Movement-based Safety Performance Functions

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16. **Abstract**
This research project provides NCDOT with a planning-level safety analysis method and tool for estimating crashes at signalized intersections. The method uses Movement-based Safety Performance Functions (MBSPFs) that estimate crashes based on conflict point types and movement based volumes while also considering other traffic control and geometric features present at an intersection. A dataset of 282 signalized, 3 and 4-leg, intersections was utilized from Charlotte, NC. Several model forms were considered with the most promising forms including negative exponential, negative binomial, and Hurdle. Although model forms that used traffic control and geometric variables were more statistically significant, our research team found that simple MBSPFs based on traffic volumes were robust enough when compared to the more data-intensive models including intersection features. Cumulative residual (CURE) plots found showed that, when considering major and minor road AADT, the overwhelming majority of predictions were within the bounds of the 95% confidence interval – the only exceptions were for some volumes on the major road between 10.000 and 20,000 AADT. When testing Highway Safety Manual (HSM) predictions versus MBSPF models, HSM crash predictions were approximately double the root mean square error (RMSE) and mean absolute percentage error (MAPE), indicating that MBSPF was able to predict crashes more accurately. Last, an Excel-based tool was provided as part of the project to assist NCDOT with crash prediction for HSM and MBSPF models. The outputs from this tool related to MBSPFs allow for identification of high risk movements in addition to predicting overall crashes because the predictions are made at the individual conflicts.

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Executive Summary

Alternative Intersections and Interchanges (AIIs) are a fast-growing design solution for locations with complex operational or safety concerns. Previous research funded by NCDOT identified a new family of AII designs composed of Grade-Separated Intersections. This project implemented existing operational analysis for planning level design and alternative analysis and developed a new planning-level safety performance estimation method – Movement-based Safety Performance Functions, or MBSPFs.

MBSPFs make up a planning-level safety analysis method for estimating project-specific crash rates at intersections. The method estimates crashes at individual conflict points comprising an intersection primary influence area and non-conflict point crashes outside that influence area. In addition, MBSPFs utilize individual turning movement volumes of conflicting movements rather than approach level AADT. The methodology showed promising results for both traditional and alternative intersection designs. The research team and StIC of the past project identified a set of improvements for the methodology to include traffic control and geometric features while also recommending further study and validation of the proposed prediction method(s).

A robust dataset of 282, three and four-leg, signalized intersections in Charlotte, North Carolina was utilized for crash modeling. In addition to individual turning movement volumes, several traffic control and geometric elements were collected to help the modeling process. For traffic control, posted speed limit, left turn signalization type, and presence of no right turn on red sign were collected. Geometric elements included the number and type of lanes, the relative angle between movements, lateral offset for left turns, right turn channelization type, and presence of a one-way street and/or proximity to a central business district (CBD).

The model form for MBSPF utilized the traditional conflict point (CP) types noted in the literature – crossing, merge, and diverge – separately. Other crashes not fitting one of the types of CPs were noted as non-conflict point (NCP) crashes. These included crashes such as U-turns, rear-ends, run off road, or any other crash type not easily defined as a CP. Several model forms were tested, with the most promising forms including negative exponential, negative binomial, and Hurdle. Models were tested separately for NCP and each individual CP type using a simplified (volume only) and an expanded version which included traffic control and geometric variables found to be statistically significant. Akaike Information Criterion (AIC) were used to directly compare model fit results across all model forms. In addition to movement based volumes, three variables were found to be significant (with several correlated) – NCP: posted speed limit greater than 35mph and Crossing CP: approach angle and left turn signal protection. Although statistically significant, the additional data collection effort needed for the effort was not deemed worthwhile based on our assessment, with a recommendation to use the simplified model forms for prediction – i.e. NCP AIC of 1652 vs. 1654 and CP_Crossing AIC of 6791 vs. 6959 (expanded vs. simplified, respectively).

Cumulative residual (CURE) plots were plotted to compare the results of the models to the training dataset from the Charlotte intersections (75%). The residuals show when bias may be present in one or more model estimates if the cumulative residual line passes beyond the confidence interval. Based on this effort, CURE plots (95% confidence interval) showed a slight bias in the data at lower volumes between 10,000 and 20,000 AADT. For minor AADT, the data fell within the bounds of the confidence interval in all ranges of AADT.

Next, predicted crashes were plotted for traditional Highway Safety Manual (HSM) and MBSPF methods. A test dataset was utilized from the Charlotte sample (25% set-aside) and 15 additional intersections from Cary, NC which were collected from a previous project. Root mean square error (RMSE) and mean absolute percentage error (MAPE) showed that HSM crash predictions were approximately double the RMSE and MAPE values of MBSPF, indicating that MBSPF was able to predict crashes more accurately.

Last, a planning level, Excel-based, crash prediction tool was provided which implemented the MBSPF and HSM models. Detailed outputs allow for identification of high risk movements with the MBSPF model.

Table of Contents

List of Figures

LIST OF TABLES

Chapter 1 : Introduction

1.1 Background and Motivation

To best understand the concerns of transportation professionals as it pertains to safety, one must first understand how the problem surfaced in the first place. Safety studies using crash data from treatment sites is not a new concept; however, the methods used to conduct these studies have evolved significantly over several decades. These methods have been deployed with great success on many intersection and interchange forms and usually provide insight on safety as it pertains to various crash types and severities for one or more modes. However, safety studies require crash samples over an extended period of time to be able to evaluate the safety of an intersection or treatment. This approach is especially problematic when considering new or innovative intersection concepts that have limited (or even no) crash history from which to draw conclusions. Even more frustrating is the fact that when new intersections are constructed, practitioners must wait at least two-to-three years to determine if the intersection was safe. Lastly, the intersection conversion collision modification factors (CMFs) that are eventually developed often have limited applicability because they do not account for the variation in site conditions.

The most direct evidence of the challenges of evaluating the safety of new intersection types can be seen in FHWA's guidance documents on alternative intersections. The first edition of the *Alternative Intersections and Interchanges Report* (AIIR) covers guidance on a number of topics for a plethora of alternative intersection types (Hughes, et. al, 2010). The major gaps in that guidance document center around understanding safety for motorists and multimodal users – especially intersection and interchange designs that had little-to-no implementations at that time. Beyond a small handful of designs, the safety guidance is relegated to basic conflict analysis. Even when looking at updated, stand-alone guidebooks which are based on several sites actually constructed in practice, the safety findings were often limited in application. This is due to limited sample sizes and sites with varying features and conditions. Thus, it was not possible to drill down to individual features to see where improvements can be made in designs, and no methods are provided to assess the safety for multimodal users.

Recently, the FHWA has adopted a Safe System Approach, or SSA (FHWA, 2022), which among other things, helps mitigate some of the problems in addressing the safety of new intersection types. For roadway systems, SSA means looking at factors contributing to high severity crashes such as speed, relative angle, risk, and even movement complexity. The SSA framework is flexible in the choice of application to measure intersection safety because its goal is reducing relative risk to the driver, pedestrian, or bicyclist.

At this time, a few options exist in the literature that could extend SSA frameworks to intersections for all modes. The two primary conflict-based frameworks that are proposed in the literature are the 1) Safe System for Intersections (SSI) method and 2) Movement-Based Safety Performance Functions (MB-SPF). The SSI method for analyzing intersections uses a ***dimensionless safe system score, or "index"***, based on the presence of various factors describing the intersection conflict points (Dunn, 2022). The SSI method is useful in that it can be applied to any type of intersection and accounts for pedestrians. However, its SSI score only provides an indication of relative crash severity (i.e., it is not crash frequency based), and it is an aggregated score for the intersection. As a result, the SSI score cannot be used to assess individual conflict points to determine where safety problems may be present and warrant safer alternatives. Because of this, SSI is best suited as a screening tool, such as during Stage 1 Intersection Control Evaluation (ICE) or the scoping phase of a project.

The MB-SPF method proposed by this team is based on crash data and computes expected crash frequency.

On the other hand, the MB-SPF method developed by members of our team ***computes expected crash frequency*** based on many factors describing the individual conflict points. The primary differences between this method and the SSI method is that the MB-SPF is crash based (thus aligning with the Highway Safety Manual, or HSM), and it allows for individual conflict-point crash predictions to be calculated (which can support improving pieces of an intersection) – the SSI method and HSM methods do not provide a way to do this currently. This also means that the MB-SPF method could be adopted during the planning, design, and even operation of an intersection. In addition, the MB-SPF framework is easily extended to the evaluation of vehicle-pedestrian and vehicle-bicycle conflicts and to a variety of conventional and unconventional intersection types.

1.2 Research Objectives

This project aimed to document and consider additional factors to include in the data collection and modeling process to better support NCDOT's estimation of planning level safety performance. This will include extensive crash and turning movement analysis to enable analysis of more signalized intersection types and the individual design components present at a particular intersection. The objectives of this research effort are:

- Identify intersection features to be included in an improved MB-SPF model;
- Collect operational and safety data across a broad spectrum of signalized intersection types;
- Develop an improved MB-SPF model allowing for estimation of crashes using planning-level project inputs; and
- Develop MB-SPF spreadsheets for use by NCDOT staff and consultants.

1.3 Organization of the Report

This report is organized as follows. Following this introductory chapter, Chapter 2 covers the pertinent technical literature on the topic of novel approaches to intersection crash risk and prediction methods. Chapter 3 covers the data collection and development of the classified crash database. Chapter 4 provides a discussion on the analysis and modeling methods used. Chapter 5 summarizes the results and performance of the model and recommendations for future use.

Chapter 2 : Literature Review

The HSM relies on the application of CMFs to investigate the expected safety of intersection designs. To develop a CMF, a sufficient number of existing facilities must have been open long enough to capture multiple years of crash data. This requirement for non-typical design elements and intersection types results in a lack of CMFs and therefore, limited ability to apply HSM methods. These limitations motivated researchers to test and establish numerous surrogate safety metrics, and conflict point analysis is one of them. Surrogate measures such as conflict points have also been proposed to assess pedestrian/bicycle safety at intersections due to the rarity and randomness of pedestrian and bicycle crashes.

A conflict point is the meeting of two movement lines through an intersection. For vehicles, these conflict points are categorized as either merging, diverging, or crossing. Crash types like rear-end, head-on, and sideswipe are not related to any conflict point; together, those are referred to as non-conflict point crashes. Tools for counting and modeling conflict points have been used as a planning-level approach to compare the safety of different intersection and treatment designs.

2.1 Summary of Vehicle-Vehicle Conflict-Based Crash Prediction Methods

The rudimentary concept of conflict points at intersections seems simple, but it laid the foundation for assessing the safety of alternative intersections and incorporating other features, for example, traffic operational and geometric characteristics and crash severity, specific to each conflict point (Chase et al., 2020; Lee, 2021; Lee et al., 2022; VDOT, 2022; Dunn ,2022)). Chase et al. (2020) and Lee (2021) proposed a modeling framework that predicts crashes by conflicting points where traffic volumes (AADT-based) of the associated movements are the predictor variables. Our team is endeavoring to improve the model by including different operational and geometric features in the model input data in an ongoing research effort. The generic model form is called the movement-based safety performance function (MB-SPF). The details of the model form are described in Task 3 of the proposal.

The current model form includes traffic volume and conflict type as the primary categorical variables; however, ongoing research (Cunningham, 2023) led by our team is investigating other features such as number of lanes, lane configurations (shared vs. exclusive), the lateral offset between thru and left movements, right-turn on red allowance, presence of turn-bay, relative angle, speed limit, approach curvature, movement-based counts (replacing AADTs), and left turn signal type (i.e. protected, permissive, and protected-permissive movements). Additionally, intersection skew was identified by Harkey (2013) as a potential significant predictor of intersection level crashes..

Like crash frequency, crash severity is also associated with the conflict point type. To factor it in, the Virginia Department of Transportation (VDOT) proposed a weighted conflict-point count, where the weights are determined based on the relative crash costs (VDOT, 2017). The average crash cost was estimated based on the records of crashes with varying severities reported in Virginia between 2011 and 2015. It suggests that the weight ratio for a crossing, merging, and diverging conflict should be 2:1:1. The VDOT Junction Screening Tool (VJuST) was developed to compare the weighted conflict points of different alternative intersection designs.

Dunn et al. (2022) incorporated both exposure, crash severity, and the momentum change associated with crashes through a dimensionless metric called the safe system intersection (SSI) score. At the core of SSI, it utilizes the concept of conflict points. First, two parameters representing traffic exposure and crash severity and two representing movement complexity are combined (Eq. 1). An intersection is ranked between 0 to 100 for each conflict type by scaling the combined parameter E as shown in Eq. 2.

$$(1)\ E_t = \sum_{i=1}^{n_t} [I_{i,t} * P(FSI)_{i,t} * L_{1,i,t} * L_{2,i,t}]$$

$$(2)\ Safe\ System\ Intersection\ score, SSI_t = 100 * \exp\left(-\frac{1}{z} * E_t\right)$$

where:

$I_{i,t}$ = the exposure index for conflict point i of type t ($t \in \{merging, diverging, crossing\}$). It depends on the daily volume of two movements associated with the conflict point;

$P(FSI)$ = the probability of at least one fatality or serious injury resulting from a crash related to the conflict point, estimated based on the conflict angle and the change in momentum for the conflicting vehicles. The second parameter is estimated from the expected operational speed of the movements;

L_1, L_2 = complexity factors. L_1 captures complexity added by the characteristics of conflicting traffic and how much of that complexity is moderated by the traffic control system. L_2 accounts for indirect and counter-intuitive movements that may add complexity for pedestrians and cyclists.

z = a scaling parameter.

Some challenging aspects of such disaggregated models based on conflict points are a) correctly identifying the conflict point associated with a crash, b) crash frequency becoming sporadic due to the categorization of crashes, c) accurately collecting crash severity and traffic operational data, and d) monetizing dimensionless scores.

Regarding the first challenge, past studies developed separate SPFs by crash type to address the limitation of traditional models (Abdel-Aty et al., 2005; Harwood et al., 2000; Persaud & Nguyen, 1998; Wang et al., 2019), but the ambiguity in crash data could lead to imprecise classification (Hauer et al., 1988). Hauer et al. (1988) remarked that crash classification based on vehicle maneuvers is more appropriate. They developed separate models for fifteen crash patterns, but only four yielded statistically significant coefficients. Similarly, Persaud and Nguyen (1998) developed separate models for 25 crash patterns by vehicle streams, but only six yielded statistically significant coefficients. The same issue led Lee et al. (2022) to group merge, diverge, and rear-end crashes into “inbound approach” and “outbound approach” crashes based on the crash locations relative to the intersection.

Regarding the second challenge, both Persaud and Nguyen (1998) and Hauer et al. (1988) stated that many crash patterns yielded very few crashes, so the estimated models showed low reliability when they were modeled separately. The third challenge is critical for MB-SPF and SSI-based approaches since collecting data on features like approach speed, traffic control types, and horizontal and vertical curvature of roads requires astute planning and execution. Knowing these challenges from the literature and addressing them are essential for accomplishing the project goals. To the fourth challenge, predicted safety assessments are often monetized to analyze the benefit-cost ratio of potential improvements. As proposed by the research team, crash-based predictions allow for such monetization as it predicts a quantifiable number of crashes and related severity.

Traditionally, negative exponential or negative binomial models are utilized for crash prediction models (Hauer et al. 1988) which can typically handle the skewed distributions of crashes. Crashes become much rarer with MBSPF definitions, thus additional models were considered to handle the high number of zero crash observations. Hosseinpour et al (2014) present seven model forms including two formulations of the hurdle model which separately models the probability of a zero outcome and the (truncated) count distribution. The hurdle model has been used since in many other safety studies involving frequent zero observations (Yu et al., 2019; Ma et al., 2015; Chen et al., 2016)

2.2 Summary of Vehicle-Multimodal Conflict-Based Crash Prediction Methods

Investigation of conflict-based crash prediction models for pedestrians and bicycles dates to the late twentieth century. An early study by Davis et al. (1989) found promising relationships between pedestrian and vehicle conflicts and developed a reliable model to predict pedestrian crashes. The study intersections were divided into three groups based on high, medium, and low pedestrian crash frequencies. A discriminant equation was developed for each group to estimate pedestrian crashes based on the number of pedestrian and vehicle conflicts, pedestrian volumes, vehicle volumes, and number of lanes. This method is challenging for intersections not yet built, as it is not known to which of the three groups the intersection belongs.

Amini et al. (2022) developed a conflict risk model using video data to evaluate pedestrian conflicts with other road users. Several other studies processed video data using trajectory tracking software to extract and analyze the conflicts between vehicles and pedestrians/bicycles (Darzian et al., 2020; Zhang and Abdel-Aty, 2022, Kittelson et al., 2022). Such approaches are often used as a real-time evaluation to improve traffic safety and may be challenging to use in predicting multimodal crash frequency and severity.

While investigating the relationship between conflict and crashes, El-Basyouny et al. (2013) proposed a two-phase model where a lognormal model is applied in the first phase to predict conflicts using traffic volume, area type (urban/suburban) and some geometric-related variables as covariates. In the second phase, a conflict-based negative binomial (NB) safety performance function (SPF) is employed to predict crashes. The results show that the moderating effects of conflicts on collisions are non-linear with decreasing rates. Although this research is not focused on pedestrian/bicycle crashes, the two-phase model with a conflict-based mentality was adopted in similar research (Sacchi & Sayed, 2015; Sacchi & Sayed, 2016).

Bonneson et al. (2012) calibrated regression models to predict pedestrian-vehicle conflict frequencies. The analysis revealed that conflict frequency is correlated with pedestrian volume, left-turn volume, and other geometry characteristics. The pedestrian and vehicle conflict frequencies were used to obtain the number of pedestrian and vehicle crashes at a site.

Review of previous research on conflict-based pedestrian/bicycle crash prediction methodology revealed that the potential limitation towards prediction of pedestrian and bicycle crashes is the lack of a reliable exposure data to represent the amount of pedestrian and bicyclist activities at a given intersection. Bonneson et al. (2012) utilized regression models to estimate pedestrian volumes based on pedestrian delay, the conflicting vehicle flow rate, and the probability that the WALK indication is presented. A similar concept can be applied to estimate bicycle volumes. In addition, the current research shows a lack of consistency in defining vehicle-pedestrian and vehicle-bicycle conflict point types.

Last, multimodal crashes are rare events, and as such, could make modeling challenging in certain situations. Below describes some of the issues noted in the literature that must be considered when modeling multimodal users.

- **Excess zeros.** Common in pedestrian and bicycle crash data, the presence, in a database, of many sites with zero crashes often results in a crash distribution that is not well-described by the negative binomial distribution. A zero-inflated negative binomial distribution has been found by Shankar et al. (2003) to provide a better statistical fit to crash data. However, it has some theoretical inconsistencies that limit the interpretation of regression coefficients (Lord et al. 2007). Thus, Lord et al. (2007) recommend increasing the time scale (i.e., number of years in the data time-period) or including unobserved heterogeneity terms in the regression analysis (e.g., random parameters). Our team employed these techniques for NCHRP Project 17-70 to develop predictive models for roundabouts, which also have a number of zero crash sites.
- **Data time period**. Increasing the time scale associated with each site is one technique for overcoming the adverse effects of having a large number of sites with no crashes. The time scale is increased by increasing the number of consecutive years in the crash data time period. A generalized estimating equation (GEE) model can be used to control for time trends in the data while allowing for a crash period that is multiple years in duration (Lord and Persaud, 2000). Another challenge related to increasing the data time period is it

increases the possibility that the infrastructure has changed (e.g., turn bay added), so it is important to use historical records and aerial imagery to confirm the sites in the database have not changed.

- **Pedestrian and bicycle exposure.** Including pedestrian and bicycle exposure measures in the predictive model improves its reliability. Using surrogates for pedestrian or bicycle volume (e.g., land use, sidewalk width, bike lane presence) as inputs to a model produces less reliable estimates of average crash frequency. Using crowd-sourced pedestrian and bicycle activity data (e.g., Strava, CycleTracks) in a model has been found to provide more reliable estimates (relative to other surrogates), but the proprietary nature of these activity data will likely limit implementation of the predictive models. Using pedestrian or bicycle volume will likely provide the most reliable model predictions.

Chapter 3 : Data Collection and Extraction

This chapter describes the data collection effort carried out by the research team for developing the safety performance functions. It begins with a discussion of the site selection criteria and a description of the characteristics of the selected sites. Then, it describes the geometric and crash data elements for which the team collected and cleaned field data. Following that, we present a summary of the data elements.

3.1 Identify Study Sites

The choice of a data collection site for any research purpose is strongly governed by what data elements must be observed and data availability. For developing a movement-based safety performance function, the key element related to the response variable is the crash information for each intersection over a three to five years period, with details like movement types of the involved units in each crash. The duration of the study period is important in order to estimate the long-term average crash statistics for each site.

On the predictor variable side, one would need traffic and geometric characteristics, such as, traffic volumes, number of lanes, and lane types for each movement, posted speed limit and relative angle of each approach, and traffic control type for each intersection. Details about these data elements are described later in this chapter. Based on these required data elements, the research team defined a set of criteria for selecting each data collection site:

- Availability of detailed crash, road geometric, and traffic data
- No significant change in the geometric features of the sites during the study period

Based on these criteria, the research team selected 282 signalized intersections in Charlotte, NC as the study sites. This list is a subset of the sites that NCDOT used to test the initial MBSPF models that the research team developed earlier. The advantage was that the list of crashes for each of these intersections was already available—thanks to NCDOT. Several intersections with adjacent stop-controlled driveways, confusing road names, and with significant geometric changes during the study period were removed from the original set. Figure 3-1 shows the location of the selected sites in Charlotte.

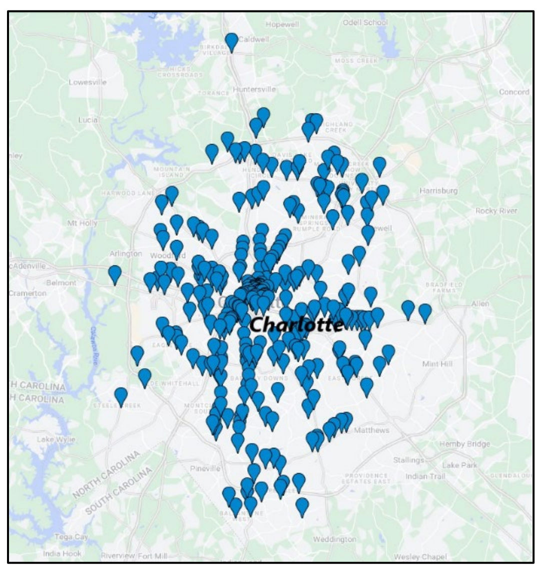


Figure 3-1: Location of the study intersections in Charlotte

3.2 Data Elements

In the proposed model forms, the response variable is the crash frequency by conflict point types and the predictors are various geometric and traffic parameters by intersections, approaches, or movements. The following subsections describe each, starting with the response variable. Each data element was identified using a combination of crash reports, Google Earth and NCDOT-provided datasets. Details on the methods for conflict point classification and the relative angle between movements is located in Appendix A.

3.2.1 Crash Frequency by Conflict Points

The MB-SPF consists of two independent model forms: the conflict point safety performance function (CP-SPF) and non-conflict point safety performance function (NCP-SPF). The CP-SPF estimates the CP crash frequency at the CP-level. **The CP crashes are ones that occur between two conflicting movements at a CP**. The form under this category is subdivided into three parts based on FHWA's (Rodegerdts et al., 2004) classification of intersection conflict points: crossing, merging, and diverging. Figure 3-2 shows conflict point diagrams for a conventional four-legged intersection.

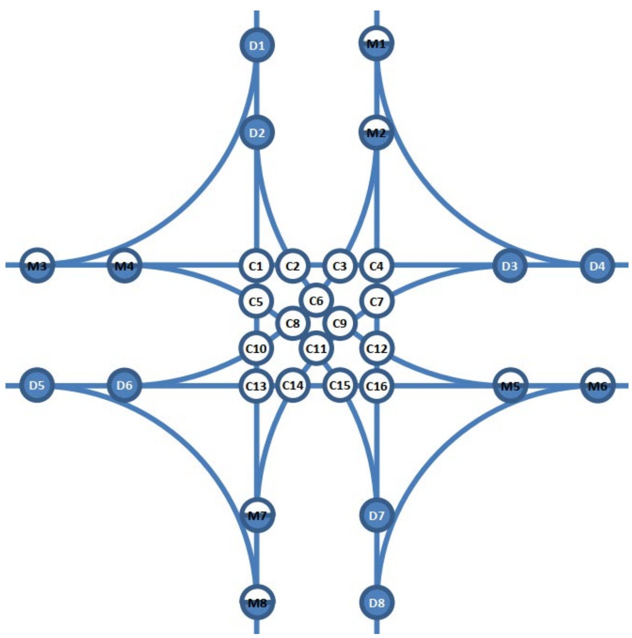


Figure 3-2: Conflict point diagram for a conventional four-legged intersection (Rodegerdts et al., 2004)

The NCP crashes are those not associated with conflicting movements at the intersection. They include but are not limited to rear-end, sideswipe, head-on, and single-vehicle crashes. Rear end crashes are considered NCP despite many instances being associated with conflict points due to the difficulty of assigning which conflict point may have contributed to the rear end collision. For instance, a vehicle intending to diverge stopped cautiously, creating a queue, and a vehicle failed to notice the queue, causing the rear end. The officer will note the presence of the queue in the report, but fail to state what causes it. Similarly, the queue may have been the result of cycle failure, where even vehicles with different destinationshave not yet reached the actual conflict point. Hence, the team felt confident assigning rear ends collisions to the NCP category if conflict-point related information was not present.

Considering that many intersection crashes are not associated with a conflict point, the separate modeling of NCP crashes from the rest seems an appropriate approach for quantitative evaluation of intersection safety performance.

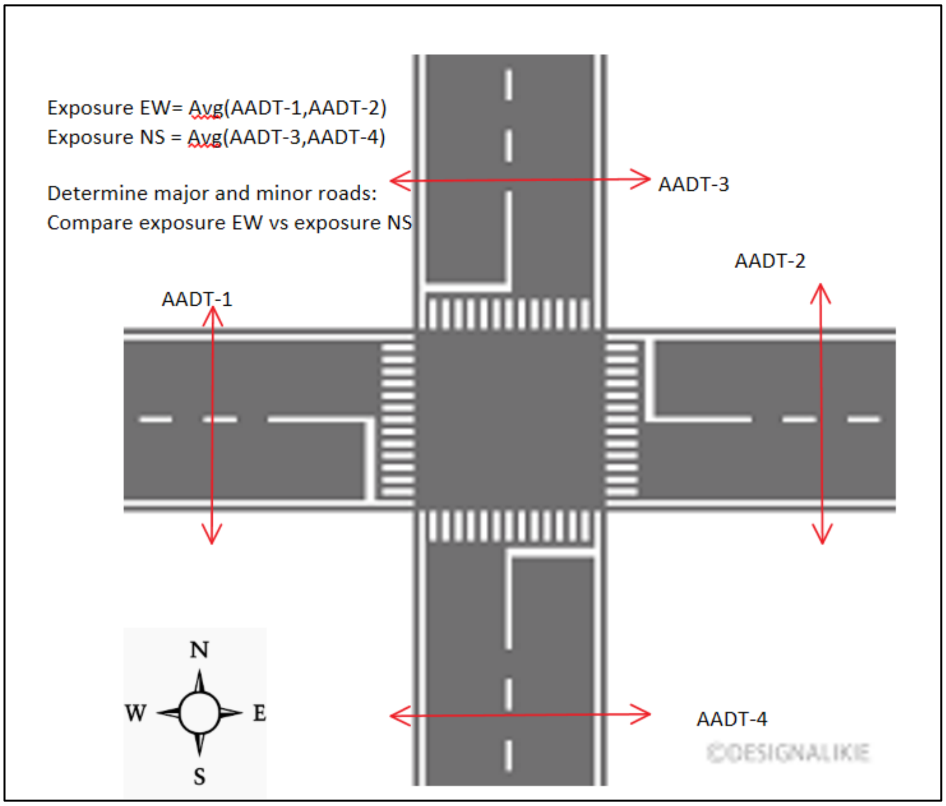
The team obtained detailed reports of all crashes that occurred between January 2015 to December 2019 for 282 signalized intersections in Charlotte, North Carolina. Each crash was assigned to an intersection if it occurred within 150' from any approach of the intersection. The team put an extensive effort to cross-check the data and to identify the conflict point type of each crash by reviewing the police report. In total, the team reviewed more than 18,000 crash reports, identified the correct directions of travel of the entities involved in a crash for about 6,000 crashes, and went through a multi-level cross checking of the work. A detailed description of the effort is presented in Appendix A.

Since pedestrian and bicycle crashes are typically modeled separately from vehicular crashes, the team removed any crash that involved such entities. Also, the team removed the following categories because either the vehicles' maneuver was complex or factors outside the intersection likely played a role: crashes involving U-turning or parked vehicles and at intersections where there is a driveway within 150' of any approach.

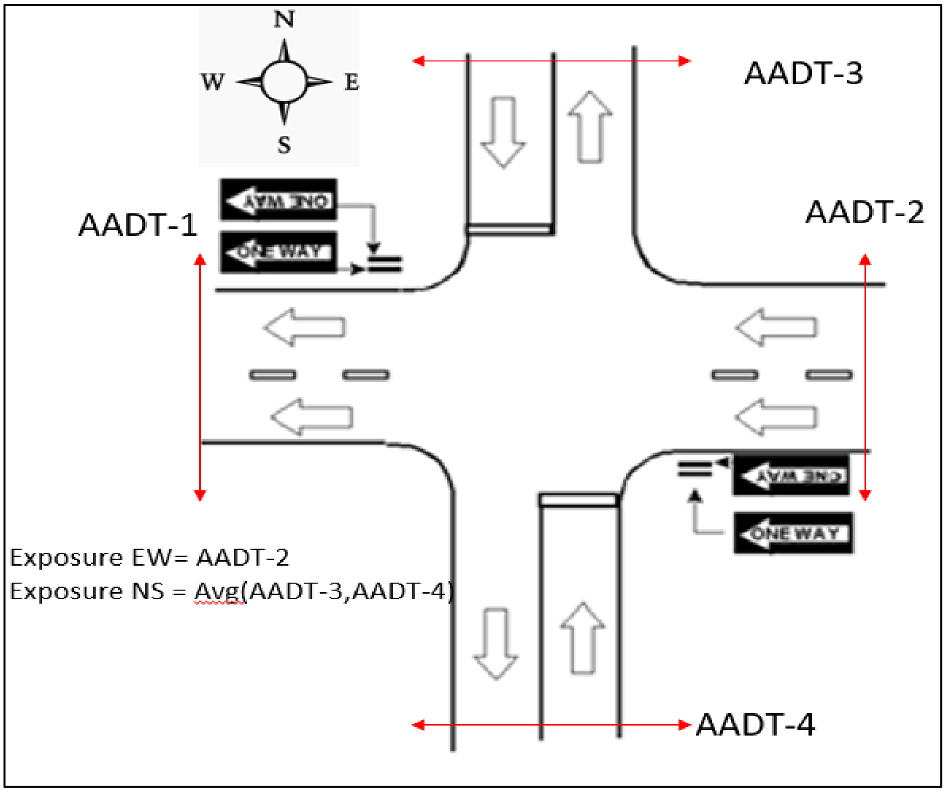
3.2.2 Movement-based Volume

Traffic volume represents the exposure of traffic to crashes. The main data here are the AADT information for each road at an intersection. For non-conflict point crashes, the total entering traffic per day from each of the two intersecting roads are used as the predictor variable for exposure. Hence, we have two exposure variables: one for the major and another for the minor direction. The major and minor directions are determined based on AADTs. Since AADT for a leg is reported for the total bidirectional traffic, the average AADT of the opposing legs are used to estimate the exposure from that direction. Figure 3-2(a) shows a typical four-legged intersection with two-way streets on all legs, along with the equation to estimate exposures and how to determine major and minor directions. The same equation would apply for T-intersections if the AADT for the missing leg is set to zero. For intersections with one-way streets, however, it would be different—the AADT on the entry leg should be used to estimate the exposure on the one-way direction instead of averaging it with the exit leg AADT. Figure 3-2(b) illustrates it with an example. NCDOT provided the AADT data to the research team which we verified later with the NCDOT AADT web-based map (NCDOT, 2023).

For conflict-point crashes, the exposure variable requires more fine-grained data than AADT. The movement-specific volumes are estimated from the AADT and turning movement percentages for each movement. For example, for the crossing conflict between the northbound and eastbound thru movements, the estimated volumes for them are used as the predictor variables representing the exposure to the conflict point. Similar to non-conflict point crashes, the higher of the two is regarded as the major volume. Note that for merge and diverge crashes, determining the exposure is more complex than for crossing and NCP crashes because the actual merge and diverge points of crashes may vary significantly. A detailed explanation of that process is provided in Chapter 4.



(a)



(b)

Figure 3-3: Estimating exposures from AADTs

3.2.3 Number and Type of Lanes

This variable is used for conflict point crash models only. We used satellite images from Google Earth to get the number and lane type for each movement. The movements are classified into two groups—one with exclusive lanes only and another when one or more lanes are shared with another movement.

3.2.4 Posted Speed Limit

Posted speed limit data for each leg were collected from NCDOT's speed limit web-based map (NCDOT, 2023) and from Google Street view (when needed). The posted speed limit informs the estimation of the relative speed drivers are moving with respect to each other at each conflict point. For example, if the North-South approach has a posted speed limit of 55 mph, and the East West approach as a posted speed limit of 25 mph, then at conflict point C4 (from figure 3-2), the conflicting vehicles are travelling with a difference of around 30 mph.

3.2.5 Relative Angle between Movements

The heading (i.e., the angle with respect to the compass North) of each leg at an intersection was measured using Google Earth's Ruler tool. The relative angle between a pair of movements was estimated from that. For diverge conflict, the movement pairs are always on the same approach, so the relative angle is always zero. Hence, this predictor is used only for the other two conflict-point crashes.

For crossing and merge conflicts at an intersection where all the legs are cardinally aligned (i.e., aligned either with the compass N-S or E-W), the angle between the conflicting movement pairs will be 90 degrees. If this angle is less than 75 degrees, it is considered as acute whereas angle greater than 105 degrees is considered as obtuse. The angle is always measured on the outgoing side of both arrows as shown in Figure 3-4.

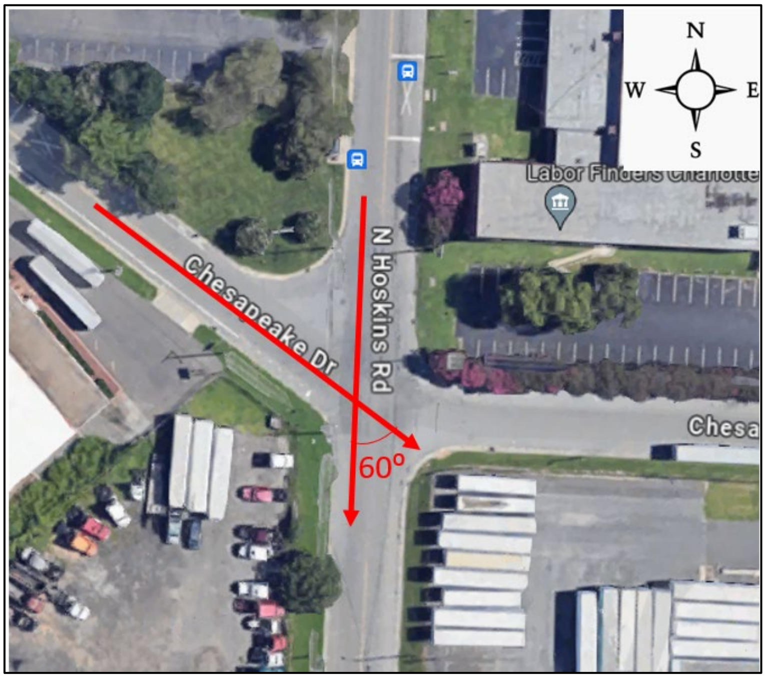


Figure 3-4: Relative angle between movements

3.2.6 Traffic Control Type for Left-turns

The traffic control type for left-turn movements is of three types: protected, permitted, and protected-permitted. If the signal head is found to have three sections (from Google Street view), the presence of arrow or ball indicates whether it is a protected or permissive movement. For a four-section or dog-house signal, we classified them as the third type but it is difficult to know the exact control type; it can be either protected or permissive or their combination. This is useful for crossing conflicts, specifically the points which involve through and right turn movements conflicting with left turn movements.

Table 3-1: Determining traffic control type for left-turns from signal heads

Three-section head		Four-section head (**Protected/ Permissive**)	Doghouse (**Protected/Permissive**)
Green/yellow ball **(Permissive)**	Green/red/yellow arrow (**Protected**)		

3.2.7 Lateral Offset for Left-turns

This predictor represents how difficult (or easy) it is for left-turns with permissive or protected-permissive control to see the opposing thru traffic. It is one of the factors that affects the sight-distance for left-turn traffic—other factors like the vertical and horizontal curvature are difficult to collect field data on and hence, not included here.

The lateral offset can take one of the three levels: positive, negative, and base. If the subject vehicle's lane (see the red vehicle in Figure 3-5) is pushed inward toward the opposing thru, it would have a clear view of the oncoming traffic. In that case, the left edge of the lane (the red line in Figure 3-4) will be toward the opposing thru traffic with respect to the extended right edge of the opposing left-lane (the green line in Figure 3-5). This is a positive offset. On the contrary, if the subject vehicle's lane is laterally away from the opposing thru, it would have a less clear view of the opposing thru traffic and have a negative offset. If the distance between the green and red lines shown in Figure 3-5 is less than 3 ft, the offset is considered as zero or at base level.

Just as with the previous variable, this is useful for crossing conflicts, specifically with through movements conflicting with left turn movements.

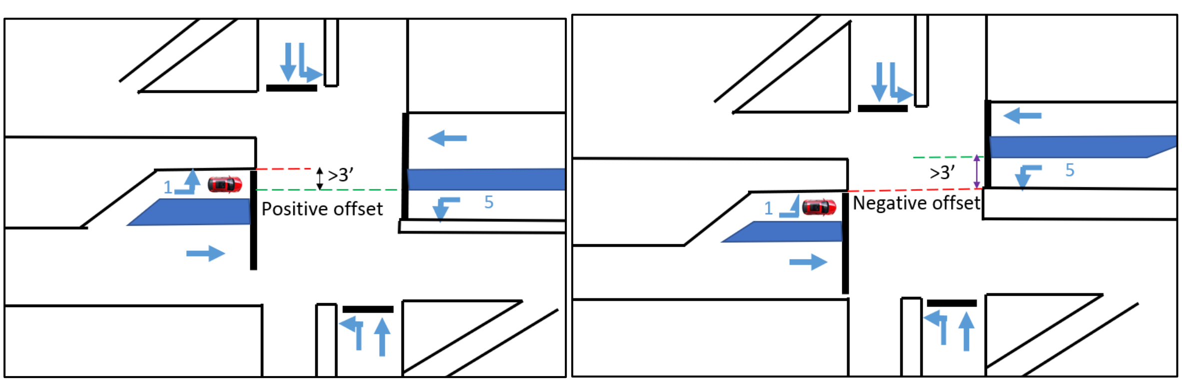


Figure 3-5: Lateral offset for permissive and protected-permissive left-turns

3.2.8 Right-turn Channel Type

There predictor can take one of the three values: no channel, channel with free-flow acceleration lane, and channel with no acceleration lane. Figure 3-6 shows the two types of channels commonly used for right-turn treatments. This and the following predictor are used for merge conflicts involving right-turns.

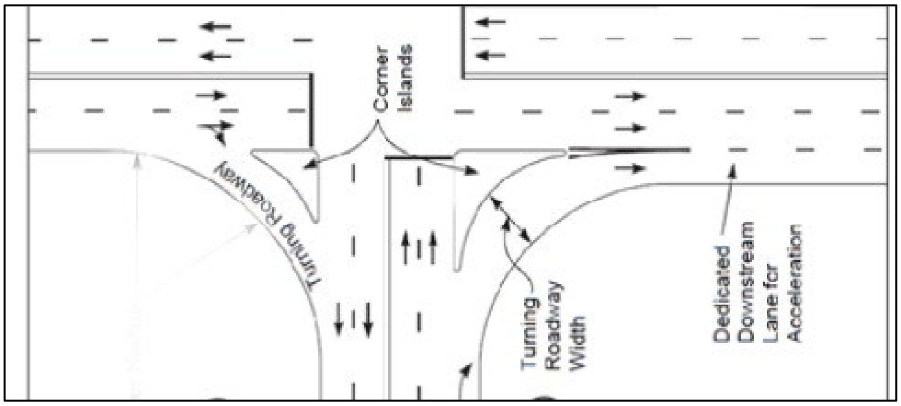


Figure 3-6: Right-turn channelization types

3.2.9 No Right-turn on Red Sign

This predictor represents whether a right-turn on red is allowed or not. We used Google Street view to find signs like the ones listed in Figure 3-7. This is useful for both merge and diverging conflict point types.

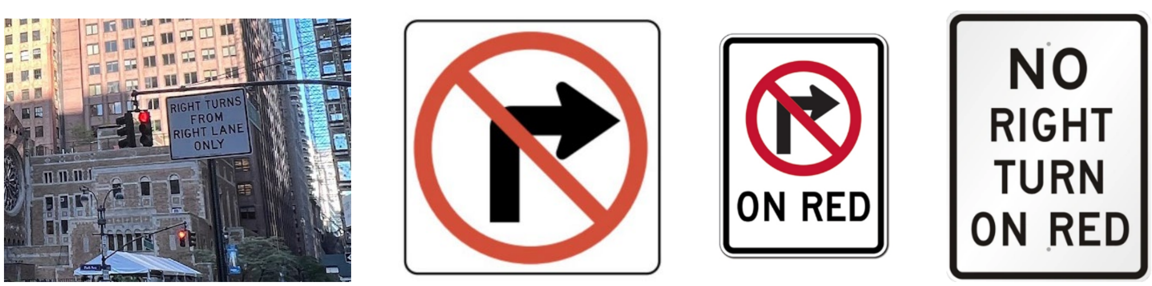


Figure 3-7: Different types of mandatory signs for right-turning traffic

3.2.10 Presence of One-way Street and Proximity to CBD

Initially, the team categorized the intersections based on whether any approach is a one-way street or not. Later, the team found that most of the sites with a one-way approach are location within the CBD of Charlotte, as shown in Figure 3-8. Because the sites in the CBD have several unique characteristics like narrow lanes and high density of driveways and on-street parking which prompt increased in-and-out traffic, a new variable is defined based on this factor. The roads shown by the callouts in Figure 3-8 create the periphery of the CBD we defined here. Note that among the study sites, there is only one intersection with a one-way street that is located outside of this CBD. At the end, we fed both variables in the modeling approach and let the process determine (more about the modeling and variable selection process are described in Chapter 4). This was specifically useful with non-conflict point crashes.

Figure 3-8: Study sites with and without one-way approaches in Charlotte CBD

3.3 Generate the Fused Database

Following the collection and cleaning of all the data described above, we developed four databases to feed in the modeling process. One for the NCP crash model and the rest for the three CP crash models.

In the NCP database, each data point (i.e., each row) is for a particular intersection. Therefore, the total number of data points in it is 282. The response variable is the total NCP crash frequency for an intersection over the study period. The database contains the following items as potential independent variables: entering volumes from the major and minor street per day, posted speed limit, presence of one-way street/CBD proximity.

In the crossing-conflict point database, each data point is for a crossing conflict point. For example, for a typical four-legged intersection, there would be 16 data points. Similarly, in the merge and diverge-conflict point databases, a typical four-legged intersection would have eight data points in each. Table 3-2 shows which independent variable is considered as a potential predictor for which models.

3.4 Discussion of Included and Excluded Crashes

Not all crash types were included in the dataset, or were assigned to NCP by default. For instance, U-Turn movements were assigned NCP as they didn't fit one of the traditional 32 conflict points. Additionally, crashes that involved more than two vehicles were assigned NCP if the originating collision could not be identified, as assigning the crash to a specific conflict point was very difficult and inconsistent depending on the narrative. Additionally, incidents that involved pedestrians, scooters, or bicycles as the second vehicle were also excluded as this also would eschew classification into traditional conflict points. Lastly, drivers who used the incorrect lane for their desired movement or traveled into opposing lanes were also categorized NCP, as this also is not a recognized conflict point.

Crashes that were included but required some additional data cleaning included crashes where the crash report diagram was misaligned. Team members used the narrative as well as satellite imagery to determine the correct alignment of vehicles.

3.5 Summary of the Variables

Table 3-2 below lists the predictors described above and their distribution in the database. Levels with few responses may be grouped together for modeling purposes.

Table 3-2: Database Variables

Predictor name	Type	Distribution	Potential use in model(s)
1. Movement-based volume	Numerical	-	All
2. Number of lanes by movement	Numerical	-	Crossing, merge, and diverge
3. Type of lane by movement	Categorical	i. All exclusive: 50% ii. All shared: 39% iii. Mix of shared/exclusive: 11%	Crossing, merge, and diverge
4. Posted speed limit	Numerical	-	All
5. Relative angle between two crossing movements	Categorical	i. Base: 81% ii. Acute: 9% iii. Obtuse: 10%	Crossing and merge
6. Left-turn control type	Categorical	i. Protected: 42% ii. Permissive: 34% iii. Protected-permissive: 24%	Crossing and merge
7. Left-turn lateral offset	Categorical	i. Base: 35% ii. Positive: 21% iii. Negative: 44%	Crossing
8. Right-turn channelized?	Categorical	i. Yes: 5% ii. No: 95%	Merge and diverge

9. Right-turn on red allowed?	Categorical	i. Yes: 99% ii. No: 1%	Merge and diverge
10. Presence of one or more one-way street	Categorical	i. Yes: 9% ii. No: 91%	Non-conflict point
11. Intersection within CBD	Categorical	i. Yes: 12% ii. No: 88%	Non-conflict point

Chapter 4 Methodology

This section presents the methodological details of the proposed safety performance function. It begins with identifying the possible data sources for the predictor variables of the model because these data must be collected or estimated in an appropriate fashion for applying the model. Then the model development and testing procedures are explained. Finally, the performance measures and limitations of the model are described. Following that, the modeling process is presented for each category of crashes predicted.

4.1 Conflicting Movement Volumes for Merge and Diverge Conflicts

In the previous chapter, we showed how we collected the data for different elements of the proposed models and how the variables are defined. While those discussions are sufficient for Chapter 3, the modeling process requires a clear delineation of how the conflict points are defined, particularly the merge and diverge conflicts. This is because the sequence of merging or diverging of thru, left-turning, and right-turning vehicles can vary across crashes.

For merge conflicts, while most predictors remain unchanged, the exposure to traffic (i.e., the conflicting movement volumes) varies based on this sequence. To further illustrate, consider Figure 4-1, which we borrowed from Figure 3-1 and zoomed in on merge conflict points M5 and M6. The eastbound thru (EBT) movement first merges with southbound left (SBL) at M5, then their combined volume merges with northbound right (NBR) at M6. Hence, the pair of conflicting movement volumes (CMVs) are CMV_{EBT} and CMV_{SBL} for M5. For M6, they are $CMV_{EBT+SBL}$ and CMV_{NBR}. Upon investigating different intersection geometry, the team decided that this sequence is prevalent if i) the right turn (in this example, NBR) is channelized AND ii) the thru movement has only one lane.

When there are multiple thru lanes, such as in Figure 4-2, the left-turn and right-turn merge with the thru movement separately. The CMVs in that case would be: $CMV_{EBT/2}$ and CMV_{SBL} for M5 and $CMV_{EBT/2}$ and CMV_{NBR}.

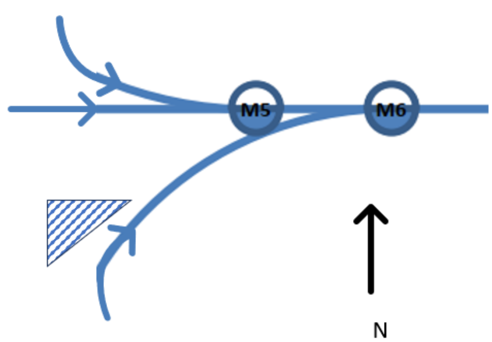


Figure 4-1: Merge condition where left turn volumes may conflict with right

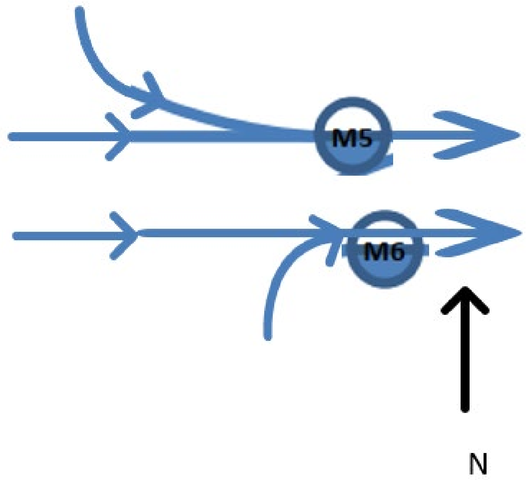


Figure 4-2: Merge condition where left turn volumes do not conflict with right

Diverge conflicting volumes can be similarly defined, with the primary consideration of including turning movement traffic that hasn't separated with the through traffic such as when turn bays open much earlier for left turns. Separation of turning movement traffic does not happen for certain lane configurations like shared LTR lane approaches.

4.2 Model Formulations and Limitations

Several models were formulated to describe the effect of volume and geometric variables on incident rates. The models were broken down into several categories, Non-Conflict Point, Crossing Conflict Point, Diverge Conflict Point, and Merge Conflict point. Details of each are in the following sections. The data used is at the conflict point level, that is, one point on the conflict diagrams above, unless otherwise noted. Three primary model formulations were attempted for each of the categories: Negative Exponential, Negative Binomial, and Hurdle. A ***Negative Exponential*** model is often used for crash modeling which is based on the Poisson distribution and assumes that the probability of observing a specific number of crashes Y in a given period follows a Poisson distribution with a constant rate parameter λ that can be estimated using regression coefficients. The crash frequency is then predicted using:

$$P(Y = k) = \frac{e^{-k}\lambda^k}{k!}, \text{ for } k\text{=0,1,2,…}$$

The negative exponential model assumes that the probability of a crash occurring at any given location is independent of other observations. If the true relationship between predictors and crash frequency is nonlinear after transformation, the linear model assumption may lead to misspecification and biased estimates. The negative exponential model does not account for overdispersion, which can result in underestimation of uncertainty and incorrect inference.

In the ***Negative Binomial*** model, the probability of success p (i.e., the probability of a single crash) can be modeled using multiple predictor variables through regression. The formulation becomes:

$$\text{logit}(p)=X\beta,$$

where X represents the matrix of predictor variables with dimensions n×m, β represents the vector of regression coefficients with dimensions m×1, and logit(p) is the log-odds of success. Additionally, the shape parameter r governing overdispersion remains constant and is typically estimated separately. To predict crash frequency, we use the negative binomial distribution:

$$P(Y=k)=\binom{k+r-1}{k}p^k(1-p)^r, \text{ for } k=0,1,2,\ldots$$

The model accounts for overdispersion, allowing the variance to exceed the mean, which is particularly useful when incorporating regression to model complex relationships. Interpreting the coefficients in the negative binomial model, particularly in the presence of overdispersion, can be challenging and may require careful consideration of model assumptions and diagnostics.

The ***Hurdle*** model attempts to address the high frequency of zero observations which can occur in crash data. The hurdle model assumes that the process governing crash occurrence can be divided into two parts: the probability of observing at least one crash and the conditional distribution of crash counts given that at least one crash has occurred, both modeled through regression. The formulation used for this research utilized a logit model for the hurdle component and a negative binomial model for the count component.

The two-part nature of the hurdle model, combined with regression, can make interpretation of results challenging, particularly for non-specialist audiences. The hurdle model's performance may be sensitive to the choice of distributional form for both parts and the specification of regression parameters, potentially leading to biased estimates if misspecified. The research team tested a number of formulations of the hurdle prior to the final selected models.

Final selection of the models was performed comparing the Akaike Information Criterion (AIC) which measures model fit and can be directly compared across all the model forms tested. Lower AIC indicates better model fit, however this comparison is only valid for a given dataset and, as an example, wouldn’t be appropriate to compare NCP vs CP models. Adjusted R squared is shown where possible for Poisson or negative binomial models which accounts for the number of explanatory variables used in addition to the model fit.

Finally, the crash dataset included 5 years of crashes summed up for each observation. In order to account for this, the number of years is used as an offset variable so that the final prediction is in units of crashes per year. For negative binomial models, this offset is added into the constant but for the Hurdle it must be re-specified in the prediction. This dataset was split into a 75% training dataset and 25% test dataset.

4.2.1 Non-Conflict Point Model

The Non-Conflict Point (NCP) model started with a basic approach with only the volume predictors using the following form. This method was also used previously in the original research that developed the MBSPF concept (Chase et al., 2020). The overall AIC for this model was 1654 and adjusted R squared of 0.6492.

$$Total\ NCP\ Crashes = e^{\beta_0+\beta_1*\log(major\ vol)+\beta_2*\log(minor\ vol)}$$

Further explanatory variables were added where they were found to be statistically significant at $p<0.05$. Initially, the model was tested with whether a one-way street was present. After further analysis, it was found that this was highly correlated with whether the site was in the CBD, however after removing insignificant predictors, the only feature included was whether all approaches were posted above 35mph. As a result, the final model was of the form:

$$Total\ NCP\ Crashes = e^{\beta_0+\beta_1*\log(major\ vol)+\beta_2*\log(minor\ vol)+\beta_3*Over35}$$

with the final variables being 1 if the condition is true, and 0 otherwise. This model has an adjusted R squared of 0.6555 and an AIC of 1652. This is the best performing model, and further model forms were not necessary due to the lack of frequent zeroes in the NCP dataset.

4.2.2 Crossing Conflict Point Model

This model began with the same basic form as the NCP model. Unfortunately, it had poor predictive power with an adjusted r-squared of 0.2297 and an AIC of 6959. Review of the response variable indicated frequent 0 observations which are likely affecting model fit.

The Hurdle model was attempted due to the frequency of zero observations found in the crossing CP dataset. In defining the model form, explanatory variables can be used for either the zero hurdle model portion, the count model, or both. Out of all the potential explanatory variables, "control" and "approach angle" were found to be significant, where Control is a categorical variable referring to whether or not the left turn is protected, permitted, or both which was significant in only the count model and Approach Angle is a binary variable that is true when the intersecting angle of the two approaches are at least 15 degrees further than the expected angle (90 or 180 depending on movement combination) which was significant in both models. Below is the model form which had an AIC of 6791, indicating that the model performance was more related to the data itself rather than a poorly developed model.

Zero hurdle (Poisson):

$$Non-zero\ CP\ Crashes \sim \beta_0 + \beta_1 \ln(major\ CMV) + \beta_2 \ln(minor\ CMV) + \beta_3 Approach\_Angle$$

Count model (negative binomial):

$$CP\ Crashes \sim \beta_0 + \beta_1 \ln(major\ CMV) + \beta_2 \ln(minor\ CMV) + \beta_3 Approach\_Angle + \beta_4 control$$

4.2.3 Diverge Conflict Point Model

The same procedure was used for Diverge crashes as crossing, with the volume-only negative binomial model resulting in adjusted R squared of 0.08993 and AIC of 1453. While all explanatory variables were significant, the low adjusted R squared indicates overall poor fit. This is to be expected with the extremely low counts for this category, as there were only 405 total Diverge crashes.

Modeling additional explanatory variables yielded no significant predictors in either model type, and even the volume only hurdle model struggled to improve the fit. The hurdle model resulted in only significant explanatory variables in the zero hurdle portion of the model and no significance in the count model, and a marginal improvement in AIC of 1450. Due to the marginal improvement in fit and lack of significance, hurdle results were not used for further analysis.

4.2.4 Merge Conflict Point Model

The negative binomial volume-only model for Merge crashes performed slightly better than the Diverge model. Overall, the model had an adjusted R squared of 0.14047 and an AIC of 2431. While still a low adjusted R squared, the model was fit on a total of 921 crashes as compared to the diverge.

Similar to the Diverge model, no explanatory variables could be added with statistical significance, and utilizing the hurdle model showed slight improvements. The Merge Hurdle model resulted in an AIC of 2414. Due to the marginal improvement in fit and lack of significance, hurdle results were not used for further analysis.

Chapter 5 : Results and Recommendations

5.1 Modeling Results

Two groups of models were selected for final comparison to consider the practical impacts of added predictors. Group 1 is composed of four best fit models including all geometric features identified as statistically significant, with one model for NCP crashes and a conflict point model for each of the three (crossing, merge, and diverge) conflict point types. Group 2 also has four total models but only includes the movement demands as predictors.

In each of the selected models for each group, the negative binomial model form or hurdle with a negative binomial count model was found to perform best, and as such the parameter estimates can be interpreted with the positive estimates indicating an increase in crashes with the parameter increasing and vice versa. For Group 1, the NCP model shown in Table 5-1 found that all approach speeds being under 35 mph reduced total crashes if volumes were held constant. Both the Group 1 and Group 2 models in Table 5-2 had increased volumes resulting in more crashes.

To compare models, AIC, or Akaike's Information Criterion, is used. AIC is a measure for comparing model performance among differing models using the same dataset. It is calculated based upon the number of predictors the model has as well as the maximum likelihood estimation of the model. There is no "magic" AIC value, but in general, lower AIC values are preferable.

Table 5-1: NCP Full Group 1 Model (Negative Binomial) – Total Crashes

Variable	Estimate	P Value
Intercept	-11.4529	<0.01
log(MajorVol)	0.86102	<0.01
log(MinorVol)	0.50789	<0.01
Max PSL > 35 mph	0.16251	<0.05

AIC = 1652, N = 211

Table 5-2: NCP Simplified Group 2 Model (Negative Binomial) – Total Crashes

Variables	Estimate	P Value
Intercept	-12.25	<0.01
log(MajorVol)	0.93737	<0.01
log(MinorVol)	0.52196	<0.01

AIC = 1654, N = 211

The Group 1 crossing conflict point model in Table 5-3 included one geometric and one control type variable as significant predictors in addition to movement volumes. Noted earlier, the approach angle indicator indicates that the two conflicting movements are at least 15 degrees (in either direction) off of the expected 90 degree or 180 degree angles on their approaches. Fewer crossing conflict crashes are predicted in both the zero hurdle and count portions of the model when approach angle is true, which could be due to additional attention drivers give to these movements with irregular approach angles. “Not all Protected” indicates that at least one of the movements contains permitted or protected/permitted control. This variable was only significant in the count portion of the hurdle, where it indicated more crashes when at least one movement was permitted or protected/permitted. The Group 1 and Group 2 models in Table 5-4 predicted more crashes as volumes increased.

Table 5-3: Crossing Full Group 1 Model – Total Crashes

Count Model		
Variable	**Estimate**	**P Value**
Intercept	-7.1495	<0.01
log(higher vol)	0.30582	<0.01
log(lower vol)	0.37669	<0.01
Approach Angle is True	-0.92466	<0.01
Not all Protected	0.51311	<0.01
Zero Hurdle Model		
Variable	**Estimate**	**P Value**
Intercept	-10.3319	<0.01
log(higher vol)	0.73283	<0.01
log(lower vol)	0.36676	<0.01
Approach Angle is True	-0.45293	<0.01

AIC = 6791, N = 2665

Table 5-4: Crossing Simplified Group 2 Model – Total Crashes

Variable	Estimate	P Value
Intercept	-8.8639	<0.01
log(CMV higher vol)	0.58038	<0.01
log(CMV lower vol)	0.35987	<0.01

AIC = 6959, N = 2665

For diverge and merge, the recommended models for Group 1 and 2 were the simplified forms only due to the very marginal AIC improvements and the high number of insignificant volume explanatory variables in the detailed hurdle models. Table 5-5 and Table 5-6 predicted more crashes as volumes increased, with slight differences where the parameter estimates for the higher volume movement are greater in the merge model compared to the diverge model where the lower volume movement has a greater parameter estimate.

Table 5-5: Diverge Simplified Group 2 Model – Total Crashes

Variable	Estimate	P Value
Intercept	-8.3855	<0.01
log(CMV higher vol)	0.32842	<0.01
log(CMV lower vol)	0.34888	<0.01

AIC = 1453, N = 1392

Table 5-6: Merge Simplified Group 2 Model – Total Crashes

Variable	Estimate	P Value
Intercept	-7.3265	<0.01
log(CMV higher vol)	0.34698	<0.01
log(CMV lower vol)	0.30371	<0.01

AIC = 2431, N = 1383

Table 5-7 through **Table 5-12** show the model results when predicting Fatal/Injury and PDO crashes separately. Overall, NCP and Crossing model results are similar to the total crash models, aside from the addition of "In CBD" to the NCP Full PDO model, where there are more PDO crashes within the CBD all else equal. However the sample size results in lower P values for Merge and Diverge models, with only the F/I Diverge model having a statistically insignificant predictor (highlighted red).

Table 5-7: NCP Full Group 1 Model (Negative Binomial) – Fatal/Injury and PDO Crashes

	Fatal/Injury		PDO	
Variable	Estimate	P Value	Estimate	P Value
Intercept	-11.4529	<0.01	-12.9832	<0.01
log(MajorVol)	0.86102	<0.01	0.97716	<0.01
log(MinorVol)	0.50789	<0.01	0.51099	<0.01
Max PSL > 35 mph	0.16251	<0.05	0.37950	<0.01
In CBD	--	--	0.17126	<0.05

AIC = 1164 | 1539, N = 211

Table 5-8: NCP Simplified Group 2 Model (Negative Binomial) – Fatal/Injury and PDO Crashes

	Fatal/Injury		PDO	
Variables	Estimate	P Value	Estimate	P Value
Intercept	-13.7709	<0.01	-12.5122	<0.01
log(MajorVol)	0.97368	<0.01	0.92423	<0.01
log(MinorVol)	0.49720	<0.01	0.53354	<0.01

AIC = 1172 | 1545, N = 211

Table 5-9: Crossing Full Group 1 Model – Fatal/Injury and PDO Crashes

Count Model				
	Fatal/Injury		PDO	
Variable	Estimate	P Value	Estimate	P Value
Intercept	-7.26278	<0.01	-6.75981	<0.01
log(higher vol)	0.35432	<0.01	0.19764	<0.05
log(lower vol)	0.39995	<0.01	0.37695	<0.01
Approach Angle is True	-1.02185	<0.01	-1.02481	<0.01
Not all Protected	0.49623	<0.01	0.45817	<0.01
Zero Hurdle Model				
	Fatal/Injury		PDO	
Variable	Estimate	P Value	Estimate	P Value

Intercept	-10.8126	<0.01	-9.64337	<0.01
log(higher vol)	0.70315	<0.01	0.60203	<0.01
log(lower vol)	0.36388	<0.01	0.34004	<0.01
Approach Angle is True	-0.38555	<0.01	-0.59968	<0.01

AIC = 4685 | 4893, N = 2665

Table 5-10: Crossing Simplified Group 2 Model – Fatal/Injury and PDO Crashes

	Fatal/Injury		PDO	
Variable	**Estimate**	**P Value**	**Estimate**	**P Value**
Intercept	-10.1449	<0.01	-8.93961	<0.01
log(CMV higher vol)	0.63575	<0.01	0.51771	<0.01
log(CMV lower vol)	0.37116	<0.01	0.35321	<0.01

AIC = 4767 | 4981, N = 2665

Table 5-11: Diverge Simplified Group 2 Model – Fatal/Injury and PDO Crashes

	Fatal/Injury		PDO	
Variable	**Estimate**	**P Value**	**Estimate**	**P Value**
Intercept	-9.39924	<0.01	-8.73796	<0.01
log(CMV higher vol)	0.2819	0.1201	0.33622	<0.01
log(CMV lower vol)	0.3123	<0.05	0.35978	<0.01

AIC = 442 | 1267, N = 1392

Table 5-12: Merge Simplified Group 2 Model – Fatal/Injury and PDO Crashes

	Fatal/Injury		PDO	
Variable	**Estimate**	**P Value**	**Estimate**	**P Value**
Intercept	-9.38636	<0.01	-7.54544	<0.01
log(CMV higher vol)	0.51276	<0.01	0.30230	<0.01
log(CMV lower vol)	0.17908	<0.05	0.35373	<0.01

AIC = 953 | 2084, N = 1383

Based on the marginal benefits of each of the detailed models, ***the research team recommends utilizing the simplified models due to the reduced data burden and easier implementation***. In addition, ***the team recommends utilizing the F/I and PDO models for implementation*** with the sum of these two used as the total estimate as this is not guaranteed to be equal to the total crash model estimates. Ideally, further data collection including other states and more intersection and control types can support a more robust group of models.

5.2 Sample Model Calculations

Intersection-level crash frequencies at traditional four approach signalized intersections are estimated using a total of 33 model outputs- one NCP, sixteen crossing CP, eight diverge CP and eight merge CP. An example implementation of the F/I model types is shown below for each of the model forms:

NCP: Major – 21800, Minor – 16000

$$F/I_{NCP} = e^{-13.7709+0.97368*\ln(21800)+0.4972*\ln(16000)} = 2.1574$$

Crossing CP 1: EBT – 3676, SBT – 6911

$$F/I_{Cross1} = e^{-10.1449+0.63575*\ln(6911)+0.37116*\ln(3676)} = 0.2283$$

Diverge CP 1: EBT – 3676, EBL – 2991

$$F/I_{Diverge1} = e^{-9.39924+0.2189*\ln(3676)+0.3123*\ln(2991)} = 0.0102$$

Merge CP 1: SBT – 6911, WBL – 381

$$F/I_{Merge1} = e^{-9.38636+0.51276*\ln(6911)+0.17908*\ln(381)} = 0.0226$$

The remaining conflict points would all receive estimates, and the sum of all 33 models would be the intersection-level estimate for F/I crashes.

5.3 Comparison of Combined Model Performance

The recommended Group 2 simplified models were then utilized to estimate the total intersection crashes for the test dataset, which were compared to the observed intersection total using cumulative residuals (CURE) plot. Shown in Figure 5-1, when the cumulative residual line exceeds the 95th percentile boundaries, there may be some potential bias in the model estimates in that volume range. In contrast, Figure 5-2 shows no extreme bias against the minor AADT.

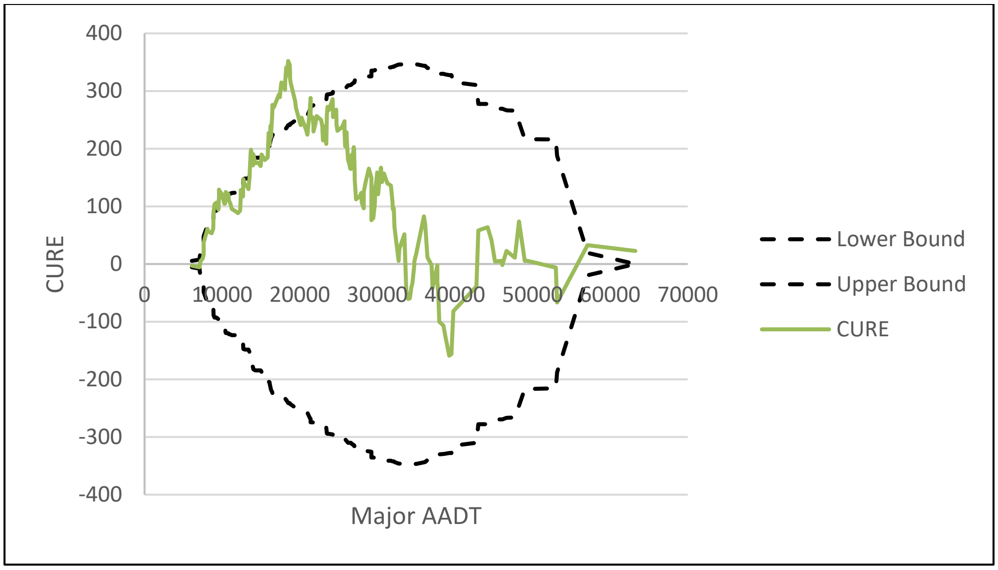


Figure 5-1: MBSPF CURE Plot vs Major AADT

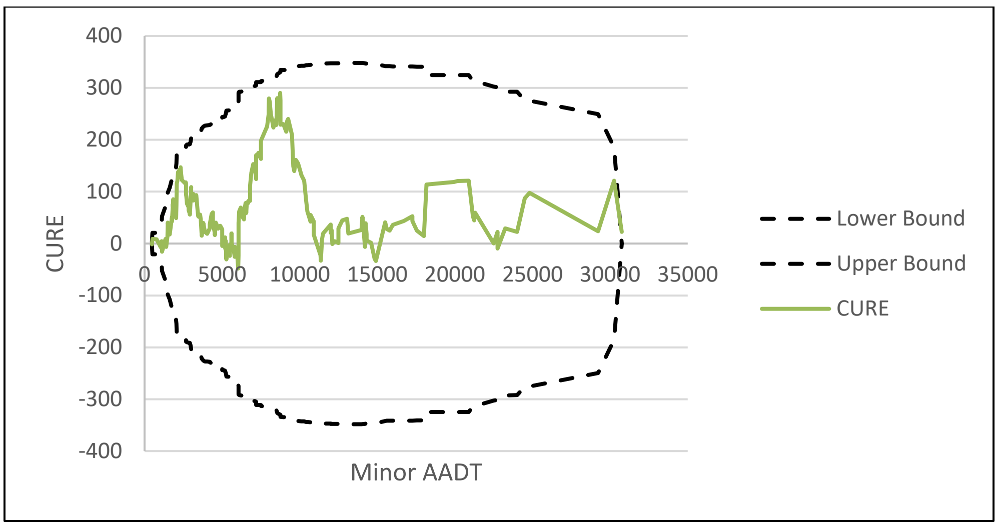


Figure 5-2: MBSPF CURE Plot vs Minor AADT

Figure 5-3 shows a comparison of MBSPF and HSM predicted crashes for all sites (test and training) from Charlotte, with a clear difference in the spread of predicted crashes for the methods and a large cluster of overestimated crashes for the HSM at low to moderate observed crash sites. The trend lines show from the slope that the MBSPF model tends to estimate fewer total crashes per site but with a much lower variance, and tends to have lower overall error. This indicates a tradeoff of accuracy vs error, where some HSM estimates are very far from the observed values. It is important to note that HSM predictions were calibrated for North Carolina before comparison with MBSPF.

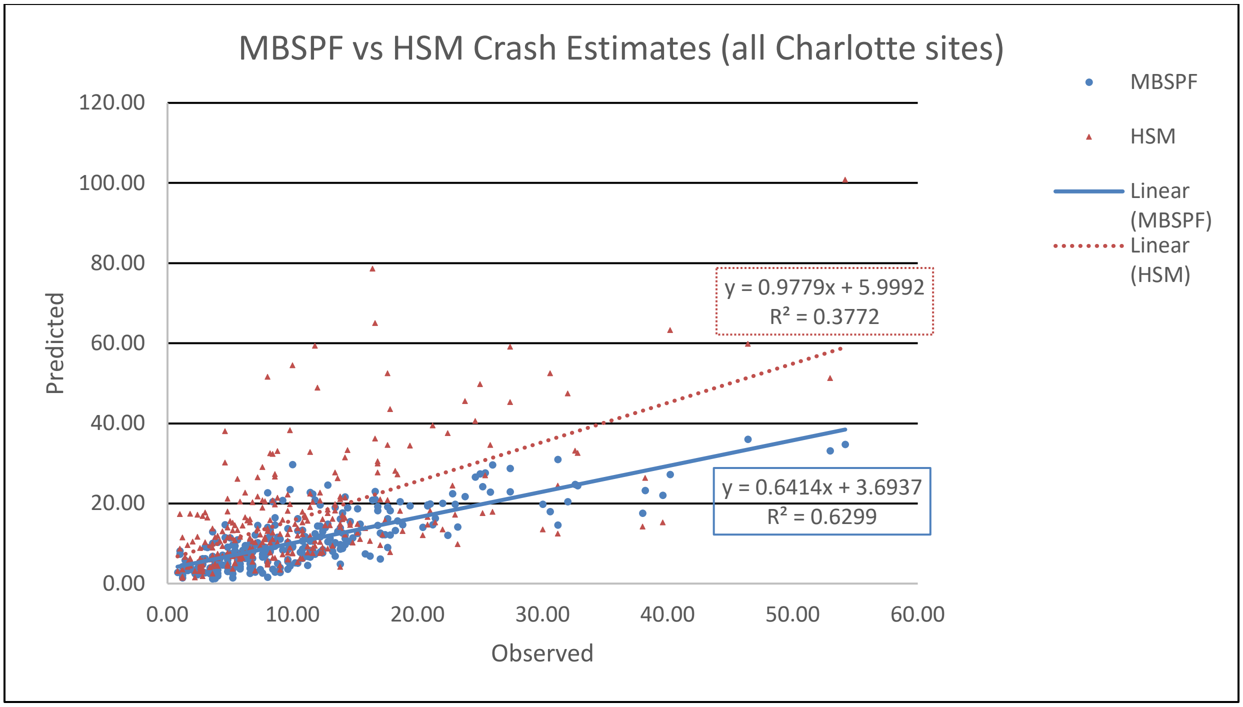


Figure 5-3: Predicted vs Observed Crashes with MBSPF and HSM Methods

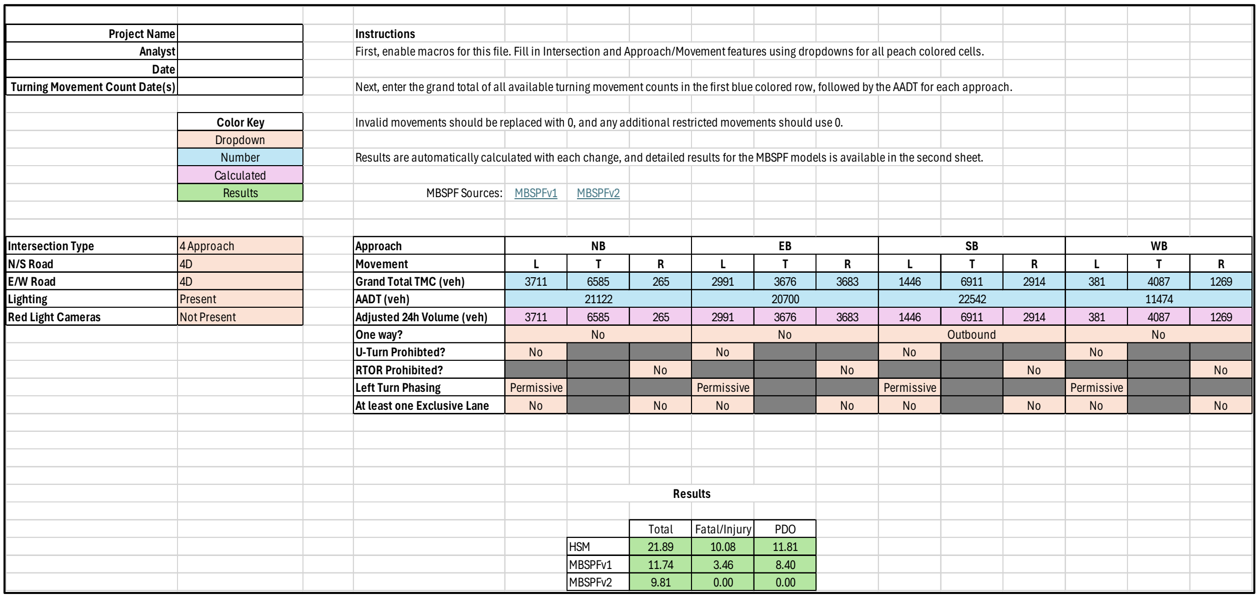
In addition, the MBSPF predicted total intersection crashes were compared to the HSM predicted crashes for the training dataset, and a test dataset which included 25% of the Charlotte dataset and 15 intersections from Cary, NC. The HSM estimates included all vehicle-related geometric and control features typically used as adjustment factors to provide the most accurate crash estimate using the state of the practice methods. The HSM inputs include Intersection Type, Major and Minor Road Type, Major and Minor AADT, Number of Approaches with Right and Left Turn Lanes, Signal Phasing by Approach, RTOR Prohibition, U-turn Prohibition, and Intersection Lighting. Table 5-13 shows that the root mean square error (RMSE) and mean absolute percentage error (MAPE) for the test dataset is approximately half for MBSPF compared to HSM predictions indicating much better predictions for the test dataset.

Table 5-13: Test Dataset Error Comparison

RMSE (Test)		MAPE (Test)	
MBSPF	HSM	MBSPF	HSM
6.1	13.2	46.5%	87.3%

5.4 Planning Level Crash Prediction Tool for Conventional Intersections

A planning level crash prediction tool was developed in Microsoft Excel to implement the MBSPF model for conventional 3 and 4 leg signalized intersections with a screenshot shown in Figure 5-4. The tool requires basic planning level inputs relevant to either the MBSPF model prediction or traditional HSM crash predictions. Summary outputs are generated, with details available for specific high risk movements in the MBSPF model. Table 5-14 shows the required inputs and which methods utilize them.



Project Name	
Analyst	
Date	
Turning Movement Count Date(s)	

Instructions

First, enable macros for this file. Fill in Intersection and Approach/Movement features using dropdowns for all peach colored cells.

Next, enter the grand total of all available turning movement counts in the first blue colored row, followed by the AADT for each approach.

Invalid movements should be replaced with 0, and any additional restricted movements should use 0.

Results are automatically calculated with each change, and detailed results for the MBSPF models is available in the second sheet.

MBSPF Sources: MBSPFv1 MBSPFv2

Color Key
Dropdown
Number
Calculated
Results

Intersection Type	4 Approach
N/S Road	4D
E/W Road	4D
Lighting	Present
Red Light Cameras	Not Present

Approach	NB			EB			SB			WB		
Movement	L	T	R	L	T	R	L	T	R	L	T	R
Grand Total TMC (veh)	3711	6585	265	2991	3676	3683	1446	6911	2914	381	4087	1269
AADT (veh)	21122			20700			22542			11474		
Adjusted 24h Volume (veh)	3711	6585	265	2991	3676	3683	1446	6911	2914	381	4087	1269
One way?	No			No			Outbound			No		
U-Turn Prohibted?	No			No			No			No		
RTOR Prohibited?			No			No			No			No
Left Turn Phasing	Permissive			Permissive			Permissive			Permissive		
At least one Exclusive Lane	No		No	No		No	No		No	No		No

Results

	Total	Fatal/Injury	PDO
HSM	21.89	10.08	11.81
MBSPFv1	11.74	3.46	8.40
MBSPFv2	9.81	0.00	0.00

Figure 5-4: Screenshot of Tool Input/Output Summary Page

Table 5-14: Crash Prediction Tool Input Needs

Inputs	Method(s) using input
Intersection Type	MBSPF + HSM
Major and Minor Road Type	HSM
Major and Minor AADT	MBPSF + HSM
Turning Movement Count(s)	MBSPF
Exclusive Right/Left Turning Lanes	HSM
Signal Phasing	HSM
RTOR Prohibition	HSM
U-Turn Prohibition	HSM
Intersection Lighting	HSM

5.5 Conclusions and Recommendations

The research team identified many components of the crash data collection and classification process which can be adopted for future movement-based crash analysis. Specifically, the value of deeper investigation into the crash diagram and narrative allows for more accurate classification of crashes which may have initially been categorized into a non-conflict category. For instance, diverge crashes can often be indicated as sideswipe same direction or rear end while the narrative may describe one turning vehicle and one through vehicle. Relying solely on summarized directional data or basic crash classifications may result in a large underestimation of conflict-based crashes. In spite of all the effort to correctly classify crashes, the researchers understand that true conflict crashes are underestimated in these analyses due to lack of clarifying details in crash reports and narratives requiring unknown crashes to be assigned to the non-conflict category.

The modeling process comprised of multiple model formulations to address the unique features of the dataset, specifically the overdispersion and frequent 0 crash observations found at individual conflict points. The researchers also considered the value of adding geometric and traffic control features relevant to each type of conflict point to better predict the crash performance. Overall, the set of models using additional data had only marginal improvements over a simplified model utilizing demand data only. Due to the small benefits seen, it is recommended that the demand only model formulation (Table 5-2, Table 5-4, Table 5-5, and Table 5-6) be used for planning level crash predictions for conventional 3 and 4 leg signalized intersections.

Overall, the simplified group of models recommended resulted in favorable prediction of test data from North Carolina, with approximately 50% lower RMSE and MAPE in comparison to the state of the practice HSM prediction methods. The recommended models should also provide much higher fidelity of crash prediction for alternative intersection designs which incorporate traditional movements such as quadrant, CFI, PFI, or Jughandle intersections. The improved fit statistics are seen in the simplified MBSPF model form, where implementation would require fewer inputs than the HSM method for planning level intersection crash prediction.

5.6 Future Research Recommendations

The results found in this research indicate that conflict-based safety predictions can be done accurately and with more confidence than HSM predictions alone. We believe there could be considerable value in considering MBSPFs for unsignalized intersection forms such as roundabouts and stop controlled intersections if future research incorporated unsignalized conflict points however there is already a strong literature basis of CMFs for these intersection types. In addition, conflict-based methods for predicting crashes along linear segments (corridors) with varying geometric elements (driveways, proximity to intersection, number of lanes on major, median type, etc.) could help build models that are more holistic and can be applied to a wider variety of projects.

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Appendix A: Data Analysis and Classification Detailed Procedures

Data analysis for this project was a massive undertaking, requiring the analysis of over 19,000 crashes. To analyze these reports in a timely manner and with greatest accuracy, the dataset was split into numerous categories and distributed to multiple teams. The first split was between intersections that were deemed "cardinal" versus "non-cardinal". Cardinal intersections had roads that could easily be identified as following a North/South and East/West categorization while non-cardinal intersections had to be assigned those unit labels. In deciding whether intersections were considered cardinal or non-cardinal, Google Earth Pro was used to find angle measurements at each intersection. If the intersection itself deviated from a 90 degree angle by more than 15 degrees then it was labeled non-cardinal. Additionally, if either road in the intersection deviated from cardinal directions by more than 15 degrees then the intersection was labeled non-cardinal. All the non-cardinal roads were assigned cardinal directions for consistency in data collection.

The reports were then further subcategorized by crash types mentioned in the police report (e.g., angle, rear-end, head-on). This was done to reduce student work and reduce error as students would be assigned one specific crash type to analyze, but this has the drawback that students can not contribute to other data collection efforts as needed without additional training. The categorized crashes were assigned to "foremen," staff members with training on the project and its requirements. In turn, each foreman would be responsible for training and leading around four students each in analyzing the reports. The foremen were generally responsible for their own QC checking.

This approach encountered several problems. Firstly, any misunderstanding among the foramen was passed down to their student interns. Secondly, the first pass through error rate among students was, on average, far too high and required a second set of eyes. As a result, each incident was likely viewed two or three times. Finally, confusing cases were handled on an ad-hoc basis, resulting in multiple rounds of re-visits. To avoid these problems in the future, the team would centralize the training among foremen and student workers, such that they all receive the same basic knowledge. In addition, each report would be viewed three times by design, and the consensus among two of the three would be taken as the truth, and anywhere they all disagree would be assumed as a confusing case. The foremen would then meet to discuss the confusing cases and assign them as a result of group consensus.

Appendix B: Instructions for Classifying Crash Reports

See attached PDF of training presentation.