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**CRASH ANALYSIS AND DEVELOPMENT OF SAFETY PERFORMANCE
FUNCTIONS FOR FLORIDA ROADS IN THE FRAMEWORK OF THE
CONTEXT CLASSIFICATION SYSTEM**

by

MA'EN MOHAMMAD ALI AL-OMARI

B.Sc. Jordan University of Science and Technology, 2012

M.Sc. Jordan University of Science and Technology, 2016

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for the degree of Master of Science
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Major Professor: Mohamed Abdel-Aty

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ABSTRACT

Nowadays, technology is employed in many safety applications and countermeasures that would enhance traffic safety by influencing some crash-related factors. Therefore, crash-related factors must be determined for every roadway element by the development of safety performance functions. Safety performance functions (SPF) are employed to predict crash counts at the different roadway elements. Several SPFs have been developed for the various roadway elements based on different classifications such as functional classification and area type. Since a more detailed classification of roadway elements leads to more accurate crash predictions, multiple states have developed new system to categorize roads based on a comprehensive classification. In Florida, the new roadway context classification system incorporates geographic, demographic, and road characteristics information. In this study, SPFs have been developed in the framework of the FDOT roadway context classification system at three levels of modeling, context classification (CC-SPFs), area type (AT-SPFs), and statewide (SW-SPF) levels. Crash and traffic data of 2015-2019 years have been obtained. Road characteristics and road environment information have been also gathered along Florida roads for the SPF development. The developed SPFs showed that there are several variables that influence the frequency of crashes, such as annual average daily traffic (AADT), signalized intersections and access points densities, speed limit, and shoulder width. However, there are other variables that did not have an influence on crash occurrence such as concrete surface and the presence of bicycle slots. CC-SPFs had the best performance among others. Moreover, network screening to determine the most problematic road segments has been accomplished. The results of the network screening indicated that the most problematic roads in Florida are suburban commercial and urban general roads.

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CHAPTER ONE: INTRODUCTION

1.1 Overview

The development of safety performance functions (SPFs) to predict crash counts at the different roadway network elements is the first step toward reducing the number of crashes. This is necessary to enhance traffic safety on our roads.

The safety performance function is a regression model used to predict the expected number of crashes based on several factors. Traffic volume is the most influential factor in crash occurrence. However, road characteristics, land use, and other information have often significant effects also. The Highway Safety Manual (HSM) defines the SPF as “an equation used to estimate or predict the expected average crash frequency per year at a location as a function of traffic volume and in some cases roadway or intersection characteristics (e.g., number of lanes, traffic control, or type of median)” (*AASHTO, 2010*).

The importance of SPFs development lies in three main applications: conduct a network screening to specify the most problematic locations, determine the effect of design changes, and evaluate the effectiveness of implementing safety countermeasures (*Srinivasan and Bauer, 2013*).

Different SPFs have been developed in the HSM for different road classes. HSM-SPFs has been developed for road segments on rural two-lane two-way roads, rural multilane highways, urban and suburban arterials, and freeways that have certain base conditions. Therefore, HSM-SPFs do not include geometric, pavement and environment conditions variables. HSM-SPFs of road segments contain only the exposure (annual average daily traffic [AADT]) and the segment length variables. The reason behind this that road segments which have been considered in the HSM-SPFs development have certain road characteristics and conditions. Therefore, base HSM-

SPFs can be only used to predict crash counts at road segments that have conditions like the base conditions. However, HSM-SPFs must be calibrated before employed to predict crash counts at road segments that have characteristics and conditions different from the base conditions by using a set of crash modification factors that adjust the prediction based on the road characteristics (AASHTO, 2010).

HSM-SPFs have perfect performance only when they applied at locations that have demographics and land use conditions similar to conditions of the locations which they have been considered for the SPFs development. As a result of this, many studies have been conducted to transfer and localize HSM-SPFs. Meanwhile, several studies developed new SPFs by utilizing local data. It was found in all previous studies that the transferred HSM-SPFs and the local jurisdiction SPFs have better crash prediction performance than the HSM-SPFs.

Recently, several states tend to develop new systems to classify roads based on different characteristics. The Florida Department of Transportation (FDOT) has developed a new system to classify Florida roads into eight categories based on geographic, demographic, and road characteristics information (FDOT, 2020A).

1.2 Contributions

This study developed new SPFs for road segments including all influence variables in the framework of the FDOT context classification system which is not used before for the SPF development for road segments. Moreover, network screening analysis was accomplished in this study to specify the most problematic road segments in Florida.

1.3 Thesis Organization

The rest of the thesis is organized as follows: Chapter two provides a literature review of SPFs development, calibration, and transformation. Chapter three introduces the FDOT context classification system. Chapter four presents the obtained data in this study. Chapter five demonstrates the methodologies of this study. Chapter six presents the results. In the end, Chapter seven summarizes the main findings of this thesis.

CHAPTER TWO: LITERATURE REVIEW

The development of SPFs and the transferability of HSM-SPFs processes have been the focus of attention during the last years and they were amply covered and discussed in many previous studies. Several studies have been performed to transfer the HSM-SPFs into different local jurisdictions, states, and even countries. *Mehta and Lou (2013)* conducted a study to calibrate and transfer HSM-SPFs for two road types in Alabama: rural two-lane two-way and four-lane divided roads. They found that the calibrated HSM-SPFs have well crash prediction performance. A Similar conclusion has been drawn by *Moraldi et al. (2020)* after performing a study to calibrate the HSM-SPF for rural two-lane two-way roads in Germany.

In contrast, many other studies indicated that HSM-SPFs have often low accuracy prediction performance in local jurisdictions. *AlKaaf and Abdel-Aty (2015)* conducted a study to calibrate and transfer the HSM-SPF for urban four-lane divided roads in Riyadh, Saudi Arabia. In this study, local crash modification factors (CMF) were developed for the calibration process. The results indicated that employing the local CMFs instead of HSM-CMF values gives better prediction performance. A study by *Sun et al. (2011)* has been performed to calibrate the HSM-SPF for rural multilane roads in Louisiana. The results indicated that the HSM-SPF underpredicts the crash frequency. Likewise, *Cafiso et al. (2012)* found that HSM-SPF underpredicts fatal and severe injury crash frequency on Italy divided multilane roads by 26%. *Brimley et al. (2012)* performed a study to calibrate and transfer the HSM-SPF of rural two-lane two-way roads in Utah. They found that the HSM-SPF underpredicts the crash frequency by 16%. On the other hand, *Srinivasan and Carter (2011)* conducted a study to calibrate the HSM-SPF for North Carolina rural divided multilane roads. They found that the HSM-SPF slightly overpredicts (less than 5%) the crash frequency. A Similar conclusion has been drawn by *Sun et al. (2014)* regarding using the

HSM-SPF to predict the total crash frequency on Missouri rural divided multilane roads. While *Xie et al. (2011)* concluded that the HSM-SPF significantly overpredicts the total crash frequency at Oregon rural divided multilane roads by 22%.

Novel techniques have been proposed by some researchers for the HSM-SPFs calibration process instead of using the HSM procedure. *Srinivasan et al. (2016)* proposed using a calibration functions instead of calibration factors for the HSM-SPFs calibration process. *Farid et al. (2018)* employed the K-Nearest-Neighbors regression for the HSM-SPFs calibration process. Both techniques had better performance than the HSM procedure. However, the K-Nearest-Neighbors technique outperformed the calibration function technique.

Meanwhile, several studies have been conducted to develop specific SPFs by utilizing local crash and road environment data. The negative binomial regression has been mainly applied for the development of SPFs in these studies. A study has been conducted by *Kim et al. (2015)* to develop specific SPFs for Alabama urban and suburban arterials by using three-years crash data. *Li et al. (2017)* performed a study to develop SPFs for rural two-lane roads in Pennsylvania by using eight-years crash data. The authors adopted three modeling levels for the SFP development and analysis: statewide, engineering district, and county levels. The results indicated that district- and county-SPFs have better crash prediction performance than statewide-SPFs. *Aziz and Dissanayake (2019)* used three-years crash data to develop specific SPFs for rural four-lane divided roads in Kansas. The results indicated that Kansas SPFs outperform HSM-SPFs. Other studies were conducted outside the USA. *Garach et al. (2016)* conducted a study to develop SPFs for rural two-lane roads in Spain. A five-year crash data along with several explanatory variables have been gathered for this purpose. *La Torre et al. (2019)* developed jurisdiction SPFs for freeways in Italy. Five-years crash data has been obtained in this study. They followed the HSM

procedure by produce base SPFs along with a set of CMFs for the SPFs calibration. The results indicated that the new developed SPFs have well crash prediction performance at Italian freeways.

CHAPTER THREE: FDOT CONTEXT CLASSIFICATION SYSTEM

The context classification system was adopted by FDOT in 2017. Based on this system, roads are classified into eight classes. One of these classes is for natural roads, two classes are for rural roads, and two classes are for suburban roads, while there are three classes for urban streets. To be specific, these classes are C1: natural, C2: rural, C2T: rural town, C3R: suburban residential, C3C: suburban commercial, C4: urban general, C5: urban center, and C6: urban core. Figure 1 shows these road classes.

Figure 1: FDOT context classes (*FDOT, 2018*)

Three classification criteria are adopted in this system: distinguishing characteristics, primary measures, and secondary measures. At the first level (distinguishing characteristics), roads are classified based on some diagnostics such as the nature of the area and road connectivity. The second level of classification (primary measures) is used in the absence of distinguishing characteristics. Different road features are used in this level such as land use, building height and placement, location of off-street parking, roadway connectivity. However, secondary measures (the third level) such as allowed residential and office/retail density and population and employment density could be utilized sometimes for more accurate classification.

For example, the C3C roads serve disconnected commercial areas (retail, office, or industrial). The block length is more than 660 feet, and the intersection density is less than 100 intersections per square mile in these areas. Wide parking lots are provided to serve separated buildings with 1 to 4 floors. Figure 2 shows a pie chart for the proportion of each context class.

Figure 2: Percentages of road context classes in Florida

Nature roads (C1 class) represent 7.5 % of Florida roads. Most of rural roads have been classified as C2 with 37.8 % percentage, while only 1.5 % of roads were classified as C2T roads. More than 37% of roads are suburban roads and they were classified as C3C and C3R with 21.2% and 16.5% percentages, respectively. The majority of urban roads were classified as C4 roads. While only 6.5% of urban roads (1% of Florida roads) have been classified as C5 and C6 roads.

Figure 3 shows the FDOT context classification map. The length (in mile) of C1, C2, C2T, C3C, C3R, C4, C5, and C6 roads are 961, 4870, 197, 2736, 2128, 1861, 93, and 36, respectively. It is notable that C2 roads are widespread along the state. C3C roads exist in major cities such as

Tallahassee, Jacksonville, Orlando, Tampa, and Miami. C3R and C4 roads are mainly concentrated on the southeast coastal cities such as Fort Pierce, Port St. Lucie, West Palm Beach, and Miami.

Figure 3: The FDOT context classification map

CHAPTER FOUR: DATA PREPARATION AND DESCRIPTION

4.1 Data Preparation

High traffic volume increases the interaction and conflicts between vehicles which in turn increases the possibility of crash occurrence. Therefore, it is the most significant variable in crash prediction (*Saha et al., 2016*). Then, traffic volume must be accurately determined. The base map was first developed based on the map of the context classification (CC) and the average annual daily traffic information. Roadway segments in the context classification map have been split according to average AADT value of 2015 to 2019 years. Consecutive road segments that have the same road identification (RID), CC, and AADT information have been merged in pursuit of getting long segments with accurate AADT information.

The road characteristics and environment information has been identified based on the FDOT data (*FDOT, 2020B*). In order to avoid very short road segments, road and environment information was determined for every roadway segment by calculating the weighted average or the weighted majority values within the segment.

4.2 Data Description

Florida crashes of 2015-2019 years have been utilized in this study. Since most roads are classified as C2, C3C, C3R, and C4 roads, most crashes have occurred on these roads. However, although more than a third of roads have been classified as C2 roads, they have been subjected to fewer crashes than C3C, C3R, and C4 roads. It was found that most of the crashes happened on C3C and C4 roads. While, urban roads (i.e. C4, C5, and C6 roads) had the highest crash rates per million vehicle miles followed by suburban roads (C3C and C3R roads). Nature and rural roads

(C1, C2, and C2T roads) had the lowest crash rates. Figure 4 shows the annual crash frequency and crash rates for different crash severities at the eight road classes, while Figure 5 shows the annual crash frequency at the eight road classes for every crash type. It was found that the rear-end crash type was the most frequent crash type at Florida roads followed by sideswipe and left-turn crashes.

Figure 4: Histogram of annual crash frequency and annual crash rate by road context class for fatal-and-injury, property damage only (PDO), and total crashes
- KABC: fatal-and-injury crashes, O: property damage only (PDO) crashes, KABCO: total crashes.

Figure 5: Histogram of annual crash frequency by crash type and road context class

Different road characteristics have been collected such as signalized intersections and access points densities (per mile), number of lanes, posted speed limit (in mph), pavement

condition (a numeric scale to describe pavement condition, it takes a value from 1 to 5), surface type (asphalt, concrete, or other) and width (in feet), median type (paved, raised, vegetation, or other) and width (in feet), and shoulder type (paved, lawn, curb and gutter, or other) and width (in feet). In addition, several pedestrian and bicyclist facilities' characteristics were collected such as sidewalk width and spacing (in feet) and the presence of bicycle lane, bicycle slot (a rack for bicycle parking), and shared path.

Tables 1 and 2 show descriptive statistics of the prepared data in this study. It is noteworthy that C1 and C2 roads have longer segments than other classes with average segment lengths 2.23 and 2.81 mile, respectively. Average signalized intersections density on C5 and C6 roads are the highest with 4.91 and 5.73 intersections per mile, respectively, because these roads are located in urban areas. C2T and C6 roads have higher average access point densities with 19.26 and 15.42 access points per mile, respectively. The average pavement condition for all road classes are satisfactory (around 3.5). C1 roads have the widest medians and shoulders, while C6 roads have the widest sidewalks.

Figure 6 shows histograms of surface, median, and shoulder types. The majority of Florida roads have an asphalt surface. Raised median type is more common than paved and vegetation median types on C3C and C4 roads. Raised and paved median types are more common than vegetation median type and they were approximately used equally on C3R, C5 and C6 roads. Rural roads (C2 and C2T roads) mostly have paved median type, while vegetation median type is most popular on natural roads (C1 roads). Shoulders are mostly paved on Florida roads except on urban roads (C4, C5, and C6 roads) where curb and gutter shoulders are the most common shoulder types. Lawn shoulders are widely used on C3R roads.

Table 1: Descriptive statistics of crash data and road characteristics and environment information at C1, C2, C2T, and C3C roads

Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	C1				C2				C2T				C3C			
T (total annual crash frequency)	6.9	13.5	0	117.6	9.9	13.94	0	199.2	8.34	11.32	0	109.6	44.2	57.21	0	637.2
FI (fatal-and-injury annual crash frequency)	2.16	3.61	0	32.8	3.61	4.72	0	64.6	2.26	3.22	0	31.8	12.16	15.61	0	148.6
PDO (property damage only annual crash frequency)	4.74	10.22	0	100.6	6.28	9.48	0	134.6	6.08	8.34	0	77.8	32.04	42.53	0	499.2
AADT (annual average daily traffic)	11177	11472	88	86800	9193	8164	14	57983	10315	6309	620	45100	25970	16317	270	108500
DVMT (daily vehicle miles traveled)	18979	33954	49	382281	21006	24363	16	277045	6108	8767	190	94221	24299	29021	90	330057
L (segment length in mile)	2.23	3	0.1	25.55	2.81	2.76	0.1	23.44	0.53	0.53	0.1	5	0.87	0.72	0.1	6.62
SID (signalized intersections density)	0.28	1.02	0	8.55	0.17	0.64	0	10.42	1.43	2.49	0	20	1.71	2.07	0	19.42
APD (access points density)	2.9	4.64	0	40.32	3.94	3.83	0	60.87	19.26	10.23	0	61.35	9.26	7.05	0	80.81
NL (total number of lanes)	2.73	1.12	1	7	2.64	1.03	1	6	2.64	0.95	2	6	4.03	1.5	1	9
SL (speed limit in mph)	53.6	7.85	25	65	55.17	6.91	25	70	37.62	6.62	25	65	44.84	6.43	15	65
PC (pavement condition)	3.71	0.58	2	5	3.75	0.56	1	5	3.76	0.5	2.5	5	3.79	0.6	1.95	5

Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	C1				C2				C2T				C3C			
SW (surface width in feet)	46.06	8.17	22	94.12	45.26	6.79	23.18	92.78	45.04	13.02	20	96	51.51	14.43	20	105.78
MW (median width in feet)	33.77	30.32	7.77	245.01	26.4	17.6	4	140	20.54	29.35	9	220	25.04	18.11	4.87	417.85
SHW (shoulder width in feet)	7.13	2.04	2	12.25	6.9	1.77	2	12	4.72	2.17	1.5	17	4.97	2.6	1.53	31.05
SWW (sidewalk width in feet)	6.81	2.53	4	21.9	5.87	2.89	4	54	5.88	2.67	4	31.95	5.7	1.58	3.41	40.99
SWS (sidewalk spacing in feet)	14.24	17.37	0	80.8	16.22	17.51	0	100	7.04	6.91	0	56.1	10.3	13.27	0	103.88
PBL (presence of bike lane: 1=yes, 0=no)	0.26	0.44	0	1	0.23	0.42	0	1	0.22	0.41	0	1	0.41	0.49	0	1
PBS (presence of bike slot: 1=yes, 0=no)	0.18	0.39	0	1	0.22	0.41	0	1	0.1	0.31	0	1	0.37	0.48	0	1
PSP (presence of shared path: 1=yes, 0=no)	0.06	0.25	0	1	0.05	0.22	0	1	0.05	0.22	0	1	0.05	0.21	0	1

- S.D.: standard deviation, Min.: minimum, Max.: maximum.

Table 2: Descriptive statistics of crash data and road characteristics and environment information at C3R, C4, C5, and C6 roads

Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	C3R				C4				C5				C6			
T (total annual crash frequency)	20	28.47	0	312.2	56.7	73.04	0	854	51.14	50.28	0.8	321.6	52.86	47.97	2.2	263.8
FI (fatal-and-injury annual crash frequency)	5.78	8.14	0	110.4	12.65	14.65	0	133.2	10.77	9.74	0	51	9.02	7.87	0.2	41
PDO (property damage only annual crash frequency)	14.22	20.87	0	214.4	44.04	59.44	0	769.4	40.37	41.67	0.8	270.6	43.85	41.15	1.8	222.8
AADT (annual average daily traffic)	16811	13525	128	82200	24817	15641	350	94000	25121	15027	2020	78400	18494	12662	1560	64900
DVMT (daily vehicle miles traveled)	15742	17843	34	188078	17630	17851	70	157642	13209	14355	220	110890	7707	9153	168	70175
L (segment length in mile)	0.99	0.81	0.1	9.59	0.68	0.44	0.1	3.21	0.5	0.35	0.1	2.21	0.41	0.31	0.11	1.74
SID (signalized intersections density)	0.55	1.22	0	12.2	2.08	2.48	0	19.05	4.91	4.86	0	29.41	5.73	6.41	0	26.48
APD (access points density)	9.82	6.75	0	57.14	14.69	8.9	0	66.27	14.4	11	0	59.41	15.42	10.12	0	50.51
NL (total number of lanes)	3.18	1.43	1	8	3.95	1.53	1	8	3.83	1.33	2	8	3.44	1.49	1	8
SL (speed limit in mph)	44.6	7.95	25	65	38.33	6.03	15	55	34.31	5.33	15	45	31.88	3.79	25	45
PC (pavement condition)	3.62	0.53	1	5	3.64	0.57	1	5	3.71	0.58	2.5	5	3.5	0.43	2.5	5

Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	C3R				C4				C5				C6			
SW (surface width in feet)	44.99	12.79	20.56	96	51.44	14.41	19.93	96	53.85	14.63	21.26	100.6	57.39	17.03	20	96
MW (median width in feet)	21.56	14.89	6	272.08	18.8	9.04	2	160	18.46	10.52	3	75	24.47	25.52	6	109
SHW (shoulder width in feet)	6.07	2.95	1.5	12.81	4.34	2.77	1	20.79	3.75	2.29	1.36	12	4.05	2.35	1.58	12.37
SWW (sidewalk width in feet)	5.93	1.94	2	42.59	5.81	1.12	0	18	6.39	1.45	3.86	14	8.59	3.24	4	25
SWS (sidewalk spacing in feet)	12.49	12.99	0	94.97	6.5	8.45	0	92.81	4.32	4.5	0	20.77	2.85	3	0	10.5
PBL (presence of bike lane: 1=yes, 0=no)	0.32	0.47	0	1	0.34	0.47	0	1	0.29	0.46	0	1	0.3	0.46	0	1
PBS (presence of bike slot: 1=yes, 0=no)	0.24	0.43	0	1	0.23	0.42	0	1	0.12	0.32	0	1	0.06	0.24	0	1
PSP (presence of shared path: 1=yes, 0=no)	0.06	0.24	0	1	0.02	0.15	0	1	0.04	0.21	0	1	0	0	0	0

- S.D.: standard deviation, Min.: minimum, Max.: maximum.

(Surface Type)

(Median Type)

(Shoulder Type)

Figure 6: Histogram of surface, median, and shoulder types by road context class

CHAPTER FIVE: RESEARCH METHODOLOGY

5.1 Safety Performance Functions

Different distributions and models have been used for the SPFs development. However, the negative binomial regression is commonly employed for SPFs development (*Abdel-Aty and Radwan, 2000; Fitzpatrick et al., 2008; Manuel et al., 2014; Mohammadi et al., 2014; Al-Omari et al., 2020*) since it is recommended by the HSM (*AASHTO, 2010*) due to its ability to handle the dispersion in the crash data. Therefore, the generalized linear model with negative binomial distribution has been used in this study.

To ensure that the negative binomial distribution represents crash counts distribution, the mean and variance of crash counts of every road class were calculated. It was found that the variance is much larger than the mean for all road classes. This means that the crash data are over dispersed, and the negative binomial distribution is appropriate for the SPFs development.

Simple (only the exposure and the offset variables were considered) and multi-variable (all variables have been used) SPFs of annual crash frequency have been developed at three modeling levels: context classification (CC-SPFs), area type (AT-SPFs), and statewide (SW-SPF) levels.

Two exposure variables have been used in this study; the annual average daily traffic (AADT) as the traditional approach and the daily vehicle miles traveled (DVMT) since it accounts for the segment length and it was used in many studies (*Li et al., 2013; Dong et al., 2015; Al-Omari et al., 2020; Abdelrahman et al., 2020*). Therefore, two simple SPFs and two multi-variable SPFs (referred to here as full SPFs) have been developed for the three modeling levels. Equations 1 and 2 are the employed equations to develop SPFs by using AADT and DVMT exposure variables, respectively.

The high correlation between variables was handled before the full SPFs development. Then, full SPFs have been developed by using all not highly correlated variables. However, only significant variables at least at 95% confidence level were kept in the developed models.

In pursuit of comparing the prediction performance of CC-SPFs, AT-SPFs, and SW-SPF; simple and full SPFs; and AADT-SPFs and DVMT-SPFs, two types of performance measures were calculated: mean absolute and root mean square errors. Equations 3 and 4 show how to calculate these error measurements.

$$N_p = e^{(\alpha + \beta \ln(AADT) + \gamma_i X_i + \ln(L))} \quad (1)$$

$$N_p = e^{(\alpha + \beta \ln(DVMT) + \gamma_i X_i)} \quad (2)$$

Where,

N_p : predicted annual crash frequency.

α : the intercept's coefficient.

β, γ_i : estimated coefficients.

$AADT$: average annual daily traffic.

$DVMT$: daily vehicle miles traveled.

X_i : a set of independent variables.

L : segment length (mile).

$$MAE = \frac{1}{n} \sum_{i=1}^n |N_p - N_o| \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (N_p - N_o)^2} \quad (4)$$

Where,

MAE : mean absolute error.

$RMSE$: root mean square error

N_P : predicted value.

N_O : observed value.

n : number of data points.

5.2 Network Screening

One of the most important applications of SPFs is the network screening process. The network screening is a part of the roadway safety management process (AASHTO, 2010). In this process, the most problematic roadway segments are identified by descending ranking them based on the potential for safety improvement (PSI) value which it is referred as “Excess Expected Average Crash Frequency” in the HSM (AASHTO, 2010). The PSI is a measure for the long-term crash frequency reduction (AASHTO, 2010).

The purpose of the network screening process is to determine the priority of implementing countermeasures to reduce the number and severity of crashes along the roadway network. Several procedures are explained in the HSM for performing network screening. However, the “Excess Expected Average Crash Frequency with EB Adjustments” method is the most powerful procedure since it accounts for regression to the mean and it does not have any limitations (AASHTO, 2010). Therefore, it was employed in this study to determine roads that have the highest PSI values.

Simple DVMT CC-SPFs for fatal-and-injury (FI) and property damage only (PDO) crashes have been developed for the usage in the network screening process. SPFs for FI and PDO crashes were used to determine the equivalent property damage only PSI (EPDO-PSI) in order to account for the crash severity during the comparison among roadway segments. Equations 5-10 have been used to calculate the EPDO-PSI (AASHTO, 2010).

$$C_n = \frac{N_{p,n}}{N_{p,1}} \quad (5)$$

$$w = \frac{1}{1 + k * \sum_{n=1}^N N_{p,n}} \quad (6)$$

$$N_{e,1} = w * N_{p,1} + (1 - w) * \left(\frac{\sum_{n=1}^N N_{o,n}}{\sum_{n=1}^N C_n} \right) \quad (7)$$

$$N_{e,n} = N_{e,1} * C_n \quad (8)$$

$$PSI = \frac{1}{n} \sum_{i=1}^n N_{e,n} - N_{p,n} \quad (9)$$

$$EPDO-PSI = PSI_{PDO} + PSI_{FI} * \frac{CC_{FI}}{CC_{PDO}} \quad (10)$$

Where,

C_n : annual correction factor for the n year.

$N_{p,n}$: predicted crash frequency for the n year (from the SPF).

$N_{p,1}$: predicted crash frequency for the first year in the analysis period (from the SPF).

w : Empirical Bayes (EB) weight.

k : overdispersion parameter of the SPF.

$N_{e,1}$: EB-adjusted estimated crash frequency for the first year in the analysis period.

$N_{o,n}$: observed crash frequency for the n year.

$N_{e,n}$: EB-adjusted estimated crash frequency for the n year.

PSI : excess expected crashes.

$EPDO-PSI$: excess expected equivalent property damage only crashes.

PSI_{FI} : excess expected fatal-and-injury crashes.

PSI_{PDO} : excess expected property damage only crashes.

CC_{FI} : crash cost for the fatal-and-injury crash.

CC_{PDO} : crash cost for the property damage only crash.

CHAPTER SIX: RESULTS

6.1 Safety Performance Functions

In pursuit of developing accurate SPFs, variables that have a high correlation with other variables have been identified and excluded (if their correlation factor is greater than 0.5) from the SPFs development process. This procedure has been conducted before modeling every SPF in this study. For example, Figure 7 shows the correlation matrix for all variables that have been used in modeling the statewide AADT-SPF. It was found that the total number of lanes, surface width, concrete surface, raised median, lawn shoulder, curb/gutter shoulder, sidewalk spacing, and presence of bicycle slot variables have high correlation factors with other variables (such as $\ln(\text{AADT})$, asphalt surface, paved median, shoulder width, and presence of bicycle lane). Therefore, they were excluded from the modeling process of the statewide AADT-SPFs.

The importance of the development of SPFs lies in the identification of factors that are associated with the crash occurrence at every road class and how these factors affect traffic safety. It was found that there are some factors have negative effects while others have positive effects on traffic safety represented by increasing/reducing the crash frequency. Tables 3-6 show the developed SPFs for the different levels of modeling.

It was found that AADT, signalized intersections density, access points density, pavement condition, median width, and raised median variables have negative effects on traffic safety. These factors have positive coefficients in AADT CC-SPFs. On the other hand, number of lanes, posted speed limit, asphalt surface, paved median, vegetation median, paved shoulder, sidewalk width, presence of bicycle lane, and presence of shared path variables have negative coefficients in AADT CC-SPFs. This means that these factors have a positive effect on traffic safety.

Figure 7: Correlation matrix of the considered variables

The number of crashes is expected to increase by increasing traffic volume, signalized intersections and access points densities because of the large number of traffic conflicts under heavy traffic volumes especially at signalized intersections and access points where conflicts are concentrated. Prefect pavement condition encourage drivers to drive with a high speed which increases the probability of crash occurrence. The existence of a raised median could cause a rollover of vehicles when a crash happens, while an unraised median is not considered as an obstacle for vehicles.

On the other hand, the number of crashes is expected to decrease by providing some conditions. Roads with a high number of lanes provide smooth movement without congestion, therefore, reducing conflicts between vehicles. High posted speed limits are only placed on roads with a low intersection and access point densities, therefore maintaining continuous traffic without many interruptions. Unpaved roads are very rare in Florida; therefore, they may cause confusion for drivers. Paved and vegetation median types are not considered as obstacles for vehicles since these median types have a small slope. Paved median and paved shoulders are usually wide. Wide shoulders and sidewalks provide a good separation between the road and the opposite traffic and the roadside environment. Presence of bicycle lane or shared path reduces the number of conflict points between bicyclists and motorized road users.

Meanwhile, some factors have a double safety effect (positive on some road classes and negative on others) such as shoulder width and sidewalk spacing factors. Wide shoulders have positive effect on traffic safety at C3C, C5 and C6 roads. However, it has a negative effect on C4 roads. Large sidewalk spacing has a negative effect on traffic safety at C1 roads. However, it has a positive effect on C4 roads. This fluctuation in the effect of these factors on crash occurrence is due to the different road environment between road classes. Similar effects for the aforementioned factors have been noticed in DVMT-SPFs. However, there are some differences.

The results indicated that there is no significant difference between the performance of simple and full SPFs. The possession of simple and full SPFs a similar prediction performance confirms that the FDOT context classification system well classifies roads. The importance of this manifests by the development of highly accurate simple SPFs since obtaining road environment characteristics is a time consuming and hard process. It was noticed that simple and full DVMT-SPFs have better performance than AADT-SPFs for most road classes. Figure 8 shows MAE

values of simple SPFs at the different modeling levels. It was found that CC-SPFs outperform AT-SPFs and SW-SPF for most road classes and if it is not the case, their error values are not significantly higher than AT-SPFs and SW-SPF error values. The reason behind this is the low variability in the road environment within the certain road class. This is in line with previous findings that more specific SPFs have better performance.

Table 3: Simple and full AADT-SPFs for context classification modeling level

Variable	Estimated Parameter (Standard Error)							
	C1	C2	C2T	C3C	C3R	C4	C5	C6
Simple SPFs								
Intercept	-8.06 (0.5563)	-7.21 (0.2064)	-5.28 (0.7144)	-4.93 (0.2073)	-5.23 (0.2246)	-3.73 (0.1890)	0.89 (0.8370)	-1.15 (1.0005)
Ln (AADT)	1.07 (0.0602)	0.97 (0.0230)	0.88 (0.0777)	0.89 (0.0207)	0.87 (0.0236)	0.81 (0.0190)	0.39 (0.0838)	0.63 (0.1038)
Dispersion	1.37 (0.1078)	0.48 (0.0218)	0.55 (0.0522)	0.68 (0.0179)	0.79 (0.0264)	0.54 (0.0153)	0.63 (0.0649)	0.41 (0.0659)
Observations	418	1703	366	3065	2080	2590	180	82
LLV	4893	29683	4859	451163	107609	522609	30220	14271
MAE	8.9	6.5	6.1	28.8	14.2	30.6	33.1	26.9
RMSE	17.6	11.9	11.7	50.4	23.3	53.4	48.5	50.8
Full SPFs								
Intercept	-4.95 (1.3312)	-4.68 (0.2444)	-6.23 (0.7098)	-4.63 (0.2165)	-4.63 (0.3769)	-3.31 (0.2262)	0.32 (0.9692)	-0.68 (0.9856)
Ln (AADT)	1.03 (0.1073)	0.80 (0.0222)	1.05 (0.0815)	0.94 (0.0207)	0.90 (0.0379)	0.72 (0.0223)	0.51 (0.0911)	0.45 (0.0968)
SID	0.30 (0.0618)	0.48 (0.0303)	0.14 (0.0175)	0.17 (0.0070)	0.23 (0.0179)	0.14 (0.0060)	0.10 (0.0137)	0.04 (0.0111)
APD	0.08 (0.0180)	0.06 (0.0056)	0.02 (0.0048)	0.03 (0.0021)	0.03 (0.0046)	0.01 (0.0016)	0.03 (0.0058)	-
NL	-	-	-0.13 (0.0483)	-	-	-	-	-
SL	-0.05 (0.0173)	-0.03 (0.0029)	-0.02 (0.0073)	-0.03 (0.0026)	-0.03 (0.0041)	-	-0.04 (0.0117)	-
PC	-	-	-	-	-	-	-	0.38 (0.1625)
AS	-1.16 (0.5324)	-	-	-	-	-	-	-
MW	-	-	-	-	0.005 (0.0018)	-	-	-

Variable	Estimated Parameter (Standard Error)							
	C1	C2	C2T	C3C	C3R	C4	C5	C6
Full SPFs								
PM	-	-	-0.25 (0.0820)	-	-	-	-	-
RM	-	0.19 (0.0616)	-	-	0.22 (0.0550)	0.13 (0.0317)	-	-
VM	-	-	-	-0.09 (0.0383)	-	-	-	-
SHW	-	-	-	-0.02 (0.0058)	-	0.01 (0.0064)	-0.08 (0.0304)	-0.09 (0.0280)
PSH	-	-	-	-	-0.12 (0.0557)	-0.16 (0.0343)	-	-
SWW	-	-	-	-	-0.04 (0.0136)	-	-	-
SWS	0.01 (0.0060)	-	-	-	-	-0.01 (0.0017)	-	-
PBL	-	-	-	-	-0.20 (0.0535)	-0.08 (0.0306)	-	-
PSP	-	-	-	-	-	-0.29 (0.0954)	-	-
Dispersion	0.67 (0.1290)	0.30 (0.0154)	0.35 (0.0392)	0.43 (0.0126)	0.49 (0.0253)	0.41 (0.0123)	0.42 (0.0482)	0.31 (0.0522)
Observations	94	1595	366	2866	971	2463	159	82
LLV	1557	29398	4916	438891	75322	509927	28018	14282
MAE	6.5	5.0	4.4	20.4	14.6	26.5	28.0	23.7
RMSE	13.4	11.0	7.7	35.0	24.0	46.0	40.9	46.6

- AADT: annual average daily traffic, SID: signalized intersections density per mile, APD: access points density per mile, NL: total number of lanes, SL: speed limit, PC: pavement condition, AS: asphalt surface, MW: median width, PM: paved median, RM: raised median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, SWW: sidewalk width, SWS: sidewalk spacing, PBL: presence of bike lane, PSP: presence of shared path, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

Table 4: Simple and full AADT-SPFs for area type and statewide modeling levels

Variable	Estimated Parameter (Standard Error)				
	Natural	Rural	Suburban	Urban	Statewide
Simple SPFs					
Intercept	-8.06 (0.5563)	-7.51 (0.2254)	-5.79 (0.1499)	-3.15 (0.1868)	-7.01 (0.1110)
Ln (AADT)	1.07 (0.0602)	1.03 (0.0250)	0.96 (0.0152)	0.76 (0.0188)	1.10 (0.0115)
Dispersion	1.37 (0.1078)	0.65 (0.0249)	0.76 (0.0157)	0.58 (0.0154)	0.99 (0.0136)
Observations	418	2069	5145	2852	10484
LLV	4893	34294	558612	567005	1162882
MAE	C1: 8.9	C2: 8.8, C2T: 5.4	C3C: 26.1, C3R: 18.9	C4: 31.6, C5: 28.4, C6: 31.3	C1: 37.5, C2: 37.0, C2T: 8.2, C3C: 31.6, C3R: 22.8, C4: 28.5, C5: 29.3, C6: 39.1
RMSE	C1: 17.6	C2: 15.3, C2T: 9.8	C3C: 46.7, C3R: 30.3	C4: 54.2, C5: 43.9, C6: 46.7	C1: 82.3, C2: 61.1, C2T: 17.6, C3C: 58.1, C3R: 38.2, C4: 54.3, C5: 45.1 , C6: 54.1
Full SPFs					
Intercept	-4.95 (1.3312)	-6.19 (0.3666)	-4.76 (0.2104)	-3.47 (0.2190)	-5.40 (0.1222)
Ln (AADT)	1.03 (0.1073)	0.91 (0.0295)	0.95 (0.0194)	0.85 (0.0251)	1.07 (0.0104)
SID	0.30 (0.0618)	0.31 (0.0196)	0.19 (0.0067)	0.11 (0.0052)	0.17 (0.0041)
APD	0.08 (0.0180)	0.05 (0.0031)	0.03 (0.0020)	0.01 (0.0016)	0.02 (0.0012)
SL	-0.05 (0.0173)	-	-0.03 (0.0022)	-0.03 (0.0032)	-0.04 (0.0012)
AS	-1.16 (0.5324)	-0.69 (0.2821)	-	-	-
MW	-	-0.004 (0.0010)	0.002 (0.0009)	-	-
PM	-	-	-0.09 (0.0309)	-0.21 (0.0323)	-0.12 (0.0188)
VM	-	-	-0.11 (0.0383)	-	-0.15 (0.0270)

Variable	Estimated Parameter (Standard Error)				
	Natural	Rural	Suburban	Urban	Statewide
Full SPFs					
SHW	-	-	-0.02 (0.0051)	-	-0.02 (0.0038)
PSH	-	-	-0.07 (0.0257)	-0.16 (0.0345)	-0.07 (0.0176)
SWS	0.01 (0.0060)	-	-	-0.01 (0.0017)	-
PBL	-	-	-0.06 (0.0245)	-	-
PSP	-	-	-	-0.20 (0.0987)	-
Dispersion	0.67 (0.1290)	0.40 (0.0195)	0.45 (0.0114)	0.40 (0.0129)	0.48 (0.0083)
Observations	94	1408	3888	2139	8906
LLV	1557	32565	513668	498531	1065241
MAE	C1: 6.5	C2: 6.7, C2T: 6.2	C3C: 20.7, C3R: 14.6	C4: 29.1, C5: 35.5, C6: 54.6	C1: 8.6, C2: 6.1, C2T: 8.4, C3C: 19.6, C3R: 13.0, C4: 30.6, C5: 51.0, C6: >100
RMSE	C1: 13.4	C2: 11.8, C2T: 11.4	C3C: 36.1, C3R: 22.8	C4: 51.4, C5: 57.8, C6: >100	C1: 15.2, C2: 10.2, C2T: 13.5, C3C: 34.8, C3R: 21.6, C4: 54.4, C5: 91.5, C6: >100

- AADT: annual average daily traffic, SID: signalized intersections density per mile, APD: access points density per mile, SL: speed limit, AS: asphalt surface, MW: median width, PM: paved median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, SWS: sidewalk spacing, PBL: presence of bike lane, PSP: presence of shared path, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

Table 5: Simple and full DVMT-SPFs for context classification modeling level

Variable	Estimated Parameter (Standard Error)							
	C1	C2	C2T	C3C	C3R	C4	C5	C6
Simple SPFs								
Intercept	-3.57 (0.4337)	-4.94 (0.1675)	-4.40 (0.3598)	-3.67 (0.1198)	-4.32 (0.1639)	-3.70 (0.1257)	-0.74 (0.4822)	-2.20 (0.6474)
Ln (DVMT)	0.57 (0.0464)	0.74 (0.0173)	0.76 (0.0428)	0.75 (0.0124)	0.76 (0.0176)	0.80 (0.0134)	0.50 (0.0530)	0.70 (0.0755)
Dispersion	1.24 (0.0979)	0.43 (0.0198)	0.50 (0.0492)	0.62 (0.0164)	0.74 (0.0251)	0.52 (0.0147)	0.56 (0.0582)	0.40 (0.0646)
Observations	418	1703	366	3065	2080	2590	180	82
LLV	4928	29788	4871	451342	107678	522672	30232	14272
MAE	6.0	5.4	5.2	24.2	13.0	29.0	27.8	25.2
RMSE	11.5	10.8	8.9	41.9	21.9	53.1	41.1	40.3
Full SPFs								
Intercept	-5.53 (0.5558)	-5.71 (0.2608)	-5.21 (0.4551)	-4.07 (0.1495)	-4.64 (0.3096)	-4.62 (0.1752)	-1.89 (0.6549)	-2.08 (0.8056)
Ln (DVMT)	0.78 (0.0482)	0.87 (0.0191)	0.89 (0.0433)	0.86 (0.0144)	0.88 (0.0286)	0.93 (0.0185)	0.69 (0.0662)	0.73 (0.0786)
SID	0.34 (0.0568)	0.42 (0.0285)	0.14 (0.0177)	0.16 (0.0071)	0.21 (0.0180)	0.12 (0.0068)	0.08 (0.0166)	0.03 (0.0120)
APD	0.06 (0.0131)	0.05 (0.0056)	0.01 (0.0048)	0.02 (0.0022)	0.03 (0.0047)	0.01 (0.0018)	0.03 (0.0069)	-
NL	0.21 (0.0453)	-	-	0.03 (0.0108)	0.07 (0.0185)	-	-	-
SL	-0.02 (0.0076)	-0.02 (0.0031)	-0.02 (0.0071)	-0.03 (0.0025)	-0.03 (0.0041)	-0.03 (0.0036)	-0.03 (0.0132)	-0.04 (0.0183)
PC	-	0.07 (0.0312)	-	-	-	-	-	-
SW	-	-	-	-	-	0.005 (0.0014)	-	-
AS	-	-	-	-	-	-	-	0.92 (0.3410)
MW	-	-	-	-	0.01 (0.0021)	0.01 (0.0022)	-0.01 (0.0066)	-

Variable	Estimated Parameter (Standard Error)							
	C1	C2	C2T	C3C	C3R	C4	C5	C6
Full SPFs								
PM	-	-	-0.20 (0.0796)	-	-	-	-	-
VM	-	-0.16 (0.0415)	-	-	-0.21 (0.0925)	-	-	-
SHW	-	-	-	-0.03 (0.0056)	-	-	-	-0.07 (0.0323)
PSH	-	-	-	-	-0.11 (0.0556)	-0.14 (0.0368)	-	-
SWW	-	-	-	-	-0.04 (0.0133)	-	-	-
SWS	-	-	-	-	-	-0.01 (0.0017)	-	-
PBL	-	-	-	-	-0.19 (0.0529)	-	-	-
PSP	-	-	-	-	0.25 (0.1104)	-	-	-
Dispersion	0.59 (0.0610)	0.29 (0.0154)	0.36 (0.0394)	0.42 (0.0123)	0.48 (0.0250)	0.36 (0.0132)	0.39 (0.0527)	0.31 (0.0556)
Observations	365	1589	366	2866	971	1701	116	72
LLV	4167	29268	4915	438933	75329	434141	23520	12600
MAE	4.8	4.9	4.4	19.9	14.5	30.0	28.5	24.7
RMSE	10.0	10.2	7.6	34.9	23.8	52.0	40.0	41.6

- DVMT: daily vehicle miles traveled, SID: signalized intersections density per mile, APD: access points density per mile, NL: total number of lanes, SL: speed limit, PC: pavement condition, SW: surface width, AS: asphalt surface, MW: median width, PM: paved median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, SWW: sidewalk width, SWS: sidewalk spacing, PBL: presence of bike lane, PSP: presence of shared path, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

Table 6: Simple and full DVMT-SPFs for area type and statewide modeling levels

Variable	Estimated Parameter (Standard Error)				
	Natural	Rural	Suburban	Urban	Statewide
Simple SPFs					
Intercept	-3.57 (0.4337)	-3.87 (0.1423)	-4.15 (0.0983)	-3.21 (0.1197)	-3.84 (0.0781)
Ln (DVMT)	0.57 (0.0464)	0.64 (0.0150)	0.78 (0.0103)	0.75 (0.0128)	0.76 (0.0083)
Dispersion	1.24 (0.0979)	0.52 (0.0206)	0.71 (0.0147)	0.54 (0.0146)	0.95 (0.0130)
Observations	418	2069	5145	2852	10484
LLV	4928	34538	558822	567106	1163256
MAE	C1: 6.0	C2: 5.7, C2T: 5.2	C3C: 23.5, C3R: 15.9	C4: 29.4, C5: 27.1, C6: 30.5	C1: 26.9, C2: 27.2, C2T: 8.0, C3C: 23.8, C3R: 17.1, C4: 31.9, C5: 30.9, C6: 38.3
RMSE	C1: 11.5	C2: 10.9, C2T: 10.1	C3C: 42.6, C3R: 23.5	C4: 53.4, C5: 41.3, C6: 45.1	C1: 40.9, C2: 36.4, C2T: 12.5, C3C: 42.1, C3R: 24.6, C4: 63.5, C5: 48.5, C6: 54.4
Full SPFs					
Intercept	-5.53 (0.5558)	-4.72 (0.1504)	-4.28 (0.1564)	-4.11 (0.1720)	-4.18 (0.0911)
Ln (DVMT)	0.78 (0.0482)	0.74 (0.0161)	0.87 (0.0143)	0.88 (0.0158)	0.88 (0.0087)
SID	0.34 (0.0568)	0.25 (0.0154)	0.18 (0.0071)	0.10 (0.0053)	0.16 (0.0041)
APD	0.06 (0.0131)	-	0.02 (0.0022)	0.01 (0.0017)	0.02 (0.0012)
NL	0.21 (0.0453)	-	0.05 (0.0107)	-	0.11 (0.0066)
SL	-0.02 (0.0076)	-	-0.03 (0.0025)	-0.03 (0.0030)	-0.04 (0.0012)
SW	-	-	-	0.004 (0.0012)	-
MW	-	-	0.003 (0.0009)	-	-
PM	-	-	-	-0.14 (0.0352)	-

Variable	Estimated Parameter (Standard Error)				
	Natural	Rural	Suburban	Urban	Statewide
Full SPFs					
RM	-	0.26 (0.0551)	-	-	-
VM	-	-0.15 (0.0431)	-	-	-0.11 (0.0256)
SHW	-	-	-0.02 (0.0056)	-	-0.02 (0.0039)
PSH	-	-0.28 (0.0602)	-0.13 (0.0267)	-0.16 (0.0343)	-0.06 (0.0173)
LSH	-	-0.31 (0.0622)	-	-	-
SWW	-	-	-0.01 (0.0073)	0.03 (0.0112)	-
SWS	-	-	-	-0.01 (0.0017)	-
Dispersion	0.59 (0.0610)	0.38 (0.0165)	0.42 (0.0117)	0.40 (0.0127)	0.48 (0.0082)
Observations	365	2069	3162	2139	8906
LLV	4167	34775	471644	498545	1065348
MAE	C1: 4.8	C2: 5.1, C2T: 5.6	C3C: 21.8, C3R: 16.0	C4: 28.7, C5: 34.8, C6: 57.2	C1: 7.4, C2: 5.7, C2T: 8.3, C3C: 19.9, C3R: 12.4, C4: 29.7, C5: 45.8, C6: >100
RMSE	C1: 10.0	C2: 10.0, C2T: 13.7	C3C: 37.8, C3R: 24.1	C4: 51.8, C5: 53.8, C6: >100	C1: 11.8, C2: 9.6, C2T: 13.2, C3C: 35.7, C3R: 20.6, C4: 53.2, C5: 79.0, C6: >100

- DVMT: daily vehicle miles traveled, SID: signalized intersections density per mile, APD: access points density per mile, NL: total number of lanes, SL: speed limit, SW: surface width, MW: median width, PM: paved median, RM: raised median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, LSH: lawn shoulder, SWW: sidewalk width, SWS: sidewalk spacing, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

Figure 8: MAE values of simple CC-SPFs, AT-SPFs, and SW-SPF

6.2 Network Screening

Road segments have been ranked in a descending order based on the EPDO-PSI value. Table 7 lists and Figure 9 shows the top twenty road segments that have the highest EPDO-PSI values. These locations have the highest potential for safety improvement by implementing safety countermeasures to reduce the number and severity of crashes along them. It was found that the most problematic road segments are C3C and C4 roads and they are located in the Miami area.

Table 7: The most problematic road segments in Florida

Road ID	Road Name	Began Post	End Post	CC	Rank
87026000	NE Miami Gardens Dr	5.529	6.584	C3C	1
72160000	San Jose Blvd	1.865	3.322	C3C	2
87080900	NW 79 th St	38.493	40.027	C4	3
87008000	NW 135 th St	5.102	7.614	C4	4
86210000	Davie Blvd	2.034	3.019	C4	5
86110000	NW 10 th St	5.018	6.086	C4	6
75010000	US-92 E	8.638	11.219	C3C	7
87170000	N Miami Beach Blvd	1.477	3.065	C4	8
13010000	14 th St W	3.007	4.277	C3R	9
93004000	Glades Rd	4.896	5.512	C3C	10
86040000	Hollywood Blvd	15.649	16.598	C4	11
86040000	Hollywood Blvd	12.486	13.986	C4	12
87038000	NW 103 rd St	8.199	8.955	C4	13
87020000	S Dixie Hwy	0.862	3.093	C3C	14
14030000	US Highway 19	0.636	2.511	C3C	15
87240000	NW 27 th Ave	10.843	11.113	C4	16
86529500	W Gopans Rd	0.698	1.176	C3C	17
87044000	SW 40 th St	3.144	4.223	C4	18
14030000	US Highway 19	8.007	11.474	C3C	19
72220000	103 rd St	6.479	7.757	C3C	20

Figure 9: The most problematic road segments in Florida

CHAPTER SEVEN: CONCLUSIONS

The new FDOT context classification system has been highlighted in this study. Roads are classified into eight classes from rural to urban roads according to this system based on geographic, demographic, and road characteristics information.

Crash and traffic data of the last five years (2015-2019) and road characteristics and environment information have been obtained to conduct crash analysis and develop safety performance functions (SPFs) for three modeling levels.

Simple and full SPFs have been developed by adopting annual average daily traffic (AADT) and daily vehicle miles traveled (DVMT) as exposure variables. Network screening has been also accomplished in this study to identify the most problematic road segments.

It was found that more than a third of road segments are rural roads (C2 roads). Suburban commercial and urban general roads according to this system (C3C and C4 roads) have been subjected to most crashes. However, urban roads (C4, C5, and C6) have the highest crash rate per million miles traveled. DVMT-SPFs were having better prediction performance than AADT-SPFs. CC-SPFs outperformed AT-SPFs and SW-SPF.

It is worth mentioning that there was no significant difference in prediction performance of the developed simple and full SPFs for all road classes. This confirms considering all road environment while classifying roads based on the FDOT context classification system. The results of the network screening indicated that the most problematic roads are C3C and C4 roads.

It transpired that intersections and access points densities are one of the most influential factors on crash occurrence. Therefore, several technological applications can be used to improve

traffic safety at intersections and access points such as infrastructure-to-vehicle (I2V), vehicle-to-vehicle (V2V), and pedestrian-to-vehicle (P2V) communications.

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