A Risk-Based Decision Support Framework for Railway-Highway Grade Crossing Closures

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Reducing the risk of collisions between trains and vehicles at railway-highway grade crossings is a high priority safety strategy set by many governments and railway authorities. To achieve this goal, one of the main engineering approaches used is to permanently close some grade crossings. Although this approach can completely eliminate the collision risk at the grade crossings being closed, it could have a huge impact on the road traffic, resulting in a significant increase in travel time for road users. This can also lead to some secondary problems, such as increased trespassing risk. Thus, the problem of which crossings should be closed must be addressed with a careful consideration of all benefits and costs that could result from the closure. This research aims to develop a specific framework for determining the priority of grade crossing closure and develop models that can be used to quantify the safety benefit and the costs.

In this study, a risk-based framework is proposed, including a preliminary screening and a cost-benefit analysis module. In the preliminary screening step, all the crossings in the area of interest are first examined on the basis of a set of pre-established rules or criteria to remove those crossings that should definitely not be considered for closure due to their critical importance to the road traffic. This step yields a set of candidate crossings. All individual crossings in the candidate set are then involved in the cost-benefit analysis module. This module determines the expected safety benefit, travel time cost, and construction cost that could result from their closure. The safety benefit of closing a given crossing is estimated using a set of collision risk models for collision frequency and collision severity. These models are calibrated using the latest crossing inventory data and six-year long collision history data (2013-2018). To estimate the extra travel time cost that road users would experience due to the closure of a crossing, an accessibility analysis tool is created in a ArcMap to calculate the extra travel distance, using the spatial data of road and railway network. Lastly, the life-cycle benefit-cost ratios of all candidate crossings for closure can be calculated and used as a ranking criterion for determining their priority of closure. The application and rationality of the proposed framework are examined through a case study of three provinces in Canada.

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Chapter 1 Introduction

1.1 Background

Grade crossings, also called level crossings, railway crossings, or train crossings, are intersections where a railway crosses a road or path at the same height, in contrast to a grade separation which crosses over or under the ground via a tunnel or overpass (GCR, 2014). According to Transport Canada, there were around 13,000 public crossings and 9,000 private crossings in 2019 in Canada (Transport Canada, 2019a). These crossings are required to install and maintain warning/control devices to meet the safety requirements outlined in regulations (Transport Canada, 2019b). Depending on the type of warning/control devices that are installed or how road users are informed of the safety risk with a passing train, grade crossings are generally classified into two types: passive grade crossings and active grade crossings. Passive grade crossings have only passive warning devices, including crossbucks, stop signs, and pavement markings, while active grade crossings are equipped with active warning and control devices, such as bells, flashing lights, and gates, in addition to the passive devices mentioned.

In 2020, 965 rail collisions were reported to the Transportation Safety Board of Canada (TSBC), and grade crossing collisions accounted for 13.4% of those accidents (TSBC, 2020). About 91% of crossing collisions are caused by accidents between vehicles and trains. Crossing collisions often represent one of the most severe types of rail accidents, with approximately 19% of them resulting in serious injury or fatal accidents, and a fatal accident includes one or more fatalities. Figure 1.1 shows the annual grade crossing collisions and their fatalities and serious injuries from 2010 to 2020. The frequency of accidents at grade crossings has not substantially decreased in the past 10 years, and thus crossing collisions remain a concern.

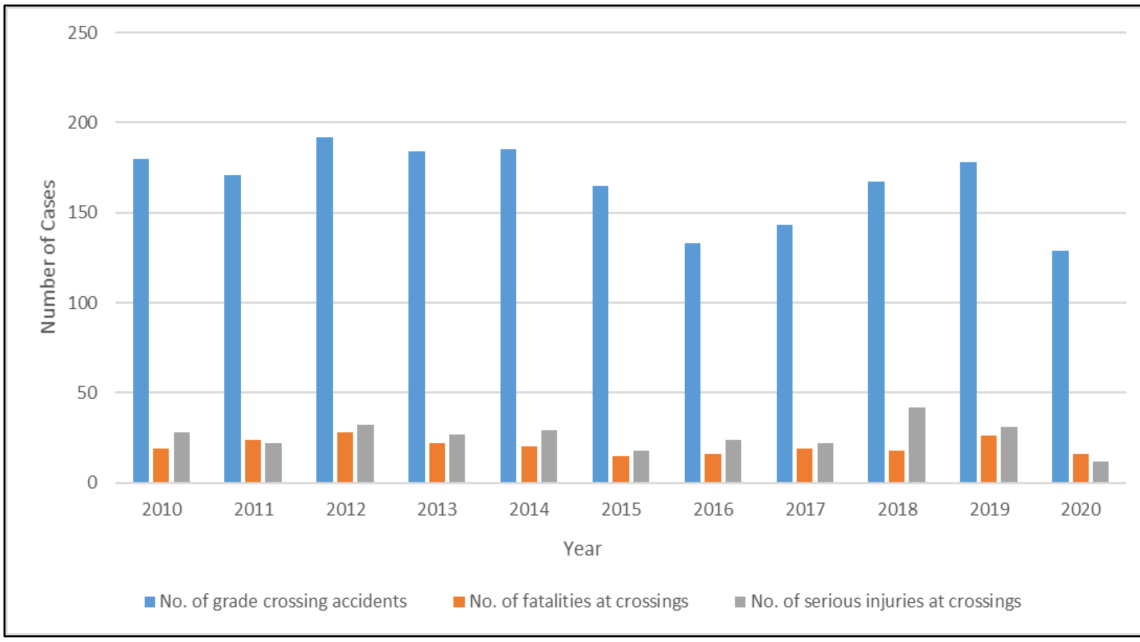


Figure 1.1 The Crossing Collisions Report to TSBC (2020)

The safety of grade crossings could be improved through a range of strategies, from engineering and education to enforcement. The main engineering solutions include improving existing crossing conditions and crossing protection, such as upgrading control devices, improving crossing visibility and road geometry, and introducing grade separations (Hal et al., 2010). Recently, vehicle-based warning systems have been explored. For example, Yang et al. (2020) proposed an in-vehicle audio warning technology that can generate an advance warning signal to the driver if a train is approaching the crossing. Education and enforcement related programs focus on the behavior aspects of the road users, which have been found to be one of the leading causes of collisions at grade crossings (Khattak & McKnight, 2008). In Canada, Transport Canada's Grade Crossing Improvement Program (GCIP) has funded more than ten million Canadian dollars per year to projects related to rail safety enhancement to reduce the collision risk (Transport Canada, 2017).

Another safety improvement strategy that is often adopted by governments is closing the grade crossings that are less important for road users and economics but still have a significant contribution to overall risk of the railway network. For example, along some railway corridors, it might be sensible to consolidate multiple crossings into a small number of crossings without having a huge impact on the accessibility of the road users. According to De Gruyter & Currie (2016), the advantages of grade crossing closure include eliminating collisions at crossings with less monetary cost, redirecting of resources to the remaining crossings, and providing convenience for future traffic design.

Because of the immediate risk reduction benefits, many countries have specific programs in place to guide and support their grade crossing closure and consolidation projects. For example, Transport Canada established the Grade Crossing Closure Program (GCCP) in 2003 that provides funds to compensate private landowners and public road authorities for the relinquishment of their crossing rights and covers the costs of closing a crossing. This GCCP has been merged to the new Rail Safety Improvement Program (RSIP), but its mandate and function remain. In 2021, RSIP provided more than $21 million to improve rail safety through two essential constituent parts: 1) Public Education and Awareness; and 2) Infrastructure, Technology and Research (Transport Canada, 2021).

Another notable example is the grade crossing consolidation program in the United States, which is an important component in the Department of Transportation's Action Plan to improve crossing safety in American. This plan asked states, political subdivisions, and railroads to reduce 25% of the 28, 000 grade crossing in ten years (FRA, 1994). Different states are allowed to develop their own methods to determine the redundant crossings. Moreover, considering that closing some crossings are very difficult due to local opposition, some incentive measures are adopted to facilitate the closure plan, such as giving cash to nearby residents and establishing quiet zones.

Although the crossing closure and consolidation strategy is perhaps the least costly and most effective way to eliminate the safety risk at grade crossings, it could have a negative impact on the road users in terms of accessibility with increased travel time and reduced accessibility, leading to objections by the public, especially those who are directly affected. Another issue for closing a crossing could be increased trespassing on railway track nearby. According to TSBC (2020), trespassing has the most severe injury in rail accidents, with 50% of Canadian grade crossing fatalities caused by pedestrian trespassing. As a result, decisions pertaining to crossing closure must be made on the basis of a comprehensive evaluation of all the expected benefits and costs, which is the primary focus of this research.

1.2 The Research Problem

Closing or consolidating grade crossings has become an important strategy for improving the safety of the railway network in many countries including Canada. However, in the absence of a comprehensive decision-support tool, decisions on which crossings should be closed have mostly been made through some informal and ad-hoc processes (Transport Canada, 2013). Several past efforts described in the literature have attempted to address this knowledge gap, which have resulted in four main methods for decision support on crossing closure, including expert diagnosis, heuristic rating, decision tree model, and risk-based benefit-cost analysis.

Expert diagnosis refers to a group of safety experts and stakeholders that determine the crossings for closure by conducting onsite inspections and having a discussion. This method relies on almost no quantitative assessment tools, and the selection is mainly based on subjective judgment. It usually takes a long time to get the final decisions for closure especially when there is a need to proactively close some crossings from a wide range of candidate crossings. Heuristic rating is essentially a scoring formula whose general expression is usually a sum of weights of factors affecting safety based on experts' experience and previous literature. The score for each crossing is the basis for the priority of closure. However, in this method, many studies use collision risk as the only scoring objective, ignoring important components such as the level of spatial accessibility. Some other studies try to consider multiple aspects to capture a bigger picture of closure problem. However, the proportion of impact on collision risk has dropped significantly, which leads to the closure decisions based on an overall impact rather than a risk-oriented analysis process. Another recently proposed method is to predict if a crossing should be closed or not by a decision tree algorithm. This model can easily involve many variables to improve the prediction result. However, it needs a large number of crossings had been closed before as the training data. Another concern is the model result is essentially simulating previous closure decisions while some of these past decisions may not have involved a rigorous analytical process.

The approaches to selecting grade crossings for closure mentioned above are sometimes expensive or inflexible. They largely concentrate on evaluating the overall effects of closing a crossing, where the various influencing factors are scored by subjective judgment. However, limited efforts have been devoted to monetizing these factors and making a trade-off between safety benefits and potential cost. Closure decisions based on a benefit-cost analysis can make a trade-off between the negative impacts and reduced collision risk. This method takes advantage of explicitly monetizing the safety benefit and costs and maximizing the overall funding efficiency, and it is not subject to the limitations of the above methods. Such a framework applied on grade crossing closure is only found in a study of Rezvani et al. (2015). However, due to it being a general methodology for prioritizing all grade crossing safety projects, there is little attention on verifying the qualification of candidate crossings for closure. Furthermore, most conventional tools for evaluating the cost and benefit were challenged by the recent one with higher accuracy and more convenience. These new tools benefit from the establishment of databases and software development. Thus, there is a need to generate a specific framework for determining the priority of grade crossing closure with a risk-based analysis and develop up-to-date models that can be used to quantify the safety benefit and the cost. This framework is also expected to provide a reference for future practice in Canada.

1.3 Research Objectives

The main objective of this study is to develop a comprehensive framework that can provide decision support for determining the crossings for closure. The specific objectives are as follows:

1) Develop a comprehensive understanding of the factors, criteria, benefits, and costs that need to be considered in the decision-making of grade crossing closures;
2) Develop a quantitative risk model that can be used to predict the expected safety improvement benefit of closing and consolidating crossings;
3) Develop an accessibility assessment method that can be used to estimate the increased inconvenience and travel time to the road users that could be induced by the closure of

a crossing;

4) Conduct a case study to illustrate the application and rationality of the proposed framework.

1.4 Structure of the Thesis

The thesis is structured into five chapters as follows:

- In Chapter 2, the existing literature and research gaps on the subject are synthesized.
- In Chapter 3, a risk-based benefit cost analysis framework is presented
- In Chapter 4, a case study to demonstrate the application of the proposed methodology for ranking crossings for their priority for closure are conducted
- Chapter 5 the research findings and discusses the future research directions are summarized.

Chapter 2 Literature Review

Closing grade crossings has become an important strategy to improve railway safety in many countries. However, decisions on which crossings should be closed are mostly made without a comprehensive decision-support tool. Several past research efforts have attempted to address this knowledge gap, but they all have limitations. This chapter provides a detailed review of the state-of-the-art literature on the problem of grade crossing closure, focusing specifically on what factors, criteria, benefits, and costs are considered and what knowledge gaps exist, which will provide a basis for this study.

2.1 Grade Crossing Closure Programs

There are a few countries or regions around the world that have specific grade crossing closure programs for various purposes. These programs provide funding support and technical guidance to solve the issues encountered during the closure process based on previous experience. This section provides an overview of current programs.

The Federal Railroad Administration (FRA) in the United States has long considered grade crossing closure and consolidation as an effective option to improve rail safety (Codjoe, 2018). To ease the strain on public funds for safety protection devices and extensive traffic enforcements, the FRA introduced the grade crossing Consolidation Program 1994, aiming at closing redundant and unnecessary highway-railway grade crossings (FRA, 1994). For example, the FRA closed more than 18,000 grade crossings over ten years from 2008 to 2018 (Codjoe, 2018). In its initial program, a comprehensive set of guidelines were developed based on more than twenty previous cases of closures and interviews with project principals, which includes screening for suitable crossings for closure, coordinating state and railroad efforts, understanding the needs of the community, building community support, and using incentives (FRA, 1994). The guidelines emphasize the importance of ensuring alternative routes for crossing the rail tracks are available for the road users before a crossing is closed. It also recommends a corridor approach; that is, a group of experts diagnose the crossings along a corridor and choose one of them to close. According to the

FRA (2009), this corridor approach can simultaneously evaluate multiple crossings along the railway, which can reduce project costs and improve community cohesion. The states facing a serious challenge of grade crossing accidents need to take the lead to develop their own method for determining the specific individual crossing for closure, which will be further discussed in the following section.

In America, one important point that has been emphasized is the use of incentives, as the main concern in crossing closure is that the program is usually opposed by those residents or road users who are adversely affected due to the reduced accessibility and increased travel time (Russell & Mutabazi, 1998). These oppositions are understandable, especially when the public is unaware of the complete information about the long-term benefit of closing these crossings. However, according to Taylor & Crawford (2009) the closure plan is worth completing though community cohesion and land use suitability may be negatively affected by the closure process. To gain more local recognition and promote the implementation of the program, various incentive programs, including track relocation, nearby road improvement, cash incentive, grade separation, and nearby crossing improvement, are applied in the United States. Moreover, the applicability of these incentive measures is a widely discussed research topic in recent years. Soleimani et al. (2018) suggested that all current incentives are either inefficient for safety improvement or pricey. For example, according to their survey results, providing a cash incentive is most popular, but it gives a limited boost to the crossing closure program; however, the most effective incentive, track relocation, has the lowest popularity (Soleimani et al., 2018; Codjoe, 2018). They also state that a decision-support method which can make the public realize the rationality of decisions on closure can be an effective incentives for the closing process.

The Grade Crossing Closure Program (GCCP) in Canada was established in 2003 to improve rail network safety by proactively closing the sites that are collision prone and less critical or redundant for traffic movement (Transport Canada, 2003). In recent years, the program has been incorporated into the Canadian Rail Safety Improvement Program (RSIP). The decisions on which crossings should be closed is mainly based on unsolicited application for closure. The details of the approach will be elaborated in the following section. This approach has led to the only a few of closures in the past years. For example, 124 of the 31,000 federally regulated crossings were closed from 2003 to 2013 (Transport Canada, 2013). An official evaluation on GCCP reveals the main reasons behind the underutilization of GCCP funding, including 1) closure requirements are limited or have not yet been funded; and 2) closure are not selected based on collision risk (Transport Canada, 2013). Another concern is that there is no clear evidence that the reduced collision risks are associated with crossing closure.

In Europe, except for a few countries, such as Spain, Italy and Germany, most crossings are designed with a grade separation. However, there is not a specific program in these countries for guiding or supporting grade crossing closures. Instead, the closure problems are usually solved by a general process for optimizing resource allocation. For example, the Sweden National Road Administration has established a model to deal with the decision-making problems on the investment in road and rail safety (MORNELL, 2006). In this model, representatives of the different agencies concerned need to have discussions for three times in succession, and these themes include to discuss objectives, to present a list of solutions, and to study action plans that have been addressed. This process is also used for the selection of grade crossing closures, and around 100 grade crossings are closed each year (MORNELL, 2006). However, the underlying process is time consuming, usually taking up to 4 months to complete with multiple organizations being involved.

2.2 Methods for Determining Crossings for Closure

This section provides an overview of four general approaches used for determining crossings for closure. These include 1) expert diagnosis, 2) heuristic rating, 3) decision tree model, and 4) risk-based benefit-cost analysis.

2.3.1 Expert Diagnosis

Expert diagnosis is essentially a decision which is based on based on professional knowledge and judgement. It usually involves conducting onsite inspections, consulting stakeholders, and making collective decisions by a team of government officials and representatives from the railway company and road authority (FRA, 1994). Britain, Australia, and Canada have used this method for many years. For example, in Canada, decisions on which crossings to close are made through the following process. First, applications for closing certain crossings are submitted by the road authorities or private parties that own the crossings. Only the crossings that belong to federally regulated railway companies and have been in existence for at least three years are eligible for application (Transport Canada, 2013). Then, these applications are evaluated by Transport Canada with the priority given to the crossings with a high safety concern, which is determined by an ad-hoc process rather than a comprehensive method based on safety risk, and further details were not available (Transport Canada, 2013). The expert diagnosis approach is generally subjective in nature and often lacks quantitative assessment tools on safety risk. In addition, the process may take a long time, especially when proactively closing a large number of crossings from a wide range of options.

2.3.2 Heuristic Rating

In a second approach, a heuristic rating is used to determine the priority of individual crossings for being considered for closure. The idea behind this approach is to apply a muti-variable equation to calculate scores for each crossing, which is a measure of priority for closure. Before applying the rating formula, researchers usually narrow down candidate crossings by setting thresholds on some variables. For example, Florida Department of Transportation (2000) suggested six criteria for narrowing the list of candidate crossings for closure:

- AADT < 2000,
- Daily number of trains > 2
- Maximum distance to the nearby crossings < 1300 ft
- Grade crossings at an extreme skewed angle
- Not on the routes of emergency vehicles.
- Grade crossings along a 1.6-kilometer line track > 5

The crossings that meet more conditions mentioned above have a higher priority to proceed to the next step of analysis. Ogden (2007) suggested to apply slightly different criteria for various types of crossings including crossings on branch lines, crossings on spur tracks, and crossing on mainline.

As part of a study to support Kansas's grade crossing consolidation program, Russell and Mutabazi (1998) proposed a heuristic rating formula for ranking a crossing's safety risk and closure priority. Based on the opinion of an advisory committee, six risk factors were incorporated into the final rating formula, including crossing angle, sight distance, approach grade, daily train number, train speed, and track number. The rating score for a given crossing is defined as the sum of weights of the six factors, expressed as Equation 2.1. To give the weights for those continuous variables, they were further divided into subcategories, as shown in Table 2.1. A higher weight means a higher contribution to the safety risk. Crossings with a higher score should be given a higher priority in closure consideration. However, this study only considers the priority of closure from the safety risk aspect, ignoring some important factors such as spatial accessibility.

$$\textit{Risk score of a given crossing} = \sum_{i=1}^{6} (Weight\ of\ Factors_i) \quad (2.1)$$

Table 2.1 Rating Formula in Kansas Study (Russell & Mutabazi, 1998)

Factor	Condition	Weight
Crossing angle	0°-30°	8
	30°-60°	4
	60°-90°	1
Sight distance	0%-25%	16
	25%-50%	8
	50%-75%	4
	75%-100%	1
Approach grade	0	1
	0%-3%	2
	4%-6%	4
	>6%	8
Daily train number	<1	2
	1-5	4
	5-10	8
	>10	16

Train speed	Fast	16
	Slow	8
Track number	1	4
	>1	8

In another recent study by Johnson (2015) and Hans et al. (2015), a similar rating formula was developed for Iowa's grade crossing closure program. Their formula, shown in Equation 2.2, was calibrated with nine important factors for crossings located in urban and rural areas. These factors for weighting are shown in Table 2.2, where the crash rate is calculated from a 5-year collision history. Weights for the individual factors are assigned by a group of experts based on their opinion on the relative importance of all factors being considered.

$$\textit{Risk score of a given crossing} = \sum_{i=1}^{9} (Weight_i * Normalized\ Factors_i) \qquad (2.2)$$

Table 2.2 Grade Crossing Safety Factors Involved in the Final Decisions

Study	**Factor**
Prioritizing importance level of grade crossings in Europe using traffic movement model (STC, 2010)	• Average daily traffic (a product of the daily number of road vehicles and the daily number of trains) • Waiting time cost
Prioritizing grade crossings for safety improvements in Europe using decision support model (Ćirović and Pamučar, 2013)	• Rail traffic frequency • Road traffic frequency • Number of tracks • Maximum train speed • Angle of intersection • Number of incidents • Visibility • Investment cost
Developing grade crossing consolidation rating formula in Lowe states (Hans et al., 2015; Johnson, 2015).	• AADT • Out of distance travel • Truck AADT • Primary or farm-to-market road system status

	• EMS location proximity count • Distance to nearest EMS location • School location proximity count • Distance to nearest school location • Alternate route crash rate
Prioritizing infrastructure investment of grade crossings considering corridor-level methods (Arellano et al., 2017)	• Probability of having a crash based on collision data
Developing a priority index for grade closure screening in Texas (TxDOT, 2013)	• Average daily traffic, • Number of trains • Alternate route • Lane number
Developing grade crossing consolidation rating formula in California (CPUC, 2013)	• Average daily traffic • Light rail train traffic • Collision history
Selecting grade crossing for closure with a machine learning method (Soleimani et al.,2019)	• In or near city • Night thru train movement • Surface (main track) • Crossbuck assemblies • Day thru train movement (6 am to 6 pm) • Maximum timetable speed • Total count of flashing light pair • Total switching train • Average number of school buses passing over the crossing on a school day • Typical maximum Speed • Typical minimum speed • AADT • Estimated percent trucks • Intersecting roadway within 500 ft.

Taylor & Crawford (2009) from Australia developed a multi-criteria assessment tool for assessing the expected benefits from converting a grade crossing to grade separation. The multi-criteria assessment method is essentially similar to the heuristic rating approach discussed previously in that it determines an overall score by considering multiple factors. In their study, the overall score for a crossing is the sum of the normalized sub-score of traditional economic factors, social factors, and environmental measures and strategic fit with their weights being 37%, 30%, 12% and 22%, respectively, as decided by experts. For each factor, their sub-score was either from the calculation value based on data or an effect level based on experts' knowledge. The final score can be negative, as the grade crossing closure may deteriorate social and environment conditions. To understand the stability of the crossings being selected in the final result, two sensitivity tests were performed. One is to double the weight of economic criteria, and the other is to change alternative strategic fit score according to the guidelines. This study tries to capture the wide impact of a crossing closure project. This method, however, is fundamentally subjective in nature, lacking a quantitative account of the associated benefits and costs.

In another recent study in Europe, Ćirović and Pamučar (2013) created an adaptive neuro fuzzy inference system model to making decisions about investing in safety equipment for grade crossings. This system can be adopted to the grade crossing closure problem. The essence of the model is a linear rating formula. However, the weighting step based on experts in normal rating process is replaced with a machine learning processing. The model generates an appropriate weighting scheme by learning from the past decisions of many experts. The factors used are shown in Table 2.2. It realizes the benefits of capturing both neural networks and fuzzy logic in one framework and reduces subjectivity and saves time in the decision-making process.

2.3.3 Decision Tree Model

In a third approach, whether a crossing should be closed is determined by a decision tree model, which is trained using data of past closure decisions for mapping between closure decisions (yes or no) and crossing attributes. This approach is essentially about trying to learn the domain knowledge of the safety experts on decisions pertaining to crossing closures using a machine learning model, which also means that the accuracy of the model would depend on the correctness of the decisions made in the past. For example, Soleimani et al. (2019) developed a machine learning-based classification model called XGboost for providing decision support on crossing closure. Their XGboost model was trained using a dataset containing a large sample of crossings with 40 factors from 18 US states, including records of 12,741 closed crossings, 424 newly opened crossings, and 5,320 existing (open) crossings, which is a balanced dataset for training. The significance of factors was determined based on gain value in XGboost, and the top ten important factors were found to be: intersecting roadway within 500 ft, estimated percent trucks, AADT, typical minimum speed, typical maximum speed, average number of school buses passing, total switching trains, total count of flashing light pairs, maximum timetable speed, day thru train movements. This study also gives a simplified prediction model with only 14 factors, as shown in Table 2.2, considering a trade-off between a R value, aggregated gain value, and area under the curve value. This approach is limited in the sense that it provides only binary decisions instead of a scalar measure of priority. As a result, when budgets are constrained, it is difficult to determine the order in which funding needs to be closed. Another limitation is that this method is challenged by the availability of data, which needs a large number of crossings which had been closed before as the training data. However, these crossings usually accounts for a small part in the whole crossings, leading to a need for converting imbalanced training data into balance one.

2.3.4 Benefit-Cost Analysis

Benefit-cost analysis seeks the greatest ratio of benefits to costs among potential investment opportunities or projects, and it has been widely used to prioritize projects and resources in engineering and economics for decades. It can simplifies the goal of project evaluation rather than using multiple perspectives in screening and analysis (Rezvani et al., 2015). Prest and Turvey (1966) describe the basic guidelines for benefit-cost analysis in four steps. These guidelines are: 1) determine the costs and benefits to be included; 2) assign a value to benefits; 3) determine the discount or interest rate; and 4) identify related constraints. In a benefit-cost analysis, costs and benefits are usually transformed into one standard unit of measurement, and in most cases, the measurement is monetary value. For example, in collision studies, a collision can be estimated in terms of property damage, emergency response costs, health service costs, legal costs, travel delay costs, and productivity costs in dollars (De Leur & De, 2018).

According to a benefit-cost analysis guide for road safety (Lawrence et al., 2018), the most basic benefit-cost analysis measurements for transport projects include present value costs, present value benefits, the net present value, cost-effectiveness index, and benefit-cost ratio. For instance, Rezvani et al. (2015) previously applied a risk-based benefit-cost ratio to prioritize transportation infrastructure projects in North Carolina. The benefit-cost ratio is shown in Equation 2.3, whereas in safety projects, the benefit usually involves only reduced crashes, and the measurement is shown in Equation 2.4. For a benefit-cost ratio, a project with a ratio greater than 1 indicates that its benefits exceed costs. In their study, the benefit is the safety benefit calculated by different probabilities of collision severity type, and (the primary and secondary) cost includes project cost, maintenance and repair, pollution safety cost, and travel time cost. Their framework was finally applied to grade separation projects, warning device installation projects, and crossing closure projects, where different costs were involved.

$$\textit{Benefit-Cost Ratio} = \frac{\textit{Present Value Benefit}}{\textit{Present Value Cost}} \tag{2.3}$$

$$\textit{Cost-Effectiveness Index} = \frac{\textit{Present Value Cost}}{\textit{Crash Reduced}} \tag{2.4}$$

In recent Canadian research, Thakali et al. (2020) introduced a benefits-risk reduction analysis to select the appropriate measurements for upgrading grade crossing controls. This method is essentially the same as a net present value, which is shown in Equation 2.5. A project with a value greater than 0 means its benefit exceeds the cost. In their study, the benefit is the reduction in collision costs per year, while the cost is not defined due to the data limitation. Moreover, a sensitivity analysis was conducted by changing the expected funding to investigate how benefits vary with various funding amounts provided by the government.

$$\textit{Net Present Value} = \textit{Present Value Benefit} - \textit{Present Value Cost} \tag{2.5}$$

In summary, most current approaches to selecting grade crossings for closure are heuristic and subjective in nature. More recent research attempts to develop crossing closure selection methods that cover as many factors as possible so that the major concerns in the grade crossing closure are considered. However, the way that all of the relevant factors are taken into account lacks systematic quantitative evaluation of all potential costs and benefits. A risk-based cost-benefit analysis can understand the closure problem from the perspective of resource allocation and safety risk reduction at the same time. This method seems to be more compatible and flexible. However, the tools for evaluating the costs and safety benefit are needed to be developed to support this approach. The following parts will elaborate the potential methods for assessing reduced collision risk, increased trespassing risk, and reduced spatial accessibility after a crossing is closed.

2.3 Statistical Modeling of Collision Risk at Grade Crossings

As indicated previously, evaluation of a grade crossing closure project requires quantifying the safety benefit that could be expected from the closure. Many approaches have already been proposed for evaluating collision risks, such as before and after analysis, spatial analysis, and simulations. However, abundant model forms and evidence-based inference logic make statistical models the most successful and widely used among these methods. In addition, continuously developing collision databases provide a detailed description of each collision and contribute to new insights into the underlying causes of traffic collisions and the severity of their injuries (Mannering & Bhat, 2014). This has resulted in the increasing application of statistical modeling in rail safety in recent years. This section reviews the factors affecting grade crossing safety and statistical models related to grade crossing closure in order to determine a suitable model which can properly fit the research scenarios under study.

2.3.1 Factors Affecting Grade Crossing Safety

In decades of research and exploration, some important factors have been gradually found and tested, which have a significant relationship with safety risk at grade crossing. These factors affecting grade crossing safety are used as the independent variables in statistical modeling of collision risk. Table 2.2 summarizes the factors affecting grade crossing safety in recent studies. Soleimani et al. (2019) state that the most examined factors are vehicle and train traffic volume, protection devices, collision history, number of tracks, visibility, train type, special vehicle, train speed, approach grade, intersection angle, pedestrian volume, environmental condition, road-track alignment, highway type, lanes, and highway speed based on the research in grade consolidation programs in America.

Based on extensive previous studies on crossing closures, three main issues can be identified when using factors. The first is the low stability of the model due to the correlations between factors. It is found that a corridor approach, multi-criteria assessment process, or a statistical model can reduce the correlation in the grade crossing closure problem (Arellano et al., 2017; Taylor & Crawford, 2009). The second issue for factor usage is ignoring data reliability. Improving data reliability is mainly about making data more complete and more accurate. Most existing railway and highway accident studies draw information from police crash reports. The information in reports can be used as explanatory variables for safety modeling. This information usually includes the time of day, driver's information, weather, causes of collisions, and road and rail information. However, crash reports sometimes have inaccurate records. For example, less serious collisions are less likely to be reported to the police, therefore, less likely to be recorded in police crash reports (Ye & Lord, 2011). Thus, this inaccurate information in the database should be screened to avoid bias in modeling results. The third issue is modelling with insufficient factors due to data availability. For example, the research of Hans et al. (2015) did not involve some important factors, such as, humped crossing, crime, noise and visual amenity, land use, and community cohesion.

2.3.2 Collision Frequency Model and Collision Severity Model

The collision frequency and severity are two dimensions to evaluate safety risks. The collision frequency is the number of collisions counted on roads in a given period, following the simple Poisson distribution. However, the Poisson variants have become the dominant approaches in collision frequency modeling since they overcome some limitations of the simple Poisson regression model. For example, the negative binomial model is widely used in collision studies since it is suitable for the data where the mean of the frequencies is much greater than the variance (Lord & Mannering, 2010). In addition, some databases for modeling include accident-free cases. To make better utilization of these accident-free observations, zero-inflated Poisson and negative binomial regressions were applied to improve the prediction result. More advanced models have been explored in recent research, as shown in Table 2.3.

Table 2.3 Previous Methodological Approaches to Collision Frequency and Collision Severity[1]

Collision frequency model:	Collision severity model:
Poisson regression model	Binary logit/probit models
Negative binomial/Poisson–gamma models	Multinomial logit models
Duration models	Nested logit models
Bivariate/multivariate models	Sequential logit/probit models
Zero-inflated Poisson and negative binomial models	Heteroskedastic ordered logit/probit models
Random effects models, spatial and temporal correlation models	Ordered logit/probit models
Generalized estimating equation models	Log-linear models
Neural network, Bayesian Neural network, and vector machine models	Generalized ordered outcome models
Hierarchical/multilevel models	Simultaneous binary logit model
Negative multinomial model	Bivariate/multivariate binary probit models
Poisson-lognormal and Poisson–Weibull models	Bivariate/multivariate ordered probit models
Gamma model	Artificial neural networks
Conway–Maxwell–Poisson model	Mixed joint binary ordered logit model
Censored regression models	Mixed logit model (random parameters logit model)
Generalized additive models	Partial proportional odds model
Random parameters count models	Finite-mixture/latent-class and Markov switching models
Finite-mixture/latent-class and Markov switching models	Heterogeneous outcome model
Negative binomial-Lindley model	Mixed ordered probit (random parameters probit) model

1

Count model recast as a generalized ordered response system	Spatial and temporal correlations

A simple Poisson regression model is the most original collision frequency model, which assumes that the data are Poisson distributed (having an equal mean and variance). However, in some research, the variance of frequency is much larger than the mean. Thus, a negative binomial regression model on the basis of simple Poisson models have been applied to address this overdispersion issue. Generally, the number of accidents (Y) is assumed to follow a Poisson distribution, and the probability of collision frequency is mathematically expressed in Equation 2.6 (Cameron and Trivedi, 1998).

$$P(Y = k) = \frac{e^{-\mu}\mu^{k}}{k!}\ ,\ k \in N \tag{2.6}$$

where P is the probability of having k accidents during a given period; Y is the number of accidents; μ is the expected number of accidents, which can vary by individual observations. A log link function is commonly used to specify the relationship between the μ and the explanatory variables of observation. In negative binomial regression, an error term is added to this log link function, which is shown in Equation 2.7:

$$ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \xi \tag{2.7}$$

where β_0 is intercept; X_k is the kth explanatory variable which related to the cause of collisions; β_k is coefficient of variable X_k; ξ is an error term, and the exponential function of ξ is assumed to be Gamma distributed. In addition, there exists Equation 2.8:

$$Var = \mu + \frac{\mu^2}{\alpha} \tag{2.8}$$

where α is an overdispersion parameter, and both of parameters in Gamma distribution is equal to $\frac{1}{\alpha}$. A maximum likelihood can estimate the value of α and the model's coefficients.

An empirical Bayes approach can be applied to improve the accuracy of the prediction result. The fundamental logic behind empirical Bayes combines both observations and prediction frequency from a cross-sectional model. To perform a Bayesian analysis, the first step is to select a prior distribution on the mean of collisions and then conduct the usual Bayesian update to get the posterior distribution (Carlin and Louis, 2000). An empirical Bayes approach was first used in road safety analysis for evaluating the effect of engineering measures by Hauer (1997). In his later research, Hauer (2002) states the empirical Bayes approach can improve the accuracy of estimates, reduce the amount of data used, and correct for the regression-to-mean bias. In other research, Mitra et al. (2009) used a Bayesian approach to improve the prediction results from a negative binomial model to identify the hazardous road locations. Their study confirms that coefficient estimation based on the Bayesian approach is close to negative binomial estimation but with higher accuracy.

Similarly, for modeling the severity level of collisions, a considerable number of models have been developed. These models predict the probabilities of the possible severity types of a categorical dependent variable. Simple severity models such as binary logit and probit models can only consider a discrete binary severity (injury or no injury). Multinomial models, such as a simple multinomial logit model, the nested logit model, and the random parameters logit model, can predict multiple discrete outcomes. For example, in a multinomial logit model, more than two injury severities can be considered, where one of the severity levels is selected as a base type, and the remaining types are estimated according to this basis. More severity models are shown in Table 2.3.

Selecting and developing a specific model based on the characteristics of the data. For example, considering that grade crossing accidents have the characteristics of high zero count frequency, and low average collision frequency, Poisson and negative binomial models should be utilized as a well-performed combination for safety risk estimation at crossings (Miranda-Moreno and Fu, 2006; Saccomanno et al. 2004). For example, Thakali et al. (2020) applied a combination of statistical models for identifying risky sites in their grade crossing safety research. In their study, a negative binomial model was calibrated with collision data and crossing inventory data to obtain a predicted collision frequency, and then the result was adjusted by an empirical Bayes approach. The collision severity was subsequently estimated by a multinomial logit model with factors related to the collisions. The risk is finally converted to a monetary value by assuming a specific cost with each severity type.

In summary, previous studies have identified the factors affecting safety at grade crossings. For statistical modeling, a large and growing methodological gap has evolved between what is used in practice and what is used by front-line research (Mannering & Bhat, 2014). Even though advanced and complex models, such as machine learning methods, often perform better than simple ones in prediction results, it is important to find a balance between the difficulty of the operation and the accuracy of prediction results.

2.4 Trespassing

As mentioned previously, grade crossing closures may lower accessibility for the road users, which could lead to increased incidents of trespassing by cyclists and pedestrians. According to Bahar et al. (2016), trespassing along the railway has been rising in recent years in America, and more than 60% of rail-related fatalities happened to trespassers. There are more fatalities in trespassing than other types of rail accidents. In 2020, 67% of trespassers involved in a rail accident died, and 50% of Canadian grade crossing fatalities occurred due to pedestrian trespassing (TSBC, 2020).

The research attention to trespassing issues has dramatically increased in the last decades. Former research primarily focused on understanding the variables related to trespassing, and solutions for reducing trespassing incidents can be made based on these variables. For example, Wang et al. (2016) employed geographically weighted regression to uncover the spatial variations between trespassing accidents and potential variables in the US. The variables include individual attributes, environmental and location, crash time, and pre-crash behaviors. They found that behavior before the collision is the most important variable related to collision severity. Their research recommended that first aid strategies and policies should be developed based on regional investigations. In a comprehensive study of relevant variables, Zhang et al. (n.d.) categorizes the influencing variables into four groups: pre-crash behavior, crash characteristics, mental health, and environments. In addition, they summarized the essential factors that are more likely to induce trespassing events: gender (man), age (youth), alcohol/drugs, weather (summer), decrease in travel time, time(night), high traffic flow, and using headphones.

In the latest report (RSSB, 2020), a risk rating method is provided to estimate the trespassing risk, including five steps: 1) frequency rating, 2) vulnerability rating, 3) frequency/vulnerability rating, 4) consequence rating, and 5) trespass risk rating. Frequency involves a rating based on residents, land use, and other factors, such as poverty. Vulnerability considers three factors: accessibility, trespassing attractions, such as shortcuts and business areas, and active security. Frequency/vulnerability rating is a combination of frequency and vulnerability getting an overall score by a rating matrix. The consequence is the possibility of trespassing resulting in casualty degree. Finally, the frequency/vulnerability and consequence ratings can be cross-referenced to give a final risk score. This method relies on experts' experience and requires an established trespassing database as support.

The statistical models for identifying the trespassing risk are similar to those used for collision risk, as discussed previously. For example, Kang et al. (2019) modeled a railroad trespassing frequency using a mixed-effects negative binomial model, and the key factors that influenced rail trespassing included county population density, length of rail tracks in a county, median age, and male proportion of the county population, and average train traffic within a county. In their study, the Akaike information criterion and the Bayesian information criterion were applied for selecting the model and variables, and model interpretation was based on percentage change. In another study, considering the structure of the data and possible heterogeneity, multilevel mixed-effect ordered logistic regressions were applied for assessing trespassing severity by Zhang et al. (2018). Their results uncovered that there are differences in the related variables of injury severity between grade crossing and non-grade crossing. These differences involve the condition before the collision, weather, age, and fluctuations for collision. In addition, the study confirmed the strong reliability of using only a single model. However, no sensitivity analysis on usage of different factors was performed in this study.

In summary, the studies on frequency and severity of trespassing risk are still limited in the existing literature. Most current research focuses on train-pedestrian collision, countermeasures of preventing trespassing, and the factors leading to trespassing (Kang et al., 2019). The related variables in crossing collision and trespassing risk have few overlaps in the previous studies. It is a challenge to model changes in trespassing risk with the factors explored in previous studies, because these factors do not vary before and after the crossing closure. Moreover, the potential increased trespassing risk is not confined to a single location after closing a crossing, where limited tools and methods are available to determine the scope of trespassing that comes with closing a particular crossing.. Thus, assessing trespassing in grade crossing closure problems by modeling or quantitative analysis is still challenging.

2.5 Spatial Accessibility Analysis

As discussed previously, consolidating crossings along a railway corridor into a fewer number of crossings would expectedly result in decreased spatial accessibility or increased inconvenience for road users. Availability of reasonable alternative routes are critical from the perspective of the road users, thus having a significant impact on the public acceptance of these crossing closure decisions. As a result, these decisions must be justified by showing that alternate routes are available within a reasonable travel distance from the closed crossings (Ogden, 2007). At the same time, the increased travel distance due to closure should be considered as an important factor affecting the priority for decisions pertaining to grade crossing closure. This section reviews the available tools and methodologies in the literature for determining if there is an alternative route and the increased travel distance for each crossing.

In earlier times, the spatial accessibility analysis was often performed manually with a paper map, such as those shown in the Kansas grade crossing consolidation study (Russell and Mutabazi, 1998). Later, some studies for conducting spatial accessibility analysis are based on subjective judgment. For example, in an Australian study aiming to evaluate possible benefits from grade separations, the transport connectivity and accessibility are scored with 5, 3, 1, 0, -1, -3, and -5, representing a situation from substantial improvement to substantial worsening (Taylor & Crawford, 2009). The scores were determined by experts' discussion considering the access and use of public transport and change in connectivity between general roads, catchment roads, and main roads around each grade crossing. In another study on grade crossing closure, increased travel time due to crossing closure was estimated by experts using data from some project surveys (Rezvani et al., 2015).

With the development of digital maps and the application of shortest path algorithms, the accessibility measures discussed previous can be easily obtained in a GIS platform. GIS tools can find the shortest (or optimal) routes automatically for various purposes. For example, a toolbox named ACCESS in ArcView GIS for spatial accessibility analysis was developed for various modes and destinations integrated with GIS functionality, OD matrix formulation, and spatial accessibility measures (Liu & Zhu, 2004). At present, the most famous algorithm for the general shortest path problem is the Dijkstra algorithm proposed by Dijkstra, which can be used to find the shortest path from a given node to all the other nodes in a graph in a computationally efficient way (Chen, 2003).

To date, the Network Analysis in GIS platform can provide many solutions for different propose, such as finding the best route, finding the closest emergency vehicle or facility, and identifying a service area around a site. For example, Hans et al. (2015) applied a GIS tool to identify the out-of-distance (the difference between the shortest alternate route and the original route travel distance) in a grade crossing closure study. The collision risk was calculated by using the mainline collision history of the roads used for the alternative route as well as the intersections used for the alternative route in five years. The out-of-distance is calculated using the Network Analyst extension in ArcGIS. They first created a road network with transport links and nodes. Then, the out-of-distance was calculated one by one for each crossing rather than being calculated by developing an automated tool, as the authors insist that manually checking whether the intersection is abandoned, closed, passable, or unlocatable can make the analysis more accurate. They also mentioned that the road network that is usually not a complete topology needs to be reviewed and maintained manually. To some extent, this combination of GIS tools and manual review ensures high accuracy of results and timely detection of data errors.

In summary, GIS tools have been the dominant approach to conducting spatial accessibility analysis due to their low time consumption and high accuracy. Thus, many accessibility analysis from previous grade crossing closure studies need to be improved by applying GIS tools. However, proactive closing crossings from a large number of candidate set may still have heavy artificial burden in accessibility analysis process, such as input and output steps. Thus, there is a need to develop an automated tool to normalize the process. .

Chapter 3 Methodology

After having a comprehensive understanding of the background knowledge that needs to be considered in decisions pertaining to grade crossing closures, the next step is developing a suitable decision support framework and then the tools and analysis required to support this framework. In this research, a risk-based benefit-cost analysis framework is proposed for ranking and determining the candidate crossings for closure. The following sections provide a detailed description of the framework and its main components including data requirements, preliminary screening, and cost-benefit analysis module.

3.1 Overview of the Proposed Framework

The proposed framework is designed to identify the priority of closure for individual crossings, and it entails three essential steps as shown in Figure 3.1. First, a preliminary screening process is applied to remove those crossings that are unlikely to be closed due to their importance, narrowing down the list of candidate crossings for the subsequent analysis. In the next step, the different types of benefits and costs associated with closure are determined. Then, their monetary values are estimated individually. Finally, the benefit and costs are integrated in a benefit-cost analysis to obtain the priority of closure. Under this framework, the crossings selected for final closure are expected to have relatively high safety risk and relatively low investment.

In this research, the benefit is determined as the reduced collision risk at grade crossings. It is quantified by statistical modeling, that is, a negative binomial model adjusted by the empirical Bayes approach for collision frequency estimation and a multinomial logit model for collision severity estimation. The cost side includes the one-time construction cost and extra travel time cost due to reduced spatial accessibility, which is calculated in a GIS platform. Another possible cost, increased trespassing risk, is not involved in our framework as suitable data and methods for evaluating trespassing risk have not been available yet.

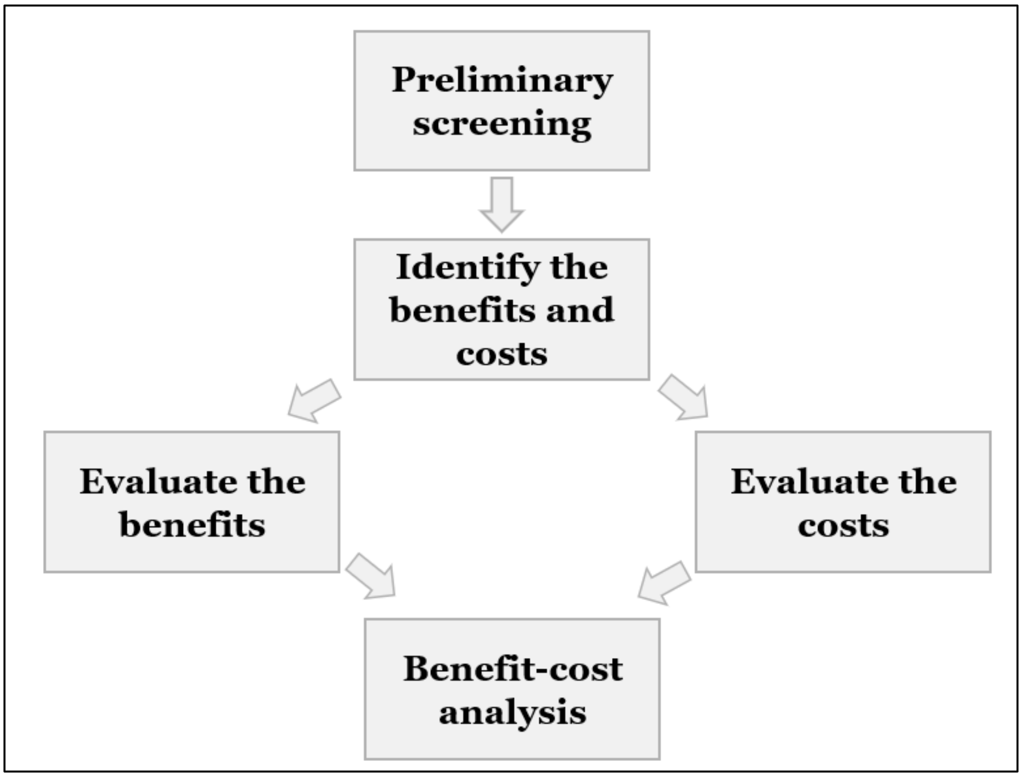


Figure 3.1 Proposed Framework

3.2 Preliminary Screening

As discussed previously, preliminary screening is a process to filter out some grade crossings that do not need to be further considered for closure from the candidate closure set. It can save a significant amount of time in the later analysis. These crossings cannot be closed, as they are important for road users. The criteria for their importance include a high traffic volume, important road class, a high road speed limit, and multiple lanes. The factors and their cut-off values can be chosen based on past studies or expert judgment. For example, in a study in Kansas, the crossings with a traffic volume larger than 750 and 150 vehicles per day for urban and rural roads, respectively, were not considered for closure (Rossel & Mutabazzi, 1998). Supposing that a serious safety issue exists at those important crossings, improving their control devices (such as installing a better protection system) converting to grade separation, and enhancing their physical characteristics (such as increasing the site distance) are preferable to closure. Moreover, to avoid reduplicative screening, only the representative factor remains if one factor is related to another. For example, important road classes are expected to have higher speed limits and more lanes under normal circumstances. As a result, only the road class is chosen as the condition in these road-related factors.

As mentioned before, selecting crossings for closure should also consider whether there are alternative routes (FRA, 1994). Thus, those crossings with no alternate route within a reasonable periphery should be excluded from the candidate set. This is realized in the later steps using a spatial accessibility analysis, where only the crossings with at least one detour route are selected in the final analysis.

3.3 Determining the Benefit and Cost of Closing a Crossing

As mentioned before, the safety benefit, extra travel time cost, and construction cost are considered in this risk-based framework. This section provides a detailed discussion on the methods to quantify and monetize them in dollars.

3.3.1 Safety Benefit of Closing a Crossing

The primary benefit of closing a crossing is increased safety, which can be quantified as the reduced collision risk at a given site due to closure. More specifically, the benefit of closing a crossing should be equal to the collision risk before its closure as it will completely remove the interaction between trains and road users. To quantify the collision risk, the standard methodology documented in Highway Safety Manual (Part, 2010) is adopted, in which the total collision risk at a site (i.e., grade crossing) can be estimated on the basis of the expected collision frequency multiplying by its severity.

Two models were used to model the collision frequency and collision severity, that is, a Negative Binomial (NB) model adjusted using the Empirical Bayes (EB) approach for collision frequency and a multinomial logit model for collision severity, following the steps in the study of Thakali et al. (2020). This approach to grade crossing safety analysis can be traced back as early as the grade crossing study of Saccomanno et al. (2003), where the NB model was tested with the best results among the frequency models. The models were calibrated based on potential sites for closure, referring to those crossings that remained after the preliminary screening. The important variables were selected from our grade crossing inventory dataset based on past studies. RStudio was used to calibrate these models. The following parts describe the detailed step of obtaining the safety benefit:

1) Negative binomial model

For frequency estimation, the number of collisions occurring at a specific grade crossing site i for a specified time (Y_i) is assumed to follow the NB distribution. Mathematically, it can be written as Equation 3.1:

$$Y_i \sim NB(\mu_i, \alpha)$$
$$\mu_i = e^{\beta_o + \Sigma(X_i\beta_i)} \tag{3.1}$$

where μ_i represents the expected collision frequency for the site i, and α is an over-dispersion parameter. X_i and β_i represent the important characteristics and their parameters, respectively, selected based on previous studies, such as traffic exposure, train speed limit, and the road speed limit for the site i, and β_o is the model intercept. The regression coefficients are estimated by the maximum likelihood method. The significance of variables is tested using a t-test at a 95% confidence interval.

2) Empirical Bayes

The application of the EB method can combine the predicted values from the NB model with the observed collision frequencies to obtain a more reliable estimate of the expected average collision frequency. It can compensate for the potential bias due to regression-to-the-mean (Highway Safety Manual, 2010). The fundamental idea of EB is to estimate the collision frequency at a given site by combining observed collisions and predicted frequency from an NB model. Then, these two parts are joined together using a weight based on the reliability of the NB model. Mathematically, the expected number of collisions from the EB method for a given site i, denoted as N_i, is provided as Equation 3.2:

$$N_i = w_i Y_i + (1 - w_i) y_i \tag{3.2}$$

where w_i is a weight given by $\frac{1}{1+\alpha\mu_i}$ at the site i; y_i is observed collision number at the site i. The time for the observed and predicted collision number should be same.

3) Multinomial logit model

After obtaining the estimated number of collisions at a given crossing site, the severity of each collision also needs to be assessed. A multinomial logit model can predict the probability of a dependent variable belonging to a category based on multiple independent variables, and in this study, it was used to estimate the probability of severity type j for a given site i (P_{ij}). The expression is shown as Equation 3.3:

$$P_{ij} = \frac{e^{Z_{ij}}}{\sum_{j=1}^{4} e^{Z_{ij}}}$$

$$Z_{ij} = \beta_o + \Sigma(X_{ij}\beta_{ij}) \tag{3.3}$$

where j is an index representing severity type, here, j =1, 2, 3, and 4 for fatality, major injury, minor injury, and no injury, respectively; Z_{ij} is a measurement representing the propensity for a collision at crossing i to experience severity type j. It is assumed that Z_{ij} is a linear function of important variables affecting collision severity (e.g., train speed)(X_{ij}) with its coefficient (β_{ij}) corresponding to each variable. These variables are selected based on previous research and only the variables that are significant at a 95% confidence interval are retained in the final model. Similarly, the model coefficients are calibrated with the maximum likelihood method.

4) Total expected benefit

With the calibrated collision frequency and severity models, the safety benefit of closing a crossing can be calculated by multiplying the collision frequency by the corresponding probability of each severity, which can then be converted to an equivalent monetary amount based on the unit cost of each severity type. Mathematically, the safety benefit for a given site i (SB_i) in a given year is given as Equation 3.4:

$$SB_i = N_i \cdot \left(\sum_{j=1}^{4} P_{ij}\, CS_j\right) \tag{3.4}$$

where CS_j is the cost associated with the severity type j.

3.3.2 Costs of Closing a Crossing

Crossing closure may lead to an increase in travel time for road users. The increased travel time is directly related to the extra travel distance. A spatial accessibility analysis is needed to measure how much road users have to bear the additional time by detouring due to the closing of the given crossing site. In our study, the distance is calculated using a GIS platform with spatial data of road network and rail network. To define the process concretely, Figure 3.1 shows the principle of conducting the spatial network (accessibility) analysis, which is created by ArcMap. As shown in Figure 3.2, a crossing located on the road network has two nearest road-road intersections (the blue squares) located on the two opposite sides of the rail track. It is assumed that all drivers have the same start point and end point from one intersection to the other, and drivers always choose the route with the shortest distance (the yellow line), and its distance is labeled original distance. Similarly, after the closure, drivers are assumed to follow the new shortest distance route (the red line) with its distance being called the detour distance. The assumption on routes chosen by drivers is very simple, and the actual situation can be much more complicated considering many aspects, such as, the location of a driver, direction of travel, and volume of traffic. However, with the consideration of nature of data and computational time, this assumption will allow for an automated spatial accessibility analysis.

Figure 3.2 Spatial Network Analysis

However, in some cases, there is no reasonable (detour) route from one intersection to another after closure within a certain range of search (e.g. 10 kilometers). These crossings should not be considered for closure as there would be no reasonable nearby access points for the road users. As a result, they are excluded from the candidate set. Another unusual situation is that an existing crossing is not located at the shortest route, as shown in Figure 3.3. That is, there is a nearby crossing that is a better alternative for the road users to cross the track. In this case, closing the crossing has no negative impact on the road users (no extra travel time cost).

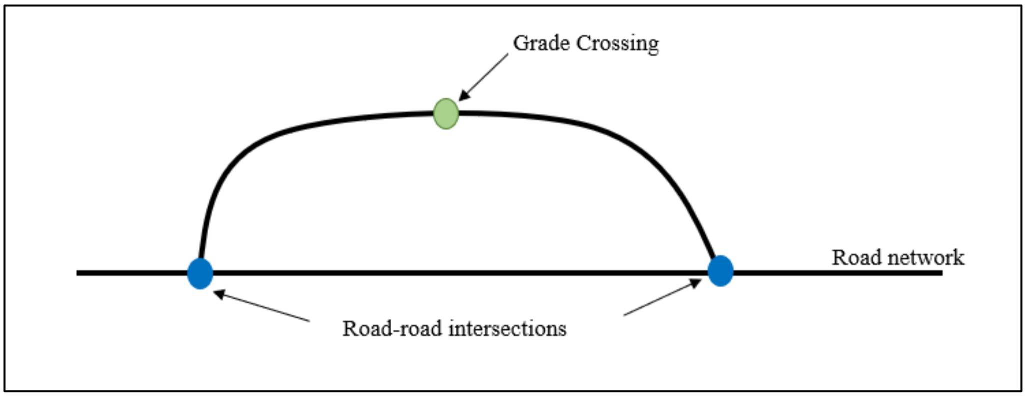


Figure 3.3 Closing a Crossing Without Extra Travel Time Cost

After obtaining the original distance and the detour distance for each crossing site, the annual travel time cost for a given site i (TC_i) in a year was calculated as Equation 3.5:

$$TC_i = \frac{365 \cdot TV_i \cdot \left(D_i^d - D_i^o\right) \cdot VT}{S_i} \tag{3.5}$$

where TV_i is the average daily traffic (ADT) in vehicles for the site i; D_i^d is the detour distance for the site i; D_i^o is the original distance for the site i; VT is the value of time in dollars; S_i is the design speed of the detour route. This study only considers the travel cost of vehicles (e.g., private cars) due to the nature of the data.

Another cost is the one-time construction cost for a given site i (CC_i), such as removing the signs and adding barriers, which can be estimated from Transport Canada's past closure projects. Finally, the travel time cost plus the construction cost is the total cost of closing a crossing in dollars.

3.4 Determining the Closure Priority with Benefit-Cost Analysis

Once the safety benefit and the cost of closing a crossing are estimated, the final step is to determine the closure priority crossings in the final candidate set with benefit-cost analysis proposed in this framework. In this research, a life-cycle benefit-cost ratio for a given crossing site i ($LCBCR_i$) was applied, which is given as Equation 3.6 as follows:

$$LCBCR_i = \frac{\sum_{t=0}^{t-1} \frac{SB_i}{(1+r)^t}}{\sum_{t=0}^{t-1} \frac{TC_i}{(1+r)^t} + CC_i} \quad (3.6)$$

where *t* is the expected life cycle of a given closed crossing in years, and r is the discount rate. The construction cost is assumed to be incurred in the first year only. A higher ratio value for a crossing means that a higher benefit with respect to the costs could result from closing the crossing, suggesting that the crossing should be considered as favorable for closure. The final decision on which crossings to be closed could be made according to this ranked list from top to bottom.

Chapter 4 Case Studies

This chapter presents three case studies to illustrate the application of the risk-based framework proposed in Chapter 3. The following sections include a brief introduction on study areas, a description of the general steps for data processing, the results for safety model calibration, the spatial accessibility analysis, and the generation of candidate crossings for closure based on benefit-cost analysis.

4.1 Study Areas

The proposed framework was examined through case studies of three Canadian provinces: Ontario, British Columbia, and Quebec, as shown in Figure 4.1. These three provinces were chosen with a consideration of geographical coverage, representative population distribution, and a high number of grade crossings and collisions.

Figure 4.1 Case Study Areas

Ontario is the most populous province in Canada and the second-largest province by area in central Canada. Most of Ontario's population (about 94%) are located in southern Ontario. Ontario has 191,000 kilometers of road and 17,000 kilometers of rail tracks.

Passenger rail is primarily operated by Via Rail and Amtrak, which provide cross-provincial and cross-country passenger services. Canadian National Railway (CNR) and the Canadian Pacific (CP) dominate the freight rail industry. There are also several well-established city rail-transit systems and regional commuter rails, such as GO Transit, which are not federally regulated and therefore not considered in this case study.

Quebec is the largest province in eastern Canada by area and the second most populated. Most of the population lives in urban areas along the St. Lawrence River. Quebec has 144,000 kilometers of road and 6,678 kilometers of railways, which are integrated into the larger North American railway network. Most freight is carried by CNR and CP, and intercity passenger rails also use the Quebec Rail network through Via Rail Canada and Amtrak.

British Columbia is Canada's westernmost province, located between the Pacific Ocean and the Rocky Mountains, and it is the third most populous province in Canada. British Columbia has a vast and rugged terrain, and it has 71,000 kilometers of roads connecting its cities. Since the 20th century, the 2,320 kilometers of railways have become the primary way of long-distance ground transportation in British Columbia. However, passenger rail service remains limited. For example, Via Rail Canada's local service is operated in only two cities.

4.2 Data Sources

Three available databases were obtained and compiled based on previous literature and the proposed framework in this research. These datasets are listed below.

1) Grade crossing inventory data

Grade crossing inventory (GCI) data provided by Transport Canada is a yearly-updated dataset that records characteristics of the crossings. A total of 22,176 highway-railway crossings with their information in Canada were registered in 2019. These crossings have 135 attributes (variables), they can be roughly divided into five categories: 1) identifier, 2) spatial information (such as longitudes and latitudes), 3) time information (such as the date of commencement in service), 4) configuration of facilities (such as protection type of crossings), and 5) traffic statistics.

2) Collision data

The Transportation Safety Board (TSB) is an independent department in Canada with a mandate to improve transportation safety. It tracks, records, and investigates major accidents involving air, sea, pipeline, and rail modes of transportation. The TSB data portal includes Canadian data on several types of rail accidents, such as trespassing and crossing collisions, and their information. This study used the data labeled crossing collisions between 2013 and 2018, totaling 294 records. The information includes environment variables (such as location ID and weather conditions), vehicle attributes (such as vehicle type), and the result of the collision (such as severity levels). A field with a common reference number (RSIG crossing ID) permits linking each accident with the Grade crossing inventory data, enabling the crossing information and its collision number to be combined in one dataset.

3) The railway & road network data

The railway network data and the road network data are both open-source data from Statistics Canada. This study employed their shapefile format updated in 2019 for mapping. These two datasets include the geometric and attributive information of all Canadian rails and roads. Manually checking the data suggests the spatial error is generally within 10 meters.

To have a clear view of the accident distribution across Canadian provinces, Table 4.1 shows the number of collisions from 2017 to 2021 and the number of grade crossings in each Canadian province (updated in 2021). The sources are retrieved from the latest grade crossing inventory data and transportation safety board data. It is found that most of the crossings (93.5%) are concentrated in the six provinces: Saskatchewan (22.0%), Ontario (21.2%), Quebec (15.1%), Alberta (13.6%), British Columbia (11.6%), and Manitoba (10.0%). It seems that no spatial correlation is discovered in the collision ratio.

Table 4.1: Collisions and Crossings in Canadian Provinces

Province	The number of collisions (A)	The number of crossings (B)	Collision Ratio (A/B)
Alberta	110	2,999	3.67%
British Columbia	**75**	**2,415**	**3.11%**
Saskatchewan	94	4,797	1.96%
Manitoba	76	2,182	3.48%
Ontario	**156**	**4,603**	**3.39%**
Quebec	**78**	**3,694**	**2.11%**
New Brunswick	10	950	1.05%
Nova Scotia	12	419	2.86%
Other areas	/	50	/

4.3 Data Processing

This section describes the detailed steps involved in processing the data obtained from various data sources for the intended case studies. Figure 4.2 is a workflow diagram that shows the essential steps of the data processing procedure and the end results. The result of data processing is used as the data for both statistical modeling and spatial analysis. It is noted that the preliminary screening step is included as a step of data processing since some crossings should be filtered out considering their obvious importance to road users. The following section will mainly elaborate on the individual steps shown in the figure.

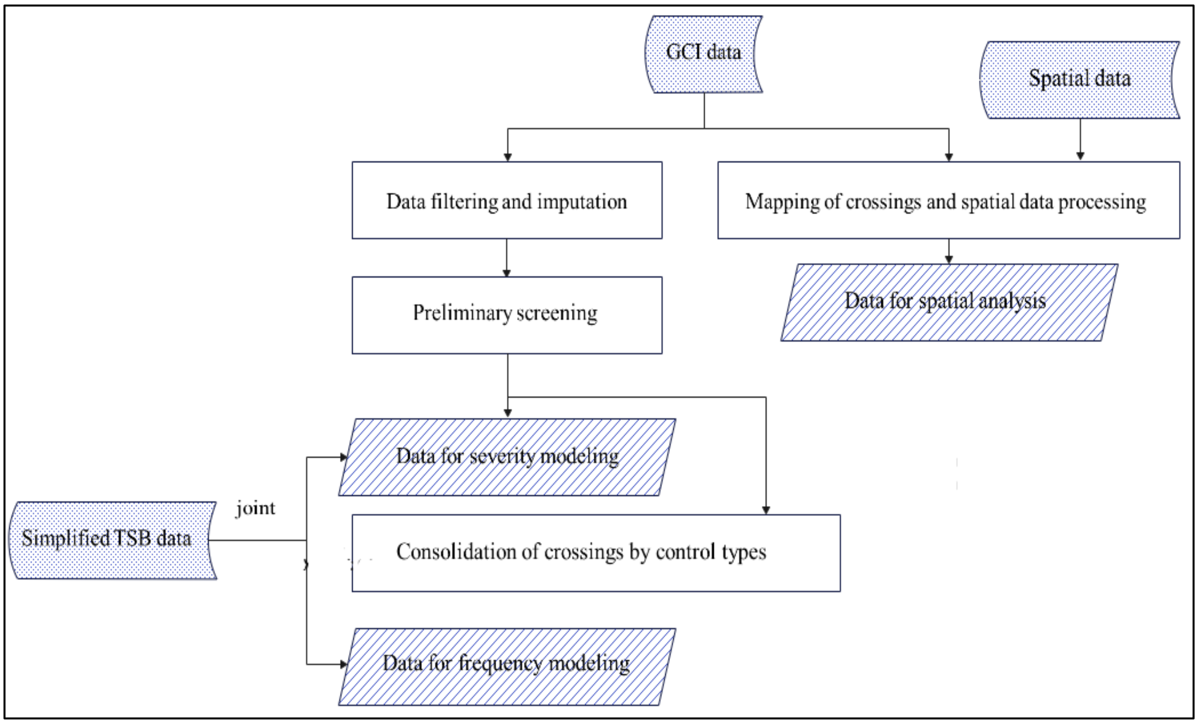


Figure 4.2 Data Preparation and Processing for Case Study

4.3.1 Data Filtering and Imputation

As mentioned before, GCI data provides 135 variables on 22,176 crossings, including environmental variables and geographic variables. However, not all the variables are useful in safety modeling. Thus, to simplify the dataset, only the variables that are likely to be highly relevant to the collision frequency and severity at grade crossings were retained. The potential variables were chosen based on past studies. These nine potential variables were train and traffic volume, train maximum speed, road posted speed, number of lanes, number of tracks, track angle, whistle prohibition condition, and environment type in terms of urban or rural. Thus, the rest variables in the database could be excluded. Similarly, for TSB data, only the crossing ID and the information related to collisions, such as severity level were retained.

For the retained data fields, it was found that there are some missing data or data that were obviously erroneous. For example, there are some crossings with the value of "Track Angle" larger than 180. However, the track angle should always value greater than zero and less than 180 degrees. To improve the reliability of subsequent analyses and retain as much data as possible, the missing or erroneous data were imputed by substituting them with reasonable values. One approach to choosing replacement values is using the values from the nearest crossing sites with complete information, assuming that these adjacent crossings had similar site conditions. However, this involves a considerable amount of spatial computation. Thus, a simplified but well-known imputation approach was taken in this study, which is to replace the missing or erroneous data of a field with the most frequent value of the same field in the database (Di, 2007; Ding, 2012). By this approach, it is expected that our data imputation can be close to the real data. For continuous data or data with a high degree of dispersion, such as train volume, the most frequent value may be not representative for the data. Thus, the missing or erroneous data could be replaced by the value reflecting the characteristics of remote crossings, which assumes that these crossings are more likely to have data problems (e.g., a lower train volume/traffic volume/train maximum speed/road posted speed than the median). Table 4.2 shows a summary of the imputation method. The total number of unique records that have been imputed is 2,231.

Table 4.2 Summary of Data Imputation

Data Fields	Value	Imputation Method	No. of Records
Train volume (per day)	0,999, or blank	Replaced by 20 (the value slightly less than the median of the data)	1,281
Traffic volume (per day)	0 or blank	Replaced by 150 (the value less than the median of the data)	818
Train maximum speed (mph)	0 or blank	Replaced by 35 (the value slightly less than the median of the data)	682
Road posted speed (kph)	0 or blank	Replaced by 30 (the value slightly less than the median of the data)	1,139
Number of lanes	0 or blank	Replaced by 1 (the highest frequency)	383
Number of tracks	0 or blank	Replaced by 1 (the highest frequency)	240
Track angle	<10 (erroneous) or blank	Replaced by 90 (the highest frequency)	431
Whistle prohibition condition (Yes for 1, No for 0)	unknown	Replaced by "no" (the highest frequency)	609

Urban (0) or rural (1)	blank	Replaced by "rural" (the highest frequency)	327

4.3.2 Preliminary Screening

As mentioned previously, the primary goal of preliminary screening is to exclude those crossings that are unlikely to be closed due to some obvious reasons, such as high road traffic volume and the presence of well-protected control. To streamline this preliminary screening process, a set of crossing attributes are first identified as the screening variables with a cut-off value set for each of them. The first important crossing attribute considered is road traffic volume. In our GCI database, the traffic volumes for crossings vary across the urban and rural roads, ranging from 0 to 65,104 vehicles per day for urban roads and 0 to 51,000 vehicles per day for rural roads. For the preliminary screening, the cut-off values for the traffic volume were set as 750 and 150 vehicles per day for urban and rural roads, respectively, similar to ones used by Rossel & Mutabazzi (1998). This means that those crossings that exceed the cut-off values are excluded for further consideration.

The second attribute used for preliminary screening is the class of the intersecting road. As shown in Table 4.3, there are a total of 18 road classes in the crossing inventory database. It is necessary to exclude those crossings for further consideration that are intersecting with high class roads, such as freeway, expressway, arterial, or collector. Note that there are a large proportion of crossings that do not have road class records, and they were retained for the following analysis. Thus, the crossings in the final closure list need a visual check for their intersecting roads via satellite images after obtaining the final closure list. Finally, of the total 22,176 crossings, 13,472 sites remained in the pre-selection list.

Table 4.3 Road Class Type and Count (22,176 Crossing Sample)

Road Class	Count
Arterial	1,723
Bike Path	3
Collector	1,820
Expressway	1
Farm Road	732
Field to Field	622
Freeway	9
Industrial Service Road	110
Local	6,003
Other	2,366
Pedestrian Path	285
Private Access	1,995
Railway Yards/Service Road	61
Recreational Vehicle Trail	53
Seasonal	1
Snowmobile Trail	1
Unmaintained Road	38
Unopened Road Allowance	85
(blank)	6,267

After preliminary screening, the GCI and TSB database need to be merged for severity modeling in the form of each collision as one record. As mentioned before, the crossings in these two databases share the same IDs to permit an attribution join. It should be noted that in TSB data, the collisions are classified as fatal, major injury, minor injury or no injury types based on the most severe outcome in each collision in our database, and the logic is given below:

- Fatal: if at least a person died, otherwise;
- Major injury: if at least a person had a serious injury, otherwise;

• Minor injury: if at least a person had a minor injury, otherwise;

• No injury.

Table 4.4 shows the descriptive statistics for important variables after preliminary screening.

Table 4.4 Descriptive Statistics for Data (13472 Crossing Sample)

Data Fields	Min.	Max.	Mean	SD
Train volume (per day)	0.01	110	7.389	9.772
Traffic volume (per day)	0.1	750	38.449	79.859
Train maximum speed (kph)	8.045	241.35	61.862	30.694
Road posted speed (kph)	1	100	51.524	27.697
Number of lanes	1	6	1.686	0.477
Number of tracks	1	9	1.123	0.414
Track angle	10	90	74.97	18.253
Whistle prohibition condition (Yes for 1, No for 0)	0	1	0.009	0.037
Urban (0) or rural (1)	0	1	0.939	0.240

4.3.3 Consolidation of Crossings by Control Types

For frequency modeling, separate safety models should be calibrated for different protection types based on previous studies. Moreover, it was found that some crossing types in our data represented only a small sample size, and they do not have enough collision records to calibrate separate models. Thus, the consolidations of protection types were done so that as many crossings as possible could be retained. Most of the types could be reasonably merged into the category of Railway Crossing Sign (RCS). Five types were applied for developing frequency models, including no protection (Nil), Railway Crossing Sign (RCS), Stop sign and Railway Crossing Sign (SRCS), Flashing Lights and Bells (FLB), and Flashing Lights, Bells and Gates (FLBG). The information on these different protection types of crossings is shown in Table 4.5. Finally, to get the data for frequency modeling, it is required to merge the two data in the form of each crossing as one record and calculate the number of collisions for each grade crossing.

Table 4.5 Summary of Crossing Protection Types (13,472 Crossing Sample)

Crossing Protection Types	**No. of Records**	**Collisions (2013-2018)**
FLB	841	26
FLBG	585	29
Nil	3,186	37
RCS	6,434	100
SRCS	2,695	119
Grand Total	**13,472**	**311**

4.3.4 Mapping of Crossings and Spatial Data Processing

GCI contains the longitude and latitude information of most crossings (~90%), which can be used to map their location using GIS software. For the crossings missing coordinates, the spatial data obtained from the Geospatial Center at the University of Waterloo was used to retrieve their coordinates by database query and match. More than half of the crossings without coordinates were added to the GCI dataset. Then, these crossing data were transformed into a shapefile format and mapped in a GIS platform, ArcMap, for visual inspection. One crossing with wrong coordinates was found and deleted. Moreover, the spatial data was tailored to the scope of the study area (ON, BC, and QC) to reduce the computation burden.

The following steps aim to build a network database or simplify the computation complexity for spatial accessibility analysis, which is the essential source for calculating the travel distances. The process was conducted in ArcGIS (ArcMap or

ArcCatalog) as below:

a. Map matching of grade crossings: To enable network analysis on the accessibility of any given grade crossing, the exact location of the crossing must be mapped out in the road network layer. This map matching process can be done in ArcMap using its geospatial analysis tool if the coordinates of the crossing are known. In our subsequent case studies, it was found that some crossings could not be mapped to any roads in the road network, as illustrated in Figure 4.3. By exploring further on Google Map, the main reason for this case is that the road network layer does not include all roads, especially local roads and trails. For the three case studies considered in this research, 22.5%, 34.4%, and 46.6% of all the crossings in ON, BC, and QC, respectively, could not be matched and therefore had to be excluded in the subsequent analysis. It should note that these crossings can be easily considered when a more complete database of the road network becomes available. However, limited data can be used to improve this process currently. Some of these crossings without information on the road network had been determined not to be closed by the preliminary screening step before. As a result, it is estimated that about 10% of total crossings are unable to be examined by the proposed framework in this research.

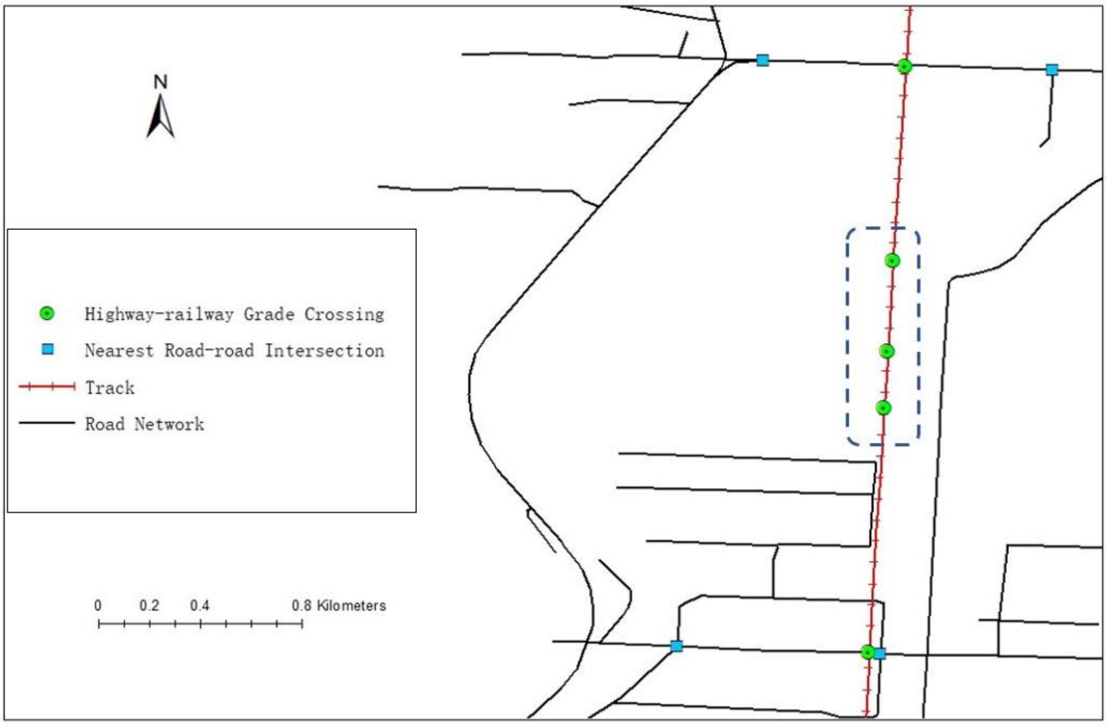


Figure 4.3 Grade Crossings Without Information on the Road Network

b. Road/rail network clipping: For each grade crossing, a buffer sub-network is generated by considering a certain range of roads around crossings that are likely to be used to cross the railway as shown in Figure 4.4. This process is called network clipping, which can help significantly accelerate the network analysis. In this study, a 10 km buffer zone around each crossing was created in ArcMap and was used to clip the road network out within the buffer area. This results in a new road network that consists of only roads located within the 10 km radius of the grade crossings being considered.

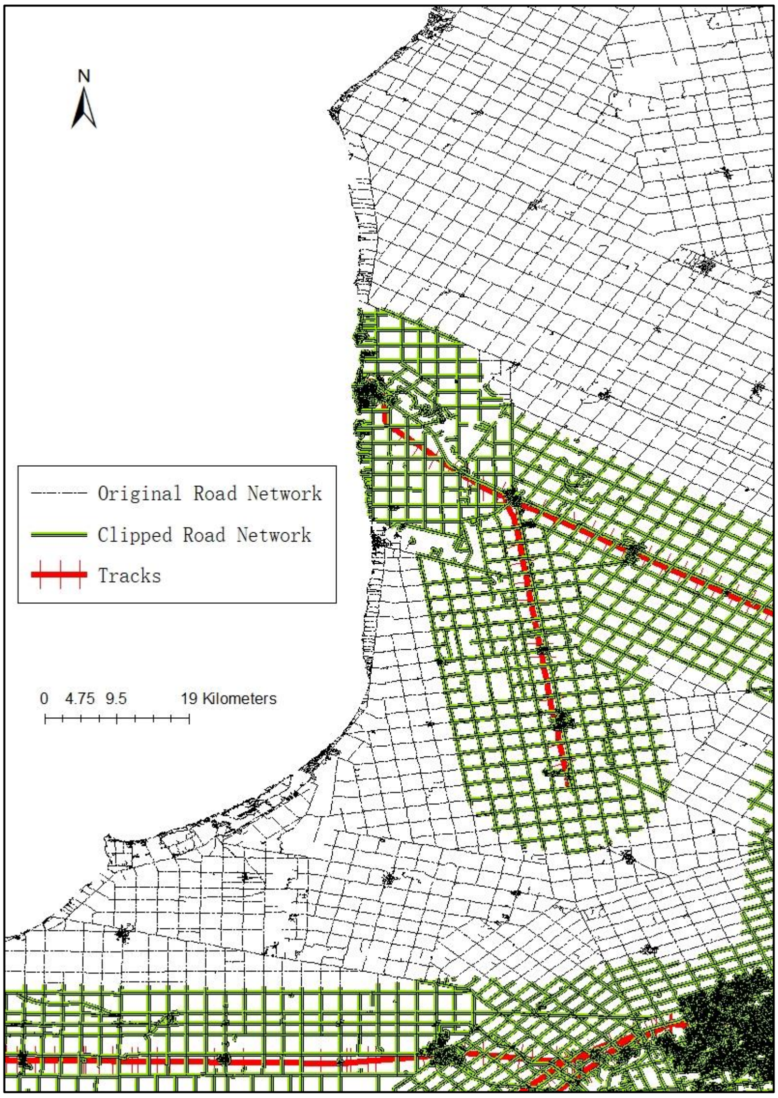


Figure 4.4 Road Network Clipping

c. Set up for network database: To activate the network analysis tool, a network dataset must be prepared, including grade crossings, all the nearest road intersections of the grade crossings, and the base road network from the previous step. For the nearest road intersections, they should be identified as the "start points" and "endpoints" of all trips that would cross the railway in ArcMap. For road networks, all the separate road lines should be merged into one continuous line for the integrity of spatial topology. An established network database enables the function network analysis such as finding the shortest route.

After these steps, the spatial accessibility can be conducted as described in Section 4.5.

4.4 Calibration of Collision Prediction Models

As described in Chapter 3, one of the key building blocks of the proposed framework is the collision frequency and severity models. These models can be calibrated using processed crossing inventory data and collision data. The calibration was conducted in RStudio, which is an integrated development environment for R. As mentioned previously, separate collision frequency models are calibrated for the five types of crossings, namely, Nil, SRCS, SRCS with STOP sign, FLB, and FLBG. The commonly used Negative Binomial (NB) model was assumed for all frequency models. The model calibration went through an iterative process, starting with the variables mentioned before, which were considered to be potentially important in explaining variation in collision frequency. Based on findings in literature, the exposure is defined as the product of train volume and vehicle volume. In addition, the 'whistle prohibition condition' were found unfit to be modelled due to nature of data. As a result, seven variables were examined in this study, namely, the product of train and traffic volume, train maximum speed, road posted speed, number of lanes, number of tracks, track angle, and environment type in terms of urban or rural. The significance of variables was tested using a t-test at a 95% confidence level, that is, only those that are significant at 95% or over were retained in the final model. The regression coefficients were determined by the maximum likelihood method with their sign indicating a positive correlation or negative correlation with collisions. The final resulting models are shown in Table 4.6.

Table 4.6: Frequency Model Calibration Results

Variables	Coefficients	std. error	z-value	p-value
	Nil crossing (sample size: 3186)			
(Intercept)	-6.59	0.83	-7.96	0.00***

Log (Total Trains * Total Vehicles)	0.44	0.14	3.19	0.00***
Train Max Speed (kph)	-0.01	0.01	-2.14	0.03**
No of Lanes	0.94	0.36	2.58	0.01***
Akaike Information Criterion (AIC)	316.07			
RCS crossing (sample size: 6434)				
(Intercept)	-8.75	0.56	-15.70	0.00 ***
Log (Total Train * Total Vehicles)	0.55	0.08	7.17	0.00 ***
Train Max Speed (kph)	0.01	0.00	3.53	0.00***
Track Angle	0.01	0.00	2.95	0.00 ***
AIC	932.08			
SRCS crossing (sample size: 2695)				
(Intercept)	-5.87	0.44	-13.27	0.00 ***
Log (Total Train * Total Vehicles)	0.51	0.08	6.38	0.00***
AIC	853.91			
FLB crossing (sample size: 841)				
(Intercept)	-5.29	0.63	-8.35	0.00***
Train Max Speed (kph)	0.02	0.01	3.16	0.00***
AIC	208.43			
FLBG crossing (sample size: 585)				
(Intercept)	-6.48	1.03	-6.32	0.00***
Log (Total Train * Total Vehicles)	0.46	0.13	3.61	0.00***
AIC	199.67			
***** significant at 5%; *** significant at 1%***				

This result showed the product of train and traffic volume, train maximum speed, number of lanes, and track angle have significant impact on the collision frequency at grade crossings. Road posted speed, number of tracks, and environment type in terms of urban or rural were not found to have a strong statistically significant, where the possible reasons include: 1) small training data set, and 2) variables with a small standard deviation.

The results from the NB model were then adjusted by the EB approach to obtain the expected collision frequency (*N*). Similarly, the multinomial severity model was calibrated based on the historical collisions that occurred at the crossing sites for the same time period (2013-2018). Note that only those crossings identified in the previous frequency model dataset were considered since they have complete information on crossing site characteristics. There are a total of 311 collisions, of which 24 belong to fatal collisions, 32 to major injuries, 41 to minor injuries, and 194 to no injuries. Table 4.7 shows the modeling results for the multinomial model. Again, this final model included the variables with a high statistical significance (more than 95%), and the model coefficients were calibrated using the maximum likelihood method.

Table 4.7: Calibration Results of Severity Models

Severity Type	Variables	Coefficients	std. error	t-value	p-value
No injury (Sample size: 194)	(Base Type)	b11=b12=0			
Fatal (Sample size: 24)	intercept	-3.73	0.80	-4.66	0.00***
	Train Max Speed (kph)	0.03	0.01	3.90	0.00***
	Road Posted Speed (kph)	-0.01	0.01	-1.35	0.18
Major injury	intercept	-3.10	0.70	-4.43	0.00***

(Sample size: 32)	Train Max Speed (kph)	0.01	0.01	1.90	0.06*
	Road Posted Speed (kph)	0.01	0.01	0.67	0.50
Minor injury	intercept	-2.46	0.60	-4.06	0.00***
(Sample size: 41)	Train Max Speed (kph)	0.01	0.01	1.34	0.23
	Road Posted Speed (kph)	0.01	0.01	0.78	0.44
Likelihood ratio test : chisq = 21.45 (p.value = 0.00*)**					
****** significant at 1%***					

The expected annual safety benefit for closing a crossing should be equal to the expected annual collision costs if it is not closed, which can be calculated on the basis of the expected collision frequency and the probabilities of all severity types that could result from each given collision. The equivalent monetary costs for one person are $7,040,000, $405,000, $205,000, and $16,800 in Canadian dollars for fatal, major injury, minor injury, no injury, respectively (Thakali et al., 2020). Note that the expected collision frequency obtained from the collision models represents risk over the six years. It was, therefore, converted to their annual measures by dividing the estimates by six. Finally, the estimated safety benefit values were converted to their dollar values and assigned to each crossing, where the maximum is 162.9 thousand dollars per year, the minimum is $30 per year, and the average is 4.04 thousand dollars per year. Figure 4.5 shows the top 30 crossings by safety benefit of crossing closure from the highest to the lowest.

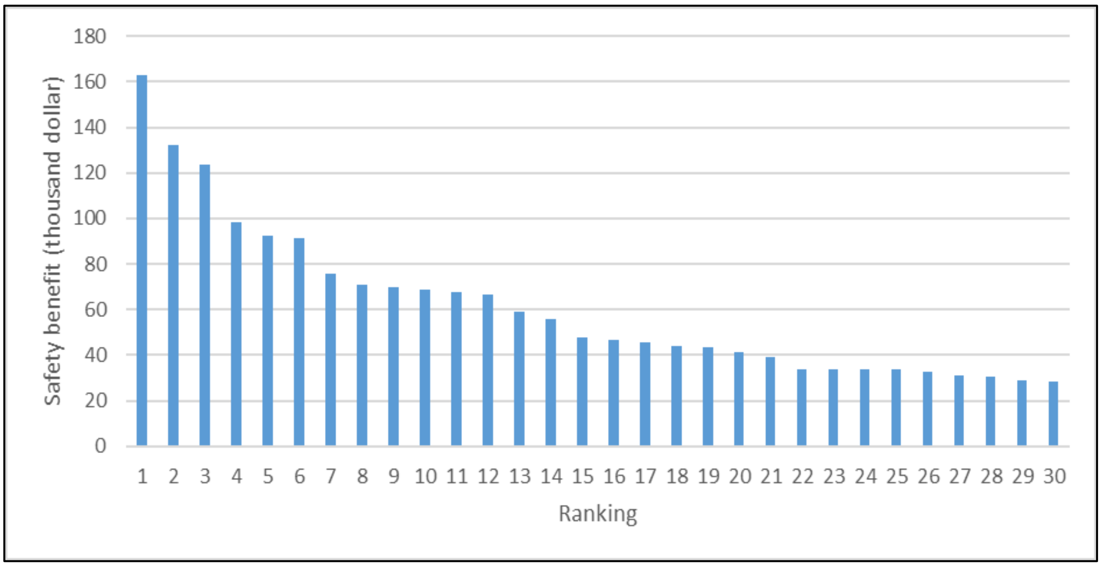


Figure 4.5 Top 30 Crossings by Safety Benefit

4.5 Spatial Accessibility Analysis

ArcMap's Network Analyst offers many tools to solve the shortest path problems required by the proposed methodology's spatial accessibility analysis component. However, conducting shortest path search for a large number of origin and destination pairs (crossings) is time-consuming. To reduce the computational burden, as discussed previously, the road network was reduced to the area within 10 kilometers of the railway crossings. If there is no shortest path found within 10 kilometers of a crossing, it is assumed that the crossing should not be considered a candidate for closure as there would be no reasonable alternative routes for road users if the crossing was closed.

For each crossing, the base travel distance (current condition) and the detour distance (if the crossing is closed) are calculated using a GIS tool called Find Closest Facilities. This tool can find one or more start points closest to the endpoint according to travel time, distance, or other costs and then calculate the optimal route and driving direction between the two points. In addition, this tool provides a visualization of the shortest path on the map, which offers convenience for visual validation.

To automate the process so that the calculation can be done for all crossings without repetitive operations, a ModelBuilder was created in ArcMap, which is a built-in application for creating and managing models with a visual workflow. This application can combine all tools in sequence like a flow chart, whose logic is as shown in Figure 4.6. In this study, the ModelBuilder only needed to be executed twice for the base distance and detour distance. For example, for calculating the detour distance, the inputs include the start points, the endpoints, the road network, and the crossing set as a barrier (no passing). The script for conducting accessibility analysis in ModelBuilder is provided in Appendix A.

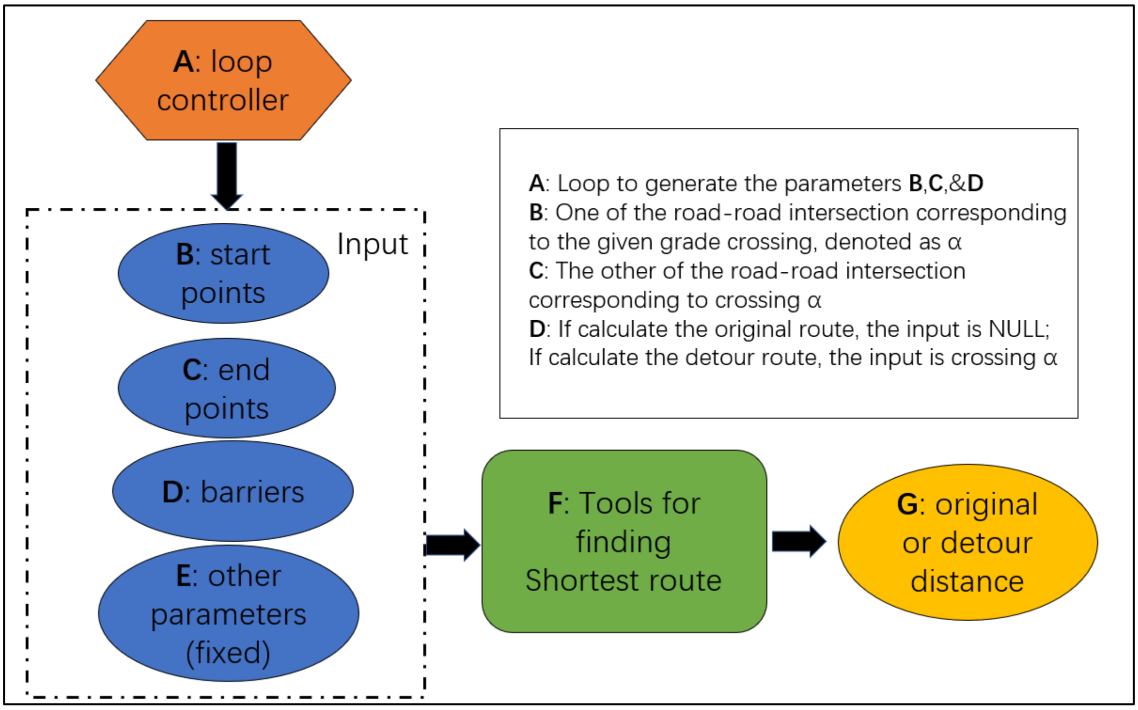


Figure 4.6: The logic of ModelBuilder

After calculating the base distance and detour distance for each crossing, the annual equivalent cost of travel time increased for a given crossing was then calculated. Although different trip types and road users have different values of time, this study only involves single one due to data limitation, and it is assumed that all of road user are local personal travel. The design speed of the detour route was assumed to be 40 kilometers per hour based on the GCI data, the value of time was taken to be 15 Canadian dollars per hour, which is estimated at 50% of hourly median household income in Canada, and the AADT could be retrieved from the GCI database (USDOF, 2016). The value of travel time cost varies from 0 to 181,234,000 Canadian dollars per year. The lower is the travel cost of a crossing due to closure, the less is the impact of closing the crossing. Figure 4.7 shows the top 30 crossings by travel time cost for crossing closure from highest to the lowest.

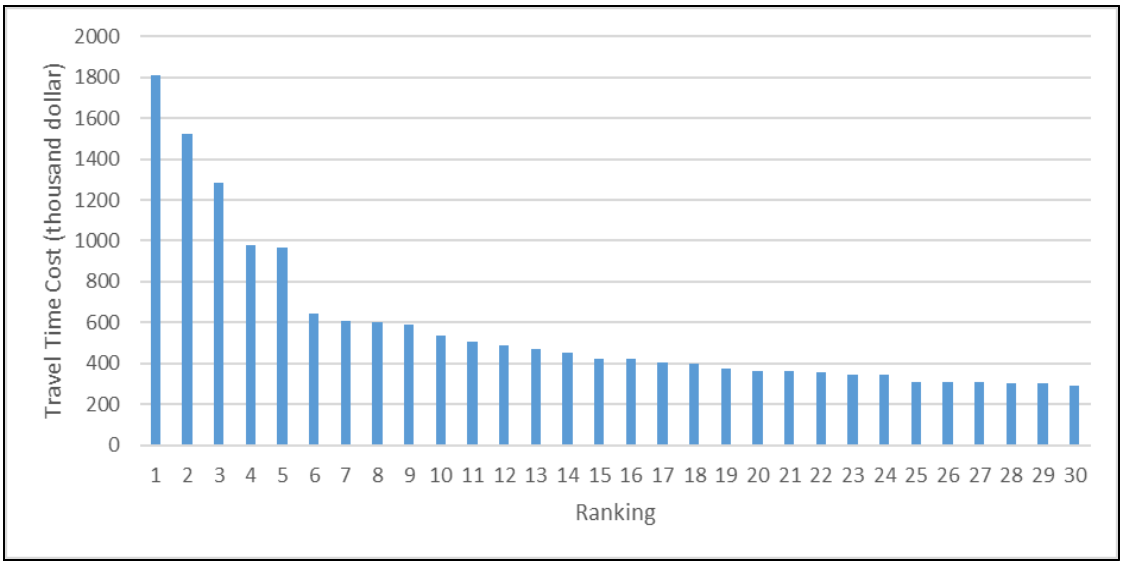


Figure 4.7 Top 30 Crossings by Travel Time Cost

As mentioned before, the construction cost of closing a given crossing is another cost considered in this study. Its value was assumed to be $25,000 according to Transport Canada.

4.6 Benefit-cost Analysis and the Results

Once the annual benefit and cost for closing a crossing are calculated, the life-cycle benefit to cost ratio of closing individual crossings can be determined and then used for ranking and selection. In our previous analysis, the benefit and travel-time cost of closing a crossing were conducted independently, which means, some crossings may not have both benefit and cost being estimated due to data issues and different data ranges used in different steps as described previously. As a result, in this cost-benefit analysis, we have considered only those crossings that have both benefit and cost estimates; as a result, a total of 2,990 crossings remained for further consideration--1339, 975, and 676 for ON, BC, and QC, respectively. Based on Equation 3.6, the life-cycle Benefit to Cost Ratio (BCR) was calculated for the remaining crossings, assuming the life cycle of a crossing closure was 20 years, and the discount rate is 3%. Figure 4.8 shows the BCR of the top 30 crossings, ordered from the highest to the lowest. Candidate crossings and their priority for closure could be identified on the basis of their BCR; a BCR value of greater than 1.0 indicates the expected benefits of closure would overweight the costs and the higher the BCR, the more economically beneficial from closure.

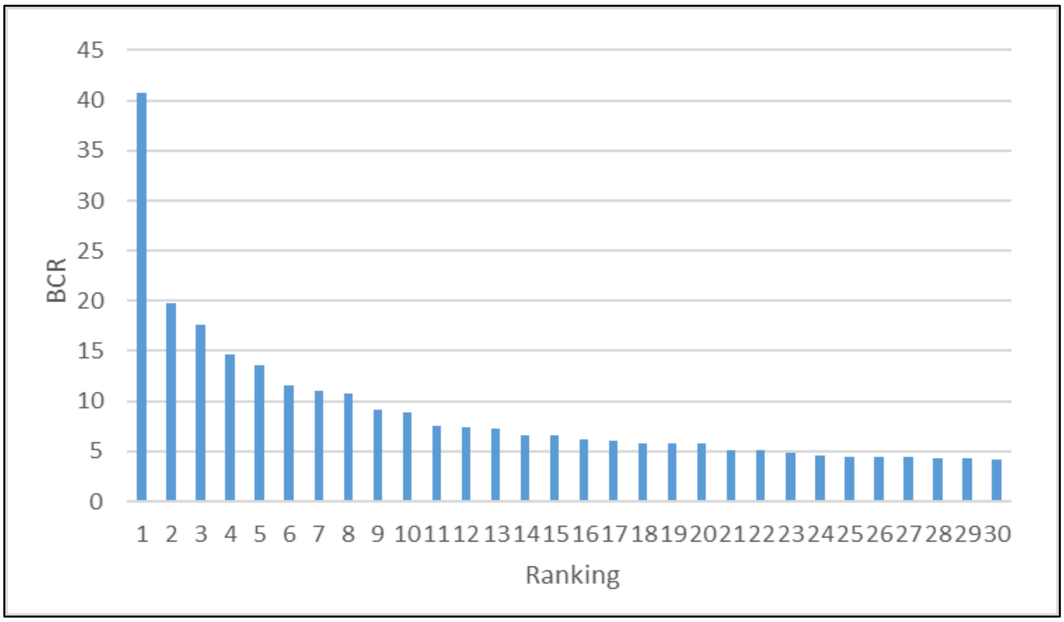
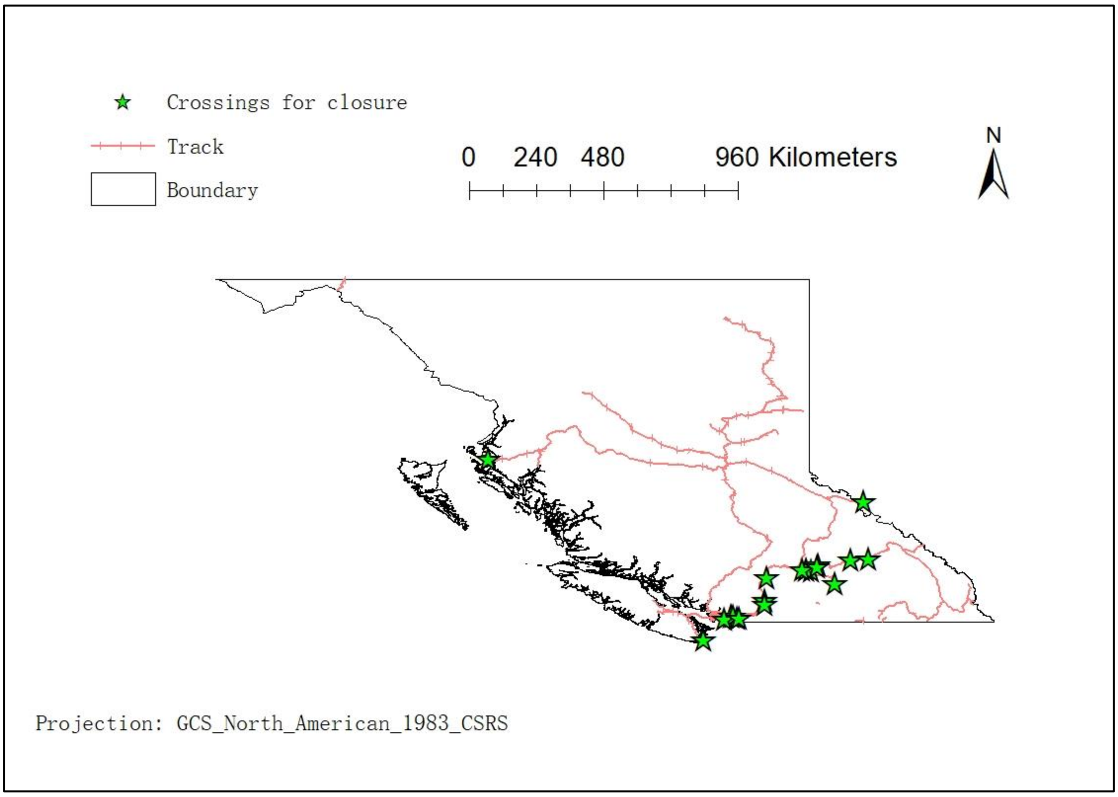


Figure 4.8 Top 30 Crossings by BCR

In this research, a separate list of crossings for possible closure was generated for each of the three provinces, considering a BCR threshold of 2.0 considering the funding constraints. This resulted in a total of 31, 21 and 24 crossings for ON, BC, and QC, respectively. These identified crossings are mapped out in ArcMap, as shown in Figure

4-9 & 4-10. More information on these crossings is provided in Appendix B.



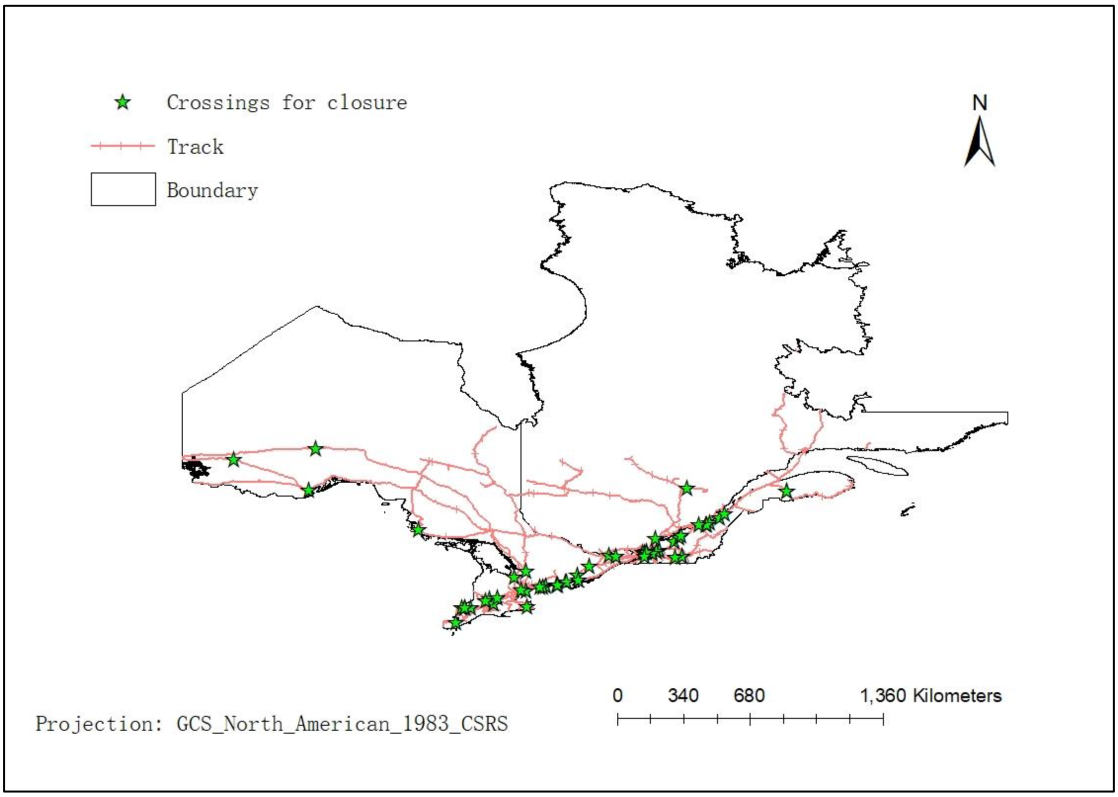


Figure 4.9 & 4.10: The Crossings for Closure

Chapter 5 Conclusions

Determining which grade crossings to close or consolidate is essentially an optimization problem that should consider all relevant costs and benefits that could result from the closures. This research proposes a risk-based life-cycle benefit-cost analysis framework for ranking the priority of candidate crossings for closure, incorporating three measures - expected risk reduction, increased travel time cost, and construction cost for closure. Reduction in collision risk is quantified using collision frequency and severity models calibrated using Canadian collision data. An automated spatial accessibility analysis tool is developed in a GIS platform for calculating the expected increase in travel time for road users. This chapter summarizes the major findings and contributions of the research and proposes suggestions for future research direction to further the goal of developing comprehensive and practical decision-support tools for closure selection.

6.1 Contributions

This research has made the following contributions:

- A comprehensive risk-based benefit-cost analysis framework was proposed and applied to identify the grade crossing priority for closure. The proposed framework takes into consideration of the potential positive and negative impacts of crossing closures, aiming at maximizing the trade-off between the benefit of risk reduction and the cost of travel time increase to the road users. It can be used to rank crossings on the basis of their benefit-to-cost ratios for closure. Such a framework for decision support on grade crossing closure projects is very limited. Most of the earlier methods and framework had limitations on the number of candidate crossing, the framework in this study, however, can select the target crossings from a large number of crossings. In addition, the framework could also be applied by transportation agencies to assess the reasonableness of their previous closure decisions. It has the potential to be applied by Transport Canada for supporting decisions related to crossing closure as part of its Rail Safety Improvement Program (RSIP).

- A statistical analysis was conducted to develop models for quantifying the collision risk at specific crossings, including collision frequency and severity models, as related to various crossing variables. These models can be used to estimate the total risk, in terms of the expected number of fatalities, serious injuries, slight injuries and property damages, at a given crossing that could be caused by collisions at the crossing over one year. As a result, they can be used to estimate the expected reduction in risk in a crossing for closure. Based on the available data, a total of seven factors were examined for their potential effect on grade crossing safety statistical modeling, including train and traffic volume, train maximum speed, road posted speed, number of lanes, number of tracks, track angle, whistle prohibition condition, and environment type in terms of urban or rural. An empirical Bayes approach was applied to correct for the regression-to-mean bias. This collision-based approach makes our estimation of the safety risk more reliable rather than an experience-based approach where the relationship between variables and safety risk is already known without modelling.
- An accessibility analysis module was developed for calculating the additional travel distance and travel time that could incur to the road users had a crossing been closed. The analysis module was implemented in a GIS platform, taking advantage of its network analysis tool. To reduce the extensive computational burden in finding the alternative paths for a large number of crossings, a ModelBuilder was designed to automatically solve all calculations, which is one of the first in the literature.

6.2 Findings

This study yielded the following findings:

- There is a significant linear positive correlation between the number of people and the number of collisions in each province (p-value<0.05). The distribution of crossing collisions shows spatial heterogeneity at the provincial level due to unbalanced population distribution.
- Among the important variables related to grade crossing safety train and traffic volume (+), train maximum speed (+), track angle (+), and number of tracks (+) were found to be statistically significant in influencing collision frequency, while train maximum speed (+) and road posted speed (+) have a statistically significant effect on collision severity[2].
- The result in our case study are these crossings with high safety benefit and low travel time cost. However, the value of safety benefit has dramatic change at its top value, while the travel time cost has slight change at its bottom range. Thus, it is shown that the safety benefit appears to have more impact on rank of the ratio.
- Our case study also shows that most of the crossings in the final closure list are located at urban with high population, and these crossings spatially aggregate along only a few tracks.

6.3 Future Work

Potential future work on the subject is identified as follows:

- Additional case studies should be conducted with a focus on other regions and provinces in Canada. The reasonableness of the case study results should be

[2] ('+' means positive relationship; '-' means negative relationship)

evaluated in accordance with the closure decisions made in the past and by the stakeholders.

- A sensitivity analysis should be performed to evaluate the potential impacts of the threshold values used in the preliminary screening process. The threshold values should be assessed in detail with input from the stakeholders such as local road authorities and railway companies.
- Our preliminary screening process also filters out those crossings that are significant to road traffic based on road traffic volume. However, the proposed framework is applicable in principle to these crossings although they are expected to be ranked low as the cost of reduced accessibility would be very high. Future research could examine the necessity of including this filter.
- The result assumes that travel time cost, construction cost, and safety benefit are the only three aspects to impact the decisions of closure. However, other potential impacts, such as increased trespassing risk and reduced productivity, that could be highly relevant with grade crossing closure, should be identified and quantified in future research.
- In the case studies, approximately 20% of crossings were excluded for consideration as potential closure sites due to missing data. There may have been some crossings that should have been on the final list but could not be identified. More detailed data or manual checks should be conducted to improve the result for the final closure decision.
- A survey designed for collecting input and knowledge from stakeholders such as road authorities, railway companies, and safety experts should be conducted in the future to understand more about their needs and suggestions on grade crossings.

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Appendix A：Spatial Accessibility Analysis Code (Python)

```
# Import arcpy module
import arcpy


# Load required toolboxes
arcpy.ImportToolbox("Model Functions")


# Local variables:
Value = "0"
Nearest_Road_road_Intersection = "Nearest Road-road Intersection"
Nearest_Road_road_Intersection__2_ = Nearest_Road_road_Intersection
startpoint = "startpoint"
startpoint__4_ = startpoint
net_ND = "net_ND"
in_memory__2_ = "in_memory"
Highway_railway_Grade_Crossing = "Highway-railway Grade Crossing"
Highway_railway_Grade_Crossing__2_ = Highway_railway_Grade_Crossing
Line_Barriers__2_ = "in_memory\\{0C039698-C493-49AA-8E82-041CDB707338}"
Routes = Line_Barriers__2_
Directions = Line_Barriers__2_
ClosestFacilities = Line_Barriers__2_
Polygon_Barriers__2_ = "in_memory\\{9C79957E-BB4C-4B64-AFF5-04201D0B53D8}"
```

```
Attribute_Parameter_Values = "in_memory\\{5ED42A13-AC0F-4B05-8ACA-B8ECB324521D}"
v_value__xls = "D:\\MASC_TASK\\data_spatial\\three_provinces\\original\\%value%.xls"
Solve_Succeeded__2_ = "true"
v_ags_gpna5b923563968445088cfb9a8936e0a761_lyr = ""
v_ags_rd85815d9a1fc049ed9f548339db773d32_zip = ""

# Process: For
arcpy.IterateCount_mb("0", "1", "1")

# Process: Select Layer By Attribute (2)
arcpy.SelectLayerByAttribute_management(Nearest_Road_road_Intersection, "NEW_SELECTION", "\"JOIN_FID\" =%Value% ")

# Process: Select Layer By Attribute
arcpy.SelectLayerByAttribute_management(startpoint, "NEW_SELECTION", "\"JOIN_FID\" =%Value% ")

# Process: Select Layer By Attribute (3)
arcpy.SelectLayerByAttribute_management(Highway_railway_Grade_Crossing, "NEW_SELECTION", "\"FID\" =%Value% ")

# Process: Find Closest Facilities (2)
```

```
arcpy.FindClosestFacilities_na(Nearest_Road_road_Intersection__2_, startpoint__4_, "Meters", net_ND, in_memory__2_, "Routes", "Directions", "ClosestFacilities", "1", "", "TRAVEL_TO", "", "NOT_USED", "GEO_LOCAL", "NO_UTURNS", Highway_railway_Grade_Crossing__2_, Line_Barriers__2_, Polygon_Barriers__2_, "time", "Seconds", "Length", "Meters", "NO_HIERARCHY", "", Attribute_Parameter_Values, "", "20 Kilometers", "\"bc_near_join\" #;\"bc_endp\" #;\"bc_startp\" #;\"bcdissovle\" #;\"bc_ND_Junctions\" #", "NO_LINES", "10 Meters", "DIRECTIONS", "en", "Meters", "NA Desktop", "", "", "", "", "", "", "", "NO_SAVE_OUTPUT_LAYER", "CUSTOM", "", "NO_SAVE_ROUTE_DATA")

# Process: Table To Excel
arcpy.TableToExcel_conversion(Routes, v_value__xls, "NAME", "CODE")
```

Appendix B: Crossings for Final Closure

Crossing ID	Safety Benefit	Travel Time Cost	Benefit-Cost Ratio	Ranking
210172	66.49254	0.383051	40.71674	1
303058	25.28461	0.024875	19.83301	2
300978	22.05816	0	17.64653	3
300979	18.33105	0	14.66484	4
214579	17.14882	0.014341	13.56344	5
209309	14.39805	0	11.51844	6
200114	13.81322	0	11.05058	7
207995	98.11464	7.889763	10.73492	8
302145	11.45729	0	9.16583	9
218318	11.05364	0	8.842911	10
218321	10.25063	0.109104	7.542199	11
205206	19.06442	1.328864	7.392566	12
208613	15.62353	0.894635	7.284937	13
213589	10.34046	0.318059	6.594434	14
211770	11.87563	0.552438	6.588647	15
214725	162.8572	24.92954	6.220783	16
300299	7.506832	0	6.005465	17
300503	10.64192	0.575072	5.830956	18
213724	7.264583	0	5.811667	19
205127	7.177385	0	5.741908	20
214585	11.301	0.933635	5.175316	21
214774	69.7345	12.55308	5.052097	22
210170	91.36447	17.76306	4.805353	23
303021	15.74186	2.162144	4.613482	24
303772	5.558691	0	4.446953	25
303773	5.558691	0	4.446953	26
208035	11.42561	1.338918	4.413274	27
213820	5.387636	0	4.310109	28
300153	10.75405	1.27709	4.255509	29
210319	7.177221	0.464011	4.187383	30
302688	5.767201	0.166285	4.072064	31
210189	12.49043	1.840868	4.041075	32
202162	4.962276	0	3.96982	33
213767	4.933861	0	3.947089	34
301608	41.1449	9.649975	3.77477	35
218313	10.88627	1.651641	3.751762	36
202230	27.19797	6.335319	3.585607	37
210188	12.49043	2.28799	3.530375	38

201035	9.468519	1.482629	3.464985	39
213744	4.562531	0.086993	3.412531	40
300137	31.09302	8.195482	3.291841	41
213590	8.716237	1.539791	3.124333	42
209162	39.19307	11.37806	3.10365	43
214491	3.878744	0	3.102995	44
304931	4.069218	0.073852	3.073772	45
200530	15.08974	3.778464	3.000865	46
201253	6.188626	0.824113	2.983746	47
202163	5.426442	0.604654	2.925851	48
213766	3.588732	0	2.870986	49
205935	3.308039	0	2.646431	50
218805	4.933861	0.652855	2.592874	51
207459	3.227265	0	2.581812	52
204341	3.366088	0.07239	2.545459	53
301682	3.418521	0.095636	2.54045	54
214772	28.23893	9.8841	2.536256	55
214771	28.23893	9.916058	2.528997	56
211202	22.80117	7.839069	2.508636	57
202154	3.177138	0.018971	2.503712	58
213750	3.489144	0.145368	2.500518	59
207275	4.655248	0.614297	2.497052	60
202159	3.177138	0.055735	2.433217	61
303004	22.1588	7.955569	2.407108	62
205859	2.97851	0	2.382808	63
205861	2.97851	0	2.382808	64
303005	28.24423	10.60518	2.382438	65
202228	18.6948	6.851013	2.307711	66
302965	28.24423	11.48537	2.217779	67
214538	3.07184	0.145566	2.201142	68
213754	4.933861	1.029058	2.164868	69
219005	11.18634	3.967398	2.144046	70
300662	4.069218	0.650669	2.140939	71
210264	5.619755	1.44134	2.088088	72
300522	5.767201	1.517439	2.083949	73
213615	2.793208	0.13312	2.019498	74
301331	18.91762	8.158163	2.010766	75
303026	16.25294	6.871022	2.001342	76