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Highway - Rail Grade Crossing Identification and Prioritizing Model Development

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HIGHWAY-RAIL GRADE CROSSING IDENTIFICATION AND PRIORITIZING

MODEL DEVELOPMENT

by

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ABSTRACT

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The United States Department of Transportation (USDOT) provides funding to state DOTs to implement highway-rail grade crossing improvement programs. These programs are suspected to develop particular safety improvement actions in order to decrease the number of accidents at highway-rail grade crossings. The current work is directed to consider various hazard index/accident prediction methodologies, carefully investigate hazard index/accident prediction methods, applied by Tennessee Department of Transportation (TDOT), develop a model to allocate available monetary resources for upgrades of highway-rail grade crossings in the State of Tennessee and maximize the total benefits in terms of accident and severity reduction.

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1. INTRODUCTION

Under title 23, United States Code, Section 130 (hereafter referred to as “Section 130”), the United States Department of Transportation (USDOT) provides funding assistance to state departments of transportation to implement highway-rail grade crossing improvement programs. These programs are dedicated to reducing crashes at highway-rail grade crossings through safety infrastructure improvements. State departments of transportation (DOT) are required to meet specific reporting criteria under the Safe, Accountable, Flexible, Efficient, Transportation Equity Act: A Legacy for Users (SAFETEA-LU) to assess the progress and effectiveness of implementing highway-rail crossing programs. More specifically under Section 130 requirements, state departments of transportation should compile and analyze data (e.g., crash data, traffic data, physical characteristic, etc.) that will allow informed decisions to prioritize highway-rail grade crossing improvements. Programs to prioritize improvements, performed at the discretion of the state DOT, are encouraged to include evaluation of data compilation and analysis methods to ensure comprehensive and efficient programs (Ogden, 2007).

According to USDOT, prioritization of grade crossings for improvement is based on several factors. A significant and integral portion of prioritization programs is the identification of hazard or collision potential associated with a crossing. There are a variety of formulae developed for ranking rail-highway grade crossing hazard indices or collision prediction. Hazard indices rank crossings in relative terms of risk, hence the larger the calculated index the more hazardous a crossing; whereas collision prediction formulae compute predicted collision frequency at the crossing. In addition to hazard index or collision prediction, consideration of additional factors to prioritize crossing improvements include but are not limited to: cost, site inspection, exposure (number of persons using a crossing), crossing use by school buses, pedestrians, bicyclists, or vehicles carrying hazardous material.

Efforts to enhance prioritization programs, as previously stated, have led to investigation into the efficiency of current methods employed by state DOT's to index hazard or predict collisions (see Elzohairy & Benekohal, 2000; Faghri & Demetsky, 1986; Ogden, 2007). The structure of the these reports was to: a) compile current accident prediction methods (referred to as methods or models within this review) used by state departments of transportation through literature review and DOT surveys, b) evaluate the effectiveness of current hazard/accident prediction formulae and comparatively assess the methods using statistical analysis tools, and c) make recommendations on accident prediction methods for use by their state DOT based upon the findings. Summary of the literature evaluating the effectiveness of currently used hazard indices and collision prediction methods are presented in the next section.

The scope of the current work also includes investigation of accident prediction/hazard index models, currently used by different states, applying of those models to all at grade public highway-railroad crossings of Tennessee. Besides, all considered models were compared with US DOT Accident Prediction Model.

Using the accident prediction model, employed by TDOT and described carefully in the chapter 3, two different approaches will be developed, such as Sorting Algorithm (SA) and Mathematical Model (MM), in order to properly allocate monetary resources and to achieve the maximum possible increasing of safety at highway-grade crossings. Both solution methods were compared in the computational results' section. All necessary conclusions and recommendations along with the scope of future research are provided as well.

2. LITERATURE REVIEW

Statistical Analyses of Existing Hazard Indices and Collision Prediction Methods

In this section literature is summarized that, as previously mentioned, compared the performance of current methods used by DOT's to prioritize grade crossings. Three comprehensive studies are discussed in this section. These reports presented comprehensive statistical analyses of factors influence on accident prediction and method performance as well as evaluated the efficacy of current DOT methods prediction capability. Comparative analyses of these reports and conclusions which can be drawn are also presented in the next three subsections.

State of Virginia

A study performed under the Virginia Highway & Transportation Research Council identified current collision prediction and hazard indexing models used nationally, and evaluated the representative models' ability to use available data in predicting hazard potential, and recommended methods for future use by the Rail and Public Transportation Division to predict accident potential at highway-rail grade crossings (Faghri & Demetsky, 1986). The report identified 13 nationally recognized models (shown in Table 1), which are currently or have previously been employed with success by multiple state DOTs for the prediction of hazard/accident potential at highway-rail grade crossings as of March 1986.

Table 1
Nationally Recognized Hazard Prediction Models

Coleman-Stewart	Oregon
Peabody-Dimmick	North Dakota Rating System
Mississippi	Idaho
New Hampshire	Utah
Ohio	City of Detroit
Wisconsin	DOT (USDOT)
Costa Contra County (California)	

Source: Faghri and Demetsky (1986)

In addition to the review of the current methods, the report presented a survey of state departments of transportation current methodology employed to predict hazard/accidents at highway-rail grade crossings. Survey respondents from 45 states provided the method, and length of time these methods have been employed. Survey results, are shown in Figure 1. The survey showed roughly 32% of the states employ unique individual formulae, and another 30% use the DOT Formula (also identified as USDOT Formula within this report). According to the survey, about 22% used either the New Hampshire or modified version and about 8% Peabody-Dimmick Methods or a modified version of the original method that is particular to that states' criteria. The method employed by each state is largely dependent on data availability and key factors used as predictor variables for the particular method. As part of the survey, the study identified the factors considered in reported methods. Table 2 presents the survey responses to the factors used in the prediction models by the states surveyed.

Survey results showed that all 13 models used by 43 of the 45 states consider vehicular and train daily volume as a prediction factor within the model's formulae. In addition to vehicular and train volumes were existing crossing protection (i.e., cross bucks, flashing lights, gates, etc.) and number of tracks. The collision prediction or hazard index method of choice is inherently dependent upon the availability of data and the factors that the prediction formulae require.

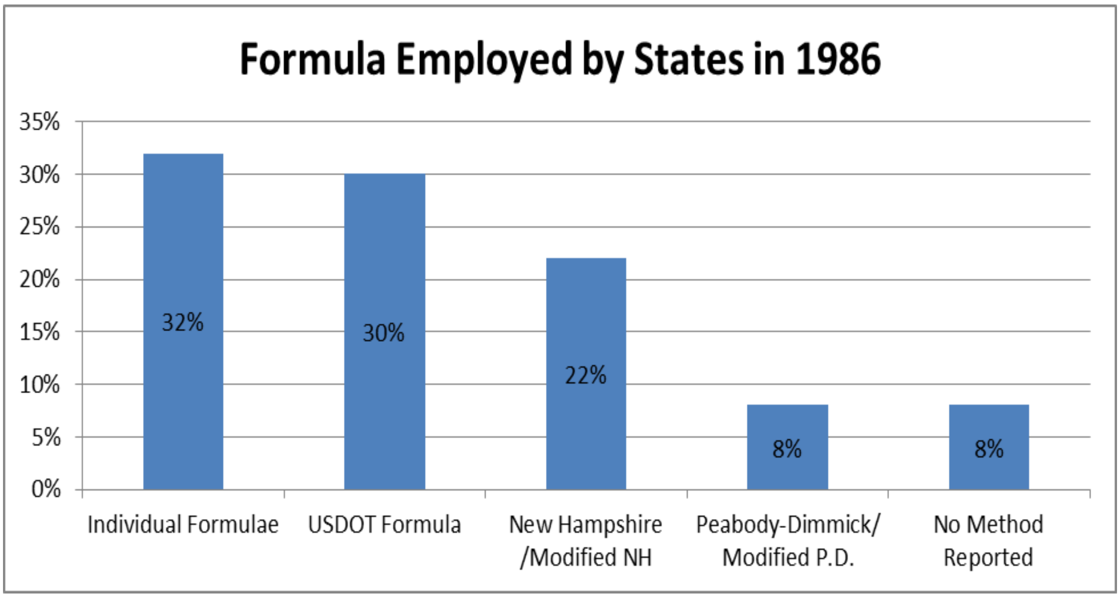

Figure 1 Utilization of Models to Predict Hazard/Accidents by State in 1986
Source: Faghri and Demetsky (1986)

Of the 13 recognized methods (shown in Table 1), currently used or previously used with success, five methods were tested and evaluated, as part of the study, to determine the methods prediction ability to that of observed accident data. The selection was based upon the available documentation of each method's development, testing, verification, and application. The five formulae selected for evaluation (shown in Table 3) were categorized into two basic groups (relative and absolute) based on each method's empirical formulae used for calculating hazard at highway-rail grade crossings (Faghri & Demetsky, 1986). The relative category group produced a measure of relative hazard (index of risk of hazard) for a variety of crossings which is used to rank crossings. The absolute category produces an expected number of accidents over a certain period of time, and the number of prevented accidents that may be observed if improvements are made. The latter method produces an expected number of accidents and the reduction of the number of accidents at any crossing.

Table 2
Factors Considered in the Existing Formulae

Factor Considered	Number of Formulae Containing the Factor (n=13)	Number of States Using the Factor in their Formulae (n=45)
Vehicles per day	13	43
Trains per day	13	43
Existing protection	10	37
Sight distance	7	14
Train Speed	6	13
Number of tracks	9	22
Highway vehicular speed	5	22
Accident records	5	23
Condition or type of crossing	3	20
Condition of approaches	3	6
Type of train	3	5
Approach gradient	2	6
Angle of crossing	2	5
Pedestrian hazard	2	1
Distribution of vehicular and/or train volumes throughout the day	3	14
Time Crossing is blocked	1	1
Darkness	1	1
Number of traffic lanes	2	15
School buses and/or carriers of hazardous materials	0	5

Source: Faghri and Demetsky (1986)

Table 3
Methods Selected for Evaluation and Testing

Relative Formulae	Absolute Formulae
New Hampshire	DOT Peabody-Dimmick NCHRP No. 50 (Virginia's Method: the current applied method by the conducting organization at that time) Coleman-Stewart

Source: Faghri and Demetsky (1986)

The primary statistical analysis tool used by researchers for this study was the power factor. A statistical chi-square test was performed for the four absolute methods to determine a goodness of fit using 1,536 crossings. Ancillary and significance statistical tests were performed to determine if sight distance and school bus traffic would affect results when included in hazard/accident prediction methods. Results of the chi-square test on the four absolute models revealed that the DOT formula produced the closest fit to the actual number of accidents at all crossings. The power factor analysis showed that the DOT model outperformed the other four absolute models, and suggested that inclusion of the DOT factors for percentiles of hazard would significantly increase the DOT formulae performance. The results also showed that the effects of sight distance and school bus traffic are not statistically significant when considering the influence on hazard/accident prediction formula. The report recommends consideration of the severity potential that school buses may present over typical crossing accidents be taken into consideration during final site evaluations. This report's findings recommended that use of the DOT hazard prediction model be employed in lieu of the NCHRP No. 50 that was in use at the time. In addition the report recommended the DOT resource allocation model could be used if the Virginia DOT saw the criteria that model uses to prioritize crossings applicable. This report, although dated, did provide accurate evaluation and comparison of the current or previously employed formula used to rank crossings, by using a large crossing sample size and applicable statistical methods.

State of Illinois

A research report prepared by the Illinois Transportation Research Center in cooperation with the Illinois DOT evaluated the effectiveness of the Expected Accident Frequency (EAF) formula used by the State of Illinois at the time, reviewed the hazard index and accident prediction formulae from other states, and made recommendations of further use of the EAF or adoption of an alternative approach, while compiling information about rail-bicycle and rail-pedestrian stand-alone crossings (Elzohairy & Benekohal, 2000). The researchers conducted a survey of state DOTs methodology and policies for accident prediction models or hazard indexing formulae used to prioritize highway-rail grade crossings. The survey elicited responses from 31 states. Results of the survey included: a) no formal methodology, b) hazard index/accident prediction formula, c) top crossings listed by the US DOT rating system, and d) top 20 crossings from FRA list (Elzohairy & Benekohal, 2000). The report summarized two sets of variables which are used in hazard index or accident prediction formulae, threshold limits used to reduce the number of crossings included for further consideration, and other criteria considered by state DOTs in their process (shown in Table 4).

Table 4
Variables in Exisitng Hazard Index/Accident Prediction Formulae

Variable in Formulae	Thresholds used by other DOTs	Other criteria in addition to formula
Daily average train movement by type and length	Highest hazard rating funding allows	Adjacent land use and development
Speed of each type of train	One crash every ten years	Political considerations
Number of school bus passengers	No firm minimum, but ADT > 1,000 vpd	Near-miss reports from railroad
Average daily train traffic (day/night, switch/through)	Project must be in top 1/3 of Index	Heavily used truck/bus route
Driveways and streets intersections near crossing	New Hampshire Index > 4,000	Age and condition of equipment
Crash history (Number of crashes in *n* years)	USDOT predicted accidents (PA) > 0.075	Restricted sight distance
Approach grade	3 crashes within 5 years	
Number of blind quadrants	One crash every nine years	
Angle of intersection		
Curvature of the roadway		
Surface type		
Heavy truck traffic		
Factor for hazardous materials		
Average daily traffic		
Average daily school bus traffic		
Number of tracks		
Number of lanes		
Type of warning device		
Type of area		
Posted speed limit		

Source: Elzohairy and Benekohal (2000)

The criteria used to prioritize crossings for improvements according to survey respondents included: a) higher hazard index/predicted accident, b) benefit/cost analysis, c) site review of vehicle types (school bus, mass transit), d) engineering judgment and crossing geometry, e) public concern/complaint, f) service condition, and g) sight distance (Elzohairy & Benekohal, 2000). The report included a literature review identifying existing accident prediction/hazard index formula. The report goes further to state that when prediction formulae are used in consideration of cost-effective allocations of improvement funds, absolute models present the most support for resource allocation decisions as opposed to hazard index rankings (Elzohairy & Benekohal, 2000). The literature review presented by Elzohairy and Benekohal (2000) identified 6 accident prediction models and 5 hazard indexing models (shown in table 5).

Table 5
Existing Methods Identified in Literature

Accident Prediction Formulae	Hazard Index Formulae
Peabody-Dimmick	Illinois Commerce Commission
Oregon Highway Commission	Mississippi Formula
NCHRP Report 50	The Oregon Method
Coleman-Stewart Model	New Hampshire Formula
TSC Model	Contra Costa County (California)
DOT Accident Prediction Formula	

Source: Elzohairy and Benekohal (2000)

The report provides a comprehensive statistical analysis of the variables that may contribute to crash occurrence presented in two categories: a) population-based rates, and b) traffic-based rates (Elzohairy & Benekohal, 2000). The results of the statistical analysis showed the relationship between population and crash rates is best described by a polynomial function. The general trend of that function was described such that crash rates will increase as the population per crossing increases. This relationship was determined to be significant when applied to the average number of accidents per county, a given number of crossings and population. The population-based rates did not directly reflect the traffic volume, and the traffic-based rates were employed to overcome this deficiency (Elzohairy & Benekohal, 2000). The correlation between average number of crashes per year and other traffic-based parameters (e.g., average daily traffic, number of total trains, number of tracks, etc.) were investigated using linear and nonlinear regression analysis for the following models: EAF, USDOT, Connecticut Hazard Index Formula, New Hampshire Index used by Michigan, and the California Hazard Index Formula. Figure 2 below shows the frequency of different formulae utilization by state in 2000.

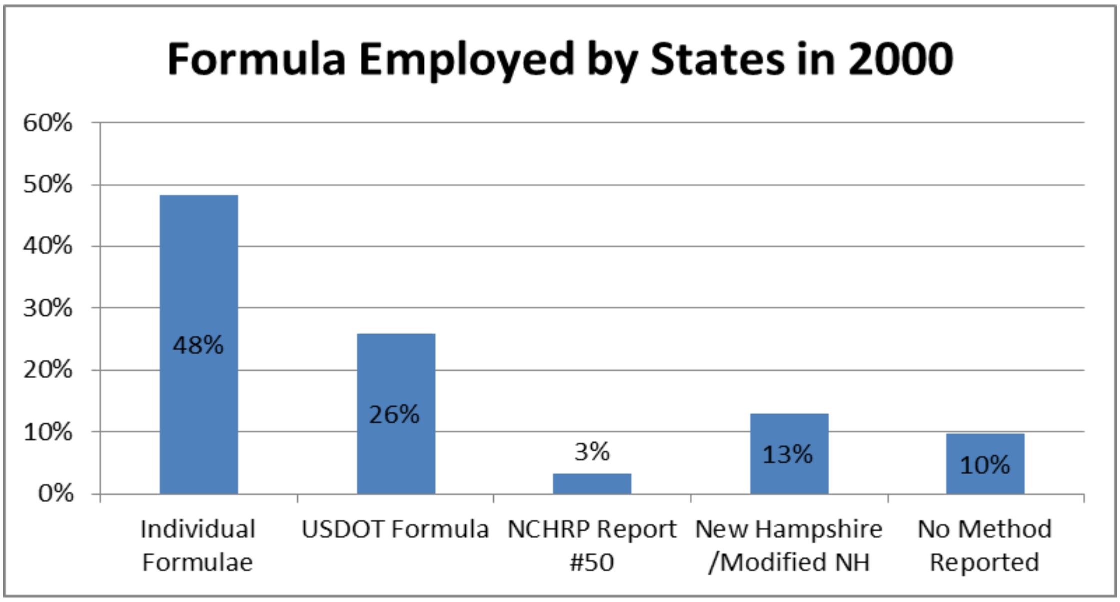

Figure 2 Utilization of Models to Predict Hazard/Accidents by State in 2000
Source: Elzohairy and *Benekohal (2000)*

The survey showed around 48% of the states employ unique individual formulae, and another 26% use the USDOT Formula. According to the survey, about 13% used the New Hampshire method and about 3% NCHRP Report 50 method. Ten percent of states didn't provide any information for this survey.

The report analyzed the efficacy of the EAF formula and other hazard index/accident prediction formulae using an inventory of 6,423 crossings throughout the State of Illinois. The suggested model for establishing a priority list, developed by Elzohairy and Benekohal (2000) was the Illinois Hazard Index (IHI).

The report presented step-wise regression analyses to determine what relationships exist between accident frequency and contributing factors. The dependent variable (number of accidents in five years) was compared with the following factors to determine their potential as predictors:

- Average daily traffic (ADT)
- Number of lanes (NOL)
- Number of main tracks (NMT)
- Number of day time trains (NDTT)
- Number of nighttime trains (NNTT)
- Number of total trains (NTT)
- Number of day switch trains (NDST)
- Number of night switch trains NNST)
- Maximum timetable speed (MTS)
- Sight distance (SD)
- Other multiplicative variables: ADT x NTT, ADT x NDTT, NOL x NMT

Results of the analysis showed that a regression relation exists between the dependent variable and the following predictors: ADT, NNTT, ADT x NTT, ADT x NDTT and NOL x NMT.

The report employed ancillary and significance statistical analysis of the effects of other factors on the IHI model including: time of day, type of area, and type of warning device. Results showed that these factors (i.e., time of day, area, and warning device), when separated into A separate formulae to consider each factor's impact on collision prediction solely, did not outperform models which employed these factors in one formula simultaneously (Elzohairy & Benekohal, 2000).

The researchers conclude that the EAF formula should be replaced with the models developed within this report, the several variations of the IHI, which more accurately identified locations that need safety improvements. The recommended IHI can potentially be applied to a crossing in any type of area (urban/rural), any with any type of warning device. The report recommended further investigation into the use of models with separate formulae for factors such as type of area (specifically to consider highway functional class) is needed. The report also states that data from selected sites should be used to compare reliability in selecting crossings in need of improvement (Elzohairy & Benekohal, 2000).

State of Missouri

A research report conducted by the University of Missouri-Columbia/Rolla in cooperation with the Missouri DOT Research, Development, and Technology Division identified models used by different states to prioritize highway-rail grade crossing improvements, evaluate and rank the models based on expert panel review, and recommend a replacement of the existing Exposure Index (EI) model that was currently used by the Missouri DOT (Qureshi et al., 2003). The report evaluated the following seven models: USDOT Accident Prediction Formula, California's Hazard Rating Formula, Connecticut's Hazard Rating Formula, Modified New Hampshire Formula, Kansas Design Hazard Rating Formula, Missouri's Exposure Index Formula, and Illinois modified IHI (developed within the previous research report). The report developed a modified EI method to include in evaluation and analysis.

The report included expert panel results for highway-rail grade crossing objectives, key variables, and eight criteria to evaluate models (Qureshi et al., 2003). Table 6 lists the results of the expert panel.

The evaluation of each model was performed by developing a baseline ranking of 6 crossings by Missouri DOT staff. The baseline rankings, used as a reference point to compare the performance of the models investigated, were developed for the list of crossing by the expert panel compiled under the report. The accuracy of the model was determined by comparing ranking of crossings to that of the baseline developed by the expert panel (Qureshi et al., 2003). Table 7 presents the results of the evaluation of the eight aforementioned models.

Table 6

Expert Panel Results for Model Evaluation

Objectives	Variables	Criteria for Evaluation
Safety (should improve safety)	Annual Daily Traffic	Accuracy of the model
Weighting Factors (account for importance in calculating number of accidents of hazard index)	Approach Sight Distance vs. recommended Sight Distance	Number of difficult variables
Data elements available in crossing inventories databases	Stopping Sight Distance vs. Recommended Sight Distance	Explanation ability
Crash rate = 0	Speed of train	Number of key variables
Accurately predict accident frequency	Number of passenger trains	Inclusion of crossing type
Explainable and definable	Speed of highway traffic	Number of unavailable data variables
Priority	Total number of trains	Number of total variables
Should suggest crossing treatments	Clearance time for motorist to clear crossing	Inclusion of weighting factors
Cover FHWA requirements		

Source: Qureshi et al. (2003)

Results of the report (shown in table 7) reveal that the EI model which was used by Missouri DOT at the time of the study could be replaced with a more accurate model. As shown in table 7, the EI model used by Missouri DOT at the time was outperformed in terms of ranking crossings when compared to baseline rankings for application to both passive and active controlled grade crossings. The report recommended that investigation into the applicability of the Kansas Design Hazard rating formula showed potential to replace the existing Missouri DOT method. Further research was deemed necessary to determine the application of the Kansas Model with larger sample sizes for evaluation. The report identifies concern for the consideration of data variables necessary and available resources for additional data collection and maintenance in inventory databases to employ the Kansas Model (Qureshi et al., 2003).

Table 7
Summary of Evaluation Results

Crossing Control Type	Model by Ranking
Passive	1. California' Hazard Index
	2. IHI
	3. Modified New Hampshire Formula
	4. US DOT Accident Prediction Formula
	5. Kansas's Design Hazard Rating
	6. Connecticut's Hazard Index
	7. Modified EI
	8. EI
Active	1. IHI
	2. Kansas's Design Hazard Rating
	3. Connecticut's Hazard Index
	4. EI
	5. Modified EI
	6. US DOT Accident Prediction Formula
	7. Modified New Hampshire Formulas
	8. California' Hazard Index

Source: Qureshi et al. (2003)

The reports reviewed in the previous section identified nationally recognized methods and presented statistical analysis for the comparison of the models presented. The recommendations for employment of models for state DOTs, although not reaching the same conclusion, show the rationale for choosing specific methodology based upon model accuracy, available data, and model formulation for accident prediction/hazard indexing. The reports reviewed provide guidance into adopting a new or improve a current method of accident prediction/hazard indexing methods. Each of the reports results, although not reaching the same conclusion, clearly define the methodology and process for their investigation and recommendations for the state DOT based on the pertinent criteria for that particular investigation. For example, as shown in many states, sight distance is intrinsic and directly correlative to accident rates, although no mathematical evidence supports this relationship. The remainder of this report presents a review of the literature related to measuring railroad crossing safety and countermeasure effects published in scientific journals.

Scientific Literature Review

While there is a significant amount of literature on the broader topic of accident prediction models and their consistency, little attention has paid to accident prediction and risk measurement in railroad crossings in the literature. Austin and Carson (2002) note the shortcomings of the four mentioned methods (Peabody Dimmick Formula, New Hampshire Index, NCHRP Hazard Index, USDOT Accident Prediction formula) and point out the need for a consistent accident prediction method. In particular, it is emphasized that the existing models focus on a restricted set of factors effective on railroad crossing accidents and ignore important safety factors.

Austin and Carson (2002) discuss three possible methods that can be used as an accident prediction method: multiple linear regression, Poisson regression, and Negative Binomial regression. Belle and Farr (1975) use multiple regression to examine the factors affecting accident rates in 1,140 railroad crossings in Florida. As noted by Austin and Carson (2002) as well, multiple linear regression is discussed to be inappropriate for accident prediction models due to inability of capturing negative correlations and heteroscedasticity issues (see, e.g., Joshua & Garber, 1990; Jovanis & Chang, 1986; Miaou & Lum, 1993). While Poisson regression may overcome these drawbacks of the multiple linear regression, it requires that the probability distribution of the number of accidents has equal expectation and variance values. Austin and Carson (2002), however, show that the test data gathered from the FRA's Office of Safety highway-rail crossing inventory does not meet this requirement (in particular, overdispersion is observed, i.e., the variance of the number of accidents is relatively high compared to the expectation of the number of accidents in the data used); thus, they utilize the negative binomial regression in their analyses. Their results conclude not only how significantly but also to what extent different traffic, roadway, and crossing characteristics influence railroad crossing accidents.

Lee, Park, and Nam (2005) also discuss compatibility of distinct statistical tools for accident prediction in railroad crossings. They use data from 100 railroad crossings in Korea for the period of September 2001 to April 2002. Analysis of this data suggests that the Poisson regression is more compatible than the negative binomial regression. Furthermore, they utilize zero-inflated Poisson regression, a modification of the Poisson regression to overcome the case when too many zeros are observed in the data than a regular Poisson process would predict. Similar to Austin and Carson (2002), Lee et al. (2005) use their proposed method to discuss how significantly different traffic, roadway, and crossing characteristics affect railroad crossing accidents.

Oh, Washington, and Nam (2006) study railroad crossing accident prediction methods for a data set collected from 162 crossings in Korea between years 1998 and

2002. Altering from Austin and Carson (2002) and Lee et al. (2005), they use a gamma model for the statistical analysis. Particularly, the reason for using the gamma model was due to the presence of underdispersion in the data (i.e., the variance of the number of accidents is relatively low compared to the expectation of the number of accidents in data collected). The gamma model is then used to discuss the significance of the effects of different traffic, roadway, and crossing characteristics on crossing accidents.

While the previously discussed studies focused on estimating the number of accidents, Hu, Li, and Lee (2010) and McCollister and Pflaum (2007) studied prediction methods for severity of railroad crossing accidents. McCollister and Pflaum (2007) proposed a logit model, which is commonly used for estimating accident severities (see, e.g., Donnel & Connor, 1996; Kweon & Kockelman, 2003; Shankar & Mannering, 1996), to report the factors affecting the injuries and fatalities in the accidents along with the accidents using data from FRA's Office of Safety highway-rail crossing inventory. Hu et al. (2010) analyzed a data set of railroad crossing accidents in Taiwan from 1995 to 1997 using a generalized logit model. Their study revealed the significantly effective factors in severity of railroad crossing accidents.

While the different studies use distinct statistical tools for accident prediction in railroad crossings, the goals are two-fold: develop a statistically sound method to estimate the accident rate at a given railroad crossing and reveal the factors significantly affecting this rate. The estimated rate can be used in resource allocation for upgrading railroad crossings, while the factors effecting accident rates can be used in developing railroad crossing specific preemptive practices, which are referred to as countermeasures. As noted by Washington and Oh (2007), there may be a set of preemptive practices for a specific railroad crossing. In that case, accurately predicting the success of countermeasures in reducing the risk, which can be considered as the ultimate goal of crossing upgrades, is important for maximization of risk reduction through effective allocation of the limited resources.

Washington and Oh (2007) document 18 countermeasures that are intended to increase safety at railroad crossings. These countermeasures are gathered from an extensive review of the literature. One may refer to Washington and Oh (2007) for definition of these countermeasures and the studies focusing on each of these countermeasures individually. They proposed a Bayesian data fusion method to estimate the expected performance of each countermeasure. Saccomanno, Young-Jin Park, and Fu (2007) develop a similar Bayesian data fusion method to predict effectiveness of countermeasures regarding the characteristics of a crossing.

Yan, Richards, and Su (2010) uses a hierarchical tree-based regression method to estimate the number of accidents at a given set of railroad crossings, which were upgraded from cross-only bucks to stop signs, to analyze the effectiveness of stop-signs as a countermeasure. Furthermore, Yan et al. (2010) analyzed the factors influencing the effectiveness of stop signs at crossings. Rudin-Brown, Lenné, Edquist, and Navarro (2011) focus on the effectiveness of traffic lights and boom-barrier controls in reducing railroad crossing accidents. They use a driver simulator on 25 drivers to demonstrate how traffic lights and boom-barrier controls may reduce possible accidents at crossings due to driver behaviors.

Rudin-Brown et al. (2011) considered different kinds of traffic devices in order to improve safety at road-rail level crossings. They investigated perception of 25 fully-licensed drivers aged between 20 and 50 years, using a driving simulator, for two active level crossing traffic control devices (such as flashing lights with boom barriers and standard traffic lights) and passive control devices (stop signs). Results showed that the less number of violations were observed at active level crossings than those controlled by stop signs. It was indicated, that the majority (72%) of drivers reported preferring flashing lights to traffic lights. Nevertheless, the installation of traffic lights at real-world level crossings would not be likely to offer safety benefits over and above those provided already by flashing lights with boom barriers. It was concluded that it was necessary to continue upgrading of rail crossing with active traffic control devices to increase the safety.

Wullems (2011) considered the issue of the low-cost level crossing warning devices (LCLCWDs) adoptions at rail crossings. The author stated that the risk along the network could be reduced by combination of low-cost and conventional level crossing interventions, similar to what was done in the road environment. The paper indicated that before application of LCLCWDs it was necessary to conduct a rigorous risk assessments and cost-benefit analyses for these devices. The strategy for progressing research and development of LCLCWDs and recommendations how the Cooperative Research Centre (CRC) for Rail Innovation can apply it were provided in the article as well.

Wigglesworth (2001) conducted a study of 85 consecutive railway crossing deaths, connected with flashing light signals. The results showed that flashing light signals gave inadequate stimulus at busy urban crossings, but many drivers behaved similarly at both active and passive rural crossings. The author proposed to use different kinds of signs for various rail crossings. For metropolitans and urban crossings it was suggested to use boom barriers instead of flashing lights. Passive rail crossings usually have small traffic volumes and it makes difficult to measure the effectiveness of countermeasures. The paper concludes that it was necessary to conduct before and after studies at rail crossings to evaluate the reliability of warning signs. Along with low-cost treatments, surrogate measures should be implemented.

Conclusion

From the reviewed literature the most commonly used prediction models, in practice, are the Peabody Dimmick Formula, New Hampshire Index, NCHRP Hazard Index, and USDOT Accident Prediction formula. The Peabody Dimmick Formula gives an estimated number of accidents in a five year period considering the average annual daily traffic, average daily train traffic, and a predetermined protection coefficient. Nevertheless, as noted by Austin and Carson (2002), it lacks validity as the data used to develop the formula was sampled from only crossings in rural regions, and the predefined protection coefficient cannot capture the recent advancements in protection methods at the railroad crossings. Similar to the Peabody Dimmick Formula, the New Hampshire Index utilizes the average annual daily traffic, average daily train traffic, and a protection factor to determine a hazard index. A large value of the hazard index implies a greater risk at the railroad crossing. The New Hampshire Index is modified by different states in various ways to include distinct roadway characteristics such as number of lanes, sight distance, vertical sight distance, crossing characteristics such as surface type, width of the crossing, approach angle, and detailed traffic characteristics such as fast and slow train traffic, hazardous material traffic, school bus traffic, train speeds, highway speeds, etc. These modifications lead to several accident prediction formulae, which result in different significance levels as discussed by Faghri and Demetsky (1986).

Furthermore, these variations of the use of the index created concern in its accuracy (Oh et al., 2006). The NCHRP index estimates collision potential using the daily traffic, train traffic, and a protection coefficient, which is defined separately for urban and rural areas. The main flaw of the aforementioned methods is that they consider three basic factors to be the drivers of railroad crossing accidents; roadway traffic, train traffic, and protection level at the crossing. Developed using the national railroad crossing accident data of years 1981 through 1986, the USDOT formula includes a variety of crossing characteristics such as maximum speed, highway lanes, highway speed, and highway paved factor in accident prediction. These crossing characteristics are discussed to be significantly related to crossing accidents based on the 1981-1986 data. USDOT formula is discussed to be an improved prediction method compared to the previous methods as it account for more explanatory factors effecting railroad crossing safety. Nevertheless, as noted by Austin and Carson (2002), the USDOT formula has shortcomings in weighting in contribution of different safety factors in estimating accident rates as well as inaccuracies in formulae updating. A number of alternative to these methods, found in the scientific literature, may address some of these issues but are data intensive and their application requires significant effort (data, modeling, dissemination) making their use restrictive by state DOTs due to insufficient resources and/or marginal benefits.

3. FRA PROCEDURE REVIEW AND EVALUATION

This review discusses the USDOT accident prediction model, accident severity calculation, resource allocation procedure, and GradeDec software utility. The accident prediction model, which is comprised of three formulae, was developed to assist individual states in maintaining requirements under Federal-Aid Policy Guidelines (FAPG). The accident prediction model is one portion of the US DOT resource allocation procedure that is intended to predict, in absolute terms, the likelihood of a collision over a period of time at a crossing. Additional equations within the US DOT model are used to predict the likelihood of fatalities and injuries. In order to provide assistance in grade crossing investment decision making processes the FRA developed a highway-rail grade crossing investment analysis tool GradeDec.NET (GradeDec). GradeDec gives the possibility to compare rail grade crossings improvement alternatives, designed to mitigate highway-rail grade crossing collision risk and other components of user costs. The following section of review discusses the accident prediction formulae that are included in that model.

US DOT Highway Rail Grade Crossing Methods

As a general description, the US DOT accident prediction model combines three independent equations to produce an accident prediction value. The three equations were developed to include as much information possible in determining the accident risk for a highway rail grade crossing. The first equation, also denoted as the basic formula, equates an initial hazard ranking for a crossing based upon the crossing's physical and operational characteristics. The second equation uses average historical accident rates over a period of time to determine an accident prediction value. This procedure uses the assumption that future collisions will be the same as previous accident occurrences. The third equation employs a normalizing constant, which is adjusted periodically, such that the procedure adheres to current accident trends. The result of these three equations is a final collision prediction that considers crossing conditions, historical accident data, and current accident trends to produce a reliable accident prediction value, ranking highway rail grade crossing risk, and in turn offering a comparative medium for crossing improvements based upon the potential for risk reduction. The remainder of this chapter details the three equation development, data factors, and processes.

Accident Prediction

The basic formula as stated previously produces an initial accident prediction per year based upon the physical and operational characteristics of each crossing. The technique used to develop the basic equation involved applying multiple non-linear regression to crossing inventories and accident data contained in the FRA Railroad Accident/Incident Reporting System (RAIRS). The equation can be expressed as a series of factors from crossing characteristics that are maintained within the crossing inventory. The basic equation is shown below

$$a = K \ x \ EI \ x \ MT \ x \ DT \ x \ HP \ x \ MS \ x \ HT \ x \ HL$$

where:

a = initial collision prediction, collisions per year at the crossing

K = formula constant

EI = factor for exposure index based on product of highway and train traffic

MT = factor for number of main tracks

DT = factor for number of through trains per day during daylight

HP = factor for highway paved (yes or no)

MS = factor for maximum timetable speed

HT = factor for highway type

HL = factor for number of highway lanes

The basic equation is developed for three g categories based upon traffic control devices present at the crossing: passive, flashing and lights, and automatic gates as shown in Figure 3.

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Crossing Characteristic Factors

Crossing Category	Formula Constant K	Exposure Index Factor EI	Main Tracks Factor MT	Day Thru Trains Factor DT	Highway Paved Factor HP	Maximum Speed Factor MS	Highway Type Factor HT	Highway Lanes Factor HL
Passive	0.002268	$\left(\frac{c \times t + 0.2}{0.2}\right)^{0.3334}$	$e^{0.2094mt}$	$\left(\frac{d + 0.2}{0.2}\right)^{0.1336}$	$e^{-0.6160(hp-1)}$	$e^{0.0077ms}$	$e^{-0.1000(ht-1)}$	1.0
Flashing Lights	0.003646	$\left(\frac{c \times t + 0.2}{0.2}\right)^{0.2953}$	$e^{0.1088mt}$	$\left(\frac{d + 0.2}{0.2}\right)^{0.0470}$	1.0	1.0	1.0	$e^{0.1380(hl-1)}$
Gates	0.001088	$\left(\frac{c \times t + 0.2}{0.2}\right)^{0.3116}$	$e^{0.2912mt}$	1.0	1.0	1.0	1.0	$e^{0.1036(hl-1)}$

c = annual average number of highway vehicles per day (total both directions)

t = average total train movements per day

mt = number of main tracks

d = average number of thru trains per day during daylight

hp = highway paved, yes = 1.0, no = 2.0

ms = maximum timetable speed, mph

ht = highway type factor value

hl = number of highway lanes

Highway Type	Inventory Code	ht Value
Rural		
Interstate	01	I
Other principal arterial	02	2
Minor arterial	06	3
Major collector	07	4
Minor collector	08	5
Local	09	6
Urban		
Interstate	11	1
Other freeway and expressway	12	2
Other principal arterial	14	3
Minor arterial	16	4
Collector	17	5
Local	19	6

Figure 3 Basic Equation Accident Prediction for Crossing Characteristic Factors
Source: Railroad-Highway Grade Crossing Handbook, Revised Second Edition. *(2007). Washington, DC: US DOT, FHWA.*

The factors listed in Figure 3 can be equated and tabulated based upon known crossing characteristics. The tabulated values are used to predict collisions based upon particular characteristics for a crossing. The tabulated values for the three categories are presented in Appendix A.

The final collision prediction formula is shown below

$$B = \frac{T_0}{T_0 + T}(a) + \frac{T_0}{T_0 + T}\left(\frac{N}{T}\right)$$

B = second collision prediction, collisions per year at the crossing

a = initial collision prediction from basic formula, collisions per year at the crossing

N/T = collision history prediction, collisions per year, where N is the number of observed collisions in T years at the crossing

T_0 = Formula weighting factor,

$$T_0 = \frac{1.0}{(0.05 + a)}$$

The final collisions prediction, B, can be tabulated based upon known crossing factors and values for initial prediction, a, and historical collision rates, N/T presented in Appendix B. The use of all obtainable historical collision data will provide the most accurate prediction results. Collision data collected prior to warning device infrastructure improvements should not be included in prediction calculations. Historical data older than five years will have minimal improvement on collision prediction accuracy.

Final collision prediction, A, applies normalizing constants to incorporate current trends in collisions at rail-highway grade crossings. Originally these normalizing constants are developed by periodically setting the sum of the predicted accidents, for each category separately, of the top 20% most hazardous crossings exactly equal to the number of accidents which occurred in a recent period for the top 20% of that group. Periodic updates of US DOT normalizing constants since inception of the procedure are presented in Table 8 below.

Table 8
Accident Prediction and Resource Allocation Procedure Normalizing Constants

WARNING DEVICE GROUPS	NEW	PRIOR YEAR CONSTANTS							
	2010	2007	2005	2003	1998	1992	1990	1988	1986
(1) Passive	**.4613**	.6768	.6407	.6500	.7159	.8239	.9417	.8778	.8644
(2) Flashing Lights	**.2918**	.4605	.5233	.5001	.5292	.6935	.8345	.8013	.8887
(3) Gates	**.4614**	.6039	.6513	.5725	.4921	.6714	.8901	.8911	.8131

Source: Federal Railroad Administration ACPD Constants 2010. *US Department of Transportation, FRA.*
http://www.fra.dot.gov/downloads/safety/ACPDConstants2010.pdf

According to reporting for the most recently developed constants, the normalizing constants were calculated by making the sum of calculated accident for calendar years 2004-2008 equal to the sum of the observed accidents that occurred in 2009 at the same crossings. The process is performed for each of the three categories of crossings to account for the trends in collisions in recent history. The current trend for collisions, as depicted by the most recent set of normalizing constants, is downward; which according to available crash data is representative of conditions.

The final collision prediction results from the US DOT accident prediction formulae can be incorporated into accident severity calculations to consider probabilities for fatal and injury accidents or into the resource allocation procedure to evaluate improvement alternatives which are described in the following sections.

Accident Severity

Additional equations within the U.S. DOT model are used to predict the likelihood of fatalities and injuries. The probability of a fatal accident given an accident, P(FA|A), is expressed as:

$$P(FA \mid A) = \frac{1}{1 + CF \times MS \times TT \times TS \times UR}$$

where:

CF = formula constant = 695

MS = factor for maximum timetable train speed

TT = factor for through trains per day

TS = factor for switch trains per day

UR = factor for urban or rural crossing

The probability of an injury accident given an accident is:

$$P(IA|A) = \frac{1 - P(FA|A)}{1 + CI \times MS \times TK \times UR)}$$

where:

P(FA|A) = probability of a fatal accident, given an accident

CI = formula constant = 4.280

MS = factor for maximum timetable train speed

TK = factor for number of tracks

UR = factor for urban or rural crossing

The equations for calculating values of the factors for the fatal accident probability formula and the injury accident probability formula are listed in Figures 4 and 5. To simplify use of the formulae, the values of the factors have been tabulated for typical values of crossing characteristics and are given in Figures 6 and 7 for the fatal accident and injury accident probability formulae.

Fatal Accident Probability Formula:

$$P(FA \mid A) = \frac{1}{(1 + CF \times MS \times TT \times TS \times UR)}$$

Crossing Characteristic Factor	Equation for Crossing Characteristic Factor
Formula constant	$CF = 695$
Maximum timetable train speed factor	$MS = ms^{-1.074}$
Thru trains per day	$TT = (tt + 1)^{-0.1025}$
Switch train per day factor	$TS = (tt + 1)^{0.1025}$
Urban-Rural crossing factor	$UR = e^{0.1880ur}$

where: ms = maximum timetable train speed, mph
tt = number of thru trains per day
ts = number of switch trains per day
ur = 1, urban crossing
= 0, rural crossing

Figure 4 Equations for Crossing Characteristic Factors for U.S. DOT Fatal Accident Probability Formula

Source: Railroad-Highway Grade Crossing Handbook, Revised Second Edition. (2007). *Washington DC: US DOT, FHWA.*

Injury Accident Probability Formula:

$$P(IA \mid A) = \frac{1 - P(FA \mid A)}{(1 + CI \times MS \times TK \times UR)}$$

Crossing Characteristic Factor	Equation for Crossing Characteristic Factor
Fatal accident probability	P(FA|A) - See Table 25
Formula constant	CI = 4.280
Maximum timetable train speed factor	$MS = ma^{-0.2334}$
Number of tracks factor	$TK = e^{0.1176tk}$
Urban-Rural crossing factor	$UR = e^{0.1844ur}$

where: ms = maximum timetable train speed, mph
tk = total number of tracks at crossing
ur = 1, urban crossing
0, rural crossing

Figure 5 Equations for Crossing Characteristic Factors for U.S. DOT Injury Accident Probability Formula

Source: Railroad-Highway Grade Crossing Handbook, Revised Second Edition.(2007). *Washington DC: US DOT, FHWA.*

Resource Allocation Procedure

Along with various economic analyses procedures, in order to improve safety at railroad-highway crossings, the US.DOT developed a resource allocation procedure. It assists state railway authorities to find those rail crossings which need to be repaired first, and to most effectively separate available funds across multiple highway-rail grade crossings.

The resource allocation procedure is directed to suggest various types of crossing traffic control improvements with multiple degrees of risk reduction and cost for implementation.

The procedure provides traffic control improvement alternatives for the following:

- For single track passive crossings two upgrade options exist:

flashing lights or gates;

- For multiple-track passive crossings, the model allows only the gate option to be considered in accordance with the Federal-Aid Policy Guide;

- For flashing light crossings, the only improvement option is gates;

Fatal Accident Probability Formula:

$$P(FA \mid A) = \frac{1}{(1 + CF \times MS \times TT \times TS \times UR)}$$

where: CF = 695.0, formula constant
UR = 1.207, urban crossing
= 1.000, rural crossing, and

Maximum Timetable Train Speed	MS	Thru Trains Per Day	TT	Switch Trains Per Day	TS
1	1.000	0	1.000	0	1.000
5	0.178	1	0.931	1	1.074
10	0.084	2	0.894	2	1.119
15	0.055	3	0.868	3	1.152
20	0.040	4	0.848	4	1.179
25	0.032	5	0.832	5	1.202
30	0.026	6	0.819	6	2.221
40	0.019	7	0.808	7	1.238
50	0.015	9	0.790	9	1.266
60	0.012	10	0.782	10	1.279
70	0.010	20	0.732	20	1.366
80	0.009	30	0.703	30	1.422
90	0.008	40	0.683	40	1.464
100	0.007	50	0.668	50	1.497

Figure 6 Factor Values for U.S. DOT Fatal Accident Probability Formula

Source: Railroad-Highway Grade Crossing Handbook, Revised Second Edition. (2007). *Washington DC: US DOT, FHWA.*

Injury Accident Probability Formula:

$$P(IA \mid A) = \frac{1 - P(FA \mid A)}{(1 + CI \times MS \times TK \times UR)}$$

where: $P(FA|A)$ = Fatal accident probability, See Tables 25 and 27
CI = 4.280, formula constant
UR = 1.202, urban crossing
= 1.000, rural crossing, and

Maximum Timetable Train Speed	MS	Total Number Of Tracks	TK
1	1.000	0	1.000
5	0.687	1	1.125
10	0.584	2	1.265
15	0.531	3	1.423
20	0.497	5	1.800
25	0.472	6	2.025
30	0.452	7	2.278
40	0.423	8	2.562
50	0.401	9	2.882
60	0.385	10	3.241
70	0.371	15	5.836
80	0.360	20	10.507
90	0.350		
100	0.341		

Figure 7 Factor Values for U.S. DOT Injury Accident Probability Formula

Source: Railroad-Highway Grade Crossing Handbook, Revised Second Edition. (2007). *Washington DC: US DOT, FHWA.*

The resource allocation procedure does not include improvement alternatives, such as: illumination, crossing surface improvements, removing of visual obstructions, train direction security improvements, etc. The initial data for the procedure includes the following contents: the number of predicted collisions; the safety effectiveness of flashing lights and automatic gates; cost of improvements; the available budget.

The US DOT, California Public Utilities Commission (CPUC), and William J. Hedley each completed safety effectiveness studies for the equipment used in the resource allocation procedure. Various effectiveness factors have been developed to evaluate signal improvements applicable for the procedure as shown in Table 9. These effectiveness factors represent the overall percentage in rail crossing collision reduction, taking place after application of the proposed improvements.

Table 9
Effectiveness of Active Crossing Warning Devices

	Effectiveness Factors (Percent)		
Category	**1980 US DOT**	**1974 California**	**1952 Hedley**
Passive to Flashing Lights	70	64	63
Passive to Automatic Gates	83	88	96
Flashing Lights to Automatic Gates	69	66	68

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: US Department of Transportation, Federal Highway Administration.*

As it as mentioned before, the model requires the information about the improvement alternatives cost. At this stage, life-cycle costs of the devices (both installation and maintenance costs) should be presented. Cost data for the resource allocation procedure should be provided for each of the following items:

- Passive devices to flashing lights;
- Passive devices to automatic gates;
- Flashing lights to gates;

It is necessary to indicate the reasons during the process of cost assignment for a particular project, taking into consideration average costs for all projects. To estimate the cost effectiveness a special resource allocation algorithm, which would be described below, should be used. The amount of funds available for application of a particular cross signal projects is the fourth step for the resource allocation procedure. The resource allocation procedure hierarchy, shown in Figure 8, incorporates all steps which were described in detail above.

The resource allocation algorithm should be implemented for any proposed signal improvements. The main characteristics of this algorithm are E_j (the effectiveness of installing a proposed warning device at a crossing with a lower class warning device) and C_j (the corresponding cost of the proposed warning device). As shown in Table 10, j = 1 for flashing lights installed at the passive crossing; j = 2 for gates installed at the passive crossing; and j = 3 for gates installed at the crossing with flashing lights.

Table 10

Effectiveness/Cost Symbol Matrix

	Existing warning device	
Proposed warning device	Passive	Flashing lights
Flashing lights		
Effectiveness	E_1	—
Cost	C_1	—
Automatic gates		
Effectiveness	E_2	E_3
Cost	C_2	C_3

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: US Department of Transportation, Federal Highway Administration.*

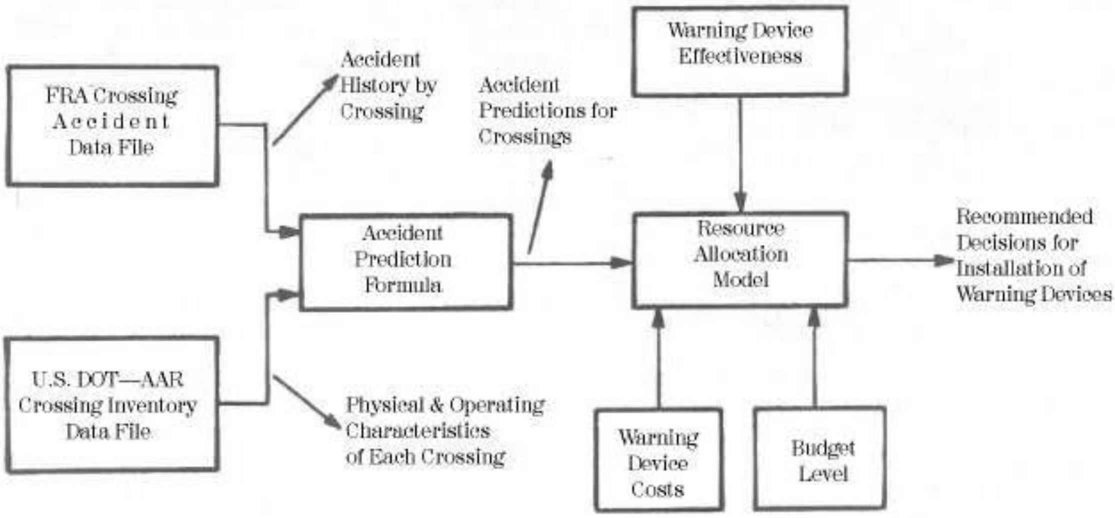

Figure 8 Resource Allocation Procedure

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: US Department of Transportation, Federal Highway Administration.*

Most of all, the resource allocation procedure evaluates possible improvements for both passive and flashing light traffic control devices. An example presented by Ogden, 2007: If a single-track passive crossing, i, is considered, it could be upgraded with either flashing lights, with an effectiveness of E_1, or gates, with an effectiveness of E_2. The number of predicted collisions at crossing i is A_i. Therefore, the reduced accidents per year are A_iE_1 for the flashing light option and A_iE_2 for the gate option. The corresponding costs for these two improvements are C_1 and C_2. The accident reduction/cost ratios for these improvements are A_iE_1/ C_1 for flashing lights and A_iE_2/C_2 for gates. The rate of increase in accident reduction versus costs that result from changing an initial decision to install flashing lights with a decision to install gates at crossing i is referred to as the incremental accident reduction/cost ratio and is equal to:

$$A_i\ (E_2 - E_1) / (C_2 - C_1)$$

If a passive multiple-track crossing, i, is considered, the only improvement option allowable would be installation of gates, with an effectiveness of E_2, a cost of C_2, and an accident reduction/cost ratio of A_iE_2/C_2. If crossing i was originally a flashing light crossing, the only improvement option available would be installation of gates, with an effectiveness of E_3, a cost of C_3, and an accident reduction/cost ratio of A_iE_3/C_3.

The individual accident reduction/cost ratios associated with these improvements are selected by the algorithm to produce the maximum accident reduction that can be obtained for a predetermined total cost. This total cost is the sum of an integral number of equipment costs (C_1, C_2, and C_3). The total maximum accident reduction is the sum of the individual accident reductions of the form AE.

The resource allocation procedure is directed to identify high-hazard crossings. To collect the necessary data and check for accuracy the input data and substantiation of each recommendation a field diagnostic team should investigate considered crossings. A sample of a worksheet for conducting this procedure is presented in Appendix C. This worksheet also includes a method for proper evaluating and revising the results, given by the computer model.

Federal Railroad Administration GradeDec Software

In order to provide assistance in grade crossing investment decision making processes the FRA developed a highway-rail grade crossing investment analysis tool GradeDec.NET (GradeDec). This software includes a full set of standard benefit-cost metrics for a rail corridor, a region, or an individual grade crossing. GradeDec gives the possibility to compare rail grade crossings improvement alternatives, designed to mitigate highway-rail grade crossing collision risk and other components of user costs, including: highway delay and queuing, air quality, and vehicle operating costs.

The online application can is available via the FRA's Website (http://safety.fhwa.dot.gov/xings/com_roaduser/07010/sec05.htm).

The software helps states' railway authorities develop the most effective (cost) and beneficial (risk reduction) grade crossing investment strategies. It helps to predict the development of the improvement project from the early stages of its application to the final steps. Most of all, the model output can be computed by using a certain range of the model inputs. It gives the opportunity to see the difference in the sets of project and to choose the most applicable of the considered conditions. GradeDec employs a corridor approach when analyzing the decrease in collision risk, which was developed as part of the Transportation Equity Act for the 21st Century's Next-Generation High-Speed Rail Program. This approach is one of the most effective ways to reduce the overall capital costs involved in constructing facilities for high-speed passenger rail service (at speeds between 111 and 125 mph), where grade crossing hazards and mitigation measures can be a major cost factor.

Accident Prediction Models Used by Different States

Tennessee Department of Transportation (TDOT) currently uses FRA (US DOT) accident prediction model, carefully described above, to estimate the number of accident at highway-rail at grade crossings within the state. Based on calculated number of accidents and resource allocation procedure, the prioritizing of rail crossings is conducted. The main aim of TDOT is to achieve the maximum total reduction of accidents with respect to available monetary resources. At this point it will be useful to make investigation on accident prediction methods, implemented by other states, and compare them with US DOT, using the data from TRIMS database for all public at grade rail crossings. The following accident prediction models were mentioned in the literature review section (previously investigated by Virginia, Illinois and Missouri states): Florida Department of Transportation Accident Prediction Model, Missouri's Exposure Index Formula, Modified New Hampshire formula, Kansas's Design Hazard Rating Formula, California's Hazard Rating Formula, Connecticut's Hazard Rating Formula, Illinois's Modified Expected Accident Frequency Formula, Peabody-Dimmick Formula, New Hamphire Formula. Some approaches cannot be applied for Tennessee rail crossings (Florida Department of Transportation Accident Prediction Model, Missouri's Exposure Index Formula, Modified New Hampshire formula, Kansas's Design Hazard Rating Formula), because they consider the effect of site distance. The information about site distance is not provided neither by TRIMS or FRA Inventory databases. If this data is collected, all accident prediction models could be implemented for all Tennessee highway-rail at grade crossings. The rest of discussed accident prediction models will be applied and the results will be presented.

California's Hazard Rating Formula

The State of California uses the hazard rating formula, which includes four factors: number of vehicles, number of trains, crossing protection type and the crash history as input to the model. The difference with US DOT model is that California Hazard Rating Formula uses a 10 – year accident history. The formula doesn't estimate the number of accident at each rail crossing, but it calculates the hazard index, which helps to rank crossings by the possibility of accident to occur. The highest priority should be assigned to the crossing with greater value of hazard index. The following equation is used to calculate California's Hazard Index:

$$CaHIF = \frac{V \times T \times PF}{1000} + AH$$

where CaHIF - California's Hazard Index value;

V = number of vehicles;

T = number of trains;

PF – protection factor (see table 11);

AH =crash history (the total number of accident in the last 10 years).

Table 11
Protection Factor Values for California's Hazard Rating Formula

Devices	PF
Stop sign or Cross buck	1.0
Flashing lights	0.33
Gates	0.13

Connecticut's Hazard Rating Formula

The State of Connecticut uses the hazard rating formula, which is relatively similar to California Hazard Rating Formula. It also incorporates four various factors: annual average daily traffic, number of trains per day, crossing protection type and the crash history as input to the model. The main difference is that Connecticut considers the accident history for the last 5 years. The formula doesn't estimate the number of accident at each rail crossing, but it calculates the hazard index, which helps to rank crossings by the possibility of accident to occur. The highest priority should be assigned to the crossing with greater value of hazard index. The following equation is used for Connecticut's Hazard Rating Formula:

$$CoHIF = \frac{(T+1) \times (A+1) \times AADT \times PF}{100}$$

where CoHIF = Connecticut's Hazard Index value;

AADT = annual average daily traffic;

T = number of trains per day;

PF – protection factor (see table 12);

A =crash history (the total number of accident in the last 5 years).

Table 12
Protection Factor Values for Connecticut's Hazard Rating Formula

Devices	PF
Stop sign or Cross buck	1.25
Flashing lights	0.25
Gates	0.01

Illinois's Modified Expected Accident Frequency Formula

The literature review section contains description of the study, conducted by the State of Illinois, which was directed to evaluate the existing accident prediction models (see Elzohairy & Benekohal, 2000). The authors also made a multiple non-linear regression analysis in order to find those variable (highway and rail crossing characteristics), which bring greater contribution to the final value of the accident prediction/hazard index. As a result of investigation the following formula has been developed (called Illinois's Modified Expected Accident Frequency Formula):

$$IHI = 10^{-6} \times A^{2.59088} \times B^{0.09673} \times C^{0.40227} \times D^{0.59262} \times (15.59 \times N^{5.60977} + PF)$$

where IHI = Illinois's Modified Expected Accident Frequency value;

A = ln (ADT * NTT);

ADT = average daily traffic;

NTT = number of total trains per day;

B = MTS = maximum timetable speed, mph;

C = (NMT + NOOT) = number of the main tracks + the number of the other tracks;

D = NOL = number of highway lanes;

N = average number of crashes per year;

PF = protection factor (35.57 – for gates; 68.97 - for flashing lights; 86.39 – for passive).

The formula doesn't estimate the number of accident at each rail crossing, but it calculates the hazard index, which helps to rank crossings by the possibility of accident to occur.

New Hamphire Hazard Index Formula

New Hamphire Hazard Index Formula is used by several states of the country. Some states conducted additional research on accident prediction, using this model, and introduced supplementary variables, such as Train speed, Highway speed, Sight distance, Crossing angle, Crossing width, Type of tracks, Surface type, Population, Number of buses, Number of school buses, Number of tracks, Surface condition, Nearby intersection, Functional class of highway, Vertical alignment, Horizontal alignment, Number of hazardous material trucks, Number of passengers, Number of accidents. As it was mentioned before Modified New Hampshire Formula cannot be applied for Tennessee rail crossings because of the lack of information. Nevertheless, the scope of this work included implementation of original New Hamphire Hazard Index Formula for Tennessee rail crossings. The formula doesn't estimate the number of accident at each rail crossing, but it calculates the hazard index, which helps to rank crossings by the possibility of accident to occur. The highest priority should be assigned to the crossing with greater value of hazard index. The following equation is used for the original New Hampshire Hazard Index Formula:

NHHI = V * T * PF

where NHHI = New Hampshire Hazard Index value;

V = annual average daily traffic;

T = average train daily traffic;

PF = protection factor (0.1 – for gates; 0.6 – for flashing lights; 1.0 – for signs only).

Peabody-Dimmick Formula

Peabody-Dimmick Accident Prediction Formula has been developed in 1941 as a result of research, conducted for 3,563 rural crossings in 29 states. This formula is used to determine the expected number of accidents in five years. The following equation describes the Peabody-Dimmick Accident Prediction Model:

$$PDF = K + 1.28 * (V^{0.170}) * (T^{0.151})/P^{0.171}$$

where PDF = the expected number of accidents in 5 years;

V = annual average daily traffic factor;

T = average train daily traffic factor;

P = protection coefficient;

K = additional parameter.

The procedure of number of accidents calculations suggests the using of various charts and graphs (see Figures 9 – 12). To simplify the process for each curve a corresponding trendline has been found (in order to get a mathematical relationship between variables). The approximation of all curves is presented at Figures 13 – 15).

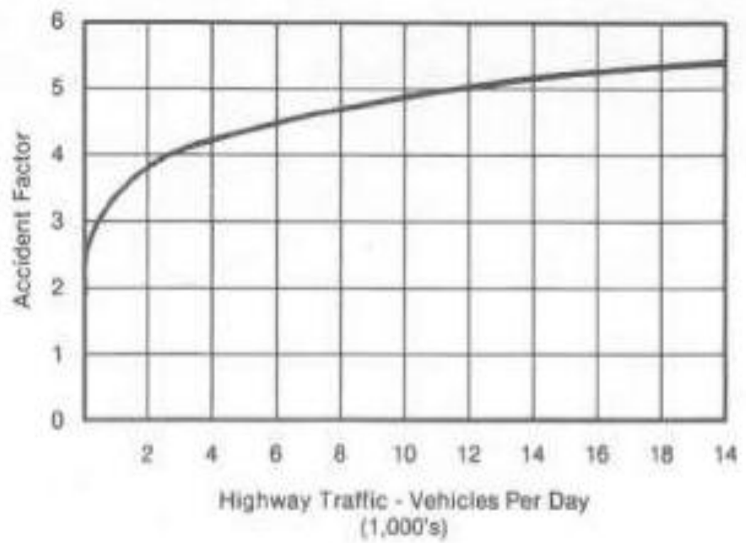

Figure 9 Relationship between Highway Traffic and Accident Factor
Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: U.S. Department of Transportation, Federal Highway Administration.*

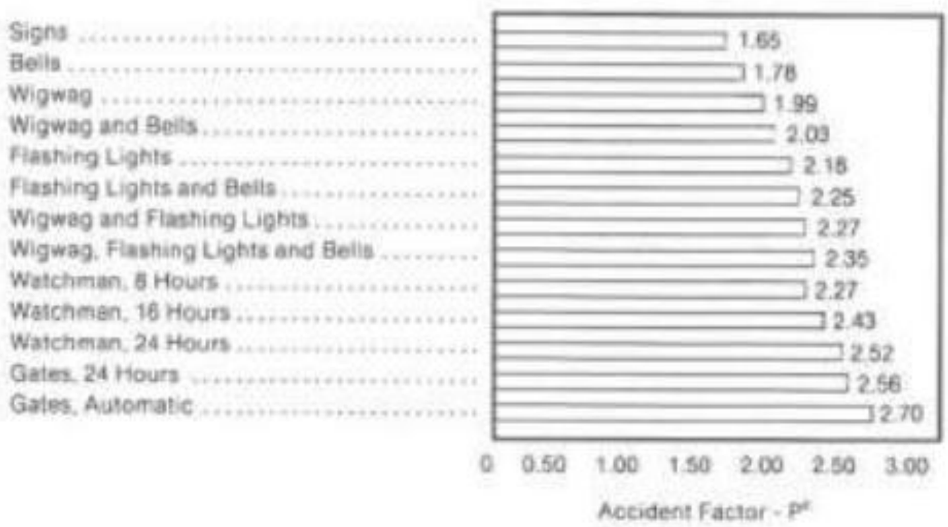

Figure 10 Relationship between Warning Device and Accident Factor
Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: U.S. Department of Transportation, Federal Highway Administration.*

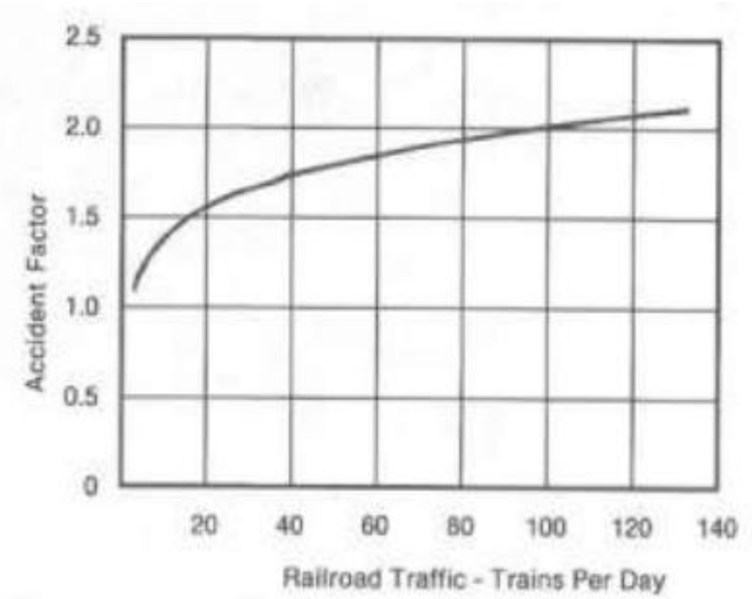

Figure 11 Relationship between Railroad Traffic and Accident Factor
Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: U.S. Department of Transportation, Federal Highway Administration.*

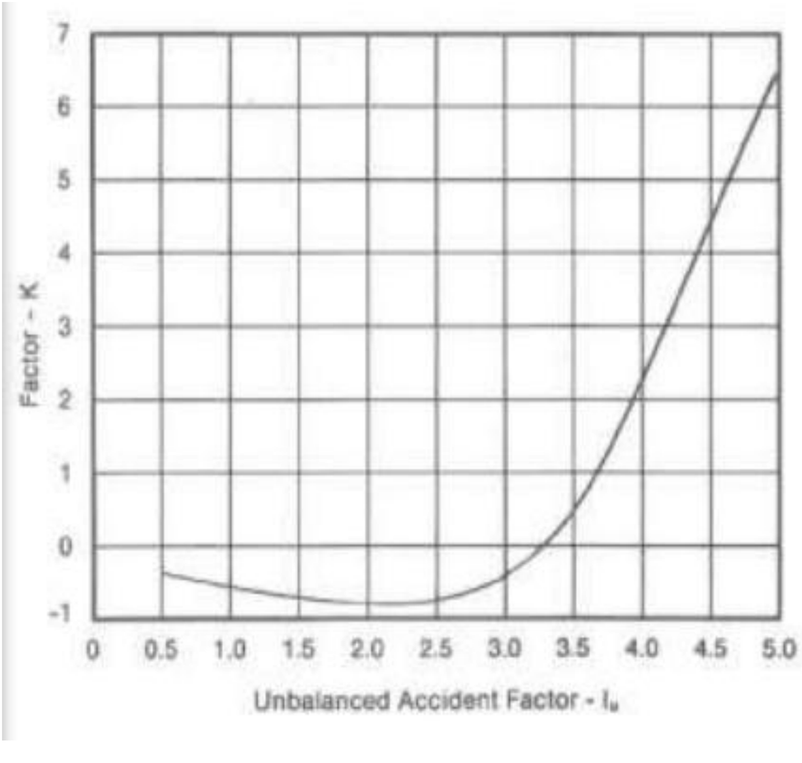

Figure 12 Relationship between K-factor and Unbalanced Accident Prediction
Source: Railroad-Highway Grade Crossing Handbook, Second Edition. (1986). *Washington, DC: U.S. Department of Transportation, Federal Highway Administration.*

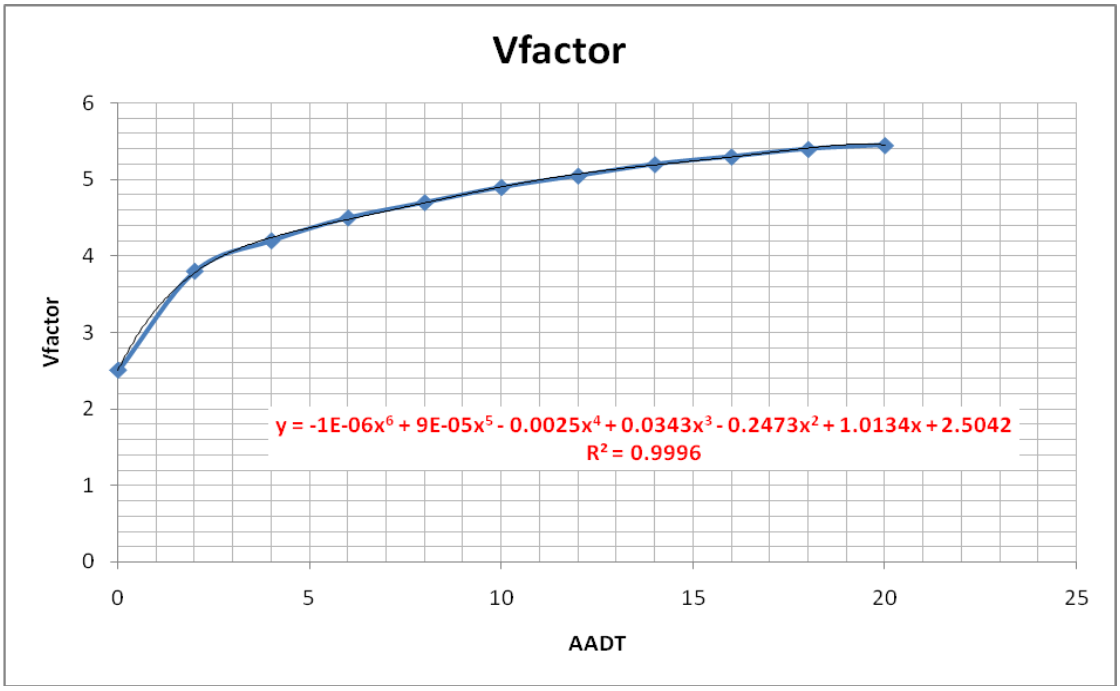

Figure 13 Relationship between Highway Traffic and V-Factor

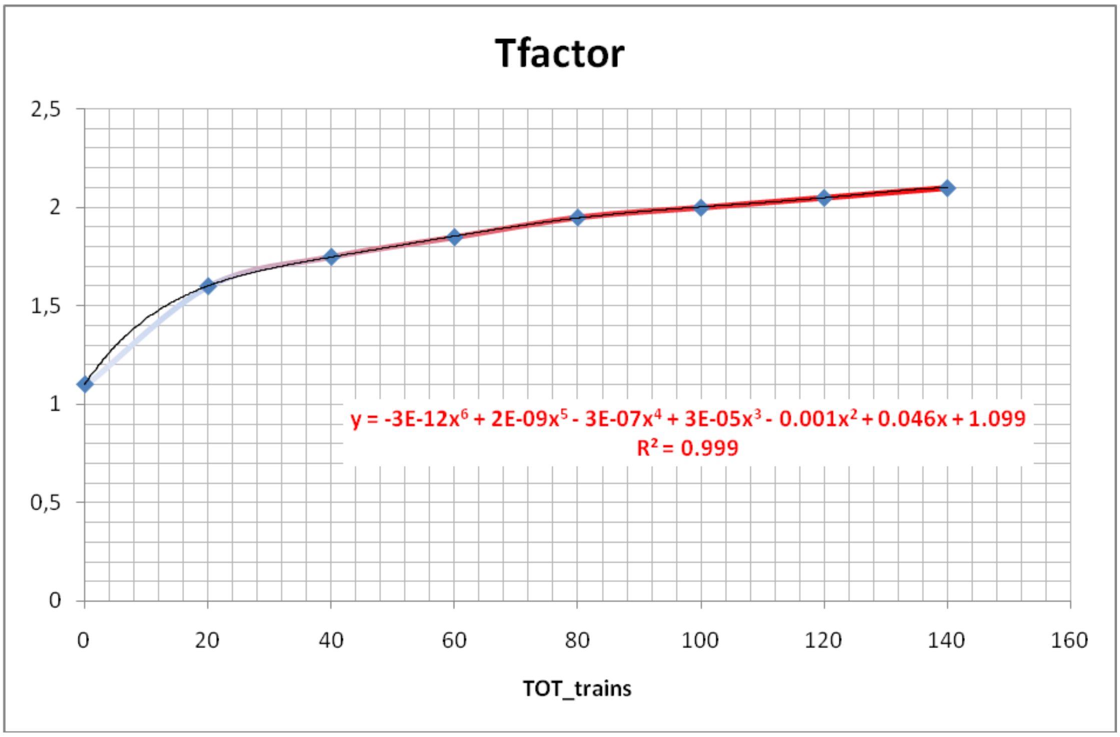

Figure 14 Relationship between Railroad Traffic and T-Factor

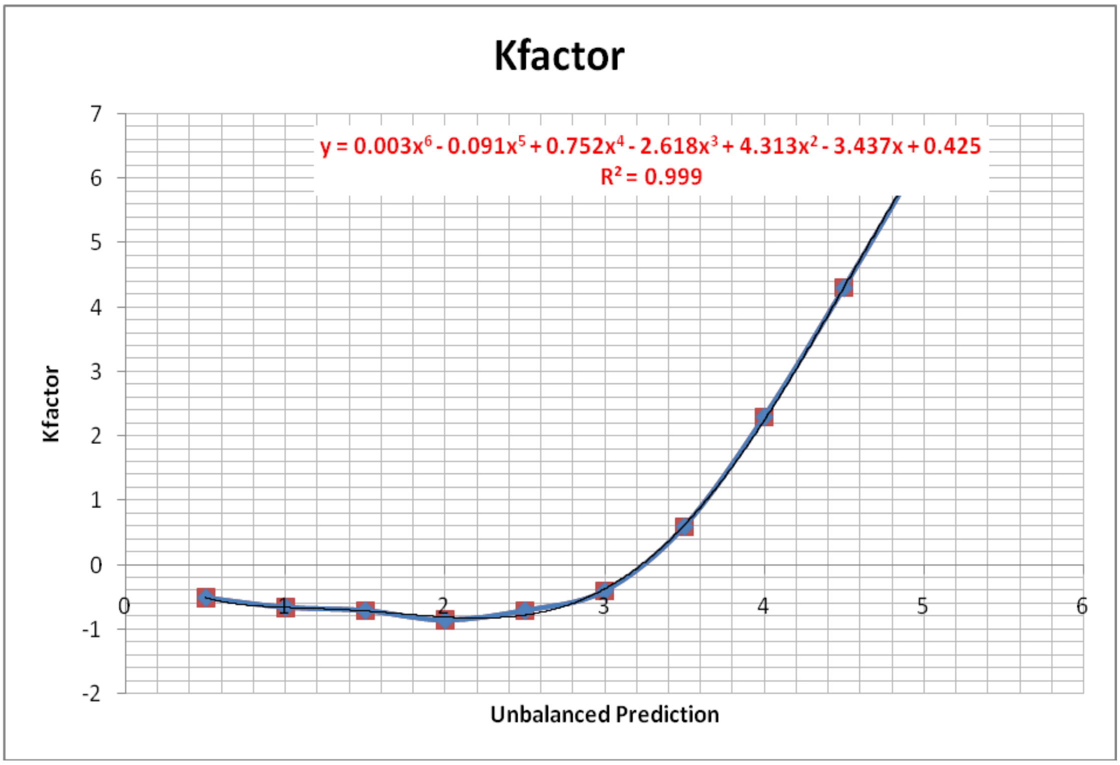

Figure 15 Relationship between K-factor and Unbalanced Accident Prediction

Comparison of FRA (US DOT) Accident Prediction Model with Models, Applied by Other States

The scope of the current work included comparison of US DOT accident prediction model with California's Hazard Rating Formula, Connecticut's Hazard Rating Formula, Illinois's Modified Expected Accident Frequency Formula, Peabody-Dimmick Formula and New Hamphire Formula. The main aim was to find the difference between models and figure out which one gives the results, close to US DOT. The analysis has been divided in two parts: comparison of approaches for passive rail crossing and comparison of approaches for active crossings. Some highway-rail at grade crossings were eliminated because of NaN values for accident prediction/hazard index (for example, Illinois's Modified Expected Accident Frequency Formula has the variable, which is equal to the natural logarithm of product ADT and NTT; there are many rail crossings in TRIMS database (around 400), which have either zero ADT or NTT). Thus, removing of NaNs will make the analysis and comparison of models more accurate.

The total number of passive crossings, taken for comparison, comprised 805. All rail crossings were sorted based on the accident prediction/hazard index from the highest value to the lowest and labeled with rank. The highest priority was assigned to the crossing with greater value of accident prediction/hazard index, as recommended by numerous studies. After that, the absolute difference between ranks, suggested by US DOT Accident Prediction Formula and those, proposed by considered models, were calculated in order to see how ranks vary. Average absolute difference in ranks with US DOT Accident Prediction Formula has been computed for each accident prediction/hazard index model. All calculations are provided in Appendix E. Final results for passive highway-railroad at grade crossings are presented at the Figure 16.

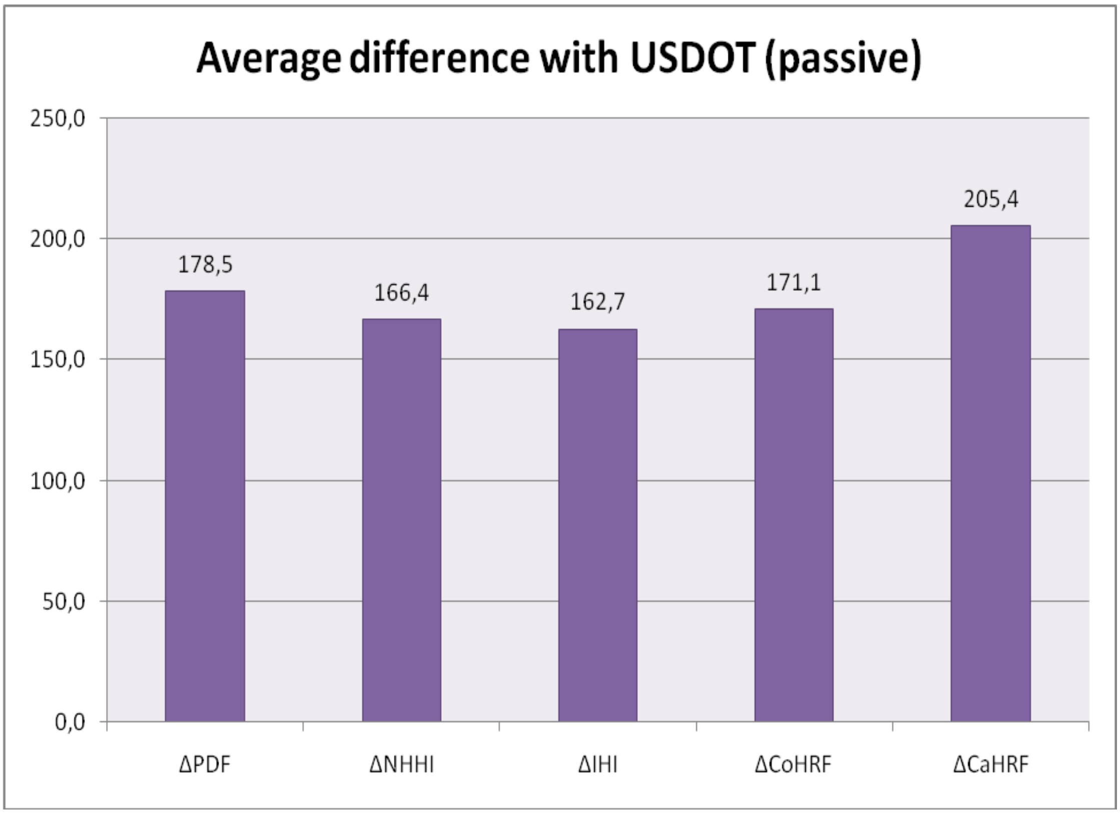

Figure 16 The Absolute Difference in Ranks with US DOT for Passive Crossings

Note:

ΔPDF – the absolute difference in ranks, suggested by US DOT Accident Prediction Formula and Peabody-Dimmick Accident Prediction Formula;

ΔNHHI - the absolute difference in ranks, suggested by US DOT Accident Prediction Formula and New Hamphire Hazard Index Formula;

ΔIHI - the absolute difference in ranks, suggested by US DOT Accident Prediction Formula and Illinois's Modified Expected Accident Frequency Formula;

ΔCoHRF - the absolute difference in ranks, suggested by US DOT Accident Prediction Formula and Connecticut's Hazard Rating Formula;

ΔCaHRF - the absolute difference in ranks, suggested by US DOT Accident Prediction Formula and California's Hazard Rating Formula;

From the analysis of Tennessee at grade public passive rail crossings we can conclude, that Illinois's Modified Expected Accident Frequency Formula has the lowest average absolute difference in ranks with US DOT Accident Prediction Formula (162.7 ranks). New Hamphire Hazard Index Formula showed relatively good results (the difference comprised only 166.4 ranks). The highest average absolute difference in ranks with US DOT Accident Prediction Formula is obtained by California's Hazard Rating Formula (according to Figure 16 - 205.4 ranks).

Similar procedure has been performed for active crossings. The total number of considered crossings, taken for comparison, comprised 1511. All rail crossings were sorted based on the accident prediction/hazard index from the highest value to the lowest and labeled with rank. The highest priority was assigned to the crossing with greater value of accident prediction/hazard index, as recommended by numerous studies. After that, the absolute difference between ranks, suggested by US DOT Accident Prediction Formula and those, proposed by considered models, were calculated in order to see how ranks vary. Average difference in ranks with US DOT Accident Prediction Formula has been computed for each accident prediction/hazard index model. All calculations and necessary details are provided in Appendix E. Final results for active highway-railroad at grade crossings are presented at the Figure 17.

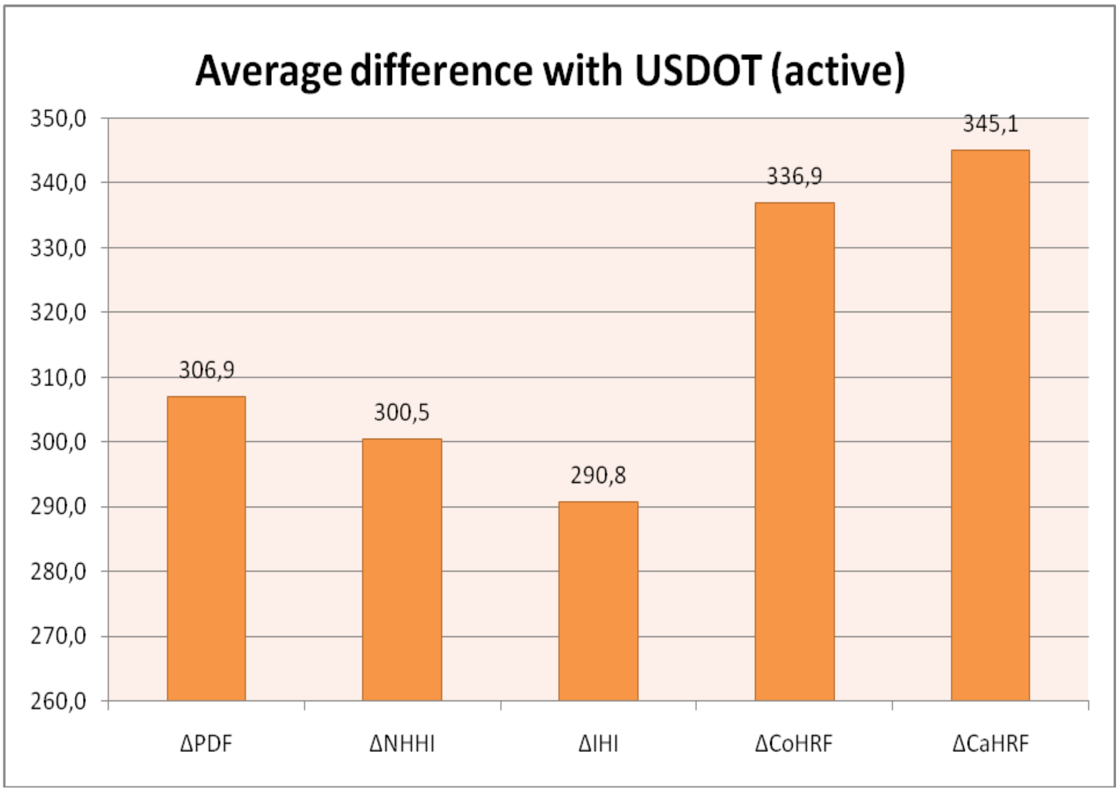

Figure 17 The Absolute Difference in Ranks with US DOT for Active Crossings

From the first analysis of Tennessee at grade public active rail crossings we can conclude that Illinois's Modified Expected Accident Frequency Formula has the lowest average absolute difference in ranks with US DOT Accident Prediction Formula (only 290.8 ranks). New Hamphire Hazard Index Formula showed relatively good results (the difference comprised only 300.5 ranks). The highest average absolute difference in ranks with US DOT Accident Prediction Formula is obtained by California's Hazard Rating Formula (according to Figure 17 - 345.1 ranks).

The scope of the current work also included supplemental comparison of accident prediction/hazard index models to confirm the initial assumption that Illinois's Modified Expected Accident Frequency Formula gives the closest results to US DOT Accident Prediction Formula. All highway-rail crossings (both passive and active categories) have been separated for 10 groups (10% of all crossings for each group). The objective was to estimate the percentage of rail crossings, suggested by US DOT Accident Prediction Formula and considered accident prediction/hazard index models for upgrading, which belongs to the same group. The average absolute difference in ranks US DOT Accident Prediction Formula can be lower for a certain accident prediction/hazard index model, but set of rail crossings, proposed for safety improvement could be significantly different from the set of rail crossings, suggested by US DOT Accident Prediction Formula. The results of this analysis are presented at the Figure 18 for passive crossings and at the Figure 19 for active crossings. Figures 20 and 21 show the cumulative percentage of common active and passive crossings.

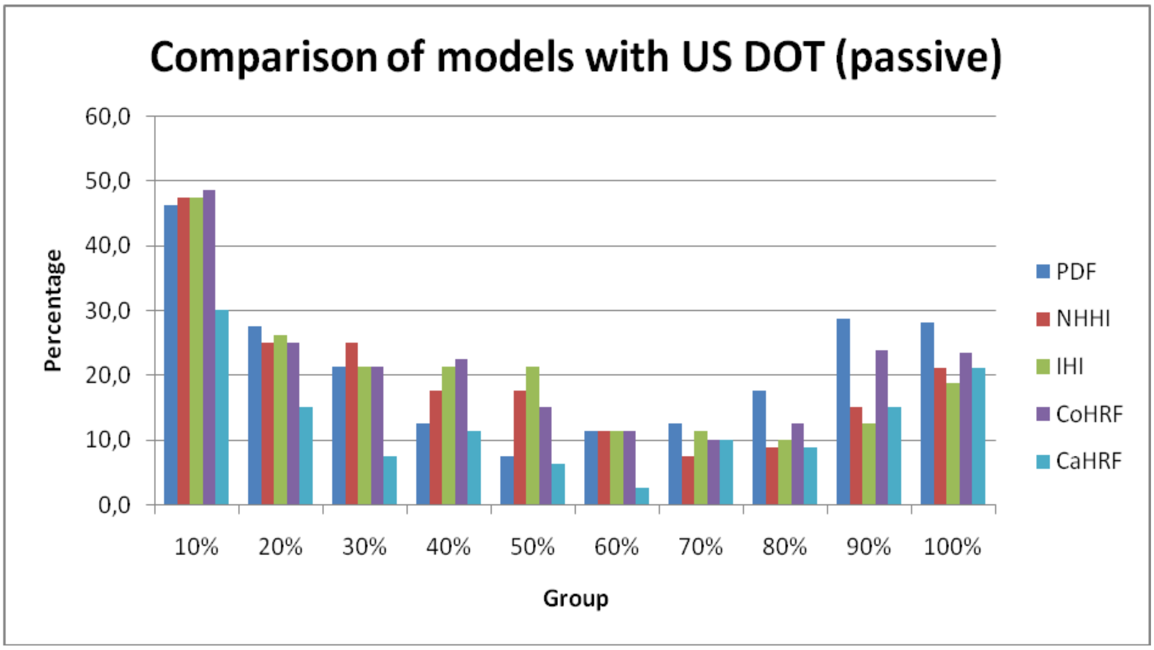

Figure 18 The Percentage of Common Passive Rail Crossings with US DOT for Each Group

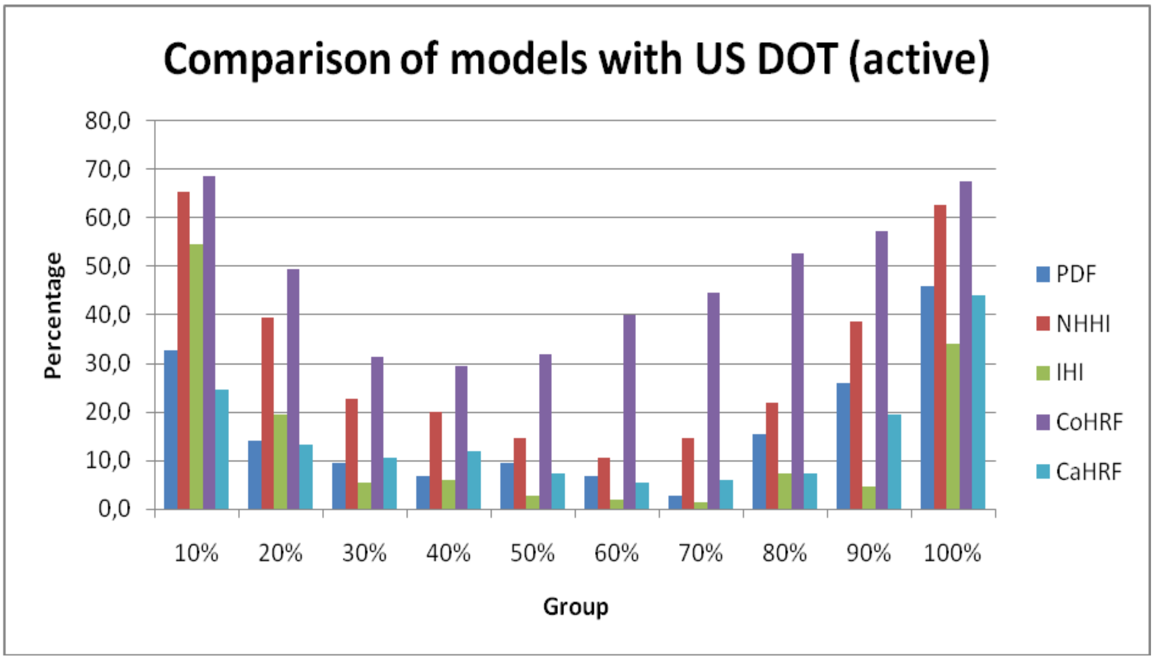

Figure 19 The Percentage of Common Active Rail Crossings with US DOT for Each Group

Consider the first group of rail crossings, which presents 10% of the most hazardous Tennessee highway-railroad public at grade crossings, proposed by various accident prediction/hazard index models for upgrading. The highest percentage of common passive crossings has been observed for Connecticut's Hazard Rating Formula (48.8%). Illinois's Modified Expected Accident Frequency Formula and New Hamphire Hazard Index Formula showed the same results (47.5% of common passive crossings). The lowest percentage of common passive crossings has been obtained by California's Hazard Rating Formula (30.0%). As for active rail crossings, the highest percentage has been demonstrated again by Connecticut's Hazard Rating Formula (68.7%). New Hamphire Hazard Index Formula has 65.3% of common active rail crossings for the first group. Illinois's Modified Expected Accident Frequency Formula has 54.7% of common active rail crossings for the first group. The lowest percentage of common active crossings has been obtained again by California's Hazard Rating Formula (24.7%).

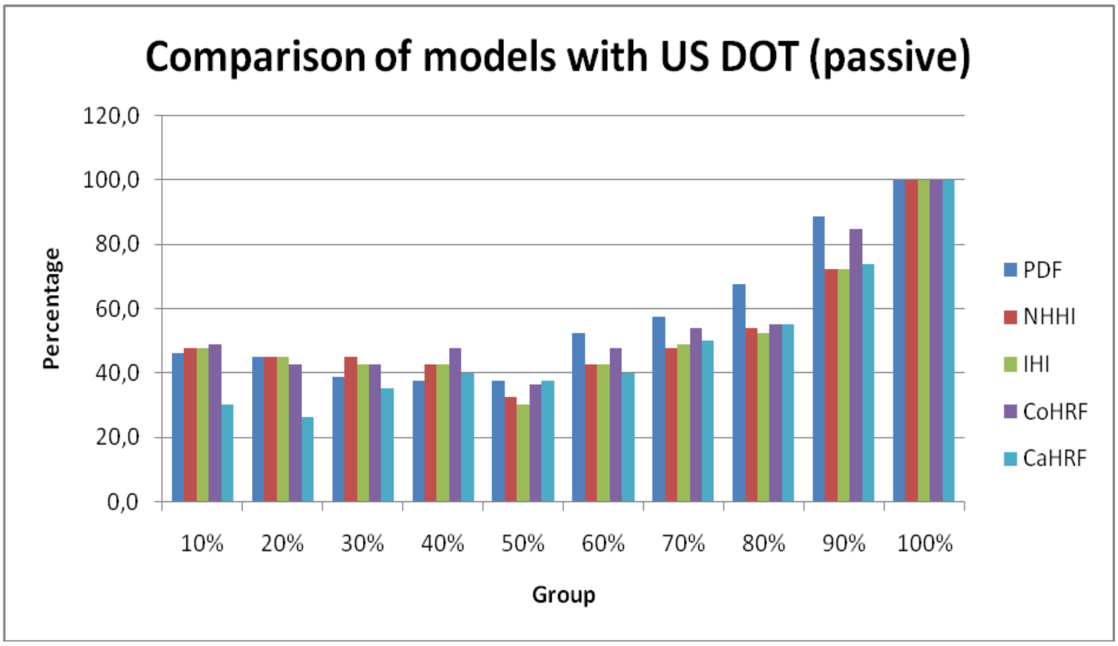

Figure 20 The Cumulative Percentage of Common Passive Rail Crossings with US DOT for Each Group

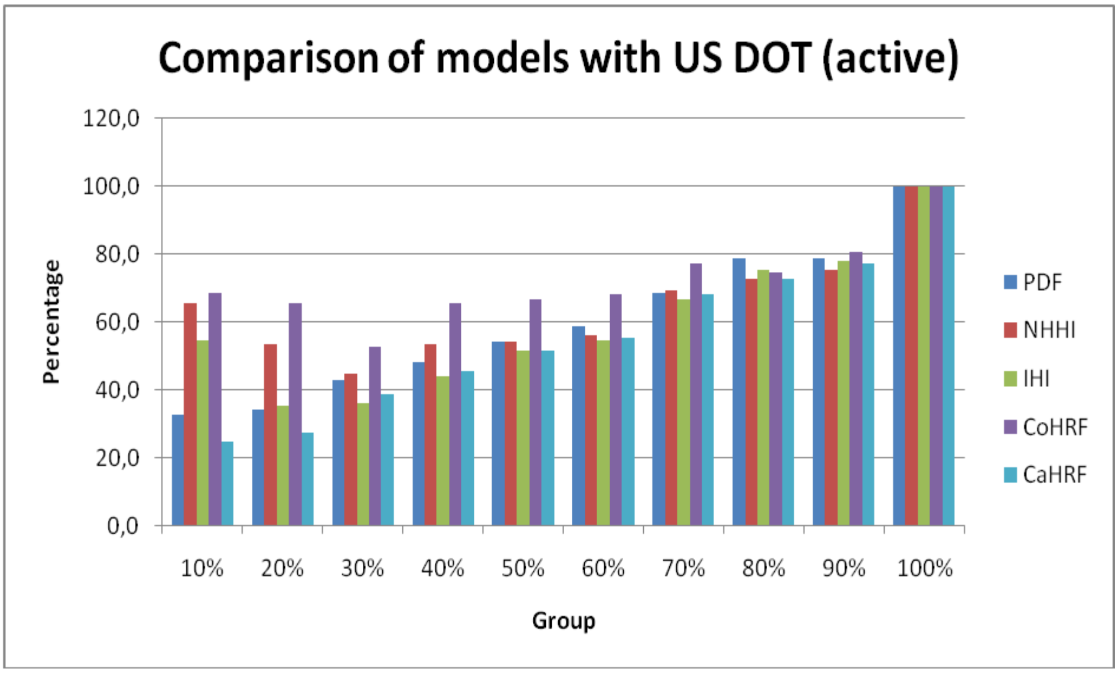

Figure 21 The Cumulative Percentage of Common Active Rail Crossings with US DOT for Each Group

Thus, from the analysis of groups for percentage of common active and passive crossings, we cannot state, that Modified Expected Accident Frequency Formula gives the closest results to US DOT Accident Prediction Formula (it has the same percentage of the common passive crossings with New Hamphire Hazard Index Formula for the first group, but lower percentage of the common active crossings).

In this case it is necessary to conduct additional test. The first group of 10% of the most hazardous highway-rail crossings has been considered. The analysis consisted in the following. The average absolute difference of a certain accident prediction/hazard index model in ranks with US DOT Accident Prediction Formula has been estimated only for those rail crossings, which were proposed for safety improvement by US DOT Accident Prediction Formula (this test combined the first two investigations). Other values of absolute difference were rejected. The results of this test are presented at the Figure 22 for passive crossings and at the Figure 23 for active crossings.

From the last test we can state that Illinois's Modified Expected Accident Frequency Formula and New Hamphire Hazard Index Formula showed almost the same weighted average difference in ranks with US DOT Accident Prediction Formula for passive rail crossings (8.8 percent and 8.7 percent correspondingly), which is lower in comparison with other models. But the weighted average difference in ranks of Illinois's Modified Expected Accident Frequency Formula with US DOT Accident Prediction Formula (10.4 percent) is considerably lower for active rail crossings than for New Hamphire Hazard Index Formula (34.1 percent).

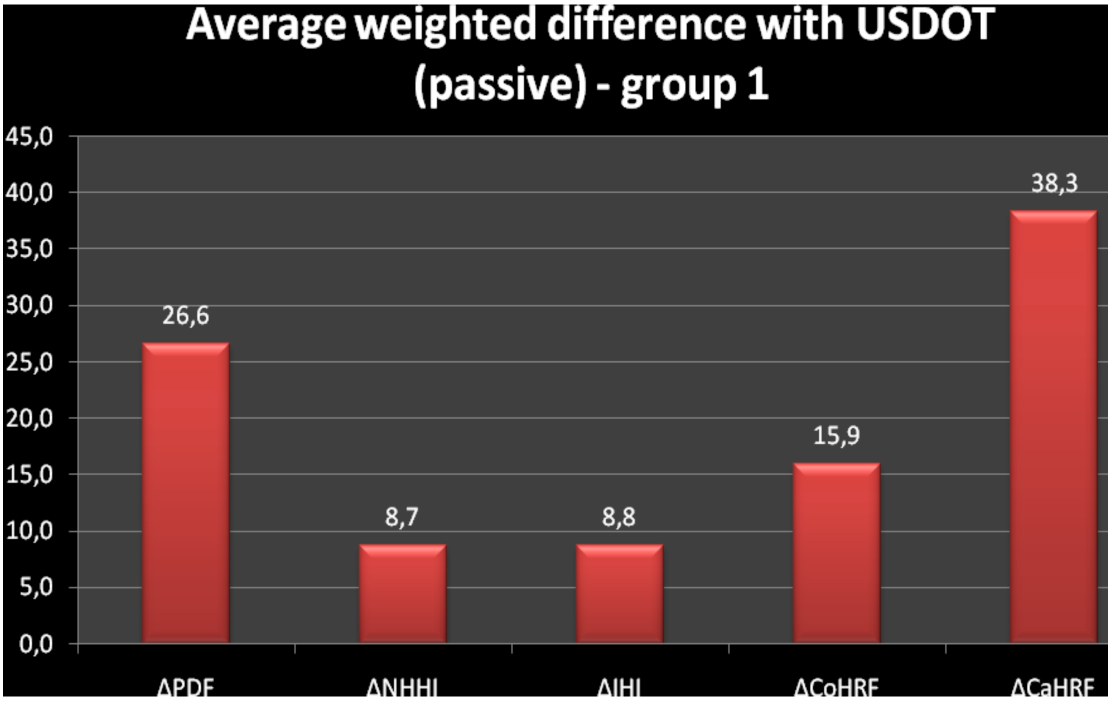

Figure 22 The Average Weighted Difference with US DOT for the First Group of Passive Crossings

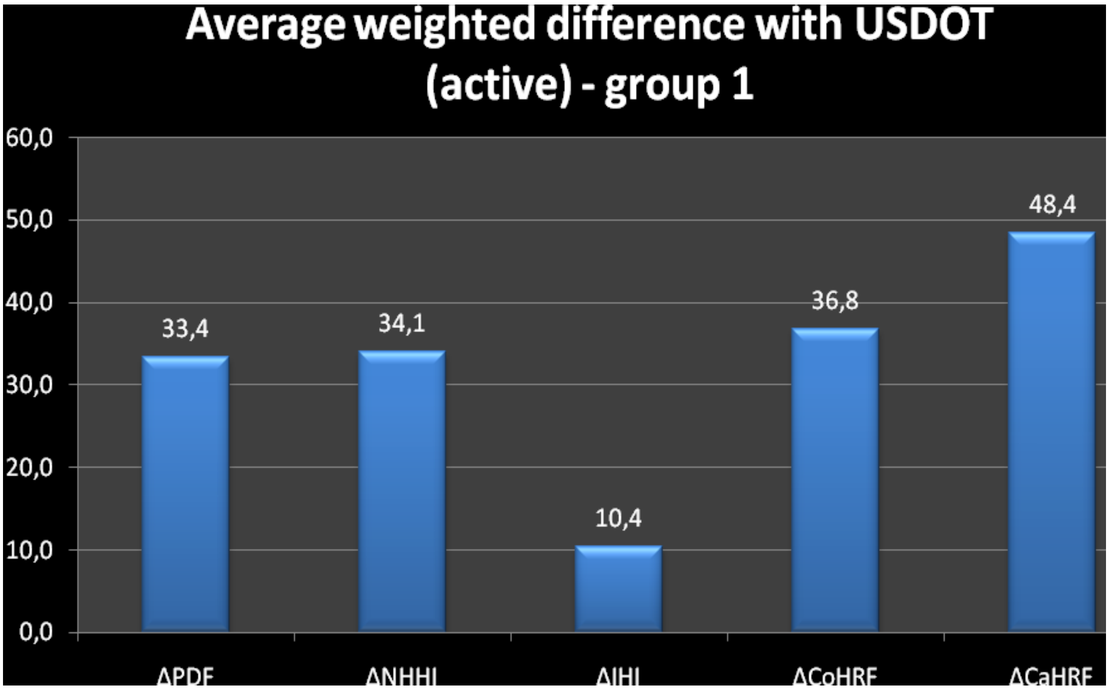

Figure 23 The Average Weighted Difference with US DOT for the First Group of Active Crossings

From the first analysis of Tennessee at grade public rail crossings we can conclude that Illinois's Modified Expected Accident Frequency Formula has the lowest average absolute difference in ranks with US DOT Accident Prediction Formula (only 162.7 ranks for passive and 290.8 ranks for active crossings). New Hamphire Hazard Index Formula showed relatively good results (the difference comprised only 166.4 ranks for passive and 300.5 ranks for active crossings). The highest average absolute difference in ranks with US DOT Accident Prediction Formula is obtained by California's Hazard Rating Formula. From the second analysis we can conclude that Illinois's Modified Expected Accident Frequency Formula and New Hamphire Hazard Index Formula showed the same results (47.5% of common passive crossings) for passive crossings. But New Hamphire Hazard Index Formula has 65.3% of common active rail crossings for the first group, while Illinois's Modified Expected Accident Frequency Formula has only 54.7% of common active rail crossings for the first group. From the last analysis we can state that Illinois's Modified Expected Accident Frequency Formula and New Hamphire Hazard Index Formula showed almost the same weighted average difference in ranks with US DOT Accident Prediction Formula for passive rail crossings (8.8% and 8.7% correspondingly), which is lower in comparison with other models. But the weighted average difference in ranks of Illinois's Modified Expected Accident Frequency Formula with US DOT Accident Prediction Formula (10.4%) is considerably lower for active rail crossings than for New Hamphire Hazard Index Formula (34.1%).

For the final conclusion, we can state that for both passive and active highway-rail at crossings Illinois's Modified Expected Accident Frequency Formula gives the closest results to US DOT Accident Prediction Formula. New Hamphire Hazard Index Formula showed relatively close results. It was also observed that

California’s Hazard Rating Formula gives the greatest variance in ranks with US DOT Accident Prediction Formula for passive and active public rail crossings.

Conclusion

The review presented herein provides useful information as to how current methods are employed to comparatively analyze highway-rail grade crossing projects for funding. The current approaches show the factors that are considered nowadays for improvement projects, such as risk reduction, project cost, and the relationship between risk reduction effectiveness and cost. Existing methods do present shortcomings associated to accurate datasets, minimal validation of method results, and reduced accuracy creating additional manual and mathematical effort to conclude processes. Current approaches provide a platform to advance the accepted state-of-practice and develop future efforts.

The methods, with modification to consider the goals of TDOT, could prove to be useful for additional highway-rail grade crossing program decision making. Future development should address the shortcomings of the current state-of-practice in addition to consideration of the outcomes and goals anticipated from the advancement of resource allocation or funding decision making methods. Comparison of US DOT Accident Prediction Model, currently used by the State of Tennessee, with accident prediction/hazard index models, employed by other states, shows that the closest results are obtained by Illinois’s Modified Expected Accident Frequency Formula. At this point it can be recommended to start implementation of Illinois’s Modified Expected Accident Frequency Formula for Tennessee rail crossings and to check its accuracy over a certain time period (several years).

4. MODEL DEVELOPMENT

As it was mentioned earlier, the main objective of the current study is to develop the model, which allocates available monetary resources between highway-rail grade crossings of the Tennessee State (information is given by TRIMS database) and maximizes the total benefits in terms of accident and severity reduction. Two different approaches were created, such as Sorting Algorithm (SA) and Mathematical Model (MM).

Sorting Algorithm (SA)

The first methodology works as follows. First of all, all data, necessary for accident prediction calculations, is collected from TRIMS and FRA Accident/Injury databases. Based on physical and operational characteristics of each crossing the initial accident prediction value is estimated. Using the information about accidents in past 5 years from FRA Accident/Injury database the final accident prediction value is computed. After the normalized accident prediction value is calculated for each crossing as multiplication of the final accident prediction by normalizing constant. In the current work the normalizing constants from 2010 were used.

The objective aims to provide investments for countermeasures implementation at those crossings, which will bring the maximum accident reduction. Most of all, severity of accidents was considered for each crossing. Severity of accident was separated by three categories:

- Fatality accident;
- Injury accident;
- Property damage accident;

To measure the difference between severity categories, the cost of accident has been introduced and applied in calculations (see Table 13).

Table 13

Cost of Accident by Severity Category

Type of accident	Cost of accident, US dollars
Fatality accident	30,000
Injury accident	20,000
Property damage accident	10,000

As it was mentioned before, according to Railroad-Highway Grade Crossing Handbook (2007), there are three possible traffic control improvement alternatives in the resource allocation procedure: from passive to flashing lights, from passive to gates, from flashing lights to gates. Effectiveness of each countermeasure and cost are provided below in Table 14.

Table 14

Characteristics of Different Countermeasure Types

Type of countermeasure	Effectiveness	Cost, US dollars
Passive to flashing lights	0.70	30,000
Passive to gates	0.83	150,000
Flashing lights to gates	0.69	150,000

The sorting procedure has been performed based on three benefit options:

- e/c ratios;
- a*e/c ratios;
- s*e/c ratios;

Computational results of Sorting Algorithm and comparison with another solution approach are presented in the next section.

Mathematical Model (MM)

The second approach was developed in order to compare it with SA heuristic and find out which one gives better results in terms of accident reduction. Sometimes heuristics provide solutions, which are considerably different from optimal and are not implemented because of inefficiency. The formulation of model is provided below.

SETS

I	Set of countermeasures
J	Set of highway-rail grade crossings

DECISION VARIABLES

$x_{ij}\ \forall i \in I, j \in J$	=1 if countermeasure *i* is implemented at rail crossing *j* and zero otherwise

AUXILIARY VARIABLES

$y_{ij}\ \forall i \in I, j \in J$	=1 if countermeasure *i* can be potentially implemented at rail crossing *j* and zero otherwise

PARAMETERS

$a_j\ j \in J$	accident prediction value at rail crossing *j*
$c_i \forall\ i \in I$	cost of countermeasure *i*
$e_i \forall\ i \in I$	effectiveness of countermeasure *i*
$FA_j\ \forall j \in J$	fatal accident prediction value at rail crossing *j*
$IA_j\ \forall j \in J$	injury accident prediction value at rail crossing *j*
$PD_j\ \forall j \in J$	property damage accident prediction value at rail crossing *j*
C	budget available
w_1	cost of fatal accident
w_2	cost of injury accident
w_3	cost of property damage accident

OBJECTIVES

$$max \sum_{i \in I, j \in J} a_j \times e_i \times x_{i,j} \quad (1)$$

$$max \sum_{i \in I, j \in J} [(w_1 \times FA_j \times e_i] \times x_{i,j} + w_2 \times IA_j \times e_i \times x_{i,j} + w_3 \times PD_j \times e_i \times x_{i,j}) \quad (2)$$

SUBJECT TO:

$$\sum_{i \in I} c_i \times x_{i,j} \leq C \ \forall j \in J \tag{3}$$

$$\sum_{i \in I} x_{i,j} \leq 1 \ \forall j \in J \tag{4}$$

$$x_{i,j} \leq y_{i,j} \ \forall i \in I, j \in J \tag{5}$$

The first objective is directed to maximize the total accident reduction. The second objective aims to maximize the total weighted accident reduction by severity category. Constraint 3 ensures that the total cost of all implemented countermeasures at chosen rail crossings will not exceed the budget available. Constraint 4 states that no more than one countermeasure *i* can be applied at rail crossing *j*. Constraint 5 indicates that countermeasure *i* can be implemented only at potentially considered rail crossing *j*.

As for parameters, accident prediction value at rail crossing *j* (*a(j)*) was taken from TRIMS database for each crossing. Cost (c_i) and effectiveness (e_i) of each countermeasure *i* were taken from Railroad-Highway Grade Crossing Handbook, 2007 (see Table 14). It was assumed that total investments for safety improvements at highway-rail crossings (*C*) comprised $2,500,000. Fatal, injury and property damage accident prediction values at rail crossing *j* were estimated using equations, provided by GradeDec software. Cost of each type of accident (w_1, w_2, w_3) is presented in Table 13.

Auxiliary binary variable y_{ij} has been introduced to indicate could be a particular countermeasure *i* be implemented at rail crossing *j* or not. There are specific restrictions, established by FRA, for certain countermeasures:

1) If the rail crossing is passive and number of trucks is equal to 1, it is possible to upgrade crossing to flashing lights and gates;

2) If the rail crossing is passive and number of trucks is more than 1, only gates can be implemented;

3) To upgrade rail crossing with flashing lights only gates can be considered as improvement;

4) Rail crossings with gates are not subject to upgrading;

A decision variable x_{ij} shows each rail crossing and suggested countermeasure, which should be applied in order to satisfy objectives 1 and 2. Computational results for all at-grade rail crossings from TRIMS database are presented in the next section.

5. COMPUTATIONAL RESULTS

Both solution approaches, Sorting Algorithm (SA) and Mathematical Model (MM), were applied for all at-grade rail public crossings of Tennessee State, provided by TRIMS database. The overall number of rail crossings in TRIMS database comprises 5716, the total number of at-grade public crossings is 2873. The main assumptions, constants and parameters for SA and MM were described in the chapter 4.

Sorting Algorithm

The first approach (SA) has been created using Matlab 7.0. Three different sorting procedures were implemented:

1) Sorting based on e/c ratio;

2) Sorting based on a*e/c ratio;

3) Sorting based on s*e/c ratio;

It was observed that all three sorting procedures suggest to make improvements for 83 passive rail crossings and upgrade them to flashing lights with the total budget usage of $2,490,000 (among $2,500,000 available). It was observed that none of sorting methods offered upgrading of passive rail crossings to gates and flashing lights crossings to gates. Table 15 represents the total accident and severity reduction for each sorting option.

Table 15
Results Provided by Sorting Algorithm

SA based on e/c			SA based on e/c		
TotalCost	a*e	s*e	TotalCost	a*(1-e)	s*(1-e)
2490000	2.360948	34153.4	2490000	1.011835	14637.17
SA based on ae/c			SA based on ae/c		
TotalCost	a*e	s*e	TotalCost	a*(1-e)	s*(1-e)
2490000	8.854448	128595.5	2490000	3.794764	55112.34
SA based on se/c			SA based on se/c		
TotalCost	a*e	s*e	TotalCost	a*(1-e)	s*(1-e)
2490000	8.822772	129100	2490000	3.781188	55328.56

It can be concluded that sorting based on e/c ratio is not efficient, because it gives considerably lower values of accident reduction and severity reduction as well. Sorting based on a*e /c ratio shows considerably higher accident and severity reduction than sorting based on e/c ratio, slightly higher accident reduction than sorting based on s*e/c ratio, and lower severity reduction than sorting based on s*e/c ratio. Most of all, it is necessary to point out that cost of accident by severity was taken randomly. It was assumed that one fatality accident is equal to 2 injury accidents and 3 property damage accidents (see section 4). To make more accurate calculations in terms of severity additional information should be provided by TDOT. And after it will be possible to judge which sorting procedure gives the best results.

Mathematical Model

Solution of the model (see the formulation in the section 4) has been performed using GAMS 23.8.2. SA approach demonstrated inefficiency of e/c ratio consideration. Thus, the first objective of MM is directed to maximize the total accident reduction with restriction of the budget available. The second objective aims to maximize the total weighted accident reduction by severity category.

The total budget usage for the first and second objectives comprised $2,490,000 (among $2,500,000 available), which is similar to the amount of investments, provided by SA. But countermeasures, proposed by MM, were different in comparison with SA. Solution of the first objective suggests making improvements for 68 passive rail crossings with upgrading them to flashing lights, and 3 flashing lights rail crossings with upgrading them to gates. Solution of the second objective suggests making improvements for 73 passive rail crossings with upgrading them to flashing lights, and 2 flashing lights rail crossings with upgrading them to gates. Similar to Sorting Algorithm, MM doesn't offer upgrading of passive rail crossings to gates. Table 16 represents the total accident and severity reduction for each objective.

Table 16
Results Provided by Mathematical Model

MM based on a*e/c			MM based on a*e/c		
TotalCost	a*e	s*e	TotalCost	a*(1-e)	s*(1-e)
2490000	9.212	132484.0	2490000	3.98	57210.54
MM based on s*e/c			MM based on s*e/c		
TotalCost	a*e	s*e	TotalCost	a*(1-e)	s*(1-e)
2490000	9.183	132888.9	2490000	3.959	57264.75

It can be concluded that MM based on a*e /c ratio shows slightly higher accident reduction than MM based on s*e/c ratio, and lower severity reduction than MM based on s*e/c ratio (which is similar to results obtained by SA). In this case it is necessary to underline again, that additional data, related to the cost of accident by severity, should be provided by TDOT to achieve more accurate results. In general, GAMS showed good results and computational time, solving the first objective of the model in 0.047 sec and the second objective in 0.093 sec for 2873 rail crossings.

Comparison of Methodologies

As it was mentioned earlier, SA and MM propose different ways of monetary resources allocation. SA based on a*e /c ratio shows, that improvements should be provided at 83 passive rail crossings to flashing lights. MM based on a*e /c ratio suggests to make improvements for 73 passive rail crossings with upgrading them to flashing lights, and 2 flashing lights rail crossings with upgrading them to gates. SA based on s*e /c ratio shows, that improvements should be provided at 83 passive rail crossings to flashing lights (similar to SA based on a*e /c ratio, but the list of recommended rail crossings for upgrading is different). MM based on a*e /c ratio suggests to make improvements for 68 passive rail crossings with upgrading them to flashing lights, and 3 flashing lights rail crossings with upgrading them to gates. In order to find which methodology is better corresponding accident reduction and weighted accident reduction by severity values should be compared. Accident reduction (a*e) and weighted accident reduction (s*e) by severity for SA and MM based on different benefit options are presented at Figures 24-27. The number of accidents after proposed countermeasures implementation (a*(1-e) and s*(1-e)) is presented at Figures 28-31.

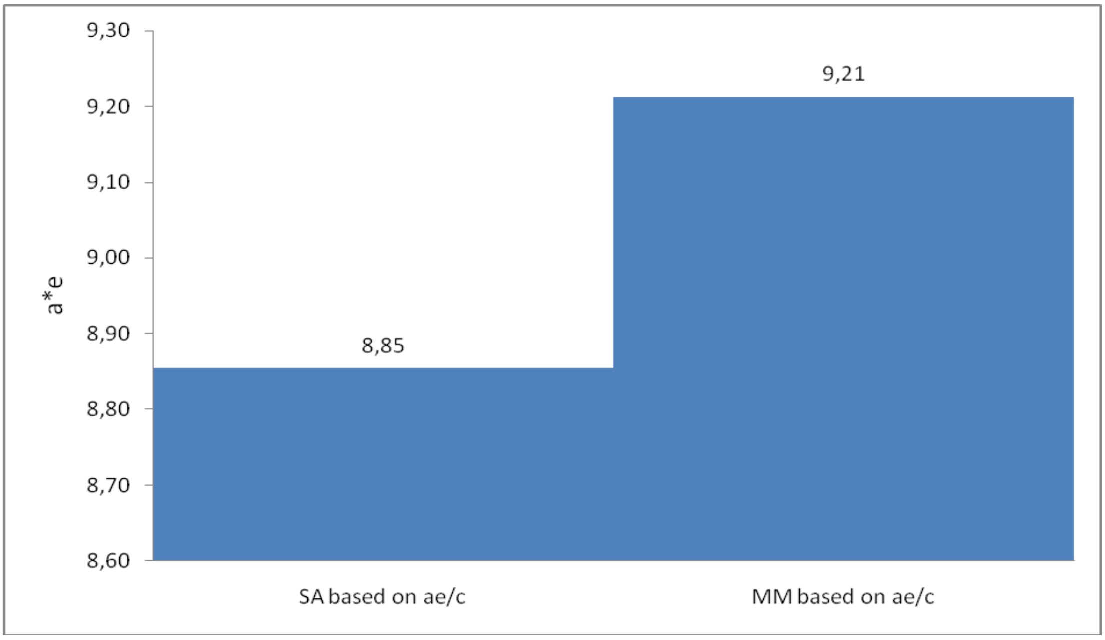

Figure 24 Comparison of SA and MM Based on a*e/c Ratio and a*e Value

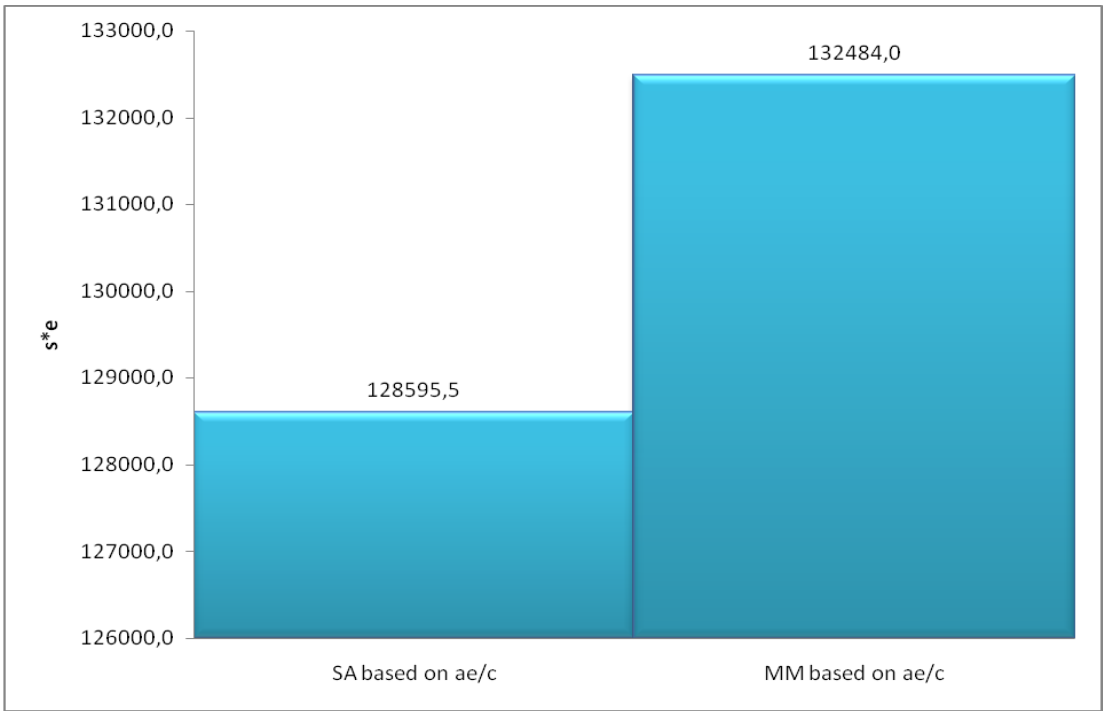

Figure 25 Comparison of SA and MM Based on a*e/c Ratio and s*e Value

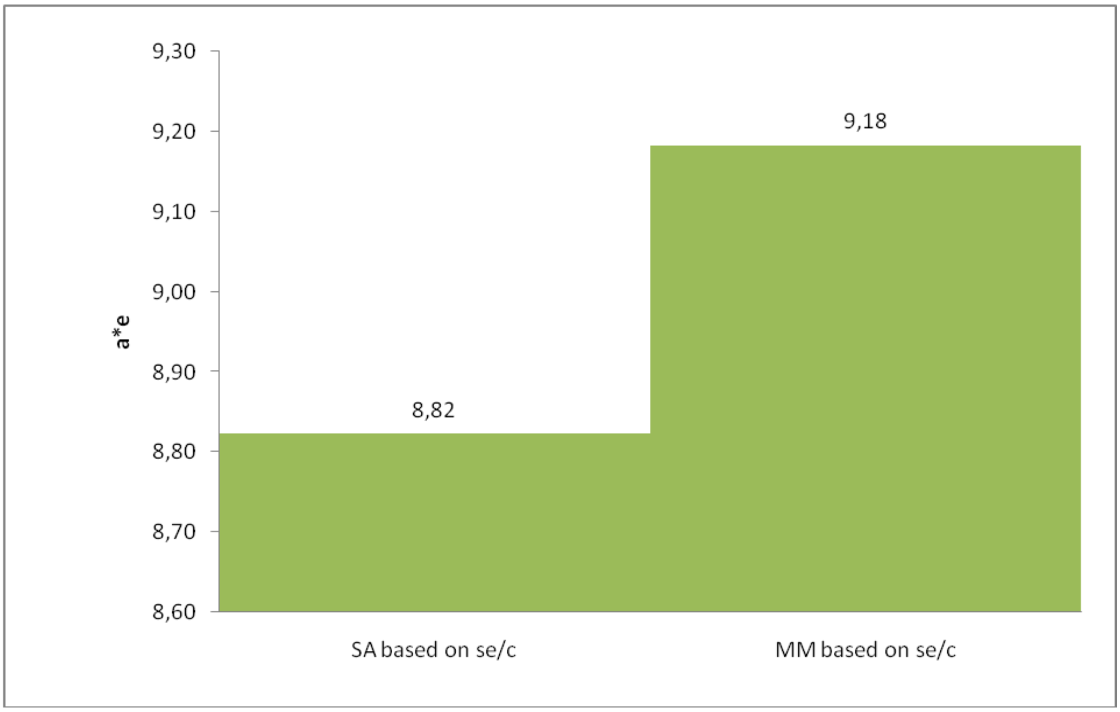

Figure 26 Comparison of SA and MM Based on s*e/c Ratio and a*e Value

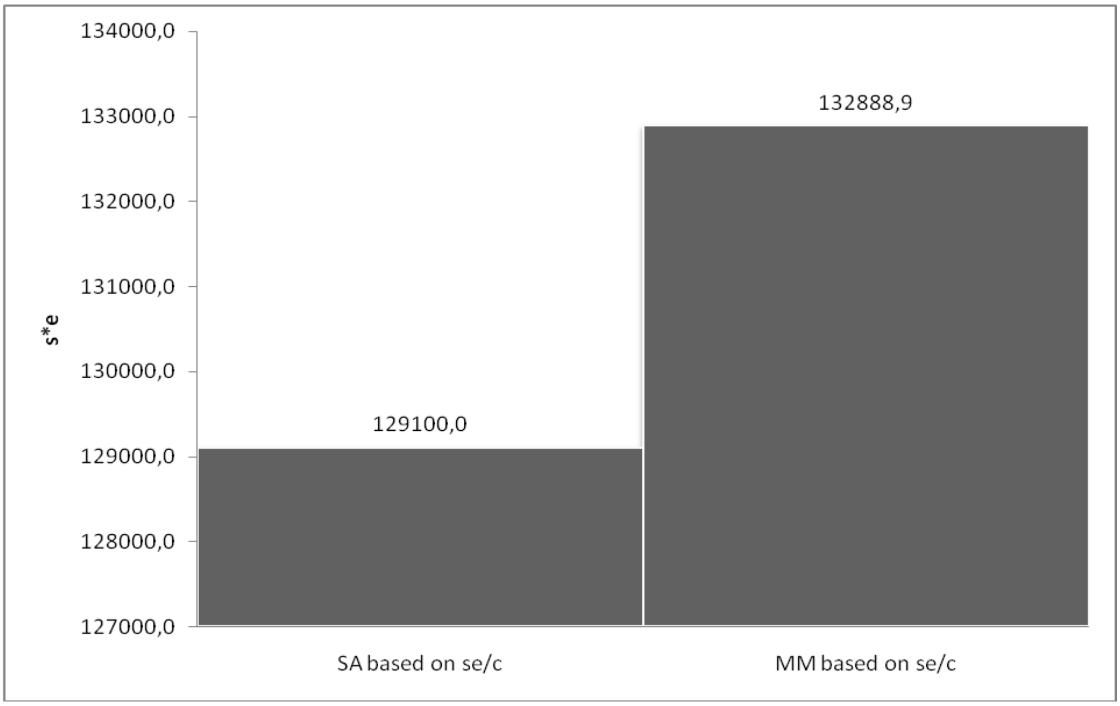

Figure 27 Comparison of SA and MM Based on s*e/c Ratio and s*e Value

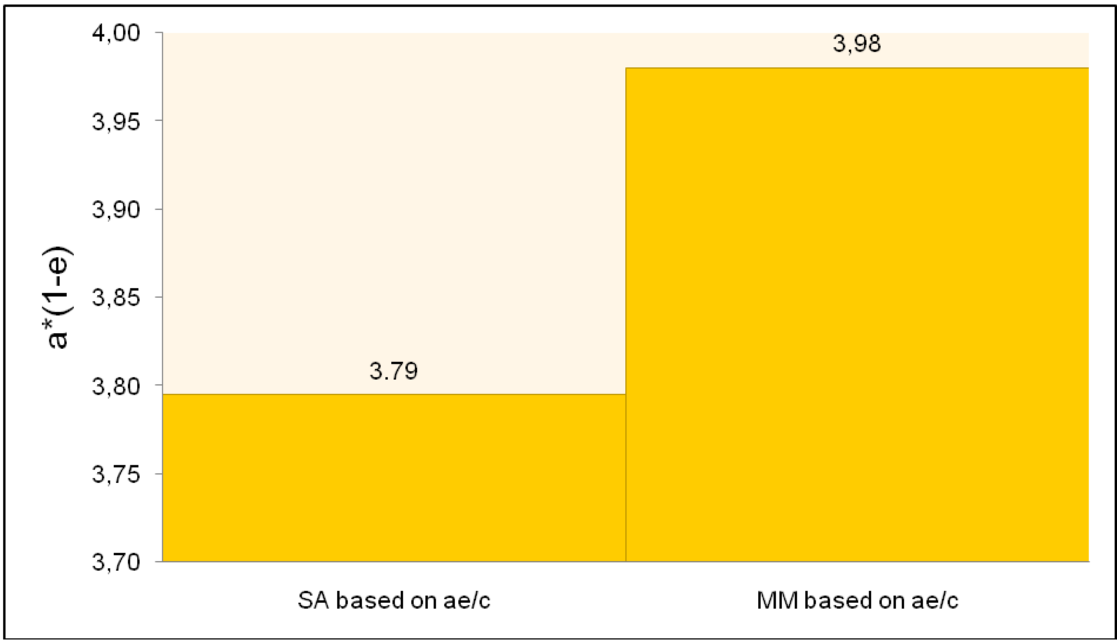

Figure 28 Comparison of SA and MM Based on a*e/c Ratio and a*(1-e) Value

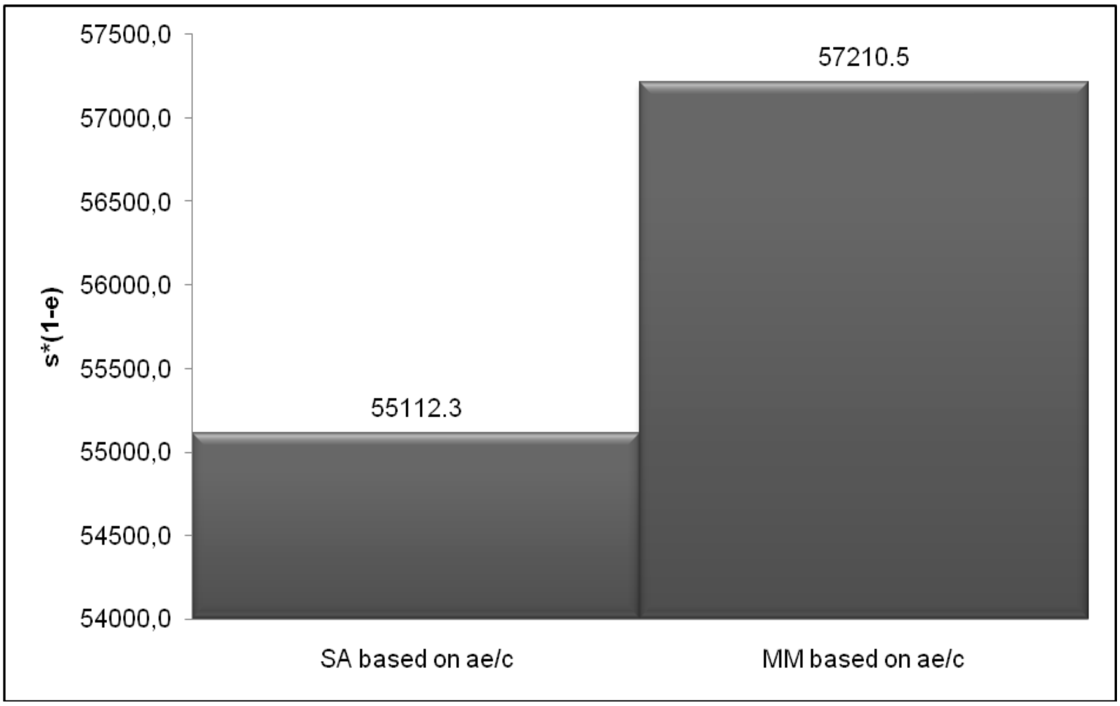

Figure 29 Comparison of SA and MM Based on a*e/c Ratio and s*(1-e) Value

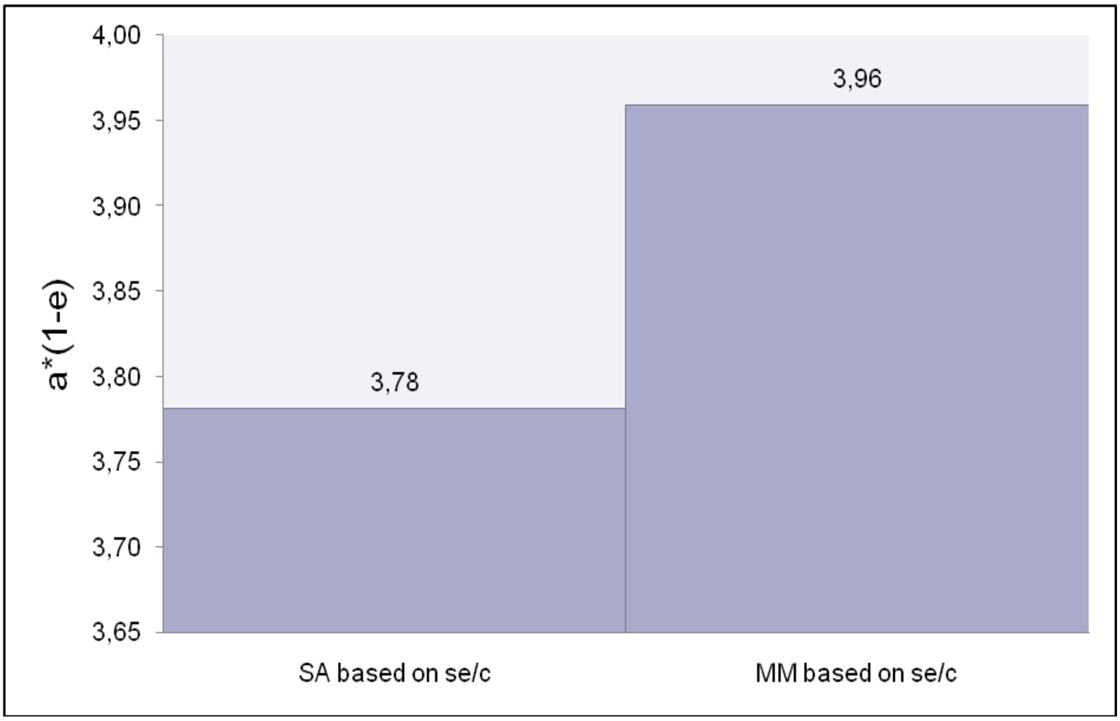

Figure 30 Comparison of SA and MM Based on s*e/c Ratio and a*(1-e) Value

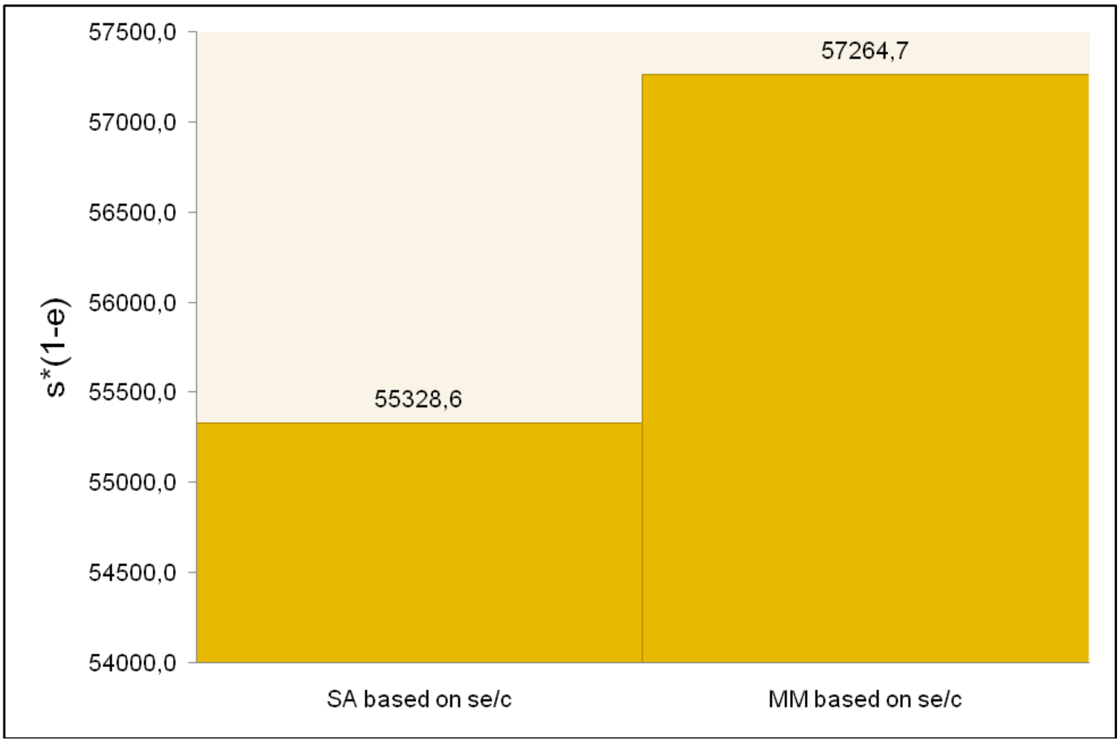

Figure 31 Comparison of SA and MM Based on s*e/c Ratio and s*(1-e) Value

Analyzing Figures 24-31, it can be concluded that Mathematical Model outperformed results of Sorting Algorithm based on a*e/c and s*e/ratios for both accident reduction and weighted accident reduction by severity. It was also observed that the overall number of accidents was higher for Mathematical Model than for Sorting Algorithm after countermeasures implementation. This fact means that Mathematical Model proposes more hazardous rail crossings for safety improvement and gives the greater accident reduction and weighted accident reduction by severity values. It is necessary to point out, the cost of countermeasures is subject to change and this fact should be considered before application of the model.

Sensitivity of the Models

For a given input data with budget available of $2,500,000 the Mathematical Model (MM) outperformed the Sorting Algorithm (SA). But we cannot state in general that MM is better than SA before checking both models for different values of budget available (sensitivity of models). Changing of constraints values makes a significant influence at the model. In the current work budget range from $200,000 up to $$4,200,000 was considered. For a particular value of budget a*e, a*(1-e), s*e, s*(1-e) were calculated applying MM and SA. The results are presented in Tables 17 - 20 and Figures 32 - 39.

Table 17

Sensitivity of SA Based on a*e/c

SA based on a*e/c				
TotalCost	a*e	a*(1-e)	s*e	s*(1-e)
180000	1.294988	0.554995	18519.23	7936.811
390000	2.226838	0.954359	31498.35	13499.29
570000	2.970597	1.273113	42122.87	18052.66
780000	3.751651	1.60785	53724.11	23024.62
1170000	5.075771	2.17533	73260.94	31397.55
1470000	6.025503	2.582358	87138.94	37345.26
1770000	6.914407	2.963317	100546.9	43091.53
2070000	7.751079	3.321891	112850.3	48364.42
2490000	8.854448	3.794764	128595.5	55112.34
2790000	9.604151	4.116065	139132.8	59628.33
3090000	10.32911	4.426761	149727.8	64169.04
3480000	11.23738	4.816021	162479.2	69633.94
3780000	11.92326	5.117131	171802.6	73720.8
4170000	12.77739	5.483186	183877.2	78895.66

Table 18

*Sensitivity of SA Based on s*e/c*

SA based on s*e/c				
TotalCost	a*e	a*(1-e)	s*e	s*(1-e)
180000	1.294988	0.554995	18519.23	7936.811
390000	2.210237	0.947244	31719.13	13593.91
570000	2.966126	1.271197	42259.96	18111.41
780000	3.747696	1.606156	53779.23	23048.24
1170000	5.055337	2.166573	73553.33	31522.86
1470000	6.013405	2.577174	87549.52	37521.22
1770000	6.88244	2.949617	100748.2	43177.8
2070000	7.736612	3.315691	113111.4	48476.3
2490000	8.822772	3.781188	129100	55328.56
2790000	9.562801	4.098343	139983.6	59992.98
3090000	10.29075	4.41032	150295	64412.13
3480000	11.19352	4.797221	163188.3	69937.86
3780000	11.87502	5.089292	172734.1	74028.91
4170000	12.71411	5.448905	184487.2	79065.95

Table 19

*Sensitivity of MM Based on a*e/c*

MM based on a*e/c				
TotalCost	a*e	a*(1-e)	s*e	s*(1-e)
180000	1.295	0.555	18519.23	7936.811
390000	2.227	0.954	31498.35	13499.29
570000	2.894	1.24	41387.39	17737.45
780000	3.819	1.65	54226.91	23418.12
1170000	5.192	2.238	74369.68	32050.74
1470000	6.204	2.682	88347.29	38175.47
1770000	7.154	3.089	102225.3	44123.19
2070000	8.043	3.47	115633.3	49869.46
2490000	9.212	3.98	132484	57210.54
2790000	10.015	4.332	143906.5	62225.75
3090000	10.794	4.666	155234.2	67080.47
3480000	11.764	5.082	169012.1	72985.27
3780000	12.481	5.389	179277.7	77384.83
4170000	13.386	5.784	191519.5	82722.45

Table 20

*Sensitivity of MM Based on s*e/c*

MM based on s*e/c				
TotalCost	a*e	a*(1-e)	s*e	s*(1-e)
180000	1.295	0.555	18519.23	7936.811
390000	2.21	0.947	31719.13	13593.91
570000	2.954	1.266	42197.54	18084.66
780000	3.819	1.65	54226.91	23418.12
1170000	5.191	2.237	74806.03	32237.74
1470000	6.15	2.649	89238.46	38423.07
1770000	7.076	3.045	102861.5	44261.51
2070000	8.011	3.457	115834.6	49955.73
2490000	9.183	3.959	132888.9	57264.75
2790000	9.995	4.324	144441.3	62454.95
3090000	10.762	4.653	155738.7	67296.69
3480000	11.716	5.061	169756.1	73304.15
3780000	12.441	5.372	179980.3	77685.96
4170000	13.34	5.757	192723.8	83147.42

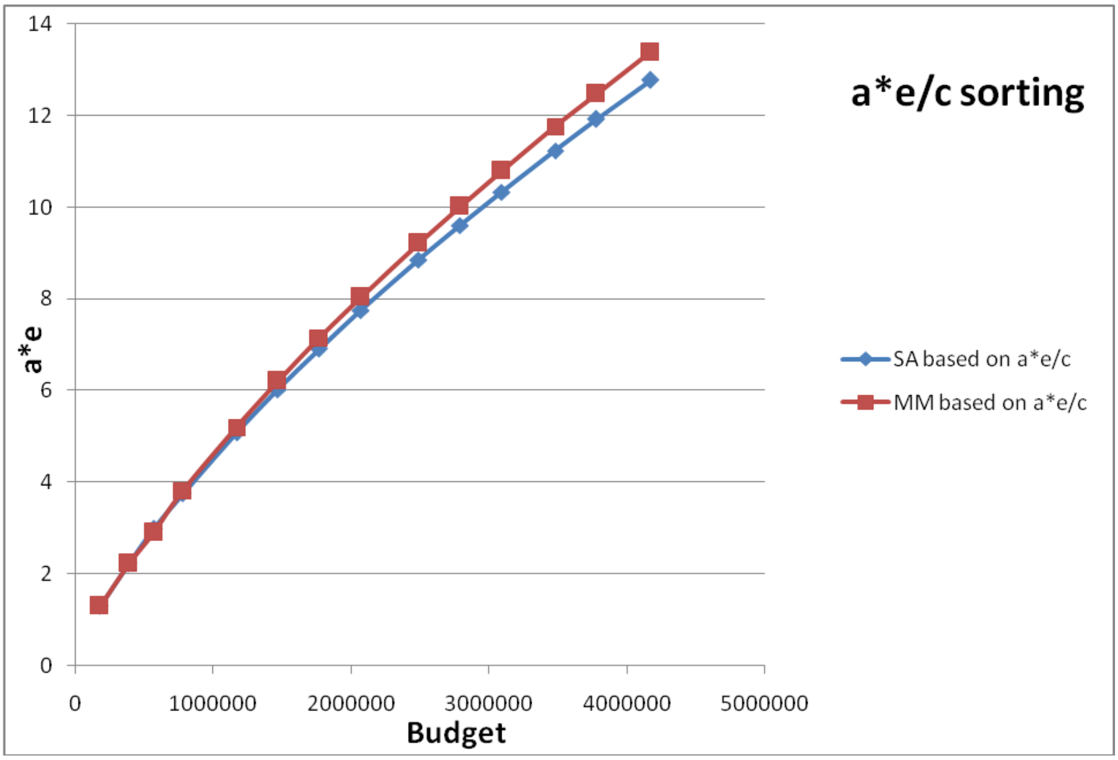

Figure 32 Values of a*e Based on a*e/c Sorting

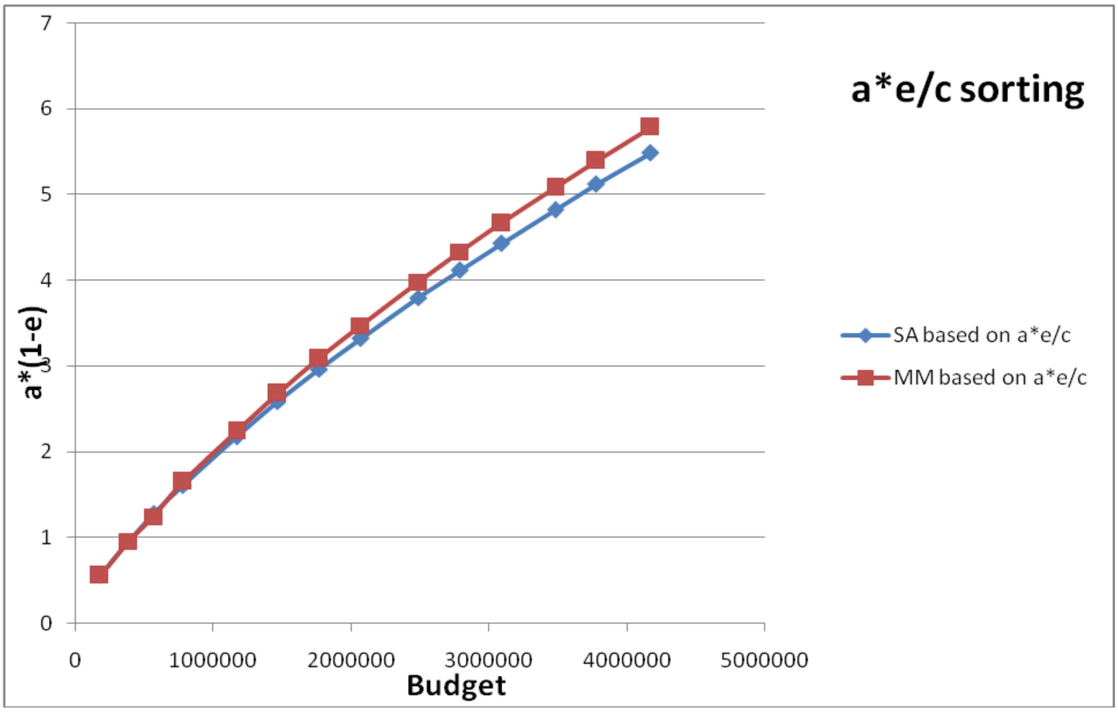

Figure 33 Values of a*(1-e) Based on a*e/c Sorting

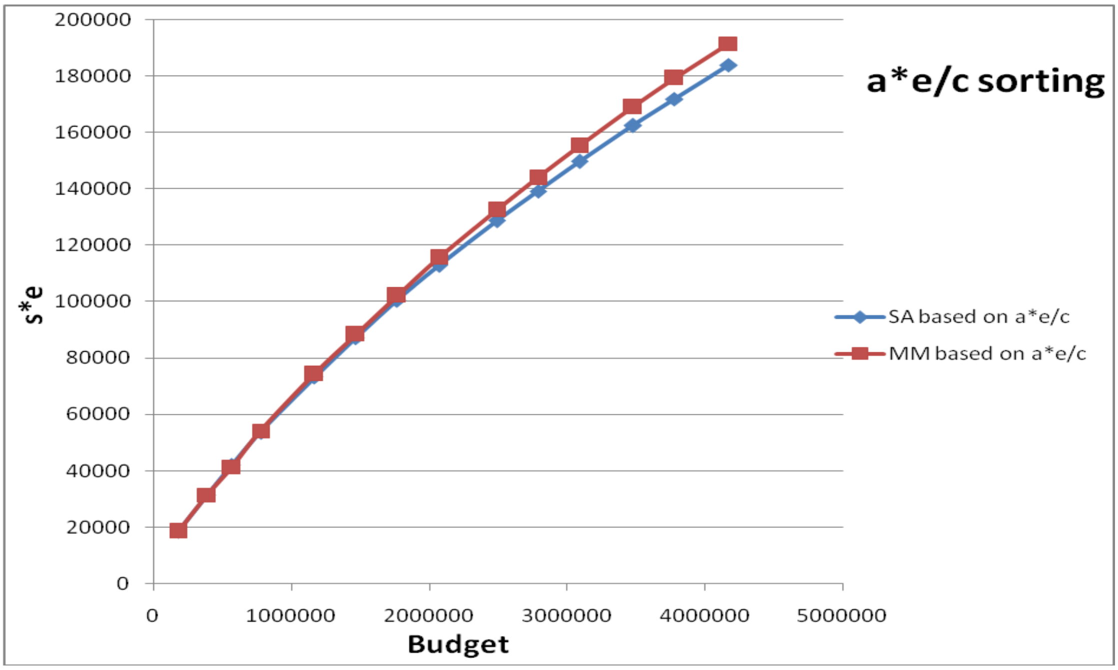

Figure 34 Values of s*e Based on a*e/c Sorting

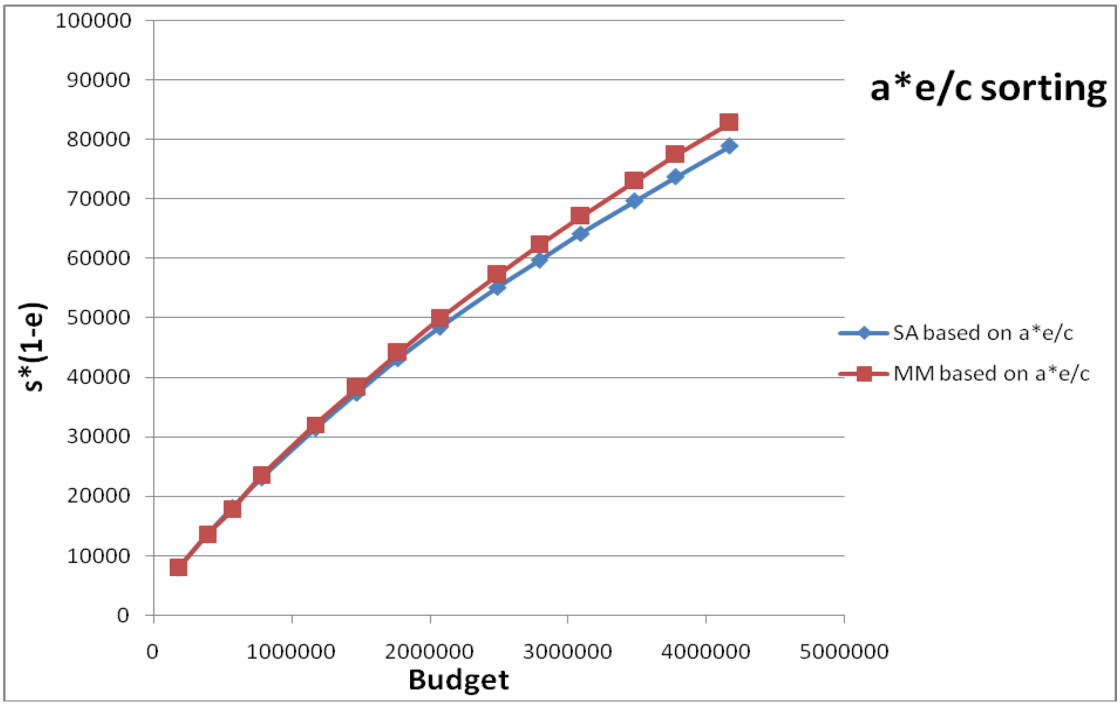

Figure 35 Values of s*(1-e) Based on a*e/c Sorting

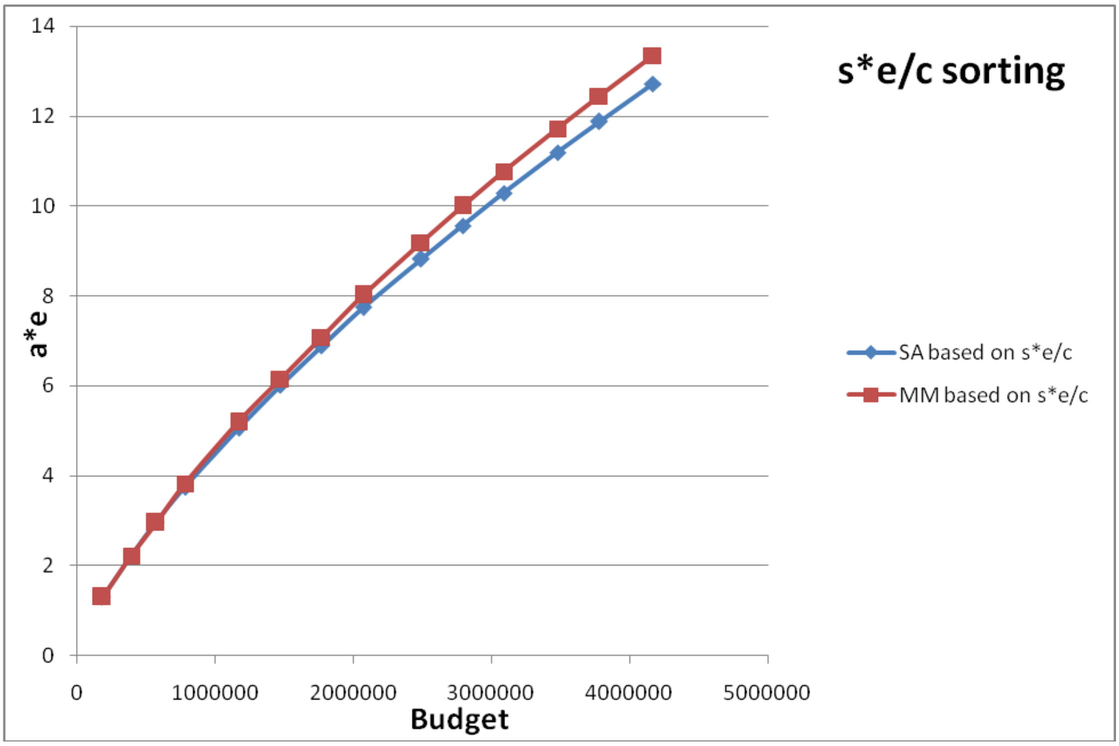

Figure 36 Values of a*e Based on s*e/c Sorting

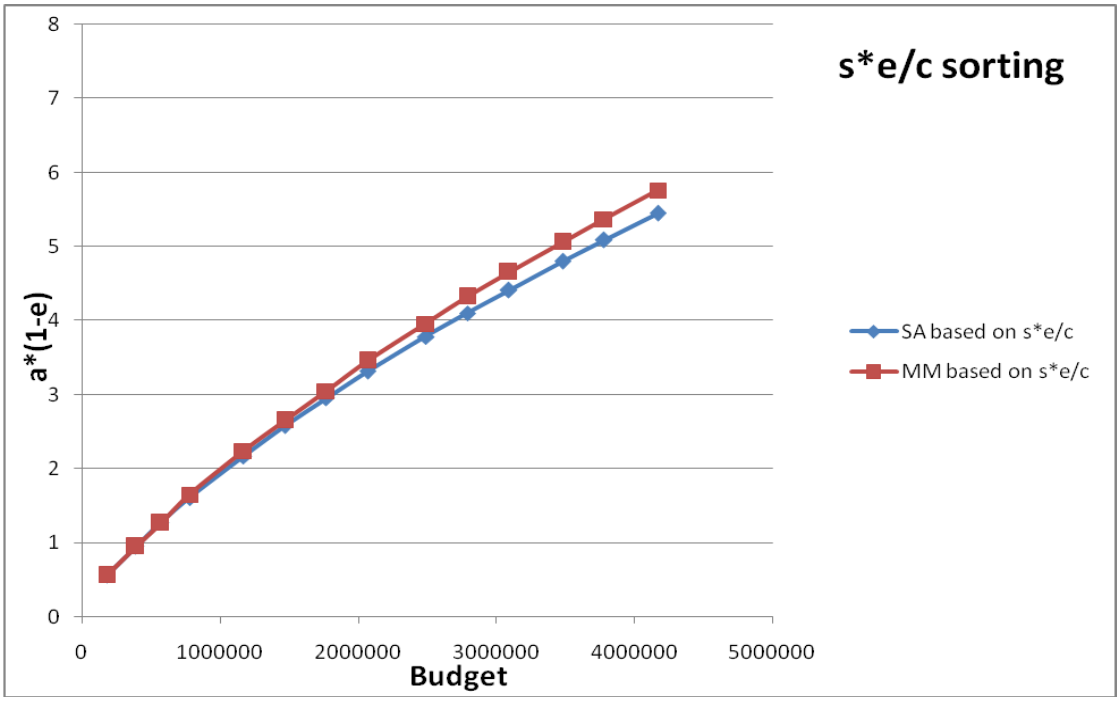

Figure 37 Values of a*(1-e) Based on s*e/c Sorting

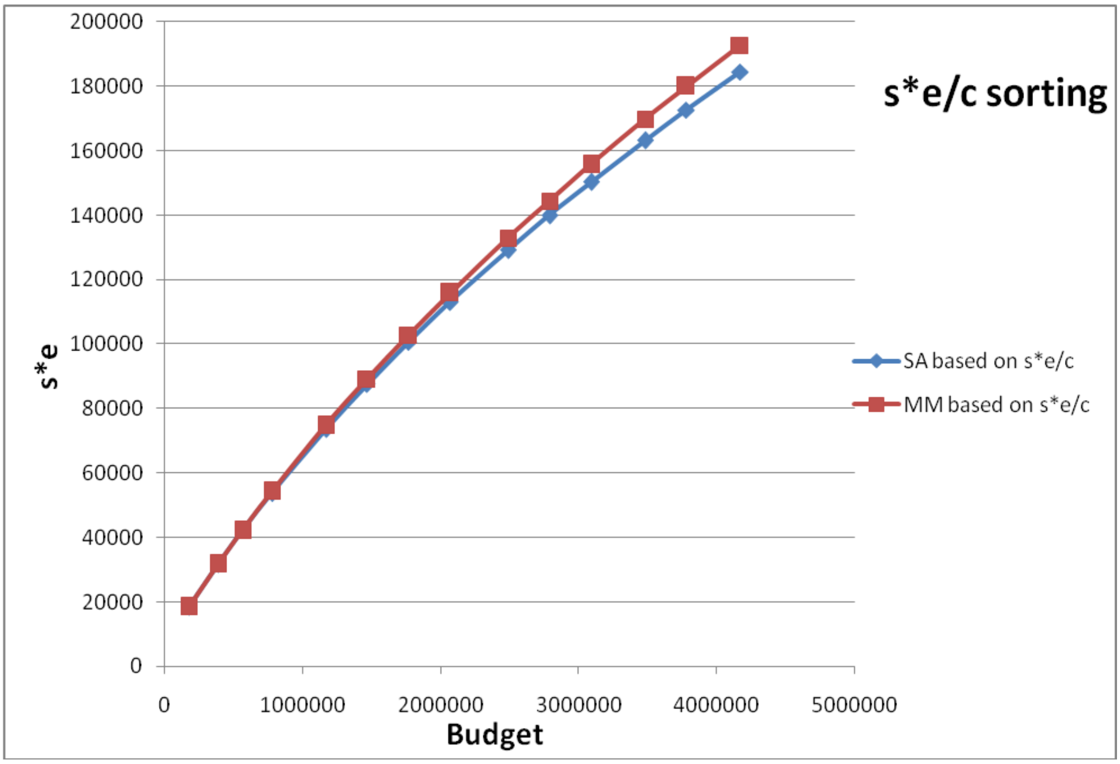

Figure 38 Values of s*e Based on s*e/c Sorting

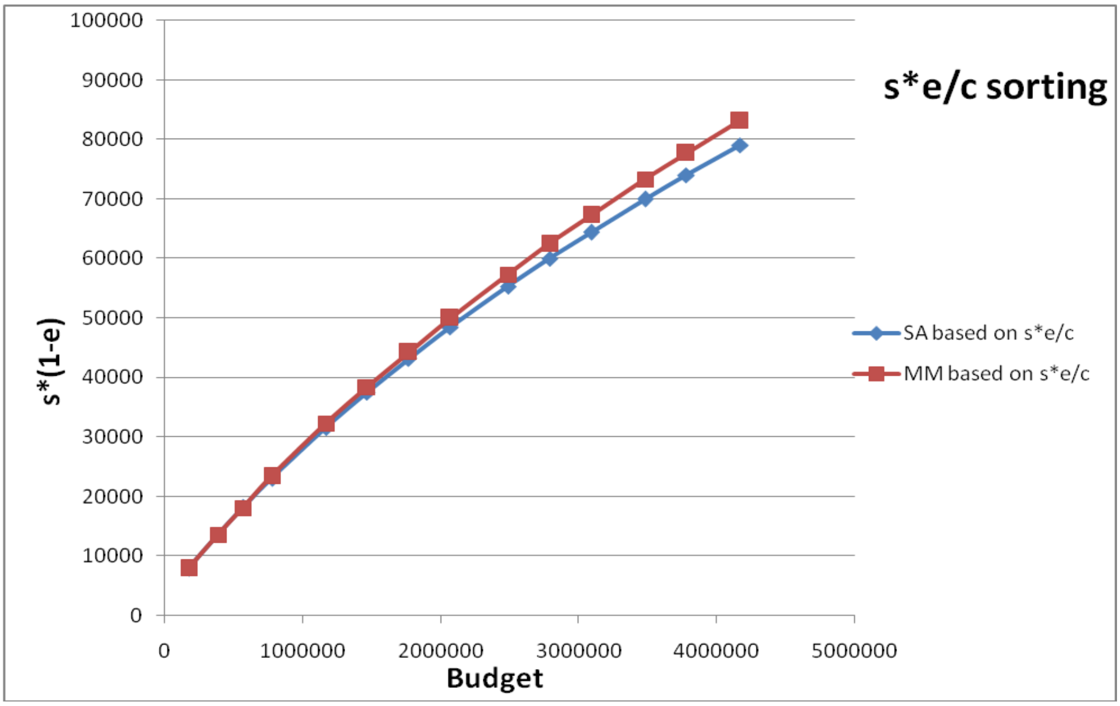

Figure 39 Values of s*(1-e) Based on s*e/c Sorting

From the conducted analysis we can conclude that for all indicators (a*e values, which represent the total accident reduction; s*e values, which represent the total weighted accident reduction by severity category; a*(1-e) values, which represent the total number of accidents left after suggested countermeasures implementation; s*(1-e) values, which represent the total number of weighted accidents by severity category left after suggested countermeasures implementation) MM outperformed SA for the budget available, ranging from $200,000 up to $$4,200,000. Thus, MM proposes safety improvements, which result in greater reduction of the total number accidents and the total number of weighted accidents by severity category as well. The difference between MM and SA for a*e and s*e values increase as the budget available enlarges. Most of all, MM suggests implementation of countermeasures at more hazardous highway-railway public crossings (which is shown by the greater a*(1-e) values and s*(1-e) values for the greater reduction of the total number accidents and the total number of weighted accidents by severity category) in comparison with SA. The difference between MM and SA for a*(1-e) and s*(1-e) values increase as the budget available enlarges.

So, the Mathematical Model (MM) outperforms the Sorting Algorithm (SA) based on sensitivity analysis and it is recommended for the further usage in order to allocate the available monetary resources between highway-railroad public at grade Tennessee crossings to apply the Mathematical Model (MM).

The Logit Model for Accident Prediction by Severity Category

The main aim of the current work is the development of highway-railroad at grade crossings prioritizing model. The model should identify those rail crossings which will result in the maximum benefit in terms of accident reduction/weighted accident reduction by severity category after certain countermeasures implementation for the given budget. Severity of accidents was separated by three categories:

- Fatality accident;
- Injury accident;
- Property damage accident;

To estimate the weighted accident prediction by severity category, it is necessary to calculate the number of predicted fatality, injury and property damage accidents. Equations, proposed by GradeDec software, were used for this purpose. In the section of literature review the paper, written by Hu et al. (2009), was mentioned. The authors use the Logit model to predict the number of accidents by severity category. In this case it will be useful to apply the Logit model and compare results with output of the GradeDec model.

Hu et al. (2009) define a generalized logit as

$$\log\text{it}[\pi_j(\mathbf{x})] = \log\frac{\pi_j(\mathbf{x})}{\pi_0(\mathbf{x})}$$

where *x* – set of highway-railroad crossing characteristics;

j – set of severity categories;

π_j – the probability of accident *j* to happen;

π_0 – the probability of a “pivot“ accident to happen;

Set of highway-railroad crossing characteristics included the same parameters, which are used by GradeDec model: maximum time table trains peed, miles per hour; through trains per day; switch trains per day; binary variable, if crossing is urban, Urban = 1,else Urban = 0; number of the main rail road tracks. As it was mentioned before set of severity categories contains fatality, injury and property damage accidents.

Hu et al. (2009) propose to form a logit as a linear predictor

$$\log\text{it}[\pi_j(\mathbf{x})] = \log\frac{\pi_j(\mathbf{x})}{\pi_0(\mathbf{x})} = \alpha_j + \mathbf{x}\boldsymbol{\beta}_j,$$

where α and β – coefficients of the multinomial logistic regression.

To find the relationship between number of each severity category and variables, describing highway-railroad crossing characteristics, the multinomial logistic regression analysis has been conducted using Matlab 7.0. The accident history for the last 10 years data has been uploaded from FRA accident/injury database to compute the actual number of fatality, injury and property damage accidents for each public at grade crossing of TN State. The results are presented in the Table 21. The relationship between predictors and response variables turned out to be:

Logit (PDO) = 29.95249 - 0.12046*X1 - 0.03353*X2 - 0.39736*X3 - 19.1145*X4 - 0.71761*X5;

Logit (Injury) = 27.43512 - 0.10406*X1 - 0.20236*X2 - 0.47232*X3 - 20.4985*X4 + 1.606862*X5,

where X1 – maximum time table train speed, miles per hour;

X2 – through trains per day;

X3 – switch trains per day;

X4 - binary variable, if crossing is urban, Urban=1, else Urban=0;

X5 – number of the main rail road tracks.

Table 21

The FRA 2010 Accident Data by Severity Category

Actual number of accidents (FRA 2010)

№ cross.\Acc. Type	Fatalities	Injuries	PDO
1	2	0	0
2	1	0	0
3	1	0	0
4	1	0	0
5	1	0	0
6	1	0	0
7	1	0	0
8	1	0	0
9	1	0	0
10	1	0	0
11	0	1	0
12	1	0	0
13	1	0	0
14	1	0	0
15	1	0	0
16	1	0	0
17	1	0	0
18	1	0	0
19	1	0	0
20	0	1	0
21	1	0	0
22	0	0	1
23	1	0	0
24	0	1	0
25	1	0	0
26	1	0	0
27	0	1	0
28	1	0	0
29	1	0	0
30	1	0	0
31	1	0	0
32	1	0	0
33	1	0	0

Fatality accident has been taken as a “pivot” accident. The probability of the accident by severity category for the given crossing can be calculated as (see Hu et al. 2009):

$$\pi_j(\mathbf{x}) = \frac{\exp(\alpha_j + \mathbf{x}\boldsymbol{\beta}_j)}{\sum_{k=0}^{2} \exp(\alpha_k + \mathbf{x}\boldsymbol{\beta}_k)},$$

This formula has been applied for each highway-railroad at grade crossing to find the probability of fatality, injury and property damage accidents to happen. To find the actual number of accidents by severity, proposed by the Logit model, the accident prediction values for each crossing (given by TRIMS database) were multiplied by corresponding probability of the considered category. The results of computations are presented in Table 22.

Comparison of the Logit and GradeDec Models

Table 22 and Figure 40 show the predicted number of accidents by severity category, using the Logit model and the GradeDec model for those at grade public highway-railroad crossings, at which accidents have been observed in 2010 according to FRA accident/injury database.

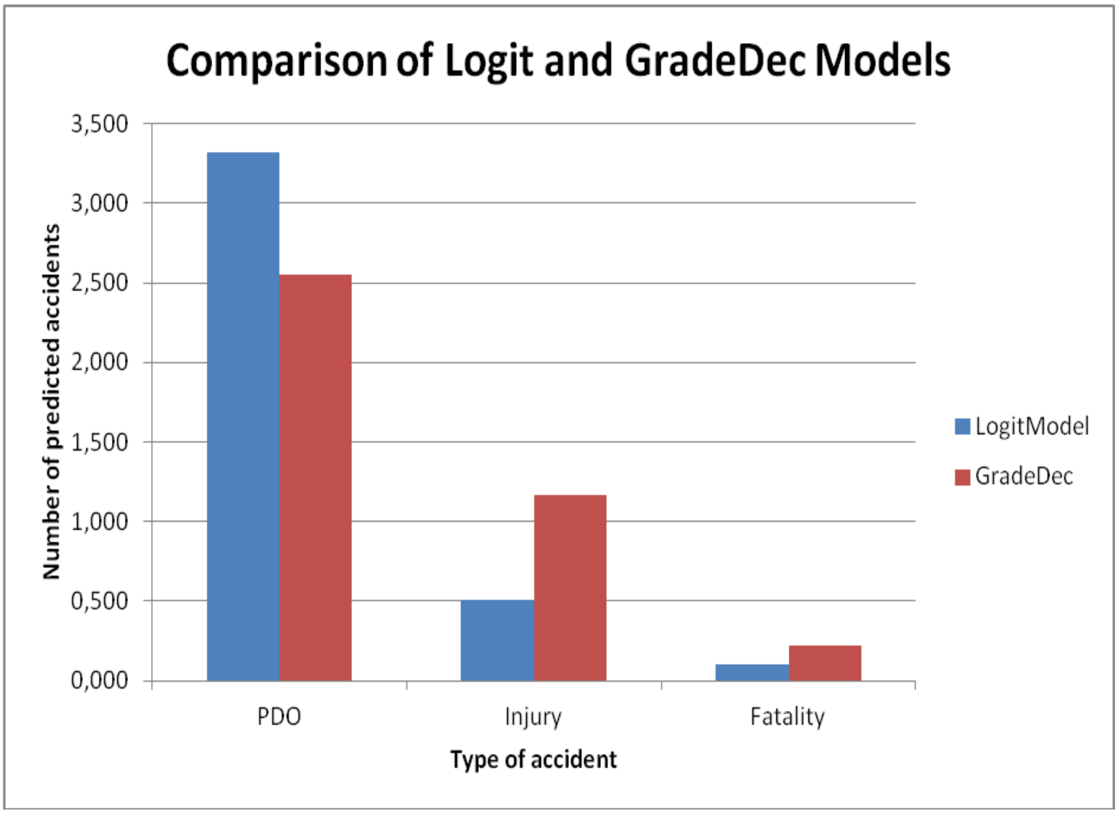

Figure 40 Comparison of the Logit and GradeDec Models

Table 22
Comparison of the Logit and GradeDec Models

Results of Logit Model			Results of GradeDec		
PDO	Injuries	Fatalities	Fatalities	Injuries	PDO
0,180243	0,015249	0,000334	0,007771	0,063427	0,124629
0,051122	0,006792	0,005512	0,006168	0,020492	0,036766
0,116204	0,030117	0,004032	0,013628	0,048815	0,087912
0,055405	0,007011	0,010470	0,005158	0,021754	0,045974
0,066708	0,008222	0,010701	0,008065	0,027192	0,050374
0,065680	0,006775	0,000428	0,005170	0,024078	0,043635
0,060986	0,012779	0,000018	0,001044	0,016525	0,056213
0,049133	0,000746	0,000035	0,000657	0,010573	0,038684
0,051482	0,000782	0,000037	0,000688	0,011079	0,040534
0,020873	0,004374	0,000006	0,000357	0,005656	0,019239
0,153394	0,117042	0,000000	0,014428	0,094376	0,161632
0,086199	0,054250	0,000000	0,011854	0,054018	0,074577
0,101667	0,001920	0,011017	0,012571	0,039385	0,062647
0,154151	0,031259	0,000036	0,002107	0,039531	0,143810
0,044302	0,010785	0,000006	0,000857	0,013244	0,040992
0,000000	0,000000	0,000000	0,000000	0,000000	0,000000
0,173383	0,014185	0,000000	0,003771	0,054145	0,129653
0,338566	0,035591	0,004721	0,024344	0,118153	0,236382
0,001516	0,000178	0,000000	0,000126	0,000654	0,000914
0,051464	0,009957	0,000078	0,001774	0,016131	0,043595
0,260047	0,027337	0,003626	0,018698	0,090751	0,181561
0,128149	0,012292	0,011640	0,013348	0,048510	0,090222
0,025253	0,003944	0,000969	0,002838	0,009991	0,017337
0,042689	0,008162	0,000083	0,001932	0,014376	0,034625
0,114525	0,001946	0,000008	0,001991	0,029995	0,084493
0,152498	0,025575	0,001399	0,006128	0,047157	0,126187
0,129523	0,006735	0,011477	0,015787	0,050118	0,081831
0,005649	0,000135	0,000000	0,000090	0,001390	0,004303
0,223782	0,002320	0,000427	0,001445	0,039409	0,185676
0,055277	0,006359	0,000395	0,000785	0,012749	0,048496
0,114425	0,016385	0,008292	0,014283	0,046243	0,078576
0,085565	0,017174	0,005798	0,010928	0,035715	0,061894
0,162573	0,014815	0,013638	0,012947	0,058003	0,120078
3,32243	0,51119	0,10518	0,2217396	1,16364	2,55344

It can be concluded that the Logit model gives lower number of fatalities, approximately the same number of injuries (slightly lower) and higher number of property damage accidents in comparison with the GradeDec model. Nevertheless, the coefficients of determination (which represent the accuracy of model and how well it fits), were relatively low for the Logit model: for PDO accidents – 0.274, for injury accidents – 0.109, for fatalities – 0.026. In order to make a correct evaluation of each model output additional research, connected with site investigation at each highway-railroad at grade crossing, should be conducted. After that it is possible to state which model is better and needs to be applied. In the current work the GradeDec model (which is used commonly used within the country) has been implemented for estimation of accidents by severity category, as it is recommended by US DOT.

6. CONCLUSIONS

According to Section 130 the United States Department of Transportation (USDOT) provides funding assistance to state departments of transportation to implement highway-rail grade crossing improvement programs. These programs are suspect to develop particular safety improvement actions in order to decrease the number of accidents at highway-rail grade crossings. The current work was dedicated to allocate available monetary resources between highway-rail grade crossings of the Tennessee State (information is given by TRIMS database) and maximize the total benefits in terms of accident and severity reduction. The scope of work included the literature review with description of hazard index/accident prediction methodologies, widely used by various DOTs; careful investigation of the accident prediction method, applied by TDOT; development of the model to satisfy the established goals and computational results, demonstrated benefits and negative sites of both models.

Comparison of US DOT Accident Prediction Model, currently used by the State of Tennessee, with accident prediction/hazard index models, employed by other states, shows that the closest results are obtained by Illinois's Modified Expected Accident Frequency Formula. At this point it can be recommended to start implementation of Illinois's Modified Expected Accident Frequency Formula for Tennessee rail crossings and to check its accuracy over a certain time period (several years).

The scope of the conducted work also included application of the Logit model for accident prediction by severity category. It was observed that the Logit model gave lower number of fatalities, approximately the same number of injuries (slightly lower) and higher number of property damage accidents in comparison with the

GradeDec model. Additional research should be provided at that point to evaluate which model is better for highway-railroad public crossings of Tennessee State.

It was concluded that Mathematical Model was more efficient than Sorting Algorithm, because MM provided greater accident reduction and weighted accident reduction by severity. In comparison with SA, MM proposed safety improvements not only from passive rail crossings to flashing lights, but also upgrading of flashing lights rail crossings to gates. Nevertheless, it is necessary to specify the main aim of investments: to reduce the overall number of accidents or to decrease the number of fatalities, injuries and property damage accidents, taking into consideration that the cost of fatality is greater than the cost of injury and the cost of injury is greater than the cost of property damage accident. For the first case it is better to use MM with the first objective. For the second case it is better to use MM with the second objective. GAMS showed a good computational time for 2873 rail crossings.

Besides, there are several issues, which should be considered in the future research. The cost of accident was set based on assumption, that one fatality is equal to 2 injuries of 3 property damage accidents. The nature of relationship between those severity categories could be more complex. This question should be addressed by TDOT before application of the proposed model. Most of all, cost of countermeasures was taken from Railroad-Highway Grade Crossing Handbook (2007), which are subject to change to higher values. The resource allocation procedure can be extended and new countermeasures may be introduced. But in this case additional information should be provided by TDOT. It is recommended to check the sensitivity of the model, using larger size of input data (e.g., consider public at-grade highway-rail crossings of other states).

For the final conclusion, Mathematical Model, developed in the current work, can be used as a powerful tool to solve a relatively complex problem of monetary resources allocation between highway-rail crossings to maximize the safety and to follow specific requirements, established by the United States Department of Transportation.

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APPENDICES

Appendix A

US DOT Accident Prediction Factor Values for Crossings with Different Warning Devices

US DOT Accident Prediction Factor Values for Crossings with Passive Warning Devices

K	"c" x "t"	EI	Main	MT	Day Thru	DT	Highway Paved	HP	Maximum Timetable	MS	Highway Type	HT	Highway Lanes	HL
	0*	1.00	0	1.00	0	1.00	1 (yes)	1.00	0	1.00	01&11	1.00	1	1.00
	1 - 5	2.22	1	1.23	1	1.27	2 (no)	0.54	5	1.04	02&12	0.90	2	1.00
	6 - 10	3.30	2	1.52	2	1.38			10	1.08	06&14	0.82	3	1.00
	11 - 20	4.24	3	1.87	3	1.45			15	1.12	07&16	0.74	4	1.00
	21 - 30	5.01	4	2.31	4	1.50			20	1.17	08&17	0.67	5	1.00
	31 - 50	5.86	5	2.85	5	1.55			25	1.21	09&19	0.61	6	1.00
	51 - 80	6.89	6	3.51	6	1.58			30	1.26			7	1.00
	81 - 120	7.95			7	1.61			35	1.31			8	1.00
	121 - 200	9.29			8	1.64			40	1.36			9	1.00
	201 - 300	10.78			9	1.67			45	1.41				
	301 - 400	12.06			10	1.69			50	1.47				
	401 - 500	13.11			11-20	1.78			55	1.53				
	501 - 600	14.02			21-30	1.91			60	1.59				
	601 - 700	14.82			31-40	2.00			65	1.65				
	701 - 1000	16.21			41-60	2.09			70	1.71				
	1001 - 1300	17.93							75	1.78				
	1301 - 1600	19.37							80	1.85				
	1601 - 2000	20.81							85	1.92				
	2001 - 2500	22.42							90	2.00				
	2501 - 3000	23.97												
	3001 - 4000	25.98												
	4001 - 6000	29.26												
	6001 - 8000	32.73												
	8001 - 10000	35.59												
	10001 - 15000	39.71												
	15001 - 20000	44.43												
	20001 - 25000	48.31												
	25001 - 30000	51.65												
	30001 - 40000	55.98												
	40001 - 50000	60.87												
	50001 - 60000	65.08												
	60001 - 70000	68.81												
	70001 - 90000	73.74												
	90001 -	79.44												
	110001 -	84.42												
	130001 -	91.94												
	180001 -	100.92												
	230001 -	109.94												
	300001 -	113.87												

General Form of Basic Accident Prediction Formula: a = K x El x MT x DT x HP x HT x HL

"c" x "t" = Number of highway vehicles per day, "c", multiplied by total train movements per day, "t"

El = Exposure index factor
MT = Main tracks factor
DT = Day thru trains factor
HP = Highway paved factor
MS =Maximum timetable speed factor
HT = Highway type factor
HL = Highway lanes factor

* Less than one train per day
** See Table 16 for definition of highway type codes

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

US DOT Accident Prediction Factor Values for Crossings with Flashing Light

Warning Devices

K	"c" x "t"	EI	Main	MT	Day Thru	DT	Highway Paved	HP	Maximum Timetable	MS	Highway Type	HT	Highway Lanes	HL
	0*	1.00	0	1.00	0	1.00	1 (yes)	1.00	0	1.00	01&11	1.00	1	1.00
	1 - 5	2.27	1	1.11	1	1.09	2 (no)	1.00	5	1.00	02&12	1.00	2	1.15
	6 - 10	2.99	2	1.24	2	1.12			10	1.00	06&14	1.00	3	1.32
	11 - 20	3.59	3	1.39	3	1.14			15	1.00	07&16	1.00	4	1.51
	21 - 30	4.17	4	1.55	4	1.15			20	1.00	08&17	1.00	5	1.74
	31 - 50	4.79	5	1.72	5	1.17			25	1.00	09&19	1.00	6	1.99
	51 - 80	5.52	6	1.92	6	1.18			30	1.00			7	2.29
	81 - 120	6.27			7	1.18			35	1.00			8	2.63
	121 - 200	7.20			8	1.19			40	1.00			9	3.02
	201 - 300	8.22			9	1.20			45	1.00				
	301 - 400	9.07			10	1.20			50	1.00				
	401 - 500	9.77			11-20	1.23			55	1.00				
	501 - 600	10.37			21-30	1.26			60	1.00				
	601 - 700	10.89			31-40	1.28			65	1.00				
	701 - 1000	11.79			41-60	1.30			70	1.00				
	1001 - 1300	12.89							75	1.00				
	1301 - 1600	13.80							80	1.00				
	1601 - 2000	14.71							85	1.00				
	2001 - 2500	15.72							90	1.00				
	2501 - 3000	16.67												
	3001 - 4000	17.91												
	4001 - 6000	19.89												
	6001 - 8000	21.97												
	8001 - 10000	23.66												
	10001 - 15000	26.08												
	15001 - 20000	28.80												
	20001 - 25000	31.02												
	25001 - 30000	32.91												
	30001 - 40000	35.34												
	40001 - 50000	38.06												
	50001 - 60000	40.39												
	60001 - 70000	42.43												
	70001 - 90000	45.11												
	90001 -	48.18												
	110001 -	50.85												
	130001 -	54.84												
	180001 -	59.56												
	230001 -	64.25												
	300001 -	68.86												

General Form of Basic Accident Prediction Formula: a = K x El x MT x DT x HP x HT x HL

"c" x "t" = Number of highway vehicles per day, "c", multiplied by total train movements per day, "t"

El = Exposure index factor
MT = Main tracks factor
DT = Day thru trains factor
HP = Highway paved factor
MS =Maximum timetable speed factor
HT = Highway type factor
HL = Highway lanes factor

* Less than one train per day
** See Table 16 for definition of highway type codes

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

US DOT Accident Prediction Factor Values for Crossings with Gate Warning

Devices

K	"c" x "t"	EI	Main Tracks	MT	Day Thru Trains	DT	Highway Paved	HP	Maximum Timetable Speed	MS	Highway Type Code**	HT	Highway Lanes	HL
	0*	1.00	0	1.00	0	1.00	1 (yes)	1.00	0	1.00	01&11	1.00	1	1.00
	1 - 5	2.37	1	1.34	1	1.00	2 (no)	1.00	5	1.00	02&12	1.00	2	1.11
	6 - 10	3.18	2	1.79	2	1.00			10	1.00	06&14	1.00	3	1.23
	11 - 20	3.86	3	2.40	3	1.00			15	1.00	07&16	1.00	4	1.36
	21 - 30	4.51	4	3.21	4	1.00			20	1.00	08&17	1.00	5	1.51
	31 - 50	5.22	5	4.29	5	1.00			25	1.00	09&19	1.00	6	1.68
	51 - 80	6.07	6	5.74	6	1.00			30	1.00			7	1.86
	81 - 120	6.94			7	1.00			35	1.00			8	2.07
	121 - 200	8.03			8	1.00			40	1.00			9	2.29
	201 - 300	9.23			9	1.00			45	1.00				
	301 - 400	10.25			10	1.00			50	1.00				
	401 - 500	11.08			11-20	1.00			55	1.00				
	501 - 600	11.80			21-30	1.00			60	1.00				
	601 - 700	12.48			31-40	1.00			65	1.00				
	701 - 1000	13.51			41-60	1.00			70	1.00				
	1001 - 1300	14.84							75	1.00				
	1301 - 1600	15.96							80	1.00				
	1601 - 2000	17.07							85	1.00				
	2001 - 2500	18.30							90	1.00				
	2501 - 3000	19.48												
	3001 - 4000	21.00												
	4001 - 6000	23.46												
	6001 - 8000	26.06												
	8001 - 10000	28.18												
	10001 - 15000	31.22												
	15001 - 20000	34.67												
	20001 - 25000	37.49												
	25001 - 30000	39.91												
	30001 - 40000	43.03												
	40001 - 50000	46.53												
	50001 - 60000	49.53												
	60001 - 70000	52.18												
	70001 - 90000	55.67												
	90001 -	59.68												
	110001 -	63.16												
	130001 -	68.41												
	180001 -	74.63												
	230001 -	80.85												
	300001 -	86.98												

General Form of Basic Accident Prediction Formula: a = K x El x MT x DT x HP x HT x HL

"c" x "t" = Number of highway vehicles per day, "c", multiplied by total train movements per day, "t"

El = Exposure index factor
MT = Main tracks factor
DT = Day thru trains factor
HP = Highway paved factor
MS =Maximum timetable speed factor
HT = Highway type factor
HL = Highway lanes factor

* Less than one train per day
** See Table 16 for definition of highway type codes

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

Appendix B

US DOT Final Accident Prediction from Initial Prediction and Accident History

US DOT Final Accident Prediction from Initial Prediction and Accident History (1 year of accident data (T = 1))

Initial Prediction from Basic Model, a	Number of Accidents, N, in T Years					
	0	1	2	3	4	5
0.00	0.000	0.048	0.095	0.143	0.190	0.238
0.01	0.009	0.066	0.123	0.179	0.236	0.292
0.02	0.019	0.084	0.150	0.215	0.280	0.346
0.03	0.028	0.102	0.176	0.250	0.324	0.398
0.04	0.037	0.119	0.202	0.284	0.367	0.450
0.05	0.045	0.136	0.227	0.318	0.409	0.500
0.06	0.054	0.153	0.252	0.351	0.450	0.550
0.07	0.063	0.170	0.277	0.384	0.491	0.598
0.08	0.071	0.186	0.301	0.416	0.531	0.646
0.09	0.079	0.202	0.325	0.447	0.570	0.693
0.10	0.087	0.217	0.348	0.478	0.609	0.739
0.20	0.160	0.360	0.560	0.760	0.960	1.160
0.30	0.222	0.481	0.741	1.000	1.259	1.519
0.40	0.276	0.586	0.897	1.207	1.517	1.828
0.50	0.323	0.677	1.032	1.387	1.742	2.097
0.60	0.364	0.758	1.152	1.545	1.939	2.333
0.70	0.400	0.829	1.257	1.686	2.114	2.543
0.80	0.432	0.892	1.351	1.811	2.270	2.730
0.90	0.462	0.949	1.436	1.923	2.410	2.897
1.00	0.488	1.000	1.512	2.024	2.537	3.049
1.10	0.512	1.047	1.581	2.116	2.651	3.186
1.20	0.533	1.089	1.644	2.200	2.756	3.311
1.30	0.553	1.128	1.702	2.277	2.851	3.426
1.40	0.571	1.163	1.755	2.347	2.939	3.531
1.50	0.588	1.196	1.804	2.412	3.020	3.627
1.60	0.604	1.226	1.849	2.472	3.094	3.717
1.70	0.618	1.255	1.891	2.527	3.164	3.800
1.80	0.632	1.281	1.930	2.579	3.228	3.877
1.90	0.644	1.305	1.966	2.627	3.288	3.949
2.00	0.656	1.328	2.000	2.672	3.344	4.016
2.10	0.667	1.349	2.032	2.714	3.397	4.079
2.20	0.677	1.369	2.062	2.754	3.446	4.138
2.30	0.687	1.388	2.090	2.791	3.493	4.194
2.40	0.696	1.406	2.116	2.826	3.536	4.246
2.50	0.704	1.423	2.141	2.659	3.577	4.296

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

US DOT Final Accident Prediction from Initial Prediction and Accident History (2 years of accident data (T = 2))

Initial Prediction from Basic Model, a	Number of Accidents, N, in T Years								
	0	1	2	3	4	5	6	7	8
0.00	0.000	0.045	0.091	0.136	0.182	0.227	0.273	0.318	0.364
0.01	0.009	0.063	0.116	0.170	0.223	0.277	0.330	0.384	0.438
0.02	0.018	0.079	0.140	0.202	0.263	0.325	0.386	0.447	0.509
0.03	0.026	0.095	0.164	0.233	0.302	0.371	0.440	0.509	0.578
0.04	0.034	0.110	0.186	0.263	0.339	0.415	0.492	0.568	0.644
0.05	0.042	0.125	0.208	0.292	0.375	0.458	0.542	0.625	0.708
0.06	0.049	0.139	0.230	0.320	0.410	0.500	0.590	0.680	0.770
0.07	0.056	0.153	0.250	0.347	0.444	0.540	0.637	0.734	0.831
0.08	0.063	0.167	0.270	0.373	0.476	0.579	0.683	0.786	0.889
0.09	0.070	0.180	0.289	0.398	0.508	0.617	0.727	0.836	0.945
0.10	0.077	0.192	0.308	0.423	0.538	0.654	0.769	0.885	1.000
0.20	0.133	0.300	0.467	0.633	0.800	0.967	1.133	1.300	1.467
0.30	0.176	0.382	0.588	0.794	1.000	1.206	1.412	1.618	1.824
0.40	0.211	0.447	0.684	0.921	1.158	1.395	1.632	1.868	2.105
0.50	0.238	0.500	0.762	1.024	1.286	1.548	1.810	2.071	2.333
0.60	0.261	0.543	0.826	1.109	1.391	1.674	1.957	2.239	2.522
0.70	0.280	0.580	0.880	1.180	1.480	1.780	2.080	2.380	2.680
0.80	0.296	0.611	0.926	1.241	1.556	1.870	2.185	2.500	2.815
0.90	0.310	0.638	0.966	1.293	1.621	1.948	2.276	2.603	2.931
1.00	0.323	0.661	1.000	1.339	1.677	2.016	2.355	2.694	3.032
1.10	0.333	0.682	1.030	1.379	1.727	2.076	2.424	2.773	3.121
1.20	0.343	0.700	1.057	1.414	1.771	2.129	2.486	2.843	3.200
1.30	0.351	0.716	1.081	1.446	1.811	2.176	2.541	2.905	3.270
1.40	0.359	0.731	1.103	1.474	1.846	2.218	2.590	2.962	3.333
1.50	0.366	0.744	1.122	1.500	1.878	2.256	2.634	3.012	3.390
1.60	0.372	0.756	1.140	1.523	1.907	2.291	2.674	3.058	3.442
1.70	0.378	0.767	1.156	1.544	1.933	2.322	2.711	3.100	3.489
1.80	0.383	0.777	1.170	1.564	1.957	2.351	2.745	3.138	3.532
1.90	0.388	0.786	1.184	1.582	1.980	2.378	2.776	3.173	3.571
2.00	0.392	0.794	1.196	1.598	2.000	2.402	2.804	3.206	3.608
2.10	0.396	0.802	1.208	1.613	2.019	2.425	2.830	3.236	3.642
2.20	0.400	0.809	1.218	1.627	2.036	2.445	2.855	3.264	3.673
2.30	0.404	0.816	1.228	1.640	2.053	2.465	2.877	3.289	3.702
2.40	0.407	0.822	1.237	1.653	2.068	2.483	2.898	3.314	3.729
2.50	0.410	0.828	1.246	1.664	2.082	2.500	2.918	3.336	3.754

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

US DOT Final Accident Prediction from Initial Prediction and Accident History (3 years of accident data (T = 3))

Initial Prediction from Basic Model, a	Number of Accidents, N, in T Years												
	0	1	2	3	4	5	6	7	8	9	10	11	12
0.00	0.000	0.043	0.087	0.130	0.174	0.217	0.261	0.304	0.348	0.391	0.435	0.478	0.522
0.01	0.008	0.059	0.110	0.161	0.212	0.263	0.314	0.364	0.415	0.466	0.517	0.568	0.619
0.02	0.017	0.074	0.132	0.190	0.248	0.306	0.364	0.421	0.479	0.537	0.595	0.653	0.711
0.03	0.024	0.089	0.153	0.218	0.282	0.347	0.411	0.476	0.540	0.605	0.669	0.734	0.798
0.04	0.031	0.102	0.173	0.244	0.315	0.386	0.457	0.528	0.598	0.669	0.740	0.811	0.882
0.05	0.038	0.115	0.192	0.269	0.346	0.423	0.500	0.577	0.654	0.731	0.808	0.885	0.962
0.06	0.045	0.128	0.211	0.293	0.376	0.459	0.541	0.624	0.707	0.789	0.872	0.955	1.038
0.07	0.051	0.140	0.228	0.316	0.404	0.493	0.581	0.669	0.757	0.846	0.934	1.022	1.110
0.08	0.058	0.151	0.245	0.338	0.432	0.525	0.619	0.712	0.806	0.899	0.993	1.086	1.180
0.09	0.063	0.162	0.261	0.359	0.458	0.556	0.655	0.754	0.852	0.951	1.049	1.148	1.246
0.10	0.069	0.172	0.276	0.379	0.483	0.586	0.690	0.793	0.897	1.000	1.103	1.207	1.310
0.20	0.114	0.257	0.400	0.543	0.686	0.829	0.971	1.114	1.257	1.400	1.543	1.686	1.829
0.30	0.146	0.317	0.488	0.659	0.829	1.000	1.171	1.341	1.512	1.683	1.854	2.024	2.195
0.40	0.170	0.362	0.553	0.745	0.936	1.128	1.319	1.511	1.702	1.894	2.085	2.277	2.468
0.50	0.189	0.396	0.604	0.811	1.019	1.226	1.434	1.642	1.849	2.057	2.264	2.472	2.679
0.60	0.203	0.424	0.644	0.864	1.085	1.305	1.525	1.746	1.966	2.186	2.407	2.627	2.847
0.70	0.215	0.446	0.677	0.908	1.138	1.369	1.600	1.831	2.062	2.292	2.523	2.754	2.985
0.80	0.225	0.465	0.701	0.944	1.183	1.423	1.662	1.901	2.141	2.380	2.620	2.859	3.099
0.90	0.234	0.481	0.727	0.974	1.221	1.468	1.714	1.961	2.208	2.455	2.701	2.948	3.195
1.00	0.241	0.494	0.747	1.000	1.253	1.506	1.759	2.012	2.265	2.518	2.771	3.024	3.277
1.10	0.247	0.506	0.764	1.022	1.281	1.539	1.798	2.056	2.315	2.573	2.831	3.090	3.348
1.20	0.253	0.516	0.779	1.042	1.305	1.568	1.832	2.095	2.358	2.621	2.884	3.147	3.411
1.30	0.257	0.525	0.792	1.059	1.327	1.594	1.861	2.129	2.396	2.663	2.931	3.198	3.465
1.40	0.262	0.533	0.804	1.075	1.346	1.617	1.888	2.159	2.430	2.701	2.972	3.243	3.514
1.50	0.265	0.540	0.814	1.088	1.363	1.637	1.912	2.186	2.460	2.735	3.009	3.283	3.558
1.60	0.269	0.546	0.824	1.101	1.378	1.655	1.933	2.210	2.487	2.765	3.042	3.319	3.597
1.70	0.272	0.552	0.832	1.112	1.392	1.672	1.952	2.232	2.512	2.792	3.072	3.352	3.632
1.80	0.275	0.557	0.840	1.122	1.405	1.687	1.969	2.252	2.534	2.817	3.099	3.382	3.664
1.90	0.271	0.562	0.847	1.131	1.416	1.701	1.985	2.270	2.555	2.839	3.124	3.409	3.693
2.00	0.280	0.566	0.853	1.140	1.427	1.713	2.000	2.287	2.573	2.860	3.147	3.434	3.720
2.10	0.282	0.570	0.859	1.148	1.436	1.725	2.013	2.302	2.591	2.879	3.168	3.456	3.745
2.20	0.284	0.574	0.865	1.555	1.445	1.735	2.026	2.316	2.606	2.897	3.187	3.477	3.768
2.30	0.286	0.578	0.870	1.161	1.453	1.745	2.037	2.329	2.621	2.913	3.205	3.497	3.789
2.40	0.287	0.581	0.874	1.168	1.461	1.754	2.048	2.341	2.635	2.928	3.222	3.515	3.808
2.50	0.289	0.584	0.879	1.173	1.468	1.763	2.058	2.353	2.647	2.942	3.237	3.532	3.827

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

US DOT Final Accident Prediction from Initial Prediction and Accident History (4 years of accident data (T = 4))

Initial Prediction from Basic Model, a	Number of Accidents, N, in T Years														
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0.00	0.000	0.042	0.083	0.125	0.167	0.208	0.250	0.292	0.333	0.375	0.417	0.458	0.500	0.542	0.583
0.01	0.008	0.056	0.105	0.135	0.202	0.250	0.298	0.347	0.395	0.444	0.492	0.540	0.589	0.637	0.685
0.02	0.016	0.070	0.125	0.180	0.234	0.289	0.344	0.398	0.453	0.508	0.563	0.617	0.672	0.727	0.781
0.03	0.023	0.083	0.144	0.205	0.265	0.326	0.386	0.447	0.500	0.568	0.629	0.689	0.750	0.811	0.871
0.04	0.029	0.096	0.162	0.228	0.294	0.360	0.426	0.493	0.559	0.625	0.691	0.757	0.824	0.890	0.956
0.05	0.036	0.107	0.179	0.250	0.321	0.393	0.464	0.536	0.607	0.679	0.750	0.821	0.893	0.964	1.036
0.06	0.042	0.118	0.194	0.271	0.347	0.424	0.500	0.576	0.653	0.729	0.806	0.882	0.958	1.035	1.111
0.07	0.047	0.128	0.209	0.291	0.372	0.453	0.534	0.615	0.696	0.777	0.858	0.939	1.020	1.101	1.182
0.08	0.053	0.138	0.224	0.309	0.395	0.480	0.566	0.651	0.737	0.822	0.908	0.993	1.079	1.164	1.250
0.09	0.058	0.147	0.237	0.327	0.417	0.506	0.596	0.686	0.776	0.865	0.955	1.045	1.135	1.224	1.314
0.10	0.062	0.156	0.250	0.344	0.438	0.531	0.625	0.719	0.812	0.906	1.000	1.094	1.188	1.281	1.375
0.20	0.100	0.225	0.350	0.475	0.600	0.726	0.850	0.975	1.100	1.225	1.350	1.475	1.600	1.725	1.850
0.30	0.125	0.271	0.417	0.563	0.708	0.854	1.000	1.146	1.292	1.437	1.583	1.729	1.875	2.021	2.167
0.40	0.143	0.304	0.464	0.625	0.786	0.946	1.107	1.268	1.429	1.589	1.750	1.911	2.071	2.232	2.393
0.50	0.156	0.328	0.500	0.672	0.844	1.016	1.188	1.359	1.531	1.703	1.875	2.047	2.219	2.391	2.563
0.60	0.167	0.347	0.528	0.708	0.889	1.069	1.250	1.431	1.611	1.792	1.972	2.153	2.333	2.514	2.694
0.70	0.175	0.363	0.550	0.738	0.925	1.113	1.300	1.488	1.675	1.863	2.050	2.238	2.425	2.613	2.800
0.80	0.182	0.375	0.568	0.761	0.955	1.148	1.341	1.534	1.727	1.920	2.114	2.307	2.500	2.693	2.886
0.90	0.188	0.385	0.583	0.781	0.979	1.177	1.375	1.573	1.771	1.969	2.167	2.365	2.563	2.760	2.958
1.00	0.192	0.394	0.596	0.798	1.000	1.202	1.404	1.606	1.808	2.010	2.212	2.413	2.615	2.817	3.019
1.10	0.196	0.402	0.607	0.813	1.018	1.223	1.429	1.634	1.839	2.045	2.250	2.455	2.661	2.866	3.071
1.20	0.200	0.408	0.617	0.825	1.033	1.242	1.450	1.658	1.867	2.075	2.283	2.492	2.700	2.908	3.117
1.30	0.203	0.414	0.625	0.836	1.047	1.258	1.469	1.680	1.891	2.102	2.313	2.523	2.734	2.945	3.156
1.40	0.206	0.419	0.632	0.846	1.059	1.272	1.485	1.699	1.912	2.125	2.338	2.551	2.765	2.978	3.191
1.50	0.208	0.424	0.639	0.854	1.069	1.285	1.500	1.715	1.931	2.146	2.361	2.576	2.792	3.007	3.222
1.60	0.211	0.428	0.645	0.862	1.079	1.296	1.513	1.730	1.947	2.164	2.382	2.599	2.816	3.033	3.250
1.70	0.213	0.431	0.650	0.869	1.088	1.306	1.525	1.744	1.962	2.181	2.400	2.619	2.837	3.056	3.275
1.80	0.214	0.433	0.655	0.875	1.095	1.315	1.536	1.756	1.976	2.196	2.417	2.637	2.857	3.077	3.293
1.90	0.216	0.437	0.659	0.881	1.102	1.324	1.545	1.767	1.989	2.210	2.432	2.653	2.875	3.097	3.318
2.00	0.217	0.440	0.663	0.886	1.109	1.332	1.554	1.777	2.000	2.223	2.446	2.668	2.891	3114	3.337
2.10	0.219	0.443	0.667	0.891	1.115	1.339	1.562	1.786	2.010	2.234	2.458	2.682	2.906	3.130	3.354
2.20	0.220	0.445	0.670	0.895	1.120	1.345	1.570	1.795	2.020	2.245	2.470	2.695	2.920	3.145	3.370
2.30	0.221	0.447	0.673	0.899	1.125	1.351	1.577	1.803	2.029	2.255	2.481	2.707	2.933	3.159	3.385
2.40	0.222	0.449	0.676	0.903	1.130	1.356	1.583	1.810	2.037	2.264	2.491	2.718	2.944	3.171	3.398
2.50	0.223	0.451	0.679	0.906	1.134	1.362	1.589	1.817	2.045	2.272	2.500	2.728	2.955	3.183	3.411

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

US DOT Final Accident Prediction from Initial Prediction and Accident History (5 years of accident data (T = 5))

Initial Prediction from Basic Model, a	Number of Accidents, N, in T Years														
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0.00	0.000	0.040	0.080	0.120	0.160	0.200	0.240	0.280	0.320	0.360	0.400	0.440	0.480		0.560
0.01	0.008	0.054	0.100	0.146	0.192	0.238	0.285	0.331	0.377	0.423	0.469	0.515	0.562		0.654
0.02	0.015	0.067	0.119	0.170	0.222	0.274	0.326	0.378	0.430	0.481	0.533	0.585	0.637		0.741
0.03	0.021	0.079	0.136	0.193	0.250	0.307	0.364	0.421	0.479	0.536	0.593	0.650	0.707		0.821
0.04	0.028	0.090	0.152	0.214	0.276	0.338	0.400	0.462	0.524	0.586	0.648	0.710	0.772		0.897
0.05	0.033	0.100	0.167	0.233	0.300	0.367	0.433	0.500	0.567	0.633	0.700	0.767	0.833		0.967
0.06	0.039	0.110	0.181	0.252	0.323	0.394	0.465	0.535	0.606	0.677	0.748	0.819	0.890		1.032
0.07	0.044	0.119	0.194	0.269	0.344	0.419	0.494	0.569	0.644	0.719	0.794	0.869	0.944		1.094
0.08	0.048	0.127	0.206	0.285	0.364	0.442	0.321	0.600	0.679	0.758	0.836	0.915	0.994		1.152
0.09	0.053	0.135	0.218	0.300	0.382	0.465	0.517	0.629	0.712	0.794	0.876	0.959	1.041		1.206
0.10	0.057	0.143	0.229	0.314	0.400	0.486	0.571	0.657	0.743	0.829	0.914	1.000	1.086		1.257
0.20	0.089	0.200	0.311	0.422	0.533	0.644	0.756	0.867	0.978	1.089	1.200	1.311	1.422		1.644
0.30	0.109	0.236	0.364	0.491	0.618	0.745	0.873	1.000	1.127	1.255	1.382	1.509	1.636		1.891
0.40	0.123	0.262	0.400	0.538	0.677	0.815	0.954	1.092	1.231	1.369	1.508	1.646	1.785		2.062
0.50	0.133	0.280	0.427	0.573	0.720	0.867	1.013	1.160	1.307	1.453	1.600	1.747	1.893		2.187
0.60	0.141	0.294	0.447	0.600	0.753	0.906	1.059	1.212	1.365	1.518	1.671	1.824	1.976		2.282
0.70	0.147	0.305	0.463	0.621	0.779	0.937	1.095	1.253	1.411	1.568	1.726	1.884	2.042		2.358
0.80	0.152	0.314	0.476	0.638	0.800	0.962	1.124	1.286	1.448	1.610	1.771	1.933	2.095		2.419
0.90	0.157	0.322	0.487	0.652	0.817	0.983	1.148	1.313	1.478	1.643	1.809	1.974	2.139		2.470
1.00	0.160	0.328	0.496	0.664	0.832	1.000	1.168	1.336	1.504	1.672	1.840	2.008	2.176		2.512
1.10	0.163	0.333	0.504	0.674	0.844	1.015	1.185	1.356	1.526	1.696	1.867	2.037	2.207		2.548
1.20	0.166	0.338	0.510	0.683	0.855	1.028	1.200	1.372	1.545	1.717	1.890	2.062	2.234		2.579
1.30	0.168	0.342	0.516	0.690	0.865	1.039	1.213	1.387	1.561	1.735	1.910	2.084	2.258		2.606
1.40	0.170	0.345	0.521	0.697	0.873	1.048	1.224	1.400	1.576	1.752	1.927	2.103	2.279		2.630
1.50	0.171	0.349	0. 526	0.703	0.880	1.057	1.234	1.411	1.589	1.766	1.943	2.120	2.297		2.651
1.60	0.173	0.351	0.530	0.708	0.886	1.065	1.243	1.422	1.600	1.779	1.957	2.135	2.314		2.670
1.70	0.174	0.354	0.533	0.713	0.892	1.072	1. 251	1.431	1.610	1.790	1.969	2.149	2.328		2.687
1.80	0.176	0.356	0.537	0.717	0.898	1.078	1.259	1.439	1.620	1.800	1.980	2.161	2.341		2.702
1.90	0.177	0.358	0.540	0.721	0.902	1.084	1.265	1.447	1.628	1.809	1.991	2.172	2.353		2.716
2.00	0.178	0.360	0.542	0.724	0.907	1.089	1.271	1.453	1.636	1.818	2.000	2.182	2.364		2.729
2.10	0.179	0.362	0.545	0.728	0.911	1.094	1.277	1.460	1.643	1.826	2.009	2.191	2.374		2.740
2.20	0.180	0.363	0.547	0.731	0.914	1.098	1.282	1.465	1.649	1.833	2.016	2.200	2.384		2.751
2.30	0.180	0.365	0.549	0.733	0.918	1.102	1.286	1.471	1.655	1.839	2.024	2.208	2.392		2.761
2.40	0.181	0.366	0.551	0.736	0.921	1.106	1.291	1.475	1.660	1.845	2.030	2.215	2.400		2.770
2.50	0.182	0.367	0.553	0.738	0.924	1.109	1.295	1.480	1.665	1.851	2.036	2.222	2.407		2.778

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*

Appendix C

Resource Allocation Procedure Field Verification Worksheet

This worksheet provides a format and instructions for use in field evaluation of crossing to determine if initial recommendations for warning device installations from the Resource Allocation Procedure should be revised. Steps 1 through 5, described below, should be followed in making the determination. In Steps 1 and 3, the initial information (left column) is obtained from office inventory data prior to the field inspection. In Step 4, the decision criteria values are obtained from the Resource Allocation Model printout.

STEP 1: Validate Data used in Calculating Predicted Accidents:

Crossing Characteristic	Initial Information	Revised Information
Crossing Number		
Location		
Existing Warning Device		
Total Trains per Day		
Annual Average Daily Highway Traffic (c)		
Day thru Trains (d)		
Number of Main Tracks (mt)		
Is Highway Paved? (hp)		
Maximum Timetable Speed, mph (ms)		
Highway Type (ht)		
Number of Highway Lanes (hl)		
Number of Years of Accident History (T)		
Number of Accidents in T Years (N)		
Predicted Accident Rate (A)		

STEP 2: Calculate Revised Accident Prediction from DOT Formula if any Data in Step 1 has been Revised.

Revised Predicted Accidents (A) = ______________________________

STEP 3: Validate Cost and Effectiveness Data for Recommended Warning Device

Assumed Effectiveness of Recommended Warning Device (E) ______________ Assumed

Cost of Recommended Warning Device (C)
Recommended Warning Device Installation

STEP 4: Determine if Recommended Warning Device should be Revised if A, E, or C has Changed.

1. Obtain Decision Criteria Values from Resource Allocation Model. Output:

DC_1 = ____ DC_2 = ____ DC_3 = ____ DC_4 = ____

2. Calculate: $R = \frac{\text{Revised A}}{\text{Previous A}} \Diamond \frac{\text{Revised B}}{\text{Previous B}} \Diamond \frac{\text{Revised C}}{\text{Previous C}}$

3. Compare R with Appropriate Decision Criteria as shown Below:

Existing Passive Crossing (Classes 1, 2, 3, 4) Single Track		Existing Passive Crossing (Classes 1, 2, 3, 4) Multiple Tracks		Existing Flashing Light. Crossing (Classes 5, 6, 7)	
Comparison	**Decision**	**Comparison**	**Decision**	**Comparison**	**Decision**
$DC_2 < R$	Gates	$DC_3 < R$	Gates	$DC_4 < R$	Gates
$DC_1 < R < DC_2$	Flashing Lights	$R < DC_3$	No Installation	$R < DC_4$	No Installation
$R < DC_1$	No Installation				

4. Revised Recommended Warning Device Installation* ______________________________

STEP 5: Determine other Characteristics that may Influence Warning Device Installation Decisions

Multiple tracks where one train/locomotive may obscure vision of another train?
Percent trucks
Passenger train operations over crossing
High speed trains with limited sight distance**
Combination of high speeds & moderately high volumes of highway & railroad traffic **

Either, or any combination of, high vehicular traffic volumes, high numbers of train movements, substantial numbers of school buses or trucks carrying hazardous materials, unusually restricted sight distance or continuing accident occurrences**

*The cost and effectiveness values for the revised warning device are assumed to change by an amount proportional to the change in these values for the initial recommended warning device as determined in Step 3.

**Gates with flashing lights are the only recommended warning device per 23CFR 646.214(b)(3)(i).

Source: Railroad-Highway Grade Crossing Handbook, Second Edition. *Washington, DC: U.S. Department of Transportation, Federal Highway Administration, 1986.*