SAFETY MANAGEMENT SYSTEM FOR HIGHWAY-RAIL GRADE CROSSINGS

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

As a result of the considerable differences in mass between vehicles and trains, accidences at highway-rail grade crossings (HRGCs) may result in severe injuries and fatalities. Therefore, HRGCs safety is considered one of the crucial transportation safety issues. Transportation decision makers and agencies need an efficient safety decision-making framework which is bale to consider crash occurrence and severity likelihood simultaneously. This study proposed a novel methodology and a statistical approach for HRGC crash analysis. The proposed method is competing risk model and the approach is Cox proportional hazard regression. This predictive method was well established in bioscience area but never been utilized in transportation area. Competing Risk Model (CRM) is a special type of survival analysis to accommodate the competing nature of multiple outcomes from the same event of interest, in transportation safety analysis the competing multiple outcomes are accident severity levels while the event of interest is accident occurrence.

Transportation decision makers need a prioritization system to categorize crossings' risk level based on their expected crash frequency and crash severity simultaneously. Therefore, with a hazard-ranking approach which considers crossings' crash severity and frequency output, transportation decision makers are able to ensure that federal and state funds for grade crossing improvement projects are spent at the crossings that are considered the most in need of improvement. In this study two hazard-ranking models are proposed, the first one is based on the crash likelihood resulted by the proposed CRM output, and the second one is a hybrid accident prediction model/hazard index based on crash severity likelihoods estimated by the same CRM. Finally, to integrate the results of both hazard-ranking approaches, and classify grade crossings and crossings' location based on their crash frequency and severity likelihood simultaneously, the risk analysis is conducted by using the risk matrix and spatial risk analysis.

Keywords: accident prediction, railroad grade crossing, competing risk models, counter-measure effectiveness, highway-railway grade geometric design, hazard-ranking model.

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CHAPTER 1. INTRODUCTION

1.1. Highway-Rail Grade Crossing Safety

The tragic consequence of traffic accident is that it causes deaths at a very high rate. As a result of the growing automobile population in the early twentieth century, the number of fatal accidents exceedingly increased. The number of fatalities in traffic accidents declined substantially after the late twentieth century after more safety research were done and more transportation safety infrastructures were constituted. However, still, deaths driven by vehicle crashes hover at more than 30,000 annually, so the transportation community must consider creating innovating, and rethinking the possibilities realm to enhance safety and decrease congestion (C. Andersen, 2013).

The highway-rail grade crossing (HRGC) is a specific spatial location where two transportation modes of rail and road intersect with each other at grade level. HRGCs accidents are mostly associated with potential points of conflict between roadway traffic and train traffic. Because of the substantial mass difference between vehicle and train, the crashes usually have relatively severe results. In addition, traffic delays of both the railway and the roadway can considerably extend the economic consequences of crashes at HRGCs, and the expenditures from disruptions to both the roadway and railway networks can also be significant.

The high fatality rate indicates that traffic accidents at HRGCS are catastrophic. Between 1990 and 2018, there were 93,597 crashes at public and private HRGCs across the United States where active traffic devices (e.g., gates, flashing lights, etc.) are in place (FRA, 2018). According to FRA (2018), about 12% of these crashes resulted in 11,269 fatalities, while only 0.06% of all traffic crash types lead to deaths (Zheng, 2018). Figure 1 shows that crash frequency and resulted injuries and fatalities at HRGC have a decreasing trend with moderate fluctuation from 1990 to

2018 in the U.S. However, based on Figure 2, in North Dakota State, the HRGC crash frequency is not managed well in the same period. Although the crash frequency was low in 2006, it starts to raise until 2014 and starts to slightly increase again after 2016. The fatality rate (fatal%) falls within a range of 0% to 44%, which is higher than the national average over 29-year. Between 2001and 2005, and from 2012 to 2015, the injury rate (injury%) in North Dakota was much higher than nation one. Recently, North Dakota injury rate has started to dramatically increase from 2017 and it is almost equal to the nation rate in 2018.

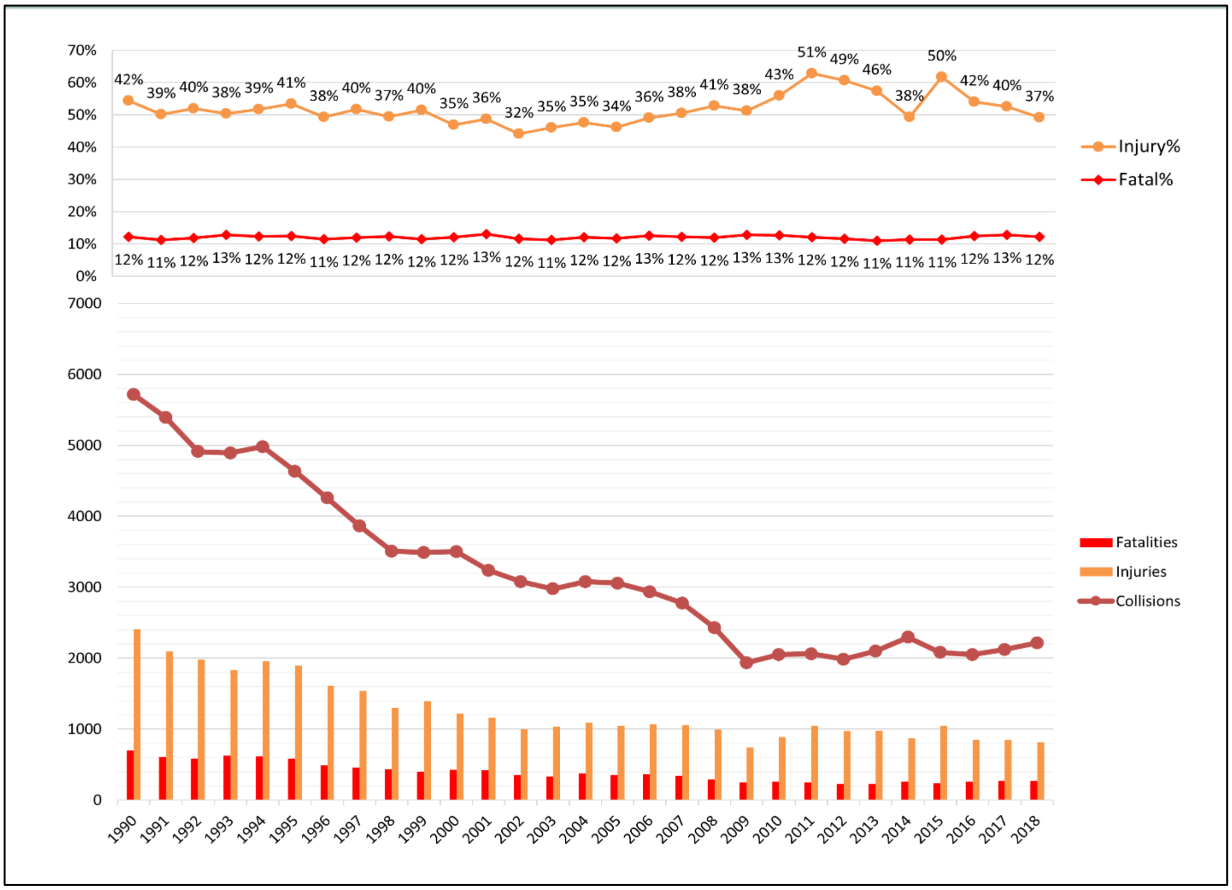

Figure 1. HRGC Crash Frequency and Severity Count Nation Wide, 1990-2018
Source: Federal Railway Administration, 2018

Accordingly, to analyze and predict both crash frequency and severity simultaneously and consistently, it is crucial for transportation agencies and decision-makers seeking to improve HRGC safety system with the aim of identifying contributing factors having impact on crash frequency and severity. A large number of literature counts and assesses the key factors contributing to the likelihood of crash frequency at HRGCs. However, an accurate accident prediction model is critical for HRGC safety improvement which is able to incorporate crash frequency and crash severity in the same model.

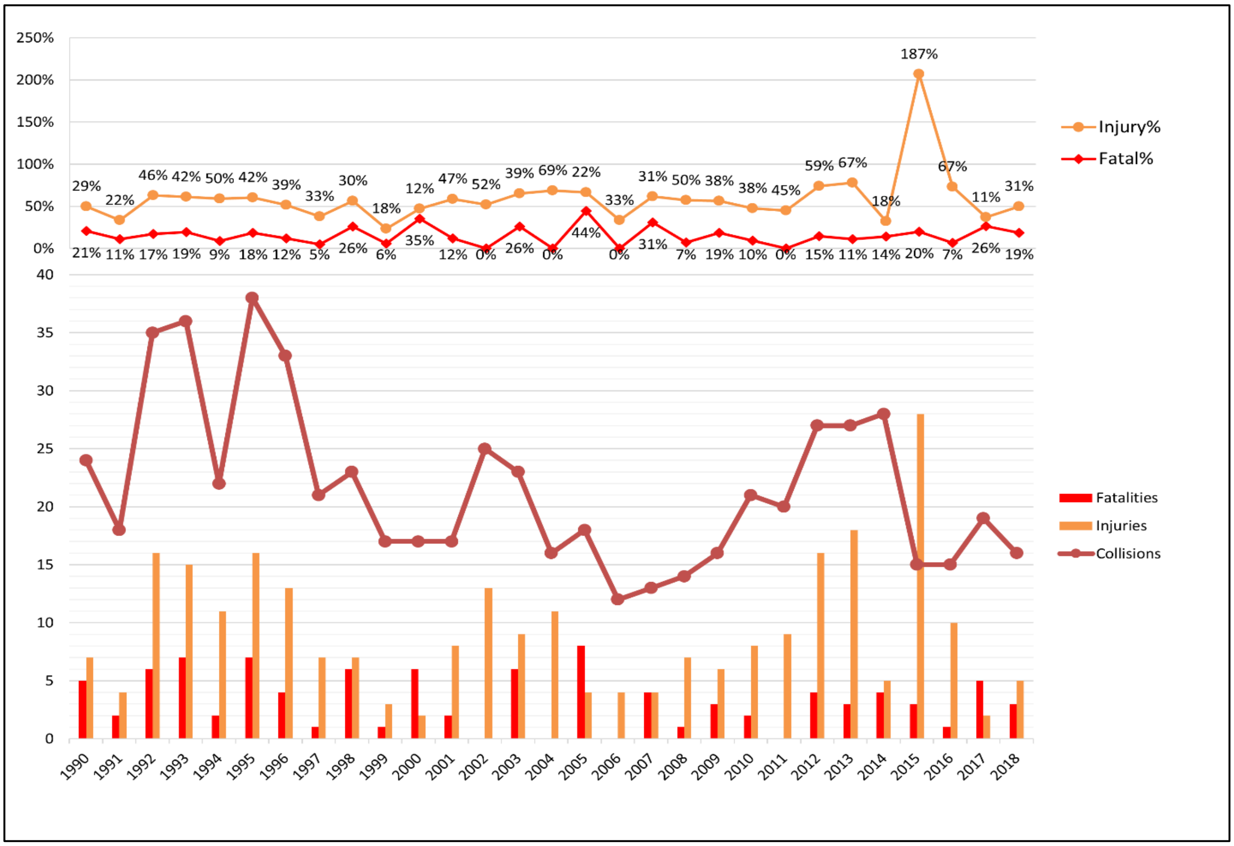

Figure 2. HRGC Crash Frequency and Severity Count North Dakota, 1990-2018
Source: Federal Railway Administration, 2018

1.2. Crash Frequency and Severity Statistical Modeling

Most research on HRGC safety has focused either on the analysis of crash frequency (Zheng, Lu, & Pan, 2019; Zheng, Lu, & Tolliver, 2016) or crash severity. HRGC crash severity studies are often based on categorical outcome modeling using historical police reports and FRA HRGC crash datasets(Eluru, Bagheri, Miranda-Moreno, & Fu, 2012; W. Fan, Kane, & Haile, 2015; Ghomi, Bagheri, Fu, & Miranda-Moreno, 2016; Haleem & Gan, 2015; W. Hao & Daniel, 2014, 2016, 2013; S.-R. Hu, Li, & Lee, 2010; Kang & Khattak, 2017; Liu & Khattak, 2017; C. Ma, Hao, Xiang, & Yan, 2018; Savolainen, Mannering, Lord, & Quddus, 2011; Zhao, Iranitalab, & Khattak, 2018; Zhao & Khattak, 2015; Zheng, Lu, & Lantz, 2018). As a result of the random, discrete, and non-negative nature of collision data, one of the most common methodologies to grade crossing safety literature is the use of generalized linear models (GLMs) with crash frequency or severity as the independent variables of models. Heydari and Fu (2015) applied a Poisson Weibull model for crash frequency. Statistical models (Jinsun Lee, Nam, & Moon, 2004; Lu & Tolliver, 2016; Oh, Washington, & Nam, 2006; Z. Ye, Xu, & Lord, 2018), including zero inflated, hurdle, and generalized event count models, were utilized to solve data issues such as the excess number of zero accidents and over/under dispersions. Data mining methods, such as the hierarchical tree-based regression technique, are also adopted by Yan et al. (2010) to predict train-vehicle crash frequencies at public passive grade crossings in the United States. Heydari et al. (2018) used a method to compare different geographic areas in terms of a pre-specified safety performance, which is able to consider collision frequency of a given type.

Majority of the modeling safety modeling techniques used in previous crash severity research focused on discrete choice approaches because of the discrete nature of crash severity levels. Hao and Daniel (2013) and Abdel-Aty and Keller (2005) used an ordered Probit model to consider U.S. collision severity levels are naturally ordered. Hao and Daniel (2014) continued the previous research projects and adopted an ordered probit model by taking into account the different traffic control devices at grade crossings. Eluru et al. (2012) measures crash severity levels by considering passive and active traffic control devices by applying a latent ordered response model using 10 years of accident dataset at grade crossings in the United States. Their results indicated that accidents at grade crossings with gates were less likely to result in severe crashes compared with crossings with crossbucks only, while crashes at crossings with flashing lights are more likely to have severe crashes like injuries and fatalities. In addition, Hu et al. (2010) applied a generalized logit model to investigate contributors impacting crash severity in Taiwan's HRGCs. Recently, Zhao et al (2018) applies both binary logit models and generalized linear mixed models to investigate the association of potential factors with pedestrian injury severity levels using 10 years of collision data at grade crossings in the United States.

It should be stressed that the characteristics of HRGCs at the time of a crash (e.g., traffic crossing control devices and highway traffic volume) may vary over time, including before and after the crash occurrence (Liu and Khattak, 2017). Therefore, estimation of crash severity likelihood by accounting for the time effects of contributing factors may improve the accuracy. The previous studies do not consider these time effects, probably because of the complexity this consideration (time effect) may add to the methodology. Consequently, to account for these time effects, the main interest is the time until the crash occurrence with a specific severity level. The analysis may be complicated as a result of 1) the need to identify an association between a set of factors by the time of collision occurrence with each severity level in a model, and (2) HRGCs' collision histories can be collected for a limited period of time, and only the time of a crash occurrence during the study period can be recorded. In other words, crossings are recorded as event-free without any information from after the analysis period, leading to right-censored data. Consequently, specific algorithms are needed to take these characteristics into account.

1.3. Survival Analysis and Competing Risk Model (CRM)

Survival analysis has been utilized to measure the failure time, such as biological death (in medical science), engineering failure including mechanical failure (J. Fan, Feng, & Wu, 2010). In survival analysis, data are modeled in the form of time-to-event and are usually open to censoring because of the study period termination. The main target of survival analysis is to investigation of the dependence of the survival time (failure time) on the contributors vector (J. Fan et al., 2010). Consequently, survival analysis is a methodology which can take into account the characteristics of a grade crossing as time-to-crash occurrence data.

To estimate the crash frequency and severity likelihood simultaneously over the timespan, the competing risk model (CRM) as the specific type of survival analysis is counted as a novel mathematical approach. In transportation safety analysis, CRM's objective function is quantifying crash occurrence likelihood in the presence of more than one crash event, including property damage only (PDO), injury, and fatal crashes. Moreover, those multiple events are considered as competing with each other. Correspondingly, the target of applying CRM approach is estimating the likelihood of accidents occurring at a crossing during a 29-year time span from 1990 to 2018, while the crossing possibly experiences more than one severity level (PDO, injury, and fatal).

Cause-specific Cox regression (Cox, 1972) is a common approach to solve the competing risk model as a complex algorithm. Knowledge-gain based benefits to be discovered through the application of this approach are 1) the ability in considering complexity in grade crossing safety analysis, e.g., non-linear relationships between HRGCs crash severities and the contributing factors, 2) ability in quantifying long-term time effects on crash frequency and severities, 3) a straight-forward and integrated one-step estimation process that is able to consider both crash frequency and severity likelihood in the same model which makes direct hazard-ranking considering both crash frequency and severity likelihood possible, and 4) interpretative impact of identified covariates from both the direction and magnitude perspective. CRM and Cause-specific Cox regression has been applied widely in medical research. However, the model has never been applied to transportation safety.

1.4. Grade Crossing Geometric Analysis

Vehicle users have the flexibility to choose both their route and speed (Ogden, 2007). On the other hand, train operators are restricted to a fixed track and changing their speed might need significant amounts of time (Ogden, 2007). Consequently, to decrease the probability of highway-rail grade crossing (HRGC) accidents, trains should have the right of way. Correspondingly, transportation engineering designers who focus on designing, constructing, and optimizing HRGCs' safety performance must take into account factors associated with geometric capacities and infrastructures, expenditure, and their effects on safety outcomes in assisting vehicle users in meeting their safety-related responsibilities (Ogden, 2007). Therefore, investigating of grade crossing geometric factors' effects on vehicle crash severity and frequency is critically important to transportation agencies and decision makers.

Four main grade crossing geometric factors are as follows:

1) Distance between crossings and their nearest roadway intersections: Nearest intersecting roadway is determined by identifying roads parallel to the railroad which intersect with the road that is part of the HRGC. According to the Railroad-highway Grade Crossing handbook (2007), some accidents at grade crossings are because of the short storage distance for vehicles waiting to move through the crossing and the intersection.
2) Crossing angle: Highway-railway angle is counted as one of the main factors effecting sight distance at a grade crossing (Ogden, 2007). However, the national HRGC inventory data only provides a categorical format of this factor.

3) Number of traffic lanes: It clearly represents the number of roadway traffic lanes crossing the railway track. According to Austin and Carson (2002), a greater number of traffic lanes at a grade crossing can have a significant association with higher accident frequencies.
4) Number of main tracks: This factor demonstrates the number of main railway tracks that cross the roadway. Ogden (2007) showed that the majority of the collisions occurred on the main tracks. In addition, Zheng et al. (2019) indicated that the higher number of crossing tracks causes the longer time for vehicles to pass the crossing which might be associated with a higher crash probability.

Grade crossing geometric factors effect on crash frequency as these factors have impacts on travel operations and sight distances at crossings. However, their precise impact on both crash frequency and crash severity probability are still unclear. In addition, the long-term effects of the geometric factors also need to be investigated to measure their effects on grade crossing safety performance over the specific timespan (Ogden, 2007).

1.5. Grade Crossing Countermeasures Effectiveness

Between 1981 and 2018, crash frequency in the U.S. decreased by around 76% at grade crossings (FRA,2018). The main reason of such reduction can be related to upgrades of passive crossing controls to active controls (Lenné et al., 2011; Meeker, Fox, & Weber, 1997; Millegan, Yan, Richards, & Han, 2009). Passive crossing controls (e.g. crossbucks signs and stop signs) are generally proved to be less effective traffic control devices to vehicle users compared to active controls including flashing lights, audible devices (bells), and gates. On the other hand, although HRGCS accidents, including fatal, and injury crashes all have fallen nearly every year since 1981, both fatality and injury rates per crash at grade crossings have raised by around 5% and

2%, respectively between 1981 and 2018 (FRA,2018). Consequently, investigating and quantifying the countermeasures' effects on HRGCs safety performance, especially on crash frequency and severity simultaneously is needed.

Countermeasures at HRGCs include all traffic control devices and other warning and barrier devices at or on approaches to crossings. The main goal of grade crossing countermeasures is to guarantee safe and efficient rail and highway operations at crossings. An extensive range of countermeasures safety operations have been investigated in the field. Previous studies analyzed the changes in crash frequency or crash severity after adding specific types of traffic control devices at grade crossing. Their research has shed more light on the understanding of countermeasures effectiveness at grade crossings. In general, active devices are more accepted as safety improvement alternatives than passive devices. However, most studies on countermeasures effectiveness have been either at the project level or have failed to address the before-improvement condition.

1.6. Grade Crossing Hazard-Ranking

In the United States, the safety of highway-rail grade crossings (HRGCs) is identified as a national priority. To identify crossings and their location with higher risk of accident, state DOTs benefit from hazard-ranking models to develop a priority list of HRGCs in their jurisdiction (Sperry et al., 2017a). According to Ogden and Cooper (2019), the following criteria must be considered in prioritizing locations for HRGCS safety improvement:

1) The potential decline in the frequency and/or severity of collisions.
2) Project costs and resource constraint.
3) Using the hazard index formula to evaluate the relative hazard of public highway-rail grade crossings.

4) Incident/accident history of a particular crossing location.

5) On-site inspections.

6) The potential risk for large numbers of people at public HRGCs used on a regular basis by passenger trains, school buses, transit buses, pedestrians, bicyclists, or by trains and/ or motor vehicles carrying hazardous materials.

7) Other criteria as appropriate in each State.

The prioritization process can be identified by the hazard index or collision prediction formula. A hazard index is applied to rank the crossings in relative terms, the higher estimated index, the more hazardous the crossing. However, the collision prediction formulae are used to calculate the crash frequency or sometimes severity at the HRGC (Ogden & Cooper, 2019; Sperry, Naik, & Warner, 2017a). To prioritize a grade crossing, the hazard index approach needs the analyst to quantify a ranking metric or value that will assign the hazard level to a particular crossing relative to other crossing locations. One of the known hazard index approaches is the New Hampshire Hazard Index ranking methodology. The New Hampshire Hazard Index method is counted as a basic approach to calculate the hazard index which considers 1) the exposure index indicating cross product of the AADT and train volume and 2) a "protection factor" to calculate the type of warning device effect at the crossing. On the one hand, the advantage of the hazard index methodologies is that they are easy to understand. On the other hand, the main disadvantage of the hazard index approach is that the estimated hazard index value is relative with other HRGCs' hazard index values, which means a single crossing's hazard index value is not interpretable without referencing to other crossings' hazard index value (Ogden & Cooper, 2019).

The crash prediction model is another approach to prioritize grade crossings by utilizing the mathematical formula to calculate the predicted crash frequency (or severity) at a crossing. Therefore, the predicted value is used as the ranking metric for HRGCs' prioritization targets. The advantage of the crash prediction model is the fact that it considers several characteristics or factors which significantly have effect on the crossings' crash risk. Moreover, prediction models' output can be integrated with economic data (e.g. crash costs) to result a comprehensive economic analysis associated with grade crossing improvement projects (Ogden & Cooper, 2019). Approximately 50% of the states used a crash prediction models to prioritize their crossings (Sperry et al., 2017a). Although the USDOT Accident Prediction Model, the NCHRP 50 Accident Prediction Model, the Peabody-Dimmick formula are common hazard-ranking models which are used by state DOTs, some states (e.g. Connecticut, Florida, Missouri, North Carolina, and Texas) have developed specific hazard-ranking models in accordance with their accident trends and available crash records (Niu, Chen, & Dowell, 2014; Sperry et al., 2017a; Weissmann et al., 2013). It is worth noting that the USDOT Accident Prediction Model is the most prevalent model among the mentioned crash prediction models and according to Sperry et al. (2017), at least 19 states or 38% of states reported utilizing this model for their HRGCS ranking.

Most state DOTs' studies and research projects on proposing or utilizing hazard-ranking models have focused on either crash prediction models (Farr, 1987b; Ogden, 2007; David W Schoppert & Hoyt, 1967) or calculation of hazard index (Abioye et al., 2020; Faghri & Demetsky, 1986; Qureshi et al., 2003; Tustin, Richards, McGee, & Patterson, 1986) and only few studies have explored hybrid accident prediction model hazard index (Niu et al., 2014; Weissmann et al., 2013). Moreover, the vast majority of designed prioritization systems by state

DOTs only consider the crash frequency at crossings. According to Sperry et al. (2017), only one state considered crash severity as a factor in grade crossing hazard-ranking. Therefore, previous studies have failed to propose the comprehensive hybrid accident prediction model hazard index which is able to consider crash frequency and severity in grade crossing hazard-ranking. Such a comprehensive prioritization system is important for transportation decision makers seeking to identify crossings and locations that have higher priority in receiving improvement services considering their both crash frequency and crash severity risks.

1.7. Current Research Gaps

Several studies have been found to conduct research on transportation accidents prediction. Most past studies have focused on roadway intersection or roadway crashes (Cai, Abdel-Aty, & Lee, 2017; Geurts, Thomas, & Wets, 2005; Y. Hao, Xu, Qi, Wang, & Zhao, 2019; Huang, Zhou, Wang, Chang, & Ma, 2017; Islam & Brown, 2017; Kumar, Toshniwal, & Parida, 2017; Jaeyoung Lee, Abdel-Aty, & Cai, 2017; Li, Shrestha, & Hu, 2017; Paul, 2019; Qin, Ivan, & Ravishanker, 2004; Ulak et al., 2019; Veeramisti, Paz, Khadka, & Arteaga, 2019; Wang & Abdel-Aty, 2006; Zheng et al., 2018). Relatively few studies have explored graded crossing collisions compared to highway accidents (Cho & Rilett, 2006; Ghomi et al., 2016; Haleem, 2016; Khattak, Gao, & Luo, 2012; Lu & Tolliver, 2016; Tung & Khattak, 2015; Yue & Jones, 2010; Zhao & Khattak, 2017; Zheng et al., 2019, 2016).

In addition, the majority of previous studies and research projects either focus only on crash frequency, which are often based on FRA inventory database (Austin and Carson, 2002; Guadamuz-Flores and Aguero-Valverde, 2017; Heydari et al., 2018; Heydari and Fu, 2015; Hu et al., 2012; Hu and Lin, 2012; Khattak et al., 2012b; Khattak and Luo, 2011; Lee et al., 2004; Lu and Tolliver, 2016; Medina and Benekohal, 2015; Millegan et al., 2009; Oh et al., 2006;

Saccomanno et al., 2007; Saccomanno and Lai, 2005; Yan et al., 2010), or on crash severity modeling, which are often based on historical FRA accident/incident database (Eluru et al., 2012; W. Fan et al., 2015; Ghomi et al., 2016; Haleem & Gan, 2015; W. Hao & Daniel, 2014, 2016, 2013; S.-R. Hu et al., 2010; Kang & Khattak, 2017; Liu & Khattak, 2017; C. Ma et al., 2018; Savolainen et al., 2011; Zhao et al., 2018; Zhao & Khattak, 2015).

To measure and predict crash frequency and severity simultaneously is critical for transportation decision makers seeking to improve safety at grade crossings, so they can identify and investigate the common factors affecting both crash frequency and severity changes. Separate crash frequency or severity predictive methods can be utilized to identify which contributes impact on one of the crossings' crash frequency or crash severity levels; however, it has failed to address consistent identified factors. For example, policy-reported surface conditions are often available for severity models but not crash occurrence models. Moreover, the expected crash severity likelihoods should be conditional probabilities considering the crash occurring according to the identified unique set of factors and not transferable for decision makers to quantify the absolute likelihood for a specific collision severity level. For instance, separate predictive method is able to estimate 65% crash occurrence likelihood with a specific set of factors, say A to E, and 20% crash occurrence with level one crash severity, 30% level two crash severity and 15% level three severity with another set of factors, say D to H. It is clear that because of F, G, and H factors, the estimated likelihoods are not transferable among the aforementioned models.

Transportation decision makers need an integrated available information to make safety improvement decisions considering both crossings' crash occurrence and crash severities. The same prediction model which is bale to quantify both crash frequency and severity with a unique set of factors is needed so that unmeasurable variance can be considered in the same error term and the estimated probabilities can be directly used by safety decision makers. Moreover, a straight-forward and integrated one-step forecasting model that considers both crash frequency and severity likelihood can be the base of the direct hazard ranking technique considering both crash frequency and severity likelihood to rank crossings and locations. Few studies have explored incorporating crash frequency and crash severity in the same prediction model.

1.8. Research Focus Area

Transportation agencies need a precise forecasting model which is able to predict crash occurrence and severity likelihood simultaneously. Many previous studies have focused only on crash frequency or on crash severity analysis, and research projects are often based on historical crash reports from FRA databases. Predicting crash frequency and severity simultaneously has practical importance for safety improvement agencies to quantify the critical factors that impact both crash frequency and severity. This study proposed a novel methodology and a statistical approach for HRGC crash analysis. The novel approach is competing risk algorithm and the approach is Cox proportional hazard regression. Moreover, model interpretive capabilities are measured by using crash severity analysis through the application of FRA grade crossings datasets and spatial analysis.

Moreover, there has been little research on the effectiveness of grade crossings' geometric factors on their safety outputs. Consequently, in this study, we evaluate the effects of grade crossings' geometric factors on crash occurrence and severity level changes. Four critical crossings' geometric parameters are investigated and measured at 3,194 public grade crossings in North Dakota. These four geometric features of crossings are: 1) acute crossing angle, 2) number of tracks, 3) the roadway distance between each crossing and the nearby intersection, and 4) number of highway traffic lanes. It should be stressed that distance to the nearest intersections and grade crossing angles are map-based calculations drawn from geographic information systems (GIS).

Similarly to the geometric analysis, a few studies have investigated countermeasures' effects on crash occurrence and severity levels by using the same model and the same database (Abdel-Aty & Nawathe, 2006; A. Keramati, Lu, Tolliver, & Wang, 2020; X. Ye, Pendyala, Shankar, & Konduri, 2013; Zalinger, Rogers, & Johri, 1977). Consequently, in this study, the CRM approach also is used because of its ability to estimate countermeasures' effects on crash occurrence and severity likelihood simultaneously by estimating their marginal effect and instantaneous risk.

In addition to forecasting models, transportation agencies need a prioritization system to classify crossings' risk level based on their estimated crash frequency and crash severity simultaneously. Subsequently, with the hazard-ranking approach which considers crossings' crash severity and frequency outputs, agencies are able to ensure that federal and state funds for HRGCs safety improvement projects are spent at the crossings that are considered the most in need of safety improvement. In this study, two hazard-ranking models are proposed based on the safety output of CRM model. The first hazard-ranking approach is accident prediction model which ranks grade crossings considering the crossings' crash frequency likelihood measured by CRM safety output. The second hazard-ranking model type is a hybrid accident prediction model/hazard index which measures the priority index for each crossing based on the calculated crash severity likelihood by applying the analytic hierarchy process (AHP) technique. Finally, crossings' risk levels are identified according to their crash likelihood and severity ranks by using both spatial analysis and the risk matrix techniques.

CHAPTER 2. STUDY DATA PREPARATION

This study uses three main data resources for this research: 1) North Dakota (ND) roadway network, railway network, roadway intersections, and HRGCs from North Dakota Department of Transportation (ND GIS Hub Data Portal); 2) highway-rail grade crossing accident/incident data from the Federal Railway Administration (FRA); and 3) the highway-rail grade crossing inventory from FRA. The final dataset includes all reported crashes/incidents records and their related information, recent and historical (from 1990 to 2018) inventory information for each crossing and measured geometric factors relative to the connecting highway and railways during the research timespan in North Dakota.

29 years of crash data were extracted from the database of public highway-rail grade crossing accidents/incidents. This database includes all reported crashes/incidents occurred at HRGCs which is reported from – FRA Form 6180.57. The form provides details about individual crashes at HRGCs, such as highway user information, crossing control devices (of the day), train speeds, and highway vehicle speeds. In particular, highway-rail grade crossing accidents/incidents database provides the frequency of fatalities, injuries, and vehicle damages costs, which based on these information, the crash severity levels of fatal, injury and, Property Damage Only (PDO) associated with each crash record were extracted to use in the study analysis respectively. To obtain more crossing-related information such as type of train service, time detection, maximum train speed, total daylight and nightlight thru trains, etc. related to both HRGCs with or without crash records in 29-year time span, this study linked the highway-rail grade crossing inventory database with the accident/incident database. FRA inventory database includes both the current and historical statuses of North Dakota state grade crossings. In addition to using the crossing identification number (Crossing ID) this study also used the time

of crash occurrence to link the historical information associated with each grade crossing. Moreover, historical information of both grade crossings with or without crash/accident records in 29 years is kept in the study database.

By using NDHUB portal (ND GIS Hub Data Portal) GIS data of roadway network, railway network, roadway intersections, and crossings, two geometric features of each crossing including distance to nearest intersecting roadway and the smallest crossing angle were estimated and were linked to the other two databases through the crossing identification number. Therefore, the final study database provides 29-year information of each crossing including crash severity level and related time occurrence, and crossing information such as train service, time detection, maximum train speed, total daylight and nightlight thru trains, etc. Since crossings' information in highway-rail grade crossing inventory dataset is not updated for all 29 years, a large amount of missing data was appeared in the study database. Therefore, because of estimation efficiency improvement, avoiding error interpretation, and preserving the population size of available grade crossing crashes, this study used rigorous data imputation methods for handling missing data (Orchard and Woodbury, 1972).

After cleaning the data, out of 66,166 crossing records in inventory database, the final research database includes features and information for 3,194 unique grade crossings including 475 crash records and 2,835 no crash records (total 3,310 records) for ND public HRGCs from 1990 to 2018 with three crash severity levels: PDO, injury, and fatal. Table 1 shows all the contributors and variables used in the study. The majority of grade crossings experienced no crash (86%) and the proportion of PDO, Injury, and fatal crashes are 8% (261 accidents), 4% (147 accidents), and 2% (67 accidents) respectively. The main variables inputs are selected based on data availability, and intuitive judgement. Finally, the model filters key contributors with their significance based on model's statistical significance test. In this study, not only the grade crossings accident information is updated through 29-year analysis periods for each HRGC, but all HRGCs' inventory information for 29 years are considered for changes. Table 1 summarizes all study variables' values for 29 years. Since variables' values might change every year, Table 1 indicates their Min and Max annual values for the 29-year study period.

Table 1. Summary Statistics of Considered Variables in the Study

Variable	Categorical Variable Values	Min Freq/Value	Max Freq/Value
Crash Severity			
	No Crash	3163	3192
	PDO	2	18
	Injury	0	11
	Fatal Crash	0	6
Type of Train Service			
	Freight	2718	2807
	Intercity Passenger	387	476
Train Detection System			
	None	2398	2402
	Constant Warning Time(CWT)	375	378
	Motion Detection (MD)	42	43
	PTC	1	1
	DC	374	376
Commercial Power (Is Commercial Power Available?)			
	Available	2107	2107
	Not Available	1087	1087
Roadway Paved Condition			
	Paved	563	563
	Not Paved	2631	2631
Crossing Control Types			
	Gate	4	22
	Gate+ Audible	6	92
	Crossbucks + Stop Sign	44	78
	Gates + StandardFLS+ Audible+ Stop Signs	2	14
	Gates + StandardFLS + Audible	27	184
	Crossbucks Only	2451	2676
	Gates+CantileverFLS+Audible	2	28
	CantileverFLS+StandardFLS+Audible	2	6
	Gates+CantileverFLS+StandardFLS	1	9
	Gates+CantileverFLS+StandardFLS+Audibl	2	21
Total Day Time Through Trains		0	35
Total Night Time Through Trains		0	33
Total Switching Trains		0	12
Maximum Train Speed		5	79
Annual Average Daily Traffic		5	25600
Percent of Trucks		1	22.67
Distance to the Nearest Intersections		0.78	2502
Crossing Angles		7.9	90
Number of Traffic Lanes		1	4
Number of Main Tracks		1	3

2.1. Geometric Factor Measurements

Two crossing geometric features, the number of traffic (roadway) lanes and the number of main tracks are used directly from FRA's crossing inventory database. The other two numerical geometric features used in this study are measured with geoprocessing methods and geographical information system (GIS) technique.

In the first phase of measurement process, North Dakota (ND) roadway and railway networks, roadway intersections, and HRGCs shape files are provided from the ND GIS hub portal (NDHUB) to calculate the numerical geometric measures of each grade crossing. As shown in Figure 3, all GIS spatial features are adjusted and digitized to spatially align and match with Google street features to provide accurate and overlaid coverage data before performing the geoprocessing estimation. Figure 3 indicates the accurate coverage map based on the four geometric features estimation. The rail track, roadway, roadway intersections, and grade crossings' locations all align accurately with the Google map associated with the area. Figure 3 also reveals that the original provided NDHUB grade crossing and rail track locations are not spatially matched with the rest of the geo-features. Instead, the spatial crossing and rail track locations are based on aligned digitized crossing and rail track locations.

Distances between crossings to their nearby roadway intersections are measured by first finding the nearest road intersection location to each crossing and then calculating the distance between the crossing and the intersection (ArcGIS, 2019). The measurement of smallest crossing angles for all crossings is shown in Figure 4. It involves three steps:

1) Generating a one-meter buffer around each grade crossing.

2) Estimating the geo-coordinates of the road/rail intersected spot within the buffer and.

3) Estimating the smallest angle considering all coordinates. Equation (1) represents the calculation of the acute (smallest) crossing angle.

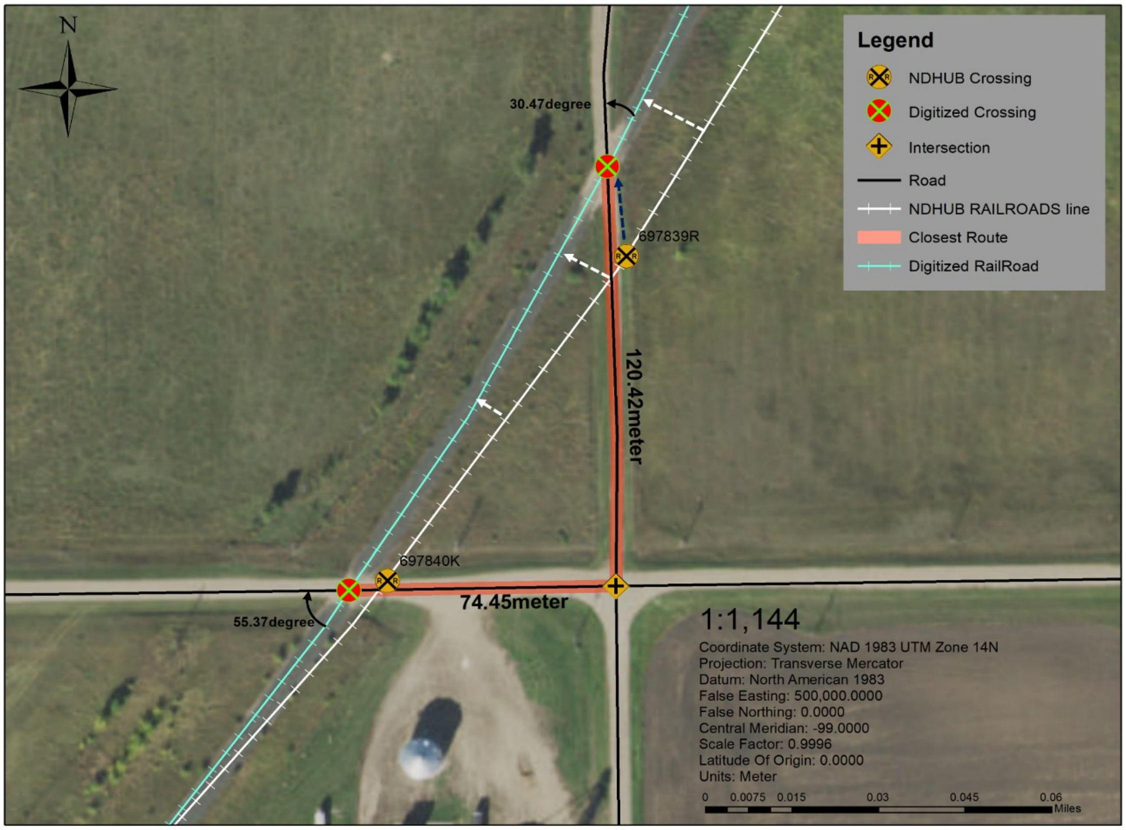

Figure 3. Integrated and Overlaid Coverage with Geometric Feature Measurements

$$\theta = \frac{\sin^{-1}\left(\frac{\left|(d_x \wedge d_y^a)-(d_y \wedge d_x^a)\right|}{r \times r_a}\right)}{\pi \times 180} \qquad \text{(Equation 1)}$$

Where, d_x denotes the difference between x-coordinates of crossing and buffer intersection with railway, d_y indicates the difference between y-coordinates of crossing and buffer intersection with railway, d_x^a represents the difference between x-coordinates of crossing and buffer intersection with roadway, d_y^a shows the difference between y-coordinates of crossing and buffer intersection with roadway,r and r_a are distances between crossing to railway-buffer and roadway-buffer intersections respectively.

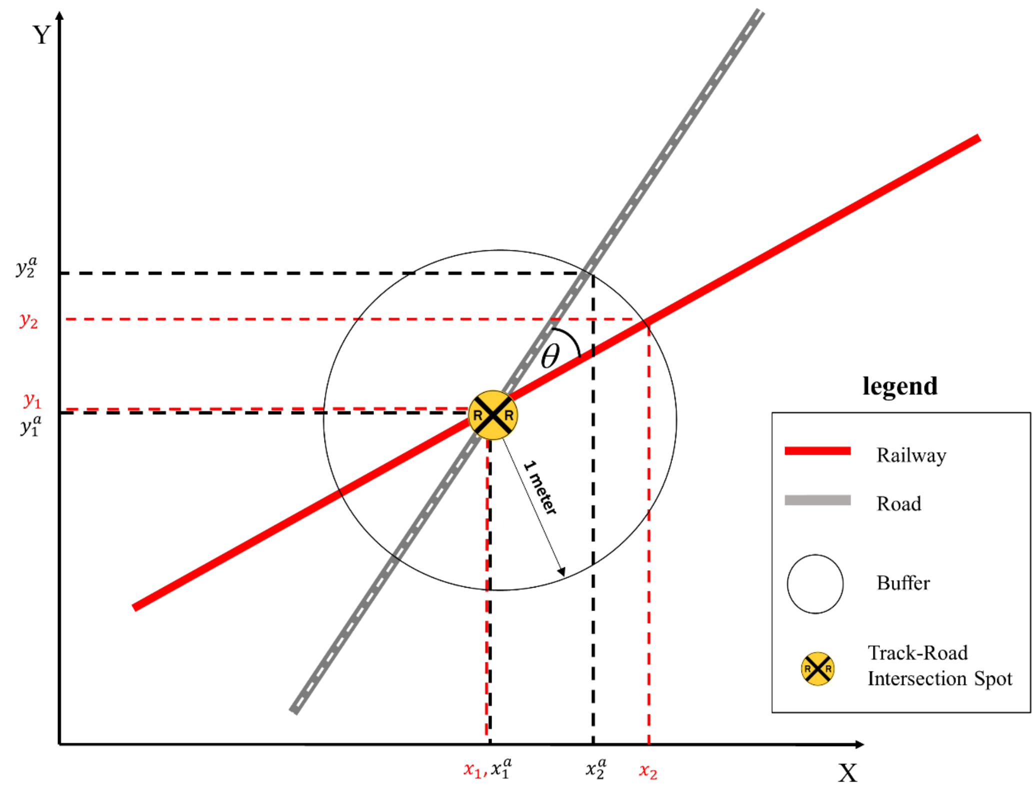

Figure 4. Crossing Angle Estimation

2.2. Handling Missing Data

2.2.1. Countermeasures Missing Data

Previous studies have indicated that crossing devices are significant contributors to the likelihood of HRGCs' crashes and their consequences. Countermeasures may change over the years, but updated information about crossing control device(s) in highway-rail grade crossing inventory dataset is not provided for each year from 1990 to 2018. Consequently, control devices missing data was appeared in the study database after joining the accident/incident data set and inventory dataset.

According to FRA Form 6180.57, in the accident/incident dataset, each crossing warning device is identified as a specific code. For example, gates specific code is "01", cantilever flashing light is "02", standard flashing light is "03", etc. If a crossing has a combination of warning devices, those codes will be concatenated where each warning is two positions long with no commas separating the crossing types. For instance, if a crossing has both flashing lights and crossbucks, the level of crossing device type (CDT) as a categorical contributor associated with that crossing is equal to 0307. Such information about the control device and its combinations are available for crossing with crash record(s). Consequently, to generate such contributors for crossings with no accident between 1990 and 2018, the crossing history dataset which is part of FRA inventory dataset is used.

Crossings' historical inventory dataset includes the quantity of warning devices from 1974 to 2018 defined as separated contributors; for example, Xbuck and stop sign columns define the number of cross bucks and stop signs at each crossing, respectively. To generate the same variable as CDT in accident/incident dataset by using inventory dataset, the device quantities were replaced by device codes. For example, if a record's Xbuck column includes a value which is equal or greater than one, that value will be replaced by crossbucks code which is "07". Then, the device codes in each column are concentrated to indicate the final warning device combination for the record. In the following, the process of countermeasures data preparation is explained using two records of inventory data set as an example.

Table 2. Inventory Dataset Format

Crossing ID	Xbuck	Stop sign	Last update
062011J	2	1	1994
062011J	2	0	1997

Table 2 indicates the inventory dataset format to represent 2-year update of the number of crossbucks (Xbuck), and stop sign for a crossing with "062011J" identification number. Table 2 represents that crossing "062011J" was controlled with two crossbucks and one stop sign in 1994. However, the new update of inventory dataset indicates that the crossing was controlled with just two crossbucks and stop sign was eliminated in 1997. To convert the crossing's quantity information in Table 2 to crossing device type (CDT) format, the crossing quantity information is replaced with crossing code type as indicated in Table 3. Note that according to the FRA Form 6180.57, the codes for crossbucks and stop sign control devices are "07" and "08", respectively.

Table 3. Converting Control Device Quantity to Control Device Code

Crossing ID	Xbuck	Stop sign	Last update
062011J	07	08	1994
062011J	07	0	1997

To indicate the crossing device combination in 1994 and 1994, and generating the CDT contributor as it is generated in the accident/incident data set, the contents of two columns of Xbuck and stop sign are concatenated, and the result is a new contributor of CDT in Table 4.

Table 4. Generating Crossing Device Type (CDT) Contributor

Crossing ID	Crossing Device Type (CDT)	Last update
062011J	0708	1994
062011J	07	1997

Table 5 indicates a pivot table based on Table 4 to indicate more details about "062011J" crossing and reveal missing countermeasure information from 1994 to 1997. The same pivot table technique was used for the 3,194 crossings in the complete study dataset which includes 28 control device combinations (e.g., 0708) from 1990 to 2018. CDT-Year variable in Table 5 indicates the crossing device type in that year. NAs in Table 5 clearly expresses that CDTs for the years 1995 and 1996 are missing data because of the lack of annual inventory dataset update.

Table 5. Creating Crossing Device Type (CDT) Contributor

Crossing ID	CDT-1994	CDT-1995	CDT-1996	CDT-1997
062011J	0708	NA	NA	07

In this study, to deal with the above-mentioned missing data ("NAs"), "NAs" are replaced with the first available CDT information belonging to the previous year(s). Accordingly, Table 6 indicates the final dataset without control device missing data for records of grade crossing "062011J". To handle countermeasure missing data of this study dataset, the similar data transformation process which converts Table 2 to Table 6 was applied for all 3,194 study public grade crossings for their 29 years' records from 1990 to 2018. As mentioned before, crossings with crash records have CDT information because this information is provided in FRA accident/incident dataset. However, the proposed missing data analysis was applied for all study grade crossings with or without crash record(s) to compare the results suggested by the proposed process and using the inventory dataset with the information provided according to the FRA accident/incident dataset. The results indicated that all provided CDT information by the proposed process was matched with the reported CDT information in the accident/incident dataset.

Table 6. Creating Crossing Device Type (CDT) Contributor

Crossing ID	CDT-1994	CDT-1995	CDT-1996	CDT-1997
062011J	0708	0708	0708	07

2.2.2. Data Imputation

Crash reports provided by investigators might be incomplete because of several reasons, such as errors or lack of entry. As mentioned in the previous section, FRA inventory data does not include the annual historical crossing information update from1990 to 2018, and contributors' records associated with several years are not available.

If there are a few of missing variables in observations or the missing values are randomly distributed, the observations can be removed. Otherwise, if e.g., the missing data are non-random or with large amounts, removing them may cause inefficient resulting in estimation and interpretation errors (Gelman and Hill, 2006). To improve prediction efficiency, avoid errors in interpretation, and also preserve the population size of available grade crossing crashes, this study applied rigorous data imputation methods for handling missing data (Liu et al., 2015; Orchard and Woodbury, 1972).

Having explained in "Data acquisition" section, 3194 active HRGCs in 29 years in North Dakota was selected as study sample. Consequently, considering crossings' annual information, the total number of records before the final transformation (input of Cox regression model) is 92,626 (3194×29). In this study, after joining inventory and accident/incident datasets, eight contributors needed imputation: type of train service, type of train detection, total day time through trains, total night time through trains, total switching trains, maximum train speed, annual average daily traffic (AADT), and percent trucks. The type train detection (nominal variable), and type of train service (nominal variable) missing values are 0.19%, and 31.26% respectively. The rest of a mentioned variables have 76.03% missing values. Multivariate imputation using chained equations (MICE) method is used to impute missing values considering several variables (Raghunathan et al., 2001; Royston, 2009; Rubin, 2004). The MIC basic idea is to impute missing values of multiple variables iteratively via a sequential series of univariate imputation models. More information and mathematical formulation of MICE can be found in (Liu et al., 2015; StataCorp, 2013).

One of the MICE advantageous is the simultaneous imputation of variables with different types by using the appropriate univariate imputation model specifications such as polytomous and predictive mean matching method (PMM). Regardless of the variables without any missing values, the most observed variable is train detection (only 0.19 % missing value) which should be imputed first, and the next variable obviously should be the type of train service. Since these two variables are unordered categorical variables, a polytomous regression imputation model was applied. Since the rests of variables with more missing values are numerical variables, the PMM was applied. After data imputation process, all variables (contributors) have complete information for 92,626 records which need to be prepared before using in competing risk model.

2.3. Data Transformation

The database with 92,626 records which was imputed in the previous section should be prepared to use in competing risk model and its format must be converted to time-to-crash format. Time-to-crash dataset (time-to-event dataset in survival analysis) is a database which provides information about each crossing's record including 1) crash occurrence, 2) crash severity level (PDO, injury, fatal, no injury) 3) crash occurrence time (year in this study) and 4) crossing's contributors (independent variables) associated with the record year.

The first step to generate time-to-crash data is defining a column (variable) in the dataset indicating the crash occurrence year (variable "time"). The value of "time" variable for crossings with no crash record is equal to the last year of the study period which is year 29 (time=29). The second step is defining a binary variable "status" which is equal to 1 in the situation of crash occurrence, otherwise 0. The third step is defining a nominal variable of "severity" with three levels of 1,2, and 3 which represents three severity levels of PDO, injury, and fatal, respectively. Consequently, a crossing record with status=1, severity=2, and time =2010, represents that the crossing had an injury crash in the year 2010. All three variables of "time", "status", and “severity” are considered as dependent (respond) variables of the competing risk algorithm and Cox regression model.

Model contributors or dependent covariates are divided into four groups including 1) engineering contributors including distance to the nearest intersection, smallest crossing angle, number of traffic lines, and number of main tracks which cannot be changed over time, 2) continuous variables with different values over the time such as total daylight thru trains, and maximum train speed, and 3) categorical variables with different levels over the time including train detection and type of train service. The first group of variables are transferred to the time-to-crash dataset with their original value. However, in terms of the second group, the value which is defined for each crossing crash record is equal to their average values associated with the years between the year after the last crash occurrence and a year of crash occurrence associated with that record. In terms of the last group transformation, variable values at the time (year) of crash occurrence were transferred. Same policies were applied to transfer contributors’ value for no crash records. For example, the average of the second group variables’ value for 29 years (because there is no range of years between two crash occurrence times), and the third group variables’ values in year 2018 (year 29) were transferred.

2.4. Data Description

In this study, a crossing’s crash severity level is identified based on the total number of killed (TOTKLD) and injury (TOTINJ) as reported by railroad on F6180.57. The total number of killed at a grade crossing includes number of users, railroad employees, and train passengers killed at the same crossing. Subsequently, the total number of injury at a grade crossing includes number of users, railroad employees, and train passengers injured at the same crossing.

If a grade crossing's accident record(s) indicates one or more than one total number of killed (TOTKLD>0), that crash record will be identified as fatal crash record (even in the condition of TOTINJ>0). Correspondingly, a crossing record is identified as injury crash record, if the record indicates the total number of injured equal to one or more than one (TOTINJ>0) with total number of killed equals to zero(TOTKLD=0). Clearly, a crossing record with both total number of killed and injured equal to zero is identified as PDO (Property Damage Record) crash record. The variable represent severity level of a crossing record is "severity".

As mentioned in previous section, three variables of "severity", "time", and "status" are considered as dependent or target variables of the model, and the rest of the variables described in Table 1 are independent variables. Although most of the variables' name or title in Table 1 describe their function clearly, Table 7 provides more information about part of independent variables' description.

Table 7. Data Description

Variable	**Description**
Type of Train Service	Describes the type of rail service that uses the crossing. Freight trains or intercity passenger trains
Train Detection System	Type of train detection equipment used to activate the warning system at the crossing for movements on the main track(s)
Roadway Paved Condition	Is highway paved or not? 1=yes, 0=no
Total Day Time Through Trains	Day through-train movements
Total Night Time Through Trains	Night through-train movements
Total Switching Trains	Day and night switching-train movements
Maximum Train Speed	The highest maximum timetable speed in miles per hour for any type of train movement over the crossing
Percent of Trucks	The estimated percentage (0–99%) of trucks in the traffic stream
Distance to the Nearest Intersections	The distance between a crossing to its nearest highway/roadway intersection (Meter)
Crossing Angles	Describes the smallest angle between the roadway and the track
Number of Traffic Lanes	The number of through traffic lanes crossing the track
Number of Main Tracks	Describes the number of main railway tracks that cross the roadway

CHAPTER 3. APPLYING COMPETING RISK MODEL IN HIGHWAY RAIL GRADE CROSSING ACCIDENT ANALYSIS

3.1. Background and Literature Review

Studies on grade crossing safety have focused either on crash frequency or on crash severity. Due to the discrete, random, and non-negative nature of accident data, generalized liner models (GLMs) have been the most common approach in crash frequency statistical modeling. For example, Heydari and Fu (2015) proposed a poisson weibull model. Other statistical models (Jinsun Lee et al., 2004; Lu & Tolliver, 2016; Oh et al., 2006; Z. Ye et al., 2018) including zero inflated, hurdle, and generalized event count models were adopted to address data issues such as the excess number of zero collisions and over/under dispersions. Previous studies (Iranitalab & Khattak, 2017; D. Lee, Warner, & Morgan, 2019; Yang, Trudel, & Liu, 2017; Zhao et al., 2018) also used data mining and machine learning techniques such as the hierarchical tree-based regression technique (Yan et al., 2010), neural network (Abdel-Aty & Keller, 2005; Zheng et al., 2019), and random forests (Zhou, Lu, Zheng, Tolliver, & Keramati, 2020) to forecast crash frequencies or severities at grade crossings. Heydari et al. (2018) proposed a spatial-statistical approach to compare different geographic areas in terms of pre-specified safety performance which is able to predict crash likelihood of a given type.

There are several studies have been focusing on modeling crash severity outcomes. Several studies have found discrete choice models to be qualified because of the discrete nature of crash severity levels. Subsequently, Hao and Daniel (2013) and Abdel-Aty and Keller (2005) used the ordered probit model in the United States to predict crash severity while they considered the crash severity levels naturally ordered. Hao and Daniel (2014) proposed an ordered probit model while they considered traffic control devices at HRGCs. Eluru et al (2012) proposed a latent ordered response model using 10 years of grade crossing accident data in the Unites States. Hu et al. (2010) used a generalized logit model to measure contributors effecting crash severity at Taiwan's railroad grade crossings. Recently, Zhao et al. (2018) used binary logit models and a generalized linear mixed model to investigate the relationship between potential contributors and pedestrian injury severity levels, applying 10 years of data at grade crossings in the United States.

The above mentioned approaches have shed light on the modeling and understanding of crash frequency and severity expected changes separately. However, to forecast crash frequency and severity outcomes simultaneously, agencies need to account for the common factors affecting crash frequency and severities based on a unique dataset. Unaccounted covariates affecting crash frequency and severity variations will be considered for in error terms for each separate models. However, these error terms are possibly interrelated because they are associated with the same concerns. Abdel-Aty and Nawathe (2006) presented a two-step approach to quantify crash frequency based on simulated geometric and traffic exposure data and then estimate crash severity by using the neural network technique. Zalinger et al., (1977) developed an integrated hazard regression model that considered both the crash frequency and severity. However, in the final version of their developed model, both crash frequency and severity are treated as collision history and only the number of accidents is selected as the hazard. Ye et al. (2013) proposed a model which only considers crash frequencies by collision types simultaneously using accident data rather than inventory data.

In this chapter, a modeling approach, the competing risk method, is developed and proposed for grade crossing accident safety analysis. This method has been applied commonly in the medical field. However, it has not been used in safety analysis. Model's interpretive capabilities in crash frequency and severity are investigated simultaneously. Moreover, the contributors' effects on the crash rate and severity outcomes and their long-term cumulative effects over 29 years are quantified.

3.2. Methodology

The competing risk algorithm is a specific sub-branch of survival analysis and its structure is designed to quantify the marginal probability of incidence outcomes in the possibility of more than one cause of failure. This method is widely used in medical and bioscience research (P. K. Andersen, Hansen, & Keiding, 1991; Fiocco, Putter, Van de Velde, & Van Houwelingen, 2006; Fiocco, Putter, & Van Houwelingen, 2005; Geskus, 2000; Geskus et al., 2003; Gooley, Leisenring, Crowley, & Storer, 1999; van Rij et al., 1998) to study patient deaths likelihood attributable to competing events such as cardiovascular and non-cardiovascular causes. Survival analysis is an approach to solve time-to-event problems. Consequently, survival analysis intends to calculate the probability of an occurrence of an event of interest before specific time *t*. In transportation safety analysis, the event of interest is accident occurrence. One of the unique features of survival data is that not all targets (e.g., crossings) experience the event of interest (e.g., crash) by the end of the study period. HRGC accident data has this feature, as well. This specific dataset feature is known as censoring. One can see from Figure 5 that the structure of competing risk algorithm is matched with transportation crash analysis, where each grade crossing is considered as a patient with a crash representing a survival failure and different crash severity levels at each crossing are identified as different causes of survival failure (crash occurrence). In this study, crash severity outcomes are defined as property damage only (PDO), injury, and fatality.

Figure 5, safety analysis part, shows the modeling structure with the three crash severity levels. The model first state is “no crash” at year one which or 1990 for all crash records. Then, during the study period, some crossings experience accident(s). According to the Figure 5, there are total 261 PDO crashes, 147 injury crashes, and 67 fatal crashes out of 3,310 crossings’ records within the 29-year study period (1990 to 2018). Note, crossings with multiple crashes in one year are excluded from the study database.

Each record in the dataset contains three main variables of statues (D), time (t), crash severity level (k) whereby the model (CRM) is able to calculate both crash occurrence and severity likelihood. Status (D) is a binary variable which is equal to 1 in the situation of crash occurrence, otherwise 0. Considering t as the collision time, model calculates the crash occurrence likelihood by using variables D and t. Crash severity variable can be equal to 1, 2, or 3 representing PDO, injury and fatal severity levels respectively. Therefore, if D associated with severity level k is equal to 1 for a specific crossing record at time t, model will calculate the crash occurrence likelihood (D=1) with severity level k before time t. If a crossing statues associated with all crash severity levels are equal to 0 (D=0) for whole study period ($t \in [0,29]$), crossing is considered as censored.

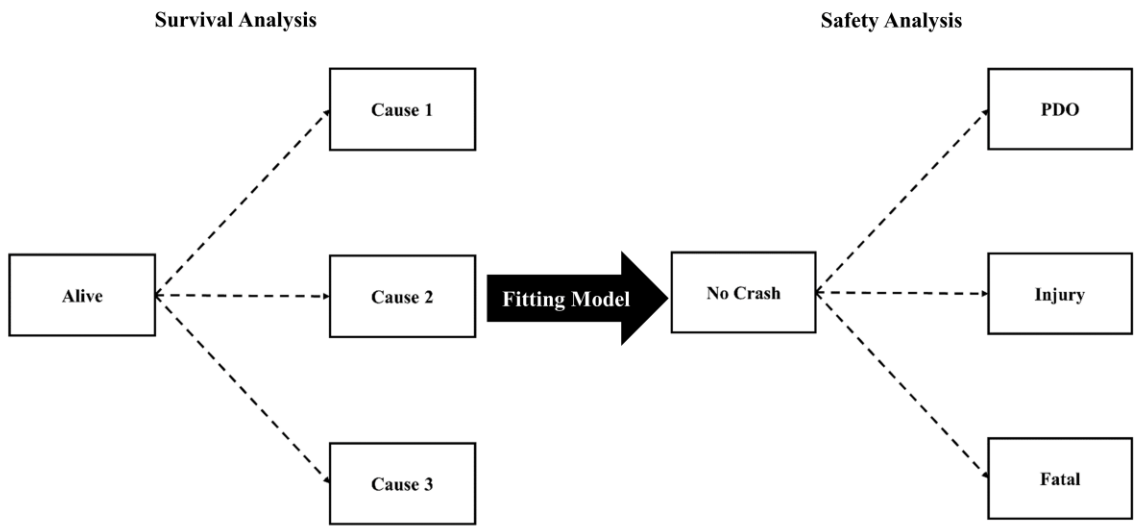

Figure 5. Fitting Competing Risk Model with Transportation Safety Problem

3.2.1. Cause-Specific Hazard Function

The main parameters of competing risks model are 1) the time of failure *T* or time of crash occurrence 2) the cause of failure of *D* or crash severity levels (PDO, Injury, and Fatal), and 3) a covariate vector *Z* indicating crossing's contributors such as type of train service and AADT. The cause-specific hazard function which is the fundamental concept in competing risk model is indicated in Equation (2). The cause-specific hazard function describes the instantaneous rate of crash with severity level *K* (event failure).

$$\lambda_k(t|Z) = \lim_{\triangle t \to 0} \frac{Prob(t \leq T < t + \triangle t, D = k | T \geq t, Z)}{\triangle t} \quad \text{(Equation 2)}$$

Competing risk model is identified as a multivariate failure time model, because each individual subject (patient) is assumed to have a possible failure time for each cause of failure. The earliest of these failures is actually observed and the others are latent. If $\tilde{T}_k$ represents the time to failure of cause *k*, only $T = min\{\tilde{T}_k\}$ and *D* can be observed while *D* is an index variable indicating which event occurred first. In competing risk models, the event time is right censored if the endpoint of interest has not yet occurred at the end of the observation window. Therefore, in crash analysis, the crossings with no accident records during the 29-year analysis period are identified as right censored data. This is one of the advantages of this algorithm, as the model is bale to consolidate and use all the available data, even the crossings' information with no accident records. Previous research only considered crossings with accident records (Eluru et al., 2012; Liu & Khattak, 2017; Liu, Khattak, Richards, & Nambisan, 2015). Let T_i denotes the time of crash occurrence for the i^{th} crossing, $i=1, \dots ,n$, D_i indicates its severity level, and C_i represents censoring time of crossing i. It can be indicated that T_i which is actual accident occurrence time of crossing i is unobserved and $T_i = min(T_i, C_i^0)$ and the event $D_i = D_i I(T_i \leq C_i)$ are observed. Consequently, if $D_i = 0$,crossing i is identified as censored at time T_i (Ishwaran et al., 2014).

3.2.2. Cox Proportional Hazard Model

Equation (3) indicates the estimation of the cause-specific hazard of crash severity level k, $\lambda_k(t|Z)$, for a grade crossing record with covariate vector $Z = (Z_1,\dots, Z_p)$. (Putter, Fiocco, & Geskus, 2007). Equation (3) is known as cox proportional hazard model (Cox, 1972).

$$\lambda_k(t|Z) = \lambda_{k,0}(t) exp(\beta_k^{\top} Z) \qquad \text{(Equation 3)}$$

Where $exp(\beta_k^{\top} Z)$ is the estimation of the hazard ratio (HR) of crash and indicates the instantaneous risk of crash occurrence with severity level k for a crossing with covariate vector Z. In other words, it explains the conditional probability that a grade crossing with the contributor vector Z has an accident with severity level k at time t given it is crash-free (event-free) just before time t. In Equation (3), $\lambda_{k,0}(t)$ indicates the baseline cause-specific hazard of severity level k, and β_k shows the calculated effects of contributors on crash with severity level

k. The baseline hazard of severity level k is quantified by the Breslow estimator which is shown by Equation (4) (De Wreede et al., 2010):

$$\Delta\tilde{A}_k\left(t, \hat{\beta}\right) = \frac{\Delta N_k(t)}{S_k^{(0)}(\hat{\beta}, t)} \qquad \text{(Equation 4)}$$

Where, $\hat{\beta}$ is the maximum likelihood estimator of β, and $\Delta N_k(t)$ represents the total number of crash records with severity level k at t, and $S_k^{(0)}(\hat{\beta}, t)$ denotes the number of records at risk. The term $S_k^{(0)}$ shows the weighted risk set and can be calculated in Equation (5):

$$S_k^{(0)}(\beta, t) = \sum_{i=1}^{n} \exp(\beta^\top Z_{ki}(t)) Y_{ki}(t) \qquad \text{(Equation 5)}$$

Where, $Y_{ki}(t)$ indicates the at-risk process, i.e. $Y_{ki}(t)$= 1 if the crossing's record i is at the risk of severity level k at time t-, the time point is just before time t. Note, to calculate the covariates effect on crash frequency likelihood, the $\Delta N_k(t)$ in equation (4) is defined as the number of crash records with any severity level.

The cause-specific function assumes independent censoring in estimating HR and coefficients. For example, when the event of interest is a crossing's PDO crash, crossings with other severe crashes (injury and fatality) will be considered as censored observations. In other words, a grade crossing coded as PDO crash failure at time t is no longer at risk of severe crashes such ad injury or fatal crashes at time t and will be treated as a censored observation (Keramati et. al., 2020). Testing whether a crossing has PDO crashes, might have injury or fatal crashes if the crossing did not have PDO crash is complicated, because the possible injury/fatal crashes occurrence is unobservable for the crossings that actually experienced PDO crash. However, in safety applications, the dependency between competing risks should exist. In other words, a crossing experiencing crash with a specific severity level might experience the crash with other severity levels.

3.2.3. Cumulative Incidence Function

Although, outputs resulting from cause-specific hazard functions can quantify the instantaneous risk of crash occurrence and crash severity at crossings, the assumption of independent censoring in Cox model causes separately estimating of crash rate for each crash severity level. However, Gray (1988) indicates that the probability of event occurrence in a specific range of time depends on the cause-specific hazards of other events. Consequently, to integrate the calculation of competing event frequency (crash occurrence at each severity level in this study safety analysis), and to calculate their marginal effect, the cumulative incident function (CIF) as another main output of CRM is adopted to solve HRGC crash analysis problem.

The integral of the cause-specific density ($\lambda_k(t)$), represents the cumulative incidence function (CIF) of crash severity *level k*. CIF is the probability of crash occurrence with severity level k before time t. CIF can be expressed in terms of cause-specific hazard in Equation (6):

$$CIF_k(t|Z) = \int_0^t \lambda_k(t|Z)S(t|Z)dt = prob(T \leq t_j, D = k) \qquad \text{(Equation 6)}$$

Where the overall survival probability $S(t)$ calculates the overall probability of not having failed from any cause at time t. In crash analysis, it estimates the overall probability of not having crash with any severity level at time t. Equation (7) expresses the calculation of $S(t)$ at t without taking into account the crash severity levels which is calculated by the Kaplan-Meirer estimator (Putter et al., 2007):

$$\hat{S}(t) = \prod_{j:\, t_j \leq t} \left(1 - \frac{d_j}{n_j}\right) \qquad \text{(Equation 7)}$$

In the above equation, let $0 < t_1 < t_2 < \ldots < t_n$ be the ordered distinct collision time. Given d_{kj}, the number of records with severity level k crash at t_j, then $d_j = \sum_{k=1}^{K} d_{kj}$ calculates the total number of accidents at t_j. n_j denotes the number of records at risk. It represents the number of records which are in follow-up situation and have not experienced a crash by the time t_j. The discretized format of cause-specific hazard of Equation (2) can be expressed as Equation (8) (Putter et al., 2007):

$$\lambda_k(t_j) = Prob(T = t_j, D = k | T > t_{j-1}) \quad \text{(Equation 8)}$$

Where $\lambda_k(t_j)$ can be calculated by $\hat{\lambda}_k(t_j) = \frac{d_{kj}}{n_j}$ which shows the proportion of records at the risk of collision occurrence with severity level *k.* To simplify and quantify the effect of covariates on the cumulative probability, Equation (7) can also be written down as Equation (9) considering the crash with severity level *k.*

$$\hat{S}(t|Z) = \prod_{j:\, t_j \leq t} \left(1 - \sum_{k=1}^{k} \hat{\lambda}_k(t_j|Z)\right) \quad \text{(Equation 9)}$$

Finally, Equation (10) expresses the estimator of the cumulative incidence function (CIF) which explains the cumulative likelihood of crash occurrence with severity level *k*:

$$\widehat{CIF}_k(t|Z) = \prod_{j:\, t_j \leq t} \hat{S}(t_j|Z) \left(\frac{d_{kj}}{n_j}\right) \quad \text{(Equation 10)}$$

Equation (11) indicates that the cumulative incidence function (CIF) of crash occurrence is equal to the sum of CIF related to each crash severity level.

$$CIF_c(t|Z) = \sum_{k=1}^{3} CIF_k(t|Z) \quad \text{(Equation 11)}$$

3.3. Results Analysis

3.3.1. Coefficient Estimation and Hazard Ratio Analysis

Table 8 indicates the calculated contributors' coefficient (Coe) and hazard ratio (HR) associated with crash rate, and each severity level of PDO, Injury, and Fatal. In Table 8 and other tables in this study, "*", "**", and "***" symbols denote whether the covariate (contributor) is significant at 90%, 95%, and 99% confidence level, respectively. It should be noted that the model output related to countermeasures and geometric factors will be expressed and explained in detail in the next chapters. Equation (3) expresses the estimation of coefficient (β_k) and hazard ratio ($exp(\beta_k^\top Z)$). In terms of categorical variables including nominal and ordinal, the estimated HR is equal to relative risk of crossing with that contributor's value-level compared to the reference level of that contributor. If a contributor is continuous, estimated HR denotes the relative independent risk associated with a one-unit variation in covariate (Logan, Zhang, & Klein, 2006). The coefficient of Cox proportional hazard model represents the magnitude of the corresponding change in the cause-specific hazard function attributable to a one-unit change in the covariate value. However, HR denotes the magnitude of the corresponding change in accident probability.

As can be seen in Table 8, positive Coefficient of 0.6 and HR of 1.82 expresses an 82% raise in PDO crash probability associated with HRGC with passenger train service in comparison with freight train service. On the other hand, negative Coefficient of -0.8 and HR of 0.45 represents a 55% (1-0.45=0.55) decline in PDO crash probability at crossings with an unpaved highway compared to a paved highway. The HR value can be any positive number with an HR of 1 which shows lack of association (change probability is no different than zero), an HR greater than 1 suggesting an increase in risk, and an HR less than 1 suggesting a reduced risk.

Table 8 indicates that intercity passenger train service (compared to freight train service as a reference), constant warning time (CWT) train detection system (no train detection system is reference), total daylight through trains, train speed, annual average daily traffic (AADT), and number of roadway traffic lanes have positive impacts on crash probability. However, total night-time through trains, direct current (DC) train detection system (compared to no train detection system), no commercial power available (reference is the availability of commercial power), and percentage of truck have negative impact on crash likelihood. Traffic exposure factors including total daylight through trains, number of traffic lanes, and train speed, all have positive effect on the crash probability at grade crossing which is matched with previous studies results. However, total night-time through trains has negative impact on the crash likelihood at grade crossing which is one of the interesting findings in this study. such negative effects might be rooted in the operating changes. More night-time idling trains switched to night-time operating trains might decrease the traffic of day-time trains and correspondingly may cause a decrease in collision probability at crossings. It is expected, since in general, highway/roadway traffic is concentrated during the daytime.

Table 8 results show some contributors significantly impact on certain crash severity likelihoods but not on others. The main reason of such results might be under-estimated because of the independent censoring assumption cause-specific hazard function. However, Equation (6) indicates that estimated CIF is not based on the assumption of competing risks independency. Consequently, estimated competing events marginal likelihood considers the competing events dependency and has higher accuracy. According to Table 8, night train traffic (total night-time through trains) has significant impact on likelihood of all three severity levels. It has a negative impact on PDO and injury crash likelihoods, but has a positive impact on likelihood of fatal crashes. One possible explanation for this positive impact on fatal crashes and negative impact on PDO and injury crashes is that night-time vehicle users are less aware of the traffic control devices and existence of a HRGCs because of lower visibility. Another reasonable explanation is that night-time drivers are more likely to drive at higher speeds, thus severe crashes like fatal one are more likely to occur because of the increase in night-time train traffic (Eluru et al., 2012).

Table 8. Calculated Coefficient and Hazard Ratio

Variable	PDO		Injury		Fatal		Crash	
	Coef	HR (CI:95%)	Coef	HR (CI:95%)	Coef	HR (CI:95%)	Coef	HR (CI:95%)
Type of Train Service (Reference: Freight)								
Intercity Passenger	0.6**	1.82 (1, 3)	-0.2	0.82 (0.4, 2)	0.7	2.01 (0.8, 5)	0.4**	1.50 (1, 2)
Train Detection(Reference: None)								
CWT	0.2	1.22 (0.7, 2)	0.5**	1.65 (1, 3)	1***	2.72 (1, 8)	0.4***	1.50 (1.2, 2)
DC	-0.7***	0.50 (0.3, 0.8)	-0.6	0.55 (0.2, 1)	-2.0	0.14 (0.03, 2)	-0.7***	0.5 (0.3, 0.7)
Is Commercial Power Available?(Reference: Yes)								
No	-0.1	0.90 (0.6, 1)	-0.7***	0.50 (0.3, 0.8)	0.3	1.35 (0.80, 2)	-0.2*	0.80 (0.6, 1)
Is Roadway/Pathway Paved?(Reference: Yes)								
No	-0.8***	0.44 (0.3, 0.7)	-0.4	0.67 (0.4, 1)	-0.2	0.82 (0.4, 2)	-0.6***	0.50 (0.4, 0.7)
Total Daylight Through Trains	0.2***	1.22 (1, 1)	0.1	1.11 (1, 1)	-0.4	0.67 (0.4, 1)	0.2***	1.22 (1.1, 1.3)
Total Night-time Through Trains	-0.2***	0.82 (0.7, 0.9)	-0.2*	0.82 (0.7, 1)	0.5*	1.65 (0.9, 3)	-0.1***	0.90 (0.8, 1)
Total Switching Trains	0.01	1.01 (0.8, 1)	0.03	1.03 (0.8, 1)	0.5**	1.65 (1, 3)	0.03	1.03 (0.9, 1.2)
Maximum Train Speed	0.004	1 (1, 1)	0.05**	1.05 (1, 1)	0.03	1.03 (1, 1)	0.02***	1 (1, 1)
Annual Average Daily Traffic	0.00009**	1 (1, 1)	0.00004	1 (1, 1)	0.0001	1 (1, 1)	0.00008***	1 (1, 1)
Percent Trucks	-0.08**	0.92 (0.9, 1)	-0.1***	0.90 (0.8, 1)	0.04	1.04 (0.9, 1)	-0.09***	0.91 (0.9, 1)

Table 9. Ranking Contributors Based on Hazard Ratio

Variable	PDO		Injury		Fatal		Crash	
	Rank	%Impact	Rank	%Impact	Rank	%Impact	Rank	%Impact
Type of Train Service:								
Intercity Passenger	1	82%	5	18%	2	101%	2	49%
Train Detection:								
CWT	5	22%	1	65%	1	172%	2	49%
DC	3	50%	3	45%	3	86%	1	50%
Is Commercial Power Available?								
No	8	10%	2	50%	6	35%	6	18%
Is Roadway/Pathway Paved?								
No	2	55%	4	33%	8	18%	3	45%
Total Daylight Through Trains	6	22%	7	11%	7	33%	5	22%
Total Night-time ThroughTrains	7	18%	6	18%	4	65%	7	10%
Total Switching Trains	10	1%	11	3%	5	65%	9	3%
Maximum Train Speed	11	0.4%	10	5%	10	3%	10	2%
Annual Average Daily Traffic	14	0.01%	14	0.004%	14	0.01%	13	0.01%
Percent Trucks	9	8%	9	10%	9	4%	8	9%

Moreover, Table 8 shows that a one-unit increase in train speed, injury and fatal crash likelihoods increased by 5%, and 3% respectively; but the likelihood of a change in PDO and crash occurrence is not significantly different than zero.

Table 9 indicates the contributors' importance ranking information based on the estimated HR. "%impact" is the estimated instantaneous risk changes associated with contributors' HR (%Impact = |HR-1|x100.); the contributors are ranked based on this value. Results in Table 9 reveal that 1) "train service" has the highest impact on PDO, and, 2"train detection" has the highest impact on injury crash, fatal crash, and crash occurrence likelihood.

As explained earlier, the hazard ratio reveals critical risk information regarding the contributor's influence to instantaneous crash and severity likelihood. However, as a result of the independent censoring assumption, the significance of the contributors can be under-estimated. For instance, the one risk effect such as a PDO crash might reflect the effect of competing risks such as an injury or a fatal crash. To accurate analysis of contributors' effects on hazard ratio and long-term crash probabilities and also consider competing characteristics of crash severity levels the cumulative-incidence-based effect analysis should be conducted.

3.3.2. Cumulative Likelihood Estimation

Hazard ratio is a direct isolated influential indicator to a specific failure event like crash occurrence in this study. The isolated influential effect is not able to consider the same contributor's impact on other competing events. Consequently, it causes the underestimating of the covariate's impact when HR estimations are applied for analyzing the marginal likelihood of cause-specific events considering the competing nature of multiple causes to the same event of interest. In addition, according to Dignam et al. (2012) Such analysis results might be very sensitive to different modeling approaches and quantify different contributing effects.

Evaluating contributors' long-term robust influence is one of the advantages that the competing risk model can provide. Wolbers et al. (2014) verified and showed that a covariate which has not a significant effect on the risk of a competing-event failure based on the results of cause-specific hazard function, but it still might indicate a significant impact on cumulative incidence function (cumulative risk probability) of the competing event. Subsequently, a covariate, which has no direct effect on one specific type of failure event, might still significantly effect on the cumulative probability (CIF) of that failure event. The marginal probability of a specific failure event can be estimated by its cause-specific probability and the overall cumulative survival probability (S(t)). Calculating cumulative probability of the failure events depends on HR for both the event of interest (crash occurrence) and the competing events (PDO, injury, and fatal crashes) based on the estimation of cumulative incidence function and Equation (10).

In this study, two contributors of "train service" and "train detection" are selected to perform the cumulative probability analysis due to the fact that they are ranked as the top impact factors for PDO, injury, fatal crashes and crash occurrence likelihood based on Table 9 information. In addition, the two-sample t-test method is applied to estimate the significance of contributors' effects on the cumulative probability for crash occurrence and each crash severity level.

Predicted cumulative crash probabilities of each crash severity level are calculated based on Equation (9), and Equation (10). To quantify the change in predicted cumulative probability by changing train service types, two subsamples are generated: one sample with freight train service only and the other one with intercity passenger train service only. The rest of the contributors' values are controlled at a fixed level, mode value. Figure 7 shows the 29-year predicted cumulative crash severity and crash occurrence probabilities for "train service" in parts a, b, c, and d respectively. In addition, Figure 7 represents the same cumulative probability results for the train detection system.

Figure 6 indicates that the cumulative crash probabilities have an increasing trend over time at different rates and with fluctuations. In general, grade crossings with intercity passenger train service are more likely to have all severity and crash occurrence risks except for injury risk in comparison with the crossings with freight train services. Figure 6 shows that the overall increase in cumulative PDO crash probability is faster than the injury and fatal crash probability for both types of train service. In addition, Figure 6, part c reveals that the absolute magnitude of the increasing rate is also small between the freight and intercity services, but the increased fatal probability proportion is almost doubled for HRGCs with intercity passenger train services in comparison with HRGCs with freight train services.

Figure 7 reveals that grade crossings which are equipped with DC systems have reduced crash probability for all crashes with all severity levels. However, grade crossings with CWT systems are more likely to have crashes including fatal, injury and PDO crash compared to crossings with no detection systems (None). It should be noted that the differences in absolute probability are all very small and about 0.1%. Figure 7, part c indicates that the fatal crash probability is more than doubled (on average 224% over 29 years) for crossings equipped with CWT detection system in comparison with crossings without detection system (None). In addition, part c shows that grade crossings with DC train detection are less likely (on average 79% over 29 years) to have fatal crashes compared to the crossings without any automatic detection system.

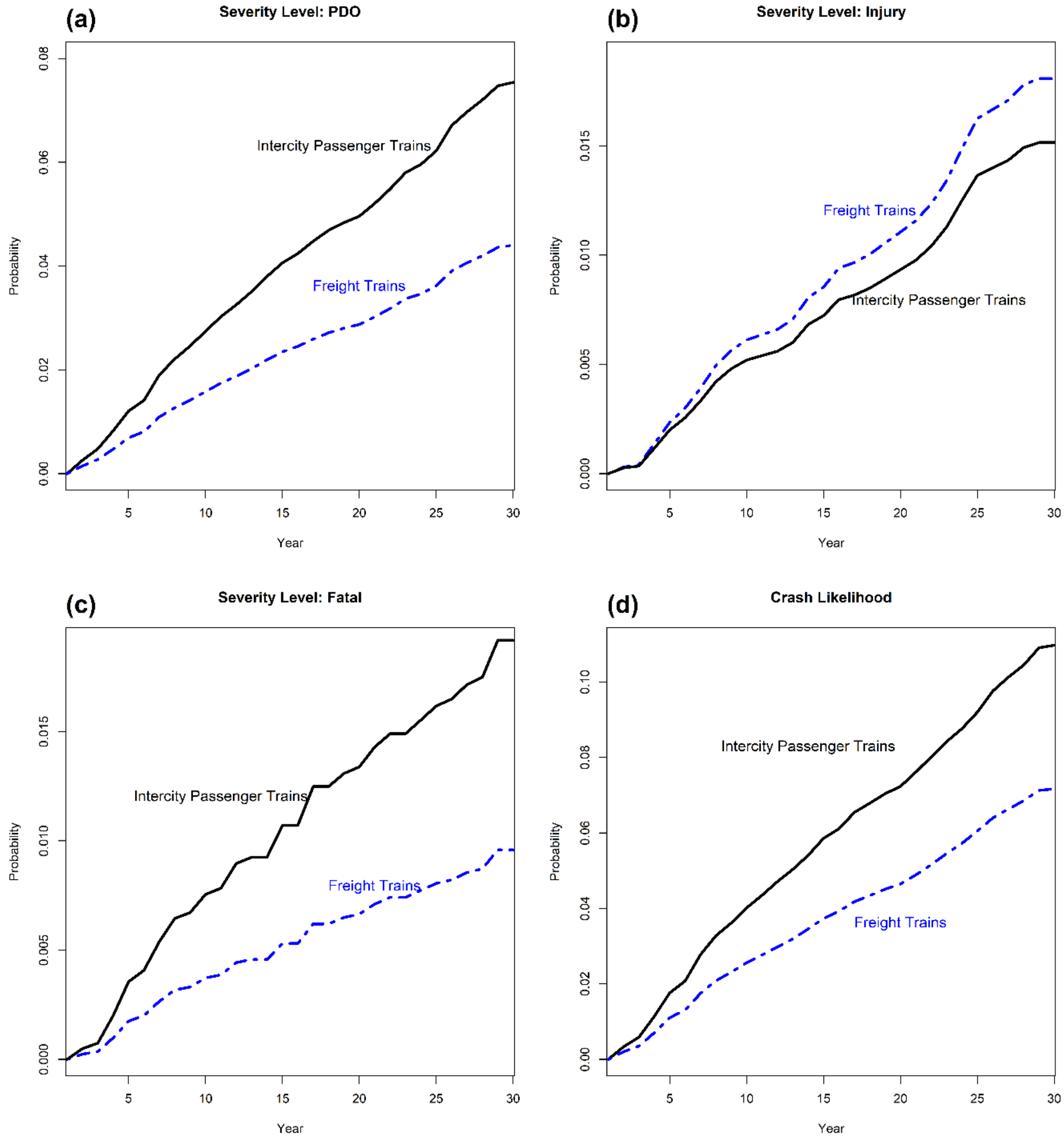

Figure 6. Estimated CIF of Crash Severity and Crash Occurrence for Train Service

The CWT results might be counterintuitive. The application of train detection warning systems is warning crossing users of an approaching train through certain automatic train detection approaches. In terms of the DC system, the current flows from a battery through a fixed rail segment to the coil of a relay. The battery and relay locations define the location of the warning-trigger rail segment. The DC approach uses the rail as an energy conductor. When a train enters the track segment, the axles short/shunt circuit which activates the crossing warning system to warn crossing users of an approaching train. This approach generates a warning according to the track occupation status, which has a fixed predefined distance from the crossing, usually between 1500 to 2000 feet.

The CWT system is a smart technology which is able to identify the speed and location of an approaching train. Therefore, it is able to forecast the train arrival time at the grade crossing. With the CWT system at a grade crossing, a warning signal is activated to intentionally to generate a constant pre-selected warning time which is around 25 seconds. So, for a train with lower speed, the distance between the train and the HRGC could be closer than for a faster-moving train. However, a CWT system cannot calculate a variation in speed accurately which causes variability in the actual warning time. For instance, if a CWT system forecasts the time of warning-activation for a slow train and then the approaching train accelerates towards to the crossing, it will result in a less-than-desired warning time. This might be the main reason that crossings with CWT systems are more likely to have collision.

Table 10 summarizes the two-sample t-test results and the average annual likelihood increasing rates over the 29-year analysis period. To apply the two-sample t-test, the average annual crash likelihood increasing rates associated with all grade crossings' records in the study database are calculated based on their cumulative incidence. The test is applied for the selected categorical covariates for each group level.

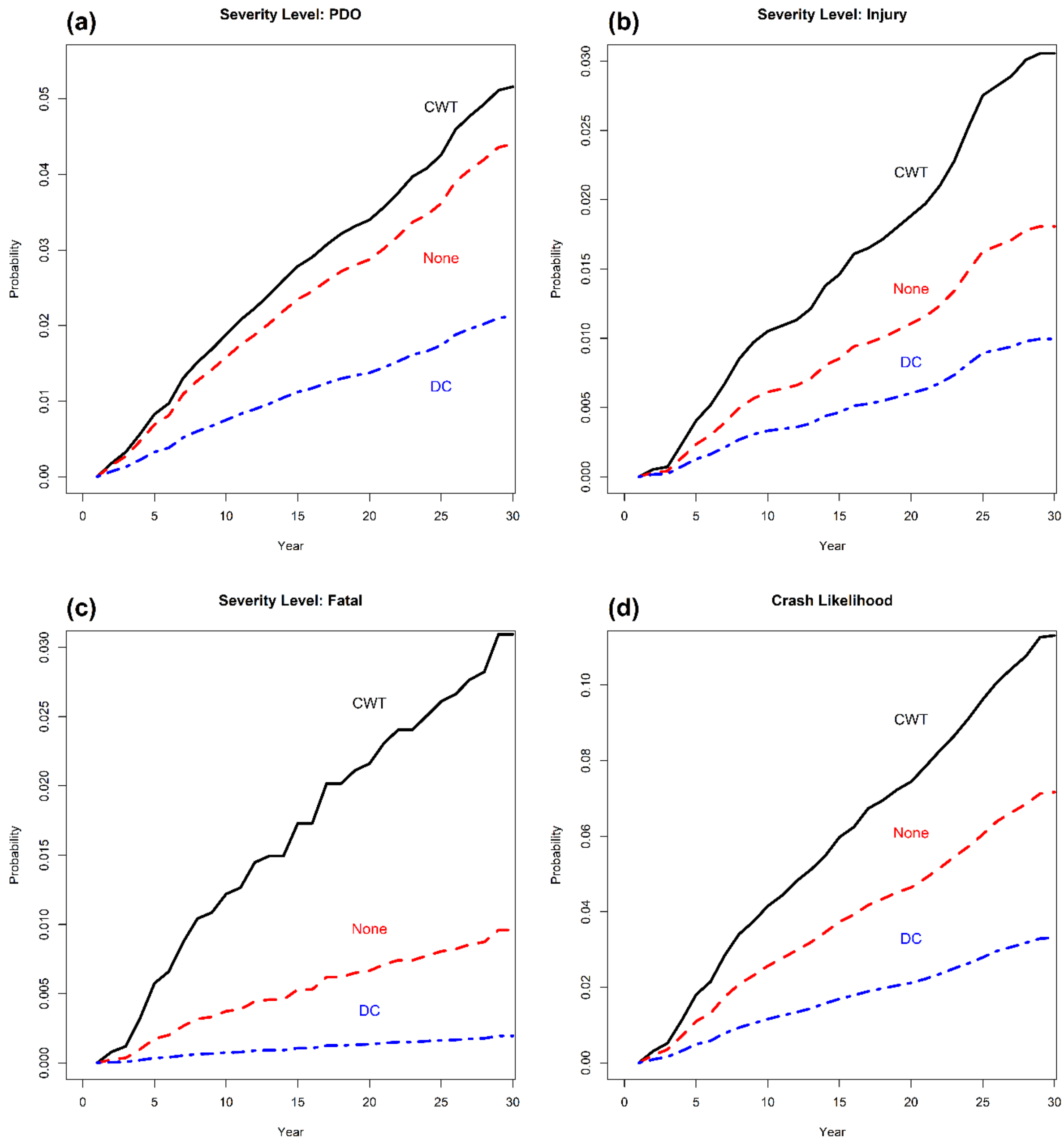

Figure 7. Estimated CIF of Crash Severity and Crash Occurrence for Train Detection

Table 10 indicates that on average, PDO crash probability increased about 0.26% each year for grade crossings with intercity passenger train service compared to 0.152% for crossings with freight train services. On average, the likelihood of PDO crash occurrence at crossings with passenger train service increases about 0.108% each year which is around 71% increase in comparison with freight train service category. The applied t-test (Table 10) indicates that the train service change is able to significantly impact PDO crash probability at a 99% significance level.

Table 10. Average Crash Probability Change for Train Service and Detection System

Variables	PDO% and Change		Injury% and Change		Fatal% and Change		Crash% and Change	
Train Service								
Freight	0.15	NA	0.06	NA	0.03	NA	0.247	NA
Intercity Passenger	0.26	0.11*** 71%	0.052***	-0.01 -16%	0.07***	0.033 100%	0.38***	0.13 53%
Train Detection								
None	0.152	NA	0.062	NA	0.033	NA	0.25	NA
CWT	0.18***	0.03 17%	0.11***	0.043 69%	0.11***	0.074 224%	0.39***	0.14 58%
DC	0.07*	-0.08 -52%	0.034***	-0.028 -45%	0.01***	-0.03 -79%	0.12***	-0.13 -54%

On the one hand, Table 8 indicates that grade crossings with intercity passenger service did not have a significant influence on instantaneous injury crash risk compared to crossings with freight train services regardless of competing risks. On the other hand, grade crossings with intercity passenger service were identified as significant to cumulative injury probability (CIF) compared to the ones with freight train services when considering competing risks. The similar result is observed for CWT detection approach for PDO accidents and for DC approach for injury and fatal accidents. As mentioned before, the estimated coefficients and HRs as the outputs of cause-specific hazard function are based on the independent censoring assumption. Accordingly, cause-specific hazard function outputs are based on estimating each severity level's coefficient and HR separately.

CIF is able to define whether a specific crossing is at risk of one of the crash severity levels (e.g. fatal) might also be at the risk of other crash severity levels (e.g. PDO or injury). In other words, CIF output is free of any assumption of events independency. Correspondingly, the significance difference between the Table 10 and Table 8 results is rooted in dependence of contributors' impact on competing events which are severity levels in this research.

3.3.3. Section Summary

The competing risk model as a novel prediction model was proposed to examine crash frequency and severity simultaneously for public highway-rail grade crossings in North Dakota from 1990 to 2018. The competing risk model has the capability to identify specific crossings' characteristics and to simultaneously model collision occurrence and crash severity probabilities. Easy-to-interoperate outputs are one of the advantages of the model. These outputs include the estimated coefficients, hazard ratios, and cumulative probabilities. Moreover, the model indicates its ability to take into account the dependence of contributors' effects on crash severity levels. The most striking observation to emerge from the competing risk model was:

1) Type of train service, train detection system, availability of commercial power, roadway surface condition, train traffic volume, highway/roadway traffic volume, train speed, truck percentage, and number of traffic (road) lanes are all identified as having significant effect on crash occurrence likelihood.
2) HRGCs with passenger train services are more likely to have PDO crashes compared to grade crossings with freight train service, but in terms of instantaneous injury and fatal crash probability, they did not perform differently. Crossings with higher night train traffic volume are more likely at fatal crash risk and are less likely to have PDO and injury crashes.
3) In contrast with night train traffic which significantly affected all three crash severity levels, the rest of the contributors have direct cause-specific effects on certain crash severity levels (one or two severity levels), but not on all of them.

4) CWT train was identified as a significant contributor according to cumulative probability perspective which considers the assumption of competing risk dependency.
5) Based on CIF results, the annual PDO crash probability increase is 0.108% in terms of grade crossings with passenger train service in comparison with crossings with freight train service, which accounts for around 76% of the increase. The reduction in annual fatal probability growth rate is 0.033% for HRGCs with passenger train service compared to freight train service. Furthermore, HRGCs with DC detection systems have lower crash likelihood growth rates in comparison with crossings without detection system. Instead, crossings equipped with CWT detection systems are more likely to have crash occurrence likelihood compared to those with no detection systems.
6) Finally, HRGCs with freight train service have around a 0.131% reduction in the average annual growth rate of crash probability compared to crossings with passenger train service.

CHAPTER 4. GEOMETRIC ANALYSIS OF HIGHWAY-RAIL GRADE CROSSING

4.1. Introduction and Background

There is an extensive literature on identifying safety performance contributors. However, a few studies (Ross D Austin & Carson, 2002; Berg, Knoblauch, & Hucke, 1982) have explored quantifying the effects of geometric features on safety performance at grade crossings. This gap could be rooted in the lack of detailed HRGC geometric measurements (Washington & Oh, 2006). Federal Railroad Administration's (FRA) highway-rail grade crossing inventory dataset is the most commonly used database for grade crossing geometric information. Smallest crossing angle and the distance between HRGC and its nearby signalized intersection are originally continuous numerical covariates. However, the provided values by FRA have been categorized into truncated groups. Accordingly, these two factors are available as nominal variables with 1) three smallest crossing angle levels of 0-29 degrees, 30-59 degrees, and 60-90 degrees; and 2) two distance levels of no greater than 500 feet and greater than 500 feet. According to Ogden (2007), these two geometric features could affect crash frequency at grade crossings because of their potential influence on sight distance and vehicle storage capacity.

Few research has explored these two grade crossing geometric factors' effects on crash frequency and severity levels. However, most research on HRGC safety utilized these geometric factors as nominal covariates in their analysis. For example, Zhao et al. (2018) considered the crossing angle in their study as one the potential contributors associated with pedestrian injury severity levels. In their study, the crossing angle feature was used as a categorical (nominal) variable including two levels (1: less than 60 degrees; 0 otherwise). Furthered more, Haleem (2016) investigated the effects of distance to the nearby (nearest) intersection with 4 levels (≤ 75 ft.; 75 ft. to 200 ft.; 200 ft. to 500 ft.; and >500 ft.). Their results revealed that those geometric features are not significant in both proposed models. Yan et al. (2010), Liu and Khattak (2017), and Oh et al. (2006) also used both variables as nominal variables with various different levels in their study and found that they are not always significant factors to grade crossing crash frequency or crash severity.

A few studies also explored the impact of some other grade crossings' geometric features in their crossing safety analyses (Ross Duane Austin, 2000; Liu & Khattak, 2017; Oh et al., 2006; Yan et al., 2010). Yan et al. (2010) explored that the number of traffic lanes has a significant effect on crash rate based on the negative binomial (NB) model results but not with the results of the hierarchical tree-based regression (HTBR) model, but the number of main tracks is significant in both models. In addition, Liu and Khattak (2017) indicated that the number of traffic lanes has a significant effect on crash injury severity while the number of tracks does not. Their results also revealed that the number of tracks has a strong association with gate violations.

Previous related studies have examined grade crossing geometric factors that significantly impact safety performance. In this chapter, the proposed competing risk model (CRM) is applied to identify contributing geometric factors and calculate their effects on grade crossing crash frequency and severity probabilities. Correspondingly, the aims of this chapter are 1) investigating the crossing geometric factors' significance on safety performance considering both crash severity and crash occurrence in the same model (CRM), and 2) calculating geometric factors' instantaneous and long-term effects on grade crossing safety performance.

4.2. Result Analysis

This study identifies HRGC geometric features' significance and their estimated instantaneous effects and long-term time effects on crossing crash occurrence and crash severity likelihoods based on North Dakota data. Detailed results are presented in this section.

4.2.1. Estimated Coefficients and Hazard Ratio

According to the Equation (3), estimated HR ($exp(\beta_k^\top Z)$) indicates contributors' instantaneous crash/severity probabilities while estimated coefficients (β_k) quantified the contributors' significance in effects on HR. Table 11 reveals estimated geometric factors' coefficients (Coef) for each severity level and crash occurrence frequency. According to CRM cause-specific function output, all the geometric factors listed in Table 11 are identified as significant contributors to at least one level of crash severity or to crash occurrence.

Table 11. Geometric Factors' Estimated Coefficient and Hazard Ratio

Geometric Factors	PDO		Injury		Fatal		Crash Occurrence	
	Coef	Pr(>|z|)	Coef	Pr(>|z|)	Coef	Pr(>|z|)	Coef	Pr(>|z|)
Crossing-Intersection Distance	-0.001	0.024 **	-0.00006	0.87	0.0005	0.32	-0.0005	0.13
Acute Crossing Angle	-0.003	0.48	-0.01	0.02 **	0.004	0.63	-0.005	0.01 *
Number of Road Lanes	0.38	0.054 *	0.20	0.37	-0.07	0.88	0.30	0.03 **
Number of Main Tracks	0.44	0.45	1.80	0.03 **	1.79	0.11	0.93	0.03 **

Table 11 shows that except the distance to a nearby intersection, all geometric factors are identified as significant contributors for crash occurrence. Hazard-ratio results will provide detailed information to calculate each geometric factor's impact on the crash frequency and severity probabilities. It should be stressed that Table 11 indicates some geometric factors which have a significant impact on the likelihood of certain crash severity levels, but not on others. As mentioned earlier in Chapter 3, these results can be a consequence of under-estimation because of the independent censoring assumption in cause-specific function.

Table 12 represents the detailed HR results for all four geometric features, and their crash probability changes are estimated as "%impact".

Table 11 shows that the distance between a crossing and the closest signalized intersection is only found positively significant in PDO crash, but not the other crash types. Moreover, according to Table 12, distance between a crossing and the closest intersection increases PDO crash likelihood by 0.11% compared to each one-unit increase in this distance. Smallest (acute) crossing angle was found to negatively affect both injury and crash occurrence probabilities. In addition, for each one-unit increase in acute crossing angle, the crash likelihood is reduced 1.05% and 0.48% for injury and crash occurrence, respectively. Table 12 reveals that the number of road (traffic) lanes is found to positively affect PDO and crash occurrence. With an increase of one traffic lane, the impacts increase about 45.65% and 34.51% for PDO and occurrence, respectively. Similarly, number of main tracks is also found to positively impact injury and crash occurrence risk. The calculated HRs are 6.06 (505%) and 2.53 (152%) for injury and crash occurrence probabilities, respectively. Interestingly, the results reveal that the number of main tracks is considerably associated with increases in injury and crash occurrence risks.

Hazard ratio analyses do not yield direct information about the magnitude of geometric factors' effects on collision risk and severity. HR results only represent the relative crash/severity probability directional proportion changes with one-unit increase in the corresponding geometric feature. To fully understand and interpret geometric factors' marginal effects with taking into account the competing risk characteristics of severity levels and cumulative long-term time effects, the proposed cumulative incidence-based effect analysis is employed in the next section.

Table 12. Geometric Factors' Hazard Ratio and their Marginal Effects

Variable	PDO		Injury		Fatal		Crash Occurrence	
	%impact	HR	%impact	HR	%impact	HR	%Impact	HR
Crossing-Intersection Distance	0.11	1.00	0.006	1.00	0.05	1.00	0.05	1.00
Acute Crossing Angle	0.268	0.997	1.05	0.99	0.36	1.004	0.48	1 .00
Number of Road Lanes	45.65	1.46	22.41	1.22	6.34	0.94	34.51	1.35
Number of Main Tracks	54.69	1.55	505.56	6.06	496.21	5.96	152.63	2.53

4.2.2. Cumulative Likelihood Estimation

According to Wolbers et al., (2014) if a geometric factor as a contribute has no direct influence on certain severity level as a failure event, but influences another severity level, then the geometric factor may still be significantly associated with the cumulative probability (CIF) of the specific severity level and identified as a significant contributor.

In this section, we focus on the four geometric factors to perform the cumulative incidence function analysis. To calculate marginal cumulative probabilities for each geometric factor in 2018 (Year 29), the cumulative probability of each severity level ($CIF_k(t = 29|Z)$)and crash occurrence ($CIF_c(t = 29|Z)$) is calculated at a specific value while all other contributors are controlled at a fixed level, mode value. The range of values for each geometric feature is defined based on the actual data information used in this study. Distance range between a crossing and the nearest intersection is defined from 0 meters to 3,000 meters. Acute crossing angle ranges from 1 degree to 90 degrees. Number of roadway lanes ranges from 1 to 4. And the number of main tracks ranges from 1 to 3. Figure 8 indicates the calculated cumulative probability and its trends for each geometric factor.

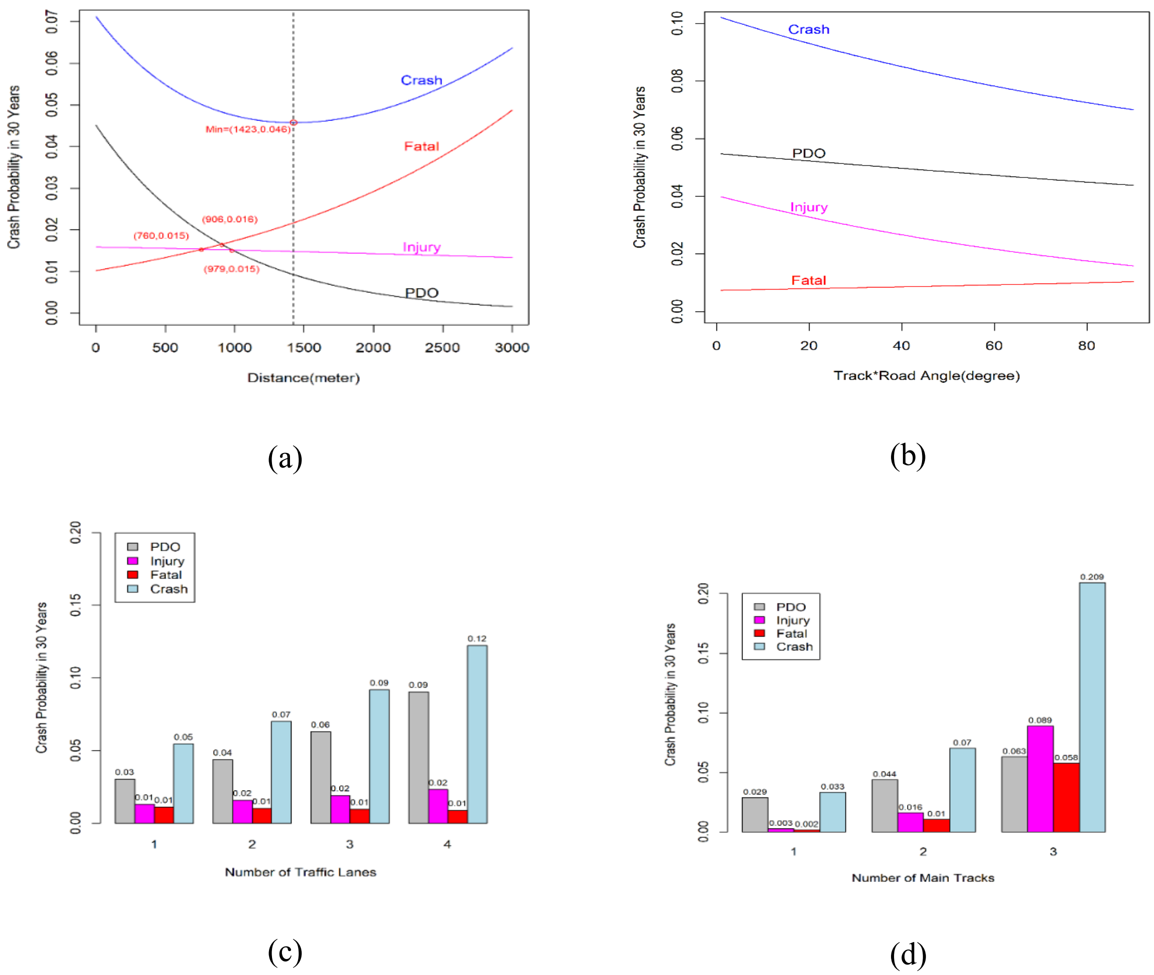

Figure 8. Cumulative Crash/Severity Probability in 2018 for Geometric Factors

Figure 8, part (a) reveals a quadratic relationship between cumulative crash probability and the distance between a crossing and the closest intersection. The trend indicates that the crash likelihood decreases from around 7% to about 4.6% as the distance increases from 0 to 1,423 meters. The crash occurrence probability then increases to around 6% while the distance to the nearest intersection increases to 3,000 meters. The distance between a crossing and the closest intersection can define vehicle storage capacity. According to Figure (8), part (a), the crash likelihood can be declined before reaching 1,423 meters, with the vehicle storage capacity increasing. On the other hand, when the distance to the intersection is more than 1,423 meters, the benefit of a larger capacity of vehicle storage will be hindered by a highway user's sight distance limits. The Railroad-Highway Grade Crossing Handbook (RHGCH) verified the minimum safe sight distance must be between 21 to 284 meters to guarantee safe stopping distances at various travel speeds (Ogden, 2007; Ogden & Cooper, 2019).

This study results suggest a substantially longer distance, 1,423 meters, when taking into account traffic operational effects with the nearest roadway intersection. From Figure 8, part (a), it can be noted that cumulative injury and POD probability have constant reduction as the distance to the intersection increases. Instead, cumulative fatal crash likelihood constantly increases as the distance increases. While the change is relatively high for probability of the PDO and fatal accidents compared to injury crashes, Figure 8 results represent that distance to intersection has a relatively smaller impact on injury than on PDO and fatal accident cumulative likelihood. It should be noted that the distance to nearest intersection positively impacts on the fatal accident probability, but negatively impacts on PDO probability. One reasonable explanation can be that better travel conditions might promote aggressive driving behavior and cause more severe crash consequences.

Figure 8, part (b) indicates that crossing angle has a negative effect on probabilities of crash occurrence, PDO, and injury crashes. In other words, the cumulative probabilities of crash, PDO, and injury crashes decrease while the acute crossing angle increases. One possible explanation for this result might be related to improved sight lines. According to Wigglesworth (2001), at acute-angled crossings, it may be difficult for highway users to detect a train while it is approaching from one of the rear quadrants. It increases the risk of an "over-the-shoulder" accidents. On the other hand, with the increasing crossing angle, the fatal crash likelihood increases moderately, from about 0.8% to 1%. This increase might be due to the fact that improved travel conditions might promote aggressive driving behavior.

Figure 8, part (c) reveals that the number of traffic lanes has substantially less impact on both injury and fatal crash likelihoods compared to the positive impacts on the likelihoods of PDO crashes and crash occurrence. As the number of traffic lanes increases from 1 to 4, crash likelihood increases from about 5% to 12%. Figure 8 part (d) shows the number of main tracks reveals a strong impact on all crash severity levels and crash occurrence likelihoods. Crash likelihood increases dramatically from 3.3% to around 21% as the number of rail tracks increases from 1 to 3. A similar increasing pattern for all three crash severity levels exists. Moreover, fatal crash likelihood considerably increases from 0.2% to 5.8% as the number of rail tracks increases from 1 to 3 which is 2,800% increasing.

As can be seen from Figure 8, all four geometric features have non-linear impacts on the cumulative crash/severity likelihood. To expresses these geometric features' average marginal impact as a proportion, change in crash/severity likelihood for one unit change in a contributor, Table 13 presents the estimated results.

Table 13. Average Marginal Probability Change

Severity Level	Crossing Angle	Distance to Intersection	Number of Road Lanes	Number of Main Tracks
PDO	-0.01%	-0.0014%	44%	48%
Injury	-0.03%	-0.00008%	21%	443%
Fatal	0.0033%	0.0013%	7%	440%
Crash	-0.036%	-0.00025%	31%	155%

Table 13 indicates that on average, one-degree increase in crossing angle results in around 0.01% decrease in PDO likelihood, a 0.03% decrease in injury likelihood, a 0.0033% increase in fatal crash likelihood, and a 0.036% decrease in crash occurrence likelihood. Distance change is in the unit of one meter. It should be noted that the change in marginal likelihood percentage only represents the average change within a geometric features' value range.

CHAPTER 5. COUNTERMEASURES EFFECTS ON HIGHWAY-RAIL GRADE CROSSING SAFETY PERFORMANCE

5.1. Introduction and Background

Several studies and research projects have focused on the effect of traffic control devices (e.g., crossbuck signs, gates, stop signs, etc.) on grade crossing safety outputs (Carroll, Lee, Haines, & Hellman, 2002; Eluru et al., 2012; FHWA, 2009; Haleem, 2016; Heathington, Fambro, & Richards, 1989; Kim et al., 2002; Jinsun Lee et al., 2004; Lerner, 2002; Liu & Khattak, 2017; Liu et al., 2015; Noyce & Fambro, 1998; Ogden & Cooper, 2019; Siques, 2002; Washington & Oh, 2006; Yan et al., 2010; Zhao et al., 2018). Haleem (2016b) applied the mixed logit and binary logit models to investigate the significant traffic causality covariates at private grade crossings. The research results revealed that relatively busy private HRGCs with higher frequency of injury and fatal accident records must be equipped with active warning devices including gates and flashing lights. Liu and Khattak (2017) proposed a spatial analysis of HRGC accidents by applying an approach which integrated path analysis and geo-spatial model. Their results showed that the likelihood of a gate violation resulting in a grade crossing accident can be associated with variables such as the presence of two or three quadrant gates, higher train speeds, and male drivers.

Moreover, Liu et al., (2015) also applied path analysis to analyze indirect impact of crossing warning devices on crash severity level changes. Their results indicated that there is not a strong (significant) direct association between crossing warning devices and crash severity changes. On the other hand, their findings express that there is a significant correlation between the type of crossing waring device and pre-crash behaviors and also between pre-crash behavior and crash severity. Eluru et al., (2012) used a latent segmentation-based ordered logit model to investigate the several contributors' effects on crash severity at grade crossings. Their results showed that low-risk crossing segments are defined by higher train traffic, roads with lower road classifications, pavement markings instead of stop signs, and the absence of permanent structures including gates, stop signs, etc. Washington and Oh (2006) verified and applied the formalization and application of the approach to rank 18 types of countermeasures (including gates, stop signs, etc.) from "best" to "worst." Their results revealed that the top three safest warning devices are in-vehicle warning systems, obstacle detection, and constant warning time. Yan et al., (2010) proposed the hierarchical tree-based regression model as a nonparametric method to forecast the annual crash rate at passive crossings with crossbucks sign-only or stop-sign-only. Their results indicated that the AADT has the most impact on crash rate prediction associated with crossings with crossbucks sign-only, while the daily train traffic is the most effective contributor for crossings controlled by a stop sign.

All these findings have shed light on understanding the effect of specific crossing warning devices on either crash rate or severity levels. However, these research have not accounted for 1) the impact of modifying the crossing controls' combination on crash frequency and severity changes considering different pre-improvement control conditions (pre-improvement condition difference), and 2) the long-term time impact of HRGC warning device improvements on crash frequency and severity changes. In addition, grade crossings characteristics including crossing traffic controls might be changed over time, including before and after a collision occurrence (Liu & Khattak, 2017). Correspondingly, estimating crash rate and crash severity level changes need to consider the long-term time effect and record information changes for all crossing's characteristics annually. This study will focus on quantifying countermeasures' effects on crash frequency and severity likelihood in one model, taking into consideration pre-improvement control conditions and countermeasure type change during a long-term analysis period (29 years in this study).

Calculating the long-term effect of countermeasures on crash occurrence and severity probabilities can increase the modeling complexity. Considering this complexity, in this study, the proposed competing risk model (CRM) is applied to investigate the crash occurrence and severity likelihood. More detailed explanations regarding this approach are introduced in the Chapter 3. In grade crossing safety analysis, the target of CRM is calculating the crash occurrence probability considering the crash severity levels (PDO, injury, fatal) as competing risk events. In other words, the CRM function in grade crossing safety analysis can be defined by calculating HRGC crash likelihood during a 29-year span considering the likelihood of crash occurrence with one of three crash severity levels. Moreover, the censoring concept in CRM also results in the consolidation and utilization of all available crossing records including crossings with no crash records, while previous literature only were able to use only crossings accident records as their model input dataset (Eluru et al., 2012; Liu & Khattak, 2017; Liu et al., 2015). By applying CRM, this study investigated 1) countermeasures' significance on both grade crossings' accident severity and crash frequency in the same model, and 2) instantaneous and long-term impacts of crossings' warning devices on crossings safety outputs considering different pre-improvement conditions.

5.2. Result Analysis

5.2.1. Estimated Coefficients and Hazard Ratio

All significant countermeasures' estimated coefficient (Coe) for each crash severity level, and crash occurrence (crash) are indicated in Table 14. The cause-specific regression coefficient is calculated based on Equation (3) (cause-specific hazard model) which shows the corresponding magnitude change in the cause-specific hazard function for each crossing warning device compared to crossbucks-only as the reference.

For crash occurrence likelihood, one can see from Table 14 that all types of crossing control devices (except crossbucks+stopsign compared to crossbucks-only) have positive impacts on crash hazard. Most of the control device impact results met the expectations with current understanding from previous studies (Lenné et al., 2011; Meeker et al., 1997; Millegan et al., 2009; Raub, 2009). The main reason for such results is because it is possible that the active controls are able to better attract a driver's attention and result in greater compliance compared to the passive controls.

Table 14 reveals that Crossbucks and stop sign compared to Crossbucks-only has a positive effect on collisions explaining that adding a stop sign to a crossing which already has a crossbucks-only control can increase the crash occurrence risk. Such results could be rooted in the indiscriminate use of stop signs at passive grade crossings. FHWA established a 10-year crossbuck assembly requirement (stopsign+crossbucks sign) for all passive grade crossings in 2009 (FHWA, 2009). One of the potential rationales for indiscriminate use of the stop sign could be peoples' acceptance and understanding of how to use stop signs correctly before 2009 and after. Table 14 shows that some countermeasures show significant effects on certain crash severity(s) likelihood but not on all three severity levels except two crossing warning devices combination, gates and standard flashing lights and audible, and crossbucks and stop signs. As mentioned earlier, the independent censoring assumption can be the main reason for such under-estimated results. Crossings with gates, standard flashing lights, and audible devices reveal a significant negative impact on all crash severity likelihoods compared to crossings with crossbucks-only. These results are supported by those from previous studies.

Table 14. Coefficient Estimation of Crossing Warning Devices

Countermeasure	PDO		Injury		Fatal		Crash	
	coef	Pr(>|z|)	coef	Pr(>|z|)	coef	Pr(>|z|)	coef	Pr(>|z|)
Gates+CantileverFLS+StandardFLS	-1.56	0.108	-1.41	0.132	-12.71	< 2.2e-16***	-1.62	0.0005***
Gates+CantileverFLS+StandardFLS+Audible	-13.95	< 2.2e-16***	-1.76	0.020**	-1.07	0.249	-2.75	0.000***
Gates+CantileverFLS+Audible	0.51	0.412	-13.73	< 2.2e-16***	-18.33	< 2.2e-16***	-0.59	0.410
Gates+StandardFLS+Audible	-2.10	0.000***	-2.04	0.00***	-2.40	0.000***	-2.22	< 2.2e-16***
Gates+Audible	-12.31	< 2.2e-16***	0.11	0.91	-17.85	< 2.2e-16***	-1.20	0.262
Gates+StandardFLS+Audible*StopSigns	-1.01	0.176	-12.59	< 2.2e-16***	-16.27	< 2.2e-16***	-1.79	0.009***
Crossbucks+StopSigns	0.85	0.007***	1.36	0.00***	1.30	0.016**	1.14	0.000***
Gates	0.03	0.948	-12.65	< 2.2e-16***	-17.98	< 2.2e-16***	-0.75	0.070*
CantileverFLS+StandardFLS+Audible	-1.02	0.222	-13.27	< 2.2e-16***	-18.79	< 2.2e-16***	-1.42	0.049**

For example, Liu et al., (2015) showed that vehicle users are more likely to stop at crossings with gates that also have flashing lights and audible warnings. Their results also indicated that highway users stopping at gates are associated with lower crash severity. On the other hand, in comparison with crossbucks-only, crossbucks and stop signs result in significant positive impact on all crash severities. The potential rational might be the fact that stop signs are among the traffic controls typically used at regular highway/roadway intersections, possibly resulting in confusion among vehicle users at grade crossings (Jeng, 2005).

As indicated earlier in Equation (3), Cox regression coefficient (β_k) represents the corresponding magnitude change in the cause-specific hazard function associated with a countermeasure compared to crossbucks-only as a reference. However, hazard ratio ($exp(\beta_k^{\top} X)$) indicates contributors' instantaneous crash occurrence or severity risk. Table 15 shows the estimated HR for all crash severity levels and crash occurrence for each crossing warning device combination based on Equation (3). In terms of a categorical variable, HR estimates the crossing's relative risk with a specific contributor's value level compared to the reference level. As explained earlier, an HR greater than 1 indicates an increase in hazard risk, and an HR below 1 shows a decline in hazard risk. Percentage change in risk probability for each crossing warning device change compared to the Crossbucks-only (reference level) is estimated as |HR-1|×100 formula and can be seen as "%impact" in Table 15.

Table 15 reveals that all crossing traffic control devices decrease crash occurrence and fatal crash risk compared to crossbucks-only except crossbucks+stopSigns as all of their corresponding HR values are less than 1. Regarding PDO crash likelihood, crossings with Gates+CantilevelFLS+Audible and Gates are more likely to have PDO crash compared to crossings with crossbucks-only. In terms of injury accident likelihood, gates+audible crossings will have higher injury likelihood compared to crossbucks-only crossings. These three estimation results seem counterintuitive. The potential rationale might be related to vehicle users' pre-crash behavior around crossing gates (Ma et al., 2018). Although, they all have a greater-than-1 HR value, all of them are near 1 except for the Crossbucks+StopSign which means they are showing moderately positive effect. Gates for PDO crashes has 3% positive impact which is almost no difference. Gates+Audible for injury crash reveals 12% positive impact. For crossbucks+StopSign combination, this study consistently reveals that adding a stop sign to a crossing that currently has crossbucks-only might increase crash occurrence, PDO, injury, and fatal crash probabilities.

As mentioned above, this might be rooted in the fact that the crossbucks assembly requirement is relatively new and stop signs were typically utilized as a passive traffic control device for roadway intersections rather than HRGCs in the community. Highway users which encounter stop signs normally just need to stop and check for approaching traffic in a limited distance range. However, for grade crossings, the distance to be checked must be much longer to ensure safe operation. Moreover, as stop signs are typically at roadway intersections, their presence at HRGCs may cause vehicle users' confusion (Jeng, 2005). Burnham's (1995) study indicated that only 18% motorists might be alerted to the stop signs and 82% were confused or semi-confused about the stop signs presence at grade crossings.

To accurately investigate the marginal effects of such warning devices, a carefully designed before-and-after comparative analysis is needed. Although, investigating both the estimated coefficient and HR reveals key information, such assessments do not yield direct estimations related to the marginal magnitude of contributors' long-term impact on probability. Consequently, the cumulative incidence function (CIF) analysis is conducted to estimate contributors' marginal effects while considering HRGC traffic control devices' cumulative long-term time impacts.

Table 15. Crossing Warning Device Hazard Ration Estimation

Variable	PDO		Injury		Fatal		Crash	
	Impact	HR	Impact	HR	Impact	HR	Impact	HR
Crossing Control (Reference: Crossbucks-only)								
Gates+CantileverFLS+Audible	67%	1.67	100%	0.000001	100%	0.00000001	45%	0.55
Gates	3%	1.03	100%	0.000003	100%	0.00000002	53%	0.47
Gates+Audible	100%	0.000005	12%	1.12	100%	0.00000002	70%	0.30
CantileverFLS+StandardFLS+Audible	64%	0.36	100%	0.000002	100%	0.00000001	76%	0.24
Gates+CantileverFLS+StandardFLS	79%	0.21	76%	0.24	100%	0.000003	80%	0.20
Gates+StandardFLS+Audible+StopSigns	64%	0.36	100%	0.0000034	100%	0.0000001	83%	0.17
Gates+StandardFLS+Audible	88%	0.12	87%	0.13	91%	0.09	89%	0.11
Gates+CantileverFLS+StandardFLS+Audible	100%	0.000001	83%	0.17	66%	0.34	94%	0.06
Crossbucks+StopSigns	134%	2.34	288%	3.88	267%	3.67	213%	3.13

5.2.2. Cumulative Likelihood Estimation

One of the competing risk model advantages is the estimation of contributors' long-term robust effects. This effect is provided by the estimation of the cumulative probability of the crash severity levels and crash occurrence based on the estimated CIF with equations (5), or (9). In this section, the cumulative probability marginal effects of the ten following combinations of active and passive controls are assessed: 1) gates, 2) gates and audible, 3) gates and standard flashing lights and audible, 4) gates and standard flashing lights and audible and stop signs, 5) gates and cantilever flashing lights and audible, 6) cantilever flashing lights and standard flashing lights and audible, 7) gates and cantilever flashing lights and standard flashing lights and audible, 8) gates and cantilever flashing lights and standard flashing lights, 9) crossbucks (only), and 10) crossbucks and stop signs.

To calculate the cumulative probability marginal effect of each crossing control combination, first predicted CIF_k, and CIF_c for all crossings with and without crash records during the 29-year study period are calculated by using equations (5) and (10), respectively. In the next stage, using Equation (12), the average annual CIF of each severity level (k) is calculated for all CIFs with the same type of crossing control.

$$\overline{CIF_k}(t|x_p) = \frac{\sum_{i=1}^{n} CIF_k(t|x_{pi})}{n} \qquad \text{(Equation 12)}$$

Where, x_p is variable of specific crossing control p and $\overline{CIF_k}(t|x_p)$ is the average CIF for every crossing control p and severity level k. Finally, the marginal countermeasure difference can be estimated by Equation (13):

$$D_{k,p-q}(t) = \overline{CIF_k}(t|x_p) - \overline{CIF_k}(t|x_q) \qquad \text{(Equation 13)}$$

Where, $D_{k,p-q}(t)$ is the marginal effect of changing crossing control q to p for severity level k at year t.

Figures 9 and 10 show the 29-year prediction of cumulative crash severity and occurrence likelihoods by comparing eight pairs of crossing control devices and their combinations. The alternative options are compared by adding a specific device into a device or combination of devices as a base option, except for Figure 9 (a). In Figure 9 (a), the base case is crossbucks-only and the alternative option is upgrading the control device to gate-only.

Figure 9 (a) reveals that upgrading from passive control device to active control will likely to decrease injury and fatal crash probability. Instead, this switching will increase both crash occurrence and PDO probabilities. These findings seem counterintuitive as it is normally expected to improve safety performance in crash occurrence and in all severities if a change is made from passive control to active control. However, the result reveals that changing the control device from gate to crossbucks only as effects on more severe crashes (fatal and injury crashes) but does not decrease PDO accidents and crash occurrence in general.

Figure 9, part b shows that adding gates to the combination of crossings equipped with cantilevered flashing lights, standard flashing lights, and audible warnings, will decrease both crash occurrence and PDO probabilities, but will increase injury and fatal crash likelihood. In other words, upgrading crossings already equipped with flashing lights and audible devices will only decrease the likelihood of crash occurrence and PDO crashes but will not decrease the more severe crash likelihood. Similar results are found in the previous studies. Gates were found to decrease the crash rate as they generate physical barriers and cause a decline in the probability of vehicle-train collisions (Austin and Carson, 2002; Elvik et al., 2009; Ogden, 2007; Ogden and Cooper, 2019; Park and Saccomanno, 2005; Raub, 2009).

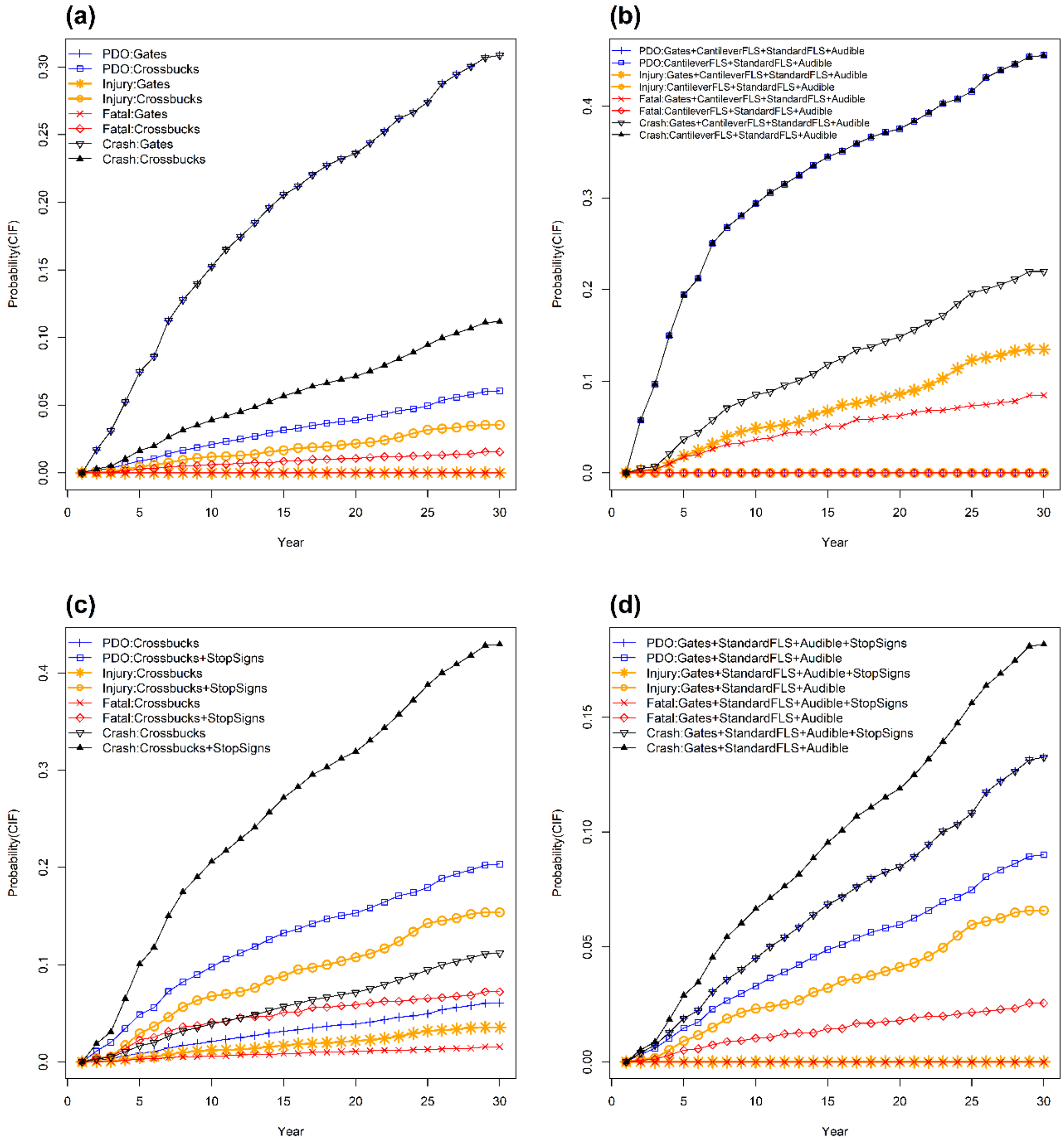

Figure 9. Crash Severity and Frequency Likelihoods for the First HRGC Control Pairs

Alternatively, because of some drivers' pre-crash aggressive behavior (e.g., going around gates, and gate-violations) might also result in more severe crash occurrences. Consequently, some previous studies' findings revealed that the gated crossing accidents are associated with higher likelihood of more severe crashes (Cooper & Ragland, 2012; Raub, 2009).

Figure 9, part c shows that adding stop signs to crossings with crossbucks will considerably increase the crash occurrence and severity likelihood. This results are consistent with previous coefficient and hazard ratio investigations. These likelihoods are increased significantly by 284%, 235%, 333%, and 364%, respectively (annually). On the other hand, Figure 9, part d indicates that adding stop signs to actively controlled crossings will decrease crash occurrence, injury, and fatal crash probability. Instead, PDO, a less severe crash likelihood, is increased cumulatively by 47% in the 29-year study period. These results are in line with previous studies' findings (Bezkorovainy & Holsinger, 1966; Burnham, 1995; Russell & Burnham, 1999; Sanders, McGee, & Yoo, 1978). For example, according to the Lerner (2002), widespread use of stop signs may result in a negative impact on other passive crossing controls safety operation (i.e., crossbucks or yield) as their use might reduce the credibility of passive crossing controls. It should be noted that this study finding reveals that adding stop signs to crossings with crossbucks-only will have negative effects on crash occurrence and all severity crashes, but adding a stop sign to an already actively controlled crossing will have additional positive effects on decreasing crash occurrence and more severe crashes. In addition, it has a negative effect of increasing the likelihood of less severe crashes such as PDO.

As can be seen from Figure 10, part a, adding audible devices to crossings with combination of gates, cantilevered flashing lights, and standard flashing lights will decrease crash occurrences and PDO crashes by 16% and 100% respectively annually. Doing so will also result moderately decrease injury crash likelihood between years 4 and 25, and shows no effect on injury crash probability for the rest of the study period. These results are expected as the presence of audible devices warns highway users approaching the crossing (Haleem & Gan, 2015). However, this type of crossing control upgrade could considerably increase the fatal crash likelihood which is counterintuitive.

Figure 10, part b shows adding an audible device to crossings already had gates will decrease PDO and fatal accidents to nearly zero. Moreover, such improvement will decrease crash occurrence by around 24% cumulatively during the 29-year study period. However, in this research, adding bells as an audio device at HRGCs equipped with gates and flashing lights will increase injury crash probability. These results differ completely from previous studies' findings. The Federal Railroad Administration (2011) research findings revealed that driving around or through the gates is more likely to happen at HRGCs with gates and flashing lights without bells, which suggests intentional trespassing behavior. On the other hand, Liu et al. (2015) suggest that there is a higher possibility of driving around or through the gate at HRGCs with gates and audible warnings compared to those with gates only. It might be that such conflicted findings are not in conflict. Increased trespassing behavior with bells might be the trespassing that tends to result in injury accidents.

Figure 10, part c, reveals that adding standard flashing lights to crossings with gates, cantilevered flashing lights, and audible devices, will result in reduce in PDO crash and crash occurrence but will result in increases in injury and fatal crashes. Adding standard flashing lights as supplemental flashing light signals or side lights at the HRGCs with cantilevered flashing lights will increase the visibility of the crossing, thus making a higher number of highway users aware that they are approaching a crossing or that a train is approaching. Accordingly, it can be expected that crash rate (frequency) will decrease (Ogden and Cooper, 2019). According to flashing lights' negative impact on more severe crashes, one possible explanation might be associated with acute angles. Guided by the traffic control device installation manual grade crossings equipped with additional pairs of light units need to be directed toward vehicular traffic approaching the HRGC from highway routes closely adjacent to and parallel to the railroads.

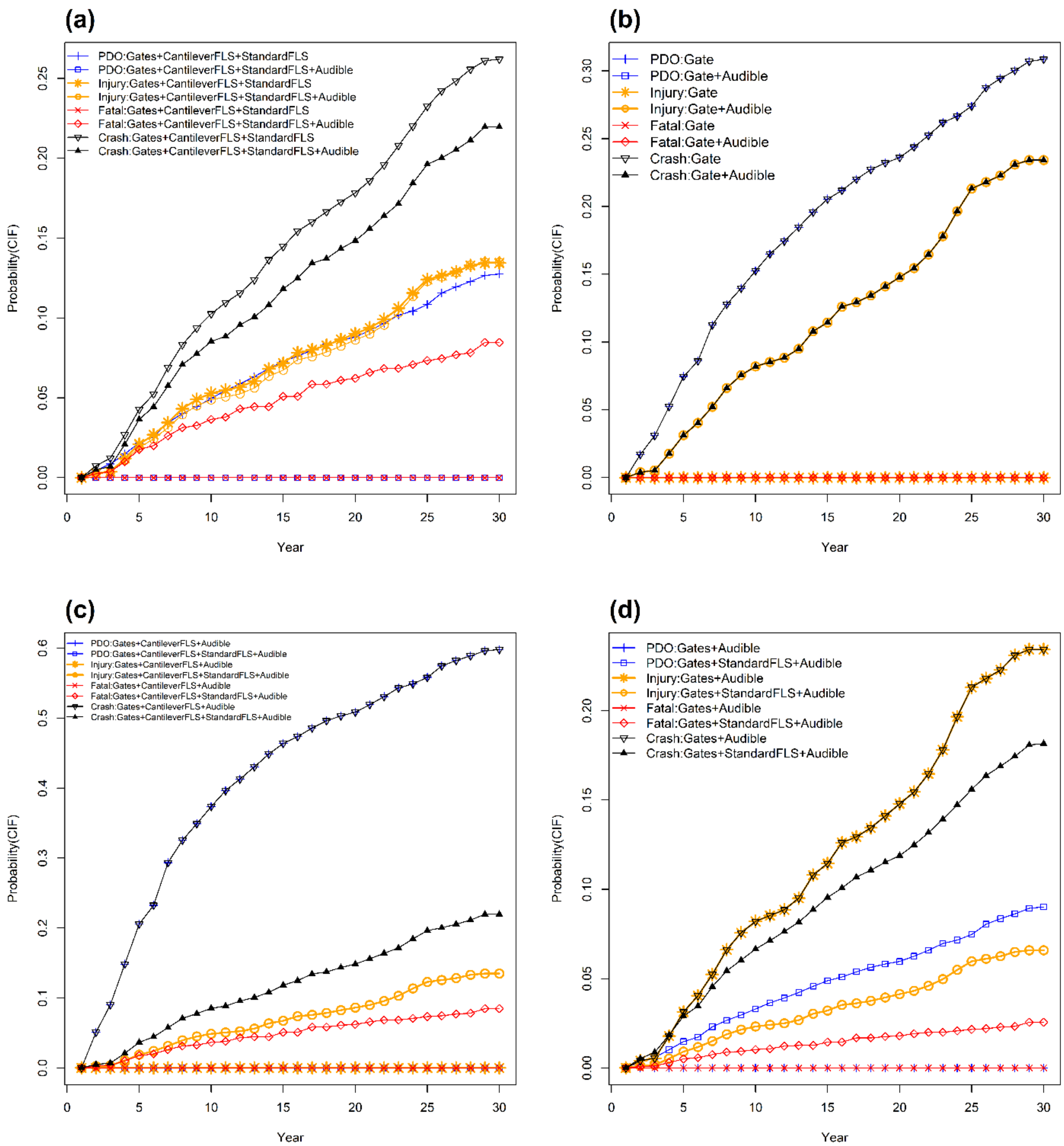

Figure 10. Crash Severity and Frequency Likelihoods for the Second HRGC Control Pairs

Such structure can generate an acute angle between the railway track and the highway at HRGC (Ogden and Cooper, 2019). Previous studies (Ross Duane Austin, 2000; A. Keramati et al., 2020; Liu & Khattak, 2017; Oh et al., 2006; Wigglesworth, 2001; Yan et al., 2010; Zhao et al., 2018) all confirmed that acute crossing angles are associated with higher levels of crash severity. Correspondingly, it is expected that crossings with standard flashing lights installed as additional warning lights are more likely to have more severe crashes.

Figure 10, part d, shows that adding standard flashing lights to crossings with the combination of gates and audible devices will reduce crash occurrence and injury likelihoods but will increase PDO and fatal crash probabilities. Lenné et al. (2011) indicates that the mean vehicle speed on approach to the HRGCs can be decreased faster in response to flashing lights compared to traffic signals. Accordingly, crash occurrence rate is expected to be decreased. Although adding flashing lights to crossings with a combination of gates and audible devices increases the crossings' fatal and PDO crash risk, the difference is small, both less than 0.1%.

To facilitate quantifying such marginal effects and to better illustrate the control devices' upgrading impacts, Figure 11illustrates a chart which summarizes the calculated marginal effect of each crossing control change. In other words, Figure 11 provides summary information of Figures 9 and 10 by estimating the average annual absolute crash likelihood changes.

One can see from Figure 11 that switching the crossing control device to gates from crossbucks-only will likely decrease injury likelihood on average by 0.12% and reduce fatal crash likelihood on average by 0.05%, each year. Instead, the PDO crash likelihood will increase by 0.83% annually. Installing a gate at a crossing already having flashing lights and bells will significantly reduce PDO likelihood by 1.52%, but will increase the injury and fatal crash probability by 0.45% and 0.28% respectively. Adding stop signs to crossings with crossbucks signs will increase the crash occurrence likelihood for all three levels, and adding stop signs to a crossing already actively controlled will reduce the overall crash rate, but will increase PDO risk by 0.14%. Adding audible warning devices to a crossing already actively controlled will decrease the crash rate but will moderately increase more severe crash risk. Moreover, adding audible warning devices to a crossing which is actively controlled by the gate only leads to decrease the crash occurrence likelihood by 0.25%, but increase the injury risk by 0.78%. Finally, adding standard flashing lights to crossings which are actively controlled leads to decrease in crash occurrence likelihood.

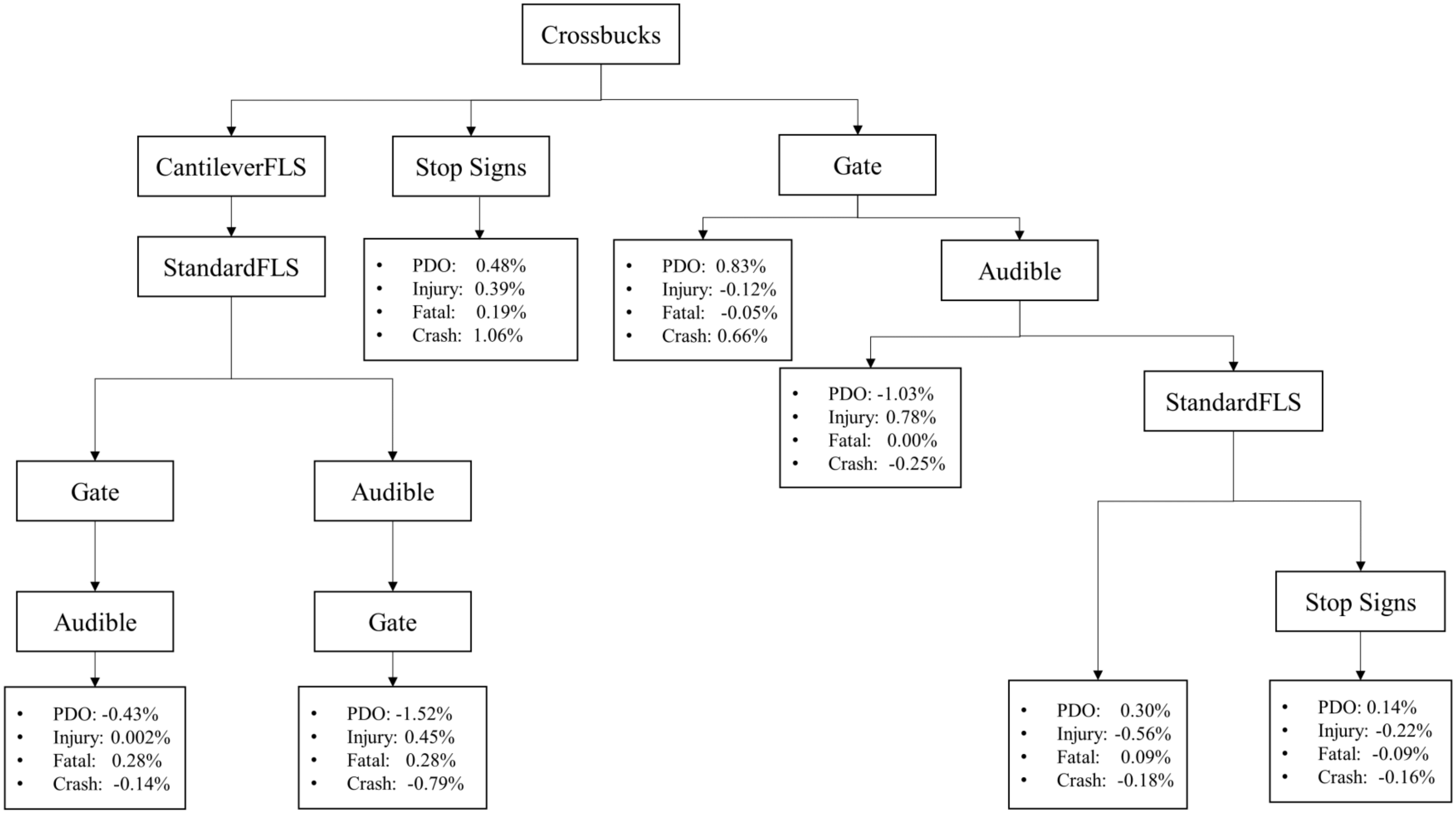

Figure 11. Average Annual Crash Likelihood Change for Crossing Traffic Control Change

CHAPTER 6 MODEL VALIDATION

6.1. Introduction

Brier score (BS) is a strictly proper scoring rule to assess the prediction performance of CRM approach by defining the prediction error (Brier, 1950; Gneiting & Raftery, 2007; Amin Keramati, Lu, Iranitalab, Pan, & Huang, 2020; Winkler & Murphy, 1968). BS can be estimated by the squared difference of the actual and predicted outcome. In this study, the time-dependent BS (Gerds & Schumacher, 2006; Graf, Schmoor, Sauerbrei, & Schumacher, 1999) is considered to assess the CIF performance of the competing risk model. The expected BS for crash severity *k* can be estimated by Equation (14):

$$\widehat{BS}_{jk}(t) = E_i\{N_{k,i}(t) - \widehat{CIF}_k(t|x_i)\}^2, x_i \in \mathrm{Z} \qquad \text{(Equation 14)}$$

In the above equation, $N_{k,i}(t)$ is equal to 1 if crossing record *i* experiences crash severity *k* before time *t*, and it is equal to 0 if record *i* has not experienced any of crash severities (event-free) until time *t*. Correspondingly, $\widehat{CIF}_k(t|x_i)$ is estimate of cumulative incidence function of severity level *k* for record *i* before time *t*.

6.2. Bootstrap Cross-Validation

To compare the prediction performance of different fitted RSF models, the specific type of bootstrap cross-validation approach is used which is “bootstrap.632 plus estimate”. The bootstrap.632 was proposed by Efron and Tibshirani (1997) as an improvement on cross-validation associated with misclassification rate. As the .632 plus was studied for other loss functions including BS, it is considered as a superior choice (Gerds & Schumacher, 2007; Jiang & Simon, 2007; Molinaro, Simon, & Pfeiffer, 2005; Wehberg & Schumacher, 2004). The term “bootstrap cross-validation” was first defined in Fu et al. (2005), whereby models are trained and tested in each bootstrap sample and cross-validated on all data. Bootstrap cross-validation method was compared with many other cross-validation algorithms and recommended by Mogensen et. al., (2012). The bootstrap cross-validation approach splits the original data D_N into a number of bootstrap training samples D_b (1000 in this study) and corresponding test samples $D_N \backslash D_b$ (*b=1,…, B*) without replacement from the original data. $\widehat{CIF}_{k,b}$ is then trained with each bootstrap training data D_b and prediction errors are calculated and tested with corresponding test sample. In the last step, the bootstrap cross-validation estimate of the prediction error for each crash severity *k* (BCvE) can be calculated by averaging over the test datasets by Equation (11).

$$BCvE\left(t, k, \widehat{CIF}\right) = \frac{1}{B}\sum_{b=1}^{B} \frac{1}{M_b} \sum_{i \in D_{N \backslash D_b}} E_i\left\{N_{k,i}(t) - \widehat{CIF}_{k,b}(t|x_i)\right\}^2 \qquad \text{(Equation 15)}$$

In Equation (15), M_b indicates the size of the bootstrap samples for resampling without replacement.

Bootstrap.632 plus estimate of the prediction error is a weighted combination of th*e* BCvE, the apparent estimate, and the no information estimate. The apparent estimate of the prediction error is estimated by resubstitute the all *n* crossings' records of D_N used to build the model as shown in Equation (16).

$$ApE\left(t, k, \widehat{CIF}\right) = \frac{1}{N}\sum_{i \in D_N} E_i\left\{N_{k,i}(t) - \widehat{CIF}_k(t|x_i)\right\}^2 \qquad \text{(Equation 16)}$$

Since the cross-validation estimators assess the prediction rule trained with less information than provided by the full data, they tend to be positively biased. Efron (1983) proposed solution is to balance the downward bias of the apparent error by linear combination with the upward bias of the bootstrap cross validation estimator which results in a bootstrap .632 error (B632E). Consequently, the bootstrap .632 estimate of the prediction error can be defined as a weighted linear combination of the apparent estimate and the bootstrap cross-validation estimate (Equation (17)) (Gerds & Schumacher, 2007).

$$B632E\left(t,k,\widehat{CIF}\right) = (1-0.632).ApE\left(t,k,\widehat{CIF}\right)$$

$$+0.632.BCvE\left(t,k,\widehat{CIF}\right) \qquad \text{(Equation 17)}$$

The constant 0.632 is independent of the sample size and refers to the probability to draw with the replacement subject or crossing record i into the bootstrap sample. Efron and Tibshirani (1997) improved the bootstrap .632 error by proposing the estimation of no-information error (NoInfErr). The idea of no-information error is to evaluate the performance of the prediction rule while the status with no crash occurrence (survival status in survival analysis) is independent of the covariates. Consequently, the no-information estimation is calculated by permuting the status indicator for crossing record i and $\acute{\iota}$ for all i = 1, …, n as it is indicated in Equation (18).

$$NoInfErr\left(t,k,\widehat{CIF}\right) = \frac{1}{N^2}\sum_{i\in D_N}\sum_{\acute{\iota}\in D_N} E_i\left\{N_{k,\acute{\iota}}(t) - \widehat{CIF}_k(t|x_i)\right\}^2 \qquad \text{(Equation 18)}$$

Finally, by using Equations (15), (16) and (18), the bootstrap .632 plus estimate of the prediction error is defined by Equation (19):

$$B632E\ \left(t,k,\widehat{CIF}\right) = \left(1-\frac{0.632}{1-0368.\omega}\right).ApE\left(t,k,\widehat{CIF}\right)$$

$$+\frac{0.632}{1-0368.\omega}.BCvE\left(t,k,\widehat{CIF}\right) \qquad \text{(Equation 19)}$$

Where ω is estimated by the following Equation:

$$\omega = \frac{\min\left(BootCvErr(t,k,\widehat{CIF}), NoInfErr(t,k,\widehat{CIF})\right) - AppErr(t,k,\widehat{CIF})}{NoInfErr(t,k,\widehat{CIF}) - AppErr(t,k,\widehat{CIF})} \qquad \text{(Equation 20)}$$

Not that Integrated Brier score (IBS) is used to summarize the prediction error curves which are created based on the calculation of *BS*. Equation (21) indicates *IBS* estimation for crash severity *k:*

$$IBS\ (BS\ ,k,\mathcal{T}) = \frac{1}{\mathcal{T}}\int_0^{\mathcal{T}} BS\ (u,k)\,du \qquad \text{(Equation 21)}$$

In the above equation, $\mathcal{T} > 0$ is any value smaller than the minimum of the maximum times for which the estimated BSs can be evaluated in each bootstrap sample.

6.3. Result Analysis

In this study, the cross-validation bootstrap approach is used to evaluate the prediction error (time-dependent BS) of proposed Cox hazard regression model for each crash severity level. A total number of 1000 bootstrap samples of training and test data are considered (B = 1000). Training set with the size of 63.2% of the original data (2,092 HRGC records), and corresponding test sets of about 1,218 records (3,310-2,092 = 1,218) were defined by using the bootstrap without replacement.

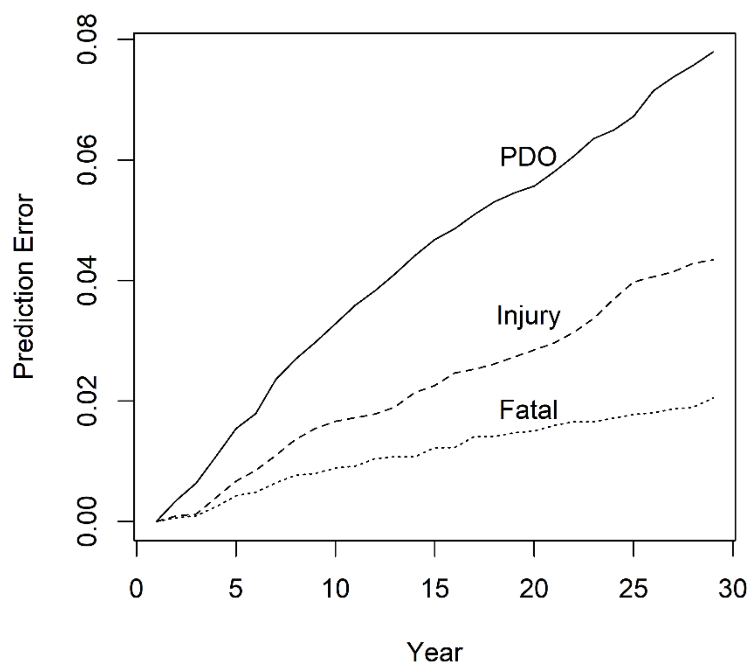

Figure 12. Cumulative Prediction Error for Each Severity Level

Figure 12 shows the cumulative prediction error curves which are estimated based on the BS of each crash severity level. Prediction error curves results indicate less than 8%, 4%, and 2%

errors for PDO, injury, and fatal crash likelihood, respectively, over the 29-year prediction period. Moreover, the integrated brier scores between 0 and 29 years resulted by the bootstrap .632 plus estimates of the prediction error are 0.04, 0.02, and 0.01 for PDO, injury and fatal crashes respectively. Applying Cox regression hazard model to solve the competing risk model in this study demonstrates its accuracy in prediction as the time-dependent Brier Score results indicated less than 8%, 4%, and 2% errors and *IBS* of the prediction error curves results showed only 0.04, 0.02, and 0.01 for three crash severity levels of PDO, injury, and fatal respectively.

CHAPTER 7. HIGHWAY-RAIL GRADE CROSSING HAZARD RANKING

7.1. Introduction

Transportation and decision makers need systematic approaches to evaluate and identify crossings that need safety improvements. Identifying these systematic methods is essential to ensure that federal and state funds for highway-rail grade crossing improvement projects are allocated to locations and crossings at higher risk of crash (Ogden & Cooper, 2019). The most prevalent prioritization approaches for ranking highway-rail grade crossings are hazard index and collision prediction formula techniques. While the hazard index is used to estimate a value that ranks crossings in relative terms (the higher the quantified index, the more hazardous the crossing), the collision prediction formula (prediction model) is utilized to quantify the predicted crash frequency or severity. A few research projects and state DOTs used a hybrid models which consists both a crash frequency (as the output of the collision prediction formula) and a hazard index approach (Niu et al., 2014; Weissmann et al., 2013).

The most common hazard-ranking approaches used by state DOTs are 1) the U.S. DOT Accident Prediction Formula, 2) the New Hampshire Hazard Index Formula 3) the NCHRP Report 50 Accident Prediction Formula, and 4) the Peabody–Dimmick Formula. Figure 13 indicates the distribution of HRGC hazard-ranking models and formulas utilized by state DOTs according to the review of the state Section 130 program reports (Section 130 Program reports, 2014). 78% of states (39 states) utilize one or more hazard-ranking formulas or provide several contributors considered in grade crossing evaluation for project prioritization and selection (Sperry et al., 2017a).

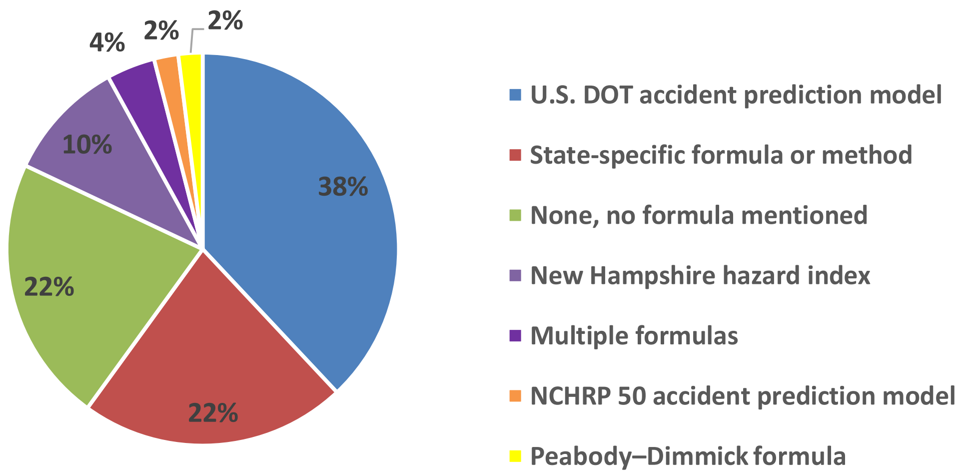

Figure 13. State DOTs' Grade Crossing Hazard-Ranking Models

One can see from Figure 13 that U.S. DOT accident prediction model is the most common hazard ranking model which is used by state DOTs. 38% percentage of states (nineteen states) that reported the use of hazard-ranking models have utilized U.S. DOT accident prediction model. 22% of states (eleven states) reported the use of their state-specific hazard-ranking approaches. In addition, a 10% percentage of states (five states) apply New Hampshire hazard index, one state uses the NCHRP 50 collision prediction model, and again only one state utilizes the Peabody-Dimmick formula. A few number of states use a modified version of one of four mentioned formulas, and some states utilize multiple hazard ranking formulas in their prioritization system. For example, state of Mississippi applies U.S.DOT model as the input of their specific weighting formula. Moreover, Nebraska DOT uses both the U.S.DOT and the NCHRP 50 models for their prioritization aims. The rest of the states (11 states or 22%) reported no information regarding their hazard-ranking approach(s) or they utilized methodologies other than a formula-based ranking approached. It should also be noted that more than 50% (six of the eleven states) of the states with no formula-based ranking approach were among the states with the fewest numbers of grade crossings.

Hazard-ranking approaches calculate crossings' rank values or crash likelihood based on the crossings' characteristics and factors. Therefore, it is important to understand which factors and contributors are used in hazard ranking approaches to quantify the crossings' ranks or crash likelihood. These factors can be geometric factors of crossings like crossing angles and distance to a nearby intersection or traffic exposure factors, such as day-time train traffic, roadway traffic, and train speed. Table 16 demonstrates the contributors that thirty nine state DOTs consider in their grade crossing hazard-ranking methodologies based on the reports provided by Sperry et al. (2017) and state section 130 program (2014). Table 16 indicates that the three most common contributors that state DOTs considered in their crossing hazard ranking analysis are annual average daily traffic (AADT), train volume, and crossing control types which are all used by more than 90% of state DOTs. According to Table 16, the other key contributors are crash history (crash frequency), train speed, and the number of main tracks.

One can see from Table 16 that around 60% of states considered highway characteristics including number of traffic lanes and road paved condition, and the rest of the contributors are considered by less than 5% of the state DOTs. In addition, Table 16 indicates that just one state (California state) considers crash severity and none of the states considered pavement markings, train detection system, commercial power, and percent of trucks as their hazard-ranking methodology variables. Current state DOTs' ranking approaches help rank grade crossings based on the factors effect on likelihoods of crash occurrence, but they are not helpful in recognizing crossings' rank considering both their crash frequency and severity likelihood and factors which can effect on crossings' crash frequency and severity. Therefore, in this chapter, two hazard-ranking models are proposed, the first one is based on the crash likelihood resulted by the proposed CRM output, and the second one is a hybrid accident prediction model hazard index based on crash severity likelihoods estimated by the same CRM. Moreover, all of contributors in Table 16 are considered in the both proposed hazard-ranking approaches. Finally, to integrate the results of both hazard-ranking approaches, and classify grade crossings and crossings' location based on their crash frequency and severity likelihood simultaneously, the risk analysis is conducted by using the risk matrix and spatial risk analysis.

Table 16. Considered Contributors by States to Rank HRGCs (Sperry et al., 2017a)

Contributors	**Number of States**
Annual Average Daily Traffic (AADT)	39
Train Volume	39
Crossing Control Types	36
Crash History	29
Train Speed	29
Number of Main Tracks	28
Number of Traffic Lanes	24
Roadway Paved Condition	23
Highway Speed Limit	5
Distance to the Nearest Intersections	3
Type of Train Service	3
Crash Severity	1
Crossing Angle	1
Pavement Markings	0
Train Detection System	0
Commercial Power	0
Percent of Trucks	0

7.2. Literature Review

Variety of hazard ranking approaches for grade crossings were used by state DOTs before proposing U.S.DOT accident prediction model in the mid-1970s (Faghri & Demetsky, 1986). The New Hampshire Hazard index, the NCHRP 50 accident prediction model, and the Peabody-Dimmick formula are the most known hazard ranking models which have been utilized by state DOTs and other local highway agencies for many decades and are still in use by some state DOTs.

One of the earliest hazard-ranking approaches for grade crossings is the New Hampshire hazard Index which is the hazard index type formula. The five states of Kansas, Louisiana, Massachusetts, Michigan, and Nevada utilize the New Hampshire hazard index as their primary approach for ranking highway-rail grade crossings and their crossings safety improvements (Sperry et al., 2017a). The New Hampshire hazard index is the basic type of the hazard index method as it considers only 1) a protection factor adjustment indicates the type of crossing warning device, and 2) the exposure index estimated by the cross product of the AADT and train traffic volume (Faghri & Demetsky, 1986; Qureshi et al., 2003; Tustin et al., 1986). The main reason that the New Hampshire hazard index or its local modifications are the most common hazard-ranking formula used by states historically is the fact that this model structure is simple and understandable.

Equation (22) indicates the New Hampshire hazard index formula (Ogden & Cooper, 2019):

$$HI = (V) * (T) * (PF) \qquad \text{(Equation 22)}$$

Where HI is the calculated hazard index value, T is Train movement per day at HRGC, and PF notes the protection factor based on the warning device type at HRGC. The classic New Hampshire Hazard Index formula considers the protection factors for automatic gates, flashing lights, and signs only are 0.1, 0.6, and 0.1 respectively. Some states modified these protection factors to consider different levels of protection for each crossing. For example, the Michigan DOT considers 13 different protection factors values associated with the presence of more types of traffic control devices in its New Hampshire Hazard Index (MDOT, 2017).

In 1968, National Cooperative Highway Research Program Report 50 (NCHRP 50) defined and evaluated contributors having effect on grade crossing safety (D W Schoppert & Hoyt, 1968). NCHRP 50 provided a prediction model to predict 1) train-vehicle accidents at HRGCs, and 2) accidents occurrence near HRGCs while trains do not involve(David W Schoppert & Hoyt, 1967). Illinois DOT utilizes the NCHRP 50 accident prediction model as the primary hazard-ranking method to rank grade crossings based their safety level. In addition, Nebraska DOT uses NCHRP 50 jointly with another method(Sperry et al., 2017a). Although the NCHRP 50 is a prediction model in contrast with the New Hampshire hazard index which is a hazard index mythology, the NCHRP 50 model considers the same factors that the New Hampshire hazard index considers plus AADT. In other words, the NCHRP 50 model is a basic multiplicative method which is able to predict the annual crossings' crash frequency by considering factors including AADT, train volume, and HRGC warning devices. The NCHRP 50 formula is as follows (Ogden, 2007):

$$EA = (A)(B)(CTD) \qquad \text{(Equation 23)}$$

In Equation (23), EA notes the expected accident frequency, A is the vehicle per day factor, B indicates a protection factor associated with type of warning device at a grade crossing, and CTD represents the current train per day.

The another hazard-ranking model which is one of the accident prediction formulas is Peabody–Dimmick formula proposed by T. B. Dimmick of the Bureau of Public Roads in 1941 (Niu et al., 2014). This collision prediction model was developed based on crash records and crossing characteristics of over 3,500 HRGCs located in 29 states. Georgia DOT is the only state which uses the modified version of Peabody–Dimmick formula for its grade crossing hazard-ranking.

The Peabody–Dimmick formula is indicated as follows (Khattak & Liu, 2018):

$$A_5 = 1.28 \times \frac{(\mathcal{V}^{0.170})(T^{0.151})}{\mathcal{P}^{0.171}} + K \qquad \text{(Equation 24)}$$

Where A_5 is the accidents expected number at a grade crossing in five years, $\mathcal{V}$ indicates AADT, T notes the average daily through trains, $\mathcal{P}$ represents a protection coefficient which indicates presence of warning devices, and K which is an additional parameter and is determined according to a graph. Formula is able to consider AADT and number of through trains to estimate crash exposure, but does not utilize the temporal distribution of roadway and rail traffic (Khattak & Liu, 2018).

Figure 13 indicates that the most popular hazard-ranking model is the U.S. DOT accident prediction model which is a multistage formula predicting annual crash frequency at HRGCs. The U.S. DOT accident prediction model was proposed in the mid-1970 with the target of HRGC selection process projects which is known as the Rail-highway Crossing Resource Allocation Procedure (Farr, 1987a). The basic steps of the U.S. DOT accident prediction model are as follows (Ogden & Cooper, 2019; Sperry et al., 2017a):

1) Developing a mathematical model to calculate the preliminary estimate of annual crash frequency at a grade crossing.
2) Provide and adjustment to the main estimate on the basis of the HRGCs' accident history.
3) Normalizing constant adjustment for current crossings' accident trends.
4) Proposing additional prediction models (mathematical formulas) to predict the probability of crash occurrence resulting in an injury or a fatality.

It is noteworthy that the last step is mentioned as an optional step based on Ogden and Cooper (2019). In comparison with above-mentioned hazard-ranking models (the New

Hampshire hazard index, NCHRP 50 accident prediction model, and Peabody–Dimmick Formula), U.S DOT accident prediction model considers a wider variety of factors. Factors which are considered in original U.S. DOT accident prediction model are the type of crossing control device (warning device), AADT, train volume, maximum train speed, number of main tracks, number of traffic lanes and roadway paved condition (paved or unpaved). In this accident prediction model, the accident records reflect a five years of a grade crossing's crash history. In other words, any HRGC has experienced an accident over the past five years, the model estimates a higher accident prediction value for that crossing.

The U.S. DOT accident prediction formula is as follows (Khattak & Liu, 2018):

$$a = (K)(EI)(DT)(MS)(HP)(HL)(HT) \qquad \text{(Equation 25)}$$

Where K is a constant, EI notes the exposure index factor, DT indicates the day through trains, MS represents the max train speed, MT is the number of main tracks, HP is the highway paved factor, HL is the highway lanes factor, and HT shows the highway type factor. Although the U.S. DOT model has been the most popular hazard-ranking model utilized by state DOTs, it has also some limitations which were noted by previous studies. For example, Austin and Carson (2002) mentioned that the model structure of the U.S. DOT accident prediction model is hard to interpret, and it is not clear which factors have a greater impact on the crash probability. In addition, Medina and Benekohal (2015) indicated that the model did not make precise predictions for crash frequency at high-crash locations.

Although the above mentioned hazard-ranking models are common models which are used by 78 % of states (39 states), some states have developed specific hazard-ranking models in accordance with their local accident trends and available crash records (Niu et al., 2014; Sperry et al., 2017a; Weissmann et al., 2013). The modified version of New Hampshire hazard index is used by Connecticut DOT as the state hazard-ranking approach. The hazard index approach considers more prediction factors associated with different types of crossing control devices. Crash history is used as the input of Connecticut DOT's hazard index method.

A hazard index methodology known as the exposure index formula was developed in 2003 by Missouri DOT (Qureshi et al., 2003). Missouri DOT provides an advanced hazard index approach which considers detailed HRGCs' characteristics including type of train service, maximum train speed, and crossings' sight distance. North Carolina is another state which uses the hazard index technic as their hazard-ranking model for grade crossings. North Carolina DOT's proposed hazard index which is known as the investigated index model. The initial version of this index was initially developed in the 1970s and updated in the 1980s (Sperry, Naik, & Warner, 2017b; Zhao et al., 2018). The investigative index model is more comprehensive in comparison with U.S. DOT model as the model incorporates contributors not included in the U.S. DOT model. These contributors are sight distances, number of main tracks, and AADT adjustments for school bus passenger counts and passenger trains (Sperry et al., 2017a).

Some states utilize the hybrid accident prediction model/hazard index. Florida is one of these states and the proposed model is known as safety hazard index which was developed by Florida State University (Niu et al., 2014). The safety hazard index is formulated based on a logistic regression model which estimates the expected crash frequency. The model includes adjustments for crash history, type of warning device, and the school buses presence at a grade crossing location. Texas DOT also utilizes a hybrid accident prediction model/hazard index which is known as Texas priority index(Weissmann et al., 2013). The model equation is able to convert the predicted crash frequency to a priority index. In this model, the negative binomial regression models are used to estimate the index based on Texas grade crossing collision records. Sight distance, the presence of a nearby intersection, area type (urban or rural), and the roadway speed limit are variables which significantly effect on crash likelihood based on Texas priority index model.

All the above mentioned hazard-ranking methods are very useful to rank HRGCs according to crossings' crash frequency. However, considering crash severity in the grade crossing hazard-ranking is important for agencies as they need to recognize grade crossings which are more likely to have severe crashes. Considering the crash severity outputs in a hazard-ranking model might increase the complexity of the prioritization model as the hazard-ranking model should be able to convert three quantities associated with fatal crash, injury crash, and PDO crash likelihoods to one priority index for each crossing. In this chapter, we proposed a hybrid prediction model/hazard index which can apply such conversion by using analytic hierarchy process (AHP) techonomic which is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology (Forman & Gass, 2001).

In addition, transportation decision makers need a prioritization system to categorize crossings' risk level based on their expected crash frequency and crash severity simultaneously. Therefore, with a hazard-ranking approach which considers crossings' crash severity and frequency output, transportation decision makers are able to ensure that federal and state funds for grade crossing improvement projects are spent at the crossings that are considered the most in need of improvement. Providing such prioritization system needs an integrated one-step model which is able to quantify crash frequency and severity likelihood simultaneously. In this chapter, two hazard-ranking models are proposed based on the safety outputs of CRM model. The first hazard-ranking model type is accident prediction model and ranks HRGCs based on the crossings' crash frequency likelihood estimated by CRM. The second hazard-ranking model type is the hybrid accident prediction model/hazard index which estimates the priority index for each crossing based on the calculated crash severity likelihood (using the same CRM model) by using AHP technique. Finally, crossings' risk levels are defined based on their crash likelihood and severity ranks by using spatial risk analysis and risk matrix.

7.3. Methodology

Two hazard-ranking models are developed based on the crash frequency and crash severity likelihoods estimated by CRM. Figure 14 summarized steps for designing the proposed prioritization system for 3,194 public grade crossings in North Dakota state. At the first step (step a), cumulative crash likelihood and cumulative fatal, injury and PDO crash likelihoods for 30 years is estimated for each crossing with its specific characteristic in year 2018. In the next step (step b), three estimated likelihoods related to each severity level are used as the AHP inputs to calculate the priority index (AHP output) for each crossing. At step c, crossings are ranked based on their AHP results or their crash likelihood in relative terms, a higher AHP results/crash likelihood indicating a more hazardous crossing. Accident prediction hazard ranking model is the process of ranking crossings based their crash likelihood, and the process of ranking based on crossings' AHP results represents hybrid accident prediction/hazard index model. In the final step (step d), the risk matrix technique is used to integrate the results of both hazard-ranking models by categorizing crossings into four main risk groups of high risk, moderate risk, low risk, and very low risk.

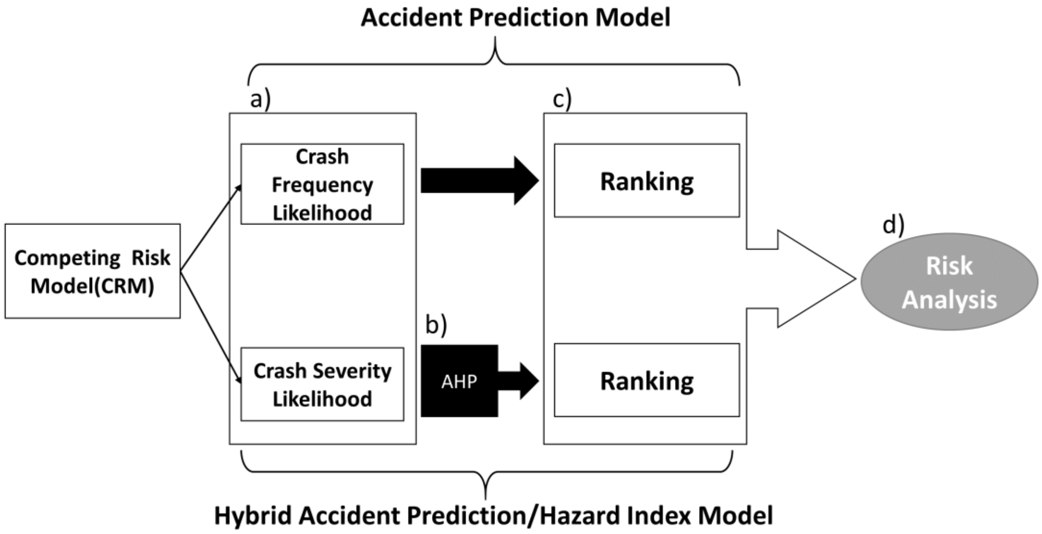

Figure 14. Hazard-Ranking Developing Model Fellow Chart

7.3.1. Accident Prediction Hazard-Ranking Model

According to the first proposed hazard-ranking model in this study, crossings are simply ranked based on their predicted cumulative crash likelihood for 29 years. Cumulative crash likelihood for 29 years can be estimated by cumulative incident function before year 30 ($CIF_c(t=29|X)$) for each crossing. To rank crossings based on their current situation, the CIF for each crossing is estimated while the contributors' values are equal to their 2018 (year 29) information. According to Equation (6) and Equation (11), $CIF_c(t=29|X)$ can be estimate as follows:

$$CIF_c(t = 29|X) = \sum_{k=1}^{3} CIF_k(t = 29|X) \qquad \text{(Equation 26)}$$

Equation (26) indicates that the cumulative probability of crash occurrence for 29 years (t=29) is equal to the sum of the CIF of PDF (k=1), injury (k=2), and fatal (k=3) crash for 29 years. Since the afford mentioned ranking approach is based on crossings' crash likelihood, this model is called Crash Likelihood Hazard Ranking (CLHR) model.

7.3.2. Hybrid Accident Prediction/Hazard Index Model

The main concept of AHP as a decision-making technique is providing a hierarchy to handle problems related to ranking alternatives considering a number of criteria. According to this model, factors playing a key role in decision-making process are compared in a pairwise manner, and a quantitative scale is created to calibrate the subsequent outputs. In the next subsections, definition and mathematical formulations needed to apply the AHP model to rank grade crossings are explained in detail.

7.3.2.1. Hierarchy Structure Design

To apply AHP model, the first step is modeling the problem as a hierarchical structure which is composed of the decision goal, alternatives, and the criteria for evaluating the alternatives. In this hierarchy, the decision goal forms the top level, the intermediate level consists the criteria and the bottom level includes the decision-making alternatives. In this study, AHP technique is applied to calculate the hazard index of crossings which is equivalent to the global scores of alternatives in AHP hieratical structure. The predicted value of 29-year cumulative PDO crash likelihood ($CIF_{i,PDO}(t = 29)$), injury crash likelihood ($CIF_{i,Inj}(t = 29)$), and fatal crash likelihood $CIF_{i,Fatal}(t = 29)$) are integrated in the procedure to measure each crossing *i's* hazardous level from the perspective of its crash severity likelihood. Figure 15 indicates the AHP hieratical structure based on crossings' hazardous level.

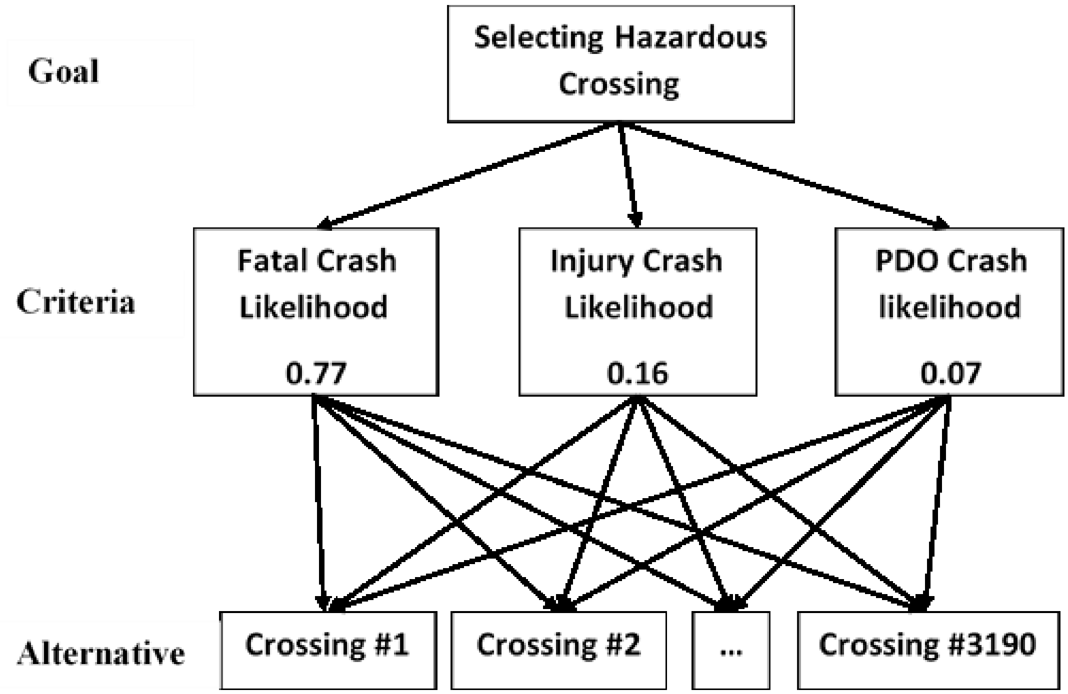

Figure 15. Analytic Hierarchy Model for Grade Crossing Ranking

7.3.2.2. Criteria Weigh Vector Estimation

By considering *m* criteria for pairwise comparison, the $m \times m$ matrix *A* is generated. Each a_{ij} entry of matrix *A* notes the relative importance of the i^{th} criterion with respect to the i^{th} criterion. Matrix A contains reciprocal value across the diagonal which shows that for each entry a_{ij} , $a_{ji} = 1/a_{ji}$.The value of a_{ij} is determined based on the ratio-scale ranging from 1 to 9. Table 17 indicates the interpretation of each scale (Saaty, 2005).

Table 17. Interpretation of Numerical Scale of Importance (Saaty, 2005)

Intensity of Importance (Scale)	Explanation
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	In between their two neighbors

The priority weight of the m^{th} criterion is estimated by Equation (27). Equation (27) indicates the calculation of the maximum eigenvalue λ_{max} and its corresponding eigenvector ω of matrix *A* (Han, Wang, Lu, & Hu, 2020; Saaty, 2005).

$$A\omega = \lambda_{max}\omega, \omega = (\omega_1, \omega_2, \dots, \omega_m)^T \qquad \text{(Equation 27)}$$

Where ω_m notes the priority weight of the m^{th} criterion. In the AHP approach, consistency index (CI) is defined as the index of the consistency of judgement across all pairwise comparisons (Alonso & Lamata, 2006). According to Saaty (2005), CI is estimated as follows:

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad \text{(Equation 28)}$$

Where n indicates the order of matrix *A*. To measure the effectiveness of the comparison matrix *A* in AHP technique, the consistency ratio (CR) is estimated as follows (Saaty, 2000):

$$CR = \frac{CI}{RI} \qquad \text{(Equation 29)}$$

Where *RI* represents the mean random consistency index and can be determined by Table 18 (Forman, 1990). The comparison can be only accepted as a consistent one if CR<0.1(Alonso & Lamata, 2006).

Table 18. Mean Random Consistency Index RI (Forman, 1990)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

In this study, crash severity levels of PDO, injury and fatal are defined as criteria in the AHP model. Subsequently, the $CIF_{i,k}$ where $k = \{PDO, fatal, Inj\}$ represents the value of 29-year cumulative crash likelihood of severity level *k* for crossing *i* based on the equations (5) and (9). Consequently, considering *n*=3,194 public grade crossings in this study, the matrix *D* with the size of $n \times 3$ can be generated as the main dataset for the AHP model:

$$D = \begin{bmatrix} CIF_{1,PDO} & CIF_{1,Inj} & CIF_{1,Fatal} \\ CIF_{2,PDO} & CIF_{2,Inj} & CIF_{2,Fatal} \\ CIF_{3,PDO} & CIF_{3,Inj} & CIF_{3,Fatal} \\ \vdots & \vdots & \vdots \\ CIF_{n,PDO} & CIF_{n,Inj} & CIF_{n,Fatal} \end{bmatrix} \quad \text{(Equation 30)}$$

In the proposed AHP model, the higher weight (a_{ij}) is assigned to the higher crash severity level. Consequently, the value of assigned weight to fatal severity level should be more than the weight amount of injury severity level. Similarly, the injury level weight should be more than PDO level weight. Based on the scales explanations in Table 17, the estimated CR of 16 different comparison matrixes with different combinations of weights were compared with each other and the comparison matrix with minimum value of CR = 0.05 was selected. Table 19 indicates the selected comparison matrix related to the three severity levels.

Table 19. Crash Severity Levels Comparison Matrix

	Fatal	Injury	PDO
Fatal	1	6	9
Injury	1/6	1	3
PDO	1/9	1/3	1

The corresponding eigenvector (ω) of the above matrix is calculated based on Equation (7) and the result is the severity level weight vector of $\omega = [0.77, 0.16,0.07]$ where 0.77, 0.16, and 0.07 are fatal, injury, and PDO estimated weights respectively. The estimated weights for each severity level can be also seen in Figure 15 at the criteria level.

7.3.2.3. The Score Matrix and Hazard Index Calculation

Considering n alternatives whose results are calibrated based on scales in Table 17, matrix $B^{(k)}$ can be generated with respect to the k^{th} criterion where $k = 1, \dots, m$. $b_{ih}^{(k)}$ as the entry of matrix $B^{(k)}$ notes the relative importance of the i^{th} alternative in comparison with the h^{th} alternative under the k^{th} criterion (Han et al., 2020). By calculating the maximum eigenvalue of matrix $B^{(k)}$ and its corresponding eigenvector $s^{(k)}$, the group of weight vectors $s^{(k)}$ generates the score matrix $S = \left[s^{(1)}, \dots, s^{(m)}\right]$. Considering n = 3,194 public grade crossings in this study, an $n \times n$ pairwise camparison matrix $B^{(k)}$, $k = \{PDO, fatal, Inj\}$ can be constructed as Equation (31) indicates. In this matrix, $b_{ih}^{(k)} = CIF_{i,k}/CIF_{h,k}$ represents the i^{th} crossing's crash likelihood with severity level k compared to the h^{th} crossing's crash likelihood with the same severity level. The weight vectors $s^{(k)}$ are grouped into the score matrix $S = \left[s^{(PDO)}, s^{(Inj)}, s^{(fatal)}\right]$.

$$B^{(k)} = \begin{bmatrix} CIF_{1,k}/CIF_{1,k} & CIF_{1,k}/CIF_{2,k} & CIF_{1,k}/CIF_{n,k} \\ CIF_{2,k}/CIF_{1,k} & CIF_{2,k}/CIF_{2,k} & CIF_{2,k}/CIF_{n,k} \\ CIF_{3,k}/CIF_{1,k} & CIF_{3,k}/CIF_{2,k} & CIF_{3,k}/CIF_{n,k} \\ \vdots & \vdots & \vdots \\ CIF_{n,k}/CIF_{1,k} & CIF_{n,k}/CIF_{2,k} & CIF_{n,k}/CIF_{n,k} \end{bmatrix} \qquad \text{Equation (31)}$$

The global scores V is the final AHP model result that alternatives can be ranked based on it. These scores are calculated by multiplying the score matrix S and the weight vector ω. In this study, the estimated global scores are crossings' hazard index. Therefore, considering $S = \left[s^{(PDO)}, s^{(Inj)}, s^{(fatal)}\right]$, and $\omega = (\omega_{PDO}, \omega_{Inj}, \omega_{Fatal})^T$, hazard index set is estimated based on the following equation:

$$HI = S.\omega \qquad \text{(Equation 32)}$$

Where the priority of the i^{th} crossing depends on the hi_i of HI. Since the above mentioned ranking approach is based on AHP results, the model is called AHP Hazard Index (AHP-HI) model and the estimated hazard index in Equation (32) is called AHP Hazard Index (AHP-HI).

7.4. Result Analysis

7.4.1. Ranking HRGCs Based on Crash Likelihood (CLHR Model)

To rank all public grade crossings in North Dakota according to their crash frequency likelihood, CIF_c for 3,194 grade crossing is estimated based on Equation (26).Then, crossings are ranked in relative terms, a higher CIF_c representing a higher hazardous crossing. For example, Table 20 lists the first ten hazardous crossings based on their crash likelihood in part a and the ten crossings with the lowest crash likelihood in part b. Table 20 indicates that the likelihood of crash occurrence at crossings listed in part a over 29 years is almost 100%, while the same likelihood for crossings in part b is almost 0%.

To understand the risk level of each crossing based on its crash frequency likelihood, crossings are classified into four risk groups of very low risk, low risk, moderate risk, and high risk. Crossings are classified as very low risk if their estimated CIF_c is less than 10%. Crossings with CIF_c between 10% and 20% are classified as low risk, and crossings with CIF_c between 20% and 40% are classified as moderate risk. Finally, if crossings' CIF_c is higher than 40%, they are classified as high risk crossings. This study dataset indicates that in North Dakota, 1) 65.3% of public grade crossings are at very low risk of crash occurrence, 2) 23.5% of grade crossings are low risk crossings, 3) 10.2% of crossings are at moderate risk of accident, and 4) only 1.01% percentage of crossing are at high risk of crash occurrence.

Table 20. Crossings with Highest (a) and Lowest (b) Crash Frequency Likelihood

a)			b)		
Crossing ID	**Crash Likelihood (CIF_c)**	**Rank**	**Crossing ID**	**Crash Likelihood (CIF_c)**	**Rank**
082143X	100.00%	1	102792E	0.00003%	3194
062486A	100.00%	2	690558H	0.00005%	3193
071099G	99.99%	3	080673F	0.00006%	3192
071735C	99.97%	4	062575S	0.00007%	3191
086876F	99.83%	5	081107Y	0.00007%	3190
086787N	99.77%	6	103407C	0.00007%	3189
071003P	99.76%	7	082305X	0.00007%	3188
087695E	99.35%	8	691842D	0.00009%	3187
093368H	99.32%	9	102477N	0.00009%	3186
695902Y	98.91%	10	102865M	0.00010%	3185

7.4.1.1. Spatial Risk Analysis Based on Crash Frequency Likelihood

Despite of identifying crossings that have the most need for safety improvements, transportation decision makers need a systematic method to ensure that federal and state funds for highway-rail grade crossing improvement projects are allocated to the locations that are considered the most in need of improvement (Ogden, 2007). Consequently, in this study, Inverse Distance weighted (IDW) interpolation is utilized to map the crossings' crash likelihood (CIF_c) resulted by CRM in North Dakota. The IDW interpolation structures a continuous crash likelihood surface covering the space for each crossing. The altitudes of this surface varies according to the grade crossing's crash likelihood in a similar location. IDW assigns unknown spots a value associated with the crossings' crash likelihood in nearby areas. This assigned value is a geographically weighted average of crash likelihoods, estimated by considering the distance between interpolated spots and the known crossings nearby. IDW assumption is that the calculated crash likelihoods have a local effect, and this effect decreases as the distance increases. The estimated crash likelihood of unknown spots $(Lat_x, Long_x)$ is calculated as follows (Liu & Khattak, 2017):

$$CIF_c(Lat_x, Long_x) = \frac{\sum_{i=1}^{M} \frac{CIF_c(Lat_y, Long_y)}{d^2}}{\sum_{i=1}^{M} \frac{1}{d^2}} \quad \text{(Equation 33)}$$

Where, $CIF_c(Lat_x, Long_x)$ is the estimated crash likelihood for an unknown spot with $(Lat_x, Long_x)$ latitude and longitude; $CIF_c(Lat_y, Long_y)$ represents the estimated crash likelihood for a known location $(Lat_y, Long_y)$; d indicates between the geographic distance between two spots of $(Lat_x, Long_x)$ and $(Lat_y, Long_y)$. A set of M geographic neighbors are selected to interpolate a coefficient for each unknown spot $(Lat_x, Long_x)$.

Figure 16 indicates the results of IDW interpolation according to the crossings' crash likelihood in North Dakota. Figure 16 illustrates locations at four risk levels of high-risk (crash likelihood more than 40%), moderate risk (crash likelihood between 20% to 40%), low risk (crash likelihood between 10% to 20%), and very low risk (crash likelihood less than 10%). Three areas of A, B, and C are defined as high-risk areas which contain crossings which are more likely to have a crash likelihood of more than 40%. Area A, B, and C includes 10, 4, and 10 high-risk crossings, respectively.

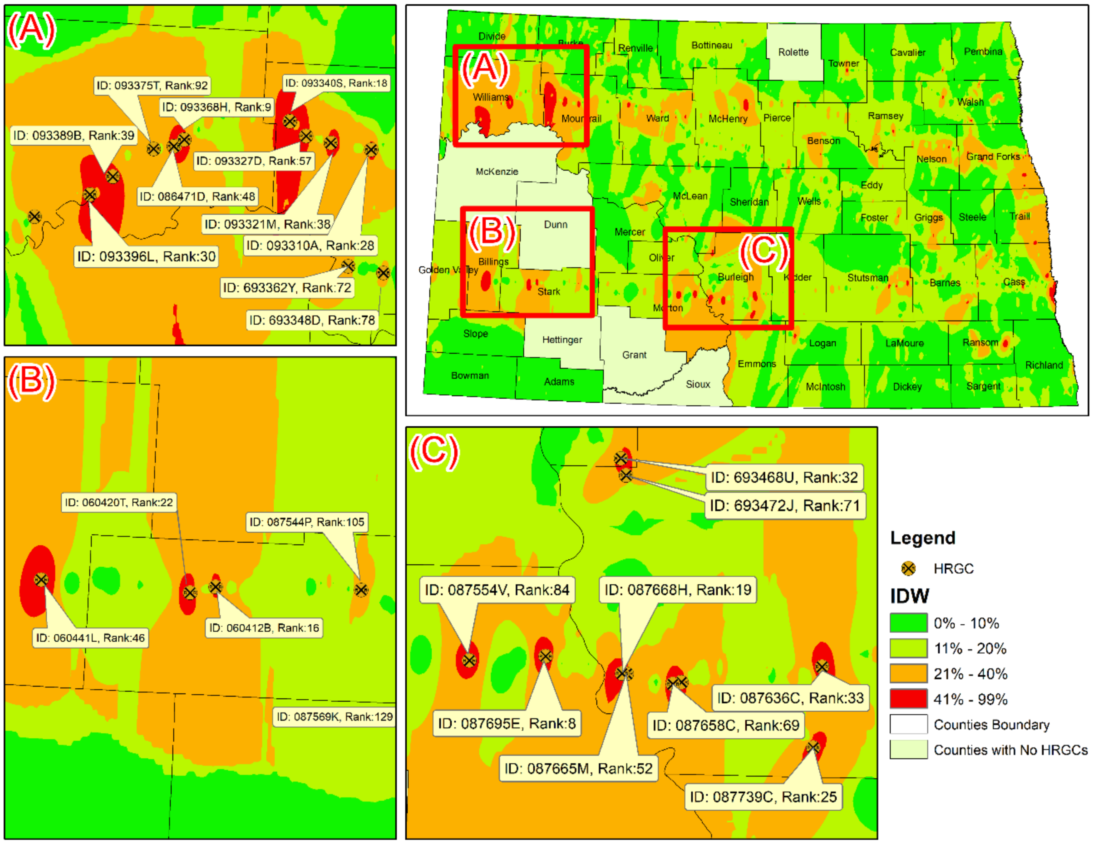

Figure 16. IDW Interpolation Based On Cumulative Rash Likelihood for 29 Years

7.4.2. Ranking HRGCs Based on AHP Hazard Index (AHP-HI Model)

The AHP hazard index (AHP-HI) of 3,194 public grade crossings in North Dakota is estimated according to Equation (32). Then, the crossings are ranked in relative terms, a higher AHP-HI representing a higher hazardous crossing. For example, Table 21 lists the first ten hazardous crossings based on their AHP-HI in part a and the ten crossings with the lowest AHP-HI in part b. Table 21 indicates that crossing’s crash severity likelihood plays a key role in their ranking. For example, crossings “087695E” and “086787N” both have an equal crash likelihood of 99%, but “087695E” is more likely to have a fatal crash (99%) compared to “086787N” (74%); consequently “087695E” has higher rank.

Table 21. Crossings with Highest (a) and Lowest (b) Crash Severity Likelihood Based On AHP-HI

a)						b)					
Crossing ID	**Fatal**	**Injury**	**PDO**	**AHP-HI**	**Rank**	**Crossing ID**	**Fatal**	**Injury**	**PDO**	**AHP-HI**	**Rank**
087695E	99%	0%	0%	0.77	1	102792E	0.00000%	0.00001%	0.00002%	0.00000003	3194
086787N	74%	14%	11%	0.60	2	690558H	0.00000%	0.00002%	0.00003%	0.00000005	3193
070810H	53%	23%	0%	0.45	3	062575S	0.00000%	0.00001%	0.00005%	0.00000006	3192
071099G	51%	17%	32%	0.44	4	080673F	0.00000%	0.00002%	0.00004%	0.00000006	3191
071735C	44%	16%	40%	0.39	5	082305X	0.00000%	0.00002%	0.00005%	0.00000007	3190
093192A	38%	29%	28%	0.36	6	081107Y	0.00000%	0.00003%	0.00004%	0.00000007	3189
698277B	36%	42%	20%	0.36	7	102477N	0.00000%	0.00002%	0.00008%	0.00000008	3188
093310A	34%	14%	42%	0.32	8	103407C	0.00000%	0.00004%	0.00003%	0.00000009	3187
087174N	31%	20%	34%	0.30	9	081440M	0.00000%	0.00002%	0.00009%	0.00000009	3186
086747R	32%	16%	23%	0.29	10	698743E	0.00000%	0.00002%	0.00007%	0.00000009	3185

To understand the risk level of each crossing based on its AHP-HI, the Centered Moving Averages (CMA) technique is used. In CMA method, a number of nearby points (K) are selected and their value average is calculated to estimate the Moving Average trend (MA trend). In this study, the MA trend of crossings' crash likelihood is calculated to classify crossings' risk level according to their AHP-HI. To apply this technique, at first all 3,194 crossings are sorted based on their AHP-HI value and the trend is plotted as can be seen in Figure 17 (AHP results' trend). In the next step, the crossings' crash likelihood MA trend are calculated and plotted by considering K=85 nearby crossings (Crash likelihood MA smoother in Figure 17). For example, to calculate a k=5 crossings moving average, the formula is:

$$CIF_i = \frac{CIF_{i-2}+CIF_{i-1}+CIF_i+CIF_{i+1}CIF_{i+2}}{5} \qquad \text{(Equation 34)}$$

Where, *i* represents the crossing's numeric ID after sorting crossings based on their AHP-HI which crash likelihood trend smoothed at.

The last step is categorizing crossings into four risk groups according to the crash likelihood MA trend. One can see from Figure 17 that crossings with AHP-HI less than 0.02, on average have 10% crash likelihood, consequently these crossings are classified as very low risk. Similarly, crossings with AHP-HI between 0.02 and 0.04 are classified as low risk, crossings with AHP-HI 0.04 and 0.07 are classified as moderate risk, and crossings with AHP-HI more than 0.07 are classified as high risk crossings. According to the mentioned risk classification, 59.8%, 25%, 10.4%, and 4.73% of public grade crossings in North Dakota are classified as very low risk, low risk, moderate risk, and high risk crossings, respectively. It should be noted that crossings' AHP-HI is estimated based on severity prioritization. Therefore, crossings with higher risk level are crossings that are more likely to have severe crashes.

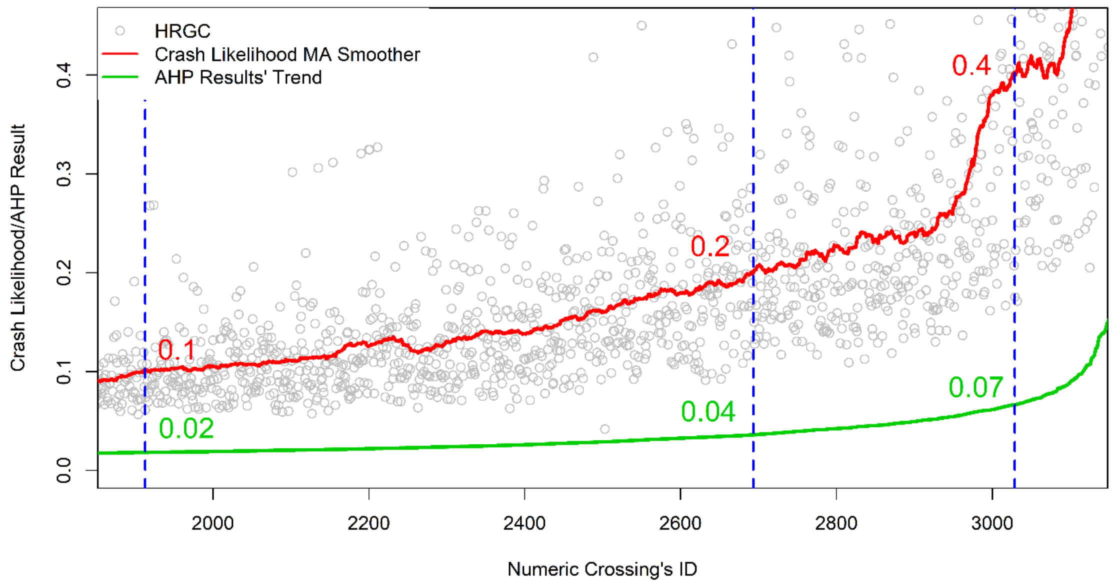

Figure 17. Crossings' Risk Classification Based On CIF Centered Moving Averages (CMA)

7.4.2.1. Spatial Risk Analysis Based on Crash Severity Likelihood (AHP-HI)

Similar to subsection 7.4.1.1, Inverse Distance weighted (IDW) interpolation is utilized to map the crossings' AHP-HI resulted by AHP model, while in Equation (12) crossing's AHP-HI is used instead of CIF_c as the input of IDW interpolation. Subsequently, Figure 18 indicates the results of IDW interpolation according to the crossings' AHP-HI. Figure 18 shows locations at four risk levels of high-risk (AHP-HI more than 0.07), moderate risk (AHP-HI between 0.04 to 0.07), low risk (AHP-HI between 0.02 to 0.04), and very low risk (AHP-HI less than 0.02). Three areas of A, B, and C are defined as high-risk areas which contain crossings which are more likely to have a AHP-HI more than 0.07. it should be noted that AHP-HI are indicated in percentage (AHP-HI×100) in Figure 18. Area A, B, and C includes 18, 9, and 10 high-risk crossings, respectively. The high risk areas indicate that these areas contain crossings which are more likely to have severe crashes.

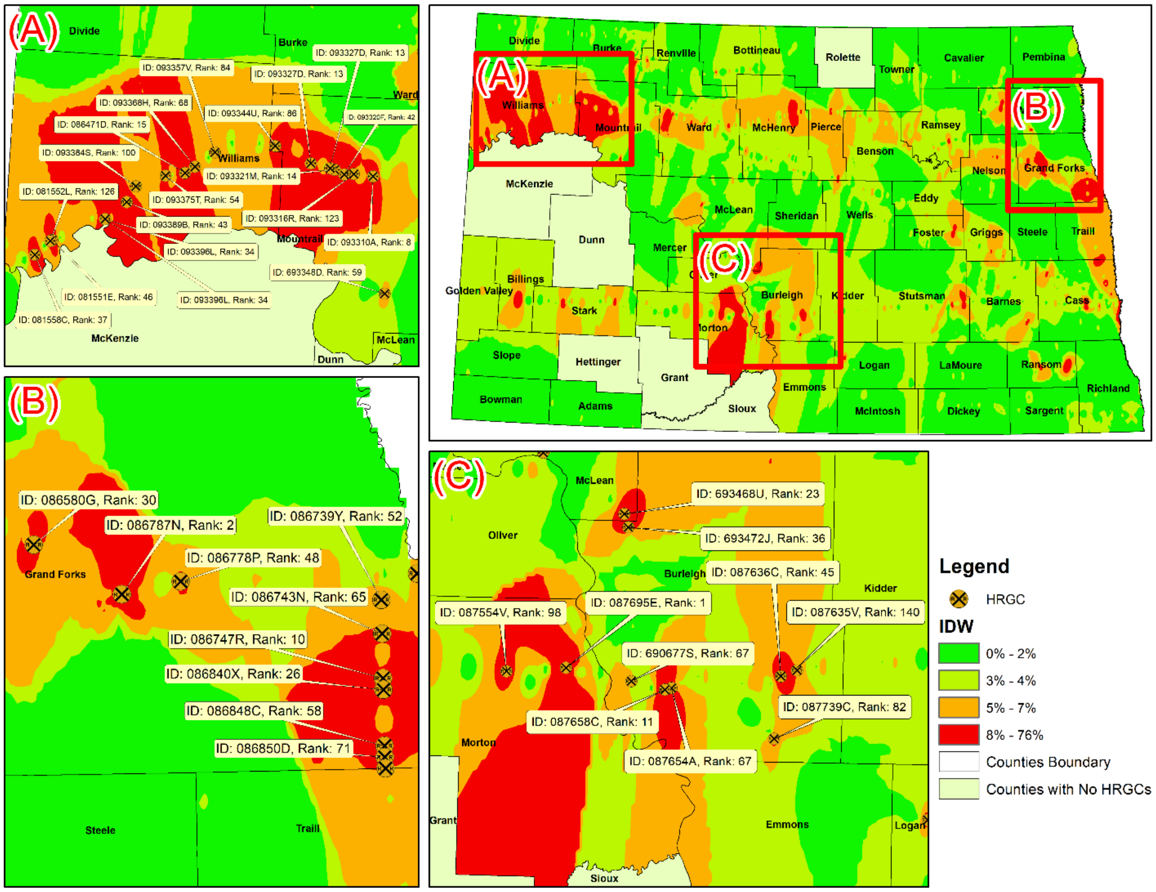

Figure 18. IDW Interpolation Based on Cumulative Crash Severity Likelihood for 29 Years

7.4.3. Comparing Ranking Based on Crossings' Crash Likelihood and AHP-HI

The pie charts in Figure 19 show the crossings' fractures according to the four risk groups based on crash likelihood and AHP-HI results. There is not considerable difference in the percentage of crossings classified as very low risk, low risk, and moderate risk between the two ranking approaches. However, the percentage of crossings classified as high risk according to AHP results is around five times more than the percentage of high risk crossings which are classified according to crash likelihood results. Comparing the expansion of high and moderate risk areas defined by two ranking approaches indicates the similar results according. One can see from Figure 6 and Figure 6 that more locations are covered by high and moderate risk areas based on AHP-HI results compared to high and moderate risk areas defined based on crash likelihood results.

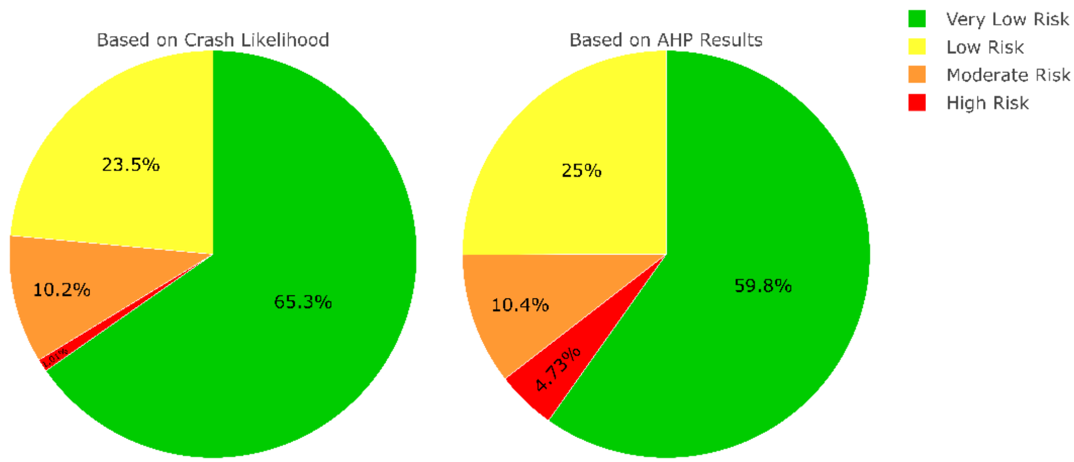

Figure 19. Comparing Risk Classification Approaches

It indicates the presence of crossings which are more likely to have severe crashes compared to the majority of crossings, but they are not considered as high risk based on the CLHR approach. It happens because these crossings' severe crash likelihood (fatal or injury) is higher than the majority of crossings, but their crash likelihood, regardless of their severity level is not high enough to be classified as high risk based on CLHR approach. To deal with such contradictory results, transportation decision makers need an approach to integrate the results of both aforementioned ranking approaches and define crossings' risk level considering their crash severity and frequency likelihood simultaneously.

7.4.4. Mixed Approach Based on Crash Likelihood and AHP-HI Results

In order to support risk ranking using the mixed approach of CLHR and AHP-HI ranking approaches, a risk matrix is devised. In the risk assessment studies, risk matrix is generally a table with several categories of probability, likelihood, or frequency as the table rows (or columns) and several categories of severity, impact, or consequences for the table columns (or rows, respectively) (S. Ma et al., 2015). In the risk matrix, a recommended level of risk, urgency, priority or management action is assigned to each row-column pair or cell (Anthony (Tony) Cox Jr, 2008). In this study, AHP-HI and crash likelihood risk levels make the risk matrix rows and columns, respectively. In addition, each cell indicates the number of crossings which have both AHP-HI and crash likelihood specific risk levels simultaneously. Four risk categories are defined based on the intersection of the risk matrix columns and rows:

1) High Risk: Resulted from intersections of high risk-high risk and high risk-moderate risk, and indicates that crossings require immediate priority in decision-making as crossings are at the risk of high crash frequency and severe crash occurrence.
2) Moderate Risk (Md Risk): Resulted from intersections of low risk-high risk and moderate risk-moderate risk, and indicates that crossings require attention and control process. Crossings might be at the risk of high crash frequency or severe crash occurrence.
3) Low Risk: Resulted from intersections of very low risk-high risk and low risk-moderate risk, and indicates that crossings might require a specific monitoring program. Crossings might be at the risk of moderate crash frequency and/or moderate severe crashes.
4) Very Low Risk (V Low Risk): Resulted from intersections of very low risk-moderate risk, very low risk-low risk, very low risk-very low risk, and low risk- low risk, and indicates that crossings can be managed based on the current standard controls and regulation.

Table 22 presents the number of crossings in each risk category. Table 22 indicates that 192 crossings are in the high risk category and 100 of them might have the higher risk as their risk level based on both AHP-HI and crash likelihood is high. In other words, these crossings are at the risk of having both high crash frequency and severe crashes. 156 and 242 crossings are at moderate and low risk, respectively, and the rest of the crossings are at very low risk.

Table 22. Risk Matrix Indicating Four Risk Categories

		Crash Likelihood					
		High Risk	Md Risk	Low Risk	V Low Risk		
AHP-HI	High Risk	100	51	0	0	High Risk	
	Md Risk	41	153	139	0	Moderate Risk	
	Low Risk	3	103	460	234	Low Risk	
	V Low Risk	0	6	126	1778	Very Low Risk	

7.4.5. Section Summary

Two hazard-ranking approaches were proposed based on 1) crossings' crash likelihood and, 2) based on crossings' AHP hazard index estimated by using crossings' crash severity likelihood. According to the crash likelihood hazard ranking (CLHR) model, 65.3%, 23.5%, 10.2%, and 1.01% of public grade crossings are at very low risk, low risk, moderate risk, and high risk of crash occurrence, respectively.

Since, transportation decision makers need a systematic method to ensure that federal and state funds for highway-rail grade crossing improvement projects are allocated to the locations that are considered the most in need of improvement, Inverse Distance weighted (IDW) interpolation is utilized to map the crossings' crash frequency and severity likelihood resulted by CRM in North Dakota. Interpolation based on crash likelihood revealed three main high risk areas located in west and central counties including Williams, Mountrail, Stark, Billings, Burleigh, and Morton.

Another proposed hazard raking model is AHP-HI model which estimates the hazard index for each crossing by using CRM crash severity likelihood results and AHP technique. Based on AHP-HI hazard ranking approach, crossings which are more likely to have severe crashes are assigned to the higher AHP-HI. Based on AHP-HI approach, 59.8%, 25%, 10.4%, and 4.73% of public grade crossings in North Dakota are classified as very low risk, low risk, moderate risk, and high risk crossings, respectively. The spatial risk analysis based on crossings' AHP-HI defines three high risk areas in the west, east, and central part of state. All of the high risk locations (red spots) defined based on crossing's crash likelihood are covered by high risk areas defined based on crossings' AHP-HI plus west area including Grand Forks.

Finally, to classify crossings' risk level considering their crash frequency and severity outputs simultaneously, the risk analysis was conducted by using risk matrix technique. The risk matrix technique can identify which crossings are more hazardous according to their predicted crash frequency and expected crash severity which is defined by AHP-HI estimation. Risk matrix results reveal that 192 crossings are classified as the high risk category and 100 of them might have the higher risk as their risk level based on both AHP-HI and crash likelihood is high. These 100 crossings are at risk of having both high crash frequency and severe crashes. 156 and 242 crossings are at moderate and low risk, respectively, and the vast majority of crossings are at very low risk.

CHAPTER 8 CONCLUSIONS

8.1. Summary and Conclusions

This study finding are based on 29-year empirical HRGC safety performance data in North Dakota. A novel safety decision-making frame work is designed to help transportation agencies and decision makers in identifying hazardous public HRGCs and locations in North Dakota. Such safety decision making frame work is generated based on a novel competing risk model and strong hazard-ranking approaches. The competing risk model was selected as a novel method to conduct simultaneous crash occurrence and severity likelihood analysis. The research results reveal knowledge about long-term marginal effects of control devices and geometric factors on grade crossing crash occurrence and severity likelihoods. A summary of findings associated with geometric and countermeasures effect analysis are as follows:

1) In general, adding a control device to a HRGC will decrease crash occurrence likelihood except when adding stop sign to a crossing already controlled by crossbucks only.
2) Adding a warning device to a HRGC will decrease crash occurrence likelihood, but the effects on the three severity levels can be very different. For example, adding stop signs to a crossing passively controlled by gate, flash lights, and audible devices will decrease injury and fatal risk. However, doing so will increase PDO crash risk even though the overall crash occurrence likelihood is decreased.
3) On average, the distance between a crossing and the nearby intersection and acute crossing angle have negative impacts on PDO, injury, and crash occurrence probability. However, they both have positive impacts on fatal crash risk. This study

results reveals that fatal crash frequency might increase with improved crossing operational conditions. This unexpected result could be rooted in aggressive drivers.

Moreover, considering the proposed hazard-ranking approaches in this study, transportation decision makers can utilize one or a combination of the following approaches to identify crossings or locations that have the most need for both safety and operational improvement:

1) Applying crash likelihood hazard ranking (CLHR) approach to rank crossings from the most hazardous crossing to the safest one, and applying safety/ operational improvement for crossing with lower rank (higher crash likelihood).
2) Applying AHP hazard index (AHP-HI) approach to rank crossings from the most hazardous crossing to the safest one, and applying safety/ operational improvement for crossing with lower rank (higher crash severity likelihood).
3) Utilizing spatial analysis proposed in 7.4.1.1 and 7.4.2.1 sections to recognize areas at deferent risk levels. Transportation decision makers might start applying safety improvements for crossings located in high risk areas for the first step; then for crossing located in areas with lower risk levels.
4) Using the risk matrix information. Transportation decision makers might start applying safety improvements for crossings with high risk situation (red cells in Table 22) for the first step; then for crossing with lower risk levels based on risk matrix categorization.

8.2. Limitation and Future Study

To conduct an accurate analysis of countermeasure's marginal effectiveness, before-and–after practical implementation is needed. However, such measurements and data have not been available and this study used North Dakota empirical data to apply countermeasures effectiveness analysis. Consequently, the uncertainty of this empirical pilot research needs more investigation before applying this information as HRGC safety decision-making frame work.

In addition, the interaction effects of contributors are not considered and quantified in this study, including interaction factors might alter the estimated coefficient of crossing warning devices. The effect of geometric features of HRGCs and countermeasures interaction on their safety performance is still under researched. Consequently, future studies on interaction impact of grade crossings' geometric and warning devices are recommended to evaluate both crash rate and crash severity level changes. In addition, countermeasures' effects with more pre-improvement conditions must be further researched when supporting data become available.

In this study, results indicated adding stop sign to a crossing with crossbucks only will increase crash rate and all three crash severity levels. Much better controlled experiments are needed and better understanding on the effects of cross-buck assembly with stop sign is needed. Moreover, safety improvement decision making cannot be accurate if it is solely determined by the marginal countermeasures' effects. Accordingly, life time total cost analysis including initial cost of construction, operational cost, and maintenance cost should be conducted in the studies to fully understand each countermeasure's cost-effectiveness. In this study Centered Moving Averages (CMA) technique was used as a discretization technique to classify crossings in different risk groups based on their AHP results. However, several unsupervised and supervised discretization techniques should be applied to identify the most accurate data binning technique to define the crossing risk group. Future studies might aim to utilize unsupervised discretization techniques such as Equal-Width, Equal-Frequency, and K-Means or supervised techniques such as Decision Tree.

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