Creating Safety Performance Functions for Two-Way Stop-Controlled Intersections in City, Delhi

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Abstract-

The first edition of the Highway Safety Manual (HSM) features a basic crash prediction model for two-way stop-controlled intersections (TWSC) on rural two-lane highways. This model considers the AADT on both major and minor roads, assuming base conditions of no intersection skewness, no turning lanes, and no lighting. A crash modification factor (CMF) is applied if the intersection conditions differ from the base conditions. However, the HSM model does not account for curvature. It is well known that curved TWSC intersections are less safe than non-curved ones, especially on rural two-lane roadways. This paper presents the development of crash prediction models that incorporate intersection geometrics for TWSC intersections on rural two-lane highways in Louisiana. It then compares the results from the developed model with the calibrated HSM model. Using the negative binomial model, 5127 TWSC intersections, including both three- and four-leg intersections from all Delhi cities, were verified individually. The estimation results indicate that AADT, curve radius, and intersection skewness angle significantly impact the expected crash frequency for both three- and four-leg intersections. This research employs cumulative residual plots; mean absolute error, and root mean square error for a comparative analysis of HSM models, HSM models with calibration. The results show that Louisiana-specific SPFs outperform the calibrated SPFs with superior reliability. Calibration factors of 0.56 for three-leg intersections and 0.42 for four-leg intersections are estimated, suggesting that the original HSM model over predicts crashes in Delhi.

Keywords: Safety performance function, Intersections, Two-way stop-controlled, Rural two-lane highway

1.0 Introduction-

Horizontal curves and intersections present challenges to drivers and other roadway users due to their unique design and function. Consequently, both have been separately identified as key areas for safety improvement in many states' highway safety strategies. On horizontal curves, vehicles are more likely to leave the travel lane when the roadway alignment changes direction, especially on curves with small radii. In 2016, approximately 25% of roadway fatalities in the United States occurred along horizontal curves, according to the Fatality Analysis Reporting System. The average crash rate for horizontal curves is about three times higher than for tangent segments [2]. Additionally, about 76% of fatal crashes on horizontal curves involve single vehicles leaving the roadway and striking trees, utility poles, rocks, or other fixed objects, or overturning [3]. Intersections are locations where two or more roads join or cross. The crossing and turning maneuvers at intersections create conflicts between vehicles and between vehicles and pedestrians or bicycles, which can result in traffic crashes. Therefore, intersections are common points for concentrations of traffic crashes [4]

Rural roadway safety remains a crucial concern in the United States. In 2023, 20,687 traffic fatalities occurred in rural areas, accounting for 55% of all traffic fatalities, with 28% involving un-signalized intersections [1]. Over 80% of T-intersection-related fatalities in rural areas occur at un-signalized intersections in Fig.1 [2]. Stop-controlled intersections present a potential safety risk not found at signalized intersections, with the probability of a fatality per 100 crashes at rural stop-controlled intersections being over 12 times higher than at urban signalized intersections [3]. On two-lane highways, crashes often result from speed differentials between vehicles stopping or slowing down to turn left or right and vehicles traveling in the same lane, or from drivers on minor roads failing to yield at these intersections [4]. Due to these combined challenges, having an intersection on a horizontal curve may increase the probability of a crash.

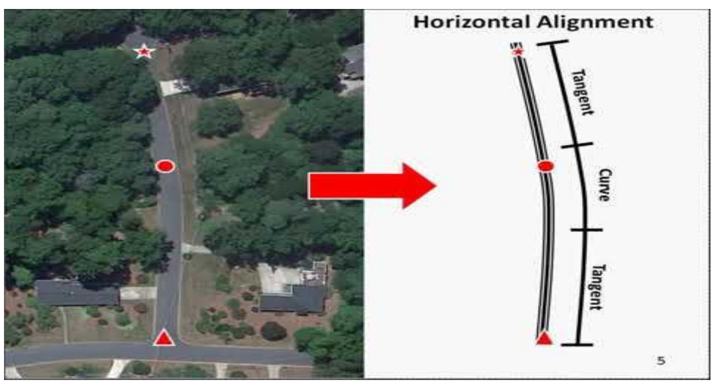

Fig. 1. An example of a crash occurred at a T-intersection on a horizontal curve.

Intersection safety has been a long-standing problem in Louisiana. Intersection-related fatalities and severe injuries accounted for 25.1% of total fatalities and 41.9% of total severe injuries in the state. Over 58% of intersection-related fatalities occurred at un-signalized intersections [6]. Many such intersections were created decades after the major roadway existed to provide access to minor streets. Our investigation found that many intersections on horizontal curves are maintained by state and local agencies in Delhi. A typical example of a crash at an intersection on a horizontal curve is shown in Fig. 2. This T-intersection is located on a rural two-lane highway with a stop sign on the minor roads. The crash involved a right-turning vehicle and a vehicle that ran off the road while attempting to negotiate the curve.

Fig. 2. An example of a crash occurred at an intersection on a horizontal curve.

To better understand the factors affecting crash frequency and injuries, safety performance functions (SPFs) presented in the Highway Safety Manual (HSM) are valuable tools for relating the number of different types of crashes or severities to site attributes. These models consistently include traffic data (Average Annual Daily Traffic or AADT) and incorporate site features in the form of Crash Modification Factors (CMFs), such as lighting conditions and the presence of turning lanes at intersections. The HSM recommends that state agencies update these functions through a calibration process with local data due to substantial variations among jurisdictions [7].

While the HSM provides detailed information on the local calibration of its models, it is important to note that the HSM's SPFs were developed based on data collected from selected state roadways and may not apply universally. Consequently, many states have developed SPFs based on local data, revealing significant state-to-state variation in the accuracy of the HSM's SPFs. However, existing SPFs and CMFs in the HSM assume that the relationship between intersection safety and traffic flow is the same for curved and tangent intersections, even though previous research suggests this may not be true. These models do not specifically investigate and consider intersections on horizontal curves. Furthermore, the rural two-lane models were developed over 20 years ago [8].

To meet Louisiana's Strategic Highway Safety Plan's goal of reducing roadway departure, intersection-related, and non-motorized user deaths and severe injuries by 60% by 2030, there is a need to further examine intersection safety performance on rural two-lane highways with specific geometric characteristics.

1.2 Research Objectives

Based on the issues noted above, the following research objectives were developed:

1. Identify crash characteristics for intersection on horizontal curves;
2. Identify risk factors or roadway characteristics associated with intersections on horizontal curves;
3. Develop Louisiana-specific SPFs for TWSC intersections;
4. Provide a list of possible countermeasures that target the identified risk factors.

1.3 Systemic Approaches in Safety Performance Functions Development

The systemic approach to safety is a data-driven, network-wide process that employs analytical techniques to identify potential safety improvements and suggest projects for safety investment that might not be discovered through traditional site analysis methods. This approach can pinpoint and address high-risk roadway features associated with specific or severe crash types. Its goal is to complement traditional site analysis with a more comprehensive and proactive strategy for preventing the most severe crashes on our nation's roadways. DMADV is one of the Six Sigma frameworks, focusing on the development of new services, products, or processes rather than improving existing ones. The DMADV approach—Define, Measure, Analyze, Design, Verify—is particularly effective for implementing new strategies and initiatives due to its reliance on data, early identification of success factors, and thorough analysis. Figure 1.2 illustrates the five steps involved in this approach.

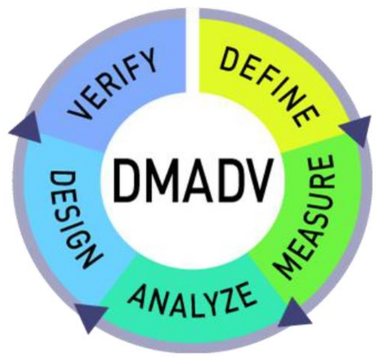

Figure 3: Five Steps in DMADV

2.0 Literature review

Previously, many studies conducted safety performance analysis at rural intersections. SPFs are regression models, as defined by HSM [7], to estimate the expected annual average number of crashes of individual highway sections or intersections. AASHTO published a safety analysis software program—Safety Analyst. The Federal Highway Administration collaborated closely with 27 state highway agencies and local organizations to develop Safety Analyst and support the application of methodological approaches in HSM. Safety Analyst "incorporates state-of-the-art safety management approaches into computerized analytical tools for supporting the decision-making process to identify safety improvement needs and develop a system wide program of site-specific improvement projects" [9–11]. Safety Analyst utilizes a series of default SPFs established with data available for four states: California, Minnesota, Ohio, and Washington. Considering different road characteristics across various jurisdictions, it is suggested to develop separate SPFs based on each state's traffic and crash data [12]. Several states have developed their state-specific intersection SPFs to address issues associated with HSM model calibration, including Illinois, Oregon, Virginia, Pennsylvania, and Michigan [13–17].

For example, Tegge, Jo, and Ouyang [13] developed Illinois-specific SPFs based on NB regression with five-year crash data (2001–2005). The following rural intersection facility types were included: (1) rural minor leg stop-control, (2) rural all-way stop-control, (3) rural signalized intersections, and (4) rural undetermined. Each SPF was developed for different crash severity levels, including fatal, injury, and fatal injury.

Monsere et al. [14] presented two SPFs for Oregon intersections: rural three-leg minor stop-control intersections and urban four-leg signalized intersections. The SPFs developed in this research were compared to the HSM base models calibrated to Oregon data. Data from 115 rural three-leg stop-controlled intersections were collected between 2005 and 2007.

Garber and Rivera [15] developed Virginia-specific SPFs based on NB regression for both rural and urban sites separately, including three-leg signalized intersections, three-leg minor stop intersections, four-leg signalized intersections, and four-leg minor stop intersections. To account for the different topography in Virginia, SPFs were also developed for three different regions. Crash data for the years from 2003 through 2007 were collected for this study. The development of rural intersection SPFs in Pennsylvania has revealed the importance of roadway geometric characteristics for rural intersections.

Donnell et al. [16] developed SPF models for TWSC three-leg and four-leg rural intersections, all-way stop-control intersections, and signal-control intersections. NB models were used to develop the SPFs. The SPFs featured variables such as major and minor AADTs, shoulder width on the major and minor roads, paved width on major roads, and posted speed limits, among others. The study showed that calibrated SPFs based on the HSM predictive method have considerably different state precisions.

Gates et al. [17] developed SPFs for rural road segments and intersections in Michigan. The facility types included two-lane and four-lane state trunklines (divided and undivided), rural county roadways, signalized intersections, and minor-road stop-controlled intersections, with data from 2011 to 2015. NB regression was used in this study. In addition to AADT, detailed models were developed, which also considered factors such as shoulder width, driveway density, horizontal curvature, median presence, road surface type, and intersection skew.

3.0 Methodology and Data Collection:

A significant effort was made to create a comprehensive TWSC intersections database. Crash data, AADT, and other relevant roadway attributes were retrieved and merged from various sources for TWSC intersections on rural two-lane roadways across all parishes (counties) in Louisiana. Three major data sources from the Department of Transportation and Development (DOTD)—the DOTD State Highway Assets Geo database, DOTD roadway inventory file, and DOTD crash database—were utilized for the years 2013 to 2023. SPF development requires intersection and roadway attributes such as horizontal curve radius, lane widths, number of intersection legs, and speed limits. These attributes were retrieved from shape files provided by the DOTD State Highway Assets Geo database in Arc GIS format. Traffic volume data, specifically AADT, was collected from the DOTD roadway inventory file, which included verified log mile and route numbers for each rural intersection. Additionally, to enhance data accuracy, Google Maps street-level imagery was used to verify turning radii and traffic control types for each intersection. As illustrated in Fig. 4, several important steps were involved in retrieving and merging different data files from DOTD for the TWSC intersection database development for SPF modeling. These steps are summarized as follows:

Step 1: Set up a curve file with a radius less than 900 feet, based on previous studies and engineering judgment. For this study, curves with radii greater than 1500 feet have negligible differences compared to tangent sections, so they are excluded. This is done using the file labeled CURVE.

Step 2: Create a new intersection file by retrieving intersections that are not controlled by signals from the file INTERSECTION.

Step 3: Merge the files from Steps 1 and 2 to identify intersections on curves.

Step 4: Verify and correct the merged file from Step 3 using Google Maps for each intersection in each parish. Remove the following:

- I. Curves or intersections with turning lanes.
- II. Roundabouts and service roads.
- III. Signalized intersections.

Step 5: Add crash data to the file developed in Step 4. According to DOTD, an intersection crash is defined as a crash occurring within a 152-foot radius of an intersection.

Step 6: Merge all relevant information into a single data file.

The research team also manually collected intersection attributes, such as intersection skewness, which were not included in the datasets mentioned above. Intersection skew angles were measured using the ruler tool in Google Earth. The HSM defines intersection skew angle as the absolute deviation from a 90-degree intersection angle, with skew ranging from zero (for perpendicular intersections) to a maximum of 90 degrees. For this study, skew was measured as the smallest angle between any two legs of the intersection. Given the large number of TWSC intersections (1126 in total), a binary parameter for intersection skewness was defined (0 if skewness is less than 30 degrees, 1 if skewness is greater than 30 degrees) to enhance manual collection efficiency and accuracy for SPF development.

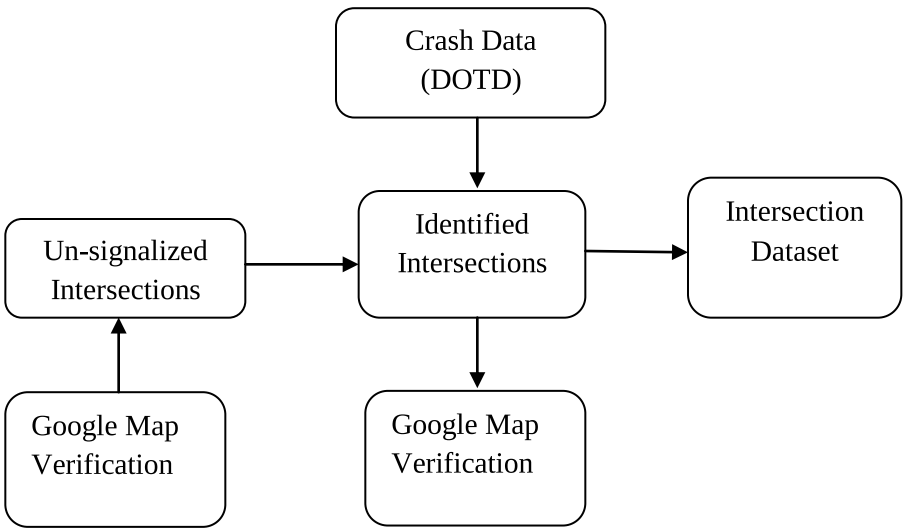

Fig. 4. Flowchart of TWSC intersection database development.

Table 1 Overview of TWSC intersections on rural two-lane highways.

		Three-Leg TWSC				Four-Leg TWSC			
Variable	Level or Unit	Mean	SD	Min	Max	Mean	SD	Min	Max
Major road AADT	Vehicles/Day	2200	2215	45	16600	2562	2156	95	14860
Major road AADT	Vehicles/Day	350	664	12	9890	582	862	9	7820
Curve radius	Ft	881.2	382	89.5	1550	850.6	385.03	82.5	1560
Intersection skewness	0 if skewness <30 degree, 1 if skewness >30 degree	0.015	0.120	0	1	0.006	0.084	0	2
Number of total crashes	annual count per intersection	0.170	0.385	0	5	0.352	0.752	0	9
Number of fatal and injury	annual count per intersection	0.072	0.185	0	2	0.156	0.356	0	5

crashes									
Number of PDO crashes	annual count per intersection	0.095	0.310	0	3	0.232	0.485	0	6

3.1 Calibration

It looks like you're discussing the process for calibrating Safety Performance Functions (SPFs) and Crash Modification Factors (CMFs) in transportation engineering. This involves adjusting models to account for differences between the conditions for which they were originally developed and the actual conditions where they're being applied.

Here's a breakdown of the calibration process based on the steps you provided:

1. **Randomly Select Intersections**: Choose a representative sample of intersections for analysis to avoid bias.
2. **Collect Site-Specific Data**: Gather detailed geometric design data for each intersection, which could include factors such as road type, lane configurations, and other relevant characteristics.
3. **Apply Base Model and CMFs**: Use the Highway Safety Manual (HSM) base model along with applicable CMFs to predict the number of crashes for each selected intersection.
4. **Compare Predictions to Observations**: Analyze the predicted number of crashes against the actual observed crash data to identify discrepancies.
5. **Calculate Calibration Factor**: Determine a calibration factor that adjusts the SPF or CMF to better fit the observed data. This factor can then be used to improve the model's accuracy for the region in question.

By following these steps, transportation engineers can ensure that SPFs and CMFs provide more reliable estimates of crash frequency under specific conditions. The model can also be adapted for future predictions by incorporating trends and changes in traffic patterns.

$$N = No *C*C*MF \quad - \qquad (1)$$

Where, N = predicted annual average number of crashes, N0 = predicted annual average number of crashes at base conditions, C = calibration factor for local condition adjustment, and CMF = the product of the set of applicable CMFs.

$$No\text{- }3ST = \exp\left[- 9.86+0.79\times\ln (AADTmaj) +0.49\times\ln (AADTmin)\right] \quad - \qquad (2)$$

$$No\text{- }4ST = \exp\left[-8.56+0.60\times\ln (AADTmaj) +0.61\times\ln (AADTmin)\right] \quad - \qquad (3)$$

Where, AADTmaj = AADT for the major road, AADTmin = AADT for the minor road.

The process of calculating a calibration factor in the Highway Safety Manual (HSM) involves a detailed comparison between predicted and observed crash data. Here’s how the calibration factor is determined:

1. **Selection of Intersections**: Identify and randomly select 30 to 50 intersections that accurately represent the region's physical and safety conditions.
2. **Minimum Sample Size Criteria**: Ensure the selected locations collectively include at least 100 crashes to meet the minimum sample size requirement.
3. **Calculation of the Calibration Factor**: Use the following equation to determine the calibration factor:

$$\text{Calibration Factor} = \frac{\text{Total Observed Crashes}}{\text{Total Pridicted Crashes}} \quad - (4)$$

This calibration factor adjusts the predictive model to better match the specific conditions of the region being studied. Here's a step-by-step outline of the process:

- **Collect Data**: Gather crash data and site-specific geometric design data for each selected intersection.
- **Apply Base Model and CMFs**: Use the HSM base model and relevant Crash Modification Factors (CMFs) to estimate the number of crashes for each intersection.
- **Compare Predicted and Observed Crashes**: Compare the predicted number of crashes with the actual observed crash data.
- **Calculate Calibration Factor**: Calculate the calibration factor using the total observed and predicted crash counts.

The calibrated model can then be used to provide more accurate predictions of crash frequency for the region under study. This ensures that the SPFs and CMFs account for regional-specific conditions and variations.

3.2 Development of SPFs:

Considering the complexity of random, discrete, and non-negative crash data, it has been studied that the Poisson distribution performs well and has been commonly used to model count data such as crash frequency

The Negative Binomial regression model is a generalization of the Poisson regression model that includes an extra parameter to account for the overdispersion. Here's a breakdown of the process:

1. **Poisson Regression Model**: Initially, the Poisson regression model is used, assuming that the mean and variance of the crash data are equal. The model is suitable for count data and is expressed as:

$$\lambda i = e^{\beta 0+\beta 1xi1+\beta 2xi2+\cdots+\beta kxik} \quad - (5)$$

where λi is the expected crash frequency, β0 is the intercept, β1,β2,…,βk are the coefficients, and xi1,xi2,…,xik are the explanatory variables.

2. **Over dispersion Issue**: If the variance of the crash data exceeds the mean, overdispersion is present, indicating that the Poisson model may not be appropriate.
3. **Negative Binomial Regression Model**: To address over dispersion, the Negative Binomial regression model introduces an extra parameter, α\alphaα, to account for the over dispersion.
4. **Model Selection**: After fitting both models, the suitability of the Poisson vs. Negative Binomial model is evaluated based on goodness-of-fit measures such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). The model with the lower AIC or BIC is preferred, indicating a better fit for the data.

By accounting for over dispersion with the Negative Binomial regression model, transportation engineers can achieve more accurate and reliable predictions of crash frequency, leading to better-informed decisions in traffic safety and management.

Table 2 Summary of calibration factors.

State	Calibration Factor	
	Three-Leg TWSC Intersections	Four-Leg TWSC Intersections
Delhi	0.60	0.46
Mumbai	0.35	0.45
Kolkata	0.80	0.85
Bangalore	0.65	0.72
Patna	0.20	0.25
Pune	0.77	0.54

3.3 Model evaluation

Evaluating the performance of Safety Performance Functions (SPFs) is crucial to ensure their accuracy and reliability. Several goodness-of-fit measures are commonly used in this process. Here’s an overview of these measures and the research methodology involving data partitioning for model development and validation:

Goodness-of-Fit Measures

1. **Over dispersion Parameter**:
   - This parameter helps identify the extent of overdispersion in the data. In the context of the Negative Binomial model, it indicates how much the variance exceeds the mean.
2. **Cumulative Residuals (CURE) Plot**:
   - A graphical tool that plots the cumulative sum of residuals (differences between observed and predicted values) against a covariate or predicted values. It helps identify systematic deviations and trends that the model may not have captured.
3. **Root Mean Square Error (RMSE)**:
   - RMSE measures the average magnitude of the errors between predicted and observed values. It is calculated as:

$$\text{RSME} = \sqrt{\frac{1}{n}} \sum_{i=1}^{n}(yi - yi)2 \qquad \text{- (6)}$$

The Cumulative Residuals (CURE) plot is an important graphical tool used in evaluating the fit of prediction models. It provides a way to assess how well a model's predictions align with the observed data across the entire range of an independent variable. Here’s a more detailed explanation of how the CURE plot is constructed and interpreted:

Construction of the CURE Plot

1. **Calculate Residuals**:

   - Residuals are the differences between the observed values and the predicted values from the model.

   ri = yi - y^I -(7)

2. **Plotting the CURE Plot**:

- The cumulative residuals are plotted against the covariate in question, showing how the residuals accumulate over the range of the covariate.
- Additionally, 95% confidence limits are plotted. These limits provide a range within which the cumulative residuals should lie if the model is unbiased.
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4.0 Results and discussions

4.1 Calibration factor

Calibration of Safety Performance Functions (SPFs) from the Highway Safety Manual (HSM) is crucial to account for variations in crash data between different jurisdictions and for factors not included in the model. The reasons for these variations are numerous and can include differences in climate, reporting criteria, topography, animal population, law enforcement practices, vehicle characteristics, and other local factors. Here's a detailed explanation of the importance of calibration and how it is applied, particularly in the context of Louisiana:

Importance of Calibration

1. **Jurisdictional Differences**:
   - Crash frequencies can vary significantly from one jurisdiction to another due to local conditions and practices. For example, differences in crash reporting thresholds and system procedures can lead to discrepancies in recorded crash frequencies.
2. **Factors Not Included in the Model**:
   - The default SPFs from the HSM may not account for all factors that influence crash frequencies. Local conditions such as climate, topography, animal population, and law enforcement practices can affect crash rates and need to be considered.
3. **Adjusting for Over prediction or Under prediction**:
   - Calibration ensures that the SPF is adjusted to accurately reflect local conditions. For instance, in Louisiana, the HSM default SPFs were found to significantly over predict the number of crashes at three-leg and four-leg TWSC intersections on rural two-lane highways.

4.2 Delhi-specific SPFs development results

In the context of rural two-lane, two-way stop-controlled (TWSC) three-leg and four-leg intersections, three models with identical structures were developed to predict different crash severity levels. These models were specifically focused on:

1. **Total Crashes**
2. **Fatal and Injury Crashes**
3. **Property Damage Only (PDO) Crashes**

The Negative Binomial (NB) regression model was employed for these estimations due to its ability to handle overdispersed crash data, where the variance exceeds the mean. R programming was used to perform the model estimation.

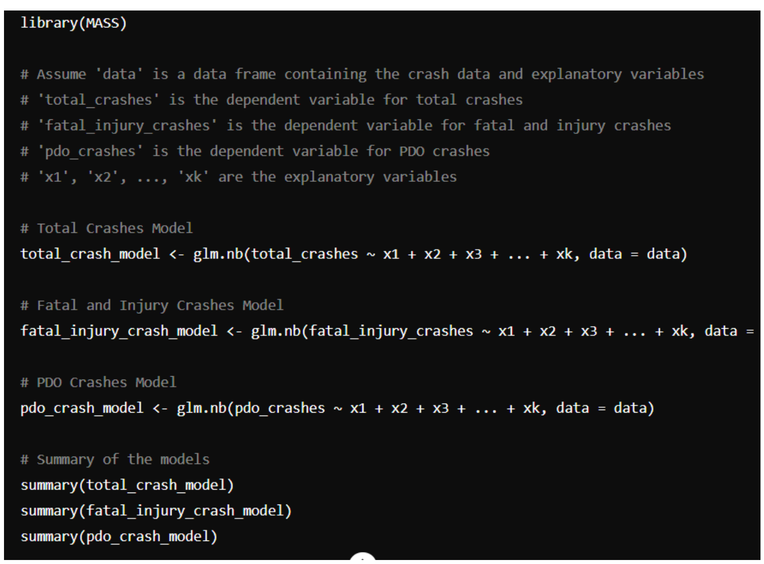
Model Development Process

1. **Data Collection and Preparation**:
   - Gather crash data, geometric design details, traffic volumes, and other relevant variables for the intersections.

  - Classify the crash data into three severity levels: total crashes, fatal and injury crashes, and PDO crashes.

2. **Negative Binomial Model Estimation Using R**:
   - **R Programming**: R is a powerful statistical computing environment that provides tools for fitting NB regression models.
   - **Package Utilization**: The MASS package in R, which includes the **'glm.nb()'** function, is commonly used for estimating NB models.

```
# Load the necessary package
library(MASS)
# Assume 'data' is a data frame containing the crash data and explanatory variables
# 'total_crashes' is the dependent variable for total crashes
# 'fatal_injury_crashes' is the dependent variable for fatal and injury crashes
# 'pdo_crashes' is the dependent variable for PDO crashes
# 'x1', 'x2', ..., 'xk' are the explanatory variables
# Total Crashes Model
total_crash_model <- glm.nb(total_crashes ~ x1 + x2 + x3 + ... + xk, data = data)
# Fatal and Injury Crashes Model
fatal_injury_crash_model <- glm.nb(fatal_injury_crashes ~ x1 + x2 + x3 + ... + xk, data = data)
# PDO Crashes Model
pdo_crash_model <- glm.nb(pdo_crashes ~ x1 + x2 + x3 + ... + xk, data = data)
# Summary of the models
summary(total_crash_model)
summary(fatal_injury_crash_model)
summary(pdo_crash_model)
```



```
library(MASS)

# Assume 'data' is a data frame containing the crash data and explanatory variables
# 'total_crashes' is the dependent variable for total crashes
# 'fatal_injury_crashes' is the dependent variable for fatal and injury crashes
# 'pdo_crashes' is the dependent variable for PDO crashes
# 'x1', 'x2', ..., 'xk' are the explanatory variables

# Total Crashes Model
total_crash_model <- glm.nb(total_crashes ~ x1 + x2 + x3 + ... + xk, data = data)

# Fatal and Injury Crashes Model
fatal_injury_crash_model <- glm.nb(fatal_injury_crashes ~ x1 + x2 + x3 + ... + xk, data =

# PDO Crashes Model
pdo_crash_model <- glm.nb(pdo_crashes ~ x1 + x2 + x3 + ... + xk, data = data)

# Summary of the models
summary(total_crash_model)
summary(fatal_injury_crash_model)
summary(pdo_crash_model)
```

Fig. 5 SPFs development results

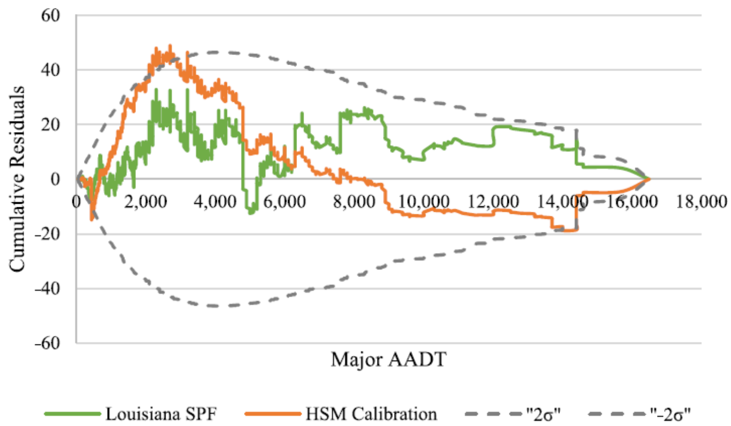


Fig. 6.CURE plots for HSM calibration model vs. SPF on three-leg intersections.

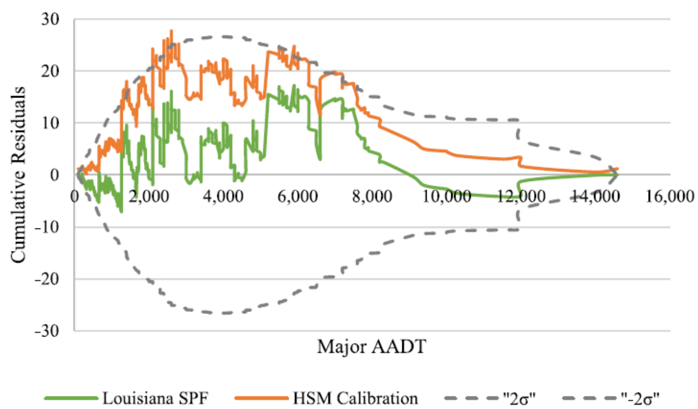


Fig. 7 CURE plots for HSM calibration model vs. Louisiana-specific SPF on four-leg intersections.

4.3 CURE plots

The Cumulative Residuals (CURE) plots for both the HSM model with calibration and the Louisiana-specific SPFs provide insight into the model's performance across different ranges of average annual daily traffic (AADT) on three-leg and four-leg intersections. Here's a detailed interpretation of the findings based on the provided CURE plots:

Three-Leg TWSC Intersections

1. **AADT Below 2500**:
    - **Underestimation of Crashes**: For AADTs below approximately 2500, the HSM model with calibration tends to underestimate the total number of crashes. This means that the observed number of crashes is greater than the predicted number, indicating that the calibration did not fully account for the factors influencing crash frequency in this range.

- **CURE Plot Interpretation**: In the CURE plot, this underestimation would be reflected by cumulative residuals that trend above the 95% confidence limits, showing a positive bias.

2. **AADT Above 2500**:
   - **Over prediction of Crashes**: For AADTs exceeding 2500, the HSM model with calibration over predicts the total number of crashes. This suggests that the model predicts more crashes than actually observed, indicating an over compensation in the calibration process.
   - **CURE Plot Interpretation**: This over prediction is reflected by cumulative residuals trending below the 95% confidence limits, showing a negative bias.

Four-Leg TWSC Intersections

While specific details about four-leg intersections were not mentioned, similar principles apply. We can infer that the CURE plots for these intersections would also show the performance of the HSM model with calibration compared to the observed data across different AADT ranges.

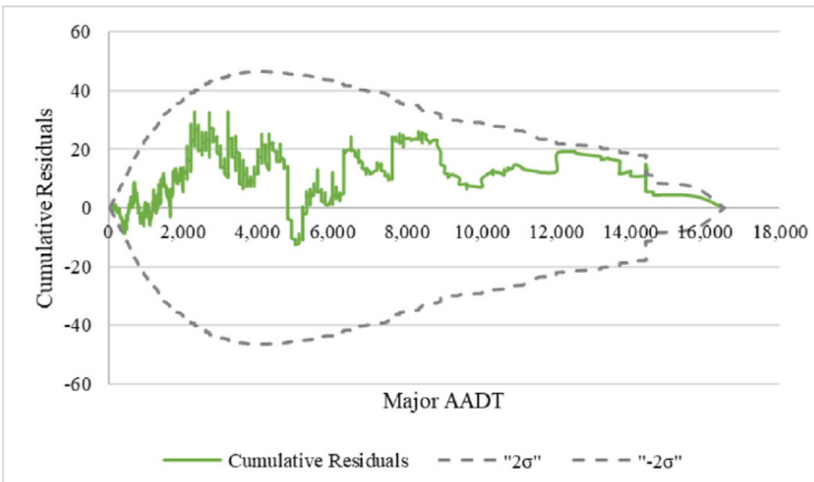


Fig. 8 Major AADT

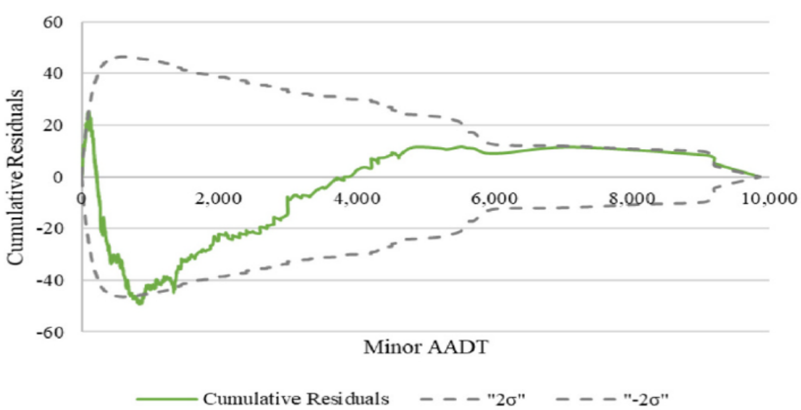


Fig. 9 Minor AADT

5.0. Conclusion

The analysis of the CURE plots for the HSM model with calibration highlights the importance of regional-specific adjustments in predictive modeling. While the calibrated HSM model provides a starting point, developing Louisiana-specific SPFs can better capture the local crash dynamics, leading to more accurate and reliable safety performance predictions. This approach helps ensure that safety interventions are appropriately targeted and effective in reducing crashes at rural intersections. By developing and calibrating these NB models for different crash severity levels, transportation engineers can achieve a more nuanced understanding of crash patterns at rural two-lane TWSC intersections. This approach allows for better-targeted safety improvements and more effective allocation of resources to reduce crashes and enhance road safety.

The results from the NB models underscore the importance of considering multiple factors in intersection safety analysis. While AADT is a primary predictor, curve radius and intersection skewness also play significant roles in determining crash frequency. By addressing these factors through thoughtful design and targeted interventions, transportation engineers can improve safety at rural two-lane intersections.

Incorporating these insights into the development of Louisiana-specific SPFs ensures that predictive models are finely tuned to the unique conditions of the region, leading to more effective safety measures and ultimately reducing the number of crashes.

The results from the NB models reveal that, besides Average Annual Daily Traffic (AADT), factors such as curve radius and intersection skewness significantly impact intersection safety. Here's a detailed analysis of these findings:

1. Average Annual Daily Traffic (AADT)

- **Impact on Crash Frequency**: AADT is a critical factor in predicting crash frequency. Generally, higher traffic volumes correlate with a higher likelihood of crashes due to increased exposure and interaction between vehicles.

2. Curve Radius

- **Impact on Crash Frequency**: The models indicate that a greater curve radius leads to a smaller expected number of crashes at rural two-lane, three-leg, and four-leg intersections.
    - **Explanation**: Larger curve radii imply gentler curves, which are easier for drivers to navigate. Gentler curves reduce the risk of losing control or misjudging the roadway, leading to fewer crashes.

3. Intersection Skewness

- **Impact on Crash Frequency**: Intersection skewness, or the angle at which roads intersect, also affects crash frequency.
    - **Explanation**: Skewed intersections (those not meeting at right angles) can be more challenging for drivers to navigate, increasing the risk of crashes. Proper alignment and minimizing skewness can enhance visibility and decision-making for drivers, thereby improving safety.

6.0. References

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