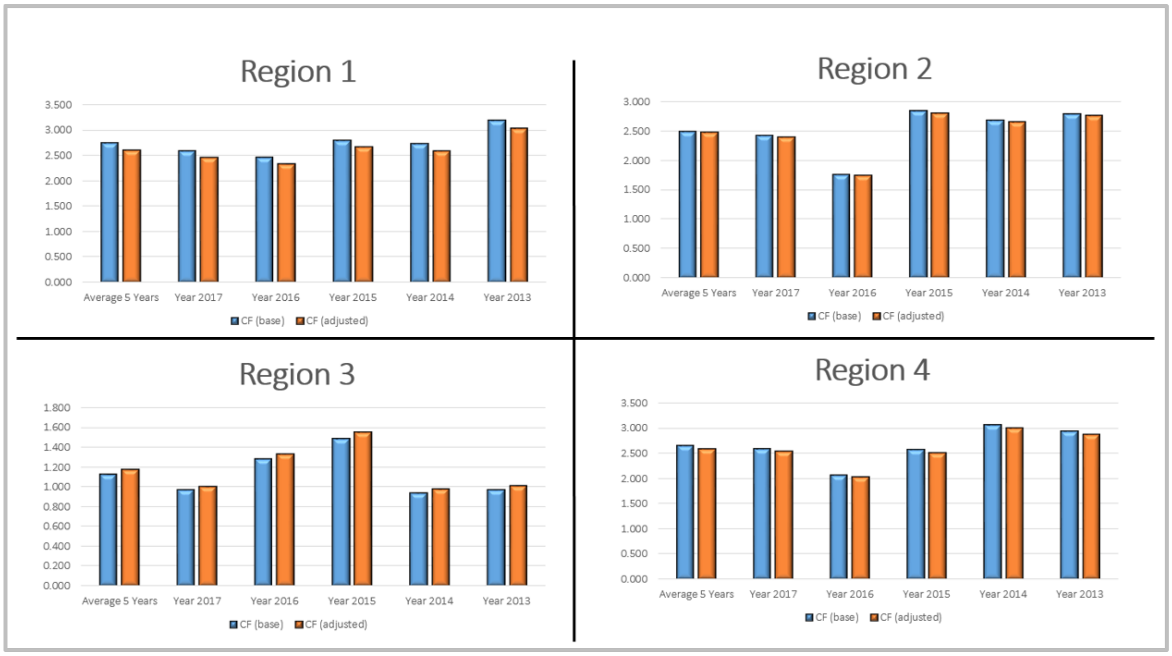

Figure 15. Base Case (*Cf_{base}*) and Adjusted (*Cf_{adj}*) for Calibration Factors 4U Segments of Rural Multilane Highways: Region Wise Comparison

Note: The scales (i.e., along Y-axis) for Cf_{base} and Cf_{adj} for various regions illustrated in Figure 15 are different depending on their calibration results and must be read carefully.

4.2. Calibration factors results: Urban and Suburban Arterials

The calibration factors (after accounting for the local adjustments), while using five-year average crash data, for 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials are found to be 4.714, 5.283, 4.126, 7.633, and 3.543, respectively (Tables 16-20). This indicates that the actual number of crashes on 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials are at least 3.714, 4.283, 3.126, 6.633, and 2.543 times higher than those estimated by the HSM predictive models after accounting for local conditions, respectively. These findings indicate that the 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials experience a significantly higher number of crashes compared to the national average (i.e., the states from which data were used in developing the HSM predictive models). Similarly, all five types of urban and suburban arterials road segments are relatively riskier in Tennessee than in other states, as the observed number of crashes is significantly higher than those predicted by the HSM predictive models (after accounting for the local adjustments), reflecting a greater potential for improvement (Figure 16, Figure 19, Figure 22, Figure 25, and Figure 28).

4.2.1. 2U Urban and Suburban Arterials

Several insights can be drawn from the figures of calibration factors of the 2U segments of urban and suburban arterials below:

- The average five-year calibration factor (assuming TN roadway segments meet the HSM base case conditions) is 4.887, with year-wise calibration factors ranging between 4.739 and 5.055 (Figure 17). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions is significantly reduced to 4.714. This indicates that after accounting for TN-specific conditions, the predicted number of crashes is relatively closer to the actual number of crashes on 2U segments of urban and suburban arterials in Tennessee which is otherwise not the case (i.e., in case of base calibration factors). After accounting for TN-specific conditions, the mean Cf_{adj} is found to be 4.714 with year-wise values ranging between 4.571and

4.877 (Figure 17).

- Considering the Cf_{adj} for 2U segments of urban and suburban arterials, Region 2 appears to be the least risky with an average five-year calibration factor (Cf_{adj}) equaling 4.185 and yearly calibration factors varying between 3.848 and 5.349 (Figure 18).

Table 12. Summary of Calibration Factors in Tennessee for 2U Urban and Suburban Arterials

Tennessee Calibration Factors for Two-lane Urban Suburban Arterials					
Calibration Factors (*Cf*)	**Statewide (N = 234)**	**Region 1 (N = 67)**	**Region 2 (N = 38)**	**Region 3 (N = 88)**	**Region 4 (N = 41)**
Base *Cf* (Cf_{base})	4.887	4.715	4.540	5.142	4.440
Modified *Cf* (Cf_{adj})	4.714	4.465	4.185	5.079	4.226

Notes: All reported calibration factors for Tennessee are the average of five years of calibration factors (See Appendix C for details).

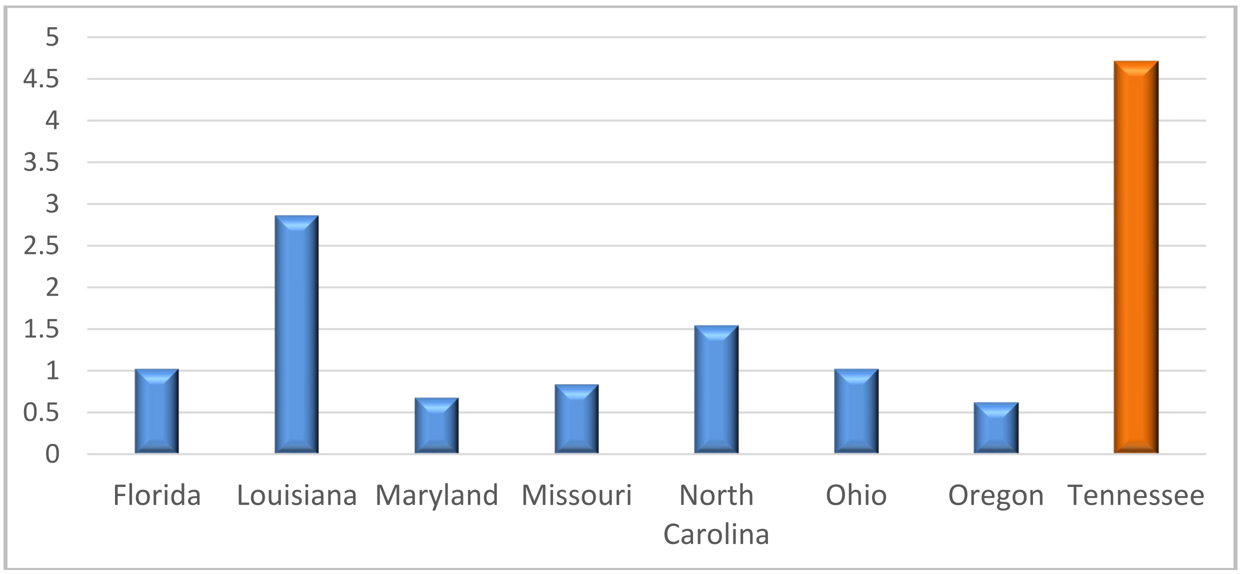

Figure 16. Comparison of Calibration Factor (Cf_{adj}) for 2U segments of Urban and Suburban Arterials in Tennessee with Other States (*7; 16; 17; 19; 20; 22; 23*)

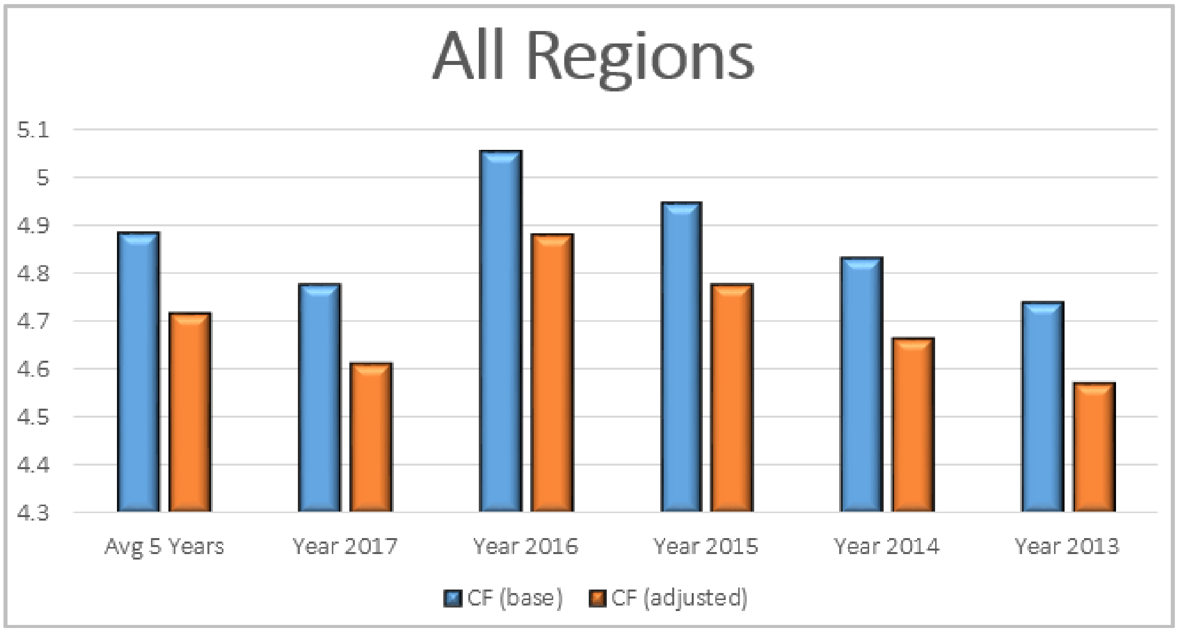

Figure 17. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) Calibration Factors for All Regions (2U Segments of Urban and Suburban Arterials)

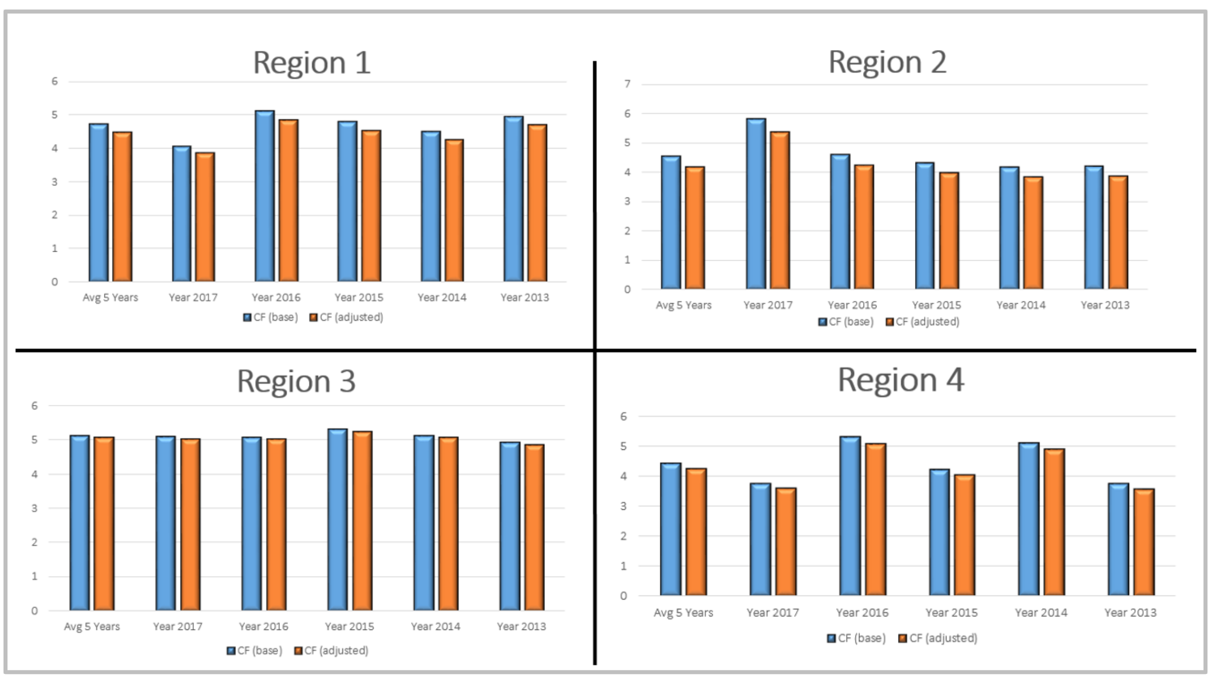

Figure 18. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) for Calibration Factors 2U Segments of Urban and Suburban Arterials: Region Wise Comparison

Note: The scales (i.e., along Y-axis) for Cf_{base} and Cf_{adj} for various regions illustrated in Figure 18 are different depending on their calibration results and must be read carefully.

4.2.2. 3T Urban and Suburban Arterials

Several insights can be drawn from the figures of calibration factors of the 3T segments of urban and suburban arterials below:

- The average five-year calibration factor (assuming TN roadway segments meet the HSM base case conditions) is 5.920, with year-wise values ranging between 5.711 and 6.112 (Figure 20). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions is significantly reduced to 5.823. This indicates that after accounting for TN-specific conditions, the predicted number of crashes is closer to the actual number of crashes on 3T segments of urban and suburban arterials in Tennessee which is otherwise not the case (i.e., in case of base case calibration factors). After accounting for TN-specific conditions the mean Cf_{adj} is found to be 5.823, with year-wise values ranging between 5.617 and 6.006 (Figure 20).

- However, the average five-year Cf_{adj} for 3T segments suggests that the number of actual crashes on 3T segments of urban and suburban arterials in Tennessee is 4.823 times higher than what is predicted by the locally calibrated the HSM predictive models.
- Considering the Cf_{adj} for 3T segments of urban and suburban arterials, Region 1 appears to be the least risky with an average five-year calibration factor (Cf_{adj}) equaling 3.130, while Region 4 is a risky region with an average five years Cf_{adj} value equal to 10.411 (Figure 21).

Table 13. Summary of Calibration Factors in Tennessee for 3T Urban and Suburban Arterials

Tennessee Calibration Factors for Three-lane (3T) including 2WLTL Urban Suburban Arterials					
Calibration Factors (*Cf*)	**Statewide (N = 80)**	**Region 1 (N = 22)**	**Region 2 (N = 16)**	**Region 3 (N = 34)**	**Region 4 (N = 8)**
Base *Cf* (Cf_{base})	5.920	3.201	8.811	6.563	11.085
Modified *Cf* (Cf_{adj})	5.823	3.130	8.921	6.468	10.411

Notes: All reported calibration factors for Tennessee are the average of five years of calibration factors (See Appendix C for details).

Table 13 shows that average C_{adj} for 3T segments of urban and suburban arterials in Tennessee is 5.82 (N = 80) which is relatively higher than other states in the US (Figure 19). This prompted us to carry out checks to explore this relatively high C_{adj} for 3T segments. The checks include: (i) confirming crash frequency, roadway geometry, and AADTs in E-TRIMS and TDOT Traffic History Application, and (ii) conducting outlier analysis based on various factors, especially Crash Rate per 100 million VMT, i.e., exploring high values in the sample. Rechecking the data for the random sample of 3T urban and suburban arterials did not indicate any inaccuracies based on E-TRIMS and Traffic History Application records. On the basis of crash rates, we found that four segments of 3T urban and suburban arterials (See Table C.71 in Appendix C) had relatively high Crash Rates per 100 million VMT (i.e., rate > 2000). Note that the average Crash Rate per 100 million VMT for 3T segments (N = 80) was found to be 527.89 (Table 9). After removing the four outlying segments, the average C_{adj} for 3T segments of urban and suburban arterials drops from 5.82 (N = 80) to 5.01 (N = 76). While removing the segments with high crash rates reduces the average value of C_{adj}, we decided to keep the four segments in the sample because (i) their accuracy (in terms of geometry and locations) was rechecked and they were found to be suitable segments, (ii) they were randomly selected (using 90 percent confidence level criteria to ensure an appropriate representation of the 3T segment population), and (iii) while the high values of the four segments were higher than the three-sigma limit, they were still within the six-sigma limits.

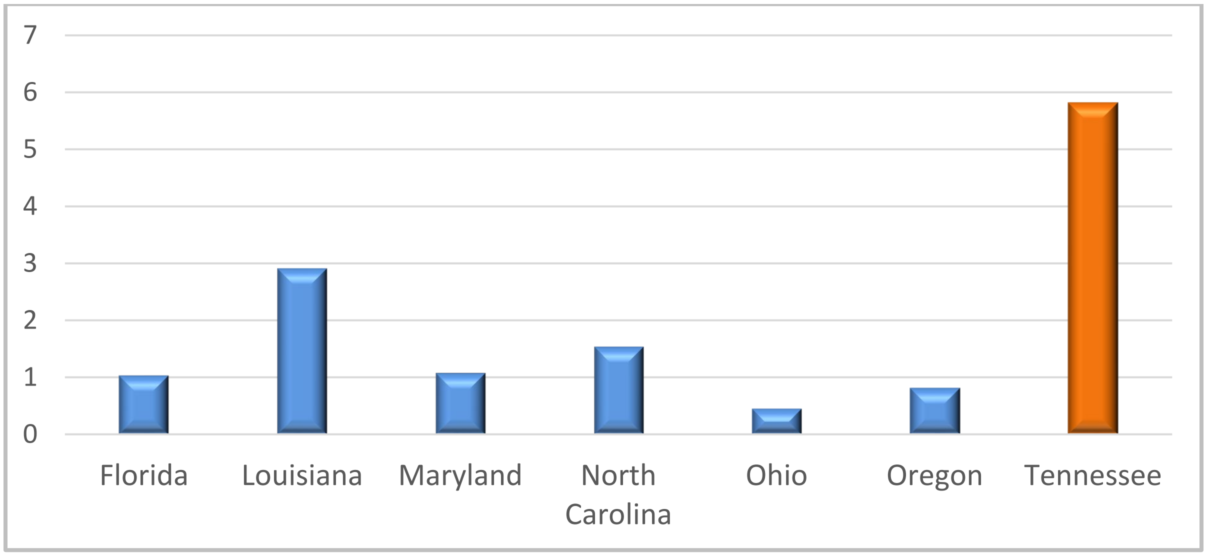

Figure 19. Comparison of Calibration Factor (*Cf_{adj}*) for 3T segments of Urban and Suburban Arterials in Tennessee with Other States (*7; 16; 17; 19; 20; 23*)

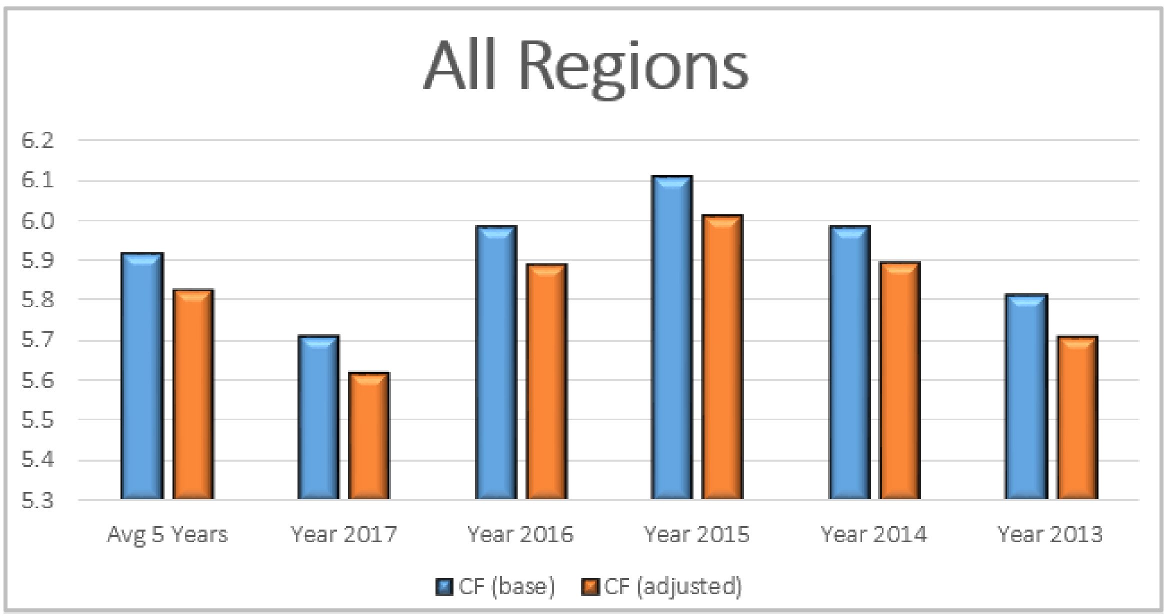

Figure 20. Base Case (*Cf_{base}*) and Adjusted (*Cf_{adj}*) Calibration Factors for All Regions (3T Segments of Urban and Suburban Arterials)

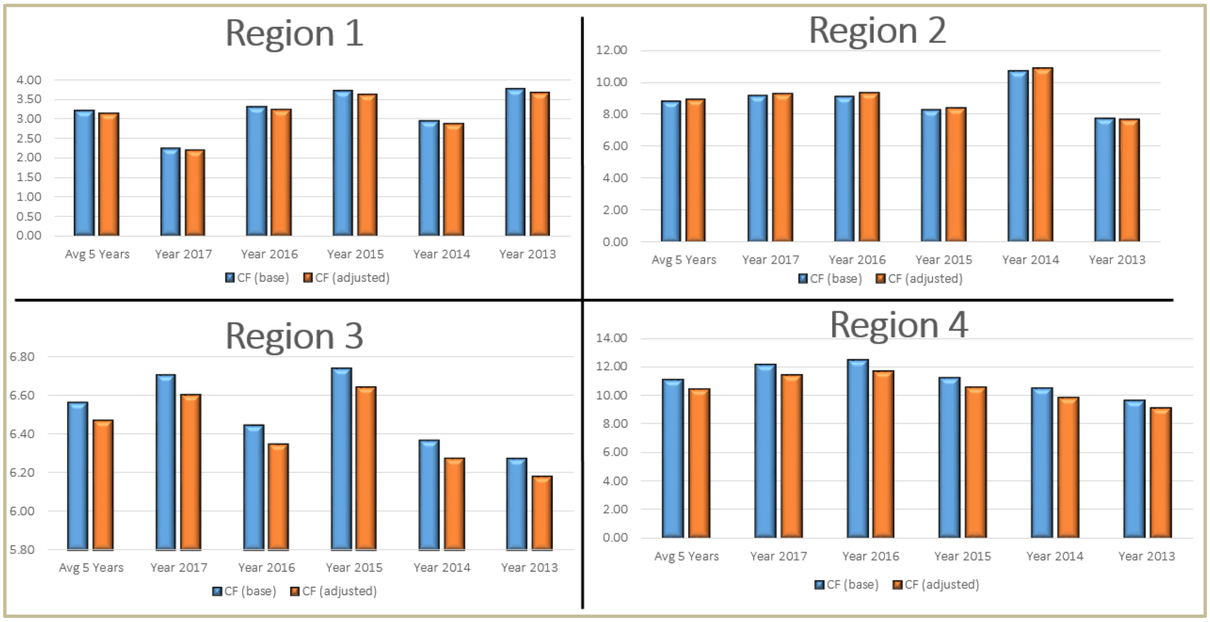

Figure 21. Base Case (*Cf$_{base}$*) and Adjusted (*Cf$_{adj}$*) for Calibration Factors 3T Segments of Urban and Suburban Arterials: Region Wise Comparison

Note: The scales (i.e., along Y-axis) for *Cf$_{base}$* and *Cf$_{adj}$* for various regions illustrated in Figure 21 are different depending on their calibration results and must be read carefully.

4.2.3. 4D Urban and Suburban Arterials

Several insights can be drawn from the figures of calibration factors of the 4D segments of urban and suburban arterials below:

- The average five-year calibration factor (assuming TN roadway segments meet the HSM base case conditions) is 4.126, with year-wise values ranging between 3.940 and 4.413 (Figure 23). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions is still greater than the national average (4.459) with year-wise calibration factors ranging between 4.257 and 4.769 (Figure 23). It was interesting to notice that even after accounting for TN-specific conditions, the *Cf$_{adj}$* was close to *Cf$_{base}$* which was expected, otherwise, *Cf$_{adj}$* was expected to be lower than *Cf$_{base}$*.
- However, the average five-year *Cf$_{adj}$* for 4D segments suggests that the number of actual crashes on 4D segments of urban and suburban arterials in Tennessee is 3.459 times higher than what is predicted by the locally calibrated the HSM predictive models.
- Considering the *Cf$_{adj}$* for 4D segments of urban and suburban arterials, Region 4 appears to be the least risky with an average five-year calibration factor (*Cf$_{adj}$*) equaling 3.566, while Region 3 is a risky region with an average five years *Cf$_{adj}$* value equal to 6.467 (Figure 24).

Table 14. Summary of Calibration Factors in Tennessee for 4D Urban and Suburban Arterials

Tennessee Calibration Factors for Four-lane Divided (4D) Urban and Suburban Arterials					
Calibration Factors (*Cf*)	**Statewide (N = 278)**	**Region 1 (N = 114)**	**Region 2 (N = 41)**	**Region 3 (N = 59)**	**Region 4 (N = 64)**
Base Cf (Cf_{base})	4.126	3.375	4.475	6.242	3.336
Modified Cf (Cf_{adj})	4.459	3.822	4.468	6.467	3.566

Notes: All reported calibration factors for Tennessee are an average of five years of calibration factors (See Appendix C for details).

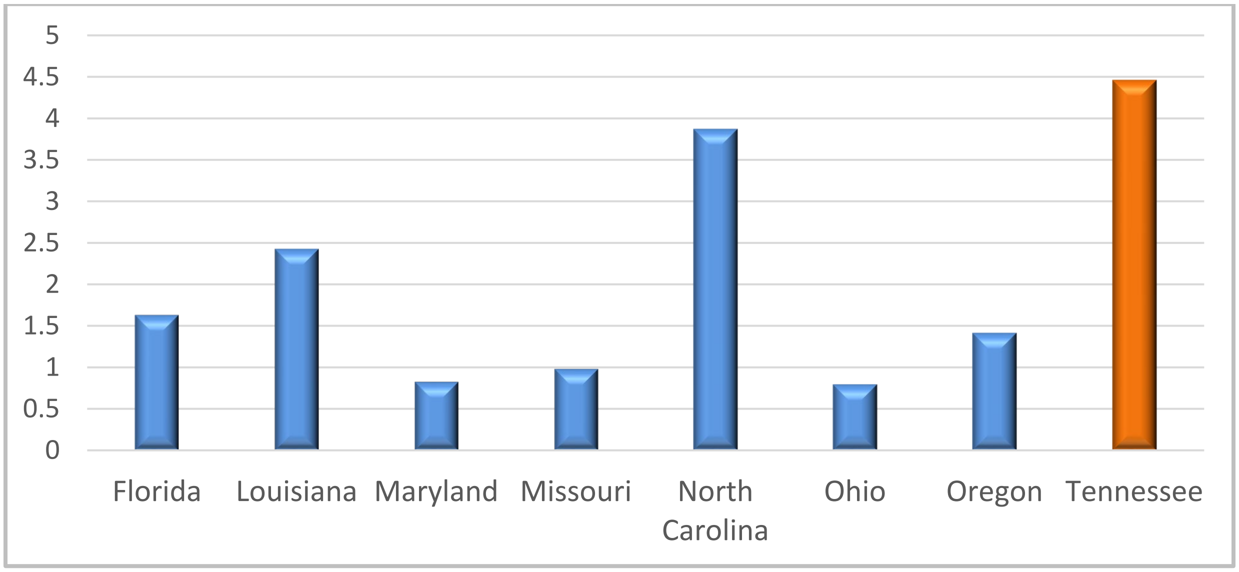

Figure 22. Comparison of Calibration Factor (Cf_{adj}) for 4D segments of Urban and Suburban Arterials in Tennessee with Other States (*7; 16; 17; 19; 20; 22; 23*)

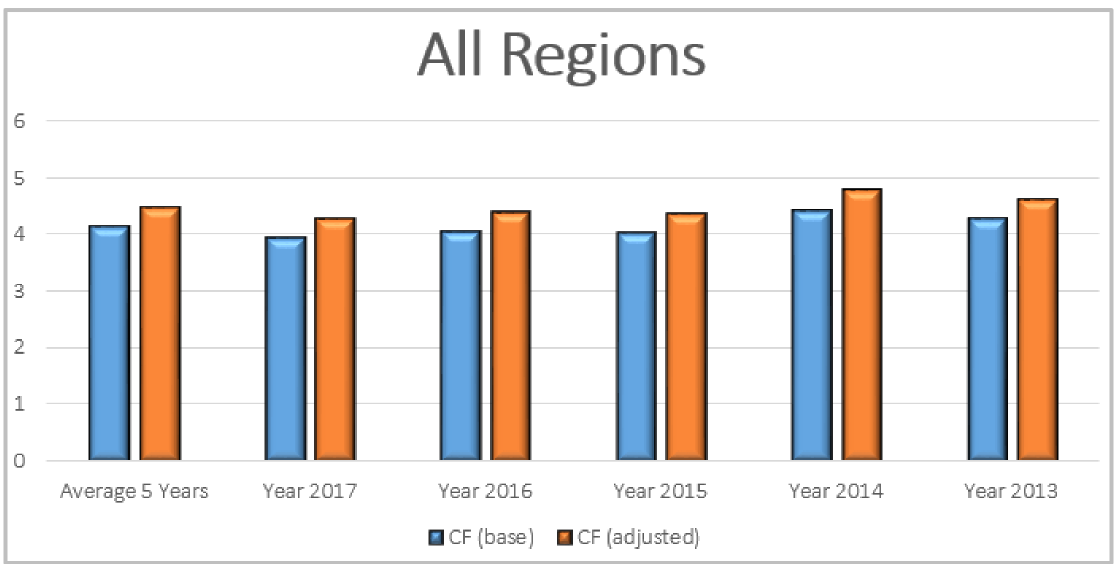

Figure 23. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) Calibration Factors for All Regions (4D Segments of Urban and Suburban Arterials)

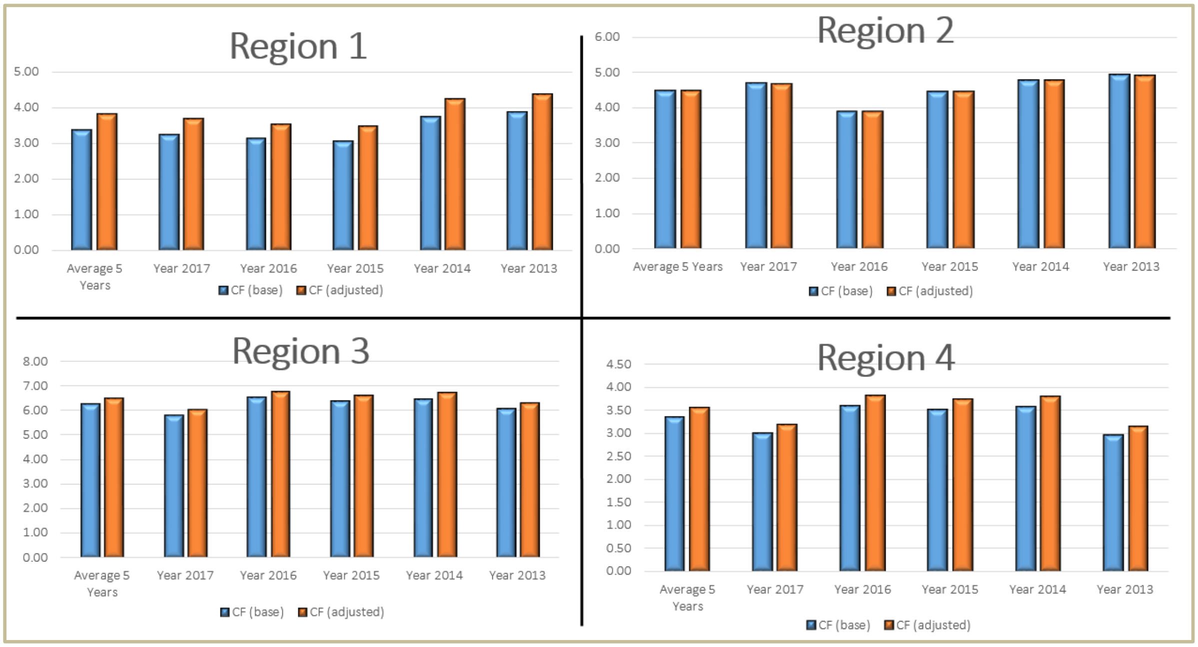

Figure 24. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) for Calibration Factors 4D Segments of Urban and Suburban Arterials: Region Wise Comparison

Note: The scales (i.e., along Y-axis) for Cf_{base} and Cf_{adj} for various regions illustrated in Figure 24 are different depending on their calibration results and must be read carefully.

4.2.4. 4U Urban and Suburban Arterials

Several insights can be drawn from the findings, the calibration factors for the 4U segments of urban and suburban arterials (Table 19 and Figures 25-27):

- The average five-year calibration factor (assuming TN roadway segments meet the HSM base case conditions) is 8.089, with year-wise values ranging between 6.829 and 9.152 (Figure 26). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions reduces to 7.633 with year-wise calibration factors ranging between 6.447 and 8.639 (Figure 26).
- However, the average five-year Cf_{adj} for 4U segments suggests that the number of actual crashes on 4U segments of urban and suburban arterials in Tennessee is 6.633 times higher than what is predicted by the locally calibrated the HSM predictive models.
- Considering the Cf_{adj} for 4U segments of urban and suburban arterials, Region 1 appears to be the least risky with an average five-year calibration factor (Cf_{adj}) equaling 5.658, while Region 2 is a risky region with an average five years Cf_{adj} value equal to 11.404 (Figure 27).

Table 15. Summary of Calibration Factors in Tennessee for 4U Urban and Suburban Arterials

Tennessee Calibration Factors for Four-lane Divided (4D) Urban and Suburban Arterials					
Calibration Factors (*Cf*)	**Statewide (N = 80)**	**Region 1 (N = 14)**	**Region 2 (N = 16)**	**Region 3 (N = 20)**	**Region 4 (N = 30)**
Base Cf (Cf_{base})	8.089	6.107	12.447	8.869	7.067
Modified Cf (Cf_{adj})	7.633	6.658	11.404	8.624	6.656

Notes: All reported calibration factors for Tennessee are an average of five years of calibration factors (See Appendix C for details).

The analysis shows that the average C_{adj} for 4U segments of urban and suburban arterials in

Tennessee is 7.63 (N = 80), which is relatively high compared with other states in the US (Figure 25). To further investigate the reasons for high values, we performed quality control checks, which included: (i) rechecking crash and geometric data, and AADT in E-TRIMS and the TDOT Traffic History Application, and (ii) conducting outlier analysis based on various factors, specifically Crash Rate per 100 million VMT. We confirmed the accuracy of the data for a random sample of 4U urban and suburban arterials using E-TRIMS and Traffic History Application records. Referring to the crash rate, we observed that three segments of 4U urban and suburban arterials (See Table C.72 in Appendix C) had high Crash Rates per 100 million VMT (i.e., rates > 3,000). Therefore, compared with the mean Crash Rate per 100 million VMT for 4U segments (N = 80) 769.77, these segments had relatively high rates. If the three segments are removed from the analysis, then the average C_{adj} drops to 6.09 (N = 77). Nonetheless, we decided to keep the three segments in the sample because (i) their accuracy (in terms of geometry and locations) was rechecked and they were found to be suitable segments, (ii) the segments were randomly chosen (using 90 percent confidence level criteria to ensure an appropriate representation of the population), and (iii) while the high values of the segments were higher than the three-sigma limit, they were still within the six-sigma limits.

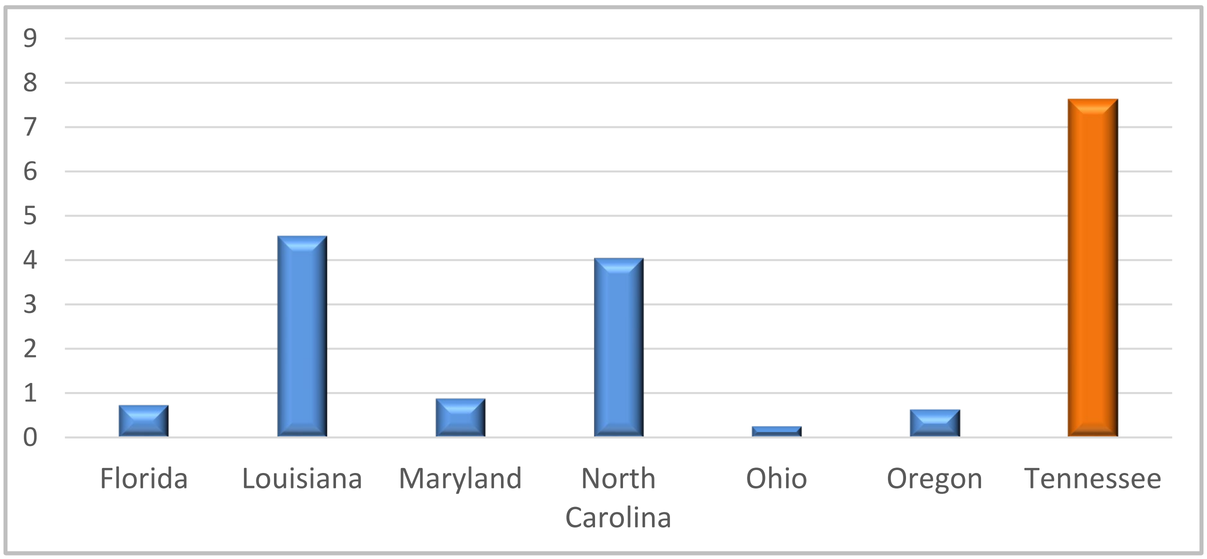

Figure 25. Comparison of Calibration Factor (*Cf_{adj}*) for 4U segments of Urban and Suburban Arterials in Tennessee with Other States (*7; 16; 17; 19; 20; 23*)

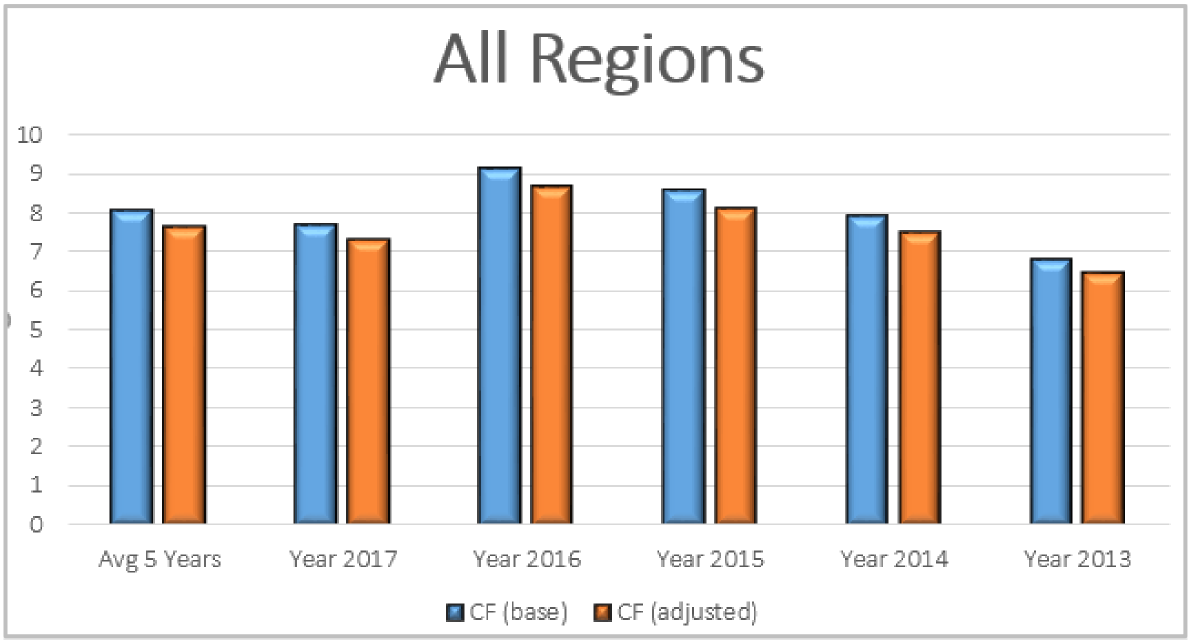

Figure 26. Base Case (*Cf_{base}*) and Adjusted (*Cf_{adj}*) Calibration Factors for All Regions (4U Segments of Urban and Suburban Arterials)

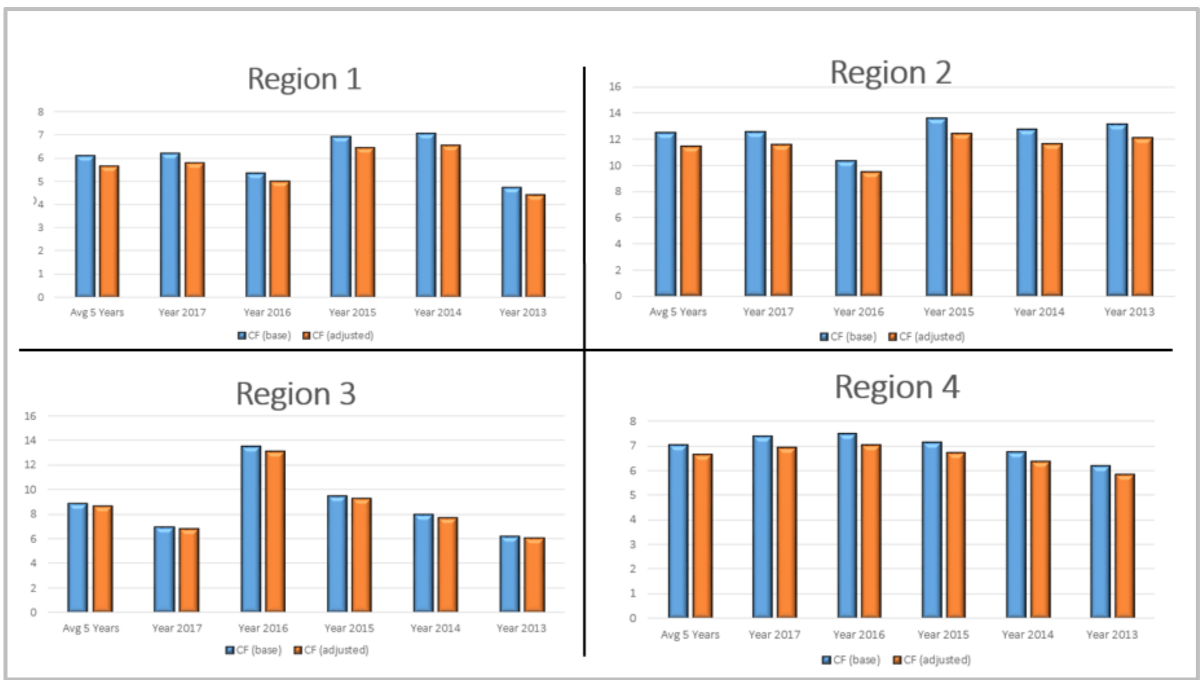

Figure 27. Base Case (*Cf_{base}*) and Adjusted (*Cf_{adj}*) for Calibration Factors 4U Segments of Urban and Suburban Arterials: Region Wise Comparison

Note: The scales (i.e., along Y-axis) for Cf_{base} and Cf_{adj} for various regions illustrated in Figure 27 are different depending on their calibration results and must be read carefully.

4.2.4. 5T Urban and Suburban Arterials

Several insights can be drawn from the figures of calibration factors of the 5T segments of urban and suburban arterials below:

- The average five-year calibration factor (assuming TN roadway segments meet the HSM base case conditions) for 5T segments of urban and suburban arterials in Tennessee is 3.584, with a year-wise value ranging between 3.509 and 3.648 (Figure 29). After accounting for the CMFs in calibration factor calculations, the average five-year calibration factor for all regions significantly reduces to 3.543. This is good indication that after accounting for TN-specific conditions, the predicted number of crashes are relatively closer to the actual number of crashes on 5T segments of urban and suburban arterials in Tennessee which otherwise is not the case (i.e., in case of Cf_{base}). After accounting for TN-specific conditions, the mean CF (adjusted) is found to be 3.543 with a year-wise value ranging between 3.470 and 3.605 (Figure 29).

- Considering the Cf_{adj} for 5T segments of urban and suburban arterials, Region 1 appears to be the least risky with the average five-year calibration factor (Cf_{adj}) equaling 2.730 while Region 2 is a risky region with average five years Cf_{adj} value equal 4.708 (Figure 30).

Table 16. Summary of Calibration Factors in Tennessee for 5T Urban and Suburban Arterials

Tennessee Calibration Factors for Five-Lane (Including 2WLTL) (5T) Urban and Suburban Arterials					
Calibration Factors (*Cf*)	**Statewide (N = 304)**	**Region 1 (N = 87)**	**Region 2 (N =46)**	**Region 3 (N = 119)**	**Region 4 (N = 52)**
Base *Cf* (Cf_{base})	3.584	2.744	4.766	3.606	4.160
Modified *Cf* (Cf_{adj})	3.543	2.730	4.708	3.551	4.110

Notes: All reported calibration factors for Tennessee are average of five-year calibration factors (See Appendix C for details).

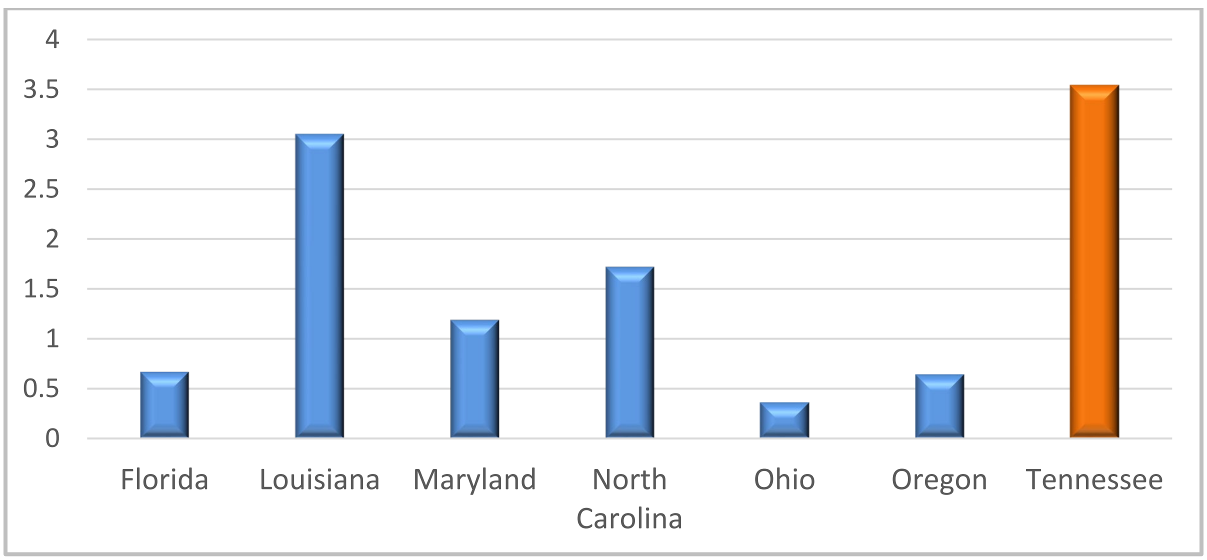

Figure 28. Comparison of Calibration Factor (Cf_{adj}) for 5T segments of Urban and Suburban Arterials in Tennessee with Other States (*7; 16; 17; 19; 20; 23*)

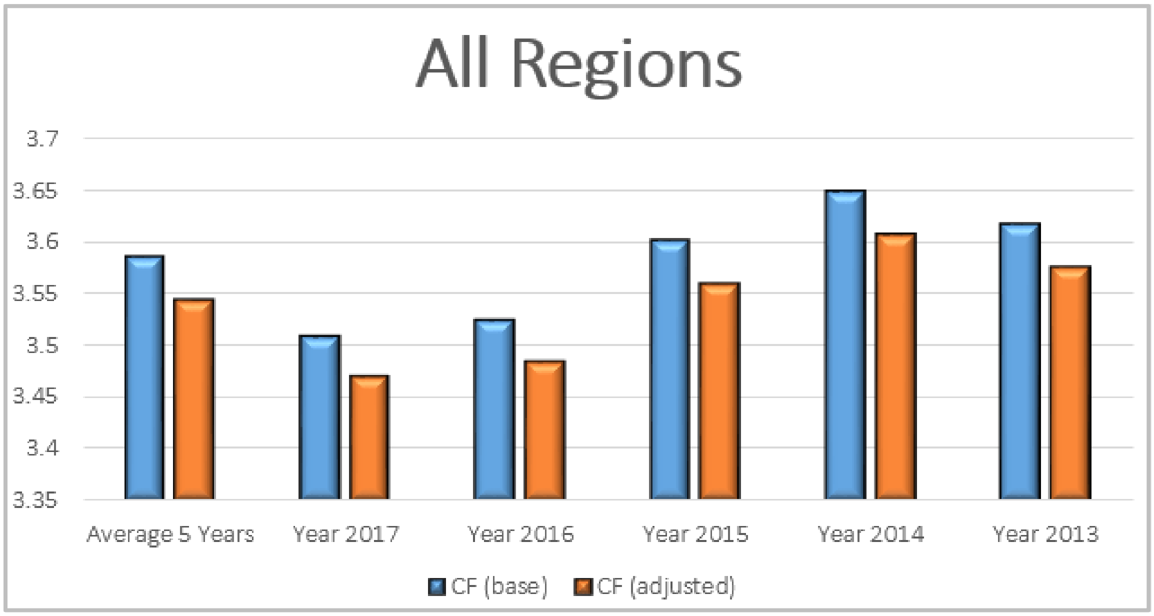

Figure 29. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) Calibration Factors for All Regions (5T Segments of Urban and Suburban Arterials

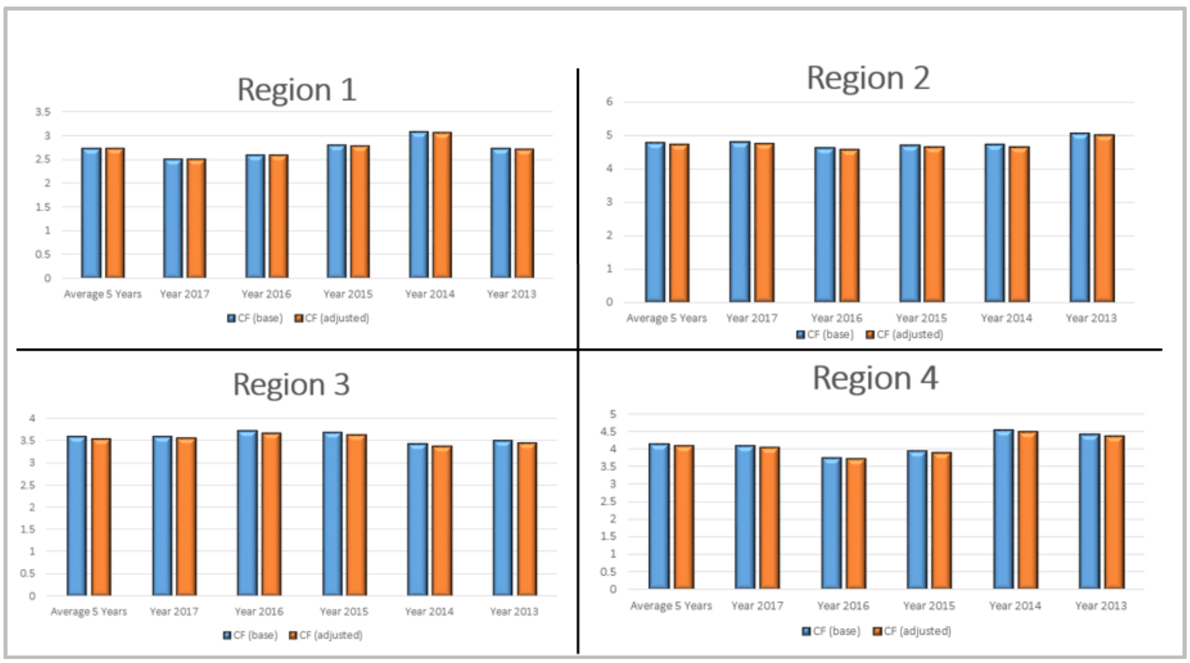

Figure 30. Base Case (Cf_{base}) and Adjusted (Cf_{adj}) for Calibration Factors 5T Segments of Urban and Suburban Arterials: Region Wise Comparison

Note: The scales (i.e., along Y-axis) for Cf_{base} and Cf_{adj} for various regions illustrated in Figure 30 are different depending on their calibration results and must be read carefully.

4.3. Tennessee-Specific Safety Performance Functions

This section presents the modeling results for various types of rural multilane highways and urban and suburban arterials. We apply count data models based on different distributional assumptions (i.e., the Poisson and negative-binomial) to explore the key correlates of average five-year crash frequency. In the case of each of the roadway types, fixed-parameter models are estimated using different distributional assumptions (i.e., the Poisson and negative binomial), and their performance is briefly discussed. All models were derived from a systematic process to include the most important variables (available in the data set) based on statistical significance, specification parsimony, and intuition. First, a series of ordinary least square regressions were estimated to spot correlations and patterns in the data. Next, the Poisson and Negative Binomial regressions were estimated. Specifically, all variables were tested, and statistically significant variables were retained in the final model specifications. Note that significant over-dispersion in the data of each of the seven roadway types (i.e., including rural multilane and urban and suburban arterials) were observed which is being addressed via negative binomial regression. TN-specific SPFs for all the seven roadway types indicate that the fixed-parameter negative binomial model shows significant improvement in estimation/in-sample prediction performance. In short, if negative binomial regression is not used to address the over-dispersion issue in the data, our results could be misleading and inappropriate.

4.3.1. Modeling Results for Rural Multilane Highways

4.3.1.1. Model Selection and Performance Comparison

Before discussing the results of Tennessee-specific SPFs for rural multilane highways in detail, for brevity, we discuss the summary statistics (goodness-of-fit measures)[3] of the models (based on the Poisson and negative binomial distribution assumptions for both 4D and 4U segments of rural multilane highways as shown in Table 17 and Table 18, respectively. Following (*14; 25*), Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) can be used to evaluate competing nested and/or non-nested models. In the case of both 4D segments and 4U segments of rural multilane highways, Model 2 (i.e., fixed-parameter negative binomial regression) outperforms with improved in-sample fit or estimation performance (i.e., having lowest AIC and BIC values) compared to their counterparts (Table 17-18).

4.3.1.2. Modeling Results for Rural Multilane Highways

Referring to the parameter estimates in different models, a positive sign on parameter estimate shows that a specific variable is positively correlated with crash frequency, and vice versa. For instance, in Model 2 (Table 17), for 4D segments of rural multilane highways, AADT and segment length are positively correlated with crash frequency on 4D segments of rural multilane highways, which is consistent with existing safety literature. The over-dispersion parameter in the fixed-parameter negative binomial model is marginally significant (Table 17). However, Model 2 (i.e., fixed-parameter negative binomial model) outperforms with the lowest AIC (728.93) and BIC (750.54) for 4D segments of rural multilane highways. Hence, we discuss the estimation results for Model 2 (Table 17).

As expected, the modeling results for 4D rural multilane highways suggest that AADT and segment length increase the average five-year crash frequency (Table 17). Importantly, the over-dispersion parameter in negative binomial models was found to be marginally significant (i.e., as per 90% confidence criteria) suggesting significant evidence of over-dispersion in the data of 4D rural multilane highways segments (Table 17). In Model 2 (i.e., 4D segments of rural multilane highways), increasing inner shoulder width (in feet) and speed limit (miles per hour) reduces crash frequency on 4D segments of rural multilane highways (Table 17). For instance, model 2 (the best model) suggests that a unit increase in the inner shoulder width

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[3] Note that the goodness of fit measures (such as log-likelihood at convergence and likelihood-ratio test statistic based on this) are presented in case of each roadway type (i.e., Table 17 and Table 18 for 4D and 4U rural multilane highways respectively) along with the modeling results (i.e., fixed-parameter Poisson and negative binomial models). Importantly, “explaining” vs “predicting” are two different dimensions for which statistical models may be estimated (*24*). While AIC is derived from a predictive viewpoint, yet it is an indicator of “in-sample” fitting capabilities of competing models (*24*). Having said this, AIC can be used to evaluate “in-sample” fits of competing models.

(i.e., in feet) and speed limit (miles per hour) reduces the average five-year crash frequency by 0.0951 and 0.0138 units, respectively (Table 17).

Table 17. Modeling Results: TN-Specific SPFs for 4D Rural Multilane Highways

Variable	Model 1 (Poisson)			Model 2 (Negative Binomial)		
	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value
Average annual daily traffic (AADT) in 1000s	0.0587	5.47	<0.0001	0.0570	4.33	<0.0001
Inner shoulder width (in feet)	-0.0951	-1.99	0.0459	-0.1061	-2.17	0.0299
Speed limit (miles per hour)	-0.0138	-1.79	0.0736	-0.0164	-1.99	0.0469
Segment length (miles)	0.7328	17.19	<0.0001	0.7992	12.74	<0.0001
Constant	0.2074	0.453	0.6503	0.3412	0.785	0.4326
Over-dispersion Parameter	---	----		0.1312	1.92	0.0547
Summary Statistics						
Number of Observations	271			271		
Log Likelihood at Null	-496.1177			-496.1177		
Log Likelihood at Convergence	-362.2281			-358.4683		
Pseudo R-square value	0.2698			0.2774		
AIC	734.4561			728.9358		
BIC	752.4586			750.5480		

Notes: Model 1 and 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression, respectively.

Referring to the SPFs for 4U segments of rural multilane highways, AADT and segment length are positively correlated with average five-year crash frequency, while the presence of rumble strips along the outer shoulder (in feet) negatively influences crash frequency on such road segments (Model 1-2 in Table 18). Importantly, the over-dispersion parameter in the fixed-parameter negative binomial model is found to be statistically significant (Table 18). The fixed-parameter negative binomial model (Model 2) outperforms Model 1 based on the AIC, BIC, and Pseudo R^2 values, indicating a superior in-sample fit (Table 18). Model 2 for 4U segments indicates that a unit increase in segment length (in miles) and average annual daily traffic (in 1000s) increases the average five-year crash frequency by 1.3730 and 0.1074 units, respectively (Table 18). Additionally, Model 2 suggests that the average five-year crash frequency on 4U rural multilane highways reduces by 1.3605 units if rumble strips exist along the outer shoulder (Table 18).

Table 18. Modeling Results: TN-Specific SPFs for 4U Rural Multilane Highways

Variable	Model 1 (Poisson)			Model 2 (Negative Binomial)		
	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value
Segment length (miles)	1.3730	7.81	<0.0001	1.3345	4.35	<0.0001
Average annual daily traffic (AADT) in 1000s	0.1074	14.06	<0.0001	0.1293	3.84	0.0001
Presence of rumble strip along outer shoulder (1/0)	-1.3605	-4.16	<0.0001	-1.0184	-3.61	0.0003
Constant	-0.5768	-4.18	<0.0001	-0.8383	-2.81	0.0049
Over-dispersion Parameter	---	----	---	0.3924	2.48	0.0129
Summary Statistics						
Number of Observations	81			81		
Log Likelihood at Null	-305.4908			-305.4908		
Log Likelihood at Convergence	-148.7064			-133.5979		
Pseudo R-square value	0.5132			0.5626		
AIC	305.4129			277.1957		
BIC	314.9903			289.1683		

Notes: Model 1 and Model 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression respectively.

4.3.2. Modeling Results for Urban and Suburban Arterials

Random samples for each roadway types were selected to develop TN-specific SPFs for 2U, 3T, 4D, 4U, and 5T segments of urban and suburban arterials. Importantly, while selecting random samples, we considered and followed the HSM (2010) minimum sample size criteria required for calibration. These SPFs and all the correlates were used to understand how key factors associate with the average five-year crash frequency on urban and suburban arterials. Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) can be used to evaluate and compare the fit of competing nested and/or non-nested models based on in-sample predictive performance (*14, 25*). We develop fixed count data models (while considering both the Poisson and Negative Binomial distributions) for all the five types of urban and suburban arterials which are briefly discussed below in detail.

4.3.2.1. 2U Segments of Urban and Suburban Arterials

Before discussing the results of Tennessee-specific SPFs for 2U segments of urban and suburban arterials in detail, we discuss the summary statistics of the four models (Model 1-2) developed for 2U segments of the urban and suburban arterials. The Model 1 and Model 2 results suggest that significant over-dispersion exists in the crash data for 2U segments of urban and suburban arterials (Table 19). Importantly, Models 2 (i.e., fixed-parameter negative binomial model) showed significant improvement (i.e., considering AIC, BIC, and McFadden "Pseudo" R^2 values) as compared to Model 1 (the fixed-parameter Poisson) (Table 19). The results of the superior model (i.e., Model 2) for 2U segments of urban and suburban arterials indicate that the AADT and segment length are positively correlated with the average five-year crash frequency (Table 19). Also, it is found that increasing the speed limit reduces crash frequency on 2U segments of urban and suburban arterials respectively (Table 19). The Model 2 estimation indicates that a unit increase in the number of minor commercial and major industrial/institutional driveways per mile increases the five-year crash frequency by 0.2328 and 0.3864 units, respectively (Table 19).

Table 19. Modeling Results: TN-Specific SPFs for 2U Urban and Suburban Arterials

Variable	**Model 1 (Poisson)**			**Model 2 (Negative Binomial)**		
	Coeff.	**t-stat**	**p-value**	**Coeff.**	**t-stat**	**p-value**
Speed limit (mile per hour)	-0.0141	-3.06	0.0022	-0.0229	-2.90	0.0037
Average annual daily traffic (AADT) in 1000s	0.1162	17.40	<0.0001	0.1391	11.19	<0.0001
Segment length (miles)	0.7378	15.29	<0.0001	0.9731	8.22	<0.0001
Number of minor commercial driveways per mile	0.2328	4.71	<0.0001	0.2016	2.51	0.0120
Number of major industrial/institutional driveways per mile	0.3864	10.82	<0.0001	0.2774	4.15	<0.0001
Constant	0.3398	1.69	0.0906	0.4087	1.29	0.1964
Over-dispersion Parameter	---	---	---	0.2987	5.43	<0.0001
Summary Statistics						
Number of Observations	234			234		
Log Likelihood at Null	-968.4007			-968.4007		
Log Likelihood at Convergence	-573.1299			-497.3120		
Pseudo R-square value	0.4081			0.4864		
AIC	1158.2602			1008.6242		
BIC	1178.9926			1032.8105		

Notes: In Table 19, Model 1 and Model 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression, respectively.

4.3.2.2. 3T Segments of Urban and Suburban Arterials

Before discussing the results of TN-specific SPFs for 3T segments of urban and suburban arterials in detail, we discuss the summary statistics of the four models (Model 1-2) developed for 3T segments of the urban and suburban arterials. Model 2 (i.e., fixed-parameter negative binomial model) showed significant improvement over Model 1 with the lowest AIC and BIC values, and higher Pseudo R^2 value (Table 20). The estimation results indicate that significant over-dispersion is present in the data as evident from a statistically significant over-dispersion parameter in the negative binomial model (Table 20). According to the results of Model 2 (superior model based on in-sample fit statistics), factors that increase the average five-year crash frequency include AADT, segment length, number of major commercial driveways, and number of minor commercial driveways residential driveways per mile (Table 20). These findings were expected and are consistent with the existing literature. Specifically, an increase in density of the two driveway types increases traffic interaction with the through traffic on 3T segments which consequently increases the average five-year crash frequency (Table 20).

Table 20. Modeling Results: TN-Specific SPFs for 3T Urban and Suburban Arterials

Variable	Model 1 (Poisson)			Model 2 (Negative Binomial)		
	Coeff.	**t-stat**	**p-value**	**Coeff.**	**t-stat**	**p-value**
Average annual daily traffic (AADT) in 1000s	0.0862	9.83	<0.0001	0.0982	3.98	0.0001
Segment length (miles)	0.7628	6.17	<0.0001	0.9823	2.13	0.0332
Number of major commercial driveways per mile	0.2840	4.27	<0.0001	0.5563	2.62	0.0086
Number of minor commercial driveways per mile	0.1886	7.03	<0.0001	0.2161	2.03	0.0419
Constant	0.1284	0.84	0.3977	-0.1992	-0.56	0.5785
Over-dispersion Parameter	---	---	---	0.7475	4.01	0.0001
Summary Statistics						
Number of Observations	80			80		
Log Likelihood at Null	-454.2245			-454.2245		
Log Likelihood at Convergence	-335.5677			-205.8952		
Pseudo R-square value	0.2612			0.5467		
AIC	681.1352			423.7904		
BIC	693.0456			438.0824		

Notes: Model 1 and Model 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression, respectively.

4.3.2.3. 4D segments of Urban and Suburban Arterials

In the case of the 4D segments, Model 2 (i.e., fixed-parameter negative binomial model) showed superior performance (based on AIC, BIC, and Pseudo R^2 values) compared to the fixed-parameter Poisson model (Table 21). The estimation results suggest that there is significant over-dispersion in the data of 4D urban and suburban arterials which can be observed from the statistically significant over-dispersion parameter in Model 2 (i.e., negative binomial model) (Table 21). Hence, we discuss the results of the best model which is Model 2 in this case. According to the results of Model 2, the average five-year crash frequency increases with increasing segment length, AADT, and the number of major commercial driveways per mile (Table 21). On the other hand, crash frequency on 4D segments of urban and suburban arterials reduces with an increase in inner shoulder width and median width, which makes sense as a wider inner shoulder provides a margin of safety to the drivers and can be used by drivers to avoid conflict. Similarly, the wider separating physical media may help in reducing the gazing problem specifically during nighttime due to opposing traffic.

Table 21. Modeling Results: TN-Specific SPFs for 4D Urban and Suburban Arterials

Variable	Model 1 (Poisson)			Model 2 (Negative Binomial)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Segment length (miles)	0.9137	15.51	<0.0001	1.1084	4.78	<0.0001
Number of major commercial driveways per mile	0.1640	8.16	<0.0001	0.1714	1.99	0.0470
Inner shoulder width (in feet)	-0.0725	-5.55	<0.0001	-0.1091	-3.74	0.0002
Average annual daily traffic (AADT) in 1000s	0.0436	19.83	<0.0001	0.0555	11.27	<0.0001
Median width (in feet)	-0.0151	-7.24	<0.0001	-0.0179	-3.60	0.0003
Constant	0.8292	9.83	<0.0001	0.6341	3.83	0.0001
Over-dispersion Parameter	---	---	---	0.8987	8.70	<0.0001
Summary Statistics						
Number of Observations	278			278		
Log Likelihood at Null	-1563.793			-1563.793		
Log Likelihood at Convergence	-1225.656			-711.2471		
Pseudo R-square value	0.2162			0.5451		
AIC	2463.3107			1436.4955		
BIC	2485.0781			1461.8880		

Notes: Model 1 and Model 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression, respectively.

4.3.2.4. 4U segments of Urban and Suburban Arterials

For the 4U segments of urban and suburban arterials, it is found that Model 2 (i.e., fixed-parameter negative binomial regression) performs better than Model 1 (i.e., the fixed-parameter Poisson model). Note that the negative binomial model was found to have the lowest values of AIC and BIC, and highest Pseudo R^2 values (Table 22). Hence, we discuss the effects of key correlates of average five-year crash frequency on 4U segments of urban and suburban arterials based on the results of the superior model (the fixed-parameter negative binomial model in this case). In Model 2, both the AADT and segment length are positively correlated with crash frequency (Table 22). For instance, the estimation results of Model 2 suggest that a unit increase in segment length increases the average five-year crash frequency by 2.3204 units (Table 22). Other key correlates which increase crash frequency on 4U segments of urban and suburban arterials include the number of minor commercial driveways and the number of major industrial/institutional driveways per mile (Table 22).

Table 22. Modeling Results: TN-Specific SPFs for 4U Urban and Suburban Arterials

Variable	Model 1 (Poisson)			Model 2 (Negative Binomial)		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Segment length (miles)	1.0143	5.04	<0.0001	2.3204	3.50	0.0005
Number of minor commercial driveways per mile	0.0803	3.27	0.0011	0.1988	2.16	0.0305
Number of major industrial/institutional driveways per mile	0.3390	9.86	<0.0001	0.2478	1.75	0.0799
Average annual daily traffic (AADT) in 1000s	0.0809	18.30	<0.0001	0.0961	5.19	<0.0001
Speed limit (miles per hour)	-0.1286	-16.91	<0.0001	-0.1243	-6.25	<0.0001
Constant	5.1006	20.54	<0.0001	4.275	6.02	<0.0001
Over-dispersion Parameter	---	---	---			
Summary Statistics						
Number of Observations	80			80		
Log Likelihood at Null	-813.7149			-813.7149		
Log Likelihood at Convergence	-416.0295			-226.9615		
Pseudo R-square value	0.4887			0.7210		
AIC	844.0592			467.9232		
BIC	858.3512			484.5976		

Notes: Model 1 and Model 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression.

4.3.2.5. 5T segments of Urban and Suburban Arterials

In the case of 5T segments of urban and suburban arterials, we found that the fixed-parameter negative binomial regression model (Model 2) has the best performance with the lowest AIC and BIC values and highest Pseudo R^2 values (Table 23). The results of Model 2 (fixed-parameter negative binomial model) indicate that the average five-year crash frequency on 5T segments of urban and suburban arterials increases with an increase in the number of minor commercial driveways, the number of major industrial/institutional driveways, and the number of minor industrial/institutional driveways per mile (Table 23). These findings confirm our expectations as an increase in the number of driveways along these segments increases traffic interaction with the through traffic, thus increasing the crash risk. As expected, AADT and segment length are found to be positively correlated with crash frequency (Table 23). Importantly, we found that as average offset distance to fixed objects increases on 5T segments, the average five-year crash frequency reduces (Table 23). It is noteworthy that modeling results provide evidence of over-dispersion in the data (Table 23).

Table 23. Modeling Results: TN-Specific SPFs for 5T Urban and Suburban Arterials

Variable	**Model 1 (Poisson)**			**Model 2 (Negative Binomial)**		
	Coef.	**t-stat**	**p-value**	**Coef.**	**t-stat**	**p-value**
Average annual daily traffic (AADT) in 1000s	0.0574	32.30	<0.0001	0.0659	11.50	<0.0001
Number of minor commercial driveways per mile	0.0924	10.24	<0.0001	0.1305	3.06	0.0021
Number of major industrial/institutional driveways per mile	0.1059	7.57	<0.0001	0.1251	1.96	0.0495
Offset to roadside fixed objects (in feet)	-0.0225	-8.49	<0.0001	-0.0161	-2.33	0.0200
Segment length (miles)	0.8567	14.84	<0.0001	1.0026	4.02	0.0001
Number of minor industrial/institutional driveways per mile	0.0379	4.32	<0.0001	0.0643	1.65	0.0992
Constant	0.8511	12.92	<0.0001	0.4170	2.40	0.0162
Over-dispersion Parameter	---	---	---			
Summary Statistics						
Number of Observations	304			304		
Log Likelihood (Null)	-2564.5570			-2564.5570		
Log Likelihood (Final Model)	-1477.1920			-937.2744		
Pseudo R-square value	0.4239			0.6345		
AIC	2968.3836			1890.5486		
BIC	2994.4030			1920.2859		

Notes: Model 1 and Model 2 refer to the fixed-parameter Poisson and fixed-parameter negative binomial regression, respectively.

5. FINDINGS: APPLICATION OF CALIBRATION FACTORS IN SAFETY ANALYST

This section aims to summarize the AASHTOWare Safety Analyst User's Manual in order to deliver a brief framework and guidance on the software and provide instruction for implementing the estimated Calibration Factors (CFs), Crash Modification Factors (CMFs), and Safety Performance Functions (SPFs) in the software to be used by TDOT users. An introduction to the software is presented in Appendix D. In the next section, a brief explanation of importing the Tennessee-specific SPFs, CFs, and CMFs into the software is provided following an example of using and evaluating countermeasures in Safety Analyst.

5.1. SPFs in Safety Analyst: Application to Tennessee

In this section, a brief explanation of importing the Tennessee-specific SPFs, CFs, and CMFs into the software is presented. As mentioned, the Administration Tool is used to edit or modify the SPFs for each subtype. As an example, the SPF for the Rural Multilane Highways for total crashes is modified based on the estimated CMFs and CFs for Tennessee. To this end, follow the below steps:

1. Open the Administration Tool
2. In the "Edit Menu" click on "Edit Agency Safety Performance Function"
3. Select the "**Seg/Rur; Multilane divided**" under the Site Subtype menu (Figure 31)
4. Click on "**Edit SPF**" toolbox to edit the selected SPF (Figure 32)

In the "**Edit Agency SPF**" window, the coefficients (c) and its functional form can be edited. New terms can be added in the SPF function, using the "Add Term" toolbox. The new term can be added as a constant term (C), an exponential term with a constant exponent (e^c), an exponential term with a variable exponent (e^{cV}), or variable power term (V^c).

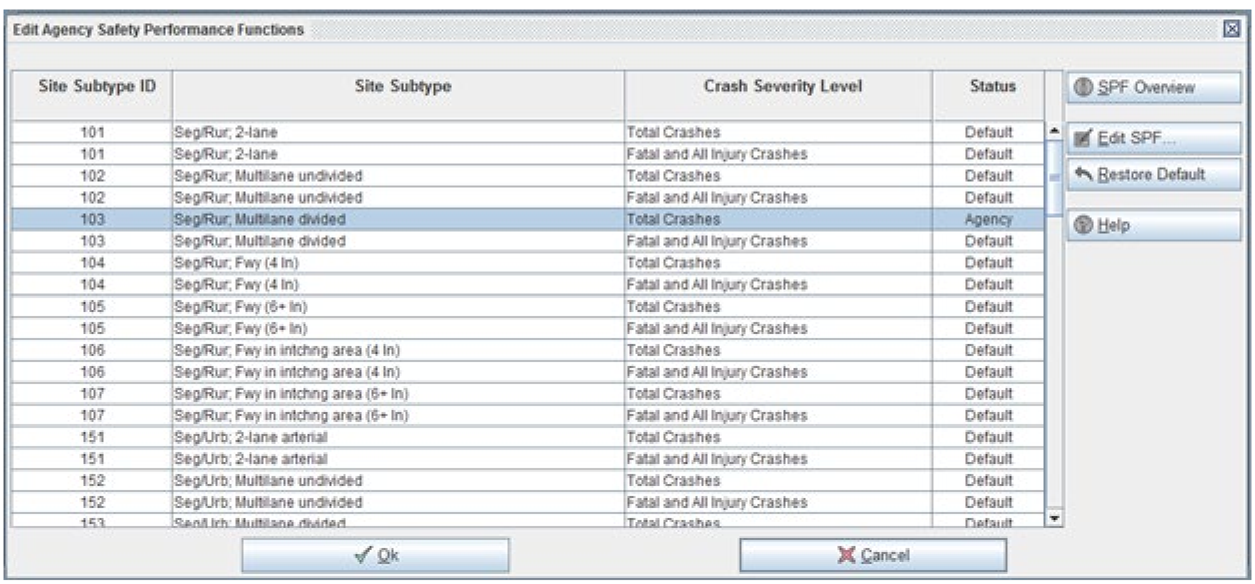

Figure 31: Edit Agency Safety Performance Function Window: AASHTOWare Safety Analyst Software

To add the CMFs or CFs, at first it is required to add a CMF or CF as a variable related to each segment in the roadway segment attributes dataset (agency dataset as shown in Figure 33). Also, it is required to add the new attributes in the roadway segment element in the Administration Tool. To this end, it is needed to do the following steps:

1- Open Administration Tool

2- Click on the “Edit” tab in the Menu Bar
3- Click on “Deployment Attribute”
4- Add a new attribute in the “Roadway Segment Element/Table” (see Figure 34)
5- Add attribute name, title, and data type (e.g. Numeric)

Note that, it is required to click on “Update Database” in the “System Database” tab to save the changes/modifications that have been made.

After adding the attributes, each CMFs or CFs can be added to SPF function as a variable as shown in Figure 32. In our example for the rural multilane divided highways, the CMFs and CFs are added in a variable power term form with a power of 1.00. The added attributes can be seen in the Analytical Tool for each segment as shown in Figure 35.

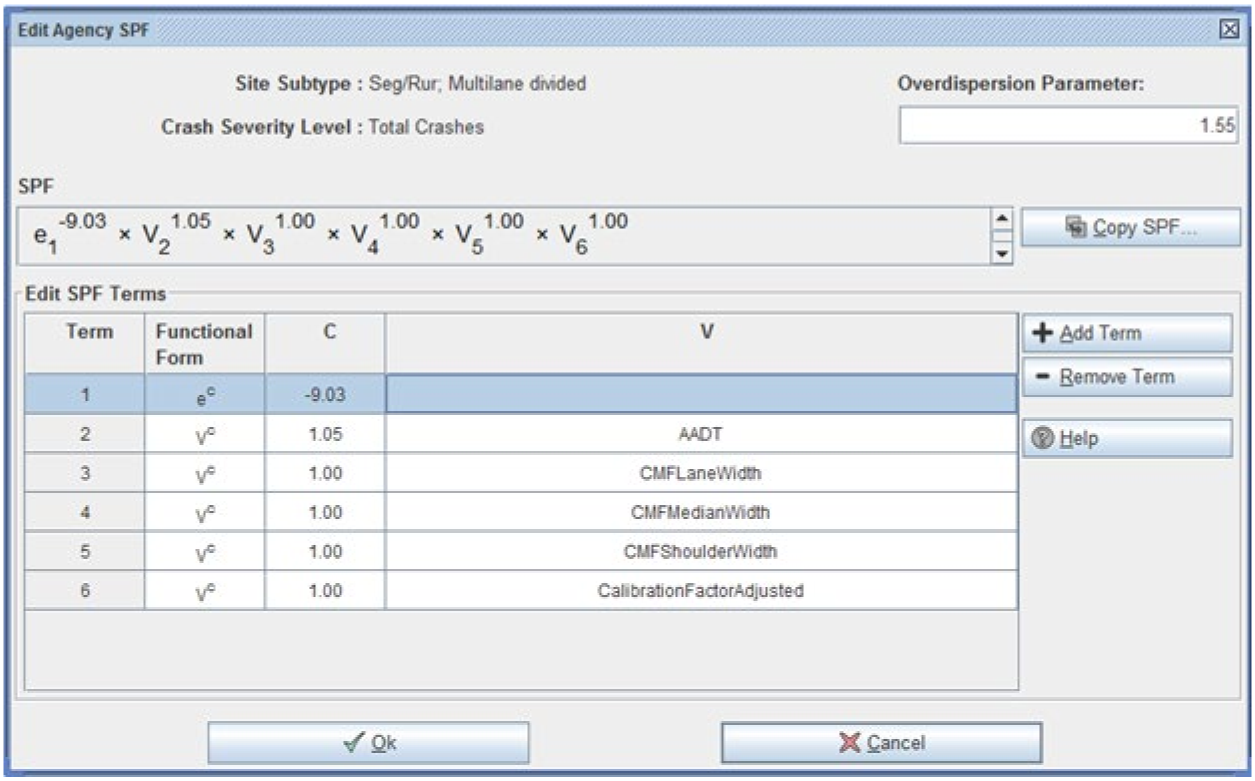

Figure 32. Edit Agency SPF Window: AASHTOWare Safety Analyst Software

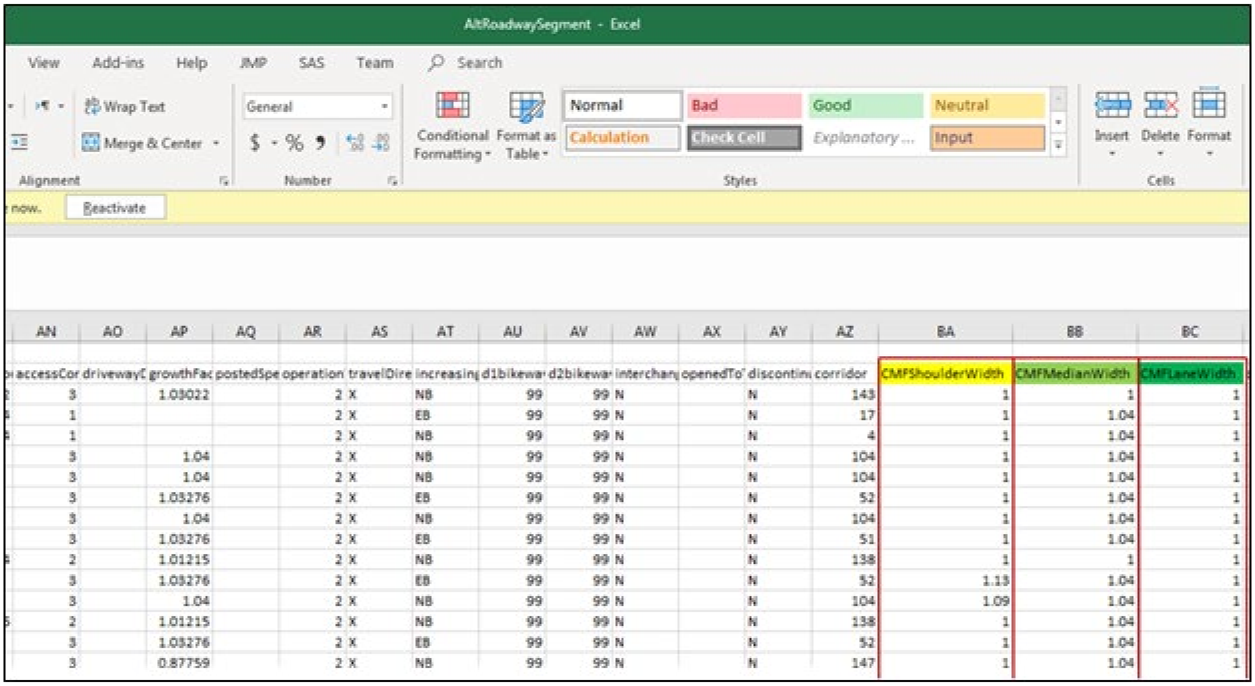

Figure 33. Roadway Segment Attributes Dataset

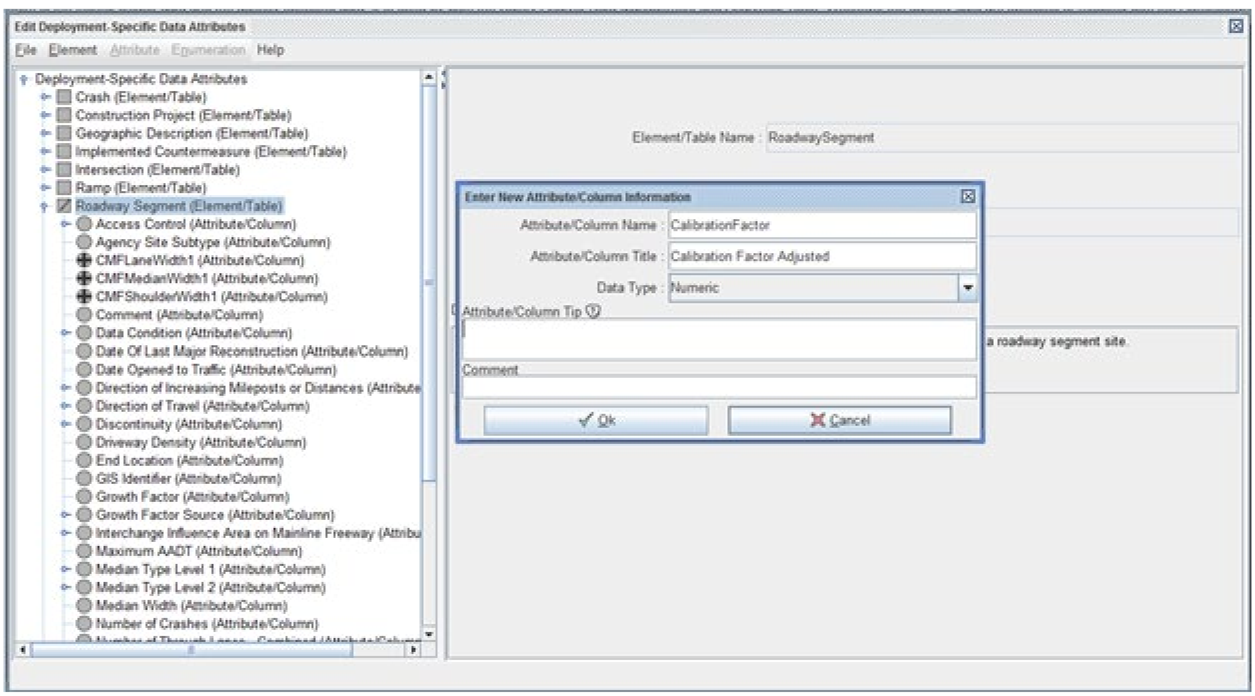

Figure 34. Edit Deployment-Specific Data Attribute: AASHTO's Safety Analyst Software

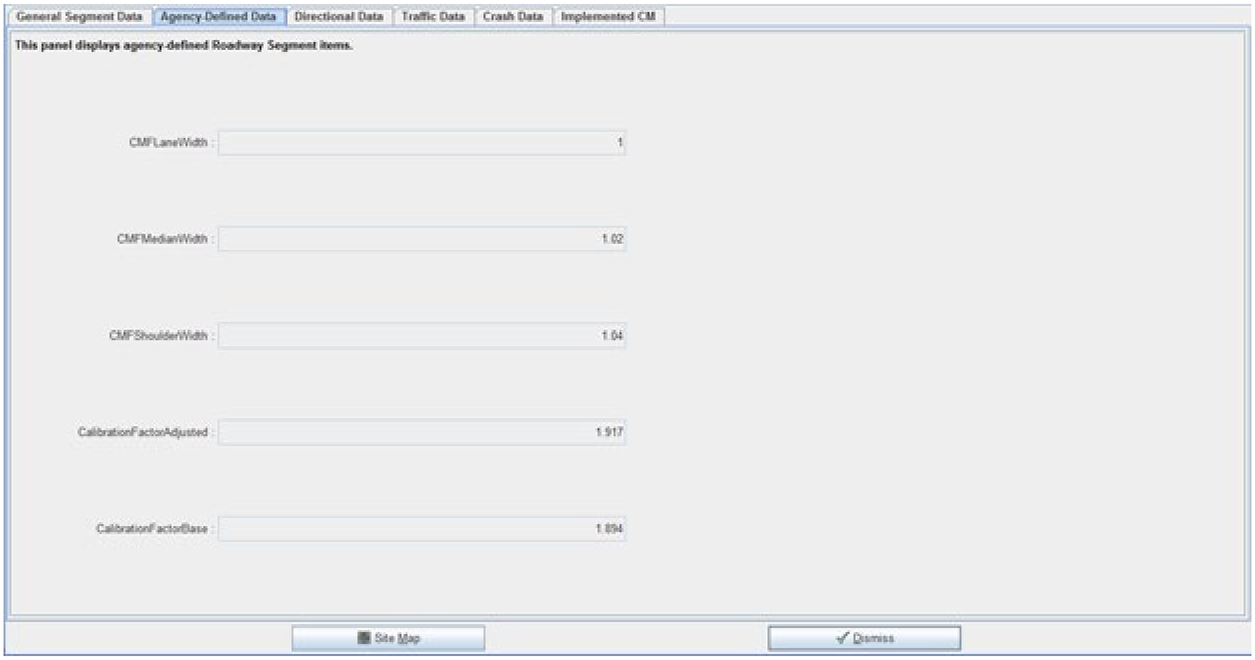

Figure 35. Agency Defined Data for a Segment in AASHTOWare Safety Analyst Software

5.1.1. A comparison of TN SPFs using Safety Analyst

In this report, in order to make a comparison between the total crash predictions using different types of SPFs for the rural multilane divided highways, after creating a sample dataset some segments are selected. Five types of SPF are defined as follows:

Eq.16. Highway Safety Manual HSM-Base SPF Model (HSM Base)

$$N_{Base} = e^{-9.025} * AADT^{1.049} \tag{16}$$

Eq.17. Tennessee SPF Estimated model-Poisson (Estimated)

$$N_{TN} = e^{-8.133} * AADT^{0.990} * Exposure \tag{17}$$

Eq.18. HSM SPF-Base with Base Calibration Factor-CF_{Base} (HSM_Base*CF-base)

$$N_{Base} = e^{-9.025} * AADT^{1.049} * Cf_{Base} \tag{18}$$

Eq.19. HSM SPF-Base with HSM Adjusted Crash Modification Factors-$CMF_{Adjusted}$ (HSM_Base*CMFs)

$$N_{Base} = e^{-9.025} * AADT^{1.049} * CMF_{Lane\ width} * CMF_{Median\ width} * CMF_{Shoulder\ width} \tag{19}$$

Eq.20. HSM SPF-Base with HSM Adjusted CMFs and Adjusted CF (HSM_Base*CMFs*CF-adj)

$$N_{Base} = e^{-9.025} * AADT^{1.049} * CMF_{Lane\ width} * CMF_{Median\ width} * CMF_{Shoulder\ width} * Cf_{adjusted} \tag{20}$$

Using the Analytical Tool, through pursuing the following steps, the observed and predicted crash frequencies can be reported for the selected sites/segments.

1. Open Safety Analyst Analytical Tool

2. Run the “Getting Started Wizard”
3. Create a new workbook and a new site list or work in an existing workbook or site list
4. Select Network Screening
5. Click on Finish and close the new pop-up window
6. Click on the “Site List” tab in the Menu bar (see Figure 36)
7. In the pop-up window (Edit Site List) select a site subtype (Rural Multilane Divided Highway) and click on “Analyze Crashes” tab and select “Safety Performance Report” (See Figure 37)
8. In the new pop-up window crash severity, analysis limits, and analytical period can be determined.

The tentative results of analyzing different segments using the five defined SPFs are presented in Table 24. The result shows that the HSM base SPF with the HSM crash modification factors and the adjusted calibration factor mostly brings about the best prediction very close to the observed crash frequencies/counts and with the minimum error compared with the other SPF types.

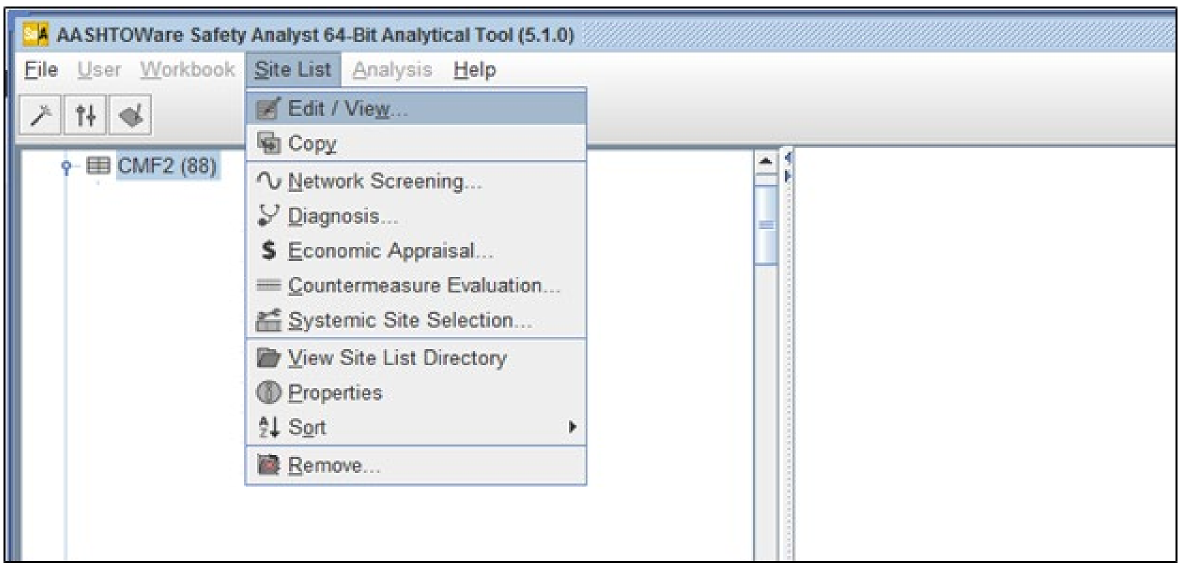

Figure 36. Analytical Tool Menu Bar

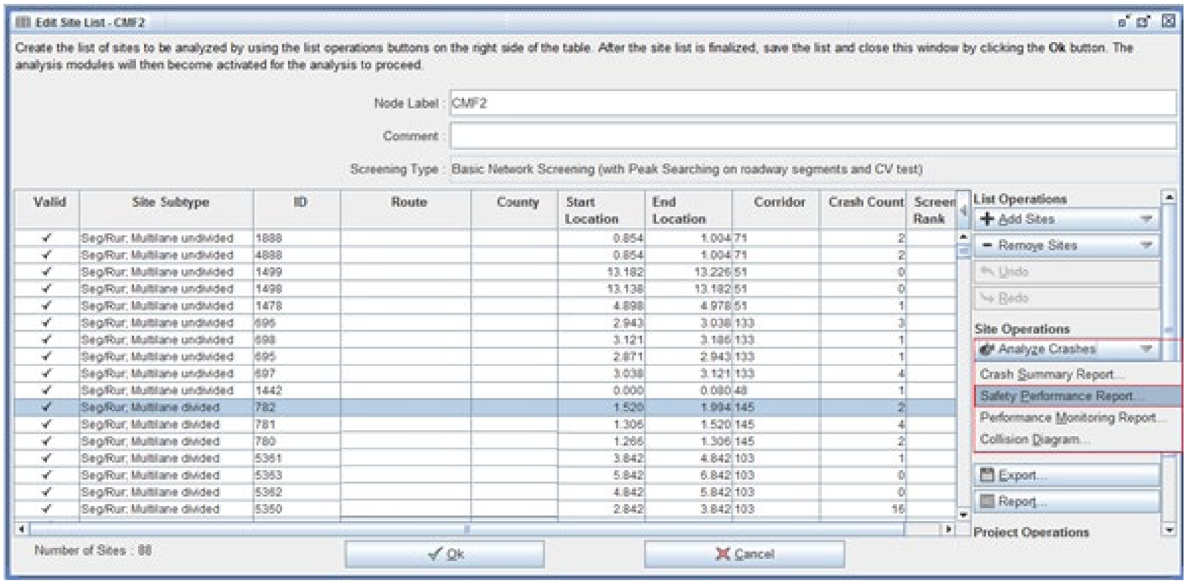

Figure 37. Analytical Tool Site Selection for SPF Report

Table 24. A Comparison between SPFs in Tennessee Rural Multilane Divided Highways

Site Subtype/ Route	Analysis Limits		Analysis Period		Observed Crash		SPF Type	Predicted Crash		Error %
	Start Location	**End Location**	**Start Year**	**End Year**	**Count**	**Freq.**		**Count**	**Freq.**	
Rural Multilane Divided/ SR040 County 139 TN	0.000	0.360	2017	2017	**5**	**13.89**	Base	2.44	6.79	51%
							Estimated	3.36	9.33	33%
							Base*CF-base	4.65	12.93	7%
							Base*CMF	2.47	6.86	51%
							Base*CMF*CFadj	**4.78**	**13.29**	**4%**
Rural Multilane Divided/ SR018 County 69 TN	26.040	26.230	2017	2017	**1**	**5.26**	Base	0.38	1.99	62%
							Estimated	0.55	2.92	45%
							Base*CF-base	0.71	3.76	29%
							Base*CMF	0.43	2.24	57%
							Base*CMF*CFadj	**0.82**	**4.3**	**18%**
Rural Multilane Divided/ SR018 County 69 TN	26.230	26.411	2017	2017	**1**	**5.52**	Base	0.37	2.06	63%
							Estimated	0.55	3.03	45%
							Base*CF-base	0.71	3.91	29%
							Base*CMF	0.42	2.33	58%
							Base*CMF*CFadj	**0.81**	**4.47**	**19%**
Rural Multilane Divided/ SR111 County 153 TN	3.490	3.600	2017	2017	**1**	**9.09**	Base	0.44	3.98	56%
							Estimated	0.62	5.64	38%
							Base*CF-base	**0.83**	**7.569**	**17%**
							Base*CMF	0.42	3.83	58%
							Base*CMF*CFadj	0.82	7.41	18%
Rural Multilane Divided/ SR009 County 13 TN	1.310	1.748	2017	2017	**3**	**6.85**	Base	0.57	1.29	81%
							Estimated	0.85	1.94	72%
							Base*CF-base	0.86	4.97	71%
							Base*CMF	0.57	1.29	81%
							Base*CMF*CFadj	**2.26**	**5.16**	**25%**
Rural Multilane Divided/ SR065 County 37 TN	10.930	10.970	2017	2017	**1**	**25.00**	Base	0.11	2.71	89%
							Estimated	0.16	3.92	84%
							Base*CF-base	0.41	10.21	59%
							Base*CMF	0.13	3.15	87%
							Base*CMF*CFadj	**0.5**	**12.36**	**50%**
Rural Multilane Divided/ SR025 County 159 TN	13.200	13.270	2017	2017	**1**	**14.29**	Base	0.36	5.14	64%
							Estimated	0.5	7.18	50%
							Base*CF-base	**1.36**	**19.40**	**36%**
							Base*CMF	0.38	5.46	62%
							Base*CMF*CFadj	1.5	21.38	50%

5.1.2. Example of How to Use Countermeasures in Safety Analyst

As mentioned before, using the Administration Tool, countermeasures can be edited, defined, and added as the Agency Countermeasures. Accordingly, the below steps should be followed.

1- Open Administration Tool
2- Click on the "Countermeasures" in the "Edit" tab to edit the agency-specified countermeasure data (see Figure 38).
3- In the pop-up window, as shown in Figure 39, countermeasures can be added and modified.

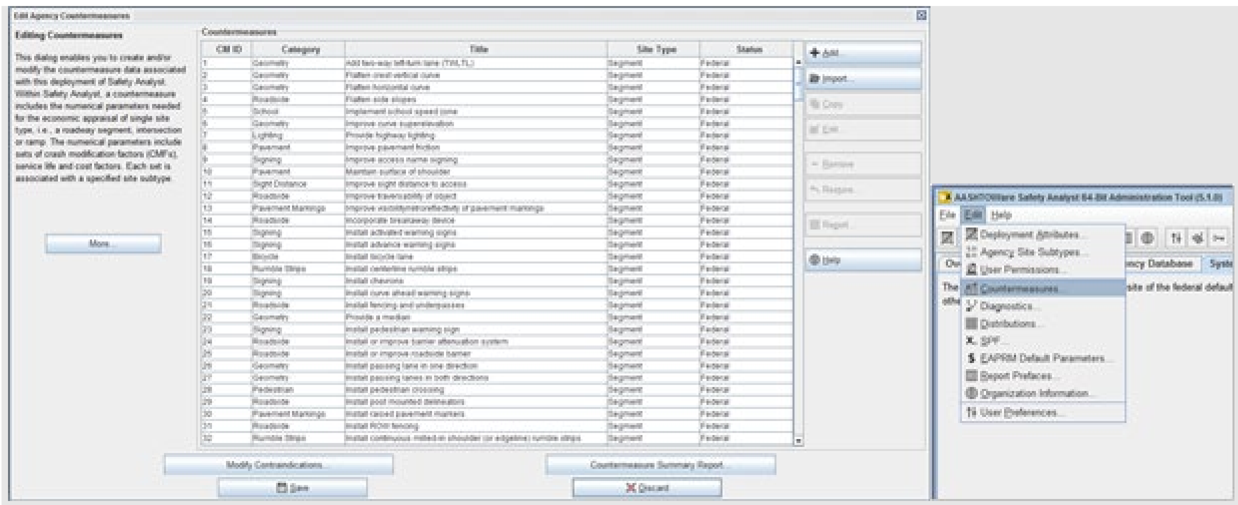

Figure 38. Edit Agency Countermeasure in AASHTOWare Safety Analyst Software

An example is provided to show how to make a countermeasure diagnosis, select countermeasures, and evaluate the economic and safety benefits of the implementation of the selected countermeasures. In Analytical Tool, using the "Diagnosis and Countermeasure Selection" module, considering the collision types and observed crash counts, different countermeasures are diagnosed and suggested by the software. Moreover, users can manually select and add countermeasures for the selected segment. The selected countermeasures can be evaluated and ranked based on their priority by using the "Economic Appraisal and Priority Ranking" module. For example, a rural multilane divided highway segment is selected, and the installation of continuous milled-in shoulder rumble strip was diagnosed for it. After evaluating the selected countermeasure, the result of the safety benefit evaluation shows that after 20 years, total crashes will be reduced by 13.76 crashes as shown in Figure 39.

Proposed Site-CM	Site ID	Site Type	Beginning Location	Ending Location	Countermeasure	CM Start Location	CM End Location	Total Crashes Reduced*
1	636	Segment	9.289	10.289	Install continuous milled-in shoulder (or edgeline) rumble strips	9.289	10.289	13.76

Figure 39. Example of the Safety Benefit evaluation of a Countermeasure

Please note that the results presented in this chapter are tentative and only provided for demonstration. For more information about AASHTOWare Safety Analyst, please refer to the AASHTOWare Safety Analyst User's Manual.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Achieved outcomes and benefits of the project

Safety is a critical concern on Tennessee roadways. To improve safety, it is important to understand and predict where safety problems are and how to mitigate them using a data-analytic approach. The adoption of procedures in the Highway Safety Manual facilitates the identification of appropriate sites for treatment and making informed investments in appropriate countermeasures. In this context, the study provides the following benefits:

1. The overall project outcome is an improvement in the current methodology of safety analysis and the ability to make more informed decisions about appropriate countermeasures.
2. The project aids in the operation and management of Tennessee's transportation system to provide a high level of safety and service to the public.
3. The project improves the safety analysis process by using data to make informed decisions about countermeasures. Specifically, the calibrated models, as well as newly developed TN-specific SPFs, predict the expected number and severity of crashes as it relates to a road type, road class and quantifies the impacts of proposed safety countermeasures for alternatives analysis.
4. The calibrated predictive models and newly developed SPFs can assist TDOT in improving the reliability of common activities such as screening a network for sites to reduce crashes or assessment of new or alternative geometric characteristics of various types of rural highways and urban and suburban arterials.

6.2. Summary

This report provides analyses of calibration factors and SPF development for rural multilane highways and urban and suburban arterials. Referring to rural multilane highways, this report summarizes the separate analysis conducted for four-lane divided (4D) and four-lane undivided (4U) segments of rural multilane highways. Similarly, separate analyses are conducted for each of the five different types of urban and suburban arterials including two-lane undivided (2U), three-lane undivided including 2WLTL (3T), four-lane divided (4D), four-lane undivided (4U), and five-lane (5T) with 2WLTL roadway segments. Random samples for each of the seven roadway types (two different types of rural multilane and five different types of urban and suburban arterials) were selected from the clean data of each roadway type (segments which were longer than 0.1 mile and were extractable in the TDOT Image Viewer Application). Data for each of the roadway types including crash data (for each of the five years) and roadway geometric data were manually extracted from various sources of TDOT requiring extensive efforts. The traffic data for each road segment for each of the five years (2013-2017) were obtained from TDOT's Traffic History Application. Once all the data collection was completed, all the data elements were merged to create a database for each of the seven types (i.e., rural multilane and urban and suburban arterials) of roadways. All the roadway segments belonging to each of the seven roadway types were identified and extracted from TDOT's E-TRIMS software by running the query suggested by TDOT. As a next step, roadway segments shorter than 0.1 miles and those which were not extractable in TDOT's Image Viewer Software were removed from the datasets of each of the roadway types. The number of clean segments for each roadway types were obtained which include: 1132 4D rural multilane segments (767.11 miles), 81 4U rural multilane segments (34.02 miles), 2,472 2U urban and suburban arterial segments (1124.76 miles), 414 3T urban and suburban arterial segments (117.73 miles), 1,735 4D urban and suburban arterial segments (585.47 miles), 430 4U urban and suburban arterial segments (120.35 miles), and 1,519 5T urban and suburban arterial segments (523.934 miles). Random samples were selected for each roadway type, except 4U rural multilane as all 81 segments were considered for analysis while keeping in view the appropriate and the minimum data requirement for the development of SPFs and the HSM calibration respectively. As a next step, crash and roadway geometry data were extracted using crash report form and TDOT's Image Viewer in the E-TRIMS software. Finally, clean datasets (after excluding outliers) for analyses include 271 4D rural multilane segments, 81 4U rural multilane segments, 234 2U urban and suburban arterial segments, 80 3T urban and suburban arterial segments, 278 4D urban and suburban arterial segments, 80 4U urban and suburban arterial segments, and 304 5T urban and suburban arterial segments.

As a first step, the crash rates for the entire state of Tennessee and all four regions were computed for all the roadway facilities to understand the existing safety situation on these facilities. The average crash rate per 100 million VMT for all regions on 4D and 4U segments of rural multilane highways are found to be 130.02 and 260.46, respectively. This indicates that in Tennessee, 4U segments of rural multilane highways are risky compared to 4D segments of the rural multilane highways, which could be due to the presence of physical medians separating the opposing traffic flow. Based on the crash rate per 100 million VMT for 4D segments of rural multilane highways, Region 3 is the riskiest while Region 2 has the least risk in Tennessee. For 4U segments of rural multilane highways, the computed crash rate suggests that Region 2 is the riskiest while Region 3 is the least risky region in Tennessee.

The calibration of the HSM SPFs for all types of rural multilane highways and urban and suburban arterials revealed that the number of actual crashes is significantly higher than those predicted by the HSM SPFs (even after accounting for local adjustments). In summary, the average five-year calibration factor (computed after accounting for TN-specific conditions) for different types of rural multilane highways and urban and suburban arterials are given below:

- State-wide Adjusted Calibration Factor (Cf_{adj}):
  - 4D Segments of Rural Multilane Highways: 1.47
  - 4U Segments of Rural Multilane Highways: 2.25
  - 2U Segments of Urban and Suburban Arterials: 4.71
  - 3T Segments of Urban and Suburban Arterials: 5.82
  - 4D Segments of Urban and Suburban Arterials: 4.46
  - 4U Segments of Urban and Suburban Arterials: 7.63
  - 5T Segments of Urban and Suburban Arterials: 3.57

The calibration of the HSM SPFs for 4D segments of rural multilane highways reveals that the average five-year calibration factor for all regions is 1.47 with year-wise calibration factors ranging between 1.43 and 1.52. This indicates that the actual number of crashes on 4D segments of rural multilane highways are at least 0.47 times greater than those predicted by the HSM SPF after applying the calibration factors. Referring to the region-wise average five-year calibration factors for 4D segments of rural multilane highways, some differences are observed as opposed to the collective calibration factors for all regions in Tennessee. These findings agree with crash rate analyses. A similar interpretation applies to the calibration factors for the remaining four different roadway classes.

As a next step, we developed TN-specific SPFs, considering the Poisson and Negative binomial distribution, for all types of rural multilane (4D and 4U segments) and urban and suburban arterials (2U, 3T, 4D, 4U, and 5T segments). In this regard, two models (including all key covariates of average five-year crash frequency) were developed including the fixed-parameter Poisson and fixed-parameter negative binomial models for each of the same roadway types. The modeling results for each of the seven roadway types suggest significant evidence of over-dispersion in the data which is confirmed by the significant over-dispersion parameter in the negative binomial model in case of each roadway type. Based on the in-sample fit statistics (AIC and BIC values), we found that Model 2 (fixed-parameter negative binomial model) out-performed all roadway types. This confirms the significance of accounting for over-dispersion in the crash data in the development of SPFs, as not accounting for over-dispersion could compromise the results. The modeling results provide insights regarding the association of key factors with average five-year crash frequency on each roadway type. For instance, the TN-specific SPFs for each of the seven roadway types suggest that the average five-year crash frequency increases with an increase in AADT and segment length. The modeling results for 4D segments of rural multilane highways suggest that crash frequency reduces with an increase in speed limit and inner shoulder width. Additionally, the presence of rumble strips along the outer shoulder reduces the average five-year crash frequency on the 4U segments of rural multilane highways.

Model 2 (fixed-parameter negative binomial model) showed better performance (with lowest AIC and BIC values) in the case of each of the five types of urban and suburban arterials. The modeling results for 2U segments of urban and suburban arterials suggest that the average five-year crash frequency on these segments increases with an increase in the number of minor commercial driveways and the number of major industrial/institutional driveways per mile. The TN-specific SPFs for 3T segments of urban and suburban arterials suggest that the average five-year crash frequency on these segments increases with an increase in the number of major commercial driveways and the number of minor commercial driveways per mile. This was expected, as these driveways increase traffic interaction with the through traffic which consequently increases the chances of a crash. The estimation results of 4D segments of urban and suburban arterials indicate that crash frequency on these segments increases with an increase in the number of major commercial driveways per mile. Note that the modeling results of 4D segments of urban and suburban arterials suggest that the average five-year crash frequency decreases with an increase in median width and inner shoulder width on these roadway segments. The TN-specific SPFs for 4U segments of urban and suburban arterials (Model 2) suggest that the density of minor commercial and major industrial/institutional driveways increases the average five-year crash frequency on these road segments. Finally, the TN-specific SPFs for 5T segments of urban and suburban arterials suggest that crash frequency increases with an increase in the number of various types of driveways (i.e., minor commercial, minor industrial/institutional, and major industrial/institutional) per mile. Importantly, TN-specific SPFs suggest that an increase in average offset distance to fixed objects reduces crash frequency on the 5T segments of urban and suburban arterials. The TN-specific SPFs for all seven roadway types show significant evidence of over-dispersion in the data. Compared to the fixed-parameter Poisson, fixed-parameter negative binomial improved the estimation and in-simple fit in case of all roadway types. This provides compelling empirical evidence that over-dispersion should be accounted for in estimating TN-specific SPFs, ignoring which can result in inappropriate estimation inferences. Based on TN-specific SPFs, several countermeasures can be developed for each roadway type to enhance road safety across the state.

6.3. Recommendations

The recommendations relate to improvements in safety analysis procedures in Tennessee:

- *TDOT should adopt the Highway Safety Manual procedures and calibration factors developed in this study for highway safety improvements.* This study has developed Tennessee-specific calibration factors as well as estimated Tennessee-specific fixed parameter models. These calibration factors and models should be considered in applying the HSM procedures, e.g., in the network screening and safety assessment process, performed by TDOT staff for the highway safety improvement program.
- *After adopting the Highway Safety Manual procedures, TDOT Strategic Transportation*

Investments Division should apply the HSM procedures to the roadways covered in the project reports. The HSM procedures can be applied using the Safety Analyst tool. It will be important to identify sites that can be improved with countermeasures and do evaluations of alternatives to demonstrate the value of the tool. This will require linking of TDOT crash and roadway inventory databases and using them for analysis in the Safety Analyst tool.

- *TDOT should continue to update calibration factors and apply them using Highway Safety Manual procedures.* This study used 5-year Tennessee crash data to calibrate SPF models suggested by the HSM and adjust it using CMFs. Results have shown that the CF values are substantially greater than 1, and also significantly vary across time and regions. This means that there is potential for safety improvement through interventions in the future. TDOT should consider updating CFs regularly, and incorporate spatiotemporal variations into the analysis.
- *TDOT can use the Safety Analyst tool to systematically select countermeasures to improve safety.* Safety Analyst was developed by AASHTO to screen network safety performance, diagnose safety issues, select appropriate countermeasures, perform an economic appraisal of alternative countermeasures, prioritize safety projects, and evaluate the effectiveness of countermeasures. For instance, the tool can be used effectively to identify hotspot locations where observed crashes and predicted crashes can be weighted to obtain more accurate estimates of future crashes. Such procedures can help TDOT improve safety by allocating their resources in safety-critical locations and select the highest-impact countermeasures.
- *For future research, TDOT should consider Artificial Intelligence (AI) methods to improve the safety outcome predictions made by traditional HSM methods.* The emergence of new methods, especially Machine Learning and Deep Learning is promising. More research is needed to understand the capabilities of these new methods and how to apply them. Adoption of these methods can help TDOT improve the prediction performance by capturing linear and nonlinear relationships between explanatory variables and crash frequency.

A request was received from TDOT staff for recommendations on how to handle the HSM analysis when considering road widening scenarios, e.g., widening from 2U to 3T, 3T to 4U, 3T to 5T, or from 4U to 5T. For such projects, the following steps for benefit-cost analysis are recommended:

- Step 1) Identify facility type (e.g., 2U, 3T, and 4U) for analysis and data collection.
- Step 2) Having identified the segments needing improvements, evaluate the expected crash frequency (PDO and injury crashes) over a time horizon (say 15 years) using calibrated SPFs for Tennessee. Say the expected number of crashes over the time horizon for the selected segment is X.
- Step 3) Select the alternative to improve the segments, e.g., widen from 2U to 3T. When changing the configuration (i.e., widening from 2U to 3T), ensure that the AADT assumptions/trends for future traffic are realistic and will hold. Using the HSM procedures, predict the crash frequencies with improvements, i.e., for the 3T configuration apply the TN calibrated SPFs for such roads; as a result, say this number of crashes is Y.
- Step 4) Assuming that X-Y > 0, calculate the benefits of reduced crashes, i.e., $/crash multiplied by (X-Y).
- Step 5) Calculate the cost of road widening-going from 2U to 3T. Then calculate the benefit-cost ratio B/C and the Net Present Value (NPV). Review if B/C > 1 and NPV is positive. If so, this justifies proceeding with the widening.

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APPENDIX A: Statistical Modeling

A.1. Modeling of crash data

Given the discrete non-negative data nature of crashes, count-data modeling techniques are typically used to model crash frequencies as a function of explanatory variables (*5*). Common techniques include the Poisson Generalized Linear Models (GLMs) and/or Negative Binomial GLMs, and these methods appear to be the two main methodological alternatives (*1; 2; 7; 9; 26-29*). The Poisson regression is reported to be the most popular of the two (*13*), where the Poisson distribution is used to approximate rare-event count data, such as crash frequency in this case. However, a restrictive assumption of the Poisson regression is the requirement of the mean of the count process be equal to its variance (*8*). When the variance of the crash counts is greater than its mean, the data are said to be over-dispersed, and in such a case, the negative binomial distribution is preferred[4] (*8*).

A.1.1. Poisson and Negative Binomial Regressions:

Next, we present a short discussion on the mathematical formulations of the Poisson and negative binomial regression. For a detailed discussion on these estimators, readers are referred to (*5; 10; 30*).

For a Poisson model, the probability of having a specific number of crashes "*n*" at road segment "*i*" can be written as (*13*):

$$P(n_i) = \frac{exp(-\lambda_i)\lambda_i^n}{n_i!} \tag{1}$$

where: $P(n_i)$ is the probability of a crash occurring at segment "*i*", "*n*" times per specific time-period on segment *i*; and λ_i is the Poisson parameter for segment "*i*" which is numerically equivalent to segment "*i*" expected crash frequency per year $E(n_i)$. The regression can be fitted to crash data by specifying λ_i as a function of explanatory variables such as Annual Average Daily Traffic, and segment length. Formally, λ_i can be viewed as a log link function of a set of independent variables (*13*):

$$ln(\lambda_i) = \beta(X_i) \tag{2}$$

where X_i is a vector of explanatory variables, and β is a vector of parameter estimates.
The Poisson function defined in Equation 1 and 2 can be maximized by the standard maximum likelihood procedure with the following likelihood function (*13*):

$$L(\beta) = \prod_{i}^{n} \frac{exp\,[-exp\,(\beta X_i)\,]\,[exp\,(\beta X_i)\,]^{n_i}}{n_i!} \tag{3}$$

Application of the Poisson regression to over-dispersed crash data can result in inappropriate results. If mean and variance of crash data are not equal, corrective measures are applied to Equation 2 by adding an independently distributed error term ∈, as follow:

$$ln(\lambda_i) = \beta(X_i) + \in_i \tag{4}$$

where $exp(\in_i)$ in Equation 4 is a gamma-distributed error term with mean one and variance α (*13*). The conditional probability of crashes then becomes (*31*):

$$P(\in) = \frac{exp\,[-\lambda_i exp\,(\in_i)\,]\,[\lambda_i exp\,(\in_i)\,]^{ni}}{n_i!} \tag{5}$$

[4] Due to the naturally high variability of crash frequencies, it is recommended that SPFs be developed using negative binomial regression techniques (*1; 13*). Such models are also referred to the mixed Poisson-gamma models because crashes within rural two-lane two-way road segments follow a Poisson distribution, whereas the variation across multiple sites follow a gamma distribution. In this analysis, both the Poisson and negative binomial regression techniques are considered.

Following (*31*), to obtain an unconditional distribution of n_i, $\in_i$ can be integrated out of Equation 5, which results in the following maximum likelihood estimation problem:

$$P(n_i) = \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta). n_i!]}. u_i^{\theta}(1 - u_i)^{n_i} \tag{6}$$

where: u_i is $\theta(\theta + \lambda_i)$ and $\theta = \frac{1}{\alpha}$, Γ is the gamma function. It can be seen in Equation 6 that the Poisson is a limiting function of the Poisson-Gamma model as variance α approaches to zero. Following (*13*), if α is significantly different from zero, negative binomial regression should be favored and if not, the Poisson model can be more appropriate (*5*).

APPENDIX B: Crash Rate Over Space across Tennessee

TABLE B.1: Region Wise Crash Rate for 4D and 4U Rural Multilane Highways

Area	Four Lane Divided (4D) Rural Highways					Four Lane Undivided (4U) Rural Highways				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
	Crash Rate per 100 Million VMT					Crash Rate per 100 Million VMT				
Region 1	44	130.07	184.78	0	870.79	20	279.31	244.85	0	866.47
Region 2	78	118.87	210.62	0	1471.25	14	341.02	651.98	0	2557.84
Region 3	41	157.64	322.14	0	1700.21	19	109.79	117.76	0	444.47
Region 4	108	127.58	198.20	0	1206.94	28	308.96	493.62	0	2591.16
	Crash per Mile of Roadway per Year					Crash per Mile of Roadway per Year				
Region 1	44	4.02	4.13	0	18.66	20	10.54	13.73	0	57.56
Region 2	78	2.63	3.40	0	24.21	14	5.61	9.68	0	36.66
Region 3	41	2.96	6.62	0	41.81	19	3.12	3.80	0	15.00
Region 4	108	2.54	2.94	0	14.28	28	5.02	5.52	0	21.49

TABLE B.2: Region Wise Crash Rate for 2U, 4D, and 5T Urban and Suburban Arterials

Area	Crash rate per 100 million VMT					Crash per mile of roadway per year				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Two Lanes Undivided (2U) Urban and Suburban Arterials (N = 234)										
Region 1	67	378.76	333.70	0	1349.76	67	9.60	12.22	0	74.40
Region 2	38	295.07	382.43	0	2349.42	38	8.10	16.85	0	105.71
Region 3	88	363.38	389.39	0	2597.76	88	11.86	15.30	0	89.00
Region 4	41	268.04	297.72	0	1489.36	41	4.77	5.22	0	22.43
Three Lanes (3T) Urban and Suburban Arterials including 2WLTL (N = 80)										
Region 1	22	321.12	391.90	0.00	1484.68	22	9.29	10.14	0.00	30.84
Region 2	16	709.74	704.20	0.00	2370.60	16	28.36	30.80	0.00	106.67
Region 3	34	558.82	767.36	0.00	3884.28	34	29.96	42.02	0.00	221.11
Region 4	8	601.45	344.44	148.02	1206.93	8	17.78	24.34	1.52	76.47
Four Lanes Divided (4D) Urban and Suburban Arterials (N = 278)										
Region 1	114	300.90	478.04	0	3800.08	114	24.18	43.04	0	332
Region 2	41	309.64	548.33	0	2645.21	41	23.29	52.06	0	309.09
Region 3	59	385.59	558.46	0	3197.77	59	33.66	49.17	0	203.12
Region 4	64	269.74	710.86	0	4949.82	64	20.93	56.60	0	370
Four Lanes Undivided (4U) Urban and Suburban Arterials (N = 80)										
Region 1	14	498.59	572.96	35.85	1974.51	14	29.07	29.24	2	86.90
Region 2	16	1006.35	846.81	228.63	3457.75	16	53.32	57.33	4.84	221.81
Region 3	20	1049.45	2153.88	19.35	7528.29	20	59.80	134.23	0.384	515.78
Region 4	30	583.69	627.06	0	2734.08	30	34.06	39.93	0	160.93
Five Lanes (5T) Urban and Suburban Arterials including 2WLTL (N = 304)										
Region 1	87	434.27	571.55	0	4119.67	87	31.32	38.09	0	185.21
Region 2	46	583.06	498.47	54.58	2568.56	46	46.50	67.65	1.90	445.61
Region 3	119	511.84	483.43	0	2324.28	119	45.26	55.57	0	280.31
Region 4	52	469.07	457.29	0	1847.73	52	29.70	33.90	0	106.31

APPENDIX C: Calibration Factors Over Space and Time

Four-Lane Divided (4D) Segments - Rural Multilane Highways

TABLE C.1: Calibration Factors All Regions (Base Case HSM) - 4D Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	271	1.378	1.952	0.000	17.80	373.400	1.445
Predicted 5 Years Crashes	271	0.953	1.329	0.038	9.82	258.349	
Observed 2017 Crashes	271	1.494	2.765	0.000	26.00	405.000	1.484
Predicted 2017 Crashes	271	1.007	1.415	0.037	10.58	272.840	
Observed 2016 Crashes	271	1.373	2.369	0.000	20.00	372.000	1.432
Predicted 2016 Crashes	271	0.959	1.291	0.039	9.16	259.854	
Observed 2015 Crashes	271	1.339	2.260	0.000	19.00	363.000	1.404
Predicted 2015 Crashes	271	0.954	1.353	0.039	10.82	258.525	
Observed 2014 Crashes	271	1.384	2.216	0.000	17.00	375.000	1.488
Predicted 2014 Crashes	271	0.930	1.326	0.037	9.78	251.938	
Observed 2013 Crashes	271	1.299	1.921	0.000	10.00	352.000	1.415
Predicted 2013 Crashes	271	0.918	1.283	0.036	9.38	248.766	

TABLE C.2: Calibration Factors All Regions (Base + CMF Adj) - 4D Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	271	1.378	1.952	0.000	17.80	373.400	1.475
Predicted 5 Years Crashes	271	0.934	1.300	0.038	9.53	253.131	
Observed 2017 Crashes	271	1.494	2.765	0.000	26.00	405.000	1.515
Predicted 2017 Crashes	271	0.987	1.384	0.037	10.26	267.361	
Observed 2016 Crashes	271	1.373	2.369	0.000	20.00	372.000	1.461
Predicted 2016 Crashes	271	0.939	1.262	0.039	8.89	254.545	
Observed 2015 Crashes	271	1.339	2.260	0.000	19.00	363.000	1.433
Predicted 2015 Crashes	271	0.935	1.323	0.039	10.50	253.317	
Observed 2014 Crashes	271	1.384	2.216	0.000	17.00	375.000	1.519
Predicted 2014 Crashes	271	0.911	1.297	0.037	9.49	246.872	
Observed 2013 Crashes	271	1.299	1.921	0.000	10.00	352.000	1.444
Predicted 2013 Crashes	271	0.899	1.255	0.036	9.10	243.738	

TABLE C.3: Calibration Factors Region 1 (Base Case HSM) - 4D Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	44	1.327	1.383	0.000	5.80	58.400	1.571
Predicted 5 Years Crashes	44	0.845	0.870	0.068	3.59	37.166	
Observed 2017 Crashes	44	1.205	1.692	0.000	7.00	53.000	1.338
Predicted 2017 Crashes	44	0.900	0.919	0.073	3.69	39.612	
Observed 2016 Crashes	44	1.273	1.561	0.000	6.00	56.000	1.493
Predicted 2016 Crashes	44	0.852	0.861	0.070	3.61	37.509	
Observed 2015 Crashes	44	1.477	2.107	0.000	10.00	65.000	1.766
Predicted 2015 Crashes	44	0.837	0.864	0.066	3.80	36.807	
Observed 2014 Crashes	44	1.273	1.590	0.000	7.00	56.000	1.573
Predicted 2014 Crashes	44	0.809	0.843	0.067	3.77	35.604	
Observed 2013 Crashes	44	1.409	1.575	0.000	7.00	62.000	1.707
Predicted 2013 Crashes	44	0.826	0.890	0.066	4.19	36.324	

TABLE C.4: Calibration Factors Region 1 (Base + CMF Adj) - 4D Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	44	1.327	1.383	0.000	5.80	58.400	1.601
Predicted 5 Years Crashes	44	0.829	0.846	0.071	3.48	36.467	
Observed 2017 Crashes	44	1.205	1.692	0.000	7.00	53.000	1.363
Predicted 2017 Crashes	44	0.884	0.895	0.076	3.58	38.876	
Observed 2016 Crashes	44	1.273	1.561	0.000	6.00	56.000	1.521
Predicted 2016 Crashes	44	0.837	0.838	0.073	3.50	36.813	
Observed 2015 Crashes	44	1.477	2.107	0.000	10.00	65.000	1.800
Predicted 2015 Crashes	44	0.821	0.840	0.069	3.69	36.120	
Observed 2014 Crashes	44	1.273	1.590	0.000	7.00	56.000	1.603
Predicted 2014 Crashes	44	0.794	0.820	0.070	3.65	34.932	
Observed 2013 Crashes	44	1.409	1.575	0.000	7.00	62.000	1.740
Predicted 2013 Crashes	44	0.810	0.865	0.068	4.07	35.622	

TABLE C.5: Calibration Factors Region 2 (Base Case HSM) - 4D Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	78	1.418	1.745	0.000	8.200	110.600	1.388
Predicted 5 Years Crashes	78	1.021	1.298	0.038	6.630	79.657	
Observed 2017 Crashes	78	1.833	3.332	0.000	26.000	143.000	1.721
Predicted 2017 Crashes	78	1.065	1.379	0.037	7.073	83.094	
Observed 2016 Crashes	78	1.551	2.526	0.000	14.000	121.000	1.503
Predicted 2016 Crashes	78	1.032	1.281	0.039	6.500	80.514	
Observed 2015 Crashes	78	1.321	2.054	0.000	10.000	103.000	1.294
Predicted 2015 Crashes	78	1.021	1.302	0.039	7.205	79.624	
Observed 2014 Crashes	78	1.167	1.615	0.000	9.000	91.000	1.165
Predicted 2014 Crashes	78	1.002	1.326	0.037	6.864	78.134	
Observed 2013 Crashes	78	1.218	1.884	0.000	9.000	95.000	1.234
Predicted 2013 Crashes	78	0.987	1.234	0.036	6.058	76.983	

TABLE C.6: Calibration Factors Region 2 (Base + CMF Adj) - 4D Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	78	1.418	1.745	0.000	8.200	110.600	1.421
Predicted 5 Years Crashes	78	0.998	1.269	0.038	6.564	77.832	
Observed 2017 Crashes	78	1.833	3.332	0.000	26.000	143.000	1.761
Predicted 2017 Crashes	78	1.041	1.347	0.037	7.003	81.189	
Observed 2016 Crashes	78	1.551	2.526	0.000	14.000	121.000	1.538
Predicted 2016 Crashes	78	1.009	1.253	0.039	6.435	78.684	
Observed 2015 Crashes	78	1.321	2.054	0.000	10.000	103.000	1.324
Predicted 2015 Crashes	78	0.998	1.274	0.039	7.133	77.811	
Observed 2014 Crashes	78	1.167	1.615	0.000	9.000	91.000	1.192
Predicted 2014 Crashes	78	0.979	1.296	0.037	6.658	76.344	
Observed 2013 Crashes	78	1.218	1.884	0.000	9.000	95.000	1.263
Predicted 2013 Crashes	78	0.964	1.206	0.036	5.998	75.195	

TABLE C.7: Calibration Factors Region 3 (Base Case HSM) - 4D Segments

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	41	1.361	2.106	0.000	11.80	55.80	1.338
Predicted 5 Years Crashes	41	1.017	1.728	0.051	9.06	41.72	
Observed 2017 Crashes	41	1.268	1.950	0.000	10.00	52.00	1.165
Predicted 2017 Crashes	41	1.089	1.824	0.056	9.16	44.65	
Observed 2016 Crashes	41	1.488	2.570	0.000	12.00	61.00	1.398
Predicted 2016 Crashes	41	1.065	1.757	0.048	9.16	43.65	
Observed 2015 Crashes	41	1.317	2.263	0.000	12.00	54.00	1.320
Predicted 2015 Crashes	41	0.998	1.694	0.048	8.72	40.90	
Observed 2014 Crashes	41	1.537	2.776	0.000	17.00	63.00	1.578
Predicted 2014 Crashes	41	0.974	1.699	0.050	9.22	39.91	
Observed 2013 Crashes	41	1.195	2.076	0.000	8.00	49.00	1.240
Predicted 2013 Crashes	41	0.963	1.679	0.053	9.03	39.50	

TABLE C.8: Calibration Factors Region 3 (Base + CMF Adj) - 4D segments

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	41	1.361	2.106	0.000	11.80	55.80	1.369
Predicted 5 Years Crashes	41	0.994	1.681	0.045	8.79	40.77	
Observed 2017 Crashes	41	1.268	1.950	0.000	10.00	52.00	1.192
Predicted 2017 Crashes	41	1.064	1.774	0.050	8.88	43.62	
Observed 2016 Crashes	41	1.488	2.570	0.000	12.00	61.00	1.430
Predicted 2016 Crashes	41	1.040	1.710	0.043	8.89	42.65	
Observed 2015 Crashes	41	1.317	2.263	0.000	12.00	54.00	1.351
Predicted 2015 Crashes	41	0.975	1.647	0.042	8.46	39.96	
Observed 2014 Crashes	41	1.537	2.776	0.000	17.00	63.00	1.615
Predicted 2014 Crashes	41	0.951	1.652	0.044	8.95	39.01	
Observed 2013 Crashes	41	1.195	2.076	0.000	8.00	49.00	1.268
Predicted 2013 Crashes	41	0.942	1.634	0.047	8.76	38.63	

TABLE C.9: Calibration Factors Region 4 (Base Case HSM) - 4D Segments

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	108	1.376	2.236	0	17.800	148.600	1.489
Predicted 5 Years Crashes	108	0.924	1.347	0.051	9.821	99.810	
Observed 2017 Crashes	108	1.454	2.930	0	25.000	157.000	1.488
Predicted 2017 Crashes	108	0.977	1.445	0.056	10.579	105.484	
Observed 2016 Crashes	108	1.241	2.464	0	20.000	134.000	1.365
Predicted 2016 Crashes	108	0.909	1.247	0.051	8.550	98.184	
Observed 2015 Crashes	108	1.306	2.478	0	19.000	141.000	1.393
Predicted 2015 Crashes	108	0.937	1.420	0.05	10.820	101.192	
Observed 2014 Crashes	108	1.528	2.559	0	15.000	165.000	1.679
Predicted 2014 Crashes	108	0.910	1.340	0.052	9.782	98.287	
Observed 2013 Crashes	108	1.352	2.034	0	10.000	146.000	1.521
Predicted 2013 Crashes	108	0.889	1.295	0.047	9.380	95.959	

TABLE C.10: Calibration Factors Region 4 (Base + CMF Adj) - 4D segments

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	108	1.376	2.236	0.000	17.800	148.600	1.515
Predicted 5 Years Crashes	108	0.908	1.323	0.050	9.526	98.063	
Observed 2017 Crashes	108	1.454	2.930	0.000	25.000	157.000	1.514
Predicted 2017 Crashes	108	0.960	1.420	0.054	10.262	103.677	
Observed 2016 Crashes	108	1.241	2.464	0.000	20.000	134.000	1.390
Predicted 2016 Crashes	108	0.893	1.224	0.049	8.294	96.394	
Observed 2015 Crashes	108	1.306	2.478	0.000	19.000	141.000	1.418
Predicted 2015 Crashes	108	0.921	1.395	0.049	10.496	99.423	
Observed 2014 Crashes	108	1.528	2.559	0.000	15.000	165.000	1.708
Predicted 2014 Crashes	108	0.894	1.317	0.050	9.489	96.588	
Observed 2013 Crashes	108	1.352	2.034	0.000	10.000	146.000	1.548
Predicted 2013 Crashes	108	0.873	1.273	0.046	9.099	94.289	

Four-Lane Undivided (4U) Segments - Rural Multilane Highways

TABLE C.11: Calibration Factors All Regions (Base Case HSM) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	81	2.538	5.559	0.000	38.800	205.600	2.309
Predicted 5 Years Crashes	81	1.099	2.066	0.013	12.128	89.055	
Observed 2017 Crashes	81	2.543	6.101	0.000	47.000	206.000	2.189
Predicted 2017 Crashes	81	1.162	2.231	0.014	13.242	94.096	
Observed 2016 Crashes	81	2.333	5.324	0.000	35.000	189.000	2.043
Predicted 2016 Crashes	81	1.142	2.214	0.010	13.119	92.498	
Observed 2015 Crashes	81	2.691	5.553	0.000	30.000	218.000	2.449
Predicted 2015 Crashes	81	1.099	2.137	0.011	13.053	89.027	
Observed 2014 Crashes	81	2.494	5.509	0.000	36.000	202.000	2.350
Predicted 2014 Crashes	81	1.061	1.978	0.013	11.278	85.959	
Observed 2013 Crashes	81	2.630	6.323	0.000	46.000	213.000	2.538
Predicted 2013 Crashes	81	1.036	1.801	0.015	10.003	83.940	

TABLE C.12: Calibration Factors All Regions (Base + CMF Adj) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	81	2.538	5.559	0.000	38.800	205.600	2.257
Predicted 5 Years Crashes	81	1.125	2.168	0.013	12.508	91.111	
Observed 2017 Crashes	81	2.543	6.101	0.000	47.000	206.000	2.138
Predicted 2017 Crashes	81	1.189	2.342	0.014	13.656	96.332	
Observed 2016 Crashes	81	2.333	5.324	0.000	35.000	189.000	1.996
Predicted 2016 Crashes	81	1.169	2.323	0.010	13.529	94.711	
Observed 2015 Crashes	81	2.691	5.553	0.000	30.000	218.000	2.395
Predicted 2015 Crashes	81	1.124	2.230	0.011	13.461	91.015	
Observed 2014 Crashes	81	2.494	5.509	0.000	36.000	202.000	2.297
Predicted 2014 Crashes	81	1.086	2.081	0.013	11.630	87.932	
Observed 2013 Crashes	81	2.630	6.323	0.000	46.000	213.000	2.482
Predicted 2013 Crashes	81	1.059	1.894	0.015	10.316	85.818	

TABLE C.13: Calibration Factors Region 1 (Base Case HSM) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	20	5.760	10.123	0.000	38.800	115.200	2.750
Predicted 5 Years Crashes	20	2.095	3.698	0.186	12.128	41.891	
Observed 2017 Crashes	20	5.900	11.336	0.000	47.000	118.000	2.600
Predicted 2017 Crashes	20	2.269	4.024	0.196	13.242	45.388	
Observed 2016 Crashes	20	5.500	9.605	0.000	35.000	110.000	2.470
Predicted 2016 Crashes	20	2.227	3.994	0.195	13.119	44.534	
Observed 2015 Crashes	20	6.000	9.814	0.000	30.000	120.000	2.802
Predicted 2015 Crashes	20	2.141	3.861	0.184	13.053	42.827	
Observed 2014 Crashes	20	5.450	9.687	0.000	36.000	109.000	2.741
Predicted 2014 Crashes	20	1.988	3.526	0.171	11.278	39.764	
Observed 2013 Crashes	20	5.950	11.265	0.000	46.000	119.000	3.208
Predicted 2013 Crashes	20	1.855	3.126	0.175	10.003	37.093	

TABLE C.14: Calibration Factors Region 1 (Base + CMF Adj) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	20	5.760	10.123	0.000	38.800	115.200	2.602
Predicted 5 Years Crashes	20	2.214	3.909	0.176	12.508	44.270	
Observed 2017 Crashes	20	5.900	11.336	0.000	47.000	118.000	2.460
Predicted 2017 Crashes	20	2.398	4.251	0.185	13.656	47.963	
Observed 2016 Crashes	20	5.500	9.605	0.000	35.000	110.000	2.337
Predicted 2016 Crashes	20	2.353	4.219	0.185	13.529	47.068	
Observed 2015 Crashes	20	6.000	9.814	0.000	30.000	120.000	2.657
Predicted 2015 Crashes	20	2.258	4.054	0.174	13.461	45.157	
Observed 2014 Crashes	20	5.450	9.687	0.000	36.000	109.000	2.591
Predicted 2014 Crashes	20	2.104	3.744	0.168	11.630	42.075	
Observed 2013 Crashes	20	5.950	11.265	0.000	46.000	119.000	3.032
Predicted 2013 Crashes	20	1.962	3.327	0.166	10.316	39.247	

TABLE C.15: Calibration Factors Region 2 (Base Case HSM) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	14	1.529	2.103	0.000	7.400	21.400	2.505
Predicted 5 Years Crashes	14	0.610	0.995	0.083	3.449	8.542	
Observed 2017 Crashes	14	1.571	2.065	0.000	7.000	22.000	2.431
Predicted 2017 Crashes	14	0.646	1.052	0.094	3.642	9.050	
Observed 2016 Crashes	14	1.071	2.401	0.000	9.000	15.000	1.765
Predicted 2016 Crashes	14	0.607	0.984	0.088	3.412	8.501	
Observed 2015 Crashes	14	1.786	2.778	0.000	10.000	25.000	2.848
Predicted 2015 Crashes	14	0.627	1.036	0.076	3.587	8.780	
Observed 2014 Crashes	14	1.643	2.790	0.000	10.000	23.000	2.694
Predicted 2014 Crashes	14	0.610	1.003	0.073	3.473	8.537	
Observed 2013 Crashes	14	1.571	2.409	0.000	8.000	22.000	2.798
Predicted 2013 Crashes	14	0.562	0.903	0.085	3.131	7.864	

TABLE C.16: Calibration Factors Region 2 (Base + CMF Adj) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	14	1.529	2.103	0.000	7.400	21.400	2.480
Predicted 5 Years Crashes	14	0.616	1.017	0.083	3.518	8.631	
Observed 2017 Crashes	14	1.571	2.065	0.000	7.000	22.000	2.409
Predicted 2017 Crashes	14	0.652	1.075	0.094	3.716	9.131	
Observed 2016 Crashes	14	1.071	2.401	0.000	9.000	15.000	1.746
Predicted 2016 Crashes	14	0.614	1.006	0.088	3.481	8.590	
Observed 2015 Crashes	14	1.786	2.778	0.000	10.000	25.000	2.817
Predicted 2015 Crashes	14	0.634	1.059	0.076	3.660	8.874	
Observed 2014 Crashes	14	1.643	2.790	0.000	10.000	23.000	2.664
Predicted 2014 Crashes	14	0.617	1.025	0.073	3.544	8.635	
Observed 2013 Crashes	14	1.571	2.409	0.000	8.000	22.000	2.770
Predicted 2013 Crashes	14	0.567	0.923	0.085	3.194	7.944	

TABLE C.17: Calibration Factors Region 3 (Base Case HSM) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	19	1.305	1.553	0.000	5.800	24.800	1.127
Predicted 5 Years Crashes	19	1.158	1.192	0.139	3.845	21.996	
Observed 2017 Crashes	19	1.158	2.035	0.000	8.000	22.000	0.967
Predicted 2017 Crashes	19	1.198	1.195	0.165	3.896	22.758	
Observed 2016 Crashes	19	1.526	2.220	0.000	8.000	29.000	1.279
Predicted 2016 Crashes	19	1.193	1.246	0.139	4.141	22.667	
Observed 2015 Crashes	19	1.684	2.212	0.000	7.000	32.000	1.487
Predicted 2015 Crashes	19	1.133	1.158	0.135	3.774	21.523	
Observed 2014 Crashes	19	1.053	1.224	0.000	3.000	20.000	0.934
Predicted 2014 Crashes	19	1.127	1.160	0.133	3.784	21.416	
Observed 2013 Crashes	19	1.105	1.595	0.000	5.000	21.000	0.970
Predicted 2013 Crashes	19	1.139	1.216	0.125	4.103	21.648	

TABLE C.18: Calibration Factors Region 3 (Base + CMF Adj) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	19	1.305	1.553	0.000	5.800	24.800	1.174
Predicted 5 Years Crashes	19	1.112	1.150	0.135	4.001	21.124	
Observed 2017 Crashes	19	1.158	2.035	0.000	8.000	22.000	1.006
Predicted 2017 Crashes	19	1.151	1.157	0.159	4.054	21.875	
Observed 2016 Crashes	19	1.526	2.220	0.000	8.000	29.000	1.331
Predicted 2016 Crashes	19	1.147	1.210	0.134	4.309	21.793	
Observed 2015 Crashes	19	1.684	2.212	0.000	7.000	32.000	1.550
Predicted 2015 Crashes	19	1.086	1.109	0.131	3.670	20.641	
Observed 2014 Crashes	19	1.053	1.224	0.000	3.000	20.000	0.974
Predicted 2014 Crashes	19	1.081	1.111	0.129	3.709	20.534	
Observed 2013 Crashes	19	1.105	1.595	0.000	5.000	21.000	1.009
Predicted 2013 Crashes	19	1.095	1.180	0.121	4.269	20.809	

TABLE C.19: Calibration Factors Region 4 (Base Case HSM) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	28	1.579	2.341	0.000	11.200	44.200	2.658
Predicted 5 Years Crashes	28	0.594	0.691	0.013	2.864	16.626	
Observed 2017 Crashes	28	1.571	1.971	0.000	6.000	44.000	2.604
Predicted 2017 Crashes	28	0.604	0.706	0.014	2.918	16.900	
Observed 2016 Crashes	28	1.250	1.756	0.000	7.000	35.000	2.084
Predicted 2016 Crashes	28	0.600	0.684	0.010	2.721	16.797	
Observed 2015 Crashes	28	1.464	2.411	0.000	11.000	41.000	2.579
Predicted 2015 Crashes	28	0.568	0.642	0.011	2.559	15.898	
Observed 2014 Crashes	28	1.786	3.213	0.000	16.000	50.000	3.078
Predicted 2014 Crashes	28	0.580	0.694	0.013	2.878	16.242	
Observed 2013 Crashes	28	1.821	3.692	0.000	16.000	51.000	2.942
Predicted 2013 Crashes	28	0.619	0.744	0.015	3.248	17.336	

TABLE C.20: Calibration Factors Region 4 (Base + CMF Adj) – 4U Highways

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	28	1.579	2.341	0.000	11.200	44.200	2.587
Predicted 5 Years Crashes	28	0.610	0.709	0.013	2.930	17.087	
Observed 2017 Crashes	28	1.571	1.971	0.000	6.000	44.000	2.534
Predicted 2017 Crashes	28	0.620	0.724	0.014	2.986	17.363	
Observed 2016 Crashes	28	1.250	1.756	0.000	7.000	35.000	2.028
Predicted 2016 Crashes	28	0.616	0.701	0.010	2.784	17.260	
Observed 2015 Crashes	28	1.464	2.411	0.000	11.000	41.000	2.509
Predicted 2015 Crashes	28	0.584	0.659	0.011	2.618	16.342	
Observed 2014 Crashes	28	1.786	3.213	0.000	16.000	50.000	2.996
Predicted 2014 Crashes	28	0.596	0.712	0.013	2.945	16.688	
Observed 2013 Crashes	28	1.821	3.692	0.000	16.000	51.000	2.862
Predicted 2013 Crashes	28	0.636	0.763	0.015	3.324	17.818	

Urban and Suburban Arterials

Two-Lane Undivided (2U) Segments – Urban and Suburban Arterials

TABLE C.21: Calibration Factors All Regions (Base Case HSM) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	234	4.128	6.830	0.000	77.00	966.000	4.887
Predicted 5 Years Crashes	234	0.845	1.126	0.048	11.26	197.651	
Observed 2017 Crashes	234	4.278	7.409	0.000	78.00	1001.000	4.778
Predicted 2017 Crashes	234	0.895	1.204	0.048	11.83	209.511	
Observed 2016 Crashes	234	4.376	6.895	0.000	66.00	1024.000	5.055
Predicted 2016 Crashes	234	0.866	1.188	0.050	12.23	202.589	
Observed 2015 Crashes	234	4.150	7.437	0.000	78.00	971.000	4.950
Predicted 2015 Crashes	234	0.838	1.072	0.049	10.41	196.169	
Observed 2014 Crashes	234	3.970	7.245	0.000	90.00	929.000	4.835
Predicted 2014 Crashes	234	0.821	1.092	0.045	10.86	192.136	
Observed 2013 Crashes	234	3.829	6.727	0.000	71.00	896.000	4.739
Predicted 2013 Crashes	234	0.808	1.091	0.047	11.00	189.064	

TABLE C.22: Calibration Factors All Regions (Base + CMF Adj) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	234	4.128	6.830	0.000	77.00	966.000	4.714
Predicted 5 Years Crashes	234	0.876	1.138	0.047	11.07	204.916	
Observed 2017 Crashes	234	4.278	7.409	0.000	78.00	1001.000	4.609
Predicted 2017 Crashes	234	0.928	1.219	0.048	11.63	217.165	
Observed 2016 Crashes	234	4.376	6.895	0.000	66.00	1024.000	4.877
Predicted 2016 Crashes	234	0.897	1.199	0.049	12.02	209.972	
Observed 2015 Crashes	234	4.150	7.437	0.000	78.00	971.000	4.774
Predicted 2015 Crashes	234	0.869	1.085	0.047	10.24	203.409	
Observed 2014 Crashes	234	3.970	7.245	0.000	90.00	929.000	4.662
Predicted 2014 Crashes	234	0.852	1.104	0.043	10.68	199.278	
Observed 2013 Crashes	234	3.829	6.727	0.000	71.00	896.000	4.571
Predicted 2013 Crashes	234	0.838	1.102	0.048	10.81	196.026	

TABLE C.23: Calibration Factors Region 1 (Base Case HSM) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	67	3.836	4.096	0.000	21.000	257.000	4.715
Predicted 5 Years Crashes	67	0.814	0.908	0.048	4.522	54.509	
Observed 2017 Crashes	67	3.522	4.409	0.000	25.000	236.000	4.063
Predicted 2017 Crashes	67	0.867	1.019	0.048	5.111	58.083	
Observed 2016 Crashes	67	4.209	5.267	0.000	26.000	282.000	5.103
Predicted 2016 Crashes	67	0.825	0.929	0.050	4.456	55.260	
Observed 2015 Crashes	67	3.851	5.329	0.000	30.000	258.000	4.775
Predicted 2015 Crashes	67	0.806	0.880	0.049	4.400	54.026	
Observed 2014 Crashes	67	3.522	3.913	0.000	23.000	236.000	4.486
Predicted 2014 Crashes	67	0.785	0.859	0.045	4.198	52.611	
Observed 2013 Crashes	67	3.896	4.072	0.000	18.000	261.000	4.944
Predicted 2013 Crashes	67	0.788	0.872	0.047	4.464	52.796	

TABLE C.24: Calibration Factors Region 1 (Base + CMF Adj) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	67	3.836	4.096	0.000	21.000	257.000	4.465
Predicted 5 Years Crashes	67	0.859	0.958	0.047	4.828	57.558	
Observed 2017 Crashes	67	3.522	4.409	0.000	25.000	236.000	3.847
Predicted 2017 Crashes	67	0.916	1.079	0.048	5.457	61.340	
Observed 2016 Crashes	67	4.209	5.267	0.000	26.000	282.000	4.836
Predicted 2016 Crashes	67	0.870	0.981	0.049	4.801	58.319	
Observed 2015 Crashes	67	3.851	5.329	0.000	30.000	258.000	4.525
Predicted 2015 Crashes	67	0.851	0.926	0.047	4.698	57.017	
Observed 2014 Crashes	67	3.522	3.913	0.000	23.000	236.000	4.243
Predicted 2014 Crashes	67	0.830	0.906	0.043	4.482	55.624	
Observed 2013 Crashes	67	3.896	4.072	0.000	18.000	261.000	4.682
Predicted 2013 Crashes	67	0.832	0.918	0.048	4.766	55.740	

TABLE C.25: Calibration Factors Region 2 (Base Case HSM) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	38	2.947	4.223	0.000	22.000	112.000	4.540
Predicted 5 Years Crashes	38	0.649	0.880	0.064	5.526	24.671	
Observed 2017 Crashes	38	3.842	6.824	0.000	36.000	146.000	5.792
Predicted 2017 Crashes	38	0.663	0.921	0.066	5.789	25.207	
Observed 2016 Crashes	38	3.000	4.690	0.000	25.000	114.000	4.583
Predicted 2016 Crashes	38	0.655	0.861	0.068	5.389	24.875	
Observed 2015 Crashes	38	2.842	3.760	0.000	18.000	108.000	4.306
Predicted 2015 Crashes	38	0.660	0.876	0.064	5.461	25.080	
Observed 2014 Crashes	38	2.684	3.488	0.000	15.000	102.000	4.177
Predicted 2014 Crashes	38	0.643	0.897	0.063	5.651	24.418	
Observed 2013 Crashes	38	2.632	4.123	0.000	23.000	100.000	4.193
Predicted 2013 Crashes	38	0.628	0.850	0.061	5.344	23.848	

TABLE C.26: Calibration Factors Region 2 (Base + CMF Adj) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	38	2.947	4.223	0.000	22.000	112.000	4.185
Predicted 5 Years Crashes	38	0.704	0.969	0.057	6.073	26.760	
Observed 2017 Crashes	38	3.842	6.824	0.000	36.000	146.000	5.349
Predicted 2017 Crashes	38	0.718	1.011	0.059	6.361	27.294	
Observed 2016 Crashes	38	3.000	4.690	0.000	25.000	114.000	4.224
Predicted 2016 Crashes	38	0.710	0.950	0.060	5.922	26.991	
Observed 2015 Crashes	38	2.842	3.760	0.000	18.000	108.000	3.971
Predicted 2015 Crashes	38	0.716	0.965	0.056	6.002	27.200	
Observed 2014 Crashes	38	2.684	3.488	0.000	15.000	102.000	3.848
Predicted 2014 Crashes	38	0.698	0.989	0.056	6.211	26.508	
Observed 2013 Crashes	38	2.632	4.123	0.000	23.000	100.000	3.863
Predicted 2013 Crashes	38	0.681	0.937	0.054	5.873	25.886	

TABLE C.27: Calibration Factors Region 3 (Base Case HSM) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	88	5.909	9.801	0.000	77.000	520.000	5.142
Predicted 5 Years Crashes	88	1.149	1.480	0.095	11.258	101.130	
Observed 2017 Crashes	88	6.227	10.096	0.000	78.000	548.000	5.102
Predicted 2017 Crashes	88	1.221	1.565	0.102	11.829	107.417	
Observed 2016 Crashes	88	6.068	9.351	0.000	66.000	534.000	5.094
Predicted 2016 Crashes	88	1.191	1.591	0.098	12.228	104.833	
Observed 2015 Crashes	88	6.057	10.530	0.000	78.000	533.000	5.324
Predicted 2015 Crashes	88	1.138	1.387	0.097	10.409	100.114	
Observed 2014 Crashes	88	5.739	10.718	0.000	90.000	505.000	5.137
Predicted 2014 Crashes	88	1.117	1.435	0.088	10.865	98.312	
Observed 2013 Crashes	88	5.364	9.703	0.000	71.000	472.000	4.935
Predicted 2013 Crashes	88	1.087	1.446	0.089	10.996	95.647	

TABLE C.28: Calibration Factors Region 3 (Base + CMF Adj) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	88	5.909	9.801	0.000	77.000	520.000	5.079
Predicted 5 Years Crashes	88	1.163	1.458	0.090	11.071	102.376	
Observed 2017 Crashes	88	6.227	10.096	0.000	78.000	548.000	5.037
Predicted 2017 Crashes	88	1.236	1.541	0.097	11.632	108.787	
Observed 2016 Crashes	88	6.068	9.351	0.000	66.000	534.000	5.032
Predicted 2016 Crashes	88	1.206	1.569	0.093	12.025	106.128	
Observed 2015 Crashes	88	6.057	10.530	0.000	78.000	533.000	5.257
Predicted 2015 Crashes	88	1.152	1.365	0.092	10.236	101.389	
Observed 2014 Crashes	88	5.739	10.718	0.000	90.000	505.000	5.075
Predicted 2014 Crashes	88	1.131	1.412	0.083	10.684	99.509	
Observed 2013 Crashes	88	5.364	9.703	0.000	71.000	472.000	4.878
Predicted 2013 Crashes	88	1.100	1.425	0.084	10.813	96.758	

TABLE C.29: Calibration Factors Region 4 (Base Case HSM) – 2U Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	41	1.878	2.238	0.000	10.000	77.000	4.440
Predicted 5 Years Crashes	41	0.423	0.339	0.057	1.719	17.342	
Observed 2017 Crashes	41	1.732	2.608	0.000	14.000	71.000	3.776
Predicted 2017 Crashes	41	0.459	0.375	0.055	1.900	18.802	
Observed 2016 Crashes	41	2.293	2.831	0.000	11.000	94.000	5.335
Predicted 2016 Crashes	41	0.430	0.355	0.055	1.865	17.620	
Observed 2015 Crashes	41	1.756	2.321	0.000	10.000	72.000	4.248
Predicted 2015 Crashes	41	0.413	0.338	0.058	1.618	16.949	
Observed 2014 Crashes	41	2.098	2.644	0.000	10.000	86.000	5.121
Predicted 2014 Crashes	41	0.410	0.337	0.059	1.759	16.795	
Observed 2013 Crashes	41	1.537	1.951	0.000	9.000	63.000	3.756
Predicted 2013 Crashes	41	0.409	0.313	0.055	1.469	16.773	

TABLE C.30: Calibration Factors Region 4 (Base + CMF Adj) – 2U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	41	1.878	2.238	0.000	10.00	77.000	4.226
Predicted 5 Years Crashes	41	0.444	0.368	0.058	1.93	18.222	
Observed 2017 Crashes	41	1.732	2.608	0.000	14.00	71.000	3.596
Predicted 2017 Crashes	41	0.482	0.407	0.056	2.13	19.744	
Observed 2016 Crashes	41	2.293	2.831	0.000	11.00	94.000	5.072
Predicted 2016 Crashes	41	0.452	0.385	0.056	2.09	18.534	
Observed 2015 Crashes	41	1.756	2.321	0.000	10.00	72.000	4.044
Predicted 2015 Crashes	41	0.434	0.366	0.059	1.82	17.803	
Observed 2014 Crashes	41	2.098	2.644	0.000	10.00	86.000	4.876
Predicted 2014 Crashes	41	0.430	0.366	0.060	1.98	17.636	
Observed 2013 Crashes	41	1.537	1.951	0.000	9.00	63.000	3.571
Predicted 2013 Crashes	41	0.430	0.338	0.056	1.65	17.641	

Two-Lane Undivided (2U) Segments – Urban and Suburban Arterials

TABLE C.31: Calibration Factors All Regions (Base Case HSM) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	80	5.800	9.188	0.000	62.00	464.000	5.920
Predicted 5 Years Crashes	80	0.980	1.093	0.031	6.44	78.374	
Observed 2017 Crashes	80	5.900	8.868	0.000	47.00	472.000	5.711
Predicted 2017 Crashes	80	1.033	1.144	0.030	6.67	82.642	
Observed 2016 Crashes	80	5.938	9.518	0.000	66.00	475.000	5.984
Predicted 2016 Crashes	80	0.992	1.110	0.030	6.53	79.383	
Observed 2015 Crashes	80	5.963	10.660	0.000	72.00	477.000	6.112
Predicted 2015 Crashes	80	0.975	1.103	0.031	6.53	78.039	
Observed 2014 Crashes	80	5.713	8.971	0.000	58.00	457.000	5.985
Predicted 2014 Crashes	80	0.954	1.050	0.029	6.25	76.358	
Observed 2013 Crashes	80	5.400	9.547	0.000	65.00	432.000	5.813
Predicted 2013 Crashes	80	0.929	1.040	0.041	5.82	74.312	

TABLE C.32: Calibration Factors All Regions (Base + CMF Adj) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	80	5.800	9.188	0.000	62.00	464.000	5.823
Predicted 5 Years Crashes	80	0.996	1.159	0.000	6.76	79.689	
Observed 2017 Crashes	80	5.900	8.868	0.000	47.00	472.000	5.617
Predicted 2017 Crashes	80	1.050	1.218	0.000	7.00	84.024	
Observed 2016 Crashes	80	5.938	9.518	0.000	66.00	475.000	5.888
Predicted 2016 Crashes	80	1.008	1.180	0.000	6.85	80.678	
Observed 2015 Crashes	80	5.963	10.660	0.000	72.00	477.000	6.006
Predicted 2015 Crashes	80	0.993	1.170	0.000	6.85	79.422	
Observed 2014 Crashes	80	5.713	8.971	0.000	58.00	457.000	5.891
Predicted 2014 Crashes	80	0.970	1.113	0.000	6.56	77.580	
Observed 2013 Crashes	80	5.400	9.547	0.000	65.00	432.000	5.706
Predicted 2013 Crashes	80	0.946	1.095	0.000	6.11	75.707	

TABLE C.33: Calibration Factors Region 1 (Base Case HSM) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	22	3.909	5.681	0.000	26.00	86.000	3.201
Predicted 5 Years Crashes	22	1.221	1.614	0.061	6.45	26.867	
Observed 2017 Crashes	22	2.909	4.011	0.000	16.00	64.000	2.229
Predicted 2017 Crashes	22	1.305	1.706	0.067	6.68	28.715	
Observed 2016 Crashes	22	4.091	6.179	0.000	25.00	90.000	3.298
Predicted 2016 Crashes	22	1.240	1.630	0.056	6.53	27.291	
Observed 2015 Crashes	22	4.545	9.334	0.000	44.00	100.000	3.720
Predicted 2015 Crashes	22	1.222	1.643	0.065	6.53	26.881	
Observed 2014 Crashes	22	3.455	4.160	0.000	16.00	76.000	2.935
Predicted 2014 Crashes	22	1.177	1.564	0.056	6.25	25.899	
Observed 2013 Crashes	22	4.136	6.120	0.000	27.00	91.000	3.750
Predicted 2013 Crashes	22	1.103	1.426	0.059	5.82	24.264	

TABLE C.34: Calibration Factors Region 1 (Base + CMF Adj) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	22	3.909	5.681	0.000	26.00	86.000	3.130
Predicted 5 Years Crashes	22	1.249	1.754	0.000	6.76	27.472	
Observed 2017 Crashes	22	2.909	4.011	0.000	16.00	64.000	2.180
Predicted 2017 Crashes	22	1.334	1.863	0.000	7.00	29.354	
Observed 2016 Crashes	22	4.091	6.179	0.000	25.00	90.000	3.217
Predicted 2016 Crashes	22	1.271	1.780	0.000	6.85	27.973	
Observed 2015 Crashes	22	4.545	9.334	0.000	44.00	100.000	3.619
Predicted 2015 Crashes	22	1.256	1.784	0.000	6.85	27.630	
Observed 2014 Crashes	22	3.455	4.160	0.000	16.00	76.000	2.878
Predicted 2014 Crashes	22	1.200	1.694	0.000	6.56	26.404	
Observed 2013 Crashes	22	4.136	6.120	0.000	27.00	91.000	3.673
Predicted 2013 Crashes	22	1.126	1.549	0.000	6.11	24.776	

TABLE C.35: Calibration Factors Region 2 (Base Case HSM) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	16	5.188	5.811	0.000	21.00	83.000	8.811
Predicted 5 Years Crashes	16	0.589	0.549	0.049	1.97	9.420	
Observed 2017 Crashes	16	5.688	7.255	0.000	23.00	91.000	9.133
Predicted 2017 Crashes	16	0.623	0.578	0.048	2.12	9.963	
Observed 2016 Crashes	16	5.375	6.791	0.000	25.00	86.000	9.112
Predicted 2016 Crashes	16	0.590	0.513	0.046	1.97	9.438	
Observed 2015 Crashes	16	4.688	5.425	0.000	17.00	75.000	8.244
Predicted 2015 Crashes	16	0.569	0.514	0.063	1.95	9.098	
Observed 2014 Crashes	16	6.438	7.014	0.000	25.00	103.000	10.694
Predicted 2014 Crashes	16	0.602	0.573	0.045	2.00	9.632	
Observed 2013 Crashes	16	4.500	4.733	0.000	17.00	72.000	7.745
Predicted 2013 Crashes	16	0.581	0.564	0.045	1.98	9.296	

TABLE C.36: Calibration Factors Region 2 (Base + CMF Adj) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	16	5.188	5.811	0.000	21.00	83.000	8.921
Predicted 5 Years Crashes	16	0.581	0.591	0.000	2.07	9.304	
Observed 2017 Crashes	16	5.688	7.255	0.000	23.00	91.000	9.245
Predicted 2017 Crashes	16	0.615	0.621	0.000	2.22	9.843	
Observed 2016 Crashes	16	5.375	6.791	0.000	25.00	86.000	9.333
Predicted 2016 Crashes	16	0.576	0.556	0.000	2.07	9.215	
Observed 2015 Crashes	16	4.688	5.425	0.000	17.00	75.000	8.410
Predicted 2015 Crashes	16	0.557	0.556	0.000	2.05	8.918	
Observed 2014 Crashes	16	6.438	7.014	0.000	25.00	103.000	10.835
Predicted 2014 Crashes	16	0.594	0.615	0.000	2.10	9.507	
Observed 2013 Crashes	16	4.500	4.733	0.000	17.00	72.000	7.685
Predicted 2013 Crashes	16	0.586	0.600	0.000	1.99	9.369	

TABLE C.37: Calibration Factors Region 3 (Base Case HSM) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	34	7.324	12.075	0.000	62.00	249.000	6.563
Predicted 5 Years Crashes	34	1.116	0.907	0.098	4.36	37.937	
Observed 2017 Crashes	34	7.853	11.160	0.000	47.00	267.000	6.701
Predicted 2017 Crashes	34	1.172	0.925	0.144	4.40	39.844	
Observed 2016 Crashes	34	7.324	12.271	0.000	66.00	249.000	6.445
Predicted 2016 Crashes	34	1.136	0.941	0.087	4.36	38.637	
Observed 2015 Crashes	34	7.500	13.258	0.000	72.00	255.000	6.735
Predicted 2015 Crashes	34	1.114	0.901	0.090	4.40	37.863	
Observed 2014 Crashes	34	6.824	11.856	0.000	58.00	232.000	6.367
Predicted 2014 Crashes	34	1.072	0.845	0.080	3.98	36.438	
Observed 2013 Crashes	34	6.794	13.131	0.000	65.00	231.000	6.275
Predicted 2013 Crashes	34	1.083	0.973	0.100	5.00	36.810	

TABLE C.38: Calibration Factors Region 3 (Base + CMF Adj) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	34	7.324	12.075	0.000	62.00	249.000	6.468
Predicted 5 Years Crashes	34	1.132	0.918	0.093	4.38	38.495	
Observed 2017 Crashes	34	7.853	11.160	0.000	47.00	267.000	6.602
Predicted 2017 Crashes	34	1.189	0.937	0.137	4.41	40.442	
Observed 2016 Crashes	34	7.324	12.271	0.000	66.00	249.000	6.350
Predicted 2016 Crashes	34	1.153	0.953	0.082	4.37	39.214	
Observed 2015 Crashes	34	7.500	13.258	0.000	72.00	255.000	6.638
Predicted 2015 Crashes	34	1.130	0.912	0.086	4.42	38.416	
Observed 2014 Crashes	34	6.824	11.856	0.000	58.00	232.000	6.274
Predicted 2014 Crashes	34	1.088	0.857	0.075	3.99	36.977	
Observed 2013 Crashes	34	6.794	13.131	0.000	65.00	231.000	6.182
Predicted 2013 Crashes	34	1.099	0.985	0.095	5.02	37.369	

TABLE C.39: Calibration Factors Region 4 (Base Case HSM) – 3T Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	8	5.750	8.531	0.000	26.00	46.000	11.085
Predicted 5 Years Crashes	8	0.519	0.537	0.031	1.71	4.150	
Observed 2017 Crashes	8	6.250	9.618	0.000	29.00	50.000	12.137
Predicted 2017 Crashes	8	0.515	0.515	0.030	1.65	4.120	
Observed 2016 Crashes	8	6.250	8.844	0.000	27.00	50.000	12.446
Predicted 2016 Crashes	8	0.502	0.498	0.030	1.59	4.017	
Observed 2015 Crashes	8	5.875	10.385	0.000	31.00	47.000	11.196
Predicted 2015 Crashes	8	0.525	0.590	0.031	1.88	4.198	
Observed 2014 Crashes	8	5.750	8.067	0.000	24.00	46.000	10.479
Predicted 2014 Crashes	8	0.549	0.578	0.029	1.83	4.390	
Observed 2013 Crashes	8	4.750	6.228	0.000	19.00	38.000	9.640
Predicted 2013 Crashes	8	0.493	0.506	0.041	1.61	3.942	

TABLE C.40: Calibration Factors Region 4 (Base + CMF Adj) – 3T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	8	5.750	8.531	0.000	26.000	46.000	10.411
Predicted 5 Years Crashes	8	0.552	0.555	0.031	1.787	4.419	
Observed 2017 Crashes	8	6.250	9.618	0.000	29.000	50.000	11.402
Predicted 2017 Crashes	8	0.548	0.531	0.030	1.720	4.385	
Observed 2016 Crashes	8	6.250	8.844	0.000	27.000	50.000	11.693
Predicted 2016 Crashes	8	0.535	0.514	0.030	1.662	4.276	
Observed 2015 Crashes	8	5.875	10.385	0.000	31.000	47.000	10.541
Predicted 2015 Crashes	8	0.557	0.611	0.031	1.959	4.459	
Observed 2014 Crashes	8	5.750	8.067	0.000	24.000	46.000	9.804
Predicted 2014 Crashes	8	0.587	0.601	0.029	1.910	4.692	
Observed 2013 Crashes	8	4.750	6.228	0.000	19.000	38.000	9.061
Predicted 2013 Crashes	8	0.524	0.524	0.041	1.681	4.194	

Four-Lane Divided (4D) Segments – Urban and Suburban Arterials

TABLE C.41: Calibration Factors All Regions (Base Case HSM) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	278	5.471	9.855	0.000	130.00	1521.000	4.126
Predicted 5 Years Crashes	278	1.326	1.463	0.051	10.94	368.629	
Observed 2017 Crashes	278	5.550	10.675	0.000	143.00	1543.000	3.940
Predicted 2017 Crashes	278	1.409	1.601	0.051	13.09	391.621	
Observed 2016 Crashes	278	5.450	11.351	0.000	151.00	1515.000	4.049
Predicted 2016 Crashes	278	1.346	1.481	0.052	10.70	374.185	
Observed 2015 Crashes	278	5.356	9.582	0.000	119.00	1489.000	4.020
Predicted 2015 Crashes	278	1.333	1.452	0.053	10.57	370.444	
Observed 2014 Crashes	278	5.640	10.093	0.000	130.00	1568.000	4.413
Predicted 2014 Crashes	278	1.278	1.419	0.048	10.58	355.347	
Observed 2013 Crashes	278	5.417	9.081	0.000	107.00	1506.000	4.269
Predicted 2013 Crashes	278	1.269	1.391	0.053	9.84	352.739	

TABLE C.42: Calibration Factors All Regions (Base + CMF Adj) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	278	5.471	9.855	0	130.00	1521.000	4.459
Predicted 5 Years Crashes	278	1.227	1.400	0	10.66	341.075	
Observed 2017 Crashes	278	5.550	10.675	0	143.00	1543.000	4.257
Predicted 2017 Crashes	278	1.304	1.537	0	12.75	362.458	
Observed 2016 Crashes	278	5.450	11.351	0	151.00	1515.000	4.375
Predicted 2016 Crashes	278	1.246	1.418	0	10.43	346.262	
Observed 2015 Crashes	278	5.356	9.582	0	119.00	1489.000	4.347
Predicted 2015 Crashes	278	1.232	1.391	0	10.30	342.569	
Observed 2014 Crashes	278	5.640	10.093	0	130.00	1568.000	4.769
Predicted 2014 Crashes	278	1.183	1.355	0	10.31	328.758	
Observed 2013 Crashes	278	5.417	9.081	0	107.00	1506.000	4.613
Predicted 2013 Crashes	278	1.174	1.328	0	9.59	326.450	

TABLE C.43: Calibration Factors Region 1 (Base Case HSM) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	114	5.070	5.306	0.000	33.000	578.000	3.375
Predicted 5 Years Crashes	114	1.502	1.487	0.157	7.267	171.282	
Observed 2017 Crashes	114	5.228	6.462	0.000	37.000	596.000	3.243
Predicted 2017 Crashes	114	1.612	1.635	0.169	8.618	183.790	
Observed 2016 Crashes	114	4.754	5.568	0.000	36.000	542.000	3.117
Predicted 2016 Crashes	114	1.525	1.487	0.169	6.888	173.859	
Observed 2015 Crashes	114	4.588	4.802	0.000	29.000	523.000	3.046
Predicted 2015 Crashes	114	1.506	1.480	0.149	7.429	171.714	
Observed 2014 Crashes	114	5.386	5.780	0.000	30.000	614.000	3.731
Predicted 2014 Crashes	114	1.443	1.453	0.148	7.084	164.549	
Observed 2013 Crashes	114	5.509	6.343	0.000	34.000	628.000	3.853
Predicted 2013 Crashes	114	1.430	1.407	0.148	6.799	162.998	

TABLE C.44: Calibration Factors Region 1 (Base + CMF Adj) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	114	5.070	5.306	0.000	33.000	578.000	3.822
Predicted 5 Years Crashes	114	1.326	1.425	0.000	7.045	151.215	
Observed 2017 Crashes	114	5.228	6.462	0.000	37.000	596.000	3.670
Predicted 2017 Crashes	114	1.425	1.575	0.000	8.355	162.399	
Observed 2016 Crashes	114	4.754	5.568	0.000	36.000	542.000	3.534
Predicted 2016 Crashes	114	1.345	1.422	0.000	6.678	153.383	
Observed 2015 Crashes	114	4.588	4.802	0.000	29.000	523.000	3.456
Predicted 2015 Crashes	114	1.327	1.419	0.000	7.202	151.330	
Observed 2014 Crashes	114	5.386	5.780	0.000	30.000	614.000	4.225
Predicted 2014 Crashes	114	1.275	1.391	0.000	6.696	145.318	
Observed 2013 Crashes	114	5.509	6.343	0.000	34.000	628.000	4.358
Predicted 2013 Crashes	114	1.264	1.346	0.000	6.426	144.097	

TABLE C.45: Calibration Factors Region 2 (Base Case HSM) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	41	4.707	7.205	0	34.000	193.000	4.475
Predicted 5 Years Crashes	41	1.052	1.156	0.11	4.772	43.132	
Observed 2017 Crashes	41	5.024	7.923	0	31.000	206.000	4.675
Predicted 2017 Crashes	41	1.075	1.195	0.12	5.017	44.061	
Observed 2016 Crashes	41	4.171	6.473	0	30.000	171.000	3.893
Predicted 2016 Crashes	41	1.071	1.231	0.12	5.249	43.928	
Observed 2015 Crashes	41	4.854	6.937	0	26.000	199.000	4.449
Predicted 2015 Crashes	41	1.091	1.222	0.11	5.187	44.730	
Observed 2014 Crashes	41	4.878	8.219	0	39.000	200.000	4.772
Predicted 2014 Crashes	41	1.022	1.091	0.09	4.456	41.914	
Observed 2013 Crashes	41	4.927	8.296	0	44.000	202.000	4.912
Predicted 2013 Crashes	41	1.003	1.057	0.1	4.239	41.127	

TABLE C.46: Calibration Factors Region 2 (Base + CMF Adj) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	41	4.707	7.205	0	34.000	193.000	4.468
Predicted 5 Years Crashes	41	1.054	1.175	0	5.018	43.198	
Observed 2017 Crashes	41	5.024	7.923	0	31.000	206.000	4.670
Predicted 2017 Crashes	41	1.076	1.213	0	5.276	44.109	
Observed 2016 Crashes	41	4.171	6.473	0	30.000	171.000	3.884
Predicted 2016 Crashes	41	1.074	1.255	0	5.520	44.026	
Observed 2015 Crashes	41	4.854	6.937	0	26.000	199.000	4.442
Predicted 2015 Crashes	41	1.093	1.243	0	5.455	44.796	
Observed 2014 Crashes	41	4.878	8.219	0	39.000	200.000	4.764
Predicted 2014 Crashes	41	1.024	1.106	0	4.495	41.978	
Observed 2013 Crashes	41	4.927	8.296	0	44.000	202.000	4.905
Predicted 2013 Crashes	41	1.005	1.074	0	4.375	41.186	

TABLE C.47: Calibration Factors Region 3 (Base Case HSM) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	59	8.576	17.708	0.000	130.000	506.000	6.242
Predicted 5 Years Crashes	59	1.374	1.782	0.057	10.942	81.066	
Observed 2017 Crashes	59	8.797	19.233	0.000	143.000	519.000	5.797
Predicted 2017 Crashes	59	1.518	2.036	0.057	13.086	89.535	
Observed 2016 Crashes	59	9.068	20.609	0.000	151.000	535.000	6.520
Predicted 2016 Crashes	59	1.391	1.795	0.057	10.699	82.050	
Observed 2015 Crashes	59	8.593	16.703	0.000	119.000	507.000	6.339
Predicted 2015 Crashes	59	1.356	1.728	0.057	10.569	79.984	
Observed 2014 Crashes	59	8.475	17.946	0.000	130.000	500.000	6.449
Predicted 2014 Crashes	59	1.314	1.720	0.057	10.579	77.528	
Observed 2013 Crashes	59	7.847	15.014	0.000	107.000	463.000	6.047
Predicted 2013 Crashes	59	1.298	1.661	0.057	9.844	76.569	

TABLE C.48: Calibration Factors Region 3 (Base + CMF Adj) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	59	8.576	17.708	0.000	130.000	506.000	6.467
Predicted 5 Years Crashes	59	1.326	1.694	0.055	10.664	78.244	
Observed 2017 Crashes	59	8.797	19.233	0.000	143.000	519.000	6.002
Predicted 2017 Crashes	59	1.466	1.943	0.056	12.754	86.468	
Observed 2016 Crashes	59	9.068	20.609	0.000	151.000	535.000	6.752
Predicted 2016 Crashes	59	1.343	1.703	0.055	10.427	79.232	
Observed 2015 Crashes	59	8.593	16.703	0.000	119.000	507.000	6.567
Predicted 2015 Crashes	59	1.309	1.643	0.056	10.301	77.207	
Observed 2014 Crashes	59	8.475	17.946	0.000	130.000	500.000	6.683
Predicted 2014 Crashes	59	1.268	1.633	0.055	10.311	74.817	
Observed 2013 Crashes	59	7.847	15.014	0.000	107.000	463.000	6.272
Predicted 2013 Crashes	59	1.251	1.572	0.056	9.594	73.819	

TABLE C.49: Calibration Factors Region 4 (Base Case HSM) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	64	3.813	6.510	0.000	37.000	244.000	3.336
Predicted 5 Years Crashes	64	1.143	1.237	0.051	7.167	73.149	
Observed 2017 Crashes	64	3.469	5.578	0.000	34.000	222.000	2.991
Predicted 2017 Crashes	64	1.160	1.238	0.051	7.182	74.235	
Observed 2016 Crashes	64	4.172	8.799	0.000	57.000	267.000	3.591
Predicted 2016 Crashes	64	1.162	1.268	0.052	7.276	74.347	
Observed 2015 Crashes	64	4.063	7.884	0.000	40.000	260.000	3.513
Predicted 2015 Crashes	64	1.156	1.234	0.053	7.059	74.015	
Observed 2014 Crashes	64	3.969	6.146	0.000	30.000	254.000	3.560
Predicted 2014 Crashes	64	1.115	1.209	0.048	7.019	71.354	
Observed 2013 Crashes	64	3.328	5.393	0.000	31.000	213.000	2.957
Predicted 2013 Crashes	64	1.126	1.262	0.053	7.302	72.044	

TABLE C.50: Calibration Factors Region 4 (Base + CMF Adj) – 4D USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	64	3.813	6.510	0	37.000	244.000	3.566
Predicted 5 Years Crashes	64	1.069	1.179	0	6.822	68.418	
Observed 2017 Crashes	64	3.469	5.578	0	34.000	222.000	3.195
Predicted 2017 Crashes	64	1.086	1.182	0	6.836	69.482	
Observed 2016 Crashes	64	4.172	8.799	0	57.000	267.000	3.835
Predicted 2016 Crashes	64	1.088	1.215	0	6.925	69.622	
Observed 2015 Crashes	64	4.063	7.884	0	40.000	260.000	3.755
Predicted 2015 Crashes	64	1.082	1.174	0	6.719	69.236	
Observed 2014 Crashes	64	3.969	6.146	0	30.000	254.000	3.811
Predicted 2014 Crashes	64	1.041	1.148	0	6.681	66.645	
Observed 2013 Crashes	64	3.328	5.393	0	31.000	213.000	3.163
Predicted 2013 Crashes	64	1.052	1.202	0	6.950	67.348	

Four-Lane Undivided (4U) Segments – Urban and Suburban Arterials

TABLE C.51: Calibration Factors All Regions (Base Case HSM) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	80	10.080	16.760	0.000	98.00	806.400	8.089
Predicted 5 Years Crashes	80	1.246	1.426	0.085	9.72	99.691	
Observed 2017 Crashes	80	9.875	15.501	0.000	85.00	790.000	7.709
Predicted 2017 Crashes	80	1.281	1.499	0.085	10.38	102.480	
Observed 2016 Crashes	80	11.625	29.346	0.000	238.00	930.000	9.152
Predicted 2016 Crashes	80	1.270	1.514	0.084	10.74	101.619	
Observed 2015 Crashes	80	10.700	18.277	0.000	114.00	856.000	8.592
Predicted 2015 Crashes	80	1.245	1.391	0.090	9.09	99.622	
Observed 2014 Crashes	80	9.700	15.613	0.000	76.00	776.000	7.957
Predicted 2014 Crashes	80	1.219	1.351	0.080	8.55	97.526	
Observed 2013 Crashes	80	8.500	12.168	0.000	55.00	680.000	6.829
Predicted 2013 Crashes	80	1.245	1.490	0.080	10.16	99.578	

TABLE C.52: Calibration Factors All Regions (Base + CMF Adj) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	80	10.080	16.760	0.000	98.00	806.400	7.633
Predicted 5 Years Crashes	80	1.321	1.483	0.081	9.60	105.642	
Observed 2017 Crashes	80	9.875	15.501	0.000	85.00	790.000	7.277
Predicted 2017 Crashes	80	1.357	1.557	0.081	10.26	108.566	
Observed 2016 Crashes	80	11.625	29.346	0.000	238.00	930.000	8.639
Predicted 2016 Crashes	80	1.346	1.576	0.080	10.61	107.655	
Observed 2015 Crashes	80	10.700	18.277	0.000	114.00	856.000	8.109
Predicted 2015 Crashes	80	1.320	1.451	0.086	8.98	105.562	
Observed 2014 Crashes	80	9.700	15.613	0.000	76.00	776.000	7.494
Predicted 2014 Crashes	80	1.294	1.418	0.077	8.45	103.554	
Observed 2013 Crashes	80	8.500	12.168	0.000	55.00	680.000	6.447
Predicted 2013 Crashes	80	1.318	1.548	0.077	10.04	105.480	

TABLE C.53: Calibration Factors Region 1 (Base Case HSM) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	14	8.871	10.757	0.200	31.20	124.200	6.107
Predicted 5 Years Crashes	14	1.453	1.118	0.379	3.59	20.337	
Observed 2017 Crashes	14	9.429	11.745	0.000	39.00	132.000	6.227
Predicted 2017 Crashes	14	1.514	1.113	0.437	3.61	21.198	
Observed 2016 Crashes	14	8.000	9.207	0.000	29.00	112.000	5.370
Predicted 2016 Crashes	14	1.490	1.112	0.411	3.57	20.858	
Observed 2015 Crashes	14	10.214	13.045	0.000	44.00	143.000	6.957
Predicted 2015 Crashes	14	1.468	1.140	0.382	3.52	20.554	
Observed 2014 Crashes	14	9.857	13.002	0.000	38.00	138.000	7.066
Predicted 2014 Crashes	14	1.395	1.093	0.335	3.48	19.530	
Observed 2013 Crashes	14	6.857	9.071	0.000	24.00	96.000	4.758
Predicted 2013 Crashes	14	1.441	1.219	0.331	3.88	20.176	

TABLE C.54: Calibration Factors Region 1 (Base + CMF Adj) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	14	8.871	10.757	0.200	31.20	124.200	5.658
Predicted 5 Years Crashes	14	1.568	1.247	0.375	3.78	21.952	
Observed 2017 Crashes	14	9.429	11.745	0.000	39.00	132.000	5.770
Predicted 2017 Crashes	14	1.634	1.242	0.422	3.83	22.878	
Observed 2016 Crashes	14	8.000	9.207	0.000	29.00	112.000	4.984
Predicted 2016 Crashes	14	1.605	1.236	0.397	3.80	22.472	
Observed 2015 Crashes	14	10.214	13.045	0.000	44.00	143.000	6.446
Predicted 2015 Crashes	14	1.585	1.273	0.362	3.86	22.184	
Observed 2014 Crashes	14	9.857	13.002	0.000	38.00	138.000	6.537
Predicted 2014 Crashes	14	1.508	1.229	0.332	3.79	21.111	
Observed 2013 Crashes	14	6.857	9.071	0.000	24.00	96.000	4.403
Predicted 2013 Crashes	14	1.557	1.355	0.328	4.04	21.803	

TABLE C.55: Calibration Factors Region 2 (Base Case HSM) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	16	10.125	13.039	0.600	46.400	162.000	12.447
Predicted 5 Years Crashes	16	0.813	0.966	0.195	4.308	13.015	
Observed 2017 Crashes	16	10.563	12.982	0.000	46.000	169.000	12.541
Predicted 2017 Crashes	16	0.842	1.064	0.194	4.729	13.475	
Observed 2016 Crashes	16	8.500	10.469	1.000	38.000	136.000	10.299
Predicted 2016 Crashes	16	0.825	0.955	0.192	4.244	13.205	
Observed 2015 Crashes	16	10.625	15.409	0.000	60.000	170.000	13.584
Predicted 2015 Crashes	16	0.782	0.903	0.171	4.031	12.515	
Observed 2014 Crashes	16	10.250	17.113	0.000	59.000	164.000	12.730
Predicted 2014 Crashes	16	0.805	1.039	0.169	4.586	12.883	
Observed 2013 Crashes	16	10.688	11.429	0.000	42.000	171.000	13.123
Predicted 2013 Crashes	16	0.814	0.999	0.201	4.412	13.030	

TABLE C.56: Calibration Factors Region 2 (Base + CMF Adj) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	16	10.125	13.039	0.600	46.400	162.000	11.404
Predicted 5 Years Crashes	16	0.888	1.004	0.211	4.458	14.206	
Observed 2017 Crashes	16	10.563	12.982	0.000	46.000	169.000	11.523
Predicted 2017 Crashes	16	0.917	1.102	0.210	4.894	14.667	
Observed 2016 Crashes	16	8.500	10.469	1.000	38.000	136.000	9.466
Predicted 2016 Crashes	16	0.898	0.989	0.208	4.393	14.367	
Observed 2015 Crashes	16	10.625	15.409	0.000	60.000	170.000	12.403
Predicted 2015 Crashes	16	0.857	0.944	0.185	4.172	13.706	
Observed 2014 Crashes	16	10.250	17.113	0.000	59.000	164.000	11.635
Predicted 2014 Crashes	16	0.881	1.083	0.183	4.747	14.095	
Observed 2013 Crashes	16	10.688	11.429	0.000	42.000	171.000	12.049
Predicted 2013 Crashes	16	0.887	1.040	0.219	4.566	14.193	

TABLE C.57: Calibration Factors Region 3 (Base Case HSM) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	20	12.650	23.969	0.200	98.00	253.000	8.869
Predicted 5 Years Crashes	20	1.426	2.050	0.317	9.72	28.527	
Observed 2017 Crashes	20	10.400	15.922	0.000	66.00	208.000	6.966
Predicted 2017 Crashes	20	1.493	2.188	0.334	10.38	29.861	
Observed 2016 Crashes	20	19.700	53.367	0.000	238.00	394.000	13.464
Predicted 2016 Crashes	20	1.463	2.259	0.314	10.74	29.263	
Observed 2015 Crashes	20	13.500	26.836	0.000	114.00	270.000	9.495
Predicted 2015 Crashes	20	1.422	1.934	0.308	9.09	28.437	
Observed 2014 Crashes	20	10.900	19.496	0.000	76.00	218.000	7.965
Predicted 2014 Crashes	20	1.369	1.801	0.299	8.55	27.371	
Observed 2013 Crashes	20	8.750	13.018	0.000	49.00	175.000	6.236
Predicted 2013 Crashes	20	1.403	2.170	0.268	10.16	28.064	

TABLE C.58: Calibration Factors Region 3 (Base + CMF Adj) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	20	12.650	23.969	0.200	98.00	253.000	8.624
Predicted 5 Years Crashes	20	1.467	2.015	0.319	9.60	29.338	
Observed 2017 Crashes	20	10.400	15.922	0.000	66.00	208.000	6.786
Predicted 2017 Crashes	20	1.533	2.152	0.337	10.26	30.652	
Observed 2016 Crashes	20	19.700	53.367	0.000	238.00	394.000	13.101
Predicted 2016 Crashes	20	1.504	2.220	0.316	10.61	30.073	
Observed 2015 Crashes	20	13.500	26.836	0.000	114.00	270.000	9.230
Predicted 2015 Crashes	20	1.463	1.904	0.311	8.98	29.252	
Observed 2014 Crashes	20	10.900	19.496	0.000	76.00	218.000	7.732
Predicted 2014 Crashes	20	1.410	1.770	0.302	8.45	28.195	
Observed 2013 Crashes	20	8.750	13.018	0.000	49.00	175.000	6.067
Predicted 2013 Crashes	20	1.442	2.136	0.270	10.04	28.847	

TABLE C.59: Calibration Factors Region 4 (Base Case HSM) – 4U Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	30	8.907	15.567	0.000	69.20	267.200	7.067
Predicted 5 Years Crashes	30	1.260	1.263	0.085	5.40	37.812	
Observed 2017 Crashes	30	9.367	18.403	0.000	85.00	281.000	7.405
Predicted 2017 Crashes	30	1.265	1.295	0.085	5.60	37.945	
Observed 2016 Crashes	30	9.600	18.011	0.000	78.00	288.000	7.521
Predicted 2016 Crashes	30	1.276	1.310	0.084	5.96	38.293	
Observed 2015 Crashes	30	9.100	15.196	0.000	67.00	273.000	7.162
Predicted 2015 Crashes	30	1.271	1.286	0.090	5.55	38.116	
Observed 2014 Crashes	30	8.533	13.607	0.000	61.00	256.000	6.783
Predicted 2014 Crashes	30	1.258	1.275	0.080	5.47	37.741	
Observed 2013 Crashes	30	7.933	13.547	0.000	55.00	238.000	6.213
Predicted 2013 Crashes	30	1.277	1.281	0.080	5.44	38.309	

TABLE C.60: Calibration Factors Region 4 (Base + CMF Adj) – 4U USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	30	8.907	15.567	0.000	69.20	267.200	6.656
Predicted 5 Years Crashes	30	1.338	1.402	0.081	6.67	40.146	
Observed 2017 Crashes	30	9.367	18.403	0.000	85.00	281.000	6.961
Predicted 2017 Crashes	30	1.346	1.443	0.081	6.91	40.370	
Observed 2016 Crashes	30	9.600	18.011	0.000	78.00	288.000	7.069
Predicted 2016 Crashes	30	1.358	1.479	0.080	7.36	40.742	
Observed 2015 Crashes	30	9.100	15.196	0.000	67.00	273.000	6.754
Predicted 2015 Crashes	30	1.347	1.418	0.086	6.59	40.420	
Observed 2014 Crashes	30	8.533	13.607	0.000	61.00	256.000	6.376
Predicted 2014 Crashes	30	1.338	1.420	0.077	6.75	40.153	
Observed 2013 Crashes	30	7.933	13.547	0.000	55.00	238.000	5.857
Predicted 2013 Crashes	30	1.355	1.419	0.077	6.71	40.637	

Five-Lane Undivided (5T) Segments – Urban and Suburban Arterials

TABLE C.61: Calibration Factors All Regions (Base Case HSM) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	304	11.035	13.969	0.000	80.00	3354.600	3.584
Predicted 5 Years Crashes	304	3.079	3.142	0.151	24.72	935.876	
Observed 2017 Crashes	304	11.072	14.618	0.000	100.00	3366.000	3.509
Predicted 2017 Crashes	304	3.155	3.223	0.164	25.97	959.219	
Observed 2016 Crashes	304	11.010	14.651	0.000	90.00	3347.000	3.524
Predicted 2016 Crashes	304	3.124	3.182	0.156	24.43	949.745	
Observed 2015 Crashes	304	11.280	14.582	0.000	83.00	3429.001	3.602
Predicted 2015 Crashes	304	3.132	3.221	0.132	25.14	952.059	
Observed 2014 Crashes	304	10.938	14.071	0.000	77.00	3325.000	3.648
Predicted 2014 Crashes	303	2.999	3.061	0.148	23.56	911.569	
Observed 2013 Crashes	304	10.875	14.485	0.000	74.00	3306.000	3.617
Predicted 2013 Crashes	303	3.006	3.066	0.135	24.56	913.952	

TABLE C.62: Calibration Factors All Regions (Base + CMF Adj) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	304	11.035	13.969	0.000	80.00	3354.600	3.543
Predicted 5 Years Crashes	304	3.114	3.176	0.000	24.72	946.785	
Observed 2017 Crashes	304	11.072	14.618	0.000	100.00	3366.000	3.470
Predicted 2017 Crashes	304	3.191	3.256	0.000	25.98	970.108	
Observed 2016 Crashes	304	11.010	14.651	0.000	90.00	3347.000	3.484
Predicted 2016 Crashes	304	3.160	3.215	0.000	24.41	960.652	
Observed 2015 Crashes	304	11.280	14.582	0.000	83.00	3429.001	3.560
Predicted 2015 Crashes	304	3.169	3.257	0.000	25.15	963.227	
Observed 2014 Crashes	304	10.938	14.071	0.000	77.00	3325.000	3.605
Predicted 2014 Crashes	303	3.034	3.095	0.000	23.56	922.232	
Observed 2013 Crashes	304	10.875	14.485	0.000	74.00	3306.000	3.574
Predicted 2013 Crashes	303	3.043	3.102	0.000	24.57	924.938	

TABLE C.63: Calibration Factors Region 1 (Base Case HSM) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	87	8.614	10.573	0.000	52.80	749.400	2.744
Predicted 5 Years Crashes	87	3.139	3.498	0.260	23.87	273.070	
Observed 2017 Crashes	87	8.149	10.229	0.000	61.00	709.000	2.517
Predicted 2017 Crashes	87	3.238	3.627	0.261	24.47	281.711	
Observed 2016 Crashes	87	8.356	10.432	0.000	53.00	727.000	2.605
Predicted 2016 Crashes	87	3.208	3.569	0.267	24.43	279.055	
Observed 2015 Crashes	87	8.908	11.558	0.000	63.00	775.000	2.800
Predicted 2015 Crashes	87	3.182	3.574	0.266	25.01	276.812	
Observed 2014 Crashes	87	9.322	12.171	0.000	56.00	811.000	3.077
Predicted 2014 Crashes	87	3.030	3.412	0.262	23.14	263.606	
Observed 2013 Crashes	87	8.333	11.254	0.000	74.00	725.000	2.742
Predicted 2013 Crashes	87	3.039	3.331	0.231	22.31	264.379	

TABLE C.64: Calibration Factors Region 1 (Base + CMF Adj) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	87	8.614	10.573	0.000	52.80	749.400	2.730
Predicted 5 Years Crashes	87	3.155	3.481	0.277	23.84	274.518	
Observed 2017 Crashes	87	8.149	10.229	0.000	61.00	709.000	2.504
Predicted 2017 Crashes	87	3.254	3.608	0.271	24.45	283.135	
Observed 2016 Crashes	87	8.356	10.432	0.000	53.00	727.000	2.591
Predicted 2016 Crashes	87	3.225	3.552	0.285	24.41	280.546	
Observed 2015 Crashes	87	8.908	11.558	0.000	63.00	775.000	2.785
Predicted 2015 Crashes	87	3.198	3.558	0.283	24.98	278.259	
Observed 2014 Crashes	87	9.322	12.171	0.000	56.00	811.000	3.061
Predicted 2014 Crashes	87	3.046	3.394	0.279	23.11	264.963	
Observed 2013 Crashes	87	8.333	11.254	0.000	74.00	725.000	2.727
Predicted 2013 Crashes	87	3.056	3.318	0.247	22.29	265.904	

TABLE C.65: Calibration Factors Region 2 (Base Case HSM) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	46	13.509	15.483	0.400	62.00	621.400	4.766
Predicted 5 Years Crashes	46	2.835	2.064	0.606	8.21	130.395	
Observed 2017 Crashes	46	13.522	16.835	0.000	68.00	622.000	4.784
Predicted 2017 Crashes	46	2.826	2.035	0.644	8.31	130.012	
Observed 2016 Crashes	46	13.087	14.192	1.000	51.00	602.000	4.608
Predicted 2016 Crashes	46	2.840	2.023	0.604	7.97	130.654	
Observed 2015 Crashes	46	13.609	15.594	0.000	55.00	626.000	4.693
Predicted 2015 Crashes	46	2.900	2.143	0.602	8.52	133.403	
Observed 2014 Crashes	46	13.130	16.245	0.000	68.00	604.000	4.697
Predicted 2014 Crashes	46	2.795	2.065	0.584	8.20	128.587	
Observed 2013 Crashes	46	14.196	16.622	0.000	74.00	653.000	5.046
Predicted 2013 Crashes	46	2.813	2.087	0.542	8.08	129.411	

TABLE C.66: Calibration Factors Region 2 (Base + CMF Adj) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	46	13.509	15.483	0.400	62.00	621.400	4.708
Predicted 5 Years Crashes	46	2.869	2.071	0.590	8.22	131.988	
Observed 2017 Crashes	46	13.522	16.835	0.000	68.00	622.000	4.730
Predicted 2017 Crashes	46	2.859	2.037	0.617	8.32	131.496	
Observed 2016 Crashes	46	13.087	14.192	1.000	51.00	602.000	4.552
Predicted 2016 Crashes	46	2.875	2.030	0.589	7.97	132.249	
Observed 2015 Crashes	46	13.609	15.594	0.000	55.00	626.000	4.636
Predicted 2015 Crashes	46	2.936	2.150	0.587	8.53	135.037	
Observed 2014 Crashes	46	13.130	16.245	0.000	68.00	604.000	4.641
Predicted 2014 Crashes	46	2.829	2.071	0.570	8.20	130.151	
Observed 2013 Crashes	46	14.196	16.622	0.000	74.00	653.000	4.981
Predicted 2013 Crashes	46	2.850	2.100	0.519	8.08	131.102	

TABLE C.67: Calibration Factors Region 3 (Base Case HSM) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	119	12.627	15.725	0.000	80.00	1502.600	3.606
Predicted 5 Years Crashes	119	3.502	3.544	0.151	24.72	416.743	
Observed 2017 Crashes	119	12.941	16.819	0.000	100.00	1540.000	3.609
Predicted 2017 Crashes	119	3.586	3.624	0.169	25.97	426.746	
Observed 2016 Crashes	119	13.311	17.931	0.000	90.00	1583.999	3.728
Predicted 2016 Crashes	119	3.571	3.583	0.167	24.35	424.946	
Observed 2015 Crashes	119	13.118	16.658	0.000	83.00	1561.000	3.685
Predicted 2015 Crashes	119	3.559	3.628	0.132	25.14	423.578	
Observed 2014 Crashes	119	11.740	14.372	0.000	77.00	1397.001	3.429
Predicted 2014 Crashes	118	3.423	3.449	0.148	23.56	407.373	
Observed 2013 Crashes	119	12.025	15.182	0.000	71.00	1431.000	3.502
Predicted 2013 Crashes	118	3.434	3.500	0.139	24.56	408.659	

TABLE C.68: Calibration Factors Region 3 (Base + CMF Adj) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	119	12.627	15.725	0.000	80.00	1502.600	3.551
Predicted 5 Years Crashes	119	3.556	3.600	0.154	24.72	423.207	
Observed 2017 Crashes	119	12.941	16.819	0.000	100.00	1540.000	3.555
Predicted 2017 Crashes	119	3.640	3.679	0.172	25.98	433.218	
Observed 2016 Crashes	119	13.311	17.931	0.000	90.00	1583.999	3.672
Predicted 2016 Crashes	119	3.625	3.637	0.170	24.35	431.338	
Observed 2015 Crashes	119	13.118	16.658	0.000	83.00	1561.000	3.629
Predicted 2015 Crashes	119	3.615	3.686	0.134	25.15	430.148	
Observed 2014 Crashes	119	11.740	14.372	0.000	77.00	1397.001	3.376
Predicted 2014 Crashes	118	3.478	3.505	0.151	23.56	413.860	
Observed 2013 Crashes	119	12.025	15.182	0.000	71.00	1431.000	3.447
Predicted 2013 Crashes	118	3.489	3.557	0.142	24.57	415.167	

TABLE C.69: Calibration Factors Region 4 (Base Case HSM) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (base)
Average 5 Years Crashes	52	9.254	12.744	0.000	58.80	481.200	4.160
Predicted 5 Years Crashes	52	2.224	1.995	0.154	9.06	115.669	
Observed 2017 Crashes	52	9.519	12.564	0.000	57.00	495.000	4.099
Predicted 2017 Crashes	52	2.322	2.058	0.164	9.46	120.750	
Observed 2016 Crashes	52	8.346	11.606	0.000	54.00	434.000	3.771
Predicted 2016 Crashes	52	2.213	1.993	0.156	9.32	115.090	
Observed 2015 Crashes	52	8.981	12.395	0.000	65.00	467.000	3.949
Predicted 2015 Crashes	52	2.274	2.091	0.158	10.00	118.266	
Observed 2014 Crashes	52	9.865	14.291	0.000	68.00	513.000	4.563
Predicted 2014 Crashes	52	2.162	1.911	0.153	8.69	112.427	
Observed 2013 Crashes	52	9.558	15.168	0.000	73.00	497.000	4.440
Predicted 2013 Crashes	52	2.153	1.947	0.135	8.81	111.930	

TABLE C.70: Calibration Factors Region 4 (Base + CMF Adj) – 5T USUB Arterials

Variable	Obs	Mean	Std. Dev.	Min	Max	Sum	C (adj)
Average 5 Years Crashes	52	9.254	12.744	0.000	58.80	481.200	4.110
Predicted 5 Years Crashes	52	2.251	2.112	0.000	9.75	117.072	
Observed 2017 Crashes	52	9.519	12.564	0.000	57.00	495.000	4.049
Predicted 2017 Crashes	52	2.351	2.179	0.000	10.18	122.260	
Observed 2016 Crashes	52	8.346	11.606	0.000	54.00	434.000	3.725
Predicted 2016 Crashes	52	2.241	2.112	0.000	10.02	116.520	
Observed 2015 Crashes	52	8.981	12.395	0.000	65.00	467.000	3.899
Predicted 2015 Crashes	52	2.304	2.211	0.000	10.53	119.783	
Observed 2014 Crashes	52	9.865	14.291	0.000	68.00	513.000	4.512
Predicted 2014 Crashes	52	2.187	2.021	0.000	9.18	113.703	
Observed 2013 Crashes	52	9.558	15.168	0.000	73.00	497.000	4.390
Predicted 2013 Crashes	52	2.177	2.062	0.000	9.48	113.211	

TABLE C.71: Details of 3T Segments of Urban & Suburban Arterials with High Crash Rates

BLM	ELM	County	Route	Special Case	County Sequence
18.97	19.23	PUTNAM	SR024	0-NONE	1
15.205	15.31	BRADLEY	SR074	0-NONE	1
13.99	14.17	RUTHERFORD	SR096	0-NONE	1
7.5	7.66	WILLIAMSON	SR252	0-NONE	1

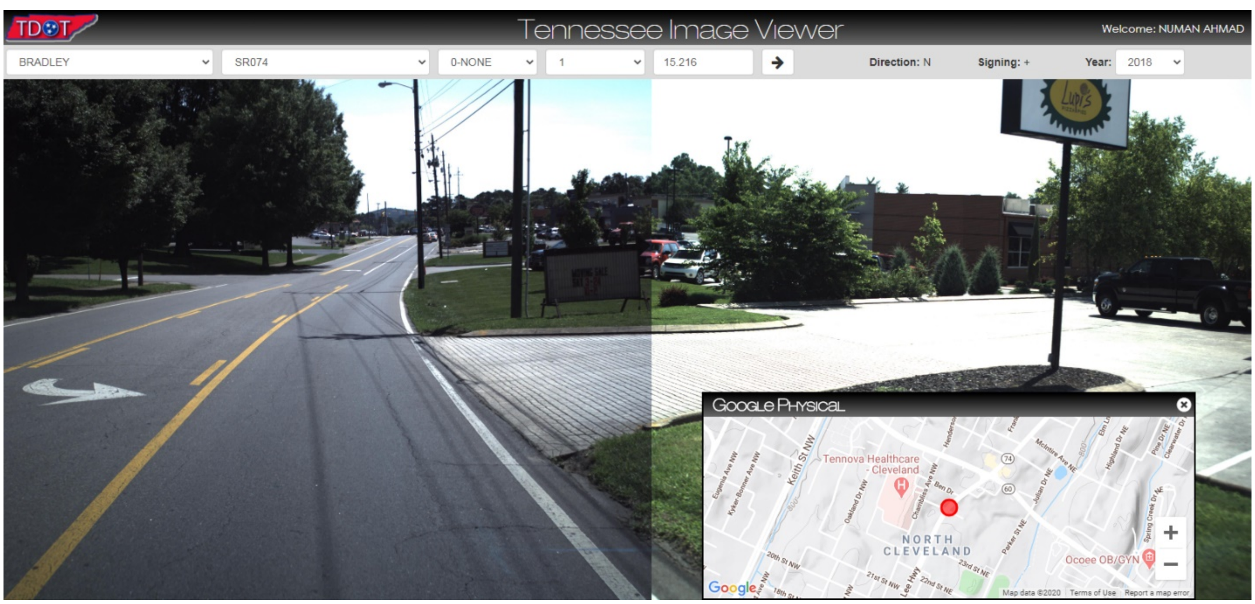


Figure C.1: Location Details and Geometric Overview of a Sample 3T Segment of Urban & Suburban Arterials with High Crash Rates (On Route SR 074 in Bradley County)

TABLE C.72: Details of 4U Segments of Urban & Suburban Arterials with High Crash Rates

BLM	ELM	County	Route	Special Case	County Sequence
11.11	11.22	PUTNAM	SR135	0-NONE	1
12.478	12.63	DAVIDSON	SR024	0-NONE	1
5.43	5.62	MONTGOMERY	SR048	0-NONE	1

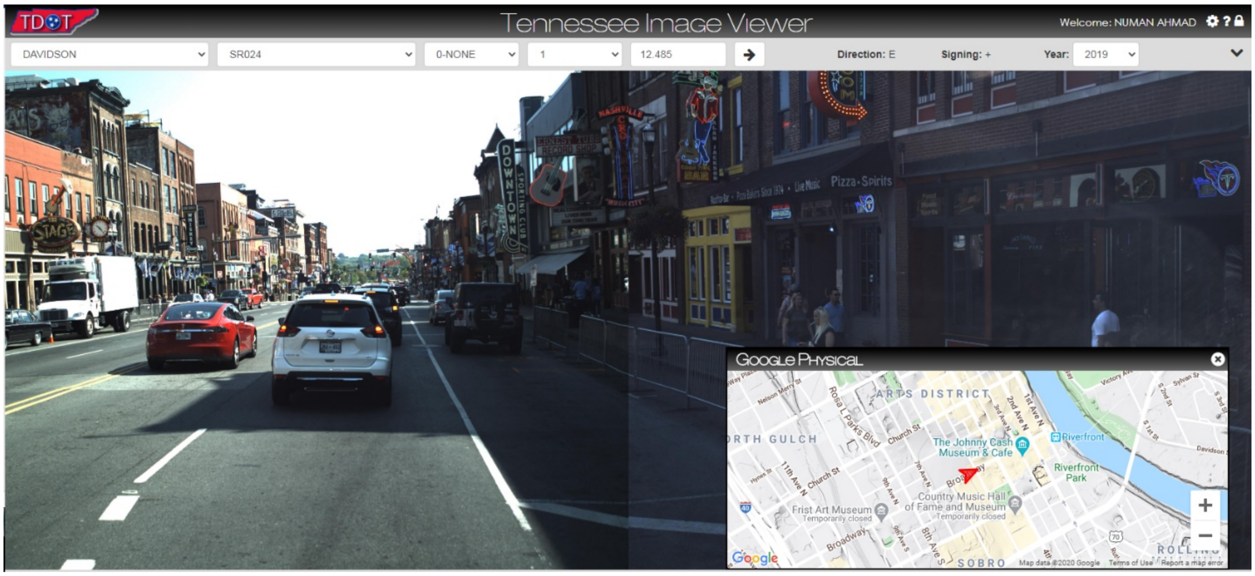


Figure C.2: Location Details and Geometric Overview of a Sample 4U Segment of Urban & Suburban Arterials with High Crash Rates
(On Route SR 024 in Davidson County: A Portion of Broadway St., Nashville, TN)

APPENDIX D: Introduction to AASHTOWare Safety Analyst User's Manual

An introduction to AASHTOWare Safety Analyst software is presented in this section. Note that the contents of Appendix D are directly from the AASHTOWare Safety Analyst User's Manual. For more information, please refer to the User's Manual.

D.1. Introduction to Tutorial

Safety Analyst is a set of computerized analytical tools to aid state and local highway agencies in highway safety management and to improve a highway agency's system-wide programming of site-specific safety improvements. Safety Analyst incorporates state-of-the-art safety management approaches for guiding the decision-making process to identify safety improvement needs and has a strong basis in cost-effectiveness analysis. Safety Analyst will help highway agencies get the greatest possible safety benefit from each dollar spent in the name of safety.

Safety Analyst addresses site-specific safety improvements that involve physical modifications to the highway system. Also, Safety Analyst has the capability to determine the frequency and percentage of particular crash types along specified portions of the highway system. These capabilities can be used to investigate the potential need for engineering improvements at a site.

Safety Analyst has been developed to:

- Address site-specific safety improvements that involve physical modifications to a highway system
- Use state-of-the-art methodologies to advance the state-of-the-practice of highway safety management
- Be comprehensive and include all stages of the safety management process
- Be rigorous enough to have scientific merit, yet flexible enough to fit into diverse highway agency operating environments
- Draw upon knowledge and experience from previous and ongoing safety initiatives

A general safety management process can be described in six main steps:

1: Identification of sites with potential for safety improvement
2: Diagnosis of the nature of safety problems at specific sites
3: Selection of countermeasures at specific sites
4: Economic appraisal for sites and countermeasures under consideration
5: Priority rankings of improvement projects
6: Safety effectiveness evaluation of implemented countermeasures

Safety Analyst comprises four modules that implement the six main steps for highway safety management:

Module 1 - Network screening
Module 2 - Diagnosis and countermeasure selection
Module 3 - Economic appraisal and priority-ranking
Module 4 - Countermeasure evaluation
Module 5 - Systemic site selection evaluation

Safety Analyst is packaged with default safety performance function, countermeasure, site diagnosis, and crash distribution data used by the analysis algorithms. Furthermore, Safety Analyst provides an Administration Tool that enables an agency to modify those default data or to provide its own values. Safety Analyst also provides a Data Management Tool to import an agency's highway inventory, traffic count, and crash data and to convert those data into a format usable by the Analytical Tool for conducting safety analyses.

Safety Analyst consists of a set of multiple independent tools that interact with a database using a two-tier, client-server architecture. The database management system (DBMS) acts as the server, performing user authentication and data integrity functions for the deployed Safety Analyst tools. Figure D.1 illustrates the relationships and flow of data between the Safety Analyst applications.

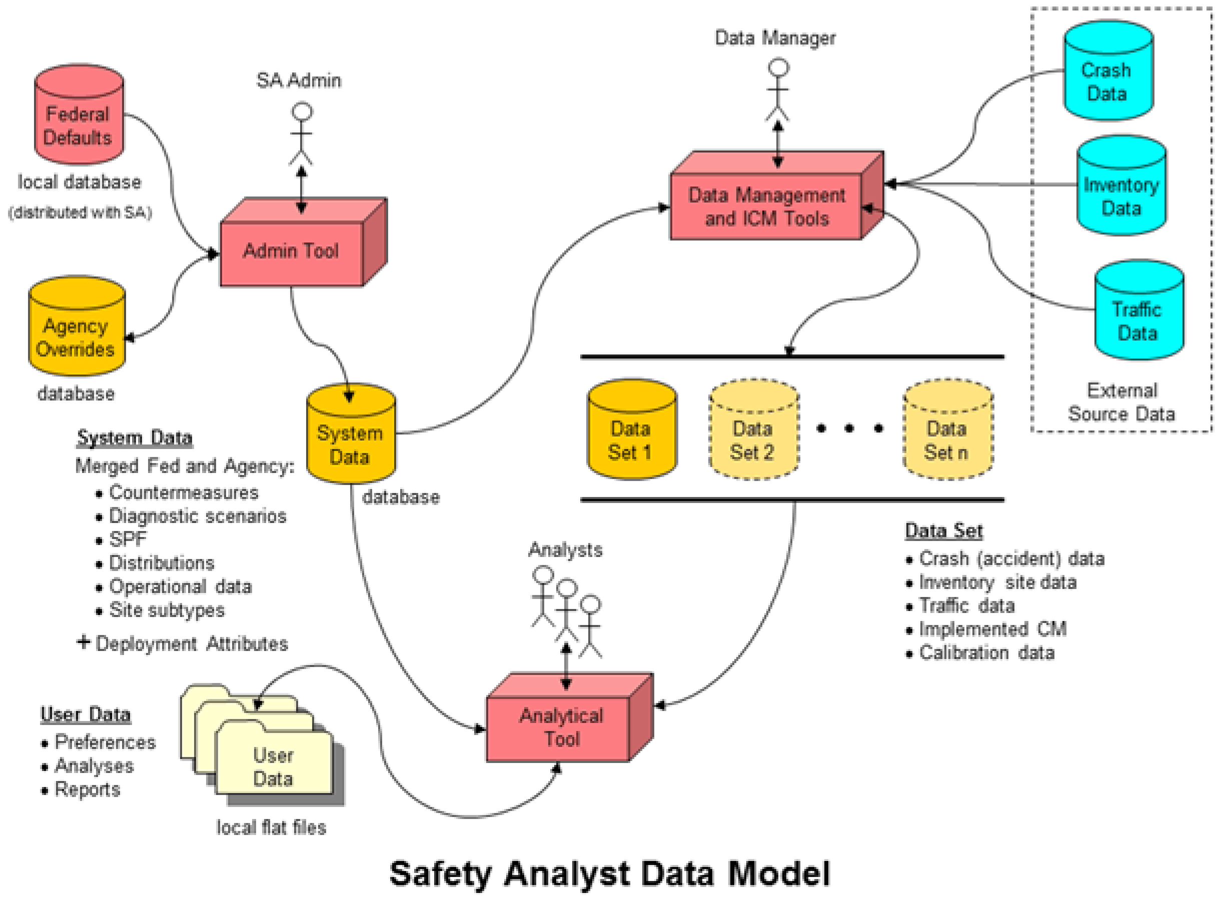


Figure 36: Safety Analyst Architecture (Source: AASHTOWare Safety Analyst User's Manual)

Safety Analyst is implemented in the Java programming language and uses the Java Database Connectivity (JDBC) API to support connectivity to a wide variety of DBMS vendors. This interface supports connectivity to an embedded version of the JavaDB (a.k.a. Apache Derby) that allows Safety Analyst to operate as a desktop application, providing an alternative to a client-server deployment.
The Safety Analyst toolset consists of three primary applications as follows:

1. **Administration (Admin) Tool** - This tool is used to set up and manage the Safety Analyst deployment. It enables an agency to tailor the Safety Analyst data model and to modify the federally-supplied default data used in conducting safety analyses.
2. **Data Management Tool** - This tool is used to import and prepare an agency's inventory, traffic volume, and crash data for analysis. (In the current release, a separate application is provided to manage the set of countermeasures that have been applied to an agency's inventory.)
3. **Analytical Tool** - This tool is used to conduct safety analyses of an agency's inventory. To ensure data integrity, this client application accesses the agency data in a read-only mode.

Administrators and data managers use the corresponding Safety Analyst Administration and Data Management tools to prepare Safety Analyst and the agency data for use by safety analysts.

Administrators install Safety Analyst and configuring system attributes, collision distributions, countermeasures, and diagnostic scenarios. Data Managers configure, import, post-process, and calibrate the agency's site data (segments, intersections, ramps, traffic, and crash data). Analysts use the Safety Analyst Analytical Tool to conduct safety analyses on an agency's inventory.

D.1.1. Administration Tool

The Safety Analyst Administration Tool Manual introduces administrators and data managers to the capabilities and features of the Safety Analyst Administration tool. It explains in detail the mechanics of using the software and accessing all of its functionality. It is the primary source of information concerning the operation of the Safety Analyst Administration tool.
Getting started using the Safety Analyst system can be a difficult task. There are many roles and software tools to understand and use. The initial setup of the tools and the inventory data can be time-consuming. However, if the initial setup is done properly, future updates to the inventory data should be fairly quick.

D.1.1.1. Using the Administration Tool

The Safety Analyst Administration Tool should be used by administrators to create and maintain agency-defined, non-inventory, data. These data include deployment attributes, countermeasures (CM), diagnostics, crash distributions, and Safety Performance Functions (SPF). These agency-defined data are available for use in the Safety Analyst Analytical Tool but can be modified only by Safety Analyst administrators. This section describes how to use the Administration Tool to create and maintain these agency-defined data. The Administration Tool operates with three separate and distinct databases:

- Federal
- Agency
- System

The Federal database is a read-only local (embedded) database that is distributed with the Administration Tool in the Administrative installation. It contains federal default values for the CM, diagnostics, and SPF data plus national averages for the crash distributions. This database is not edited by the Administration Tool and should not be modified by the agency because it may be overwritten by future updates to Safety Analyst. No connection information is required for the Federal database because it is a local database.

The Agency database is a local or remote database that a user creates and maintains using the Administration Tool. It is the repository for the agency-specified deployment attributes, agency-specific countermeasures, agency-specific diagnostic scenarios, state-wide crash distribution averages, or modified federal defaults. Use the Agency database tab to specify the connection information for the database.

The System database is a local or remote database that a user maintains using the Administration Tool. It contains the merged Federal and Agency data and is the source of that information for the Safety Analyst Analytical Tool. Analyst can view and edit these different data using the editing tools listed in the Edit pull-down menu. The User must first create an Agency database to enable data editing tools. After editing the data, the user must merge the agency data with the Federal database using the System database tab's **Update Database** button. Once the System database has been created and populated (updated), the user can start the data management process using the Data Management Tool.

D.1.1.2. Agency-Defined Safety Performance Functions (SPF)

Safety Performance Functions (SPF) are regression models used to predict crashes for a site and are also used to perform Empirical Bayes calculations within the Safety Analyst analytical modules. For each site subtype in Safety Analyst, default or agency-defined, there must be two associated SPF: one for ***Total Crashes*** and one for ***Fatal and All-Injury Crashes***. In Safety Analyst, an SPF **must** have a multiplicative, exponential form consisting of one or more terms of the following forms:

- C - constant term
- e^c - exponential term with a constant exponent
- e^{cV} - exponential term with a variable exponent
- V^c - variable power term
- L - site length (roadway segments and ramps)

In these forms, ***c*** indicates a regression coefficient and ***V*** represents the value of a numeric site variable (e.g., Annual Average Daily Traffic).

Note: Safety Analyst does not accommodate additive SPF forms, like those obtained from ordinary least squares regression, because those are not considered appropriate for use with non-normal data like crash data.

D.1.1.2.1. Built-In Safety Performance Functions

Built-in SPFs have been developed for each of the default site subtypes associated with the site types supported by Safety Analyst (Roadway Segments, Intersections, and Ramps). The general functional forms of these default SPF are as follows:

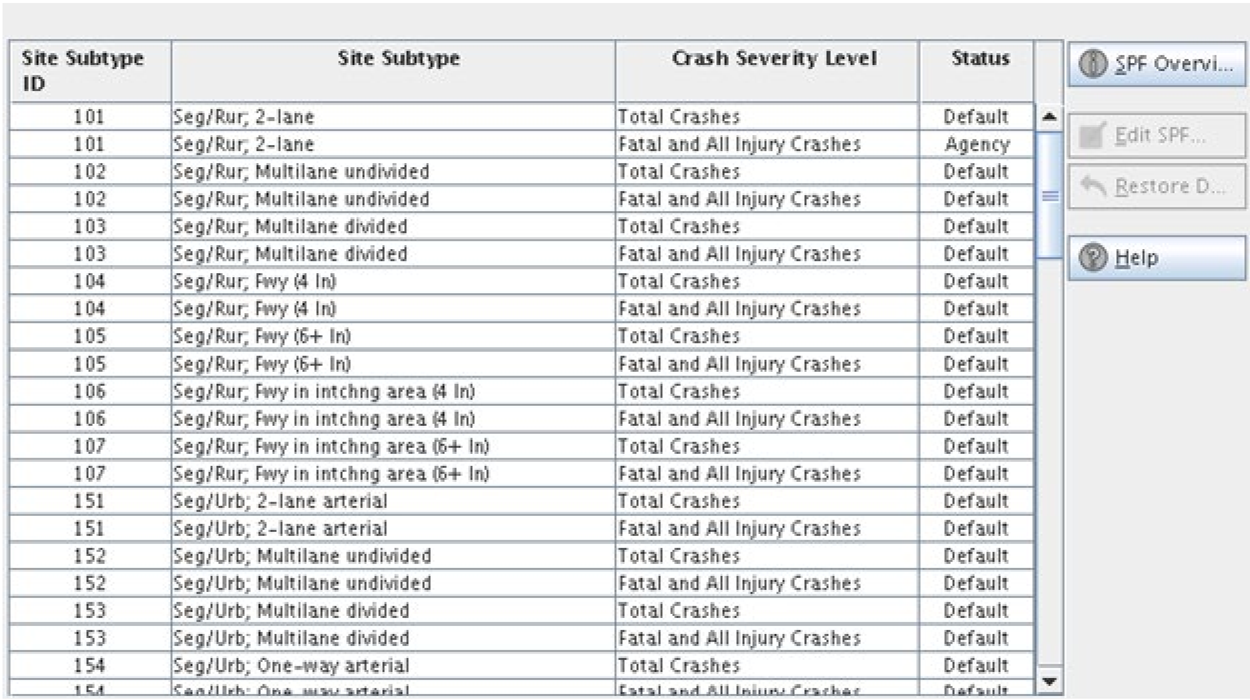
Roadway segments and Ramps: $\kappa_y = SPF(AADT) = C_y \times P_{CT} \times e^{\alpha} \times AADT_y{}^{\beta}{}_1$ (D.1)

where:

κ_y = predicted number of crashes at a site during year ***y*** (expressed on a per-mile basis for roadway segments and a per-site basis for intersections and ramps)
AADT = annual average daily traffic (vehicles/day)
C_y = yearly calibration factor
P_{CT} = proportion of a specified collision type
α, β_1= log-scale regression coefficients

D.1.1.2.2. SPF Editor Dialog

Figure D.2 illustrates the primary interface for agency-management of Safety Performance Functions (SPF) within Safety Analyst. An agency may choose to use the built-in (default) SPF provided with Safety Analyst or may choose to modify (or replace) the SPF for one or more of the subtypes supported by the Safety Analyst. When the user defines a new subtype for use in Safety Analyst, the user must select an existing subtype from which to copy the SPF for the new subtype. The user can then modify (or replace) the SPF for the subtype using this interface.



Site Subtype ID	Site Subtype	Crash Severity Level	Status
101	Seg/Rur; 2-lane	Total Crashes	Default
101	Seg/Rur; 2-lane	Fatal and All Injury Crashes	Agency
102	Seg/Rur; Multilane undivided	Total Crashes	Default
102	Seg/Rur; Multilane undivided	Fatal and All Injury Crashes	Default
103	Seg/Rur; Multilane divided	Total Crashes	Default
103	Seg/Rur; Multilane divided	Fatal and All Injury Crashes	Default
104	Seg/Rur; Fwy (4 ln)	Total Crashes	Default
104	Seg/Rur; Fwy (4 ln)	Fatal and All Injury Crashes	Default
105	Seg/Rur; Fwy (6+ ln)	Total Crashes	Default
105	Seg/Rur; Fwy (6+ ln)	Fatal and All Injury Crashes	Default
106	Seg/Rur; Fwy in intchng area (4 ln)	Total Crashes	Default
106	Seg/Rur; Fwy in intchng area (4 ln)	Fatal and All Injury Crashes	Default
107	Seg/Rur; Fwy in intchng area (6+ ln)	Total Crashes	Default
107	Seg/Rur; Fwy in intchng area (6+ ln)	Fatal and All Injury Crashes	Default
151	Seg/Urb; 2-lane arterial	Total Crashes	Default
151	Seg/Urb; 2-lane arterial	Fatal and All Injury Crashes	Default
152	Seg/Urb; Multilane undivided	Total Crashes	Default
152	Seg/Urb; Multilane undivided	Fatal and All Injury Crashes	Default
153	Seg/Urb; Multilane divided	Total Crashes	Default
153	Seg/Urb; Multilane divided	Fatal and All Injury Crashes	Default
154	Seg/Urb; One-way arterial	Total Crashes	Default
154	Seg/Urb; One-way arterial	Fatal and All Injury Crashes	Default

Figure 37: SPF Editor in AASHTOWare Safety Analyst Software

D.1.1.2.3. Edit Agency SPF Table

This table provides access to the Safety Performance Functions (SPF) for all site subtypes. For each site subtype in Safety Analyst, default, or agency-defined, there must be two associated SPF: one for ***Total Crashes*** and one for ***Fatal and All-Injury Crashes***. Thus, the SPF editor table includes two rows for every subtype defined in Safety Analyst.

To ***modify*** an existing SPF, select the desired SPF (click on the desired row in the table) then press the **Edit SPF** button. Alternatively, double click on the desired row to invoke the editor for the selected SPF. From the editor dialog, the terms of the SPF can be modified or removed, and new terms can be specified.

To ***restore*** a modified SPF to its default (built-in) SPF provided with Safety Analyst, select the desired SPF (click on the desired row in the table) and then press the **Restore Default** button. **Note:** SPF that the agency has specified for agency-defined site subtypes cannot be restored.

- Table Column Items
    - **Site Subtype ID** - Identifier for the site subtype, which indicates the facility classification of the site (see help for the Site Subtype column). The data type associated with this item is enumerated. Enumeration values are created dynamically at run time.
    - **Site Subtype** - Site subtype indicates the facility classification of a site.
      Safety Analyst provides all the required functionality to support the following:
        - 17 subtypes (i.e., classes) of roadway segments. Site subtypes for roadway segments are determined based upon inventory data elements such as area type, number of lanes, median type, access control, one-way vs. two-way operation, and interchange influence.
        - 12 subtypes of intersections. Site subtypes for intersections are determined based upon inventory data elements such as area type, type of traffic control, and the number of legs.
        - 16 subtypes of ramps. Site subtypes for ramps are determined based upon inventory data elements such as area type and ramp configuration.

For each site subtype, safety performance functions (SPFs) are available to predict total (TOT) and fatal and injury (FI) crash frequencies.

Note: Agencies can also define their own subtypes for segments, intersections, and ramps, but will also need to provide the SPFs to support those subtypes. The data type associated with this item is enumerated. Enumeration values are created dynamically at run time.

- **Crash Severity Level** - The crash severity level associated with the SPF. The data type associated with this item is enumerated. Enumeration values:
    - *Total Crashes* - All crashes.
    - *Fatal and All Injury Crashes* - Fatal and all injury crashes.
- **Status** - An indicator of the current state of the SPF. The data type associated with this item is enumerated. Enumeration values:
    - *Agency* - Agency-specified SPF.
    - *Default* - Federally-specified (default) SPF.
    - *Modified* - Modified federal SPF.

- Table Buttons
    - **SPF Overview button -** (Keyboard shortcut: *Alt-S*) Press this button to display an overview of Safety Performance Functions (SPF) as used in Safety Analyst.
    - **Edit SPF button -** (Keyboard shortcut: *Alt-E*) Press this button to display a dialog for editing the specification of the selected SPF.
    - **Restore Default button -** (Keyboard shortcut: *Alt-R*) Press this button to restore the selected SPF to the default (built-in) SPF provided with Safety Analyst. **Note:** SPF that the agency has specified for agency-defined site subtypes cannot be restored.
    - **Help button -** (Keyboard shortcut: *Alt-H*) Press this button to display a dialog that describes the table and its associated columns.

D.1.1.2.. Edit SPF Dialog

Figure D.3 illustrates the dialog used for modifying an individual Safety Performance Function (SPF). The labels on the top left of the Edit dialog panel indicate the site subtype and the crash severity level to which the SPF applies. The top right of the Edit dialog panel presents a field for specifying the over-dispersion parameter for the SPF. Below the SPF identification labels and the over-dispersion parameter field, is a text area that displays the SPF equation, including the numeric regression coefficients. Each term in the equation is subscripted with the term number for reference to the term table. As terms are added, removed, or modified in the term table, the SPF display area updates to reflect the changes.

The button to the right of the SPF display is used to copy the SPF from another site subtype/crash severity level. Press the button to display a Copy dialog with a drop-list that enables users to select the SPF specification from another subtype to copy. When users press the **Ok** button on the Copy dialog, the contents of the SPF Edit dialog update to match the selected SPF. Below the SPF display area is the table of terms that define the SPF. Each row in the table represents one term of the SPF. Users can add and remove terms via the buttons on the right side of the table. Users can edit the cells in each row to specify the functional form of the term, and the regression coefficients and site variables if required by the selected functional form. Press the **Ok** button to save changes. The editor will validate all terms for missing coefficients and variable specifications. It will also check for duplicate terms. If there are missing items or duplicates, the editor will issue an error and will not close. The editor will also check for the same site variable used in multiple terms. The editor does not consider this as an error, but if it occurs, the editor will issue a warning and request the user's confirmation.

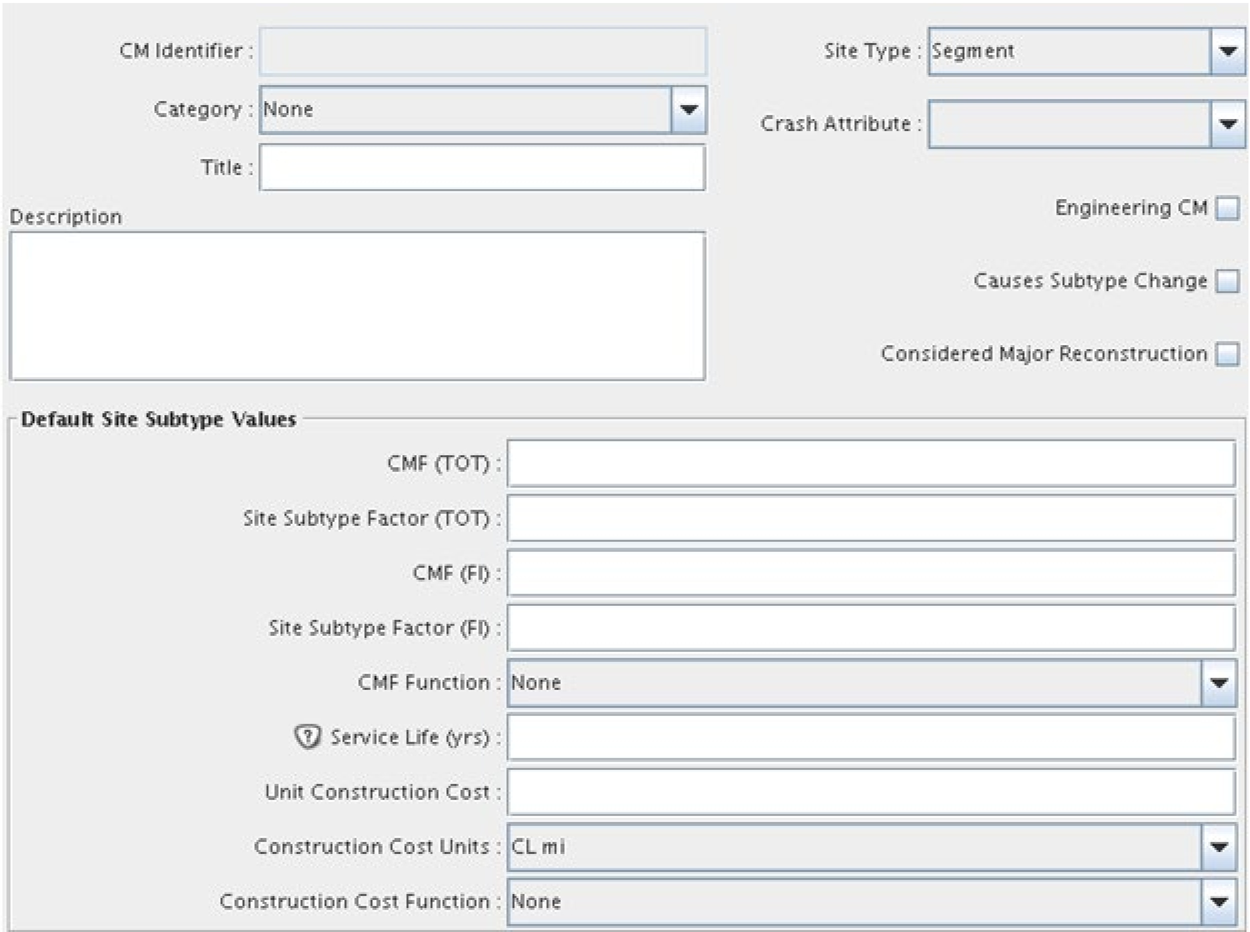


Figure 38: Illustration of SPF Editor in the AASHTOWare Safety Analyst Software

Edit SPF

- **Site Subtype** - Identifies the site subtype, to which the SPF being edited applies. The data type associated with this item is enumerated. Enumeration values are created dynamically at run time.
- **Crash Severity Level** - Identifies the crash severity level, to which the SPF being edited applies. The data type associated with this item is enumerated. Enumeration values:
  - *Total Crashes* - All crashes.
  - *Fatal and All Injury Crashes* - Fatal and all injury crashes.
- **Overdispersion Parameter** - Overdispersion Parameter (d): Indicates the extent to which the mean crash frequency is exceeded by the variance of crash frequency. The overdispersion parameter is expressed as a constant for all site types. The data type associated with this item is numeric.
- **SPF** - This window displays the SPF equation with the currently specified terms. The numeric subscript on each term indicates the term number.

Copy SPF button - (Keyboard shortcut: *Alt-C*) Press this button to display a dialog for copying an SPF from another subtype/severity level into this subtype/severity level.

Edit SPF Terms Table

This table presents a row for each term of the SPF, with columns that identify the term and its functional form, and columns that specify the regression coefficient and site variable associated with the term.

To ***edit*** a term, double click the cell that contains the data item that users want to specify or change. For

enumerated items (e.g., Functional Form or Site Variable) select a value from the drop list. For the regression coefficient, type in the value.
To ***add*** a term, press the **Add Term** button to the right of the table. A new row will appear in the table with default values in the cells of the row. Edit the values in the cells as desired.
To ***remove*** a term, select a row in the table and then press the **Remove Term** button to the right of the table.
Note: As users edit, add or remove terms, the equation display box above the table will update to reflect the current term specifications.

- Table Column Items
    - **Term** - Identifies the term of the SPF equation. This item is assigned and managed internally by Safety Analyst. The data type associated with this item is an integer.
    - **Functional Form** - This item is the functional form of the SPF term.
      Double click a cell to display a drop list from which users can select the functional form of the term. The data type associated with this item is enumerated. Enumeration values:
        - C - Constant term.
        - e^c - Exponential term with constant exponent.
        - e^{cV} - Exponential term with site-variable exponent.
        - V^c - Power term.
    - **C** - This item is the regression coefficient associated with the SPF term.
      Double click a cell to edit the regression coefficient in the term. The data type associated with this item is numeric. The default value for this item is 1.00.
    - **V** - This item is the site variable (site characteristic) associated with the SPF term. The variables that appear in the selection list are specific to the type of the site (roadway segment, intersection, or ramp) to which SPF applies.
      Double click a cell to display a drop list from which users can select the site variable for the term. The data type associated with this item is enumerated. Enumeration values are created dynamically at run time.

D.1.1.3. Agency-Defined Countermeasures

Safety Analyst comes pre-configured with a set of common countermeasures that are used to reduce crashes. These countermeasures are referred to as the *Federal default values*. The countermeasures that are delivered with Safety Analyst may not exactly describe the countermeasures in use at the different agencies where Safety Analyst is being deployed. The edit dialog enables the Safety Analyst administrator to create and/or modify the countermeasure data associated with this deployment of Safety Analyst. Within Safety Analyst, a countermeasure includes the numerical parameters needed for the economic appraisal of single-site type, i.e., a roadway segment, intersection or ramp. The numerical parameters include sets of crash modification factors (CMFs), service life, and cost factors. Each set is associated with a specified site subtype.

Using this interface, the Safety Analyst Administrator can maintain the set of agency-defined countermeasures for use by all agency analysts. To manage the set or modify individual agency-defined countermeasures, select the **Edit|Countermeasures...** menu item, or **Edit the agency-defined countermeasures** toolbar button. This invokes the **Edit Agency Countermeasures** dialog.
NOTE: Modifications to the agency-defined countermeasures will be available to the Analytical tool after the System database has been updated.
When finished, press the dialog's **Save** button to save the countermeasures to the Agency database. If the **Discard** button is pressed, any changes to the list or to individual countermeasures will be discarded.

D.1.1.3.1. New Countermeasure Dialog

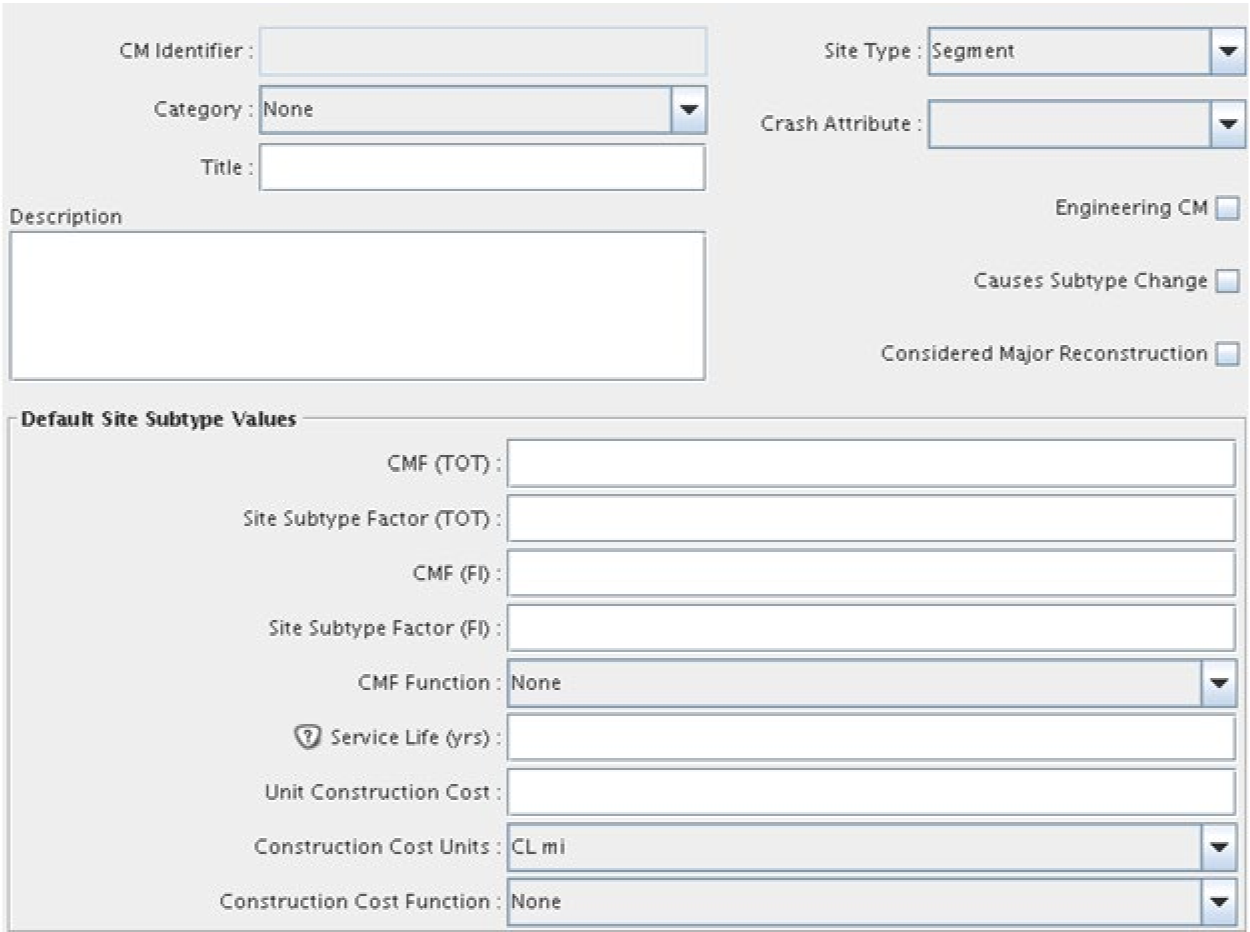


Figure 39: Illustration for Adding New Countermeasure: AASHTOWare Safety Analyst Software

- **CM Identifier** - This item is a unique identifier associated with the countermeasure. For the federal default countermeasures, the identifier is generated by the system and is not prefixed. For agency-defined countermeasures, the identifier is generated by the system and prefixed with an 'a'. The data type associated with this item is a string. The maximum number of characters for this item is 10.
- **Category** - This item is used to group countermeasures to aid in searching and sorting. The data type associated with this item is enumerated. Enumeration values:
    - *None* - No category.
    - *Access Management* - Access Management.
    - *Bicycle* - Bicycle.
    - *Drainage* - Drainage.
    - *Education* - Education.
    - *Enforcement* - Enforcement.
    - *Geometry* - Geometry.
    - *Lighting* - Lighting.
    - *Other* - Other.
    - *Pavement* - Pavement.
    - *Pavement Markings* - Pavement Markings.

    - *Pedestrian* - Pedestrian.
    - *Railroad* - Railroad.
    - *Roadside* - Roadside.
    - *Roadway* - Roadway.
    - *Rumble Strips* - Rumble Strips.
    - *School* - School.
    - *Sight Distance* - Sight Distance.
    - *Signals* - Signals.
    - *Signing* - Signing.
    - *Vegetation* - Vegetation.
- **Title** - This item is a short description of the countermeasure. The maximum number of characters for this item is 256.
- **Description** - This item is a detailed description of the countermeasure. The maximum number of characters for this item is 2048.
- **Site Type** - This item represents the site type (roadway segment, intersection, or ramp) associated with the countermeasure.
  Note: Once a countermeasure has been created, its site type cannot be changed. The data type associated with this item is enumerated. Enumeration values:
    - *Segment* - Single roadway segment.
    - *Ramp* - Ramp.
    - *Intersection* - Intersection.
- **Crash Attribute** - This item is the specification of the primary crash attribute affected by the implementation of this countermeasure.
  Note: Once a countermeasure has been created, its related crash attribute cannot be changed. The data type associated with this item is enumerated. Enumeration values are created dynamically at run time.
- **Engineering CM** - If checked this countermeasure is used for *engineering* purposes. *Non-engineering* countermeasures include, for example, training or public education. The data type associated with this item is boolean. The default value for this item is true.
- **Causes Subtype Change** - Checking this box indicates that this countermeasure has the ***potential*** to affect a site subtype change at any site at which the countermeasure is implemented.
  There are some situations where the implementation of this countermeasure may not affect a subtype change, depending on the existing subtype of the site at which the countermeasure is implemented. For example, a countermeasure that installs actuated control at an intersection with an existing subtype that indicates no control or sign control will change the subtype. However, the subtype will not change if the intersection has a pre-timed control system because the Safety Analyst subtypes do not distinguish between actuated and pre-timed control. The data type associated with this item is boolean. The default value for this item is false.
- **Considered Major Reconstruction** - Checking this box indicates that this countermeasure is considered a major reconstruction at any site at which the countermeasure is implemented.
  Note: Any countermeasure that effects a change in subtype at a site is, by default, considered a major reconstruction. The data type associated with this item is boolean. The default value for this item is false.

D.1.1.3.2. Default Site Subtype Values

The Default Site Subtype Values section enables the administrator to designate values that will be used as defaults when the program automatically creates each associated site-subtype countermeasure as the **Define New Countermeasure** dialog is closing. These values can be modified for individual site-subtype countermeasures by using the **Edit Countermeasure** dialog that is shown when the **Ok** button is pushed on the **Define New Countermeasure** dialog. The site-subtype countermeasures for the selected countermeasure can also be edited by using the **Edit** button on the table of countermeasures after the initial creation of the countermeasure.

These data are used in the Analytical Tool's Economic Appraisal and Priority Ranking analysis module. During the analysis setup in the Analytical Tool, most of these values can be further modified when applied to a specific site.

- **CMF (TOT)** - The crash modification factor (CMF) for *all* or *total* crashes. A value of 1 implies no improvement. A value of less than 1 implies that if this countermeasure is implemented at sites with similar characteristics, the anticipated number of crashes would be less than it would be if this countermeasure is not implemented. For example, a value of 0.95 would imply that a five percent reduction in crashes is expected by implementing this countermeasure. Conversely, a value greater than 1 implies an increase in crashes is expected by implementing this countermeasure. The CMF values sometimes differ due to the characteristics of the site. When this occurs for a countermeasure, CMFs will be calculated as functions of the site characteristics at a given site using the CMF function. The data type associated with this item is numeric. The value of this item must be greater than 0.00000.
- **Site Subtype Factor (TOT)** - The site subtype factor for *all* or *total* crashes. The CMF values sometimes differ due to characteristics of the site subtype where it is applied. The CMF value is multiplied by this factor to get a resultant CMF. A value of 1 or blank implies no change to the CMF value. The data type associated with this item is numeric. The value of this item must be greater than 0.00.
- **CMF (FI)** - The crash modification factor (CMF) for *fatal and all injury* crashes. A value of 1 implies no improvement. A value of less than 1 implies that if this countermeasure is implemented at sites with similar characteristics, the anticipated number of crashes would be less than it would be if this countermeasure is not implemented. For example, a value of 0.95 would imply that a five percent reduction in crashes is expected by implementing this countermeasure. Conversely, a value greater than 1 implies an increase in crashes is expected by implementing this countermeasure. The CMF values sometimes differ due to the characteristics of the site. When this occurs for a countermeasure, CMFs will be calculated as functions of the site characteristics at a given site using the CMF function. The data type associated with this item is numeric. The value of this item must be greater than 0.00000.
- **Site Subtype Factor (FI)** - The site subtype factor for *fatal and all injury* crashes. The CMF values sometimes differ due to characteristics of the site subtype where it is applied. The CMF value is multiplied by this factor to get a resultant CMF. A value of 1 or blank implies no change to the CMF value. The data type associated with this item is numeric. The value of this item must be greater than 0.00.
- **CMF Function** - The crash modification function used to calculate the CMF. The CMF values sometimes differ due to the characteristics of the site. When this occurs for a countermeasure CMFs will be calculated as functions of the site characteristics at a given site. For example, implementing a countermeasure where the shoulders are widened has a different crash modification factor depending on the existing shoulder width and the proposed shoulder width. Constructing a ten-foot shoulder where there was none would have a significant reduction in crashes compared to widening the shoulder from nine feet to ten feet. In the Analytical Tool, when proposing a countermeasure that uses a CMF function, user input, or verification of variables specific to the function will be required. Refer to the Analytical Tool's manual for further explanation of the different functions. The data type associated with this item is enumerated. Enumeration values:

- *None* - No CMF function.
- *Add Two Way Left Turn Lane* - Add Two Way Left Turn Lane.
- *Widen Lanes* - Widen Lanes.
- *Widen Shoulders* - Widen Shoulders.
- *Change Shoulder Type* - Change Shoulder Type.
- *Flatten Horizontal Curve* - Flatten Horizontal Curve.
- *Improve Curve Super-elevation* - Improve Curve Super-elevation.
- *Install Raised Medians At Marked Crosswalks* - Install Raised Medians At Marked Crosswalks.
- *Install Raised Medians At Unmarked Crosswalks* - Install Raised Medians At Unmarked Crosswalks.
- *Generic Intersection* - Generic Intersection.
- *Install Turn Lane* - Install Turn Lane.

- **Service Life** - The service life is the number of years safety is improved when this countermeasure is implemented. Only when this value is non-zero will the countermeasure be active for the site subtype. For some analyses, multiple countermeasures may be implemented at a site. In this case, the service life for the multiple countermeasures implemented will be the maximum of each individual countermeasure service life. The data type associated with this item is an integer. The unit of measure associated with this item is years. The value of this item must be greater than or equal to 1 yr. The default value for this item is 1 yr.
- **Unit Construction Cost** - The construction cost for a countermeasure is determined in a manner similar to CMFs. Sometimes it will appear as a single value, and sometimes it will need to be calculated with a Cost Function based upon site characteristics. The data type associated with this item is numeric. The value of this item must be greater than 0.00. The default value for this item is 0.00.
- **Construction Cost Units** - This item represents the units in which the cost to implement the countermeasure is expressed. These units are used in the generation of reports. The data type associated with this item is enumerated. Enumeration values:
  - *CL mi* - per centerline mile.
  - *INT LG* - per intersection leg.
  - *LN mi* - per lane mile.
  - *site* - per site.
  - *sq ft* - per square foot.
  - *TL* - per turn lane.
- **Construction Cost Function** - The construction cost for a countermeasure is determined in a manner similar to CMFs. Sometimes it will appear as a single value, and sometimes it will need to be calculated with a function based upon site characteristics. For example, implementing a countermeasure where the shoulders are widened has a different cost depending on the existing shoulder width and the proposed shoulder width. Constructing a ten-foot shoulder where there was none would be costlier than widening the shoulder from nine feet to ten feet. In the Analytical Tool, when proposing a countermeasure that uses a cost function, user input, or verification of variables specific to the function will be required. Refer to the Analytical Tool's manual for further explanation of the different functions. The data type associated with this item is enumerated. Enumeration values:
  - *None* - No cost function.
  - *Cost Per Site* - Cost Per Site.
  - *Cost Per Centerline Mile of Roadway* - Cost Per Centerline Mile of Roadway.
  - *Cost Per Lane Mile of Traveled Way* - Cost Per Lane Mile of Traveled Way.

- *Cost Per Square Foot of Traveled Way* - Cost Per Square Foot of Traveled Way.
- *Cost Per Square Foot of Shoulder* - Cost Per Square Foot of Shoulder.
- *Cost Per Square Foot of Lane Widening* - Cost Per Square Foot of Lane Widening.
- *Cost Per Square Foot of Shoulder Widening* - Cost Per Square Foot of Shoulder Widening.
- *Cost Per Added Turn Lane* - Cost Per Added Turn Lane.
- *Cost Per Intersection Approach* - Cost Per Intersection Approach.

D.1.2. Data Management

The analytical procedures in the five Safety Analyst modules utilize several types of data. The databases containing these data are created and maintained using Safety Analyst applications. It is envisioned that most highway agencies will import data into the Safety Analyst databases from existing agency data sources (files and/or databases). The Safety Analyst Data Management Tool is used to import specific data items from highway agency sources and code them to a common Safety Analyst format.

This section summarized the different types of data used and maintained within the Safety Analyst databases. The data within the Safety Analyst can be categorized as follows:

- Agency Data
- Site Characteristics
  - Roadway segments
  - Intersections
  - Ramps
- Crashes
- Implemented countermeasures
- Data Maintained for Computational Purposes
- Safety performance functions (SPFs)
- Crash proportions
- Countermeasure defaults
- Crash Costs
- EPDO weights
- Beta distribution parameters
- Other defaults

The agency data represent data that will likely be imported into Safety Analyst from existing agency data sources. The data maintained for computational purposes represents data that are either provided as default values within the Safety Analyst program or are calculated during the data import process.

D.1.2.1. Agency Data

It is anticipated that highway inventory data, crash data, and possibly data related to implemented countermeasures will be imported into Safety Analyst from existing agency data sources. These data pertain to individual sites within an agency's highway network. Location identification information links the respective data to a particular site on the highway network. A site refers to a single roadway segment, intersection, or ramp within the highway network.

Within Safety Analyst the inventory data, referred to as site characteristic data, are divided into three facility types, or site types that make up the entire roadway network:

- Roadway segments
- Intersections
- Ramps

The site characteristic data contain inventory data unique to the respective site type.

Location identifier data are used to describe the exact location of a site within the highway network.

Highway agencies have adopted different location identifier systems for their inventory highway data and other data files. Four basic systems of location identifier information are used by most highway agencies. These basic location identifier systems include:

- Route/county/milepost
- Route/milepost
- Route/segment identifier/distance
- Segment identifier/distance

Safety Analyst can accommodate data that utilize any one of these systems to link the respective data to a particular location within the highway network. The location identifier systems are used to link the other site-specific data (i.e., crash data and implemented countermeasure data) to a given site.

The other data maintained in the Safety Analyst databases are used for computational purposes when analyzing a site. For the most part, these other data (i.e., safety performance functions (SPFs), crash proportions, countermeasure defaults, crash costs, EPDO weights, beta distribution parameters, and other defaults) do not pertain to individual sites, but rather the data elements pertain to a collection of sites or to all sites.

D.1.2.2. Site Characteristics Data

The Safety Analyst inventory database is composed of records, likely imported from an agency's existing inventory files, pertaining to three types of sites: roadway segments, intersections, and ramps. For each individual site, the record contains geometric, traffic control, and traffic volume data and location identifier data to link these site characteristics to a location on the highway system. The individual site characteristic data elements are classified as either mandatory (i.e., required) or optional variables.

D.1.2.3. Crash Data

The Safety Analyst database includes data elements that characterize the type of crash and data to link the crash to a specific location on the highway system (i.e., the location identifier variables). The crash data elements included in the Safety Analyst database can be broadly categorized as crash-level, vehicle-level, or person-level data elements.

D.1.2.4. Implemented Countermeasures

The Safety Analyst database contains data pertaining to the construction or improvement history of sites. These implemented countermeasure data elements are used primarily during the execution of a module analysis. Specifically, the data elements are used to determine the available crash history at a site. If an analyst elects to limit the analysis period by excluding years prior to major reconstruction, the flag for major reconstruction data element serves as an indicator for the program to limit the analysis period as so indicated. By including periods prior to major reconstruction in an analysis, there is the potential for miscalculating the expected crash history at a site and/or the safety effectiveness of a countermeasure. This potential exists because Safety Analyst may not account for the differences in the site characteristics between the current conditions and those prior to reconstruction. As indicated already, the site characteristic data elements describe the current status of the geometric design features of a site. For Module 4, the implemented countermeasure data are used to determine sites for inclusion in a countermeasure effectiveness evaluation.

D.1.2.5. Safety Performance Functions (SPFs)

SPFs are regression models used to predict crashes for a site on an agency's highway system. Each Safety Analyst module utilizes SPFs in its processing procedures to perform the Empirical Bayes calculations. The Safety Analyst system database contains values of parameters (default) that describe these functions.
Equation D.2 shows the general functional forms of the SPFs for roadway segments used in the Safety

Analyst.

$$K = e^{\alpha} * AADT^{\beta_1} * SL \tag{D.2}$$

where K denotes crash frequency per mile per year; ADT denotes average daily traffic (vehs/day); α is the intercept; β_1 is coefficient of ADT; SL is segment length (mi).
Table D.1 presents the default values of SPF for roadway segments for total crashes.

Table D.1: SPFs for Roadway Segment (Total Crashes)

Site Subtype Description	State	Regression Coefficients Log Intercept (α)	Regression Coefficients Log AADT (β_1)	Overdispersion Parameter (d)
Rural multilane divided highway segments	OH	-4.60	0.64	0.28
Urban multilane divided arterial segments	OH	-11.85	1.34	5.91

The SPFs developed for use in Safety Analyst are valid only for application to the states and time periods for which they were developed. However, Safety Analyst includes a calibration procedure that allows SPFs developed for one particular state and one particular time period to be applied to other states and time periods. When SPFs provided with Safety Analyst are subsequently calibrated for application to a different state and time period using a state's own crash data, useful safety predictions are obtained.

D.1.2.6. Crash Proportions and Rates

Crash proportion data are maintained in the Safety Analyst database for different crash data elements and severity levels. Crash proportions are used during analyses of particular collision types, in procedures to calculate weighted crash costs for fatal-and-injury crashes, to calculate equivalent property-damage-only (EPDO) crashes in Modules 1 and 3, and to perform analyses based on fatal and severe (FS) injuries. Crash proportions are also used when generating crash summary statistics. Default values of crash proportions are provided in the Safety Analyst database.

D.1.2.7. Countermeasure Defaults

The Safety Analyst database contains default data related to countermeasures, or construction improvements, that can be made to a site to potentially improve the site's safety performance. The countermeasure default data maintained within the Safety Analyst database is primarily used during diagnosis and countermeasure selection procedures and during the economic appraisal and priority ranking procedures. The list of default countermeasures is the complete list of countermeasures that an Analyst can select from during the countermeasure selection procedures within Module 2 and during economic analyses within Module 3.

D.1.2.7.1. Crash Modification Factor (CMF)

A CMF function is necessary when the incremental effect on safety for a countermeasure varies due to site characteristics at a given site. Since CMF functions vary by certain site characteristics, some site characteristic data may be utilized in calculating a CMF. If a value needed to determine a CMF is not available in the Safety Analyst database, Safety Analyst provides a dialog box for data entry of these values.

D.1.3. Analytical Tool

As mentioned, the Analytical Tool has 5 modules which are described below.

D.1.3.1. Overview of Module 1 - Network Screening

The basic purpose of the network screening module is to review the entire roadway network, or portions of the roadway network, under the jurisdiction of a highway agency and identify and prioritize those sites that have promise as sites for potential safety improvements and; therefore, merit further investigation (i.e., sites to which the other Safety Analyst modules should be applied). The network screening process makes use of information on roadway characteristics and safety performance to identify those sites that are the strongest candidates for further investigation. The data used in the network screening process fall under the following categories:

- Geometric design features
- Traffic control features
- Traffic volumes
- Crash history
- Crash characteristics
- Safety performance functions (SPFs)

In Module 1 the analyst first identifies a set of sites to be included in the screening. This set of sites may include all roadway segments, intersections, and ramps under the jurisdiction of an agency or may include a subset of the network. Analysts have various ways of identifying sites to be included in the screening. Once an analyst has settled upon a site list for which screening is to be performed, the analyst specifies the type of screening to be conducted. The analyst can select from among the following types of screening to perform:

- Basic network screening (with Peak Searching on roadway segments and Coefficient of Variation (CV) Test)
- Basic network screening (with Sliding Window on roadway segments)
- Screening for a high proportion of specific crash type
- A sudden increase in mean crash frequency
- A steady increase in mean crash frequency
- Corridor screening

The first five types of screening listed above are conducted on a site-by-site basis, while corridor screening performs an analysis across a group of sites, and the group of sites is treated as a single unit or entity. Corridors may include all site types (i.e., roadway segments, intersections, and ramps). The final output from Module 1 is a report which identifies a list of sites (or corridors) that are the strongest candidates for further investigation within Safety Analyst. The list will vary depending on the type of screening conducted.

D.1.3.2. Overview of Module 2 - Diagnosis and Countermeasure Selection

The purpose of Module 2 - Diagnosis and Countermeasure Selection is to guide the analyst in the diagnosis of safety problems and the selection of a possible array of countermeasures for a specific site. This module

combines the second and third steps of the safety management process into one module. A site evaluated with the diagnosis and countermeasure selection module may have been selected by the network screening module or may have been selected by the analyst on some other basis.
To diagnose the nature of safety problems at a specific site, this module provides the capability to:

- Generate collision diagrams
- Generate crash summary statistics
- Conduct statistical tests on crash frequencies and/or proportions

Through the use of an expert system, this module guides the analyst through appropriate office and field investigations to identify particular safety concerns at a site. The end result of this diagnosis process is a list of recommended countermeasures that, if implemented at the site, could serve to mitigate particular collision patterns. The decision as to which countermeasure(s) will actually be considered for further economic analysis is made by the Safety Analyst user as part of countermeasure selection.

D.1.3.3. Overview of Module 3 - Economic Appraisal and Priority Ranking

The purpose of the economic appraisal and priority ranking module is to provide the analyst with a means to conduct an economic appraisal of implementing a countermeasure or combination of countermeasures at a site and for the programming of the implementation of safety countermeasures across a network. The extent of the economic appraisal performed is dependent upon the needs of the analyst. Several different scenarios exist for how an analyst might utilize Module 3. For example, for a particular roadway segment, intersection, or ramp, an analyst might have already selected a countermeasure, either based upon output from Module 2 or through personal experience/knowledge, for which the analyst would like to know the safety benefits in terms of the expected number of crashes to be reduced and in economic terms. In this situation, Module 3 can be used to perform an economic appraisal for that particular countermeasure at that specific site, based upon economic criterion selected by the analyst. In another scenario, an analyst might have selected several countermeasures or combinations of countermeasures for possible implementation at a specific site. The analyst is able to use Module 3 to evaluate the cost-effectiveness of each countermeasure and combination of countermeasures, based upon economic criterion selected by the analyst, to determine which countermeasure(s) should receive top priority. In a final scenario, an analyst might have selected candidate countermeasures (or combinations of countermeasures) at multiple sites throughout the highway network and would like to know which countermeasures should be implemented at which sites to maximize the net benefits, given budgetary constraints. Module 3 can perform this type of analysis through an optimization program.

The economic appraisal functionality within Module 3 provides a means for estimating the safety effectiveness of countermeasures at a specific site within the highway network, expressing this effectiveness estimate in economic terms. The priority ranking functionality within Module 3 provides the means to rank which countermeasure(s) should be implemented at a specific site using the safety effectiveness estimates and provide recommendations on which countermeasures should be implemented across numerous sites given certain budget constraints.

D.1.3.4. Overview of Module 4 - Countermeasure Evaluation

The purpose of the countermeasure evaluation module is to estimate the safety effect of countermeasures implemented at specific sites. The module is capable of assessing the safety-effectiveness of a single countermeasure at specific sites or the collective effectiveness of a group of countermeasures in which the same countermeasures were implemented at a specified list of sites. In most cases, the effectiveness measures are expressed as a percentage change (decrease or increase) in crash frequencies or specific target crash types. In other cases, the change of interest might be a shift in the proportion of specific collision types.

The effectiveness of countermeasures is determined through before-after evaluations performed using appropriate statistical techniques. The primary statistical approach to perform the before-after evaluation is the Empirical Bayes (EB) technique. This technique uses SPFs developed from a set of reference sites similar to the improved site(s) to estimate the change in crash frequency that would have occurred at the improved site(s) had the improvement not been made. In stand-alone applications of the EB method, the SPFs are developed by regression modeling using a selected group of reference sites. An advantage in performing evaluations using Safety Analyst is that appropriate SPFs already incorporated within Safety Analyst is available to perform the evaluation. EB concepts are also used in other Safety Analyst modules.

D.1.3.5. Overview of Module 5 - Systemic Site Selection

The purpose of the systematic site selection module is to identify the most appropriate sites for the implementation of a selected countermeasure. Rather than taking a traditional approach to managing the safety improvement process by identifying and correcting high-crash locations where concentrations of crashes are found, the systemic site selection module provides the capability to take a system-wide view of safety improvement needs and, in conjunction with benefit-cost analyses, identifies sites where safety improvements (i.e., typically low-cost countermeasures) are needed and economically justified. Having selected a countermeasure for potential implementation, the module is capable of identifying potential sites for implementation covering the full range of site subtypes for a given site type (i.e., roadway segment, intersection, or ramp).

The systemic site selection module makes use of existing functionality in Module 1 (Network Screening) and Module 3 (Economic Appraisal and Priority Ranking) to efficiently identify appropriate sites for implementation of a selected countermeasure. The module utilizes the basic network screening peak searching and sliding window approaches to identify sites with the highest long-term average crashes of the type mitigated by the selected countermeasure. The module also uses the full range of capabilities of Module 3 to identify sites where the implementation of the selected countermeasure is economically justified and determines the optimal sites for implementation of the selected countermeasure given a defined budget. This module improves the efficiency in using Safety Analyst to implement a systematic safety analysis approach to safety management.