IMPROVING TRAFFIC SIGNAL WARRANT SYSTEMS BY INCORPORATING

ROBUST COLLISION ANALYSES

by

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ABSTRACT

Traffic signal warrants (TSWs) are typically the first tool used by traffic engineers to determine if a stop-controlled intersection should be signalized due to their shorthand, objective, and consistent analytical methods that estimate net operational benefits. The majority of Canadian jurisdictions rely on the TSW procedure published by the Transportation Association of Canada (TAC), and this procedure is notably different from most others due to its exclusion of any empirical safety measures. Changes in collision severity and frequency are two of the most significant impacts of signalization, so the lack of a collision history component in the TAC warrant procedure limits the robustness of any findings.

This dissertation presents collision adjustment factors (CAFs) that allow crash history to be incorporated into the TAC warrant procedure. Developing the CAFs required novel statistical analyses of the severity/cost and frequency of collisions at stop-controlled and signalized intersections in North America, evaluation of the safety benefits of signalization, and conversion of those benefits into points used by the TAC warrant procedure. Each of the research phases are presented in separate chapters of this dissertation.

There are several primary findings derived from this research. It was found that the intersection characteristics with the greatest influence on collision severity and cost were posted speed limit, land use (rural/urban), and the presence of divided approaches. In developing North American collision prediction models it was found that the uncalibrated models in the Highway Safety Manual were not a good representation of the average collision frequency at stop-controlled and signalized intersections. By combining the
analyses of collision severity and frequency it was found that the majority of intersection configurations studied were not projected to exhibit a safety benefit from signalization. Lastly, the recommended method for converting the safety benefit/cost of signalization into TAC warrant points was through expert opinion on the valuation of collisions versus delays.

Further areas for study include surveying practitioners to gain a more robust expert opinion on the relative values of collisions and delays for TSWs and replication of the statistical analyses in this dissertation using alternative data sources.
DEDICATION

This dissertation is dedicated to everyone who made sacrifices to help me achieve my dream of completing my PhD, with special consideration to:

- **Kristin Elton**: The one whom I convinced that moving to the Maritimes from Ontario, away from family and friends, would be an exciting adventure.
- **Marita and Bill Northmore**: The ones whose children moved to the opposite ends of Canada in the search for better opportunities.
- **Tobias, Daphne, and Evian (my cats)**: The ones who were the most stressed out by the 14-hour drives between Toronto and Fredericton and were the most annoyed by my periodic smothering affection.
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Special thanks to the financial support for this project received from the Natural Sciences and Engineering Research Council, New Brunswick Innovation Foundation, University of New Brunswick, and Canadian Institute of Transportation Engineers. The generous support of these groups made the entire process much less stressful than it otherwise would have been.

I would also like to thank the National Highway Traffic Safety Administration for the public availability of the collision severity data used in this research, as well as the dozens of researchers and practitioners who published safety performance functions that I incorporated into the collision prediction analysis in this research. Without their unknowing support this research project would not have been manageable in a timely fashion.

Lastly, I would like to thank my friends and family for their continued support through this journey. Without your support and encouragement I would never have been able to achieve my dream of earning my PhD.
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<th>Description</th>
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<tr>
<td>AADT:</td>
<td>Average Annual Daily Traffic</td>
</tr>
<tr>
<td>AIC:</td>
<td>Akaike Information Criterion</td>
</tr>
<tr>
<td>AIS:</td>
<td>Abbreviated Injury Scale</td>
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<tr>
<td>CAF:</td>
<td>Collision Adjustment Factor</td>
</tr>
<tr>
<td>CDS:</td>
<td>Crashworthiness Data System</td>
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<td>CFM:</td>
<td>Cumulative-Factors Methodology</td>
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<td>Fatal Accident Reporting System</td>
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<td>ITE:</td>
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<td>KABCO:</td>
<td>Police reported collision severity scale where K=fatal collision, A=severe injury, B=minor injury, C=possible injury, and O=property damage only</td>
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<tr>
<td>LOS:</td>
<td>Level of Service</td>
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<td>MAD:</td>
<td>Mean Absolute Deviation</td>
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<tr>
<td>MPB:</td>
<td>Mean Prediction Bias</td>
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</table>
MSPE: Mean Squared Prediction Error
MUTCD: Manual of Uniform Traffic Control Devices
NASS: National Automotive Sampling System
NHTSA: National Highway Traffic Safety Administration
PDO: Property Damage Only
PSL: Posted Speed Limit
SPF: Safety Performance Function
TAC: Transportation Association of Canada
TSW: Traffic Signal Warrant
VRU: Vulnerable Road User

Chapter 3:
Model Development

$i$ subscript indicating a specific intersection

$j$ subscript indicating a specific jurisdiction

$N_{ij}$ annual collision expectation

$X_i$ matrix of intersection characteristics

$AADT_{maj_{ij}}$ annual average daily traffic on the major road

$AADT_{min_{ij}}$ annual average daily traffic on the minor road

$Region_i$ the geographical region in which the intersection is located

$\beta$ matrix of coefficients

$\beta_0$ coefficient associated with the intercept term

$\beta_1$ coefficient associated with $AADT_{maj}$

$\beta_2$ coefficient associated with $AADT_{min}$

$B$ coefficient associated with $Region$
\[ \varepsilon_{ij} \] error term (gamma or normal distributed, as specified)

\[ \eta_j \] jurisdiction random-effect parameter

**Model Evaluation**

\[ N_i \] annual collision expectation calculated from the model

\[ \hat{N}_i \] observed collision history from the simulated dataset

\[ n \] the total number of observations in the simulated dataset

**Chapter 4:**

\[ B \] the resulting safety benefit, with negative values indicating a benefit

\[ F_B \] collision frequency before signalization

\[ SPF_B \] collision frequency expected before signalization calculated from an SPF

\[ SPF_A \] collision frequency expected after signalization calculated from an SPF

\[ C_B \] multiplier for the before collision frequency that changes for the different methods of evaluating safety benefits

\[ C_A \] multiplier for the after collision frequency that changes for the different methods of evaluating safety benefits

\[ \alpha \] the dispersion coefficient for the stop-controlled intersection SPF

\[ n \] number of years worth of collisions predicted by the SPFs

**Chapter 5:**

**Canadian Traffic Signal Warrant Matrix Procedure**

\[ W \] score output from the calculation

\[ X_{V-V} \] cross-product of all vehicle-vehicle conflicts in the intersection

\[ X_{V-P} \] cross-product of all vehicle-pedestrian conflicts in the intersection

\[ F \] pedestrian demographics factor
\( L \)  
number of lanes that pedestrians must cross on the main road

\( C_s \)  
intersection spacing factor

\( C_{mt} \)  
main street truck factor

\( C_v \)  
posted speed limit factor

\( C_p \)  
population demographics factor

\( K_1 \) and \( K_2 \)  
scaling factors

**Collision Adjustment Factor Methodology**

\( W_C \)  
collision adjustment factor

\( F_B \)  
collision frequency before signalization

\( F_A \)  
collision frequency after signalization

\( C_B \)  
average cost of a collision before signalization

\( C_A \)  
average cost of a collision after signalization

\( S \)  
scaling factor used to convert the net collision costs into TAC warrant points

\( SPF_B \)  
collision frequency expected before signalization calculated from an SPF

\( SPF_A \)  
collision frequency expected after signalization calculated from an SPF

\( \alpha \)  
the dispersion coefficient for the stop-controlled intersection SPF

\( n \)  
number of years worth of collisions predicted by the SPF's
CHAPTER 1: Introduction

This chapter contextualizes and provides a roadmap for the dissertation. A review is provided on the safety considerations when signalizing a stop-controlled intersection and the state-of-the-art on collision analyses within traffic signal warrant (TSW) systems in order to frame the research problems and hypotheses that are addressed by this dissertation. The research objectives, scope and limitations, and a reader’s guide for the dissertation are also presented in this chapter.

1.1 Background

Between 2012 and 2016, intersection collisions in Canada resulted in about 70,000 injuries and 470 fatalities per year (Transport Canada 2017). Many of these collisions were a by-product of the conflicting travel paths of motorists and pedestrians and were thus a trade-off for the improved mobility that intersections provide, primarily to motorists. The conflicting travel paths themselves are not the cause of collisions; for intersection collisions, causation is normally attributed to a combination of human error, deficiencies in vehicle performance, and the design characteristics of the intersection. While traffic engineers do not have perfect control over human errors and vehicle deficiencies, it is important for them to consider the relative safety of their design choices for the public’s well-being.

One intersection design question that practitioners are often asked is if it would be beneficial to signalize a stop-controlled intersection. From a safety perspective, stop-controlled intersections are prone to high proportions of collision between vehicles on conflicting paths that largely result from drivers choosing inappropriate gaps to attempt
their crossing or turning movements through. These collisions are typically referred to as ‘angle collisions’ due to the orientation of the vehicles at impact. Signalized intersections are less prone to angle collisions due to the traffic signals allocating right-of-way for drivers to complete their crossing or turning movements, but are more prone to rear-end collisions that result from the decision-making and/or inattention of drivers at the change intervals between signal phases. Rear-end collisions typically result in fewer injury and fatality outcomes than angle collisions due to the lower momentum transfer between vehicles, greater strength of the portions of the vehicles coming into contact (bumper-to-bumper instead of bumper-to-side), and because occupant protection such as seatbelts, seatbacks, and airbags better restrict the forward/rearward movement of occupants than sideways movement.

There are numerous tools that practitioners can use to assess the various potential benefits of signalizing an intersection, but the most common tools used are TSWs. TSWs are shorthand analytical tools that have been developed to provide standardized, objective guidance on the benefits of signalizing stop-controlled intersections. TSWs are normally developed at a national or regional level so that there is both consistent guidance for practitioners and consistent expectations for motorists across large geographies (FHWA 2009, Guebert et al. 2014, MTO 2012) and primarily deal with the potential benefits to road user delays and safety that result from signalization.

Traditionally, consideration of collision outcomes in North American TSWs has relied on rule-of-thumb measures that were originally published in the 1935 Edition of the Manual of Uniform Traffic Control Devices (MUTCD) (McGee et al. 2003). The rule-of-thumb was that there would be a net safety benefit from signalization if there were at least
5 collisions per year over the previous three years. The collisions needed to be ‘reducible’ through signalization and that a sufficient trial of other collision reduction measures had been undertaken. The ‘reducible’ collision frequency refers to angle collisions, which as previously discussed occur in a greater proportion at stop-controlled intersections than signalized intersections and typically result in injuries and/or fatalities of motorists. This collision-based warrant was modified slightly with updated revisions of the MUTCD including the 2009 Edition which also required that the intersection needed to meet at least 80% of the threshold requirements for one of two delay-based warrants (FHWA 2009). The Ontario Ministry of Transportation uses similar warrant criteria to the 2009 Edition of the MUTCD, with the additional recommendation of conducting an analysis using safety performance functions (SPFs) (MTO 2012).

While the original justification of these warrants originating in 1935 is unknown (McGee et al. 2003), there are numerous methodological issues with this and similar collision-based TSWs. Issues include assuming that the ‘reducible’ collisions will actually be mitigated with signalization, ignoring the likely increase in rear-end collisions as a result of signalization, and using a single subjective threshold to compare partial collision frequencies to delay metrics instead of allowing for a sliding-scale between the two potential benefits. Given that TSWs are shorthand analytical tools intended to provide standardized, objective guidance on the benefits of signalizing stop-controlled intersections, these issues with collision-based warrants are serious failings.

In 2014, an updated collision-based TSW was created for use in the United States that improves upon many of these failings (Bonneson et al. 2014). This new warrant relies upon the statistical methodology presented in the Highway Safety Manual (HSM)
(AASHTO 2010), and thus uses a more robust method for accounting for the changes in
collision frequency and severity that result from intersection signalization. While this
warrant was a substantial step forward, it also has shortcomings including being based on
collision data from almost two decades ago from a limited number of American
jurisdictions and for continuing to not include a sliding-scale of the combined benefits from
delay and collision metrics.

The Canadian Signal Warrant Matrix Procedure (Guebert et al. 2014), published
by the Transportation Association of Canada (TAC), does not include a collision history
component within its analysis. The authors of this procedure noted several justifications
for excluding a collision history component when it was first published in 2003, including
the random fluctuations of collisions around a mean, that most warrants based on collision
history do not anticipate future safety issues, and because collision expectations are
dependent on the vehicle conflict analysis that was already included in the TAC warrant
procedure (Guebert et al. 2014, TAC 2003). The first two of these concerns can be
addressed by employing statistical methods for analyzing collision expectations that were
not widely in use when the TAC warrant procedure was first created in 2003. The third
concern is an issue of calibration; traffic conflict models can be used to predict intersection
safety, but the TAC warrant procedure was not calibrated to achieve this result so it is
unlikely that an additional collision analysis would be double-counting collisions.
Regardless, by not providing practitioners with a means for comparing the expected change
in safety to the expected change in delays from signalization, the TAC warrant procedure
fails to provide a comprehensive means for evaluating the net potential benefits of
intersection signalization.
The TAC warrant procedure also estimates delay benefits through a substantially different procedure than the other North American warrants. The TAC warrant procedure follows a cumulative-factors methodology (CFM) wherein numerous potential benefits are evaluated simultaneously to generate a total score that provides both a warrant threshold (100 or more points indicates that signals may be beneficial) and a priority ranking system for intersections (higher scores indicate higher priority). The other North American systems follow a discrete-factors methodology (DFM) wherein numerous potential benefits are evaluated separately, and if any one of these separate justifications is met then signals may be warranted. Due to this difference, creating a collision analysis component for the TAC warrant procedure requires direct integration into the existing calculation procedure; a challenge not faced when creating a collision-based TSW under other methodologies.

1.2 Research Problems and Goal

Based on the review of the default collision analyses contained in TSWs, the proposal for this research outlined that TSWs are deficient in terms of:

1. Understanding the differences in severity between collisions at stop-controlled and signalized intersections.
2. Estimating the change in collision frequency between the two forms of traffic control in a way that is non-intensive for the practitioner using the warrant system.
3. Comparing the benefits or costs of collisions to the benefits and costs of other impacts of changing forms of traffic control, such as user delay costs.
It was further identified that overcoming these challenges would allow practitioners to make more informed approximations of the benefits of signalization, which ultimately allows them to prioritize and allocate their resources more efficiently. Based on these research problems, a goal was set to create a framework that incorporates collisions into traffic signal warrant systems using proposed novel research on predicting collision severities based on the configuration of intersections and on synthesizing existing research on the factors that influence the frequency of intersection collisions.

1.3 Objectives

There were four research objectives delineated at the onset of this study:

1. To analyse intersection collision data to determine the factors that affect the severity of these collisions and determine the impact of these factors.
2. To synthesize the existing literature on intersection collision prediction models to determine a model for the typical collision modification factor between stop-controlled and signalized intersections.
3. To compile the severity and prediction analyses into a framework for determining if changing from stop control to signal control improves overall safety and apply economic analysis to this framework to provide a basis for comparing the collision costs to the other benefits and costs associated with changing forms of traffic control.
4. To demonstrate the applicability of the developed framework by developing a supplemental collision score to the Transportation Association of Canada’s Canadian Traffic Signal Warrant Matrix Procedure.
Objectives 1 and 2 respond to Research Problems 1 and 2, respectively. Objectives 3 and 4 respond to Research Problem 3.

1.4 Research Scope and Limitations

Data sources used within this research project were limited to Canadian and American sources. This limitation was set so that the results would be relevant to practitioners analyzing the safety benefits of signalization in Canadian jurisdictions. While ideally the analysis would have strictly been based on Canadian data, American data was required to improve the geographic diversity of data available. It was important that the analysis considered changes in collision severity and frequency at a national scale, as opposed to a regional scale such as exclusively using data from Atlantic Canada. This did not skew the results from being applicable to Canadian practitioners due to the similarities between Canadian and American roadway infrastructure and driver behaviour.

The research was also specifically limited to the analysis of signalizing a stop-controlled intersection. There are numerous other forms of traffic control that can be implemented by practitioners, such as roundabouts, yield control, or interchanges; however, the available data for other forms of traffic control was more limited and therefore similarly robust analysis could not be completed for these other forms of traffic control.

Beyond these two limitations, there were others more specific to completing individual objectives within the research project. These limitations were identified in the relevant chapters of this dissertation.
1.5 Reader’s Guide

This dissertation is presented in six chapters. Chapter 1 identifies the research needs and presents the hypotheses, objectives, scope, methodology, and format of the dissertation. Chapters 2 through 5 are presented as stand-alone papers that address specific research objectives. Chapter 6 presents the overall conclusions, contributions, and future research needs that were found through the course of this research. Due to the nature of this paper-based dissertation, there is substantial repetition between the individual chapters including the introductions, literature reviews, and results that are presented in one chapter and then used in subsequent chapters. The content of Chapters 2 through 5 are described below:

**Chapter 2: Intersection characteristics that influence collision severity and cost**

Chapter 2 addresses the first research problem and objective: investigating the differences in collision severity and cost between stop-controlled and signalized intersections and identifying the intersection characteristics that have the greatest impact on collision severity.

The dataset used for this analysis was developed from the General Estimates System (GES) and Fatal Accident Reporting System (FARS) that are collected as part of the National Highway Traffic Safety Administration’s (NHTSA’s) National Automotive Sampling System (NASS). These datasets were designed to be representative of the severity expectations of collisions from a geographically diverse set of sampling units across the United States and included several intersection characteristics that could be analyzed, making them ideal for use towards this dissertation’s research goal.
Forward selecting generalized ordered logit models were developed to rank fourteen intersection characteristics and control variables by their effect on the severity of collisions at stop-controlled and signalized intersections. In general, it was found that the posted speed limit (PSL) on the major road, whether the major road was divided or undivided, and whether the intersection was in a rural or urban area were the intersection characteristics most likely to have a significant effect on the average severity outcome of collisions. The collision data in the dataset was then stratified by these variables to find the distribution of collision severities, and these distributions were then used to calculate the average cost of a collision in each configuration.

This chapter was published in the Journal of Safety Research with the following citation:


*Chapter 3: Aggregated North American safety performance functions for signalized and stop-controlled intersections*

Chapter 3 addresses the issue raised with the second research problem and objective: estimating the average change in collision expectation when signalizing an intersection in North America.

An extensive literature review of published SPFs from North American jurisdictions for stop-controlled and signalized intersections was conducted. These published models were used to create synthetic collision data, which were then amalgamated into datasets based on traffic control and collision severity to create new aggregate SPFs using a traditional negative binomial (Poisson-gamma) model with
additional regional and jurisdictional covariates in an attempt to reduce variance. Due to
the geographic diversity of the SPFs found in the literature, the aggregate models
developed through this process were reflective of the average collision frequency at stop-
controlled and signalized intersections in North America.

Overall this analysis found that adding a random-effect to the negative binomial
model that accounted for the jurisdiction that the data was from consistently produced the
lowest variance models. Further analysis was conducted to compare these models to those
published in the Highway Safety Manual (HSM) and to investigate the applicability of the
aggregate models to predicting the change in collision expectation due to signalization.

This chapter was accepted for publication in the Canadian Journal of Civil
Engineering in August 2019, and a preliminary version of this chapter was published in the
proceedings of the 2019 Annual Meeting of the Transportation Research Board, with the
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signalized and stop-controlled intersections in North America. In the Proceedings of the
2019 Transportation Research Board Annual Meeting, Washington, D.C., 13-17
January 2019.

Chapter 4: Evaluating the safety benefits of intersection signalization in North America

using safety performance functions

Chapter 4 uses the statistical analyses of collision severity and frequency developed
in Chapters 2 and 3, respectively, to assess the overall safety impacts of intersection
signalization. In doing so, this chapter addresses a portion of the third research problem and the entirety of the third research objective for this dissertation.

Three common metrics were used to evaluate the safety benefits of signalization in this chapter: change in collision frequency, change in frequency of collisions resulting in serious injuries and fatalities, and change in collision cost. For the analysis, several intersection configurations were used based on a combination of the intersection characteristics found to have the greatest impact on collision severity in Chapter 2 and the categories that were used to define the aggregate SPFs developed in Chapter 3.

Overall this research found that the majority of the intersection configurations would exhibit a decrease in safety as a result of signalization, with rural and high-speed intersections being the most likely to see an increase in safety. These findings, being based on safety performance functions, were representative of the ‘typical’ intersection for each configuration, making these results useful for developing network screening tools.

This chapter has been submitted for publication in the Journal of Transportation Safety and Security.

**Chapter 5: Development of collision adjustment factors for the Canadian Signal Warrant Matrix Procedure**

The analyses in Chapter 5 take the safety benefit evaluation conducted in Chapter 4 and adapts it to fit with the existing TAC warrant procedure. In doing so, Chapter 5 successfully completes the fourth research objective and third research problem for this dissertation.

To compare the change in collision costs from signalization to the TAC warrant procedure, an evaluation of the change in delay costs from signalization for intersections
near the threshold for signalization under the TAC warrant system was conducted. This evaluation found that the change in collision costs from signalization was either comparable to or significantly greater in magnitude than the change in delay costs; as a result, the collision adjustment factors (CAFs) calculated through a direct economic comparison resulted in collisions having a dominating impact on the TAC warrant procedure, which is likely an undesirable result for practitioners.

Chapter 5 also investigates, and ultimately recommends, scaling the change in collision costs using expert opinion to create CAFs that are more likely to be applied by practitioners. This procedure used the updated collision-based TSW in the United States (Bonneson et al. 2014) and the discrete collision-based warrant thresholds previously used in the United States and Ontario, Canada (FHWA 2009, MTO 2012) as a reference for comparing collision costs and delay costs within a TSW. Future research is recommended into creating a more robust definition of how practitioners subjectively value collisions and delays in their decision-making regarding the signalization of intersections.

This chapter is targeted for submission to the proceedings of the 2020 Transportation Association of Canada Annual Conference.

References


CHAPTER 2: Intersection Characteristics that Influence Collision Severity and Cost

Abstract

Introduction: Traffic engineers require robust tools to assist with their day-to-day decision making, and there is no better example of this than traffic signal warrants. North American traffic signal warrant systems are lacking in how they incorporate motor vehicle collisions from both a severity and prediction perspective. The objective of this study was to produce reliable collision costs for the development of improved traffic signal warrants that accounted for the variations in severity that practitioners should expect based on the characteristics of the intersection being studied.

Method: The primary data used for this analysis were from the National Automotive Sampling System (NASS) Crashworthiness Data System, with adjustments from the NASS General Estimates System and Fatality Accident Reporting System. Generalized ordered logit models were used to identify the most significant intersection characteristics, which were then used to segregate the data to determine expected collision severity profiles and average costs of both casualty and total collisions at intersections.

Results: The average collision at a signalized intersection was found to have a lower severity than the average collision at a stop-controlled intersection. A combination of posted speed limit, urban/rural, and divided/undivided were identified as the most

significant intersection characteristics in most cases and were used to delineate the data for developing collision cost estimates.

**Conclusions:** Posted speed limit, rural/urban land use, and the presence of divided approaches are intersection characteristics that traffic engineers can readily determine and/or control for that have significant effects on intersection collision severity.

**Practical Applications:** The collision costs produced through this process give traffic engineers a reliable estimate that can provide a more substantial foundation for justifying a proposed change in intersection traffic control.

### 2.1 Introduction

Selecting the type of traffic control for an intersection is a delicate, budget-constrained balance between safety and efficiency. The challenge of making the right decision is further complicated by many of the variables that affect safety and efficiency being outside the direct control of traffic engineers: namely the vehicle, environmental, and driver behaviour components. Nevertheless, traffic engineers must select traffic control methods for their intersections and therefore require robust tools to understand the impacts of their decisions.

One of the most common first assessment tools for considering the type of traffic control at an intersection is the traffic signal warrant. Several traffic signal warrant systems are in use across North America, and the main considerations of these tools are traffic delays (based on volumes) and collisions (FHWA 2009, MTO 2012, TAC 2014). Traffic signal warrants are meant to provide an approximation of where there is sufficient benefit to merit installing signals in place of stop sign control, but the collision components of existing warrants have gaps that leave uncertainty for practitioners. Historically, collision-based
warrants have been rule-of-thumb judgements for which there was either minimal or no known empirical backing (McGee et al. 2003). The current warrant in the United States (Bonneson et al. 2014) was developed using the tools published in the Highway Safety Manual, and as such this warrant is based on nearly 20-year old collision analysis from only a few hundred intersections from up to three states per model (Harwood et al. 2008, Lord et al. 2008). While this new warrant is a vast improvement over its predecessor, a need still exists for modern and robust methods to account for collisions within traffic signal warrant frameworks.

Improving the collision analysis in traffic signal warrants requires an understanding of how changes in traffic control affect the severity and predictability of intersection collisions. Great advancements have been made in the statistical analysis of collision severity and frequency over the last two decades. This study focuses on using these statistical tools to improve the collision severity component of traffic signal warrants, with emphasis on identifying the intersection characteristics that most significantly affect collision severity and stratifying collision costs for intersections by the identified characteristics. The influence of intersection characteristics is of specific importance to practitioners because these are factors that can be readily identified and accounted for in the intersection design process by the practitioner. Further studies will examine changes in collision expectation nationally from signalization and the incorporation of collisions into existing signal warrant systems.

Despite the current interest in roundabouts, this study did not include the severity of collisions at roundabouts due to a lack of robust data for modelling. Additionally, a
separate study will be undertaken to assess the national-average change in collision expectations from intersection signalization.

### 2.2 Literature Review

Collision severity is evaluated on categorical scales based on the injuries sustained by the persons involved in the collision. Two types of categorical scales are found in the literature: those based on the police reported outcome of injuries (eg. KABCO: K=fatal collision, A=severe injury, B=minor injury, C=possible injury, O=property damage only) and those based on the medically assessed probability of the sustained injuries resulting in a fatality (eg. Abbreviated Injury Scale, or AIS). Due to its underpinnings in medical research, the AIS is a more robust severity measurement tool than systems like KABCO, but police reported measures are the most widely studied collision severity outcome due to their availability in regional collision databases maintained by police officers. AIS is only included in smaller surveys of national collisions due to its complexity (Blincoe et al. 2015).

Eluru 2013, Michalaki et al. 2015, Quddus et al. 2010, hierarchal (C. Chen et al. 2016, Kim et al. 2017), and mixed (Fountas et al. 2018, Rash-ha Wahi et al. 2018, Uddin and Huynh 2017, Wu, Zhang, Zhu et al. 2016) logit/probit models. Non-parametric methods such as fuzzy-networks (Ren et al. 2012) and decision trees (Prati et al. 2017) are also applied, but to a lesser extent. Predictive models can be used to study any possible subset of collisions (intersection, pedestrian, heavy vehicle, etc.), each of which comes with its own specific considerations and modeling techniques.

Over the years, researchers have moved away from the traditional ordered and multinomial models towards specifications that allow for greater flexibility (Lord and Mannering 2010). In general, the model specification chosen by researchers is dependent on the type of input data on-hand and the type of output data required from the study.

None of the contemporary studies in the literature were developed from national datasets of collisions. Analyses of national datasets are important to the development of national guidelines, because regional analyses may not be broad enough to account for national variations in driver behaviour, environment, roadway design, vehicle use, and vulnerable road user exposure. Additionally, there was little consistency in the roadway design factors that were found to be significant in the literature. Various studies found that surface type, lane configuration, grade, traffic control method, speed limit, road class, intersection skew, shoulder width, road width, alignment, and other factors had significant influences on severity. Part of the inconsistency between studies is due to the differences in the datasets they are based on, as some variables may be missing or classified differently depending on the collision reporting authority. Some of the inconsistency may also be due to model overspecification. A common trend in the literature was the specification of
models with a plethora of variables, seemingly to ensure a high level of fit at the expense of possibly finding spurious correlations.

Several studies were also found that determined how collision severity corresponds to collision cost, which is a useful output as it allows for comparison to traffic delay, environmental, and other factors that impact intersection design decision making. The work of Council et al. (2005) determined collision costs based on the study of AIS severity in the National Automotive Sampling System (NASS) Crashworthiness Data System (CDS), and several other works were found connecting police reported severity outcomes to collision cost (Blincoe et al. 2015, de Leur et al. 2010).

The approach of Council et al. (2005) was unique in that they determined the average costs of various collision configurations instead of the typical approach of determining costs for each categorical level of collision severity. This average cost approach is particularly useful because fatal collisions are rare events and having one fatal collision in the recent collision history for a site may not be indicative of the long-term likelihood of fatal collisions. Using an average expected collision cost instead of categorical costs helps to normalize for any short-term anomalies.

2.3 Methods

This research required substantial data processing before the statistical models could be created. The processing included identifying the pertinent data sources, determining the type of traffic control at each intersection, selecting and defining intersection characteristics and control variables to include in the models, and adjusting the supplied
collision weights to ensure the data were reflective of all police reported collisions nationally.

Once data processing was completed, generalized ordered logit models were created for each form of intersection traffic control and collision severity level. The output from the models was used to identify the most significant intersection characteristics, and these characteristics were then used to segregate the intersection collision data to determine collision severity profiles and collision costs.

2.3.1 Data Sources

Three data sources were used as part of the collision severity analysis: 1985-1986 and 2011-2015 data from the NASS CDS, 2011-2015 data from the NASS General Estimates System (GES), and 2011-2015 data from the Fatality Analysis Reporting System (FARS). Each of these data sources is detailed below.

The NASS CDS (NHTSA 2015) contains a stratified sampling of collisions that occur annually in the United States. The most recent annual sets of the CDS each contain data from approximately 5,000 collisions, where each collision resulted in either a passenger car, van, or light truck being towed from the scene. Some older sets of CDS data (1986 and prior) contain a sampling of all police reported collisions. The relatively small sample size allows for a great amount of detail to be collected about each collision, such as a medical assessment of injury severity and the measured deformation of each involved vehicle. The stratified sampling method allows a weighting factor to be applied to each collision, based on the likelihood of that collision being selected, that expands the sample
to be representative of all collisions covered by the study that occurred in the United States that year.

The NASS GES (NHTSA 2016a) is another stratified sampling of annual collisions in the United States, with some key distinctions from the NASS CDS. The GES is a much larger sampling of approximately 50,000 collisions per year, though each collision record does not carry the same level of technical detail as the CDS. The GES is a representative sampling of all police reported collisions and is similarly weighted to allow representation of all collisions that occurred in the United States in the sampling year.

The FARS (NHTSA 2016b) is a census of annual fatal collisions in the United States. FARS and GES data are collected in a similar manner and have many common data elements. The FARS also has a few more specific variables of interest to the study of fatal collisions.

The 2011-2015 CDS data is the primary dataset used in this research, with the 1985-1986 CDS data being used to incorporate collisions not covered by the 2011-2015 CDS sampling method. The GES/FARS data are used to adjust the case weights of the CDS data to ensure that the data is reflective of the overall collision severity profile for the United States, particularly for fatal collisions and the 1985-1986 CDS data. The modelling in this research was not carried out on the GES/FARS directly due to this dataset missing some of the desired study variables (e.g. urban v. rural) and the large number of cases (approx. 50%) that would be removed due to missing data.
2.3.2 Study Variables

The effect of traffic control, intersection design, and regional variables on the severity of collisions at intersections is the main interest of this research. The CDS dataset contains two measures of collision severity: the KABCO scale and AIS. The KABCO scale was used as the dependent variable in this study because the 2011-2015 CDS data did not determine AIS for occupants of vehicles more than 10 years old at the time of the collision, which led to a substantial number of potentially misclassified maximum AIS scores for collisions.

Traffic Control

The CDS reports traffic control devices on a per-vehicle basis, so determining the type of traffic control at an intersection required cross-referencing the types of traffic control recorded for each involved vehicle with the ‘Accident Type’ variable. ‘Accident Type’ identified if vehicles were initially on the same, opposing, or intersecting trafficways prior to the collision, which was useful in determining the configuration of the traffic control devices. The specific criteria used are summarized in Table 2-1.
Table 2-1: Criteria used to identify the form of traffic control at the intersection

<table>
<thead>
<tr>
<th>Identified Traffic Control</th>
<th>Criteria</th>
<th>Percentage of Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>All vehicle records indicated that ‘traffic signal’ was the type of traffic control.</td>
<td>49%</td>
</tr>
<tr>
<td>Stop Sign (All-way)</td>
<td>The vehicles involved in the first harmful event were initially travelling on intersecting roads, both of which reported ‘stop control’.</td>
<td>1%</td>
</tr>
<tr>
<td>Stop Sign (2-way)</td>
<td>All remaining cases in which at least one vehicle record reported ‘stop control’ and at least one vehicle record reported ‘no control’.</td>
<td>16%</td>
</tr>
<tr>
<td>Stop Sign (Other)</td>
<td>All remaining cases in which each vehicle record reported that ‘stop control’ was the type of traffic control.</td>
<td>5%</td>
</tr>
<tr>
<td>No Control (Intersecting)</td>
<td>The vehicles involved in the first harmful event were initially travelling on intersecting roads, and both vehicles were not controlled by a traffic control device.</td>
<td>1%</td>
</tr>
<tr>
<td>No Control (Same Road)</td>
<td>All remaining cases in which each vehicle record reported that ‘no control’ was the type of traffic control.</td>
<td>18%</td>
</tr>
<tr>
<td>Other</td>
<td>All collisions where a vehicle is controlled by a ‘traffic signal’ that does not fit the above criteria for a signalized intersection, and all other collisions.</td>
<td>10%</td>
</tr>
</tbody>
</table>

Through the criteria summarized in Table 2-1 it was possible to identify some collisions that definitively occurred at signalized, 2-way stop control, and all-way stop control intersections. The collisions identified as ‘Stop Sign (Other)’ were rear-end collisions that could have occurred at either 2-way or all-way stop-controlled intersections. Those identified as ‘No Control (Same Road)’ could have been either on the through road at a 2-way stop-controlled intersection or at an uncontrolled intersection. To account for these traffic control categories, the identified types of traffic control were divided into four
study groups as defined in Table 2-2. The effects of possible misclassification of traffic control is discussed in Section 2.5.2.

### Table 2-2: Traffic control study groups

<table>
<thead>
<tr>
<th>Traffic Control Group</th>
<th>Identified Traffic Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signalized</td>
<td>Signal</td>
</tr>
<tr>
<td>2-Way Stop Control</td>
<td>Stop (2-way), Stop (Other), No Control (Same Road)</td>
</tr>
<tr>
<td>All-Way Stop Control</td>
<td>Stop (All-way), Stop (Other)</td>
</tr>
<tr>
<td>General Stop Control</td>
<td>Stop (2-way), Stop (All-way), Stop (Other), No Control (Same Road)</td>
</tr>
</tbody>
</table>

*Intersection Characteristics*

The CDS contained six additional intersection characteristics that could be incorporated into the study: alignment, divided/undivided roads, posted speed limit (PSL), profile, region, and pavement surface type. The number of lanes is also recorded in the CDS, but the way it is recorded on a per-vehicle basis led to many missing values particularly for divided roadways, so the number of lanes was excluded from this study.

Each of these variables could have multiple values per collision, depending on the number of approaches to the given intersection. The roadway design variables are recorded on a per-vehicle or per-driver basis in the CDS, so information will only be known for approaches on which one of the involved vehicles was travelling. It was also found that while there were usually several response options for each variable, one response tended to dominate the others in terms of response proportion; for this reason, most of the responses were merged to create binary variables as described in Table 2-3. The exception to this rule is the PSL. Two PSL thresholds, 35 mph and 40 mph, were chosen as they
provided relatively even splits of the overall dataset, there was no known systematic reason to choose one over the other, and choosing them minimized the impact of some misclassification of the highest PSL at an intersection, which is detailed further in Section 2.5.2.

Table 2-3: Study variable response definitions and response proportions from CDS combined dataset

<table>
<thead>
<tr>
<th>Study Variable</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alignment</td>
<td>‘Straight’ if every known approach is straight [80%], otherwise ‘Curved’ [20%]</td>
</tr>
<tr>
<td>Divided</td>
<td>‘No’ if every known approach is undivided or one-way [66%], otherwise ‘Yes’ [28%] or missing [6%]</td>
</tr>
<tr>
<td>PSL ‘X’ or Greater</td>
<td>‘No’ if none of the known approaches have a PSL of ‘X’ or greater, otherwise ‘Yes.’ Threshold values used for ‘X’ were 35 mph and 40 mph. PSL 35 or Greater: No [35%], Yes [63%], missing [2%] PSL 40 or Greater: No [61%], Yes [37%], missing [2%]</td>
</tr>
<tr>
<td>Profile</td>
<td>‘Level’ if every known approach is level [66%], otherwise ‘Unlevel’ [34%]</td>
</tr>
<tr>
<td>Region</td>
<td>Urban [52%], Rural [48%]</td>
</tr>
<tr>
<td>Surface Type</td>
<td>‘Paved’ if every known approach is asphalt, concrete, or brick [99%]; otherwise ‘Unpaved’ [1%]</td>
</tr>
</tbody>
</table>

The region data were derived from the census data for population and land area of each sampling unit attached to the annual analysis guides published with the CDS data. The population density of each sampling unit was calculated and the ‘urban’ or ‘rural’ label was applied based on census definitions (Ratcliffe et al. 2016).

Control Variables

Several control variables were selected to account for non-roadway factors identified in the literature review as potentially significant to collision severity: vulnerable road user (VRU)
involvement, vehicle type, weather/road condition, lighting condition, collision type, user impairment, and seat belt usage. For this study, a collision was considered to have a VRU involved if a pedestrian or cyclist was struck during the collision. At-fault user gender and user distraction were also identified as potentially significant variables; however, these variables could not be isolated due to the nature of the datasets being used. Table 2-4 outlines and defines the control variables used in this study.

Table 2-4: Control variables used to account for non-roadway factors and response proportions from CDS combined dataset

<table>
<thead>
<tr>
<th>Control Variable</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alcohol Involvement</td>
<td>‘No’ if no users are reported as impaired by alcohol [91%], ‘Yes’ if at least one user (either a driver or VRU) is reported as impaired by alcohol [9%]</td>
</tr>
<tr>
<td>Collision Type</td>
<td>Angle [57%], Head-On [2%], Rear-End [18%], Sideswipe [3%], Single Vehicle [20%]</td>
</tr>
<tr>
<td>Lighting Condition</td>
<td>Daylight [69%], Dusk/Dawn [4%], Dark [24%], Dark with Artificial Lighting [4%], missing [0.5%]</td>
</tr>
<tr>
<td>Unbelted</td>
<td>‘No’ if all known occupants wearing seatbelts [73%], ‘Yes’ if at least one known occupant unbelted [27%]</td>
</tr>
<tr>
<td>Vehicle Type – Heavy Vehicle</td>
<td>‘No’ if no heavy vehicles involved [93%], ‘Yes’ if at least one heavy vehicle involved [7%]</td>
</tr>
<tr>
<td>Vehicle Type – Motorcycle</td>
<td>‘No’ if no motorcycles involved [94%], ‘Yes’ if at least one motorcycle involved [6%]</td>
</tr>
<tr>
<td>VRU Involvement</td>
<td>‘No’ if no VRUs involved [91%], ‘Yes’ if at least one VRU involved [9%]</td>
</tr>
<tr>
<td>Weather/Road Condition</td>
<td>‘Good’ if all roads are dry and weather is clear or cloudy [81%], all other combinations of conditions [19%]</td>
</tr>
</tbody>
</table>
2.3.3 Data Processing

The CDS, GES, and FARS data are contained in multiple datasets per year, which were consolidated to produce one record per case that contained all the required study variables. In filtering and processing the CDS data, guidance was taken from relevant studies by Council et al. (2005), Blincoe et al. (2015), Spicer and Miller (2011), and Klinich et al. (2016).

The non-fatal GES cases were merged with the FARS dataset to produce a collision estimate database that accurately reflected the number of fatal collisions. Each of the GES cases had a weight assigned to them based on the stratified sampling method of the study, and since the FARS was a census a weight variable of ‘1’ was assigned to each FARS case. The GES/FARS data were used to adjust the case weights of the CDS data to ensure that the CDS dataset was reflective of the overall severity trends from the larger collision dataset. This process was carried out for each of the four traffic control study groups to ensure each had appropriate collision severity distributions. The 2011-2015 CDS case weights were adjusted by multiplying each original weight for each case by the ratio of the sum of the GES/FARS weights for CDS applicable collisions to the sum of the CDS weights for each combination of traffic control group and collision severity level. Separate variables were created for each of the four resulting weight groups, corresponding to the four traffic control study groups.

The 1985-1986 CDS data were used to incorporate collisions that were no longer part of the CDS mandate post-1986 (those that did not involve a passenger car, van, or light truck being towed). Datasets prior to 1985 were excluded as they did not contain the ‘Accident Type’ variable required to identify the type of traffic control at the intersections.
A similar adjustment procedure was used to adjust the weights of the 1985-1986 cases, though the data were stratified by alcohol involvement and seat belt usage in addition to traffic control group and collision severity. These two extra variables were added, following the methodologies of other research (Blincoe et al. 2015, Council et al. 2005), to account for variations in alcohol involvement and seat belt usage in collisions over the last two decades. When this stratification procedure subdivided the data too thinly for cases to be available for reweighting, seat belt usage was removed before alcohol involvement.

Collisions with a rating weight (before adjustment) greater than 5000 were removed so that no individual collision had an overstated influence on the analysis. Only 182 of the 10,535 intersection collisions (1.7%) had a rating weight greater than 5000.

2.3.4 Statistical Methodology

Predictive models were used in this study to identify the intersection characteristics that have the most significant effects on collision severity, with the identified characteristics being used to stratify intersection collision costs for use in traffic control decision making. Considering this end use, a generalized ordered logit model with partial-proportional odds and forward selection was selected for use in this study. This model specification combines the benefits of traditional ordered and multinomial logistic regression analysis by determining cumulative ordered probabilities while allowing flexibility for variables that are better represented by separate effects for each collision severity level. Forward selection allowed the modeling procedure to order the intersection characteristics by their significance to the model. A partial proportional odds approach was used to ensure no negative predicted probabilities existed in the results. The variables allowed to have
unequal slopes were selected by first creating a model with all unequal slopes, calculating the standard deviation of the severity estimates for each variable, ranking the variables from highest standard deviation to lowest, and then creating the final model where variables with unequal slopes were incrementally added until just before the model converged with negative predicted probabilities. Details on the statistical foundations of generalized ordered logit models are found in numerous sources (Abegaz et al. 2014, Eluru 2013, Michalaki et al. 2015, Quddus et al. 2010).

More recent model specifications that account for unobserved heterogeneity, such as the mixed logit or random-effect generalized ordered probit models, were not used in this study because of the inability to isolate random-effects when stratifying the intersection collision costs. The control variables described in Table 2-4 were included in the models to systematically account for as much heterogeneity as could be accounted for within the dataset based on the literature review.

Generalized ordered logit models were created for each combination of the stratification groups shown in Table 2-5. The traffic control groups refer to the study groups identified in Table 2-2, ‘total collisions’ refers to the dataset using every level of the KABCO scale while ‘casualty collisions’ refers to just the K, A, B, and C severity levels (no PDO collisions), and the PSL thresholds were defined in Table 2-3. In total, 16 generalized ordered logit models were created for this study.
Within each collision severity and traffic control group, the most significant PSL threshold was identified by comparing the variable selection order from the models and, in the case of ties, comparing the chi-squared score calculated at the selection levels and the overall fit of each model. With the most significant PSL identified, the matching multinomial and ordinal models were compared, again by variable selection order and chi-squared scores from selection, to rank the study variables from greatest to least significance.

Collision severity distributions were then created by segregating each data set by the most significant study variables. Due to the relatively small number of cases in each dataset, only the two most significant study variables were applied in splitting the data to determine the severity distributions. Minimizing the number of splits helps to ensure that the results produced are not outliers based on limited samples. Since the objective of this research was to better estimate collision severity and not perfectly estimate it, limiting the splits to ensure validity of the results is a reasonable approach.

2.3.5 Collision Costs

Collision costs were applied from a Blincoe et al. (2015) study on the economic impact of collisions in the United States. The Blincoe et al. study determined comprehensive...
collision costs for each KABCO severity level including injury related costs (medical, emergency services, market and household productivity, insurance, workplace, and legal), collision related costs (congestion and property damage), and quality-of-life costs. The costs determined by Blincoe et al. are shown in Table 2-6. Note that the quality-of-life value for ‘O’ collisions comes from the misclassification of injurious collisions as property damage only.

Table 2-6: Blincoe et al. KABCO Collision Costs, 2010 US Dollars

<table>
<thead>
<tr>
<th>Costs</th>
<th>O</th>
<th>C</th>
<th>B</th>
<th>A</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injury</td>
<td>$10,631</td>
<td>$23,422</td>
<td>$28,671</td>
<td>$88,100</td>
<td>$1,381,984</td>
</tr>
<tr>
<td>Collision</td>
<td>$2,650</td>
<td>$3,416</td>
<td>$3,460</td>
<td>$4,903</td>
<td>$16,932</td>
</tr>
<tr>
<td>Quality-of-Life</td>
<td>$31,849</td>
<td>$108,274</td>
<td>$252,268</td>
<td>$919,158</td>
<td>$7,747,082</td>
</tr>
<tr>
<td>Total</td>
<td>$45,140</td>
<td>$135,123</td>
<td>$284,399</td>
<td>$1,012,161</td>
<td>$9,145,998</td>
</tr>
</tbody>
</table>

2.4 Results

The first step of the modelling procedure involved identifying the most significant PSL threshold for each combination of traffic control and severity level. By running generalized ordered logit models for every combination of traffic control, collision severity group, and PSL threshold identified in Table 2-5, it was found that the 40 mph threshold was most significant for signalized intersections (both Casualty and Total) while 35 mph was most significant for each of the stop-controlled intersection groups. In all cases, the most significant PSL threshold was identified by a combination of variable selection order, the Chi-square score for the variable, and the overall likelihood of the models.
The variable selection orders for the models with the most significant PSL thresholds are shown in Table 2-7. The intersection characteristic variables in this table are bolded/highlighted for emphasis, and variables with unequal slopes are noted with an asterisk. There were no variables with unequal slopes included in the all-way stop control models due to negative predicted probabilities, so the generalized ordered logit model was reduced to an ordered logit model.

Table 2-7: Variable selection order from the generalized ordered logit models, with intersection characteristic variables highlighted/bolded and asterisks indicating the variables with unequal slopes

<table>
<thead>
<tr>
<th>Signal Control</th>
<th>2-Way Stop Control</th>
<th>All-Way Stop Control</th>
<th>General Stop Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Casualty</td>
<td>Total Casualty</td>
<td>Total Casualty</td>
<td>Total Casualty</td>
</tr>
<tr>
<td>1 VRU* Coll. Type*</td>
<td>VRU* Coll. Type*</td>
<td>VRU Coll. Type</td>
<td>VRU* Coll. Type*</td>
</tr>
<tr>
<td>2 Unbelted* Region</td>
<td>Motorcycle* Motorcycle*</td>
<td>Coll. Type Lighting</td>
<td>Motorcycle* Motorcycle*</td>
</tr>
<tr>
<td>3 Coll. Type* Unbelted</td>
<td>PSL 35 Unbelted</td>
<td>Alignment Motorcycle</td>
<td>PSL 35 Unbelted</td>
</tr>
<tr>
<td>4 Region* Heavy Veh.*</td>
<td>Coll. Type* Divided</td>
<td>Conditions Region</td>
<td>Coll. Type* Divided</td>
</tr>
<tr>
<td>5 PSL 40 Lighting* Unbelted</td>
<td>VRU* Lighting</td>
<td>Sur. Type Unbelted</td>
<td>Region</td>
</tr>
<tr>
<td>6 Motorcycle Motorcycle*</td>
<td>Lighting Heavy Veh.*</td>
<td>Unbelted PSL 35</td>
<td>Lighting Lighting</td>
</tr>
<tr>
<td>7 Alcohol Inv. Alcohol Inv. Conditions Region</td>
<td>Heavy Veh. Alcohol Inv. Conditions</td>
<td>Heavy Veh.*</td>
<td></td>
</tr>
<tr>
<td>8 Profile Divided</td>
<td>Heavy Veh.* Lighting</td>
<td>Region Alignment</td>
<td>Heavy Veh.* VRU*</td>
</tr>
<tr>
<td>9 Heavy Veh.* PSL 40 Alcohol Inv.</td>
<td>PSL 35 Divided</td>
<td>PSL 35 Divided</td>
<td>Alcohol Inv. PSL 35</td>
</tr>
<tr>
<td>10 Lighting VRU* Divided Alcohol Inv.</td>
<td>Divided</td>
<td>Divided</td>
<td>Alcohol Inv.</td>
</tr>
<tr>
<td>11 Conditions Profile Alignment Sur. Type* Divided</td>
<td>Aligned VUR</td>
<td>Divided</td>
<td>Alignment</td>
</tr>
<tr>
<td>12 Sur. Type Sur. Type* Profile Profile Sur. Type Profile</td>
<td>Profile Sur. Type*</td>
<td>Profile Sur. Type*</td>
<td></td>
</tr>
<tr>
<td>13 Alignment Alignment Region Conditions Profile Conditions Region Conditions</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>14 Divided Conditions Sur. Type Alignment - Heavy Veh. Sur. Type Profile</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The severity distributions and collision costs associated with the most significant intersection characteristics are shown in Table 2-8 and Table 2-9 for total and casualty collisions, respectively. The data presented in these tables include the number of cases in the CDS dataset that match each set of intersection characteristics, the sum of the weights from all of those cases, the weighted percentage of cases that were classified at each level.
of the KABCO severity scale, and the average cost of a collision at an intersection with the specified set of intersection characteristics. The all-way stop control datasets were not stratified by the study variables due to small sample sizes after the split that were unlikely to be true representations of differences in collision severity; alignment split the total collisions dataset where one category consisted of only 68 cases, and the casualty dataset was already too small to reasonably split (384 cases). The PSL less than 35 mph and divided road subset of the total collision models for 2-way stop and general stop both reported no fatal collisions, which was deemed to be an unreasonable result, so the less than 35 mph data were not subdivided further.
<table>
<thead>
<tr>
<th>Region</th>
<th>Signal Controlled – Total Collisions</th>
<th>2-Way Stop-Controlled – Total Collisions</th>
<th>General Stop-Controlled – Total Collisions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intersection Characteristics</strong></td>
<td><strong>CDS Cases</strong></td>
<td><strong>CDS Cases - Weighted</strong></td>
<td><strong>Weighted Severity Distribution</strong></td>
</tr>
<tr>
<td><strong>Region</strong></td>
<td><strong>PSL</strong></td>
<td><strong>n</strong></td>
<td><strong>%</strong></td>
</tr>
<tr>
<td>Rural</td>
<td>&lt; 40 mph</td>
<td>898</td>
<td>18%</td>
</tr>
<tr>
<td></td>
<td>&gt;= 40 mph</td>
<td>1923</td>
<td>39%</td>
</tr>
<tr>
<td>Urban</td>
<td>&lt; 40 mph</td>
<td>1674</td>
<td>43%</td>
</tr>
<tr>
<td></td>
<td>&gt;= 40 mph</td>
<td>3855</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>5913</td>
<td>100%</td>
<td>5,394,776</td>
</tr>
</tbody>
</table>

*Table 2-8: Severity distributions and collision costs associated with the most significant intersection characteristics for total collisions.*
Table 2-9: Severity distributions and collision costs associated with the most significant intersection characteristics for casualty collisions

<table>
<thead>
<tr>
<th>Region</th>
<th>Divided</th>
<th>CDS Cases</th>
<th>CDS Cases - Weighted</th>
<th>Weighted Severity Distribution</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
</tr>
<tr>
<td>Rural</td>
<td>No</td>
<td>841</td>
<td>23%</td>
<td>393,813</td>
<td>24%</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>634</td>
<td>17%</td>
<td>280,221</td>
<td>17%</td>
</tr>
<tr>
<td>Urban</td>
<td>No</td>
<td>1257</td>
<td>35%</td>
<td>589,997</td>
<td>36%</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>905</td>
<td>25%</td>
<td>378,400</td>
<td>23%</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>4960</td>
<td>100%</td>
<td>5,394,776</td>
<td>100%</td>
</tr>
</tbody>
</table>

2.5 Discussion

The results presented in Tables 2-8 and 2-9 show that the average collision at a signalized intersection was less severe than the average collision at a stop-controlled intersection. For example, the average collision at a signalized intersection costs $50,096 less than the...
average collision at a 2-way stop-controlled intersection, with the cost differential increasing to $145,741 when comparing casualty collisions. It was expected that the average signalized intersection collision would be less severe than at stop-controlled intersections, as the conventional wisdom is that signalizing an intersection reduces the number of higher-severity angle collisions at the expense of more frequent lower-severity rear-end collisions. Ultimately, this knowledge of collision cost must be combined with the change in collision frequency between different types of traffic control.

The remaining discussion focusses on the results of the explanatory variable selection and the potential for misclassification of the study variables due to the design of the CDS dataset.

2.5.1 Significant Variable Selection

While the study variables that were tested through the generalized ordered logit analysis were selected because they all have logical connections to collision severity, the most significant variables identified to delineate the data for estimating collision costs were logical results.

Region, PSL threshold, and Divided were the only variables identified as being the most significant intersection characteristics and used to delineate the data in Tables 2-8 and 2-9. The classification of intersections as urban and rural provides detail into the driving environment surrounding the collision scene, which has a well-known impact on driver behaviour. Since the datasets were not split further by the roadway curvature variables, the Region split may also be accounting for some of the natural variance in the geometry of rural roads when compared to typical urban roads. PSL threshold is another expected
selection because of the direct link between higher vehicle speed and collision severity. In the absence of a useful variable for the number of lanes, identifying whether a road at the intersection is divided or undivided gives a general measure of the size of the intersection. 2-way stop-controlled intersections are notorious for collisions wherein drivers are required to judge appropriate gaps to attempt their turning or crossing maneuvers, and larger roads can make selecting appropriate gaps more difficult.

It was also unsurprising that the selection and results from the general stop dataset so closely matched the 2-way stop dataset selection and results. The general stop dataset consisted of the 2-way stop data and the relatively small amount of data identified as being all-way stop-controlled, which only had a marginal impact on the overall analysis.

Any in-depth analysis of the all-way stop data is severely limited by the relatively small sample size of collisions and the potential misclassification of collisions through the ‘Stop Control (Other)’ category defined in Table 2-2. In the total collisions model it was unsurprising that most of the study variables were selected toward the end of the set of covariates as severe collisions at all-way stop intersections are less dependent on driver decision-making and more on drivers identifying that there is an intersection.

An interesting finding was that PSL threshold was selected significantly later in the order from the casualty datasets than the total collision datasets for signalized, 2-way stop, and general stop, likely because of how relatively low the PSL thresholds were set. Lower PSL thresholds should do a better job of predicting a PDO collision versus a fatality or injury collision than they will at predicting an injury collision versus a fatality. Higher PSL thresholds may be more useful within the casualty datasets, but these could not be
reasonably used for delineating the data due to the greater impact of misclassifying the highest PSL at an intersection.

2.5.2 Misclassification Error

The largest source of potential error in the results comes from how roadway design variables are defined in the GES and CDS datasets. Roadway design variables are assigned on a per-driver basis instead of a per-collision or per-intersection basis. This means that the only way that information will be known about every approach to an intersection within this dataset is if there happens to be a vehicle involved in the collision from every approach to the intersection. While this is technically possible, it is unlikely to occur at intersections that have some form of stop or signal control.

From a practical perspective, having knowledge of two intersecting approaches to an intersection should be sufficient to accurately determine the status of the study variables in the greater majority of cases. While there are scenarios where PSLs, roadway alignment, and road division (as examples) will definitively change at an intersection such that opposing approaches would be categorized differently, this is not the norm.

Cases that do not involve vehicles on intersecting approaches (head-on, rear-end, sideswipe, and single vehicle) have the potential for misclassification of the study variables. Reviewing the data used in this study, about 20% of the signal-controlled cases and 13% of the stop-controlled cases are susceptible to this error for determining the highest PSL approach to the intersection. The application of PSL thresholds in this study mitigate some of this error. Considering the objective of the research and the proposed application, improving collision severity estimation for tools such as traffic signal warrants,
the average collision costs developed are still useful references despite the misclassification of the highest PSL (and other study variables) at the intersection.

The final way that the study variables can be misclassified is if there is missing data within the CDS. Due to the design of the study variables, if one vehicle in a multiple vehicle collision does not report a PSL, the highest PSL at the intersection will be selected from the remaining vehicles that do report this value. Within the combined CDS dataset there are 20,164 vehicle records that contribute information to the 10,535 cases. Of those 20,164 vehicle records, 418 (2%) do not report a PSL and 1,001 (5%) do not report if the road is divided or undivided. These are relatively low rates of missing data that should not have a significant impact on the interpretation of the results of this study, particularly in the context of developing collision costs that better reflect the expected severity of collisions than overall averages do.

2.6 Conclusions

This study highlights variables that traffic engineers can readily determine and/or control for that have significant impacts on the severity of intersection collisions. The average costs determined in this study are representative of the long-term average expectation of collision severity, which are useful in normalizing the risk of higher severity and fatal collisions over time when compared to directly assessing a short-term collision history from a site. There were caveats to the average costs developed due to misclassification of the study variables and missing data; however, the objective of this work was to establish a better means to account for the severity of collisions at intersections, and the recommended collision costs still meet this objective regardless of the potential errors.
2.7 Recommendations

The limiting factor of any collision severity analysis is the reliability of the dataset being studied. The NASS CDS data have been found to be particularly reliable, but collision-level definition of the type of traffic control and PSLs on the intersecting roads would have been particularly useful for this research. Interestingly, the 2015 NASS CDS data used in this study was the last year that CDS data will be available because it is being replaced by NHTSA’s Crash Investigation Sampling System (CISS) starting in 2016 (C. Chen et al. 2015), and similarly the GES is being replaced by the Crash Report Sampling System (CRSS) (NHTSA 2018). The CISS is reportedly going to contain substantially more scene data from collisions, possibly allowing for greater analysis of the roadway design factors involved in collisions. Once several years of data have been collected in these new systems, a rework of this research would be merited to determine if the new collision sampling methods employed by NHTSA shed more light on how the roadway environment influences collision severity.

References


CHAPTER 3: Aggregated North American Safety Performance Functions for Signalized and Stop-Controlled Intersections

Abstract

The statistical analysis of intersection collisions has allowed practitioners to develop reliable local models for collision prediction. While many North American jurisdictions have developed such models, a gap remains for the development of safety performance functions that represent the average North American intersection collision expectation. Such models could be used in the development of national guidelines, benchmarking local models and hotspots, and by jurisdictions lacking the capacity to develop their own models. This research bridged that gap by developing aggregate models of collision expectations at stop-controlled and signalized intersections in North America. In analyzing the results, it was found that the Highway Safety Manual predictive equations are not a good representation of the average intersection collision expectation. Further, it was found that the aggregate models are particularly useful to practitioners looking to estimate the change in collisions resulting from signalization given the partial cancelling out of jurisdiction-level effects.

3.1 Introduction

One of the primary objectives for traffic engineers is to ensure that their transportation networks are reasonably safe for all users. Statistical methods have been rapidly evolving to allow practitioners to develop safety performance functions (SPFs) with less variability for their jurisdictions, and these advancements have led to dozens of jurisdictions across North America developing their own SPFs.

One of the drawbacks of jurisdiction-specific SPFs is their lack of transferability (Faisal 2011, J. Wang et al. 2016). Many studies have shown that calibration is required for a model developed by one jurisdiction to be used in another as an accurate predictor of collisions (Abdel-Rahim and Sipple 2015, Shin et al. 2014, Troyer et al. 2015). While this calibration approach can be used in many circumstances, a gap exists for SPFs that represent average collision expectation. Such models could be used in the development of national traffic signal warrant guidelines, for estimating collision frequencies in jurisdictions that lack the capacity to develop their own models or calibrated models, and for benchmarking locally developed SPFs and hotspot intersections against the national average to gain a better understanding of the potential for improvement.

To-date, the predictive equations provided in the Highway Safety Manual (HSM) have been the most well-known resource for generalized intersection SPFs (AASHTO 2010) and were used as the basis of the most recent collision-based traffic signal warrant in the United States (Bonneson et al. 2014). While the HSM models were a great advancement in their time they were based on limited data from a few jurisdictions and the underlying collision data is going on twenty years old (Harwood et al. 2008, Lord et al.)
2008), so they may not be reliable as a predictor of collisions for an average North American intersection today.

This study aims to fill this research gap by developing aggregate models of 2-way stop-controlled and signalized intersection collision expectations in North America based on a review of published jurisdiction-specific SPFs and calibrations of the HSM predictive equations. This work was a continuation of previous research into the development of aggregate SPFs (Northmore and Hildebrand 2019a), with key new contributions being a broader literature review of existing jurisdiction models to improve the robustness of results and in-depth analysis of jurisdiction variability and applicability of the models. Other forms of intersection traffic control, such as all-way stop or roundabouts, were excluded from this study due to a lack of geographically diverse and robust models to include in the study.

3.2 Safety Performance Functions

Over the last few decades, practitioners have made great strides in the development of statistical intersection collision models (Lord and Mannering 2010), widely referred to as safety performance functions. Instead of attempting to predict the behaviour of individual road users, SPFs predict the number of collisions at an intersection as a function of the approaching traffic volumes and design characteristics of the intersection. As an extension of this predictive capability, SPFs are often used to compare the expected collision frequencies of design alternatives, such as signalizing a stop-controlled intersection (Bonneson et al. 2014, Hadayeghi et al. 2006, McGee et al. 2003).
As the development of these models has become more commonplace, the complexity of the covariates and model structure has evolved. Since the dependent variable used in the creation of SPFs is a count of collisions, the Poisson regression model forms the foundation of many methodologies (Lord and Mannering 2010). Collision data is also commonly over-dispersed, wherein the variance of the data is greater than the mean, so the negative binomial variant of the Poisson model is frequently used (Lord and Mannering 2010). The negative binomial model (also referred to as a Poisson-gamma model) relaxes the Poisson model by introducing a gamma distributed error term, which allows the variance of the model to differ from the mean. The most common specification for a negative binomial model of intersection collisions is shown in Equation 3-1 (Donnell et al. 2016, Green et al. 2015, Tegge et al. 2010), where ‘i’ represents the individual intersection, ‘$N_i$’ is the collision count for the intersection, ‘$\beta$’ is a matrix of coefficients that correspond to the matrix of intersection characteristics ‘$X_i$’, and ‘$\varepsilon_i$’ is a gamma distributed error term with a mean of 1 and a variance of ‘$\alpha$’.

$$N_i = EXP(\beta X_i + \varepsilon_i)$$

While the negative binomial model has been the most popular amongst practitioners (Abdel-Rahim and Sipple 2015, Claros et al. 2018, Garber and Rivera 2010, Qin et al. 2018), numerous other model specifications have been used by practitioners and researchers to improve the predictive capabilities of SPFs. A common variant is the zero-inflated negative binomial model, which has improved flexibility for collision data which often has an overabundance of ‘zero’ collision counts (Lord and Mannering 2010).
Random-effects, Bayesian techniques, neural networks and other more complex modelling techniques have been applied to study collision expectation (Lord and Mannering 2010).

3.2.1 Highway Safety Manual Models

During the development of the Highway Safety Manual (HSM), predictive models were developed based on data from a few jurisdictions to provide a generalized estimate of collisions at intersections (AASHTO 2010, Harwood et al. 2008, Lord et al. 2008). These predictive models were developed using the negative binomial specification and have been used as the basis for the generalized analysis of intersection collisions in the most recent traffic signal warrant guideline in the United States (Bonneson et al. 2014).

Application of the HSM SPFs in specific jurisdictions has demonstrated a need for local calibration. The authors of the HSM identified this as a need and provided a methodology for practitioners to develop a calibration factor for their jurisdiction based on the analysis of a limited pool of intersections (AASHTO 2010). This calibration technique has been used by numerous road authorities across North America (Abaza 2016, Aziz and Dissanayake 2017, Faisal 2011, Karmacharya and Dissanayake 2018, Sun et al. 2014, Xie and Chen 2016). Despite calibration of the HSM providing improved predictive results for jurisdictions, it is still recommended that jurisdiction specific SPFs be developed in lieu of HSM calibrations if sufficient data and expertise are available to do so (AASHTO 2010).

3.2.2 Jurisdiction Models

Developing aggregate models for generalized North American collision expectations requires collision data from a broad set of jurisdictions across the continent. Collision data was not readily available from a geographically diverse set of jurisdictions, so a literature
review was conducted to identify published jurisdiction models for inclusion in this research. The criteria used in the search to identify models for this study were outlined as follows:

- The paper or report containing the model had to be published on or after January 1, 2000.
- Models must be representative of the general collision expectations for the jurisdiction.
- Jurisdiction specific SPFs were preferred over HSM calibrations, with exceptions made when the HSM calibrations were significantly newer than the SPFs.
- If multiple models of the same type were found for a jurisdiction, the most recent model was included.
- The models had to include traffic volume on both the major and minor roads at the intersection as independent variables.

In total, 33 reports and papers were identified that provided estimations of collision expectations from 28 jurisdictions across North America. This is a notable improvement from the previous research, which developed models based on 21 reports and papers on collision expectations from 22 jurisdictions (Northmore and Hildebrand 2019a). The models identified for this study are summarized in Table 3-1, which also identifies if the models are HSM calibrations (H) or jurisdiction specific SPFs (S), for signalized or 2-way stop intersections, in rural or urban settings, the collision severity predicted by the models, and the number of intersection legs (3,4) included in the models. The jurisdictions were also assigned a ‘Region’ based on US Census divisions, with Canadian jurisdictions being
assigned either Northeast, Midwest, or West based on the logical northward extensions of the US regions.

Table 3-1: Jurisdiction models

<table>
<thead>
<tr>
<th>Jurisdiction (ref.)</th>
<th>Region</th>
<th>Dataset Stratification</th>
<th>Stop Control</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<td>Urban</td>
<td>Rural</td>
<td>Urban</td>
<td>Rural</td>
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<td>FI</td>
<td>Total</td>
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</tr>
<tr>
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<td>-</td>
<td>-</td>
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<td>-</td>
<td>H(3,4)</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>S(4)</td>
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<td>(El-Basyouny and Sayed</td>
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<td>West</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Chen 2016)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Michigan (Gates et al.</td>
<td>Midwest</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
</tr>
<tr>
<td>Savolainen et al. 2015)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minnesota (Harwood et al.</td>
<td>Midwest</td>
<td>H(4)</td>
<td>H(4)</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
<td>H(3,4)</td>
<td>H(3,4)</td>
</tr>
<tr>
<td>2008, Lord et al. 2008,</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Storm and Richfield 2014)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
### Table 3-1 (Cont.): Jurisdiction models

<table>
<thead>
<tr>
<th>Jurisdiction (ref.)</th>
<th>Region</th>
<th>Dataset Stratification</th>
<th>Stop Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Missouri (Claros et al. 2018, Sun et al. 2014)</td>
<td>Midwest</td>
<td>-</td>
<td>S(4)</td>
</tr>
<tr>
<td>North Carolina (Harwood et al. 2008, Smith et al. 2016)</td>
<td>South</td>
<td>-</td>
<td>H(4)</td>
</tr>
<tr>
<td>Ohio (Troyer et al. 2015)</td>
<td>Midwest</td>
<td>-</td>
<td>H(4)</td>
</tr>
<tr>
<td>Ontario – Toronto (Faisal 2011)</td>
<td>Northeast</td>
<td>-</td>
<td>H(3,4)</td>
</tr>
<tr>
<td>Ontario – Waterloo (Region of Waterloo 2014)</td>
<td>Northeast</td>
<td>H(4)</td>
<td>H(4)</td>
</tr>
<tr>
<td>Oregon (Dixon et al. 2012)</td>
<td>West</td>
<td>-</td>
<td>H(4)</td>
</tr>
<tr>
<td>Quebec (Barber 2014)</td>
<td>Northeast</td>
<td>-</td>
<td>H(4)</td>
</tr>
<tr>
<td>Saskatchewan - Regina (Young and Park 2013)</td>
<td>West</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>South Carolina (Rajabi et al. 2018)</td>
<td>South</td>
<td>-</td>
<td>H(4)</td>
</tr>
<tr>
<td>South Dakota (Qin et al. 2018)</td>
<td>Midwest</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Texas (Bonneson and Pratt 2008)</td>
<td>South</td>
<td>-</td>
<td>S(3,4)</td>
</tr>
<tr>
<td>Virginia (Garber and Rivera 2010)</td>
<td>South</td>
<td>S(3,4)</td>
<td>S(3,4)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>10</td>
<td>14</td>
</tr>
</tbody>
</table>

### 3.3 Methodology

The methodology for this research was a two-step process. The first step was the creation of synthetic collision data based on the models identified in Table 3-1 by applying a set of predetermined traffic volume pairs to each model to calculate the average collision expectations from each region over a reasonable range of traffic volumes. Once collision data were synthetized for each of the published models, the aggregate models were
specified and developed to calculate the national average total and casualty (FI) collision expectations for stop-controlled and signalized intersections in urban and rural areas.

3.3.1 Dataset Generation

To develop the new aggregate models for collision expectations, collision data were required. Each of the papers and reports summarized in Table 3-1 provide a mathematical model linking traffic volume, and in some cases other factors, to intersection collision expectations. For this research, the models identified in Table 3-1 were used to synthesize collision data for each jurisdiction by calculating the number of expected collisions for select pairs of major and minor road traffic volumes.

Two sets of data were generated to assist with developing the aggregate models. The first set contained 4 data points per jurisdiction model, each consisting of a pair of traffic volumes and the corresponding collision expectation calculated from the jurisdiction model. This dataset was used to generate more reliable estimations of the aggregate models coefficients based on the average collision expectations. The AADT pairs for the major/minor roads were 5000/1500, 5000/5000, 15000/1500, and 15000/6000, corresponding to the traffic volume limits used in the development of the most recent TSW guideline in the United States (Bonneson et al. 2014). The inclusion of more interstitial traffic volume pairs was considered to improve model fit, but interstitial pairs were ultimately not used because the additional data points would artificially increase the significance of the aggregate model coefficients.

The second data set was generated so that dispersion parameters could be estimated for the aggregate models. To accomplish this, synthetic collision counts were developed
from each jurisdiction model following a negative binomial distribution with an average collision expectation calculated at each traffic volume pair and a dispersion parameter equal to either the parameter published with the jurisdiction model or the dispersion parameter from the HSM SPFs. Through trial and error it was found that 207,000 data points were required per model to create a set of dispersed synthetic collision data that reliably reproduced the model coefficients found through analysis of the first data set, corresponding to a set list of 207 traffic volume pairs spanning the same ranges as the first data set but subdivided into 500 AADT intervals repeated 1000 times.

There are benefits and drawbacks to using this approach. The ideal solution would be to collect real collision data from each jurisdiction and use that to create an aggregate model instead of synthesizing data for each jurisdiction from their published models. Unfortunately, the ideal solution is not a practical one, as collecting and merging datasets from 28 different jurisdictions would be a cumbersome process. The synthetic approach used in this research creates data from each published model that, by definition, represent the average collision expectations for each jurisdiction, so the development of an aggregate model based on this synthetic data creates an average-of-the-averages. This can lead to an issue known as the “ecological fallacy” which occurs when it is assumed that what is true for the group is true for the individual within the group (Langbein and Lichtman 1978). While the effects of this phenomenon should be explored in future work with real-world collision data, it will likely not have a substantial impact in practice because SPFs are typically used to compare the effect of different design options, or to identify intersections that deviate from the average for further investigation, instead of being applied as a precise predictive tool.
Most of the jurisdiction models used in this research were based solely on traffic volume. For models that included other covariates, the following set of assumptions were made in accordance with the Highway Safety Manual design assumptions (AASHTO 2010):

- No designated turning lanes, lighting, red-light cameras, or skew.
- No nearby bus stops, schools, or alcohol sales establishments.
- Permissive left-turn signal phasing.
- Permissive right-turn on red.
- Daily pedestrian volume at signalized intersections: 400/day for 3-leg, 700/day for 4-leg.
- Pedestrians cross 2 lanes per maneuver.

In many cases, separate jurisdiction models were found for 3-leg and 4-leg intersections. In these situations, one of the two following rules were used to determine an average collision expectation for the jurisdiction:

- If the number of intersections used to develop each model was unknown, a simple average of the two collision expectations was taken.
- If the number of intersections used to develop each model was known, a weighted average of the two collision expectations was taken based on the number of intersections used by the jurisdiction to develop each model.

Lastly, adjustments were made to the collision expectations from models reporting FI collisions to ensure that the expectation was reflective of all injury severity classification levels. This was particularly for American jurisdictions using the KABCO severity scale.
(K=fatal, A=incapacitating injury, B=Non-incapacitating injury, C=Possible injury, O=No injury) that developed models for KAB collisions instead of KABC. The KAB only models would report fewer collisions than KABC models, so multipliers were calculated from the NASS GES (NHTSA 2016a) based on the expected proportion of ‘C’ collisions at intersections. The multipliers were 2.1857 for signalized intersections and 2.6917 for stop-controlled intersections.

3.3.2 Aggregate Model Specification

Following from the literature, the primary variables of interest for intersection SPFs are the traffic volumes on the intersecting roads. More recent models have included numerous other intersection characteristics in their specifications (Donnell et al. 2016, El-Basyouny and Sayed 2010); however, the characteristics included were inconsistent between models built from different datasets. To maintain consistency and maximize the number of models that could be included, the only intersection characteristic that the aggregate models included was the traffic volumes on the intersecting roads.

Two additional variables were used in the aggregate model specifications with the intent to reduce model variability. A ‘Region’ fixed-effect was included, based on the region information provided in Table 3-1, to identify if regional differences in collision expectation across North America were significant. A ‘Jurisdiction’ random-effect was also included to account for unobserved factors at the jurisdiction level that would affect collision expectation. These variables were included as intercept adjustments, so both could be considered as calibration factors to the aggregate model.
Four specifications were used to develop aggregate models based on the synthetic collision data. The first specification was the base model, the second added a region fixed-effect to the base model, the third added a jurisdiction random-effect to the base model, and the fourth added both a region fixed-effect and jurisdiction random-effect to the base model. These specifications are shown in Equations 3-2 through 3-5. Since the first set of synthetic collision data was not count data, the error terms were assumed to be gamma distributed, while a negative binomial distribution was used for the error term for the second dataset.

\begin{align*}
(3-2) \quad N_i &= e^{\beta_0 AADT \text{maj}_i^{\beta_1} AADT \text{min}_i^{\beta_2}} e^{\epsilon_i} \\
(3-3) \quad N_i &= e^{\beta_0 AADT \text{maj}_i^{\beta_1} AADT \text{min}_i^{\beta_2} e^{(B \times \text{Region}_i + \epsilon_i)}} \\
(3-4) \quad N_{ij} &= e^{\beta_0 AADT \text{maj}_{ij}^{\beta_1} AADT \text{min}_{ij}^{\beta_2} e^{(\eta_j + \epsilon_{ij})}} \\
(3-5) \quad N_{ij} &= e^{\beta_0 AADT \text{maj}_{ij}^{\beta_1} AADT \text{min}_{ij}^{\beta_2} e^{(B \times \text{Region}_i + \eta_j + \epsilon_{ij})}}
\end{align*}

Where:

\begin{align*}
N_i &= \text{annual collision expectation}, \\
AADT \text{maj}_i &= \text{annual average daily traffic on the major road}, \\
AADT \text{min}_i &= \text{annual average daily traffic on the minor road}, \\
\beta_0, \beta_1, \text{ and } \beta_2 &= \text{associated coefficients}, \\
\text{Region}_i &= \text{the region associated with the data}, \\
B &= \text{the associated coefficient with the region}, \\
\eta_j &= \text{the random-effect associated with the jurisdiction}, \text{ and} \\
\epsilon_i \text{ and } \epsilon_{ij} &= \text{gamma or negative binomial distributed error term}.
\end{align*}
Model coefficients were determined using PROC GENMOD for the fixed-effect only models and PROC GLIMMIX with the Laplace for the models including random-effects. The resulting aggregate models were compared using the Akaike information criterion (AIC) for the overall models and the t-statistics for the fixed-effect coefficients. AIC is a likelihood-based estimation of model strength that penalizes for the number of model parameters included and lower AIC scores indicate better model fit, given that the models being compared are based on the same datasets.

3.3.3 Model Evaluation

Evaluating the predictive performance of the aggregate models involved two steps: calculating calibration factors for the HSM models based on the aggregate model results and calculating the mean squared prediction error (MSPE), mean prediction bias (MPB), and mean absolute deviation (MAD) for each model from a simulated set of collision data.

To calculate calibration factors for the HSM models based on the aggregate models, collision expectations were calculated from each model using a predetermined matrix of major and minor traffic volumes. Ranges of 5,000 to 15,000 AADT on the major road and 1,500 to 6,000 AADT on the minor road were used in increments of 500 AADT such that there were 207 traffic volume combinations in the matrix. The average collision expectation was calculated for each of the aggregate and HSM models, and the ratio of the averages between corresponding aggregate and HSM models were taken to calculate the calibration factors.

Traditionally, SPFs are evaluated by applying several statistical tests to encompass different aspects of model variability. For this research, three tests were selected (MSPE,
MPB, and MAD) to provide this baseline understanding (Young and Park 2013). The equations for MSPE, MPB, and MAD are shown in Equations 3-6, 3-7, and 3-8 respectively, and smaller results indicate better model fit.

\[(3-6)\quad MSPE = \left[\frac{\sum_{i=1}^{n} (\bar{N}_i - N_i)^2}{n}\right]
\]

\[(3-7)\quad MPB = \left[\frac{\sum_{i=1}^{n} (\bar{N}_i - N_i)}{n}\right]
\]

\[(3-8)\quad MAD = \left[\frac{\sum_{i=1}^{n} |\bar{N}_i - N_i|}{n}\right]
\]

Where:

\[N_i = \text{annual collision expectation calculated from the model,}\]

\[\bar{N}_i = \text{observed collision history from the simulated dataset, and}\]

\[n = \text{the total number of observations in the simulated dataset.}\]

A third dataset was created to evaluate the models using these metrics. The procedure for synthesizing this data was the same as for the second dataset detailed previously (allowing for the creation of synthetic collision counts that follow their negative binomial error distributions) but without the 1000 repetitions. This was done to create subsets of synthetic collision count data that could be expected to be observed without oversaturating the data to the extent that cumulative errors would naturally reduce to zero.

### 3.4 Results

The results of the aggregate modelling for signalized and stop-controlled intersections are shown in Tables 3-2 and 3-3, respectively. These tables show the parameter coefficients, variance of the jurisdiction random-effect and residual, and the AIC value for each model.
Shaded cells indicate that the coefficient was not statistically significant (p>0.05), bolded fonts indicate that that coefficient had the highest t-statistic within each set of aggregate models, and the Northeast region was omitted because it was selected as the reference region for the models.

Table 3-2: Model outputs for signalized intersections

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Model</th>
<th>Intercept</th>
<th>AADT Major</th>
<th>AADT Minor</th>
<th>Region</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Midwest</td>
<td>South</td>
<td>West</td>
<td>Jur.</td>
</tr>
<tr>
<td>Rural</td>
<td>-</td>
<td>-10.637</td>
<td>0.756</td>
<td>0.474</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>J</td>
<td>-10.284</td>
<td>0.706</td>
<td>0.473</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>R</td>
<td>-10.675</td>
<td>0.738</td>
<td>0.478</td>
<td>0.416</td>
<td>-0.064</td>
</tr>
<tr>
<td></td>
<td>J &amp; R</td>
<td>-10.333</td>
<td>0.706</td>
<td>0.473</td>
<td>0.240</td>
<td>-0.131</td>
</tr>
<tr>
<td>Urban</td>
<td>-</td>
<td>-9.588</td>
<td>0.708</td>
<td>0.499</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>J</td>
<td>-9.589</td>
<td>0.708</td>
<td>0.484</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>R</td>
<td>-9.434</td>
<td>0.704</td>
<td>0.500</td>
<td>0.078</td>
<td>-0.314</td>
</tr>
<tr>
<td></td>
<td>J &amp; R</td>
<td>-9.388</td>
<td>0.708</td>
<td>0.484</td>
<td>0.044</td>
<td>-0.335</td>
</tr>
</tbody>
</table>

Table 3-3: Model outputs for stop-controlled intersections

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Model</th>
<th>Intercept</th>
<th>AADT Major</th>
<th>AADT Minor</th>
<th>Region</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Midwest</td>
<td>South</td>
<td>West</td>
<td>Jur.</td>
</tr>
<tr>
<td>Rural</td>
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<td>-10.575</td>
<td>0.802</td>
<td>0.316</td>
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<td>-</td>
</tr>
<tr>
<td></td>
<td>J</td>
<td>-10.866</td>
<td>0.808</td>
<td>0.332</td>
<td>-</td>
<td>-</td>
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<tr>
<td></td>
<td>R</td>
<td>-10.945</td>
<td>0.809</td>
<td>0.325</td>
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<td>0.412</td>
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<tr>
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<td>0.808</td>
<td>0.332</td>
<td>-0.036</td>
<td>0.264</td>
</tr>
<tr>
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<td>0.779</td>
<td>0.364</td>
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</tr>
<tr>
<td></td>
<td>J</td>
<td>-9.780</td>
<td>0.803</td>
<td>0.361</td>
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<tr>
<td></td>
<td>R</td>
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<td>0.803</td>
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</table>
Aggregate models were also created specifically for 3- and 4-leg signalized and stop-controlled intersections. For this set of models, only the jurisdiction random-effect specification (Equation 3-4) was used based on the analysis of the results from Tables 3-2 and 3-3. These models are shown in Table 4 along with the covariates for the jurisdiction random-effect models from Tables 3-2 and 3-3 and the associated dispersion parameters.

**Table 3-4: Jurisdiction random-effect model covariates for all, 3-, and 4-leg intersections with associated dispersion parameters**

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Control</th>
<th>Land Use</th>
<th>Severity</th>
<th>Legs</th>
<th>Intercept</th>
<th>AADT Major</th>
<th>AADT Minor</th>
<th>Dispersion Parameter</th>
</tr>
</thead>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Signal</td>
<td>FI</td>
<td>-</td>
<td></td>
<td></td>
<td>-8.270</td>
<td>0.703</td>
<td>0.237</td>
<td>0.395</td>
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<td>0.230</td>
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<td>0.536</td>
<td>0.198</td>
<td>0.417</td>
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<td>4</td>
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<td>-5.960</td>
<td>0.601</td>
<td>0.229</td>
<td>0.296</td>
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<tr>
<td><strong>Urban</strong></td>
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<td></td>
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<td>-9.561</td>
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<td>0.347</td>
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<tr>
<td></td>
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<td>3</td>
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<td>-9.044</td>
<td>0.755</td>
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<td>0.364</td>
</tr>
<tr>
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<td></td>
<td>-9.561</td>
<td>0.833</td>
<td>0.264</td>
<td>0.353</td>
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<tr>
<td></td>
<td>Total</td>
<td>-</td>
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<td>-9.063</td>
<td>0.880</td>
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<td>0.923</td>
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<td></td>
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<td>-10.022</td>
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<tr>
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<td>-10.866</td>
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<td></td>
<td>3</td>
<td></td>
<td></td>
<td>-11.697</td>
<td>0.899</td>
<td>0.453</td>
<td>0.841</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td></td>
<td></td>
<td>-8.355</td>
<td>0.723</td>
<td>0.309</td>
<td>0.402</td>
</tr>
</tbody>
</table>
3.5 Discussion

There are four parts to the discussion of the aggregate models presented in Tables 3-2 and 3-3. First is the model selection process, identifying which model specification produced the best overall fit of the data. This is followed with a discussion of how the aggregate models compare to the HSM predictive models. Then the jurisdiction random-effects are analyzed in order to understand the magnitude of the limitations of applying the aggregate models in a general context. The last part of the discussion is on the application of the aggregate models by practitioners and the care that should be taken when interpreting their results.

3.5.1 Model Selection

The most notable pattern from the results shown in Tables 3-2 and 3-3 was that inclusion of the jurisdiction random-effect greatly reduced AIC scores, indicating greatly improved model fit compared to the specifications without the random-effect. This was expected because it is well known that collision expectations vary significantly between jurisdictions and that models designed for one jurisdiction typically require some form of calibration to be applicable elsewhere. The individual coefficients assigned to each jurisdiction through the random-effect are akin to local calibration coefficients for the aggregate models.

Inclusion of only the region fixed-effect typically improved model fit to some degree; however, most of the region coefficients for the aggregate models were not statistically significant. Further, including the region fixed-effect with the jurisdiction random-effect only improved model fit over the jurisdiction random-effect only model with
the Signalized-Rural-Total dataset. This suggests that, in general, the regions used in this analysis did not show significant differentiation in collision expectations.

In seven of the eight datasets, the best fitting model was the one incorporating only the jurisdiction random-effect. Due to this majority, the analysis in the remainder of this study will only consider the jurisdiction random-effect only models from all eight datasets.

3.5.2 Comparison to the HSM Predictive Models

The average, minimum, and maximum collision expectations from the aggregate and HSM models and the calibration factors required to adjust the HSM predictive models to match the results from the aggregate models are shown in Table 3-5. These results show that the HSM predictive models underpredict the aggregate model collision expectation for signalized urban intersections and overpredict the aggregate model collision expectations from stop-controlled and signalized rural intersections. While not surprising, given the limited data sources used in the development of the HSM models, these findings indicate that the HSM predictive equations are not a good representation of the average collision expectations at signalized or stop-controlled intersections in North America.

Table 3-5: Collision expectation comparison between the aggregate and HSM models

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Aggregate Models</th>
<th>HSM Models</th>
<th>Calibration Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>Rural</td>
<td>FI</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>FI</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td>4.14</td>
</tr>
<tr>
<td>Stop</td>
<td>Rural</td>
<td>FI</td>
<td>1.09</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>FI</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td>1.76</td>
</tr>
</tbody>
</table>
The aggregate model collision expectations shown in Table 3-5 also demonstrate that the average signalized intersection is expected to exhibit more collisions than the average stop-controlled intersection within the range of traffic volumes used in this study. This result contrasts with most of the literature on collision modification factors for signalizing an intersection, which tend to show a reduction in collisions due to signalization in most studied jurisdictions (Harkey et al. 2008, McGee et al. 2003, Pernia et al. 2002, Sacchi et al. 2016, R. Srinivasan et al. 2014, J. Wang et al. 2016). While these findings suggest that signalizing an intersection may not have the collision reduction benefit that has been traditionally expected, there are numerous methodological reasons why a collision modification factor (CMF) developed through the before-after study of intersection signalization would produce a more reliable estimate of the change in collision expectation than a ratio of generalized SPFs. As both taking the ratio of SPFs and applying CMFs are commonly recommended and applied methods for estimating the change in collision frequency due to signalizing a stop-controlled intersection, these findings highlight a need for more research into the current state of the practice.

The results of the MSPE, MPB, and MAD tests for each of the aggregate, uncalibrated HSM, and calibrated HSM models are shown in Table 3-6, with cell shading highlighting the results with the lowest variability from each test. The aggregate and calibrated HSM models show very similar predictive performance in these results, and this is unsurprising due to how many of the jurisdiction models incorporated in this research were calibrations of the HSM models. The uncalibrated HSM models generally showed more error than the other models, except for when the calibration factor was reasonably close to one. These results show that either the aggregate models or the calibrated HSM
models are preferred for predicting average North American collision expectations over the uncalibrated HSM models.

Table 3-6: Comparison of the aggregate and HSM models through MSPE, MPB, and MAD tests

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Calibration Factor</th>
<th>Aggregate Model</th>
<th>HSM - Uncalibrated</th>
<th>HSM - Calibrated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>Land Use</td>
<td>Severity</td>
<td>MSPE</td>
<td>MPB</td>
</tr>
<tr>
<td>Rural</td>
<td></td>
<td>Fl</td>
<td>0.35</td>
<td>2.36</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>Fl</td>
<td>1.78</td>
<td>2.05</td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td>Fl</td>
<td>2.16</td>
<td>61.88</td>
</tr>
<tr>
<td>Stop</td>
<td></td>
<td>Fl</td>
<td>0.54</td>
<td>3.20</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>Fl</td>
<td>0.56</td>
<td>10.24</td>
</tr>
<tr>
<td>Rural</td>
<td></td>
<td>Fl</td>
<td>0.70</td>
<td>0.88</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>Fl</td>
<td>0.88</td>
<td>5.31</td>
</tr>
</tbody>
</table>

3.5.3 Jurisdiction Random-Effects

Given that the aggregate models developed in this research represent nationally averaged collision expectations, it is important to consider how the actual expectations in local jurisdictions may differ from the aggregate models. To do this, the jurisdiction random-effect estimates were extracted from the aggregate models. Figure 3-1 shows box and whisker plots of the random-effect estimates and their natural exponentials (‘e’ to the power of ‘random-effect estimate’) from each of the datasets, wherein the whiskers extend to the minimum and maximum values. The natural exponentials of the random-effects are akin to a multiplicative local correction factor. Figure 3-1 shows that there was substantial variation in collision expectations between jurisdictions.
Figure 3-1: Box-and-whisker plots of the jurisdiction random-effects (a) and exponentials of the jurisdiction random-effects (b) from each model

![Box-and-whisker plots with linear trendlines and lines of equivalence](image)

Given the broad range of local variation exhibited in Figure 3-1, jurisdictions that had random-effects available for both stop and signal controlled intersections in the Rural FI, Rural Total, Urban FI, and Urban Total groups were identified and the natural exponentials of signalized and stop-controlled random-effects were plotted on opposing axes to determine if there was any correlation between the random-effects. The Missouri data for Urban Total collisions was identified as an outlier, likely due to a difference in methodology between the models combined from Missouri in this analysis, so it was excluded from these charts. The resulting plots with linear trendlines (bold) and lines of equivalence (dashed) are shown in Figure 3-2.
Figure 3-2: Comparison of the exponentials of the jurisdiction random-effects from jurisdictions that reported models for both stop and signal controlled intersections from the Rural FI (a), Rural Total (b), Urban FI (c), and Urban Total (d) datasets

The plots in Figure 3-2 show that the jurisdiction random-effect for stop-controlled intersections is a fairly good predictor of the jurisdiction random-effect for signalized intersections in the Rural Total (R-squared = 0.8845) and Urban Total (R-squared = 0.5765) collisions and that it is not as good of a good predictor for Rural FI (R-squared = 0.0195) or Urban FI (R-squared = 0.3265) collisions. None of the trendlines follow the line of equity exactly, though both the Rural and Urban total have slopes of 1.2 and 0.8 respectively which are close to equity (a slope of 1). Table 3-7 shows the average, minimum, and maximum ratios or signalized to stop-controlled jurisdiction random-effects. The results in Table 3-7 further illustrate that there is less variability in the ratio of jurisdiction random-effects for the total collision models than the FI collision models.
Table 3-7: Average, minimum, and maximum ratios of signalized to stop-controlled jurisdiction random-effects

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Avg.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural FI</td>
<td>1.22</td>
<td>0.37</td>
<td>2.19</td>
</tr>
<tr>
<td>Rural Total</td>
<td>1.10</td>
<td>0.84</td>
<td>1.65</td>
</tr>
<tr>
<td>Urban FI</td>
<td>1.09</td>
<td>0.62</td>
<td>2.58</td>
</tr>
<tr>
<td>Urban Total</td>
<td>0.91</td>
<td>0.60</td>
<td>1.70</td>
</tr>
</tbody>
</table>

It is logical, from a road safety perspective, that the jurisdiction random-effects for Rural Total and Urban Total collisions are correlated. The results shown in Figure 3-2 and Table 3-7 control for the type of traffic control in use at the intersection and traffic volume. Once these factors are controlled, most other factors that would be expected to affect total collisions (driver behavior, environment, roadway infrastructure) should affect signalized and stop-controlled intersections similarly at the jurisdiction level. The same cannot be said for FI collisions, particularly because the types of collisions that occur at stop-controlled intersections are more likely to result in injuries or fatalities than the types of collisions that occur at a signalized intersection.

3.5.4 Application of the Aggregate Models

The objective of this research was to develop aggregate models of collision expectations at stop-controlled and signalized intersections in North America that can be applied by jurisdictions that do not have the capacity to build their own models, for benchmarking locally developed SPFs and collision hotspots against an average collision expectation, and for the development of more robust collision-based traffic signal warrants and other similar national guidelines. The aggregate models developed in this research can be used in these scenarios, but there are limitations of which practitioners should be aware.
The analysis of jurisdiction effects suggests that the aggregate models are most useful to practitioners when being applied to predict the change in collisions when converting a stop-controlled intersection to signalized, or vice versa. The cancelling out of jurisdiction effects that occurs when using the aggregate models to predict the change in collisions results in lower variability than attempting to use the aggregate models to accurately predict collisions, particularly from the total collision models. The aggregate models could still be used as a baseline collision prediction tool, but it is recommended that a calibration process be undertaken to adjust the results to better match local expectations.

When using the aggregate models to predict a change in collisions, it would be prudent for practitioners to consider using the minimum and maximum values shown in Table 3-7 as adjustment factors to create a range of possible results. For detailed design purposes, it is recommended that practitioners use the aggregate models with their before and after expected traffic volumes to develop the most accurate change in collision expectations for their intersection. For more generalized cases, the collision modification function model parameters shown in Table 3-8 can be applied. These functions were calculated by dividing the signal controlled aggregate models by the stop-controlled aggregate models and simplifying the exponential parameters, and therefore assume the same traffic volumes before and after changing the form of traffic control.
### Table 3-8: Model parameters for signalization CMFs based on the aggregate models in Tables 3-2 through 3-4

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Land Use</th>
<th>Severity</th>
<th>Legs</th>
<th>Intercept</th>
<th>AADT Major</th>
<th>AADT Minor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural FI</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2.013</td>
<td>-0.002</td>
<td>-0.235</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3.422</td>
<td>-0.209</td>
<td>-0.159</td>
<td>-0.332</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>2.947</td>
<td>-0.061</td>
<td>-0.254</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>3.557</td>
<td>-0.102</td>
<td>-0.254</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>3</td>
<td>4.547</td>
<td>-0.228</td>
<td>-0.244</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>3.202</td>
<td>-0.059</td>
<td>-0.269</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban FI</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.305</td>
<td>0.010</td>
<td>-0.067</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3.180</td>
<td>-0.124</td>
<td>-0.147</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.553</td>
<td>0.053</td>
<td>-0.051</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>-</td>
<td>0.718</td>
<td>0.076</td>
<td>-0.070</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2.240</td>
<td>-0.003</td>
<td>-0.188</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>-0.571</td>
<td>0.166</td>
<td>-0.038</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 3.6 Conclusions

In this study, aggregate models for total and FI collisions were developed for stop-controlled and signalized intersections in urban and rural environments in the United States and Canada. It was generally found that the inclusion of a jurisdiction random-effect produced the most statistically significant models of the specifications tested, though the additional inclusion of region fixed-effects improved the total collision model at rural signalized intersections.

There were three main findings drawn from the analysis of the aggregate models. The first was that the current HSM models underpredict collisions at signalized urban intersections by a factor of about 2 and overpredict collisions at stop-controlled and rural signalized intersections by factors of 1.1 to 2.7 depending on the model. These results indicated that the HSM predictive equations are not representative of the average collision
expectation at North American intersections and can only be used in analyses after calibration.

The second main finding was that the average collision expectation at stop-controlled intersections is lower than the average collision expectation at signalized intersections, when keeping traffic volumes constant, within the range of traffic volumes assessed in this research. This finding runs against the traditional understanding of the collision expectations at these types of intersections, and suggests the need for further research.

The third main finding was that the variability of the jurisdiction random-effects is greatly reduced when calculating the change in collisions from intersection signalization compared to the variability of predicting collisions at an intersection. This demonstrated that some jurisdiction level safety characteristics (driver behavior, intersection design, climate, etc.) affect signalized and stop-controlled intersections in a similar manner. The reduced variability also suggests that the aggregate models are particularly useful to practitioners when they are being applied to predict a change in collisions due to changing the form of intersection traffic control, though the variability observed in this report should be used as upper and lower bounds on any analysis.

3.7 Recommendations

Future research should be conducted on a multi-jurisdiction analysis of SPFs based on raw collision data. Such a study would likely have a smaller scope than this research but would be able to provide valuable insight into how the variabilities from each jurisdiction overlap and further investigate the difference in collision expectation between signalized and stop-
controlled intersections. Such a study could also investigate the effects of a wider range of model covariates, depending on data availability, and examine the impact of the ecological fallacy on the results of this research.

Similar research should also be carried out for other subjects where many models or calibrations have been developed by multiple jurisdictions, such as for 2-lane or multi-lane highway segments.

Lastly, this research should be repeated on a periodic basis to ensure that the most up-to-date aggregate models are available to practitioners.

References


Garber, N. and Rivera, G. 2010. Safety Performance Functions for Intersections on Highways Maintained by the Virginia Department of Transportation. FHWA/VTRC 11-CR1, Virginia Department of Transportation and Federal Highway Administration.


FHWA/NC/2013-11, University of North Carolina Highway Safety Research Center, Chapel Hill, NC.


CHAPTER 4: Evaluating the Safety Benefits of Intersection Signalization in North America Using Safety Performance Functions

Abstract

Practitioners are often asked to evaluate the safety benefits of signalizing a stop-controlled intersection. Few standardized modern resources are available to explicitly assess the safety benefits of signalization due to transferability issues with jurisdiction-specific research. Default collision analyses embedded in traffic signal warrants are often the best, if not only, resource available for practitioners in jurisdictions lacking the capacity to develop their own statistical tools.

This research bridged this gap by evaluating how collision frequency and net collision costs are affected by signalizing several common configurations of stop-controlled intersections in North America. The evaluation was built upon underlying research on aggregated safety performance functions (SPFs) developed through the analysis of SPFs from 28 North American jurisdictions and research into the intersection characteristics that influence collision severity and cost in the United States.

It was found that signalizing most of the intersection configurations considered (for various traffic volumes) did not result in a projected net safety benefit. This contrasted with the existing literature and practitioner expectations; however, it is important to note that analyses based on SPFs have different foci and practical applications than those based on

3 Intended for submission to the Journal of Transportation Safety and Security.
other tools. Further research is recommended into evaluating the long-term effects of intersection signalization.

4.1 Introduction

Practitioners are often asked to determine if changing the form of traffic control at an intersection would improve the intersection’s operational performance. The two main components to this analysis are how changing the form of traffic control will impact the delays experienced by motorists and pedestrians, and the relative safety of the intersection. Numerous resources are available for practitioners to quantify these changes, though notably the change in safety has fewer standardized models that can be used compared to the delay analysis due to the jurisdiction-specific nature of changes in collision frequency and severity.

While many jurisdictions across North America have conducted their own statistical analyses into the local changes in collision frequency (Abdel-Rahim and Sipple 2015, Donnell et al. 2016, Sacchi et al. 2016, R. Srinivasan and Carter 2011) and severity (Council et al. 2005, Fountas et al. 2018, Y. Wang and Zhang 2017, Wu, Zhang, Zhu et al. 2016) due to signalizing a 2-way stop-controlled intersection, developing these models is out of the reach of many, predominantly smaller, road authorities. If a road authority does not have their own models, applying those from other jurisdictions often leads to inaccurate analysis due to issues with model transferability (Faisal 2011, J. Wang et al. 2016).

As a network screening tool or shorthand analysis, practitioners also rely on the default collision analyses incorporated in traffic signal warrant (TSW) systems. Historically, collision-based TSWs in North America have been reliant on rule-of-thumb
collision count thresholds with no known empirical backing (FHWA 2009, MTO 2012, TAC 1988). New developments in the United States have created collision thresholds following the HSM methodology (Bonneson et al. 2014), but these models are based on old collision data from select jurisdictions so the results of these analyses may not translate to modern collision expectations and severity across North America.

The objective of this research was to use modern statistical analyses to evaluate the safety benefit of signalizing a 2-way stop-controlled intersection in North America. To examine the average safety benefit across a wide geography, this study relied on previously published research into the change in collision severity/cost due to signalization in the United States (Northmore and Hildebrand 2019b) and the expected change in collision frequency found through aggregated SPFs developed using published SPFs from jurisdictions across North America (Northmore and Hildebrand 2019a, Northmore and Hildebrand In Press). The results of this analysis were then compared to the existing literature on the safety benefits of signalization to provide a complete perspective on the state-of-the-research.

4.2 Literature Review

To provide a foundation for this research, a literature review was conducted to synthesize how practitioners quantify the safety benefits of signalization. These methods are the change in collision frequency either in total or a subset thereof, the change in net collision costs, and by using collision based TSWs.
4.2.1 Change in Collision Frequency

At a basic level, most collision analyses are focused on the reduction of collisions. There are two main methods used by practitioners to quantify the change in collision frequency due to signalization: developing Collision Modification Factors (CMFs) for signalization or developing Safety Performance Functions (SPFs) for stop-controlled and signalized intersections.

CMFs are preferably developed through before-after studies of collision frequency (Harkey et al. 2008, Hauer 1997, Sacchi et al. 2016, J. Wang et al. 2016). In the case of signalization, a 3- to 5-year period of collisions before the intersection was signalized can be compared to the same length of period directly after signalization to determine the change in collision frequency. Contemporary efforts typically adjust the ‘before’ collision history through an Empirical-Bayes (EB) analysis to account for regression-to-the-mean effects, which requires creating a SPF for stop-controlled intersections similar to those that were converted to signals.

SPFs are functions that predict the average collision expectation for a specific element of road infrastructure (Hauer 1997, Qin et al. 2018, Savolainen et al. 2015, R. Srinivasan and Bauer 2013). They can be used to predict the change in collision frequency due to signalization by assuming that once the intersection is signalized it will have a collision frequency similar to that of the other already signalized intersections in the jurisdiction. Similar to CMFs, the EB method is recommended to account for regression-to-the-mean in the collision history for a site being evaluated using SPFs.

Since CMFs and SPFs provide methodologically different approaches to predicting the change in collision frequency, they fill separate niches within the realm of collision
analysis. Both CMFs and SPFs suffer from issues with transferability between jurisdictions, so practitioners without the ability to create their own CMFs or SPFs may be reliant on models that do not reflect the expected change in collision frequency for their jurisdiction (Faisal 2011, J. Wang et al. 2016).

The final consideration for quantifying safety benefits in terms of the change in collision frequency is selecting which collisions to include. The two main ways to categorize collisions for counting is either by the severity or by the configuration. Common ways to group collisions by severity is to count all collisions together, property damage only (PDO) and casualty collisions separately, or only counting casualty collisions. Practitioners following the Vision Zero approach to road safety would typically only be interested in including the collisions that resulted in a serious injury or fatality. The severity categories used by the practitioner are typically determined based on their priorities and data availability/reliability.

The collision configuration describes how and/or with what the vehicle collided. Common categories include rear-end, angle, sideswipe, head-on, pedestrian, and cyclist. These categories are less frequently used in the development of CMFs or SPFs than the collision severity categories but are used by the North American TSWs to identify intersections that may benefit from signalization (Bonneson et al. 2014, MTO 2012).

4.2.2 Change in Net Collision Cost

Solely considering the change in collision frequency ignores that the severity of the average collision can change when a stop-controlled intersection is signalized. This change in severity is due to stop-controlled intersections being prone to high proportions of higher-
severity angle collisions resulting from drivers choosing inappropriate gaps to make turning and crossing maneuvers across main road traffic; whereas signalized intersections are more prone to high proportions of lower-severity rear-end collisions resulting from the intermittent nature of needing to stop. As a result, it is disingenuous to directly compare collision frequencies between stop- and signal-controlled intersections.

The most widely used method to equate collisions of different severity is through collision costs. Extensive research has been conducted into the cost of collisions, which are normally subdivided into collision costs attributed to vehicle damage, injury costs such as medical bills and lost wages, and reduced quality-of-life costs from the long-term effects of sustained injuries (Council et al. 2005, de Leur et al. 2010, Litman and Doherty 2016, Zhang et al. 2005). Using collision costs for different severity levels and distributions of the expected severity of collisions at stop-controlled and signalized intersections, average collision costs can be calculated that allow for a comparison between the collisions under each form of traffic control. Under this methodology, a ‘safety benefit’ is achieved when the expected cost of annual collisions is reduced.

4.2.3 Collision Based Traffic Signal Warrants

TSWs are shorthand tools that are intended to help practitioners easily identify stop-controlled intersections that may benefit from signalization. TSWs are normally developed for use at a national or regional level to provide consistent, objective justification for the signalization of stop-controlled intersections across large road networks.

For most of the last century, the collision analysis in most North American TSWs has been based on the criteria presented in the original 1935 edition of the Manual of
Uniform Traffic Control Devices (MUTCD) (McGee et al. 2003). This document outlined that an intersection would require 5 or more collisions during a one-year period that were susceptible to correction through signalization and a trial of alternatives to reduce collision rates before meriting signals. These requirements were modified slightly over the decades to the criteria published in the 2009 Edition of the MUTCD, which a warrant threshold of 5 collisions per year that are susceptible to correction, 80% of one of the delay-based warrants must be met, and sufficient trial of alternatives to reduce collision rates (FHWA 2009). The 2009 MUTCD warrant is also similar to the TSW used in Ontario, Canada (MTO 2012). Due to the age of this warrant threshold, there is no known empirical justification for the 5 collisions per year that are susceptible to correction benchmark (McGee et al. 2003).

The upcoming edition of the MUTCD will be getting an updated collision based TSW (Bonneson et al. 2014). The authors of the update applied the predictive tools from the Highway Safety Manual to estimate collision expectations and severities and used this to establish new collision rate thresholds for varying intersection configurations. The warrant thresholds presented in this work are a vast improvement over the previous MUTCD warrants, though questions remain over the validity of using the HSM predictive methods as the basis for a modern national warrant system due to the narrow geographical scope of the models and the age of the collision data that the models were based on.

The current TSW published by the Transportation Association of Canada does not contain an explicit collision history component, but the warrant system that it replaced did (TAC 1988). The previous TSW included a chart that allowed for the conversion of annual reportable collisions to collision priority points for use in the warrant scoring. The chart
was set up in such a way that 8 collisions per year earned ‘0’ points, with lower collision frequencies getting negative points and higher frequencies receiving positive points; this suggested that signalizing an intersection with fewer than 8 reportable collisions per year would have a negative effect on intersection collisions. The underlying assumptions used to develop this chart are unknown to the authors of this study.

Additional TSW systems with collision components were found for the UK and Australia. The Design Standards for Signal Schemes in London specified that signals may be warranted if the collision history at the proposed site has a greater collision rate than the average of intersections in similar areas (Transport for London 2011). The UK’s Circular Roads 5/73 specified that signals may be warranted if five persons were injured in collisions per year (Huddart 1980). In Australia, it was found that many of the states and territories have collision TSWs either identical to or similar to the MUTCD (Department of Transport and Main Roads 2013, Huddart 1980, Roads & Maritime Services 2013, Roads and Traffic Authority 2010, Vicroads 2015).

4.3 Methods

This research relied on published research into aggregated SPFs (Northmore and Hildebrand 2019a, Northmore and Hildebrand In Press) and average collision costs (Northmore and Hildebrand 2019b) for stop-controlled and signalized intersections. Considering the use of SPFs, the overall framework for evaluating the safety benefits in this research is shown in Equation 4-1. This formulation follows the standard procedure for predicting the change in collision frequency based on SPFs and using the EB method
to account for the regression-to-the-mean effect (Hauer 1997, Qin et al. 2018, Savolainen et al. 2015, R. Srinivasan and Bauer 2013).

\[(4-1) \quad B = \left( \frac{SPF_B \times \left( F_B + \left( \frac{1}{\alpha} \right) \right)}{\left( \frac{1}{\alpha} \right) + n SPF_B} \right) \left( \frac{SPF_A C_A - C_B}{SPF_B} \right) \]

Where:

- $B$ is the resulting safety benefit, with negative values indicating a benefit;
- $F_B$ is the collision frequency before signalization;
- $C_B$ and $C_A$ are multipliers for the before and after collision frequencies that change for the different methods of evaluating safety benefits;
- $SPF_B$ and $SPF_A$ are the collision expectations from before and after signalization calculated from the aggregate SPFs;
- $\alpha$ is the dispersion coefficient associated with the stop-controlled intersection SPF, and;
- $n$ is the number of years worth of collisions predicted by the SPFs.

An initial sensitivity analysis was conducted on the inputs to this equation and it was found that adjusting the collision frequency before signalization did not affect whether there was a benefit to signalization; the ratio of SPFs and collision multipliers were the determining factors in there being a benefit. Due to these results, a before signalization collision frequency of 5 collisions per year was used throughout the rest of this study. Adjusting the before signalization collision frequency does adjust the magnitude of the benefits calculated and this should be taken into consideration when interpreting and
applying the results. Additionally, the range of traffic volumes considered in this research was 5000 to 15000 AADT on the major road and 1500 to 6000 AADT on the minor road, to be consistent with the AADT ranges used in developing the most recent traffic signal warrant guidelines in the United States (Bonneson et al. 2014) and in the development of the aggregate SPFs applied in this study (Northmore and Hildebrand In Press).

Several metrics for safety benefits were evaluated in this research to cover a broad assortment of metrics commonly used by practitioners: changes in total, casualty, and fatal/serious injury collision frequency and changes in annual net collision costs from total and casualty collisions. For the total and casualty collision frequency metrics, $C_B$ and $C_A$ were set equal to ‘1’. For the fatal/serious injury collision frequency metrics, $C_B$ and $C_A$ were set equal to the proportion of fatal/serious injury collisions at each type of intersection according to the underlying collision severity research. Finally, for the net cost analyses the average intersection collision costs from the underlying research were used for $C_B$ and $C_A$.

The change in collision frequency was estimated using SPFs for annual collision frequency developed through the aggregate analysis of SPFs and HSM calibrations from jurisdictions across North America (Northmore and Hildebrand In Press). A literature review was undertaken to identify reports and papers published since January 1, 2000 that included models for collision frequency at stop and signal-controlled intersections, primarily AADT only models or HSM model calibrations using the base scenario conditions. In total, 33 reports were identified that published a total of about 190 models or calibration factors from 28 jurisdictions that could be included in the aggregation process. A map with the 28 jurisdictions highlighted is shown in Figure 4-1; the majority
of the jurisdictions were state or provincial road authorities with a few of the Canadian jurisdictions being municipal road authorities, including two in Ontario. The jurisdiction models were aggregated by creating synthetic collision data as a function of major and minor road traffic volumes for each jurisdiction; aggregating the synthetic data into datasets stratified by type of traffic control, land use, collision severity, and number of intersection legs; and developing models for annual collision frequency from the aggregated datasets including traffic volume fixed effects and a jurisdiction random effect. The resulting models from the aggregation process were used in this study because they represent the average collision expectations in North America and because they were a better fit to randomly generated synthetic collision data than the uncalibrated HSM models. A summary of the aggregate SPF\s and their dispersion coefficients is presented in Table 4-1.
Figure 4-1: Map highlighting the jurisdictions included in developing the aggregate SPFs (MapChart 2019)
Table 4-1: Aggregate SPFs for Signalized and Stop-Controlled Intersections (Northmore and Hildebrand In Press)

<table>
<thead>
<tr>
<th>Category</th>
<th>Safety Performance Function</th>
<th>Model</th>
<th>Dispersion Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Signal</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Casualty</td>
<td>( N = e^{-7.629} AADT_{maj}^{0.619} AADT_{min}^{0.222} )</td>
<td>0.515</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-7.227} AADT_{maj}^{0.591} AADT_{min}^{0.240} )</td>
<td>0.319</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>( N = e^{-5.476} AADT_{maj}^{0.536} AADT_{min}^{0.198} )</td>
<td>0.417</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-5.960} AADT_{maj}^{0.601} AADT_{min}^{0.229} )</td>
<td>0.296</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Casualty</td>
<td>( N = e^{-9.044} AADT_{maj}^{0.755} AADT_{min}^{0.233} )</td>
<td>0.364</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-9.596} AADT_{maj}^{0.833} AADT_{min}^{0.264} )</td>
<td>0.353</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>( N = e^{-9.457} AADT_{maj}^{0.896} AADT_{min}^{0.265} )</td>
<td>0.374</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-8.926} AADT_{maj}^{0.889} AADT_{min}^{0.271} )</td>
<td>0.373</td>
<td></td>
</tr>
<tr>
<td><strong>Stop</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Casualty</td>
<td>( N = e^{-11.051} AADT_{maj}^{0.828} AADT_{min}^{0.381} )</td>
<td>0.702</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-10.174} AADT_{maj}^{0.653} AADT_{min}^{0.572} )</td>
<td>0.923</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>( N = e^{-10.022} AADT_{maj}^{0.747} AADT_{min}^{0.442} )</td>
<td>0.556</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-9.162} AADT_{maj}^{0.660} AADT_{min}^{0.498} )</td>
<td>0.615</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Casualty</td>
<td>( N = e^{-12.224} AADT_{maj}^{0.879} AADT_{min}^{0.380} )</td>
<td>0.894</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-10.149} AADT_{maj}^{0.781} AADT_{min}^{0.314} )</td>
<td>0.585</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>( N = e^{-11.697} AADT_{maj}^{0.899} AADT_{min}^{0.453} )</td>
<td>0.841</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( N = e^{-8.355} AADT_{maj}^{0.723} AADT_{min}^{0.309} )</td>
<td>0.402</td>
<td></td>
</tr>
</tbody>
</table>

The collision costs applied in this research, as summarized in Table 4-2 along with the average proportions of fatal/serious injury collisions, were based on per-severity collision costs published by Blincoe et al. (2015) and a study of the average severity of intersection collisions in the United States (Northmore and Hildebrand 2019b). Note that this study used posted speed limit (PSL) thresholds on the major road of 35 mph for stop-controlled intersections and 40 mph for signalized intersections. Since these PSLs were close, the thresholds were used to split the costs into intersections with high speed and low speed approaches and were assumed to be approximately analogous. Using average collision costs allows the typical difference in average collision severity between stop-
controlled and signalized intersections to be highlighted while also mitigating the impact of fatal and severe injury collisions in a given intersection’s collision history. These severe collisions are rare occurrences that are not typically indicative of another collision of this severity occurring at the intersection in the near future and intersections that consistently exhibit above average frequencies of these severe collisions should be further evaluated through a traditional road safety study.

Table 4-2: Average Collision Costs and Proportions of Fatal/Serious Injury Collisions for Signalized and Stop-Controlled Intersections (Northmore and Hildebrand 2019b)

<table>
<thead>
<tr>
<th>Control</th>
<th>Severity</th>
<th>Land Use</th>
<th>PSL (km/h)</th>
<th>Divided</th>
<th>Average Collision Cost (2010 US dollars)</th>
<th>Average Proportion of Fatal/Serious Injury Collisions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>Rural</td>
<td>-</td>
<td>No</td>
<td></td>
<td>$346,545</td>
<td>10.40%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td>$414,293</td>
<td>17.10%</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>-</td>
<td>No</td>
<td></td>
<td>$244,977</td>
<td>4.38%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td>$276,725</td>
<td>5.26%</td>
</tr>
<tr>
<td>Total</td>
<td>Rural</td>
<td>Low</td>
<td>-</td>
<td></td>
<td>$115,448</td>
<td>2.42%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>High</td>
<td></td>
<td></td>
<td>$139,515</td>
<td>3.98%</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>Low</td>
<td>-</td>
<td></td>
<td>$110,751</td>
<td>1.64%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>High</td>
<td></td>
<td></td>
<td>$140,713</td>
<td>1.75%</td>
</tr>
<tr>
<td>Stop</td>
<td>Rural</td>
<td>-</td>
<td>No</td>
<td></td>
<td>$483,333</td>
<td>15.10%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td>$357,168</td>
<td>22.30%</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>-</td>
<td>No</td>
<td></td>
<td>$652,947</td>
<td>7.30%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td>$414,962</td>
<td>8.90%</td>
</tr>
<tr>
<td>Total</td>
<td>Low</td>
<td>-</td>
<td>No</td>
<td></td>
<td>$124,011</td>
<td>2.74%</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>-</td>
<td>Yes</td>
<td></td>
<td>$214,592</td>
<td>4.99%</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td>$222,724</td>
<td>5.67%</td>
</tr>
</tbody>
</table>

In addition to evaluating the change in safety due to signalization, the results were assessed to determine which traffic volume variable (major road, minor road, or combined) had the greatest impact on the safety benefits for each category. This was accomplished by plotting the calculated safety benefits against each of the traffic volume variables for visual
evaluation and calculating a linear regression trendline and the associated R-squared value. A combination of these measures was used to determine which traffic variable had the greatest impact and the directionality of that impact with increasing traffic volume (either trending towards a positive benefit or trending towards a negative benefit). The plots were also used to identify range of traffic volumes where the safety benefit transitioned between negative to positive values for the categories with traffic volume combinations that resulted in both positive and negative benefits.

4.4 Results

The results of the safety benefit evaluation were subdivided into three tables. Table 4-3 shows the evaluation of total and casualty collision frequency, Table 4-4 shows the evaluation of fatal/serious injury collision frequency, and Table 4-5 shows the evaluation of total and casualty net collision costs. As detailed previously, the results in these tables assume a before signalization collision frequency of 5 collision per year and traffic volumes of 5000 to 15000 AADT on the major road and 1500 to 6000 AADT on the minor road. Each table shows the range of change in safety benefit (negative numbers indicate an increase in safety due to signalization, either through a reduction in collision frequency or net collision cost), identifies the traffic variable with the most impact on the calculated benefit as traffic volumes increased, and the directionality of the change in safety benefit as the identified traffic variable increased.
Table 4-3: Evaluation of the change in total and casualty collision frequency due to signalization

<table>
<thead>
<tr>
<th>Category</th>
<th>Change in Collision Frequency</th>
<th>Dominant AADT Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
</tr>
<tr>
<td>Casualty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Rural</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>1.27</td>
</tr>
<tr>
<td>4</td>
<td>Rural</td>
<td>-1.83</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>0.89</td>
</tr>
<tr>
<td>Total</td>
<td>Rural</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>2.15</td>
</tr>
</tbody>
</table>

Table 4-4: Evaluation of the change in fatal/serious injury collision frequency due to signalization

<table>
<thead>
<tr>
<th>Category</th>
<th>Change in Fatal/Serious Injury Collision Frequency</th>
<th>Dominant AADT Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Casualty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Rural</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Rural</td>
<td>-0.40</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>-0.54</td>
</tr>
<tr>
<td>Total</td>
<td>Rural</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Table 4-5: Evaluation of the change in net collision cost due to signalization

<table>
<thead>
<tr>
<th>Category</th>
<th>Change in Net Collision Cost</th>
<th>Dominant AADT Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
</tr>
<tr>
<td>Casualty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Urban</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Urban</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Urban</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

To provide an example of how to interpret the data in these tables, the first line from Table 4-4 analyses the change in fatal/serious injury frequency based on casualty collision counts for 3-leg rural intersections with an undivided major road. The change in collision frequency analysis found traffic volume combinations that resulted in safety benefits (a reduction of up to 0.13 collisions per year) and safety costs (an increase of up to 0.02 collisions per year). Plotting the relationships between traffic volume and the safety benefit, as shown in Figures 4-2 through 4-4, found that the combined traffic volume count was the most significant predictor of the change in safety benefit and that increased traffic volumes tended to result in increased safety (more negative scores). Finally, the range of
combined traffic volumes where some traffic volume combinations resulted in both positive and negative benefits was between 8000 and 9500 AADT.

**Figure 4-2:** Projected change in fatal/serious injury collision frequency vs. combined traffic volume based on casualty collision counts at 3-leg rural intersections with an undivided major road
Figure 4-3: Projected change in fatal/serious injury collision frequency vs. major road traffic volume based on casualty collision counts at 3-leg rural intersections with an undivided major road.

Figure 4-4: Projected change in fatal/serious injury collision frequency vs. minor road traffic volume based on casualty collision counts at 3-leg rural intersections with an undivided major road.
4.5 Discussion

The discussion is subdivided into sections pertaining to the evaluation of safety benefits of signalization from this research and how these results compare to those published in the literature and TSWs.

4.5.1 Evaluation of Safety Benefits from this Research

The most common finding from this research was that the majority of intersection configurations studied would not exhibit a safety benefit from signalization within the range of traffic volumes considered (5000 to 15000 AADT on the major road and 1500 to 6000 AADT on the minor road). This was true for 50% of the change in fatal/serious injury collision frequency categories (Table 4-4), 60% of the change in net collision cost categories (Table 4-5), and about 88% of the change in overall collision frequency categories (Table 4-3).

The dominant traffic volume variable for the majority of the categories was the minor road AADT. Every category where the minor road AADT was dominant was associated with increasing safety as traffic volumes increased, which was in stark contrast to every category where the major road AADT was dominant being associated with decreasing safety as traffic volumes increased. This suggests that while the majority of intersection categories in this study would eventually (at traffic volumes beyond those included in this analysis) exhibit a safety benefit from signalization due to a reduction in turning and crossing collisions from the minor road, some of the categories would not exhibit a safety benefit from signalization due to a significant increase in the rate of rear-end collisions on the major road.
Another interesting finding from Table 4-3 was that each of the rural intersection categories would exhibit a safety benefit in terms of total and casualty collision frequency reduction at higher volumes but urban intersections would not. There are a number of possible explanations for these results such as differences in driver behavior, traffic distribution throughout the day (for the same volumes, urban intersections may see higher concentrations of traffic volumes in peak hours than rural intersections), and other design or roadside characteristics that could not be covered in this or the underlying research. Ultimately, this is a topic that should be studied in greater depth in future work.

Overall, the results from Table 4-3 through Table 4-5 show that rural intersections and urban intersections with high speed major roads were the most likely to exhibit a safety benefit resulting from signalization. It is notable that these are results for the ‘average’ intersection, so intersections with significantly different proportions of collision type or with deficiencies in other design characteristics (positive guidance, sightline obstructions, etc.) could be more likely to exhibit a benefit from signalization. Such evaluations should be undertaken through a formal road safety study.

4.5.2 Comparison of Results to Published Literature

The majority of literature on the safety benefits of intersection signalization focus on either the change in collision frequency or the change in collision severity/cost. It is widely accepted in the literature that the average severity/cost of a collision decreases when an intersection is signalized (Litman and Doherty 2016, Northmore and Hildebrand 2019b). In terms of the change in collision frequency practitioners are most familiar with the published body of CMFs on signalization, the majority of which indicate that collision
frequencies decrease when stop-controlled intersections are signalized (Harkey et al. 2008, McGee et al. 2003, Pernia et al. 2002, Sacchi et al. 2016, R. Srinivasan et al. 2014, J. Wang et al. 2016). With a combination of reduced average collision severity and a reduction in collision frequency, the literature suggests that almost every stop-controlled intersection should exhibit a safety benefit from signalization.

Based on the findings from the literature review, there are numerous methodological reasons why evaluations of safety benefits based on CMFs and SPFs can result in different outcomes. The first and foremost of these is in the selection of study sites: in the development of CMFs the target sites are intersections that have been signalized and similar stop-controlled intersections for a reference group, whereas SPFs develop models based on all available intersections to develop the expectations for the ‘average’ intersection. Since CMFs are developed based on analysis of intersections that practitioners expected to benefit from signalization, likely in terms of either traffic movement or safety, the resulting CMFs are largely reaffirming the expectations of those practitioners. It’s also likely that these intersections deviate from the ‘average’ intersection in predictable ways, such as exhibiting higher proportions of turning movements, that make them more susceptible to realizing a long-term safety benefit from signalization than the ‘average’ intersection.

Most published CMFs have been developed based on intersections with substantially higher traffic volumes than were considered in this research (Harkey et al. 2008, McGee et al. 2003, Pernia et al. 2002, Sacchi et al. 2016, J. Wang et al. 2016). Since the results from this study showed that many of the intersection configurations would eventually exhibit a positive safety benefit from signalization at higher traffic volumes,
there may not be as much of a discrepancy in practice between these results and the expectations created by published CMFs. Further, this may indicate that the range of traffic volumes used in this research was inappropriate for identifying scenarios where intersections may be considered for signalization or it could further support that CMFs are typically developed based on a subset of intersections that are predictably different from the ‘average’ stop-controlled intersection.

For these reasons, this research (based on SPFs) and the CMF literature give practitioners different information about the safety benefits of signalization. Analyses based on SPFs, such as this research, provide perspective on the safety benefits of signalizing any random stop-controlled intersection. Conversely, analyses based on CMFs provide perspective on the safety benefits of signalizing intersections that practitioners have specifically identified as meriting signalization. As a result, SPF based analyses are most useful in overall planning tools such as TSWs, whereas CMF based analyses are most useful in the detailed operational analysis of a change in traffic control.

4.5.3 Comparison of Results to Traffic Signal Warrant Systems

The main difference between the results of this research and TSWs is that most TSWs make determinations based on the number of collisions that are ‘reducible’ through signalization whereas this research considered all collision types (Bonneson et al. 2014, FHWA 2009, MTO 2012). This metric is typically used as a shorthand for identifying stop-controlled intersections with a high frequency of high severity collisions without going through a more detailed analysis.
It was interesting that this research found that not all intersection categories would exhibit a reduction in fatal/serious injury collisions from signalization. In almost all scenarios the proportion of collisions that resulted in a fatal/serious injury was reduced, but the increase in total collision frequency overcompensated for the reduced average severity. It is important for TSWs to recognize that not all the ‘reducible’ collisions will be eliminated by signalization and that signalization can increase the frequencies of other collisions to the point where there is no net benefit to safety. The new TSW in the United States follows this kind of approach, albeit with SPFs that may not be reflective of the average collision expectation in the United States.

In terms of rule-of-thumb guidance often found in TSWs this research highlighted that signalizing an intersection does not guarantee a net benefit to road safety, which validates the traditional guidance that a sufficient trial of alternatives should be undertaken before considering signalization based on collision history (*FHWA 2009, MTO 2012*). The results from this research could also be used to develop additional rule-of-thumb warrants, such as that rural intersections and intersections with high speed approaches on the main road are likely to exhibit a net safety benefit from signalization (with some variation depending on the metric being considered) compared to urban or low speed intersections.

### 4.6 Conclusions

This research undertook an evaluation of the safety benefits of signalizing a stop-controlled intersection using SPFs using traditional collision frequency, Vision Zero, and net collision cost metrics. It was found that the majority of stop-controlled intersection categories would
not exhibit a safety benefit after signalization, with rural intersections and urban
intersections with high speed major roads being the most likely to exhibit a benefit.

The results from this research were in contrast to the results that would be obtained
following a similar analysis but using published CMFs. It is important to recognize that
this analysis based on SPF s is investigating the likelihood of there being a safety benefit at
a random stop-controlled intersection, whereas CMFs are targeted towards quantifying the
reduction in collision frequency at intersections that practitioners have specifically
identified as meriting signalization.

This research also highlights numerous areas for future investigation. Given the
difference in the expected change in collision frequency found through SPF s and CMFs,
future research into CMFs should investigate the effect of signalizing stop-controlled
intersections on the overall average collision expectations for signalized intersections in
the jurisdiction. It would also be of interest to investigate the long-term effects of
signalizing an intersection as most studies only examine collision frequencies in a 3- to 5-
year ‘after’ period, but once an intersection is signalized it could remain that way for
decades. Lastly, work should be undertaken to examine the simultaneous effects of
roadway characteristics on collision severity and frequency at intersections because many
variables likely have competing effects on both; such studies could allow for a more direct
understand of the benefits of intersection signalization and other design changes without
having to utilize separate statistical analyses into both collision severity/cost and
frequency.
References


Srinivasan, R., Lan, B. and Carter, D. 2014. Safety Evaluation of Signal Installation With and Without Left Turn Lanes on Two Lane Roads in Rural and Suburban Areas. FHWA/NC/2013-11, University of North Carolina Highway Safety Research Center, Chapel Hill, NC.


CHAPTER 5: Development of Collision Adjustment Factors for the
Canadian Traffic Signal Warrant Matrix Procedure\textsuperscript{4}

Abstract

Traffic signal warrants (TSWs) are important tools for traffic engineers because they provide an objective shorthand means of identifying whether a net benefit would result from signalizing an intersection. This decision can impact numerous operational facets; consequently, most TSW systems consider several factors when estimating an overall impact.

The Canadian Traffic Signal Warrant Matrix Procedure, originally published by the Transportation Association of Canada (TAC) in 2003 with subsequent minor adjustments, does not have a collision history component: a common feature in other TSWs. This creates challenges for practitioners investigating the safety impacts of signalization because the lack of a standardized approach can lead to inconsistency in their findings.

This research developed collision adjustment factors (CAFs) that convert the collision history for a site into points that supplement the existing TAC warrant procedure score outputs. The CAFs were developed based on recent research that estimates expected changes in collision severity and frequency in North America due to signalization, with the intent that they can be broadly used by all Canadian jurisdictions. Additionally, the

\textsuperscript{4} Intended for submission to the 2020 Transportation Association of Canada Annual Conference, Vancouver, BC.
procedure used to develop the national CAFs in this research can be employed by jurisdictions analyzing their intersections based on local data.

5.1 Introduction

Traffic engineers and planners often must consider whether changing the type of traffic control at an intersection would improve the intersection’s operational performance. Depending on the types of traffic control being considered there are numerous tools that can be used to assess the net impacts but the primary resource employed is normally a traffic signal warrant (TSW) analysis.

TSWs are shorthand tools that are intended to help practitioners easily identify stop-controlled intersections that may benefit overall from signalization. There are numerous reasons why a practitioner may want to signalize an intersection, though the most common warrants deal with the reduction of delays for lower rank movements and collision history (FHWA 2009, Guebert et al. 2014, MTO 2012). TSWs are normally developed for use at a national or regional level to provide consistent, objective justification for the signalization of stop-controlled intersections across large road networks.

The TSW guideline published by the Transportation Association of Canada (TAC) in 2003 with subsequent modifications, the Canadian Traffic Signal and Pedestrian Signal Head Warrant Matrix Procedure (Guebert et al. 2014), follows a cumulative-factors methodology. The TAC warrant procedure uses a calculation based on conflicting vehicle-vehicle movements, vehicle-pedestrian movements, and a few other intersection and regional characteristics to calculate a score that provides both a warrant threshold (100 or
more points indicates that signals should have a net benefit) and a priority ranking system for intersections (higher scores indicate higher priority).

The TAC warrant procedure does not include a collision history component (Guebert et al. 2014), which further differentiates it from other contemporary TSW systems (Bonneson et al. 2014, Hadayeghi et al. 2006). The authors of the TAC warrant procedure provide several arguments for why they chose not to include collision history in their system; however, this has not relieved practitioners from being obligated to assess the safety implications from signalizing stop-controlled intersections. Since the TAC warrant procedure does not provide guidance on how to compare collision history to their warrant score, practitioners are left with the task of determining how to best accomplish this themselves, which can lead to inconsistency in application.

This research presents a methodology that practitioners can employ to empirically compare collision histories to TAC warrant scores at stop-controlled intersections through the creation of a Collision Adjustment Factor (CAF). The collision analysis used in the development of the CAFs (Northmore and Hildebrand Under Review) was based on analyses of intersection collision frequency (Northmore and Hildebrand In Press) and severity (Northmore and Hildebrand 2019b) across North America. The CAFs developed were intended to be supplemental to the existing TAC warrant procedure. Provincial and municipal road authorities that have their own models for predicting the change in collision expectation due to signalization, collision cost analysis, and/or valuation of the importance of collisions and delays can also use the framework outlined in this research to develop their own CAFs to supplement the TAC warrant procedure.
5.2 Literature Review

To provide a foundation for this research, a literature review was conducted covering the details of the TAC warrant procedure, how collisions have been accounted for in TSWs, and the common methods used to evaluate the externalities of signalizing an intersection.

5.2.1 Canadian Traffic Signal and Pedestrian Signal Head Warrant Matrix Procedure

There are two general approaches that have been used in the development of TSW systems: discrete-factors methodology (DFM) and cumulative-factors methodology (CFM). DFM warrants, such as those published by the FHWA (Bonneson et al. 2014, FHWA 2009) and the Province of Ontario (MTO 2012), provide a set of individual warrants for varying intersection characteristics, where if any one of the warrant criteria are met then signalization may be warranted. CFM warrants, like the one published by TAC (Guebert et al. 2014), provide one overall recommendation for installing signals at an intersection based on a confluence of several distinct facets being considered.

The TAC warrant procedure calculates a score for an intersection based on the number of vehicle-vehicle and vehicle-pedestrian conflicts and a few other physical, demographic, and traffic characteristics of the intersection. The scoring system provides both a warrant threshold (100 or more points indicates that signals may be beneficial) and a priority ranking system for intersections (higher scores indicate higher priority). The scoring system was originally calibrated against other conflicting-movement traffic delay-based traffic signal warrants used in Canada at the time of its creation to provide results that were consistent with the expectations of practitioners (TAC 2003). The method for calculating the TAC warrant score is shown in Equation 5-1.
\[ (5-1) \, W = \left[ \frac{c_{ht} X_{V-V}}{k_1} + \frac{X_{V-p} F L}{k_2} \right] C_s C_{mt} C_v C_p \]

Where:

- \( W \) is the score output from the calculation;
- \( X_{V-V} \) is the cross-product of all vehicle-vehicle conflicts in the intersection;
- \( X_{V-p} \) is the cross-product of all vehicle-pedestrian conflicts in the intersection;
- \( F \) is a pedestrian demographics factor;
- \( L \) is the number of lanes that pedestrians must cross on the main road;
- \( C_s \) is an intersection spacing factor;
- \( C_{mt} \) is a main street truck factor;
- \( C_v \) is a posted speed limit factor;
- \( C_p \) is a population demographics factor, and;
- \( K_1 \) and \( K_2 \) are scaling factors.

The TAC warrant procedure requires counting all through, left turning, and right turning vehicles from each approach for 6-hours, typically covering the morning, midday, and evening peak periods. The hourly counts are then averaged before being used to calculate the TAC warrant score. In addition to the equation, TAC provides a methodology to account for intersection configurations where right turning vehicles from the minor road are not impeded by the other minor road traffic, such as when there are exclusive right turn lanes. This methodology adjusts the product of right turning and conflicting through volumes within the \( X_{V-V} \) component of the equation.
Notably, the TAC warrant procedure does not incorporate a collision history component. The authors of the TAC warrant procedure chose to exclude collision history because of the random fluctuations of collisions around a mean, that most warrants based on collision history do not anticipate future safety issues, and because collision expectations are dependent on the vehicle conflict analysis that was already included in the TAC warrant procedure (Guebert et al. 2014, TAC 2003). The first two of these concerns can be addressed by employing statistical methods for analyzing collision expectations that were not widely in use when the TAC warrant procedure was first created in 2003. The third concern is an issue of calibration; traffic conflict models can be used to predict intersection safety, but the TAC warrant procedure was not calibrated to achieve this result so it is unlikely that an additional collision analysis would be double-counting collisions.

5.2.2 Collision Analysis in Traffic Signal Warrants

The lack of a collision history component separates the TAC warrant procedure from the industry norm, as the majority of other TSW systems do account for collision history in some manner. This includes the previous system published by TAC in 1988, wherein collision priority points were determined by cross-referencing the police reported collision frequency for an intersection on a chart (TAC 1988). Despite other TSWs having a collision history component, most of these warrants are quite dated and the methods used to develop them are unknown to the authors of this study, including the 1988 TAC TSW.

The majority of TSWs with collision history components that were found in this literature review were based on the criteria from the original 1935 edition of the Manual of Uniform Traffic Control Devices (MUTCD) (McGee et al. 2003). The 1935 MUTCD
indicated that signalizing an intersection may be warranted if there were 5 or more angle collisions at the intersection during a one-year period and if a trial of alternative safety collision reduction measures did not improve overall intersection safety. Slight modifications to this criteria were made in subsequent editions of the MUTCD; however, the only substantial addition by the 2009 edition was that 80% of the threshold requirements from one of two delay-based warrants also needed to be met to justify signalization based on collision history (FHWA 2009). Other jurisdictions that use similar collision-based TSWs include Ontario, Canada; the UK; and Australia (Department of Transport and Main Roads 2013, Huddart 1980, MTO 2012, Roads & Maritime Services 2013, Roads and Traffic Authority 2010, Transport for London 2011, Vicroads 2015). Like the 1988 TAC TSW, there is no known empirical justification for these TSWs (McGee et al. 2003).

The upcoming edition of the MUTCD will contain an overhauled collision based TSW that was developed using the Highway Safety Manual predictive tools to establish new collision rate thresholds (Bonneson et al. 2014). These updated thresholds are a substantial improvement over the previous methodology, though the predictive tools in the HSM themselves are dated and had a narrow geographical scope, making them potentially unreliable for the development of TSWs that will see nation-wide application. Additionally, MUTCD presents a DFM warrant, so the updated methodology would still require substantial reworking to be incorporated into a CFM warrant like the current TAC warrant procedure.
5.2.3 Comparison of Signalization Externalities

When an intersection is signalized, it is generally expected that the average delay for conflicted movements at the intersection will decrease, traffic volumes will increase for conflicted movements due to the reduced delay, and that the severity and frequency of collisions will change. This follows the previous discussion of traffic signal warrant systems, wherein vehicle delays and collisions are the main variables considered.

Several externalities are often recommended for consideration in addition to travel time, collisions, and the cost of infrastructure for the general transportation project, including vehicle costs, health, parking, congestion, roadway land value, traffic services, transportation diversity, air pollution, noise, resource consumption, barrier effect, land use impacts, water pollution, and waste disposal (Litman and Doherty 2016). These additional externalities are often omitted when developing traffic signal warrant systems in the interest of developing simplified tools that focus on the localized operational effects of signalizing an intersection.

Direct comparison of the externalities involved in transportation projects is challenging due to the nature of the variables being considered. The most common way to overcome this has been through the economic comparison of costs and benefits, and numerous resources are available to assist practitioners with evaluating the economic costs and benefits of changes to their transportation networks (Council et al. 2005, de Leur et al. 2010, Litman and Doherty 2016, Treasury Board of Canada 2007). In the context of TSWs, a combination of empirical analysis and expert opinion is typically used in their development (Bonnezon et al. 2014, McGee et al. 2003) as the priorities of practitioners do not always align with the results of a cost-benefit analysis.
5.3 Methods

There were two main components to this research: quantifying the change in annual collision costs due to signalization and converting the resulting change into TAC warrant points. The intent was to create the CAFs for the TAC warrant procedure in a framework with substantial flexibility, allowing practitioners to make modifications and develop their own CAFs if desired. The general method being used to calculate the CAF is shown in Equation 5-2 and it is intended that the resulting CAFs can be added directly to the score output from the TAC warrant procedure. The equation was formulated such that a decrease in overall collision costs due to signalization results in a positive CAF.

\[(5-2) \quad W_C = (F_B C_B - F_A C_A) \times S \]

Where:

- \(W_C\) is the collision adjustment factor;
- \(F_B\) and \(F_A\) are the collision frequencies before and after signalization;
- \(C_B\) and \(C_A\) are the average cost of a collision before and after signalization, and;
- \(S\) is a scaling factor used to convert the net collision costs into TAC warrant points.

To assist with converting the net collision costs into TAC warrant points, an analysis of the change in annual delay costs associated with the TAC warrant procedure was conducted. This was not a perfect comparison because the warrant calculation includes several components that do not specifically correspond to expected changes in vehicle delay; however, it allows for an order-of-magnitude comparison between the two most significant externalities associated with signalizing an intersection. It is further notable that
the CAFs developed through this process are useful at the network screening level for identifying candidate intersections for further study, not as a replacement for the safety study that should be conducted prior to signalizing an intersection.

5.3.1 Change in Collision Cost Estimation

This research relied on a previous effort for the estimation of the change in collision costs due to signalization (Northmore and Hildebrand Under Review), which used SPFs for annual collisions developed through the aggregate analysis of SPFs from 28 jurisdictions across North America (Northmore and Hildebrand In Press) and collision costs developed through a study of the average severity of intersection collisions in the United States (Northmore and Hildebrand 2019b) to estimate the change. This prior study phase analyzed the change in collision costs for signalizing intersections exhibiting traffic volumes of 5000 to 15000 AADT on the major road and 1500 to 6000 AADT on the minor road, and a summary of the intersection configurations that resulted in either collision cost increases (+), decreases (-), or mixed results within the range of traffic volumes (+ / -) is shown in Table 5-1. Note that a high PSL is 60 km/h or greater while a low PSL is under 60 km/h in this research. It was notable that this analysis predicted an increase in collision costs after signalization for most intersection configurations; this finding was in contrast to collision cost analyses based on collision modification factors, which typically show a collision cost reduction due to signalization, because the underlying SPFs were developed based on random intersections as opposed to CMFs which are developed based on intersections where practitioners expect to see a benefit (either through delay or collision reduction) from signalization.
Table 5-1: Summary of the change in net collision costs due to signalization (Northmore and Hildebrand Under Review)

<table>
<thead>
<tr>
<th>Category</th>
<th>Severity</th>
<th>Legs</th>
<th>Land Use</th>
<th>PSL</th>
<th>Divided</th>
<th>Signal</th>
<th>Stop</th>
<th>Disp</th>
<th>Average Collision Cost (2010 US$) (Northmore and Hildebrand 2019b)</th>
<th>Change in Total Collision Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Casualty</td>
<td>Rural</td>
<td>- No</td>
<td>Urban</td>
<td>- No</td>
<td>Rural</td>
<td>- No</td>
<td>Urban</td>
<td>- No</td>
<td>$346,545</td>
<td>$483,333</td>
</tr>
<tr>
<td></td>
<td>Rural</td>
<td>- Yes</td>
<td>Urban</td>
<td>- Yes</td>
<td>Rural</td>
<td>- Yes</td>
<td>Urban</td>
<td>- Yes</td>
<td>$414,293</td>
<td>$357,168</td>
</tr>
<tr>
<td>3</td>
<td>Rural</td>
<td>- No</td>
<td>Urban</td>
<td>- No</td>
<td>Rural</td>
<td>- No</td>
<td>Urban</td>
<td>- No</td>
<td>$244,977</td>
<td>$652,947</td>
</tr>
<tr>
<td></td>
<td>Rural</td>
<td>- Yes</td>
<td>Urban</td>
<td>- Yes</td>
<td>Rural</td>
<td>- Yes</td>
<td>Urban</td>
<td>- Yes</td>
<td>$276,725</td>
<td>$414,962</td>
</tr>
<tr>
<td>4</td>
<td>Rural</td>
<td>- No</td>
<td>Urban</td>
<td>- No</td>
<td>Rural</td>
<td>- No</td>
<td>Urban</td>
<td>- No</td>
<td>$244,977</td>
<td>$652,947</td>
</tr>
<tr>
<td></td>
<td>Rural</td>
<td>- Yes</td>
<td>Urban</td>
<td>- Yes</td>
<td>Rural</td>
<td>- Yes</td>
<td>Urban</td>
<td>- Yes</td>
<td>$276,725</td>
<td>$414,962</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$115,448</td>
<td>$124,011</td>
</tr>
<tr>
<td>Total</td>
<td>Rural</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$139,515</td>
<td>$214,592</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$110,751</td>
<td>$124,011</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$140,713</td>
<td>$214,592</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$140,713</td>
<td>$222,724</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$110,751</td>
<td>$124,011</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$140,713</td>
<td>$214,592</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$140,713</td>
<td>$222,724</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$110,751</td>
<td>$124,011</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$140,713</td>
<td>$214,592</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>-</td>
<td>High</td>
<td>-</td>
<td>Rural</td>
<td>-</td>
<td>Urban</td>
<td>-</td>
<td>$140,713</td>
<td>$222,724</td>
</tr>
</tbody>
</table>
Since the prior analysis was based on SPFs, the general method shown in Equation 2 was modified to the formulation shown in Equation 3. This formulation follows the standard procedure for predicting the change in collision frequency based on SPFs and using the EB method to account for the regression-to-the-mean effect.

\[ W_C = \left[ \left( \frac{SPF_B + (\frac{1}{\alpha})}{(\frac{1}{\alpha}) + nSPF_B} \right) \left( C_B - \frac{SPF_A}{SPF_B} C_A \right) \right] \times S \]

Where:

- \( SPF_B \) and \( SPF_A \) are the collision expectations from before and after signalization calculated from the aggregate SPFs;
- \( \alpha \) is the dispersion coefficient associated with the stop-controlled intersection SPF, and;
- \( n \) is the number of years worth of collisions predicted by the SPFs.

5.3.2 Change in Traffic Delay Cost Estimation

Developing an estimate of the change in traffic delay costs due to signalization was a two-step process. First, a set of traffic volume conditions at stop-controlled intersections that would result in TAC warrant scores of around 100 points had to be developed. The 100-point value was used because it is the threshold in the TAC warrant procedure between intersections warranting or not warranting signalization, indicating that the delay reduction benefit observed at this threshold is sufficient to justify signalization. To obtain an adequate sampling of conditions around the 100-point threshold, sets of conditions that resulted in scores of 90 to 110 points were identified. Once a set of these traffic volume conditions were determined, total intersection delays were approximated and delay costs could be
calculated. Many assumptions were made in the development of the estimations, which are documented in the following subsections.

Predefined intersection geometries were used to simplify the calculation procedures while still covering most real-world scenarios. Both 3- and 4-leg intersections were considered, the main road had either one or two through lanes in each direction plus a dedicated left turning lane at the intersection, and the minor road had one lane in each direction under stop control and a dedicated left turn lane was added when signalized. All dedicated left turn lanes were assumed to have capacity for four vehicles. The remaining assumptions were taken from the standard assumptions in the Highway Capacity Manual (TRB 2016), including that the intersections have 12-foot lane widths, were at a level grade, did not have flared lanes, and that there was no skew.

Identification of Traffic Volume Conditions

There were several inputs to the TAC warrant procedure that could have substantial variation between intersections, so a Monte Carlo Simulation was conducted to identify sets of inputs that resulted in output scores of 90 to 110. In a Monte Carlo Simulation, the input parameters to a model are varied randomly within specified ranges across thousands of iterations (10,000 iterations were used in this research) to determine the range and distribution of possible outputs from the model (Robert and Casella 1999), making this an ideal analytical tool to identify combinations of input parameters that resulted in TAC warrant scores of 90 to 110.

The inputs to the TAC warrant procedure were traffic and pedestrian volumes, the distance to the nearest intersection on the main road, main road heavy vehicle percentage,
main road posted speed limit, and the population of the surrounding area. Heavy vehicle percentage was set at 3%, following guidance in the Highway Capacity Manual (TRB 2016), turning volume proportions were drawn from research conducted in Toronto, Canada in the 1980s (Hauer et al. 1981), and the population of the surrounding area was randomly set to one of the three levels designated by TAC. The remaining variables were varied randomly within upper and lower limits in the Monte Carlo analysis as summarized in Table 5-2. These ranges were set to allow the Monte Carlo simulation to generate sets of inputs that would be typical of stop-controlled intersections that are in consideration for signalization. To simplify the analysis, it was assumed that opposing approaches had the same traffic volumes and that equal numbers of pedestrians crossed on each side of the intersection.

Table 5-2: Parameter estimates for the TAC warrant procedure Monte Carlo Simulation

<table>
<thead>
<tr>
<th>Number of Intersection Legs</th>
<th>3-Leg</th>
<th>4-Leg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Lanes on the Main Road</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Lane</td>
<td>5-Lane</td>
<td>3-Lane</td>
</tr>
<tr>
<td>Traffic Volume per approach: Main Road (vph)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>300 – 525</td>
<td>300 – 600</td>
<td>225 – 450</td>
</tr>
<tr>
<td>Traffic Volume per approach: Minor Road (vph)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>125 – 200</td>
<td>125 – 200</td>
<td>100 – 175</td>
</tr>
<tr>
<td>Turning Proportions: Main Road</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left: 10% Right: 10%</td>
<td>Left: 10% Right: 10%</td>
<td>Left: 10% Right: 10%</td>
</tr>
<tr>
<td>Turning Proportions: Minor Road</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left: 50% Right: 50%</td>
<td>Left: 50% Right: 50%</td>
<td>Left: 35% Right: 35%</td>
</tr>
<tr>
<td>Pedestrian Crossing Volume Per road (pph)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-50</td>
<td>0-50</td>
<td>0-50</td>
</tr>
<tr>
<td>Nearest Intersection on Main Road (m)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>100 - 800</td>
<td>100 - 800</td>
<td>100 - 800</td>
</tr>
<tr>
<td>Posted Speed Limit on Main Road (km/h)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>40-80</td>
<td>40-80</td>
<td>40-80</td>
</tr>
</tbody>
</table>
Traffic Delay Estimation and Delay Costs

The change in annual traffic delay due to signalization was then calculated for the hypothetical intersections with the input parameters resulting in TAC warrant scores of 90 to 110 identified in the Monte Carlo Simulation. Traffic delays were estimated using the procedures outlined in the Highway Capacity Manual (HCM) (TRB 2016). Stop-controlled delays were calculated following the core methodology outlined in Chapter 20 and the signal-controlled delays were calculated following the construction of queue accumulation polygons as outlined in Chapter 31. To follow these procedures and simplify the analysis, numerous assumptions were made as follows.

One of the more substantial assumptions made in this analysis was that the traffic volumes at the intersection did not change after signalization. In areas with few alternative routes bypassing the intersection this assumption would have a negligible effect; however, signalizing a single intersection can result in a redistribution of latent traffic demand. Review of the literature did not reveal typical expectations for how traffic volumes are redistributed due to the highly site- and context-specific nature of the redistributions, so the traffic volumes were assumed to remain constant.

For the stop-controlled delay it was assumed that crossing and left-turn movements from the minor road occurred in a single stage, critical and follow-up headways were the HCM default values, u-turns are not allowed, and no capacity adjustments were made due to platoons from upstream signals.

The signalized intersection was assumed to have an 80 second cycle length with 4 second inter-green periods. The signal operates with 2-phases with all movements permissive under green and no protected movement phases. Time was allocated between
the two phases in proportion to the approach volumes, with a 20 second minimum phase length for the minor road. Base saturation flow rates were assumed as per the HCM recommendations. Arrivals are assumed to be random on the minor road, with platoon ratios on the main road corresponding to the distance between intersections and assuming a coordinated signal network. The initial queue and incremental delays were assumed to be negligible, due to the low vehicle volumes. The intersection is assumed to not be in a central business district. Additionally, it was assumed that there were no right turns on red, initial queues from previous cycles, on-street parking, bus stopping, work zones, downstream lane blockages, and no sustained spillback.

The HCM procedures are designed to yield per-vehicle delay estimate, typically for a peak 15-minute or hour interval on a weekday. The TAC warrant procedure is a segmented six-hour period that covers the typical morning, midday, and evening peak traffic periods. The per-vehicle delay estimates calculated from the HCM analysis were converted into yearly per-intersection delay estimates that align with the TAC warrant procedure by multiplying the approach delays by their respective average hourly traffic volumes, the duration of the analysis period per-day (6 hours), a growth factor of 2.17 to account for delays experienced at the intersection outside of the 6-hour study period, and the typical number of days in a year (365 days). The growth factor was calculated based on a chart published in the ITE Transportation Planning Handbook (ITE 2016) which illustrated that 46% of daily delays in the United States are experienced during the combined 7am-9am, 11am-1pm, and 4pm-6pm period (a 6-hour period that coincides with the typical period for the TAC warrant procedure).
While this approach to estimating the yearly per-intersection delays will provide an order-of-magnitude estimate of annual delays to ultimately compare to collision costs, there were some notable drawbacks to this scaling method. The assumption that each of the six study hours experiences the same traffic volume likely underestimates total delays given they typically increase exponentially as traffic volumes increase. Conversely, the assumption that the same delays would be experienced each weekday likely overestimates total delay. The TAC warrant system does not specify a day of the week on which to collect the traffic counts for the analysis, but the analysis is primarily targeted to weekday commuter traffic patterns due to the 6-hour count methodology. Intersections with substantial commuter traffic on weekdays typically exhibit a reduction in volumes on weekends and better distribution of traffic throughout the day, so the rush hour peaks where most delays are experienced are not as common. The impacts of these opposing assumptions depend on local traffic fluctuations and there was notably no guidance found in the literature to account for these impacts accurately at a national level.

To convert the delay estimates into costs, average valuations of travel time were required in units that matched the collision cost units (2010 US dollars). Values of travel time were obtained from US Department of Transportation guidelines in 2009 US dollars and inflated to 2010 US dollars. The recommended average value of travel time for all purposes surface mode trips for local travel was $12.71 per person hour ($12.50 in 2009) and for intercity trips was $18.30 per person hour ($18.00 in 2009) (*Belenky 2011*). A vehicle occupancy of 1.62 persons per vehicle was assumed, which was the Canadian average for light vehicles as published in the 2009 Canadian Vehicle Survey (*Natural Resources Canada 2011*).
5.3.3 Determination of a Scaling Factor

There are two main methods that can be used to determine an appropriate scaling factor for converting the change in collision costs from signalization into TAC signal warrant points: an economic comparison of the change in collision costs and value of TAC warrant points based on delay costs or expert opinion on the value of collisions relative to delays. The economic comparison has the advantage of being the most objective assessment method, though it can produce results that are at odds with the priorities of practitioners if the collision costs outweigh the value of TAC warrant points based on delay. TSWs that incorporate delay and collision components typically prioritize improved traffic flow and often explicitly set collision criteria such that very few intersections would merit installing signals solely based on collision history (Bonneson et al. 2014, FHWA 2009, TAC 1988).

The main justification for using expert opinion in creating scaling factors for the CAFs is the substantial variability of collision frequency and severity between jurisdictions and even between intersections within the same jurisdiction. Due to this issue of variability, the change in collision cost results developed in the prior research (Northmore and Hildebrand Under Review), being an estimate based on North American averages, cannot perfectly predict the actual change in collision costs due to signalization at any randomly selected Canadian intersection. Expert opinion can be used to mitigate this issue by discounting the change in collision costs from signalization such that the CAFs do not hold their full economic weight against delays but still provide a meaningful adjustment to TAC warrant scores based on the changes in collision frequency and severity due to signalization that would be expected at the average Canadian intersection.
For these reasons, this research examined the applicability of both a direct economic comparison of delays and collisions and expert opinion in the development of scaling factors for the CAFs.

5.4 Results and Discussion

The results and discussion cover three main subjects: the changes in collision and traffic delay costs from signalization, the recommended CAFs for the TAC warrant procedure, and some notes on the application of the CAFs in general.

The collision cost and CAF analyses are both functions of traffic volume. To simplify the results and discussion, the range of traffic volumes considered was 5000 to 15000 AADT on the major road and 1500 to 6000 AADT on the minor road, to be consistent with the AADT ranges used in developing the most recent traffic signal warrant guidelines in the United States (Bonneson et al. 2014) and in the development of the aggregate SPFs applied in this study (Northmore and Hildebrand 2019a).

5.4.1 Magnitude of Change in Collision Costs

While the change in collision costs used in this analysis was published in previous work (Northmore and Hildebrand Under Review), the magnitude of the expected change in collision costs due to signalization is important for comparison to the change in delay costs. Within the proposed CAF structure the change in collision costs is calculated based on the specific information for the intersection, but Table 5-3 provides a summary of the range of expected change in collision costs for intersections with collision histories of 0, 5, and 10 collisions per year as a reference for comparison to the change in delay costs. It is important to note that the change in collision costs with a collision history of 0 per year is due to the
analysis assuming that future collision frequencies will regress upwards towards the average collision frequency for intersections with similar traffic volumes.

### Table 5-3: Range of the Increase in Collision Costs due to Signalization

<table>
<thead>
<tr>
<th>Category</th>
<th>Change in Average Collision Cost at Varying Annual Collision Frequencies (thousands of 2010 US dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Existing Collision History (per year)</td>
</tr>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td><strong>Severity</strong></td>
<td><strong>Casualty</strong></td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
<tr>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Low</td>
<td>No</td>
</tr>
</tbody>
</table>

5.4.2 Traffic Delay Cost Estimation

The initial run through the Monte Carlo simulation and traffic delay analysis found that traffic delay costs at the hypothetical intersections increased when the intersection was signalized. The main reason for this was that those operating with the right of way experience no, or very little, delay, but after signalizing the intersection these vehicles experience some delay. Even though the change in delay time per vehicle was minimal, the volume of traffic it was applied to was large enough to produce a significant difference.

Most delay-based TSWs are focused on reducing delays for impeded movements at stop-controlled intersections (FHWA 2009, MTO 2012). This makes sense when
considering the Level of Service (LOS) metric that is often used in assessing intersection delays (TRB 2016); the increase in per vehicle delays for the unimpeded movements due to signalization typically still results in these movements being categorized as LOS A, which is the highest LOS that can be achieved, whereas the decrease in delays for the impeded movements is typically significant enough to improve their LOS rating. Even though the total traffic delay for the intersection may not be improved, this is still a desirable result for practitioners. As a result, the delay analysis in this study was modified to only assess the delays for the impeded movements under stop control (left turns on the main road and all minor road movements).

The results of the TAC warrant procedure Monte Carlo Simulation and subsequent traffic delay cost estimation for impeded movements are shown in Table 5-4. The data presented identify the number of iterations from the Monte Carlo Simulation that resulted in TAC warrant scores of 90 to 110 (out of 10,000 iterations), the average delay per vehicle under stop and signal controlled conditions, the average annual traffic delay savings in total hours and dollars, and the incremental value of a TAC warrant point within the 90 to 110 point range. The incremental value was the slope of a linear regression fit of TAC warrant points to annual savings in dollars, representing how much each additional point is worth within the range of 90 to 110 TAC points. The range of costs corresponds to using the local and intercity travel time costs as lower and upper bounds for the average, respectively.
Table 5-4: Change in traffic delay costs for impeded movements due to signalization

<table>
<thead>
<tr>
<th>Category</th>
<th>Legs</th>
<th>Lanes</th>
<th>Cases</th>
<th>Avg. Delay per vehicle (s)</th>
<th>Avg. Annual Savings</th>
<th>Value of an Incremental TAC Warrant Point (2010 US Dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Stop</td>
<td>Signal</td>
<td>Hours</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3</td>
<td>1913</td>
<td>48.1</td>
<td>19.7</td>
<td>14932</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1749</td>
<td></td>
<td>60.5</td>
<td>19.4</td>
<td>21845</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>2759</td>
<td></td>
<td>20.1</td>
<td>18.2</td>
<td>934</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>2677</td>
<td></td>
<td>19.5</td>
<td>18.4</td>
<td>519</td>
</tr>
</tbody>
</table>

It was notable from Table 5-4 that the travel time and cost savings were substantially greater for 3-leg intersections than 4-leg intersections. Since a 3-leg intersection has one fewer approach than a 4-leg intersection, more vehicles were required on each of the 3 approaches to obtain TAC warrant scores of 90 to 110 than at a 4-leg intersection and the increase in vehicles per approach directly led to increased delays under stop and signal control.

Further, it appears that the TAC warrant system has been calibrated (intentionally or unintentionally) such that 4-leg intersections achieve 100 points when they are right at the threshold of achieving a reduction in delays for impeded movements resulting from signalization. While this is a good objective measure, it does not effectively balance the benefits of delay savings against the increased capital and maintenance costs that arise when signalizing an intersection. The average annual savings for 3-leg intersections, being much more substantial than the 4-leg intersection results, suggest that signalizing a 3-leg intersection with a TAC score of about 100 would pay back the infrastructure costs of signalization within a few years.
5.4.3 Comparing the Changes in Annual Delay and Collision Costs due to Signalization

The magnitudes of the change in collision costs due to signalization shown in Table 5-3 were, in general, equivalent to the average annual delay cost savings for 3-leg intersections and much greater than the savings for 4-leg intersections as shown in Table 5-4. This suggests that for an objective warrant system, the safety implications of signalization should hold at least equal weight to vehicle delay considerations.

It is also important to note that the results shown in Table 5-3 are applicable to any randomly selected stop-controlled intersection, as opposed to strictly stop-controlled intersections that are being seriously considered for signalization. This means that while the results shown in Table 5-3 are applicable to most intersections, some intersections will exhibit drastically different changes in collision severity and frequency from the average intersection when signalized. For this reason, it is recommended that all intersections being considered for signalization be subject to an in-service road safety review.

*Scaling Factors based on an Economic Evaluation*

Scaling factors for the CAFs were calculated based on the incremental TAC score costs shown in Table 5-4. The midpoint incremental TAC score costs for 3-leg and 4-leg intersections were about $12,000 and $1,600, respectively. To convert the collision costs into TAC scores the collision costs must be divided by the cost of a TAC point, so the inverse of the incremental TAC score costs were calculated. This resulted in scaling factors of $8.33 \times 10^{-5}$ points per 2010 US dollar for 3-leg intersections and $6.25 \times 10^{-4}$ points per 2010 US dollar for 4-leg intersections. Applying these scaling factors to the results shown in Table 5-3 results in the CAFs that are presented in Table 5-5.
The results in Table 5-5 show that even relatively modest collision histories can have a substantial impact on TAC warrant scores through this CAF process. This impact could create a barrier for implementation of the CAFs due to how dramatically they will change the results of an analysis using the TAC warrant procedure. Ideally this would be mitigated by recalibrating the existing TAC warrant procedure to better reflect the economic impacts of signalization on traffic delays or creating a separate economic-based warrant procedure that could be used in conjunction with these CAFs.

Scaling Factors based on Expert Opinion

The best reference for expert opinion on the inclusion of collision history in TSWs comes from a survey conducted as part of the development of the new collision justification for...
the MUTCD in the United States (Bonneson et al. 2014). This survey identified attitudes that practitioners had towards the existing MUTCD warrant (trial of alternatives to reduce collisions, at least 5 collisions per year reducible through signalization, meeting 80% of one of two traffic volume-based warrants) as well as ways that practitioners felt that the warrant could be improved. The respondents did not propose changes to the criteria of meeting 80% of a volume-based warrant with the most common request being the inclusion of a longer collision history period than one year.

Following the results of this survey and the general practice for collision-based TSWs globally, the criteria used for creating scaling factors based on expert opinion were that 5 casualty collisions per year were equivalent to 20 TAC warrant points. For this analysis, 5 casualty collisions per year were used instead of 5 reducible collisions per year to simplify the analysis procedure for practitioners, and because casualty collisions are more likely to result from ‘reducible’ angle collisions as opposed to ‘non-reducible’ rear-end or other types of intersection collisions. The 20 TAC warrant points equivalence was used because that constitutes 20% of the TAC warrant points required to justify signalization (the remaining portion of points after 80% of the points are awarded through the delay-based analysis).

From Table 5-3, the highest expected change in collision costs for 5 casualty collisions per year was $1,815,000, and equating this to 20 TAC points results in a value of $90,750 per point. A scaling factor based on this TAC point value is $1.102 \times 10^{-5}$ points per 2010 US dollar. Notably, this scaling factor represents collision costs being discounted to about 1/8 for 3-leg intersections and 1/60 for 4-leg intersections of their economic value.
within the warrant system. Table 5-6 shows the range of expected CAFs for collision histories of 0, 5, and 10 collisions per year using this scaling factor.

**Table 5-6: Range of CAFs using Scaling Factors based on an Economic Evaluation**

<table>
<thead>
<tr>
<th>Severity</th>
<th>Casuality</th>
<th>Land Use</th>
<th>Legs</th>
<th>PSL</th>
<th>Divided</th>
<th>Collision Adjustment Factors using a Scaling Factor of $1.102 \times 10^{-5}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Category</td>
<td></td>
<td></td>
<td></td>
<td><strong>Existing Collision History (per year)</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>0</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>Lower Bound</strong></td>
</tr>
<tr>
<td>3</td>
<td>Rural</td>
<td>Low</td>
<td>No</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>No</td>
<td>-</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
<td>-</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Urban</td>
<td>Low</td>
<td>No</td>
<td>-</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>No</td>
<td>-</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
<td>-</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>Rural</td>
<td>Low</td>
<td>No</td>
<td>-</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>No</td>
<td>-</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
<td>-</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>Urban</td>
<td>Low</td>
<td>No</td>
<td>-</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High</td>
<td>No</td>
<td>-</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
<td>-</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

**Recommended Scaling Factor for CAFs**

Based on the analysis of scaling factors developed through economic comparison and expert opinion, it is recommended that the expert opinion-based scaling factor be used in conjunction with the current TAC warrant. While this scaling factor discounts collision costs substantially when compared to delay costs through the TAC warrant analysis, it provides a more meaningful adjustment to the existing TAC warrant procedure based on the expected collision expectations after signalization of the average Canadian intersection.

Figures 5-1 through 5-4 show graphs of the CAFs developed using a scaling factor of $1.102 \times 10^{-5}$ with major road AADT of 15,000 and minor road AADT of 6,000. These
graphical references are specific to traffic volume, so practitioners should determine CAFs for specific intersections by following Equation 5-3.

**Figure 5-1:** Graph of CAFs for total collisions at 3-leg intersections with major road AADT of 15,000, minor road AADT of 6,000, and scaling factor of $1.102 \times 10^{-5}$

**Figure 5-2:** Graph of CAFs for total collisions at 4-leg intersections with major road AADT of 15,000, minor road AADT of 6,000, and scaling factor of $1.102 \times 10^{-5}$
Figure 5-3: Graph of CAFs for casualty collisions at 3-leg intersections with major road AADT of 15,000, minor road AADT of 6,000, and scaling factor of $1.102 \times 10^{-5}$

![Graph of CAFs for 3-leg intersections](image)

Figure 5-4: Graph of CAFs for casualty collisions at 4-leg intersections with major road AADT of 15,000, minor road AADT of 6,000, and scaling factor of $1.102 \times 10^{-5}$

![Graph of CAFs for 4-leg intersections](image)
5.4.4 Application of the CAFs

As discussed previously, the intent for TSWs is to provide consistent and objective justification for the signalization of stop-controlled intersections across large road networks. The CAFs developed through this research are designed to provide consistent and reliable results across Canada based on the safety benefit that would be projected for signalizing any randomly selected stop-controlled intersection.

Some jurisdictions may be interested in adapting the procedures from this study to develop CAFs using locally produced SPF or collision costs. The benefit from doing so is that the CAFs will better reflect the safety benefits realized from that jurisdiction; however, this will also reduce the consistency of signalization decision making between jurisdictions.

5.5 Conclusions

This research presented a methodology for incorporating a collision history element into the TAC warrant procedure by calculating CAFs. The CAFs are applicable to network analyses where the objective is to identify and prioritize stop-controlled intersections for further evaluation and are not a replacement for a safety audit that ought to be conducted before an intersection is signalized.

The recommended CAFs were developed using expert opinion on the relative value of collisions and delays within TSWs. The expert valuation used does not have a known robust justification, so it is recommended that future work on the development of CAFs include a survey of practitioner decision making for signalizing intersections under a variety of collision history and traffic scenarios.
Additionally, it was found that there is a large discrepancy in the change in delay costs expected for 3-leg and 4-leg intersections with characteristics that result in TAC warrant scores of about 100 points. It is recommended that these be reconciled, or that a new delay-based analysis revolving around the change in delay costs be undertaken to allow more detailed refinement of the CAFs.

Lastly, while this research successfully achieved its objective of incorporating collision history into the TAC warrant procedure, it is important to recognize that collisions and delays are only two of many externalities of signalizing an intersection. An additional feature that should be studied for incorporation is the environmental footprint of signalization, particularly as efforts to mitigate climate change are increased over the coming years.

References


CHAPTER 6: Conclusions, Discussion, and Recommendations

The goal of this dissertation, to create a framework that incorporates collisions into traffic signal warrant systems using proposed novel research on predicting collision severities based on the configuration of intersections and on synthesizing existing research on the factors that influence the frequency of intersection collisions, was successfully completed through the research activities detailed in Chapters 2 through 5. This chapter presents a summary of the analysis and primary findings from each previous chapter, discussion of the most significant findings from this research for traffic engineers, and areas of further study related to collision-based TSWs that were identified through the course of this research.

6.1 General Conclusions

In Chapter 2, generalized ordered logit models were developed to identify the intersection characteristics that have the most significant impact on collision severity. It was found that the PSL thresholds used in the study, land use (rural/urban), and the presence of a divided approach were the most significant characteristics. These characteristics were used to segregate the collision data in order to create collision severity profiles for each combination of characteristics, and the severity profiles were used to calculate the cost of the average collision under each set of conditions. Overall it was found that collisions at signalized intersections have a lower average individual cost than collisions at stop-controlled intersections by $50,096 2010 USD for all collisions and $145,741 2010 USD for casualty collisions, which was in agreement with the literature and practitioner expectations.
Chapter 3 focussed on the creation of aggregate SPFs based on synthetic collision data created from SPFs published by jurisdictions across North America. A traditional negative binomial model was used, and it was found that including a random-effect for each jurisdiction provided the best model fit. The aggregate SPFs were compared to the uncalibrated HSM collision models and it was found that the uncalibrated HSM models were not a good representation of the average collision frequency for North America. There was a substantial amount of variation between the jurisdiction random-effects produced through the modelling process; however, it was found that for a given jurisdiction the calculated effects for stop-controlled and signalized intersections were comparable, suggesting that these aggregate models could be used broadly and without calibration for predicting the change in collision frequency due to signalizing an intersection.

In Chapter 4, the collision severity analysis from Chapter 2 and collision frequency analysis from Chapter 3 were used to estimate the safety benefit of signalizing a stop-controlled intersection. Three safety metrics were used (change in collision frequency, change in frequency of fatal and serious injury collisions, and change in collision cost) and it was found that the majority of intersection configurations studied would not exhibit a safety benefit from signalization. This result was substantially different from the literature on the safety benefits of signalization, which tend to estimate a net safety benefit from signalization. The source of this difference was likely from the data collection method; the published CMFs for signalization use data explicitly from intersections where practitioners expected there to be a benefit from signalization through delay and/or safety improvements whereas the SPFs used in developing the aggregate SPFs considered data from all stop-controlled and signalized intersections regardless of the expectation of a benefit from.
signalization. Due to these differences in methodology, the safety benefit analysis presented in Chapter 4 was pertinent to network-level analysis of identifying which intersections may exhibit an overall benefit from signalization, but detailed analysis of intersections where practitioners expect to realize a benefit from signalization should follow a different approach.

Chapter 5 culminated this dissertation by developing CAFs based on the safety evaluation conducted for Chapter 4. Scaling safety benefits into TAC warrant points by an economic comparison of the changes in delay and collision costs from signalization and by expert opinion were explored. To compare collision and delay costs, an analysis of the change in delay costs associated with signalizing stop-controlled intersections with TAC warrant scores of 90 to 110 was conducted; the threshold for signalization in the TAC warrant procedure is 100 points, so a range of 90 to 110 captures many combinations of intersection characteristics that are around the threshold for signalization. It was found that the magnitude of the expected change in collision costs from signalization was either comparable to, or substantially greater than, the expected change in delay costs, so scaling the safety benefits through an economic comparison resulted in CAFs that substantially outweighed the expected delay benefits of signalization. Practitioners have historically preferred TSWs where delays have a greater weight in the decision making than collisions, so expert opinion based on other TSWs was used to create the recommended scaling factors for the CAFs.
6.2 Implications of the Research

The primary implication of this research for practitioners was the development of CAFs that allow for the integration of a collision history component into the TAC warrant procedure. The CAFs were reflective of the typical Canadian intersection and can, therefore, be implemented in national-level TSWs, though there is room for jurisdictions to modify the procedure applied in this dissertation to create CAFs that better match local collision frequency and severity expectations.

Beyond the CAFs, the development of aggregate SPF{s} (Chapter 3) gave traffic engineers a national reference to which they could compare intersection collision frequencies. This could be particularly useful because practitioners are often required to compare local intersections against each other for outliers, but this approach assumes that the local average collision frequency is a reasonable benchmark to compare to. Jurisdictions with SPF{s} that predict fewer collisions than the aggregate SPF{s} may be able to better invest their safety budgets into other infrastructure projects, and conversely jurisdictions with SPF{s} that predict more collisions than the aggregate SPF{s} may benefit more from system-wide safety programs than improvements at a single intersection.

The evaluation of safety benefits in Chapter 4 could also have a profound impact on practitioners because the results found in that chapter were significantly different from the conventional wisdom that signalizing an intersection improves the overall safety of the intersection. The methodological reasons for the difference in findings was discussed in-depth in Chapter 4, but this analysis highlights the importance of traffic engineers understanding the limitations of different tools that are commonly used when estimating the change in safety due to signalization or any other change to existing infrastructure.
6.3 Areas for Future Research

Many of the areas for future research that were identified through the course of this dissertation focus on three major themes: challenging the underlying assumptions made in the research, repeating the analysis using real-world collision data from different jurisdictions, and investigating how practitioners subjectively value collisions compared to the other externalities impacted by signalization.

Numerous assumptions were made through the course of this dissertation that may inadvertently skew the results. One such example was using the traditional negative binomial (Poisson-gamma) model to create SPFs for collision frequency based on data from multiple jurisdictions. While this is the most frequently used model for creating SPFs and has output that is easy to contextualize, it is possible that a more niche model specification or some form of machine learning tool could better discern collision frequency trends from multiple jurisdictions instead of using the traditional model structure with an added random-effect.

Basing the statistical analyses in Chapters 2 and 3 on national collision severity data and data synthesized from published SPFs, respectively, was done in an effort to conduct an analysis that would be representative of the average jurisdiction across a large geographic range without requiring extensive data collection and management efforts. While this approach was methodologically sound, it would be of interest for future research to undertake a similar scale of analysis based on collected real-world collision data. Such a study could allow for jurisdictional differences in the overall safety benefits of signalization (Chapter 4) to be investigated and compared, along with identifying if there
are jurisdictional characteristics that influence collision severity (Chapter 2) and validating the aggregate SPFs that were developed for this dissertation (Chapter 3).

Lastly, this research identified that the ways practitioners have been incorporating collision history into TSWs do not correspond well to the change in collision and delay costs that result from signalization. To better study how practitioners value these costs, future researchers should conduct a survey of Canadian practitioners to examine their opinions about intersection signalization for a set of carefully constructed scenarios including a variety of traffic and collision history conditions. Such a study could identify what weight practitioners assign to collisions in their justification processes, which would allow for the development of more refined and useful scaling factors for CAFs (Chapter 5).
Curriculum Vitae

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Publications:


Conference Presentations:


Northmore, A. and Hildebrand, E. Adding Collision History to the TAC Signal Warrant Procedure. ITE Atlantic Provinces Section Fall 2019 Technical Meeting, November 7, Fredericton, NB.


Northmore, A. and Tighe, S. 2012. Developing innovative roads using solar technologies. In the Proceedings of the 9th International Transportation Specialty Conference of the Canadian Society of Civil Engineers Annual Conference, June 6-9, Edmonton, AB.

**Academic Awards:**

2017 Dr. Michel Van Aerde Memorial Scholarship, CITE

2016 – 2019 NSERC Postgraduate Scholarship

2016 – 2019 New Brunswick Innovation Foundation Scholarship

2016 – 2019 Board of Governors Merit Award, UNB

2016 Stevens Wilson Graduate Fellowship in Civil Engineering, UNB

2012 – 2013 Ontario Graduate Scholarship

2012 – 2013 President’s Graduate Scholarship, University of Waterloo

2012 3rd Place in Transportation Engineering Graduate Student Paper Competition, CSCE Annual Conference

2011 Canadian Provinces and Territories Scholarship, TAC

2006 University of Waterloo Merit Scholarship