Improving Crash Predictions – A More Relevant Exposure Measure than AADT for Highway-Rail Grade Crossing Safety Models

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16. Abstract

Safety at the junction of highways and rails has been a concern for a long time and highway-rail grade crossing (HRGC) safety models have been around since 1940s. One of the main inputs to these models is the annual average daily traffic (AADT). It is an estimate of vehicular use of roadways and serves as a measure of exposure of motor vehicles to crashes with trains in HRGC safety models. This project considered a conceptually more relevant measure of vehicular exposure to train-involved crashes at HRGCs—the portion of AADT that actually encounters trains at HRGCs, termed as (AADT)TP in this research. This is a more reasonable and better exposure measure because the probability of having train-involved crashes arises only in the presence of trains at HRGCs. However, obtaining (AADT)TP for a large number of HRGCs is difficult in practice. This report presents a simulation-based method to estimate (AADT)TP for a study location including validation of the results with field-observed data. A comparison between the use of AADT and (AADT)TP in several HRGC safety models showed the possibility of reaching different conclusions; arguments for preferring results obtained by using the conceptually more relevant (AADT)TP are given. This report also presents a classification method to classify HRGCs into groups for estimation of (AADT)TP.

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Abstract

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Chapter 1 Introduction

Railroads transport large quantities of goods across the United States and make a significant contribution to the economy. Railroad crossings are junctions between the rail and the highway network where the two meet. More than 97% of these crossings are at the same level, meaning that the two transportation modes cross at the same grade. Such crossings are commonly referred to as highway-rail grade crossings (HRGCs). While trains have the right-of-way, every year there are a number of reported crashes when motor vehicles fail to yield to the right-of-way at HRGCs. Motor vehicle-involved crashes at railroad crossings are invariably more severe compared to crashes on the rest of the highway network due to train involvement. In 2017, the number of crashes reported at HRGCs was 2,144, resulting in 271 fatalities; fatal crashes were 12.64% of the total reported incidents (Federal Railroad Administration 2017).

Public safety at HRGCs has been an ongoing concern for more than a century. Rail crossing safety models based on reported crash data have been widely used for understanding the crash phenomenon at these locations, identifying associated factors in an attempt to improve safety, and for ranking competing rail crossings for expenditure of limited safety resources. A staple of these models is the annual average daily traffic (AADT), representing the exposure of motor vehicle traffic to the possibility of a crash. While AADT is a relatively straightforward measure of vehicular activity at any location, it is not an accurate estimate of motor vehicle crash exposure at rail crossings. However, obtaining a more accurate vehicular exposure at rail crossings is time-consuming and expensive. This research explores a potentially time-saving and lower-cost method that is based on field-collected data and provides for the use of a theoretically more accurate vehicular crash exposure measure at HRGCs. Furthermore, a new HRGC safety estimation model with proposed vehicular exposure is estimated to provide a comprehensive and unbiased estimation of crashes at HRGCs.

This proposal is organized as follows. Chapter 2 presents an in-depth literature review. Chapter 3 provides additional details on the research problem and objectives. The research framework is introduced, followed by the methodology. Chapter 4 briefly presents the work schedule in this research, and Chapter 5 shows a preliminary study as an example of the proposed method.

Chapter 2 Literature Review

The U.S. Department of Transportation (DOT) Accident Prediction Model is the most widely-used hazard ranking model. It is currently used in 19 states for ranking grade crossing hazards. Most states are generally satisfied with the performance. States such as Florida, Kansas, and Texas have undertaken research studies to assess the adequacy of existing grade crossing hazard ranking models and/or to develop new statistical models for hazard ranking. Other states, including Illinois and Missouri, have undertaken similar research studies, but DOT staff reported that the results of the studies could not be practically applied and therefore were not adopted [1]. Recent models developed for Florida and Texas utilize more modern statistical analysis for predicting crash frequency at a grade crossing. States such as North Carolina are moving toward an economic analysis model of hazard ranking to incorporate the U.S. DOT model in a more comprehensive economic analysis of the grade crossing. Table 1 gives a summary of those models.

Table 2.1 Current Usage of Hazard Ranking Methods

Formula/Method	Number of States	Percent of States
U.S. DOT Accident Prediction Model	19	38%
State-Specific Formula or Method	11	22%
None/No Formula Mentioned	11	22%
New Hampshire Hazard Index	5	10%
Multiple Formulas	2	4%
NCHRP 50 Accident Prediction Model	1	2%
Peabody-Dimmick Formula	1	2%
Total All States	50	100%

2.1 U.S. DOT Accident Prediction Model

The U.S. DOT accident prediction formula was more comprehensive than previous models with the following form:

$$\mathrm{a} = (K)(EI)(DT)(MS)(MT)(HP)(HL)(HT)$$

where K is a constant, EI is the exposure index factor, DT is the day through trains, MS is the max train speed, MT is the number of main tracks, HP is the highway paved factor, HL is the highway lanes factor, and HT is the highway type factor.

The FRA has developed additional tools and resources to make the U.S. DOT Accident Prediction Model more accessible to users by way of its GradeDec.net evaluation tool (https://gradedec.fra.dot.gov/) and the Web Accident Prediction System (WBAPS; http://safetydata.fra.dot.gov/webaps/).

The model structure of the U.S. DOT Accident Prediction Model has not changed substantially since its initial development in the mid-1970s. There were some updates in the 1980s. The latest version was developed in 1987 by removing a variable for highway functional classification [2].

2.2 New Hampshire Hazard Index

The New Hampshire Index is given by [3]:

$$\mathrm{HI} = (V)(T)(P_f)$$

where HI is hazard index, V is the AADT, T represents the average daily through trains and P_f represents a protection factor (indicating presence of warning devices). The basic formulation of the New Hampshire Index is based on AADT and train traffic. Several states developed their own hazard index formulae by using different values for P_f and adding other factors, such as train speed, highway speed, population, sight distance, number of tracks, surface condition, alignment, presence of nearby intersections, etc.

2.3 NCHRP 50 Accident Prediction Model

The National Cooperative Highway Research Program (NCHRP) Report 50 [3] reported the NCHRP Hazard Index for rail crossing assessment, which has the following form:

$$\mathrm{EA} = (A)(B)(CTD)$$

where EA is the expected accident frequency, A is vehicles per day factor (provided in tabular format as a function of vehicles per day), B is a protection factor indicative of warning devices present, and CTD is the current trains per day. According to Austin and Carson [4], no formal definition of urban and rural areas accompanied the index, and significantly different crash predictions were possible by switching between urban and rural values.

2.4 Peabody-Dimmick Formula

An early rail crossing crash prediction model was the Peabody Dimmick formula, which was published in 1941 and used extensively through the 1950's [5]. It was based on five-year crash data reported at rural crossings in 29 states; the formula is:

$$A_5 = 1.28 * \frac{(v^{0.170})(T^{0.151})}{p^{0.171}} + K$$

where A_5 is the expected number of accidents at a rail crossing in five years, v is the AADT, T represents the average daily through trains, p is a protection coefficient (indicating presence of warning devices), and K an additional parameter determined from a graph. The formula utilized AADT and the number of through trains to measure crash exposure but does not take into account the temporal distribution of roadway and rail traffic.

2.5 Connecticut DOT Hazard Ranking Index

This hazard index was first mentioned in the Connecticut Railway-Highway Crossing Program 2014 Annual Report (http://www.ct.gov/dot/lib/dot/documents/dtrafficdesign/safety/rhgcp_report_ct_2014.pdf),

$$HI = \frac{(T+1)*(A+1)*AADT*PF}{100}$$

where HI is the Calculated Hazard Index, T is Train Movements per day, A is number of vehicle/train accidents in the last 5 years, $AADT$ is annual average daily traffic, and PF is the protection factor.

2.6 Florida DOT Safety Hazard Index

The Florida State University developed an accident prediction model for the Florida Department of Transportation (FDOT). The model was developed using stepwise regression analysis, transformation of data, dummy variables, and transformation of the accident prediction model to its original scale [3].

In 2014, FDOT updated its hazard ranking index, which was developed by researchers at Florida State University (FSU) [6]. This is a hybrid accident prediction model/hazard index [1].

Logit model:

$$\mathrm{t} = -8.896 + 0.780*Risk + 0.020*MTS + 0.014*HWSPD$$
$$+1.023*Track + 0.965*Lane - 0.540*Flash$$

Prediction model

$$\mathrm{P} = \exp(t)/[1+\exp(t)]$$

Adjustment for Acc. History

$$P^* = \mathrm{P}\sqrt{\frac{H}{P*Y}}$$

Safety Index $$I = 90 + \left(1 - \sqrt{\frac{P^*}{MaxP}}\right) - 5 * \left(log_{10}(B+1)\right) * F$$

where $Risk$ $\log(Train) * AADT$, $Train$ is yearly average of the number of trains per day, $AADT$ is annual average daily traffic, MST is maximum timetable speed, $HWSPD$ is posted vehicle speed limit, $Track$ is $\log(main\ tracks + other\ tracks)$, $Lane$ is number of highway lanes, $Flash$ is dummy variable, Y is predicted number of accidents per year at crossing adjusted for history, H is number of accidents at crossing during history period, P is number of years of accident history period, I is safety index value, $MaxP$ is maximum value of incident prediction, B is number of school buses at crossing, and F is a variable for warning devices.

<u>2.7 Missouri DOT Exposure Index</u>

This index was developed in 2004 [7].

Passive Crossings: $\mathrm{EI} = \mathrm{TI} + \mathrm{SDO(TI)}$

Active Crossings: $\mathrm{EI} = \mathrm{TI}$

where TI is traffic index, $\mathrm{TI} = \frac{(VM*VS)[(FM*FS)+(PM*PS)+(SM*10]}{10000}$, SDO is sight distance obstruction factor, and $\mathrm{SDO} = \frac{Required\ sight\ distance - Actual\ sight\ distance}{Requuired\ sight\ distance}$. VM is annual average daily traffic, VS is vehicle speed, FM is daily freight train movements at crossing, FS is freight train speed, PM is daily passenger train movements at crossing, PS is passenger trains speed, and SM is the daily switching movements at a crossing.

<u>2.8 North Carolina DOT Investigative Index</u>

This index was described in the North Carolina Railway-Highway Crossing Program 2014 Annual Report. The index was initially developed in the 1970s and updated in 1980s [1].

$$\mathrm{TI} = \frac{PF * ADT * TV * TSF * TF}{160} + \left(70 - \frac{A}{Y}\right)^2 + SDF$$

where PF is protection factor, ADT is average daily traffic, TV is daily train volume, TSF is train speed factor= $\frac{Maximum\ train\ speed}{50} + 0.8$, TF is track factor, A is number of crashed over history period, Y is number of years in crash history, and SDF is sight distance factor $\frac{sum(SDF_n)}{4} * 16$

2.9 Texas DOT Priority Index

This index was first developed in 2013 [8]. The Texas Department of Transportation (TxDOT) revised the formula in 2015. It's a state-specific hybrid accident prediction model.

$$\begin{aligned}\mu = \exp[-6.9240 + PF + (0.2587 * HwyPaved) - (0.3722 * UrbanRural) \\ + (0.0706 * TrafLane) + (0.0656 * TotalTrack) + (0.0022 * ActualSD) \\ + (0.0143 * MaxSpd) + (0.0126 * MinSpd) \\ + \left(1.0024 * log_{10}(TotalTrn + 0.5)\right) + \left(0.4653 * log_{10}(AADT)\right) \\ - (0.2160 * NearbyInt) + (0.0092 * SpdLmt)]\end{aligned}$$

where μ is predicted number of crashes per year, PF is protection factor, $HwyPaved$ is dummy variable, UrbanRural is dummy variable, TrafLane is number of roadway lanes, TotalTrack is total number of tracks at crossing, ActualISD is actual stopping sight distance for approach, MaxSpd is maximum typical train speeds, MinSPd is minimum typical train speeds for switching, TotalTrn is total daily trains, AADT is annual average daily traffic, NearbyInt is dummy variable, SpdLmt is roadway speed limit on approach.

Table 2 lists the variables used in each model.

Table 2.2 Variable Usage in Each Method

	U.S. DOT Accident Prediction Model	New Hampshire Hazard Index	NCHRP 50 Accident Prediction Model	Peabody-Dimmick Formula	Connecticut DOT Hazard Ranking Index	Florida DOT Safety Hazard Index	Missouri DOT Exposure Index	North Carolina DOT Investigative Index	Texas DOT Priority Index
Hazard Ranking Model Type	AP	HI	AP	AP	HI	HB	HI	HI	HB
Number of States Using	19	5	1	1	1	1	1	1	1
Traffic Volume (AADT)	☐	☐	☐	☐	☐	☐	☐	☐	☐
Train Volume	☐	☐	☐	☐	☐	☐	☐	☐	☐
Existing Warning Device	☐	☐	☐	☐	☐	☐	☐	☐	☐
Crash History	☐			☐	☐	☐		☐	☐
Train Speed	☐					☐	☐	☐	☐
Number of Tracks	☐					☐		☐	☐
Highway Lanes	☐					☐			☐
Highway Surface	☐								☐
Highway Type/Context			☐						☐
Sight Distance							☐	☐	☐
School Bus/Special Vehicles						☐		☐	
Highway Traffic Speed						☐	☐		☐
Nearby Intersection									☐
Train Type							☐	☐	
Note: ☐Indicates factor included with selected formula. Formula Type AP: Accident Prediction Model; HI: Hazard Index; HB: Hybrid Accident Prediction Model/Hazard Index.									

Some research has questioned the effectiveness of the predominant hazard index formula. Missouri [7] found that the model did not address the state's hazard ranking needs better than the existing state-specific model. Austin and Carson [4] commented that the general structure of the U.S. DOT model is difficult to interpret and understand which factors have a greater influence on crash probability. Medina and Benekohal [9] concluded that the model was more likely to under-predict crash frequency at some locations. Modern computing technology has allowed for new model structures to be explored as alternatives to the current multi-stage U.S. DOT model, including the zero inflated negative binomial model [9][10], negative binomial model [10], and logit models [11][12].

2.10 Summary

The nine reviewed models illustrate the common use of AADT in HRGC safety models. All those models consider vehicular exposure and protection devices as main influence factors. Besides the aforementioned models, transportation agencies have utilized other models all using AADT in one form or another.

Chapter 3 Data Collection

Three major datasets will be used in this research.

1. Dataset 1: Federal Rail Administration (FRA) HRGC inventory data and accident data. The FRA HRGC inventory data includes detailed information related to configurations of both railroad and highway, such as the number of highway lanes, number of tracks, type of warning devices, and vehicular exposure related variables. However, as mentioned, the exposure variables are difficult to collect as they are outdated and some have not been updated more than 20 years ago. Therefore, those variables will be only used for preliminary study. Other variables used in the database are the latest version requested on May 30, 2018.
2. Dataset 2: Gate activity data at N 33rd Street and Cornhusker Hwy crossing from BNSF. The rail crossing gate activity log provided train traffic data. It records the gate arm closure and open times for 60 days. This data will be used for preliminary study.
3. Dataset 3: Field collected data. Field data were collected at 14 HRGCs in Lancaster County, Nebraska. Two cameras are installed at each study site to record highway traffic and train traffic respectively for at least two full days. The camera used for monitoring highway traffic is a continuously recording camera, while the camera used for monitoring train traffic is a motion activated camera. A tube counter is also installed to provide a vehicle count. These data will be used to obtain data of vehicle speed and type, build simulation models as an input, and calculate the real vehicular exposure at each site.

3.1 Study Sites

According to the FRA HRGC inventory database, there are 564 HRGCs located in Lancaster County, Nebraska. Among them, 204 are active HRGCs that have daily passing train traffic. Six main corridors run directly to the north, west, south-west, south, south-east, and north-east, respectively. As shown in Figure 1, the main rail near the Lincoln area are the S track, NE track, W track, and SW track according to daily train volume (N track and SE track have less than 2 trains/day). Although the W track has busy train traffic, it is not of interest in this study due to few HRGCs. Therefore, crossings on the NE track, S track, and SW track will be selected as data collection sites. Further, sites with AADT less than 100 will be removed due to a low collection efficient. Fourteen sites listed in Table 3-Table 5 are finally selected according to DTT, AADT, and historical accident frequency.

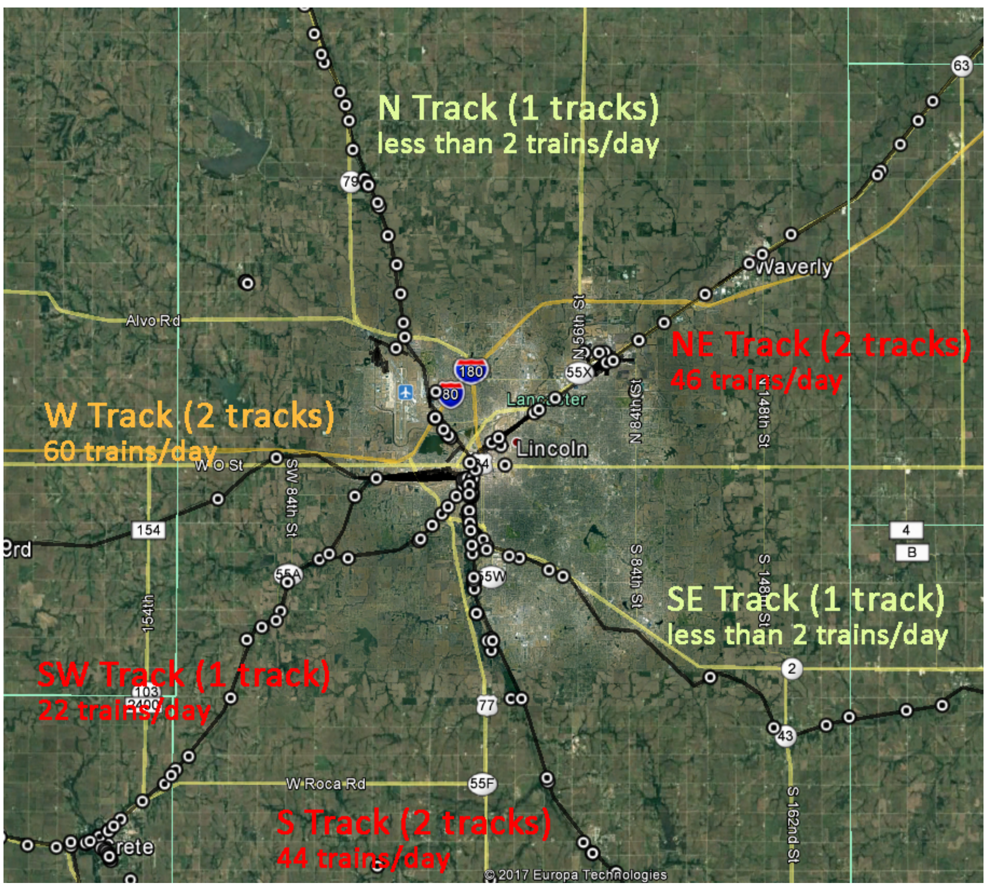


Figure 3.1 Lancaster Train Track Map

Table 3.1 Selected HRGCs on NE Track

	NE track 2 tracks				
HRGC ID	098443J	074942G	074940T	074860A	064128X
Latitude	40.8775	40.9206	40.916136	40.848341	40.841021
Longitude	-96.6032	-96.5209	-96.529614	-96.658883	-96.67282
Location	N 84th St & Cornhusker Hwy	N 148th St & Cornhusker Hwy	N 141st St & Cornhusker Hwy	N 44th St & Cornhusker Hwy	N 33rd St & Cornhusker Hwy
AADT	120	700	2350	2600	9250
DTT	48	46	46	48	48
Acc. Freq.	1	1	2	0	9
Tracks	2	2	2	2	2

Table 3.2 Selected HRGCs on SW Track

	SW track 1 track					
HRGC ID	083048F	083050G	073289S	073291T	064130Y	083044D
Latitude	40.7768	40.7679	40.7412643	40.733208	40.799118	40.79391
Longitude	-96.7494	-96.7966	-96.8413297	-96.853846	-96.724688	-96.7302
Location	S Coddington Ave & W Calvert St	SW 56th St & W Pioneers Blvd	W Denton Rd & Front St	SW 98th St & Haley Lynn Ln	W A St & Salt Creek Levee Trail	S Folsom St & Folsom Ln
AADT	425	65	1515	1445	8500	4800
DTT	22	22	22	22	22	22
Acc. Freq.	0	2	5	5	1	4
Tracks	1	1	1	1	1	1

Table 3.3 Selected HRGCs on S Track

	S track 1 track			
HRGC ID	083516X	074406N	064362N	064361G
Latitude	40.6973743	40.7556	40.788708	40.791812
Longitude	-96.6814059	-96.71278	-96.716345	-96.716675
Location	Saltillo Rd and S 27th St	Old Cheney Rd & Jamaica North Trail	Park Blvd & S 4th St	South St & S 3rd St
AADT	9050	14560	8400	3300
DTT	44	44	44	44
Acc. Freq.	1	3	5	10
Tracks	2	2	2	2

3.2 Collection Method

At each study site, two cameras and one tube counter will be installed to monitor highway traffic and railway traffic as well as traffic characteristics such as vehicle speed, vehicle type, and vehicle count. To minimize the influence of the devices, two cameras were installed in traffic barrels with camera brackets. Figure 2 gives an illustration of those devices installed at HRGC near Park Blvd and S 4th St, Lincoln. Camera 1 is setup as shown in Figure 3. This camera is powered by two RV batteries and an inverter. The camera is continuously recording highway cameras for at least 48 hours at each site. Before camera 1, two tubes are anchored with a 36-inch space. Tubes are connected to a counter that detects abrupt pressure variation in the tubes. The counter can be connected to a smartphone via Bluetooth. The setup interface is shown in Figure 4 in which beginning and ending time, configurations, direction, tube spacing, location, and speed limit must be set before collection. A vehicle detection algorithm installed on a smartphone can convert the tube activity into a vehicle event. The algorithm is capable of calculating the time stamp, vehicle type, and speed. Note that the tubes are installed before camera 1 for calibrating the time stamp between camera 1 and the tube counter later in the data process. Camera 2 is a motion activated camera. It is equipped with a solar panel, 6 rechargeable AA batteries, and a built-in lithium battery. The camera is triggered and records 90s of video once a motion is detected in an image. The timestamp will be printed on the recorded video. Camera 2 is used to provide the train count at one site and the timestamp of each train. Figure 5 shows setups of camera 2. Screenshots of captured video from these two cameras are provided in Figure 6.

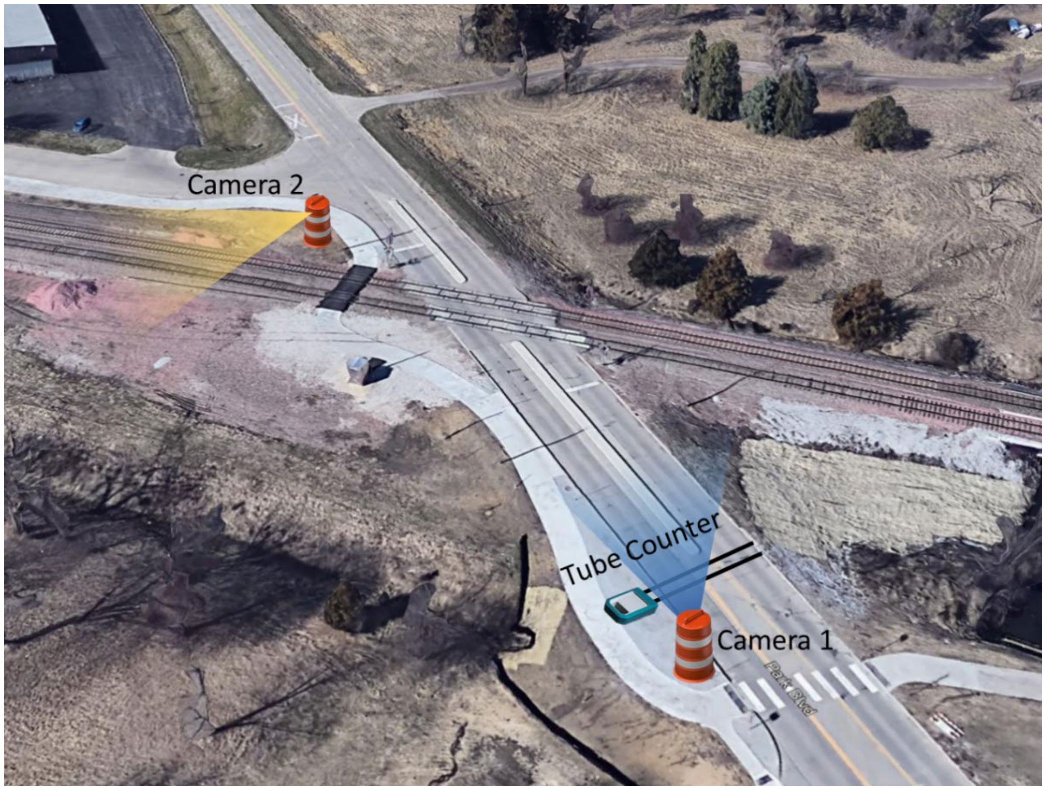


Figure 3.2 Overview of Data Collection Devices at HRGC

Figure 2.3 Camera 1 Setup

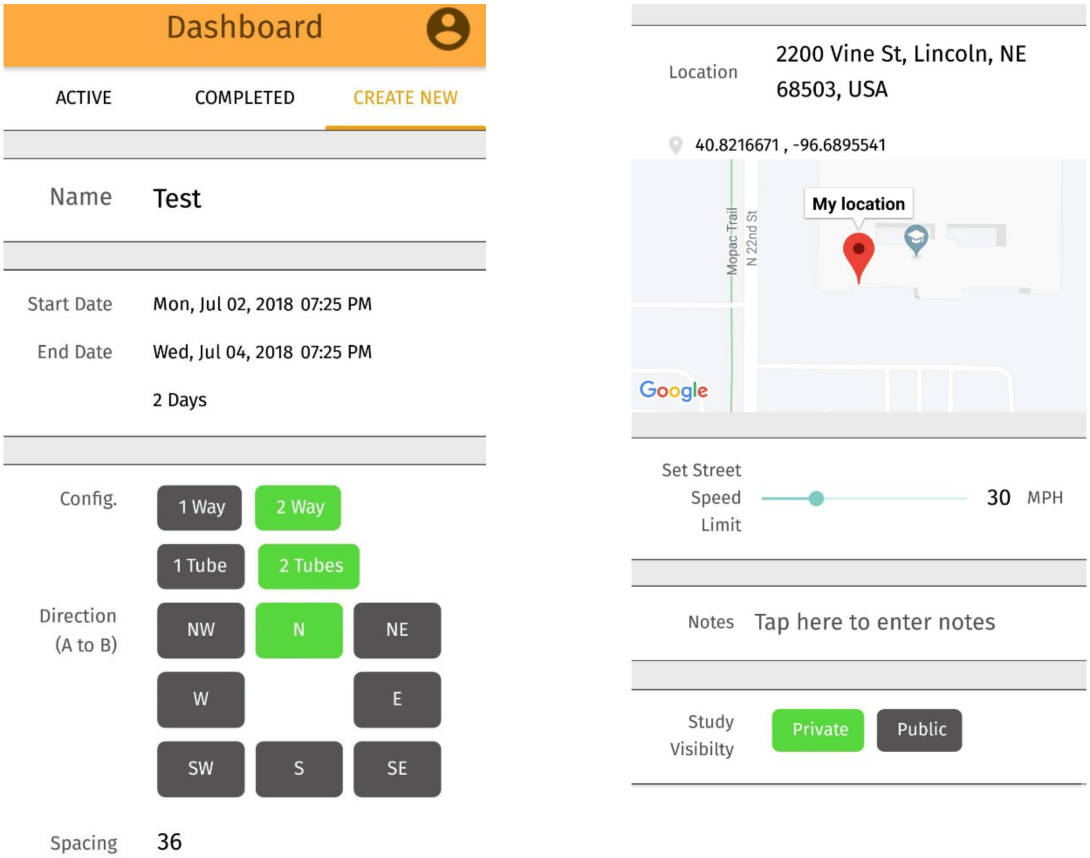


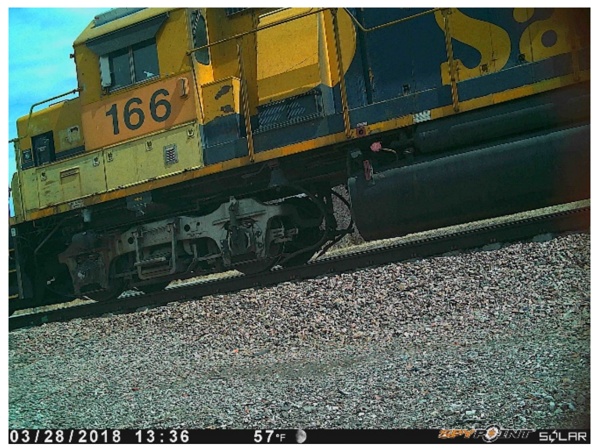
Figure 3.3 Tube Counter Setup

Figure 3.4 Camera 2 Setup

Camera 1

Camera 2

Camera 1 Screenshot



Camera 2 Screenshot

Figure 3.5 Video Screenshot

3.3 Data Process

The raw tube data will be first processed by a vehicle detection algorithm. The vehicle event is detected by the time difference between two air pressure change in tubes. As two tubes are used, vehicle speed and type are also available with the algorithm. Next, the vehicle event data will be calibrated with video data. The reason for calibration is that the camera system and tube counter are not synchronized, which results in a difference of time between the two systems. The timestamp of the vehicle event is calibrated to the timestamp on the videos from camera 1.

The vehicle detection algorithm can perform at a 95% level of accuracy when the average traffic speed is above 20 mph. However, it becomes unsatisfactory when the speed is below 10 mph. This often occurs when a train is present and vehicles slow down or stop at the crossing. To remedy the drawback of the tube counter, video data from camera 1 is manually processed. The video reviewers first obtain the train's present time from camera 2. Then, the vehicles are manually counted until the queue dissipates and the traffic speed returns to normal. More information, such as detection accuracy, headway, vehicular exposure, and train duration, can be automatically calculated by a program when the video viewer inputs train data and missing vehicle events. Appendix 1 gives an example of the post data process when a train is present. The date, time, speed (MPH), FHWA class, and axles column are obtained from the vehicle detection algorithm. The 4th, 11^{th}, 12th, 16^{th}, and 17th columns, which are system delay, real time, direction, incident time and incident, are manually input by the video viewer. The calibrated timestamp, detection correctness, final time, final direction, # of delayed vehicles, # of trains, and train duration can be automatically calculated by the program. Those data will be applied in the next step of data analysis.

Chapter 4 Data Analysis

4.1 Simulation-Based $(AADT)_{TP}$ Estimation

This section illustrates the estimation of (AADT)TP for a selected HRGC located in Lincoln, NE, by building a simulation model. The selected crossing (Crossing ID: 064128X) is on the BNSF network laid out in a northeast-southwest direction and intersects the roadway network at N 33rd Street (besides other locations). It has relatively high train traffic (50-80 per day) and roadway traffic (about 9000 vehicles per day). This rail crossing is equipped with two flashing lights, two crossbuck assemblies, and dual gate arms. Figure 7 shows the study crossing.

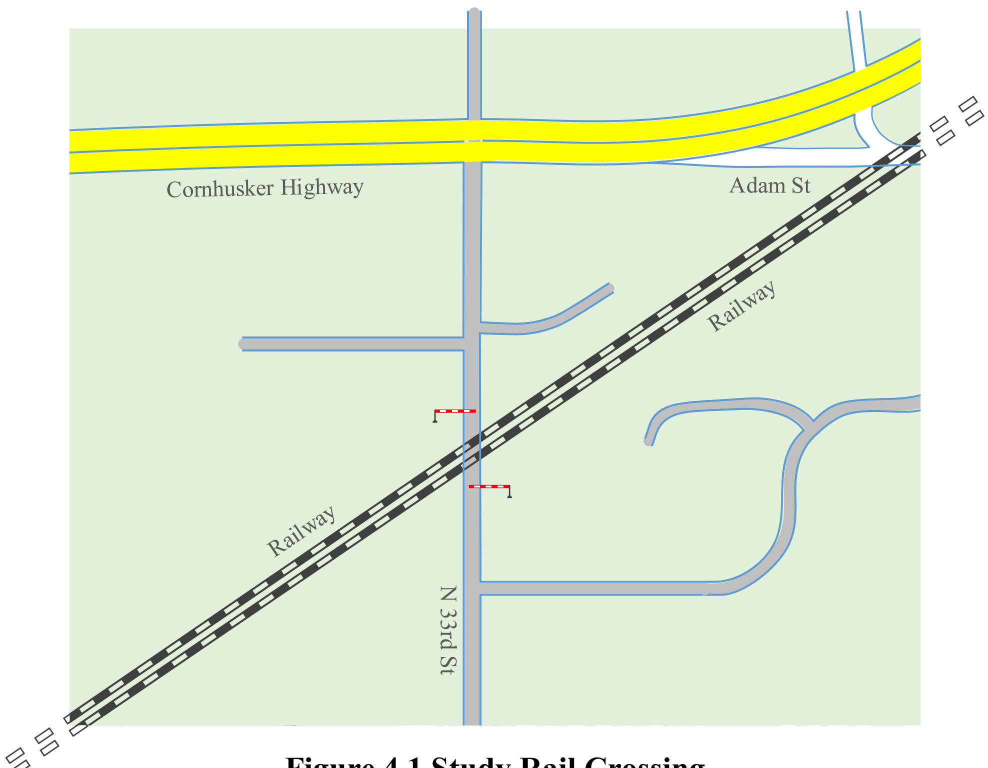


Figure 4.1 Study Rail Crossing

4.1.1 Data

Data for this case study has two components: (1) train traffic from BNSF, (2) area roadway traffic data from the Nebraska Department of Transportation (NDOT), (3) and AADT data from the City of Lincoln, NE. The rail crossing gate activity log, obtained from BNSF, provided 60 days worth of train traffic data as it records the gate arm closure and open times for each passing train.

4.1.1.1 Train Traffic Data

Exploration of the time distribution of train arrival activity required the classification of arrival times into 24 one-hour groups (e.g., group 1: 0:00-0:59, group 2 1:00-1:59), each group recording the number of trains arriving in that hour. Since the whole dataset is comprised of 60 days, each one-hour group had 60 observations. Train traffic varied from one hour to another, which was statistically assessed by exploring the group means using the Analysis of Variance (ANOVA) test. The null and corresponding alternative hypotheses for the test were:

H_0: $\mu_1 = \mu_2 = \cdots = \mu_{24}$ (i.e., all group means are equal)

H_a: $\mu_1 \neq \mu_k$ (at least one group mean is different from others)

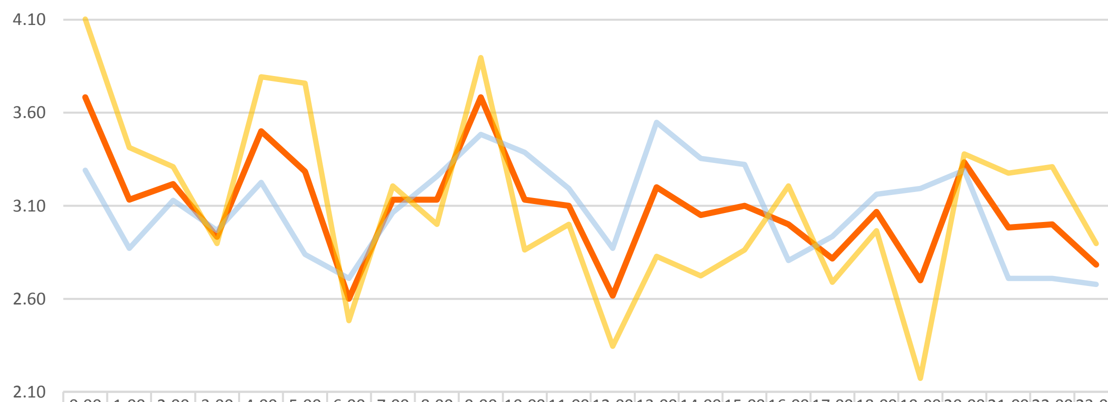
where μ is a group mean and k ∈ [1, 2, ⋅⋅, 24]. Non-rejection of H0 implies a uniform distribution of hourly train traffic volume. Rejection of H0 is indicative of variations in hourly train traffic and implies the input of group means as hourly train traffic in the simulation model.

Table 6 presents results of the ANOVA tests. The p-value is 0.0197, indicating marginal evidence that the mean number of hourly arriving trains varies during different hours. As such, the mean number of trains for each hour was used as input for the simulation model. Figure 8 shows the time distribution of the number of arriving trains at the HRGC study. Note that the blue line and yellow line in Figure 8 indicate the mean of hourly train traffic distribution for each month. It can be seen that the train traffic hourly distribution is somewhat similar from month to month.

Table 4.1 ANOVA Test on Hourly Train Traffic

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	110.6326	23	4.8101	1.7077	0.01970	1.53690
Within Groups	3988.45	1416		2.8167		
Total	4099.0826	1439				



	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
Total Average	3.68	3.13	3.22	2.93	3.50	3.28	2.60	3.13	3.13	3.68	3.13	3.10	2.62	3.20	3.05	3.10	3.00	2.82	3.07	2.70	3.33	2.98	3.00	2.78
1st Month Average	3.29	2.87	3.13	2.97	3.23	2.84	2.71	3.06	3.26	3.48	3.39	3.19	2.87	3.55	3.35	3.32	2.81	2.94	3.16	3.19	3.29	2.71	2.71	2.68
2nd Month Average	4.10	3.41	3.31	2.90	3.79	3.76	2.48	3.21	3.00	3.90	2.86	3.00	2.34	2.83	2.72	2.86	3.21	2.69	2.97	2.17	3.38	3.28	3.31	2.90

Figure 4.2 Hourly Distribution of Train Traffic

4.1.1.2 Roadway Traffic Data

According to 2015 traffic records from the City of Lincoln, AADT at the study rail crossing was 9,250 vehicles. Unfortunately, detailed hourly distribution of motor vehicle traffic at this location was not available. However, such information was available for a nearby crossing (about 1.5 mile from the study crossing) from NDOT. The study crossing was assumed to have similar temporal traffic distribution as the nearby crossing; this assumption was necessary for the research to progress. Table 7 shows the proportion of AADT during each one-hour time interval. The corresponding hourly traffic flow was calculated as well.

Table 4.2 Hourly Distribution of Roadway Traffic

Hourly period	AM											
	12	1	2	3	4	5	6	7	8	9	10	11
Percentage	1.41	1.12	0.98	0.97	1.04	1.37	2.18	3.47	4.65	5.64	6.30	6.42
Traffic flow	130	104	91	90	96	127	202	321	430	522	583	594

Hourly period	PM											
	12	1	2	3	4	5	6	7	8	9	10	11
Percentage	6.37	6.71	7.08	7.32	7.44	7.03	5.92	4.92	4.03	3.22	2.53	1.87
Traffic flow	589	621	655	677	688	650	548	455	373	298	234	173

4.1.2 Simulation Model

The simulation model was built according to the HRGC layout in VISSIM (Version 9.0, PTV Inc.). Roadway and railway were intersected at the same grade level. Hourly train and roadway traffic volumes were input to the model. Since train traffic was extracted from crossing gate activity, it was not possible to distinguish trains coming from opposite directions. Therefore, the simulation used one directional train traffic that was equal in magnitude to the sum of the bidirectional train traffic. In case of two simultaneous approaching trains, a block signal (blue line in Figure 9) was set upstream of the crossing to stop the latter train and make sure the gate would close n times when there were n approaching trains. The distribution of train passing time (i.e., time between the lowering and raising of gates) was obtained from the original gate activity log as well. To simulate the gate closure time, train length distribution was calculated based on train speed (40 mile/hour) and distribution of passing time. Next, a train approaching signal was created to simulate the crossing gate operation. Once the upstream train arrival detector (black detector in Figure 9) is triggered by a train, the signal at the gate first turns yellow for 5 seconds to simulate gate flashing lights. Then the signal turns red to stop motor vehicle traffic, and the data collection points in the vicinity of each gate start to record the vehicular queue length. When the train leaves the departure detector (purple line in Figure 9) and no other arriving train is detected, the signal at the gate turns green to simulate the lifting of the gates. To simulate the operation of the rail crossing for one month, the model was set to run 30 loops with different seeding and each loop simulating 24-hour train and motor vehicle traffic.

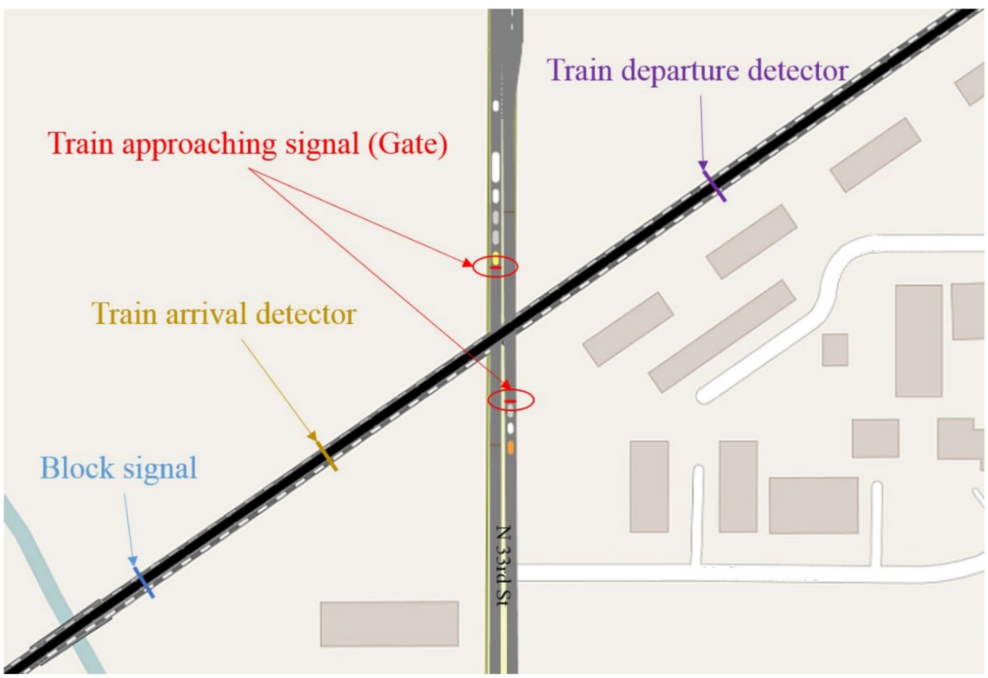
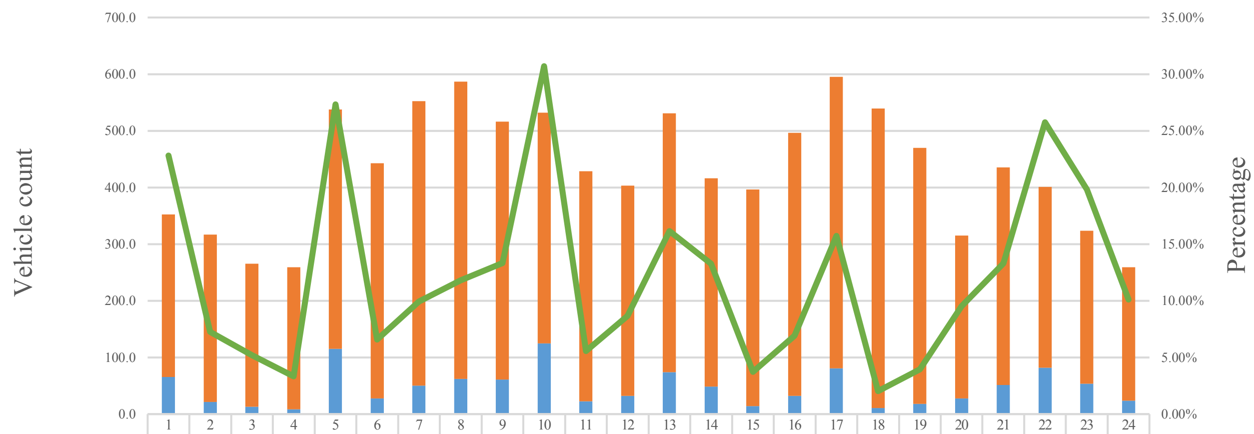


Figure 4.3 Simulation Settings

4.1.3 $(AADT)_{TP}$ Calculation

After simulation, raw data for motor vehicle activity, including speed, passing time, queue length, etc., was obtained from data collection points. The number of vehicles that encountered a train (number of delayed vehicles) was calculated for each day and then averaged over 30 days. Figure 10 presents the average proportion of delayed vehicles (green line), total traffic volume, and number of delayed vehicles (stacked columns) during each hour and the corresponding number of delayed vehicles. For example, during time period 1, on average 286.8 vehicles arrived, of which an average of 65.4 (22.82%) were delayed due to passing trains. For the entire 24-hour period, an average of 1,120 out of 9,252 vehicles were delayed due to passing trains representing 12.10% of the daily average traffic.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Vehicle(output)	286.8	295.1	252.3	251.1	422.4	415.3	502.2	524.8	455.8	407.0	405.8	371.3	457.0	367.7	382.0	464.1	514.1	528.4	452.2	288.0	384.4	318.9	270.1	235.6
Delayed vehicle	65.4	21.4	13.1	8.3	115.4	27.4	50.0	61.9	60.7	124.9	22.6	32.1	73.8	48.8	14.3	32.1	80.9	10.7	17.8	27.4	51.2	82.1	53.5	23.8
Percentage	22.82%	7.26%	5.19%	3.32%	27.32%	6.59%	9.95%	11.79%	13.32%	30.70%	5.57%	8.65%	16.15%	13.27%	3.74%	6.92%	15.74%	2.03%	3.95%	9.50%	13.31%	25.75%	19.82%	10.10%

Figure 4.4 Simulation Results

Figure 11 shows the hourly distribution of motor vehicle volume, train volume, and delayed vehicle count, which represents (AADT)TP. Hourly variations in (AADT)TP follow variations in hourly total traffic as well as variations in train traffic. For example, both train and motor vehicle traffic volume is high during the 4:00-5:00 and 8:00-9:00 periods, and the corresponding (AADT)TP is also high during these two periods. Therefore, (AADT)TP is not only related to AADT and number of daily trains but also associated with the variations in hourly traffic volume.

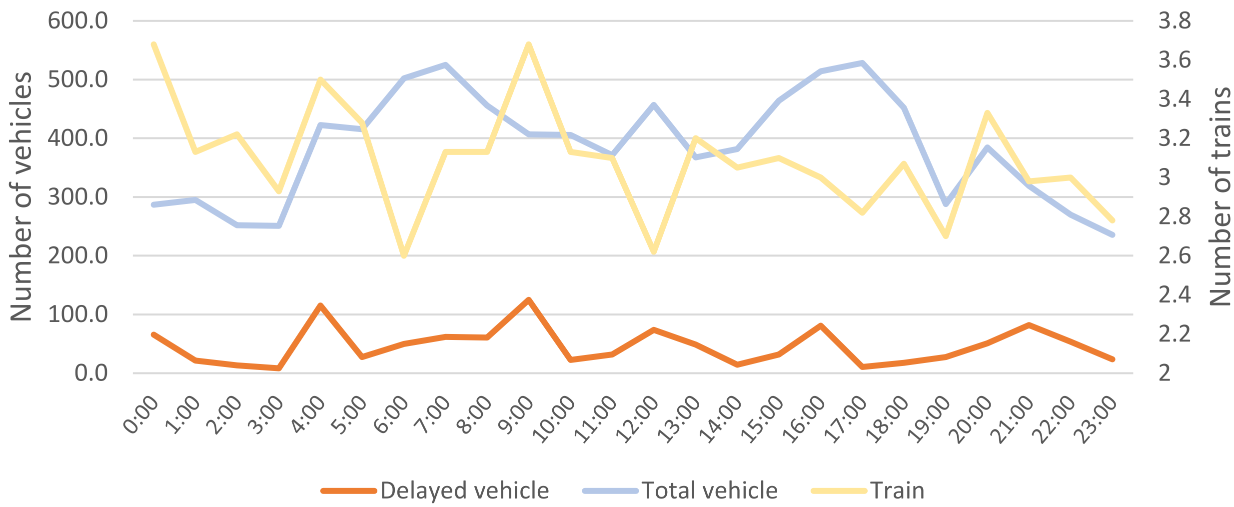


Figure 4.5 Temporal Distribution of Three Volumes

4.1.4 Simulation Validation

Validation of the simulation method involved first estimating (AADT)TP for three different HRGCs (using the simulation) and then comparing those estimates to true values of (AADT)TP obtained by field observation. These three HRGCs are located in the City of Lincoln; all have two-lane highways, two sets of rail tracks, and are equipped with automatic gates and flashing lights. Continuous video recording at each location recorded train and motor vehicle traffic. From the video, hourly motor vehicle counts, hourly train traffic, and hourly vehicles that encountered trains were carefully extracted by watching the recorded video and populating traffic counts in a spreadsheet.

All three HRGCs were simulated using VISSIM in a similar fashion as before. The proportion of vehicles encountering trains from the simulation model was estimated for each HRGC and summarized in Table 8. As can be seen, the simulation estimates are close to the field-observed percentages. The differences between simulation results and actual data are in the range of -0.3% to +0.5%, thus showing validity of the simulation approach.

Table 4.3 Validation Results

	HRGC 1		HRGC 2		HRGC 3	
Observed daily average traffic	Highway	Train	Highway	Train	Highway	Train
	10860	8	4035	32	1159	32
Field observed percent of motor vehicle traffic encountering trains [100*$(AADT)_{TP}$/AADT]	4.2%		10.3%		9.8%	
Simulation estimate of percent motor vehicle traffic encountering trains [100*$(AADT)_{TP}$/AADT]	4.5%		9.8%		9.5%	
Difference	-0.3%		0.5%		0.3%	

<u>4.2 Categorization of Rail Crossings</u>

To obtain (AADT)TP for different HRGCs in an area, this research developed a classification scheme for rail crossings. Four key factors influence the true vehicular exposure at rail crossings: (1) roadway traffic, (2) train traffic, (3) temporal variation in roadway traffic, and (4) temporal variation in rail traffic. This procedure classified all rail crossings in a geographic area into several groups. Crossings in each group share some similarities across the four factors mentioned above. Research is available on factors influencing hourly roadway traffic variation, such as peak hour factor (PHF). However, to the authors' knowledge there is no research on hourly variations in train traffic. The best subsets algorithm and stepwise forward selection were used to explore factors that have an influence on roadway AADT and the number of daily trains at a rail crossing.

4.2.1 Data

Crossing inventory data for Nebraska was obtained from the Federal Railroad Administration (FRA) consisting of 3,733 observations. Among them, 2,213 observations were removed due to inaccurate records, lack of key information, or outdated information (e.g. information recorded during 1970s or 1980s). Considering the purpose of this method is to classify crossings by their roadway AADT and total number of through train characteristics. Only variables potentially related to those two responses were selected (e.g., type of crossings, region development type, paved highway, etc.). In the end, 1520 observations with 29 variables were selected for model building.

4.2.2 Methodology

To build the classification tree, the key step is to select several variables that have the most significant influence on the 4 factors. Then, a tree can be expanded according to the selected levels of variables. For example, if V1, V2, and V3 are finally selected, then V1 and V3 have 2 levels, and V2 has 3 levels. Next, the categorization can be done like in Figure 12. The variables influencing those 4 factors will be discussed in the following.

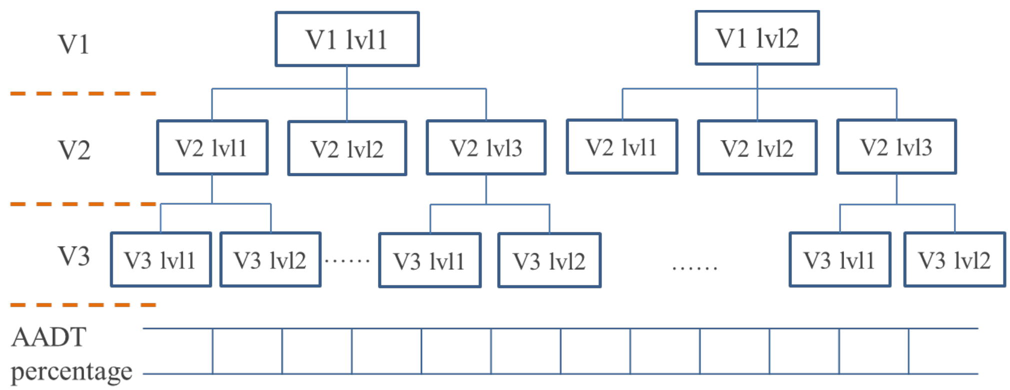


Figure 4.6 Building A Tree Structure

4.2.2.1 Variation in Hourly Roadway and Railway Traffic

Plenty of research has been done about the factors influencing hourly roadway traffic variation. The Florida Department of Transportation (FDOT) found that the proportion of AADT occurring in an hour, which is represented as K-factor, is related to area (urban, suburban, and rural) and roadway class (freeways and arterials) [13]. In the Highway Capacity Manual (HCM), PHF and K-factor are related to area (urban, rural) and roadway class. Sandra Almeida et al. found that roadway traffic shares similar characteristics in area (urban, residential, and suburban) and road type (main roads and other) [14]. Andrew P. Tarko [15] did a research on PHF and found that road class, population, and rash hour volume are related to the hourly traffic variation. In most of the above research, area type and roadway class are treated as key influencing factors on roadway traffic variation.

Compared to roadway traffic variation, there is little research on railway traffic variation due to less volume on the track. Different from roadway traffic, the variation of railway traffic usually keeps the same at the same track segment. As what have been done in the third section, the ANOVA test is able to tell the variation in railway traffic at different hours. Therefore, the number of track segments in one area is the key influencing factor on railway traffic variation, and an ANOVA test can be employed to test the variation.

4.2.2.2 Roadway AADT and Number of Daily through Trains

To determine which variable should be selected to build the tree, the stepwise forward selection and best subsets algorithm are used in this procedure. The stepwise selection is a method of fitting regression models in which the choice of predictive variables is carried out by an automatic procedure [67]. Forward selection is one of the approaches. It starts with a model with no predictor variable, then testing the addition of each variable using a chosen model fit criterion, and adding the variable (if any) whose inclusion gives the most statistically significant improvement of the fit. The progress is repeated until there is no improvement to the model to a statistically significant extent. The best subset algorithm is used to find the best model for each specific number of predictor variables. Those two methods work in a similar way. The reason both of those two methods were used here is that too many variables would make a huge tree. The stepwise selection can provide a general image of which variable should be considered in the final categorization, and the best subset algorithm gives the rank of importance of the variables.

4.2.2.3 Stepwise Selection

Stepwise selection was done first. The selection criterion was the model Akaike information criterion (AIC) value. The variable was selected if it reduced the AIC value by adding it. Both roadway AADT and the number of through trains were treated as a response, respectively. The best model for two responses and corresponding estimate coefficients, standard error, and p-value of each selected variable are given in Table 9 and Table 10. Note that region, number of gates, type of roadway and speed limit are included in both models. Among them, region and number of gates are significant in both models. Most of the type of roadway levels are significant in both models. Speed limit is significant in the second model at α = 0.05 level, but not significant at the first model.

Table 4.4 Stepwise Selection for Roadway AADT Model

Roadway AADT	Best model: AADT ~ Region + HwyClass + DevelpTyp + #_of_lanes + #_of_gates + #_of_bells + Hwypved + Speed_limit				
	Selected variables	Levels	Estimate	Std. Error	p-value
	Intercept	-	3739.54	328.93	< 0.001
	Type of roadway (HwyClass)	Principal Arterial	Base	-	-
		Minor Arterial	-1331.01	284.11	< 0.001
		Major Collector	-3606.63	263.31	< 0.001
		Minor Collector	-4164.73	281.60	< 0.001
		Local	-4229.93	262.22	< 0.001
	Region	Rural	Base	-	-
		Urban	1388.48	110.33	< 0.001
	Land use (DevelpTyp)	Open Space	Base	-	-
		Residential	-25.65	104.07	0.8054
		Commercial	461.24	102.08	< 0.001
		Industrial	125.94	113.74	0.2683
		Institutional	-158.06	242.08	0.5139
		Farm	51.31	256.04	0.8412
		Recreational	1049.80	882.64	0.2345
	Number of lanes	-	227.10	59.97	< 0.001
	Number of gates	-	149.14	53.26	0.0052
	Number of bells	-	-147.87	69.33	0.0331
	Paved roadway (Hwypved)	Yes	Base	-	-
		No	-123.70	67.61	0.0675
	Speed limit	-	4.45	2.96	0.1327

Table 4.5 Stepwise Selection for Daily Train Traffic Model

Number of through trains	Best model: TotalThru ~ MainTrk + MaxSpd + SrvcTyp + Sgnleqp + Gates + HwyClass + PctTruk + OthrTrk + AADT + HwySpeed + HwyNear + Region				
	Selected variables	Levels	Estimate	Std. Error	p-value
	Intercept	-	-0.33	5.21	< 0.001
	Number of main tracks (MainTrk)	-	16.40	0.86	< 0.001
	MaxSpeed (MaxSpd)	-	0.68	0.03	< 0.001
	Type of Service (SrvcTyp)	Freight	Base	-	-
		Passenger	-0.28	1.36	< 0.001
	Signaled track (Sgnleqp)	Yes	Base	-	-
		No	-7.32	0.99	< 0.001
	Number of gates	-	2.55	0.54	<0.001
	Region	Rural	Base	-	-
		Urban	6.16	1.85	<0.001
	Percentage of Truck	-	0.27	0.10	0.0049
	Number of Other type tracks	-	0.96	0.34	0.0053
	AADT	-	0.001	0.0004	0.0036
	Speed limit	-	0.09	0.04	0.0218
	Highway Near HRGC (HwyNear)	Yes	Base	-	-
		No	1.54	0.77	0.0444
	Type of roadway (Hwyclass)	Principal Arterial	Base	-	-
		Minor Arterial	2.42	4.62	0.6007
		Major Collector	4.04	4.54	0.3728
		Minor Collector	8.54	4.82	0.0768
		Local	6.93	4.57	0.1301

4.2.2.4 Best Subset Algorithm

Next, the best subset algorithm is employed to explore the importance of each variable. The algorithm searches the best model when specifying the number of selected variables from 1 to 8 for model building. The result is given in Figure 13.

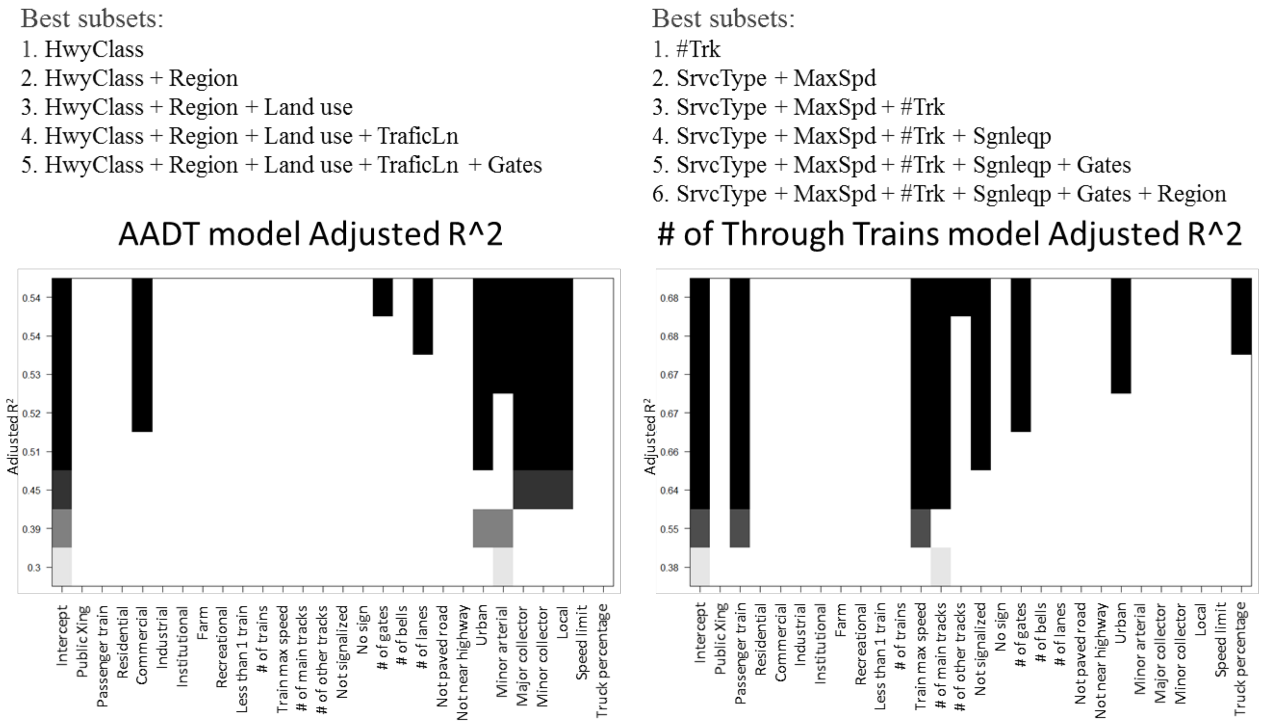


Figure 4.7 Best Subsets Algorithm

Note that both region and highway class have significant influence on the variation of roadway traffic, AADT, and number of daily through trains, which means those two variables should be selected in any case. Furthermore, in most cases, number of the tracks keep the same at the same track segment. Considering the track segment has to be selected due to its uniqueness in contribution to railway traffic variation, the number of tracks can be replaced by the railway segment. Table 11 concludes that influencing variables can be divided into 4 factors. Colored variables have an influence on more than one factor.

Table 4.6 Variable Selection

Hourly roadway traffic variation	Hourly railway traffic variation	AADT	Number of daily through trains
1. Region type	1. Track segment	1. Region type	1. Number of tracks
2. Roadway class		2. Roadway class	2. Service type
3. Land use		3. Land use type	3. Max speed
4. Population		4. Number of lanes	4. Signalized track
5. Rash hour volume		5. Number of gates	5. Number of gates
			6. Region type

Considering the above analysis, one can pick 1-2 variables that have an influence on each factor to build the classification tree. For example, if a city has two track segments, then one can pick 3 variables, track segment, region, highway class, and number of main tracks, or 4 variables, adding number of gates, to build the classification tree. After checking the field collected data and comparing it with FRA inventory data, one possible tree could be as shown in Figure 14. The SW_S track is a branch line of SW track that has a different number of daily through trains on the SW track. Therefore, the SW track is split into two parts, which are the SW_S and SW_M tracks. These two tracks are shown in Figure 15.

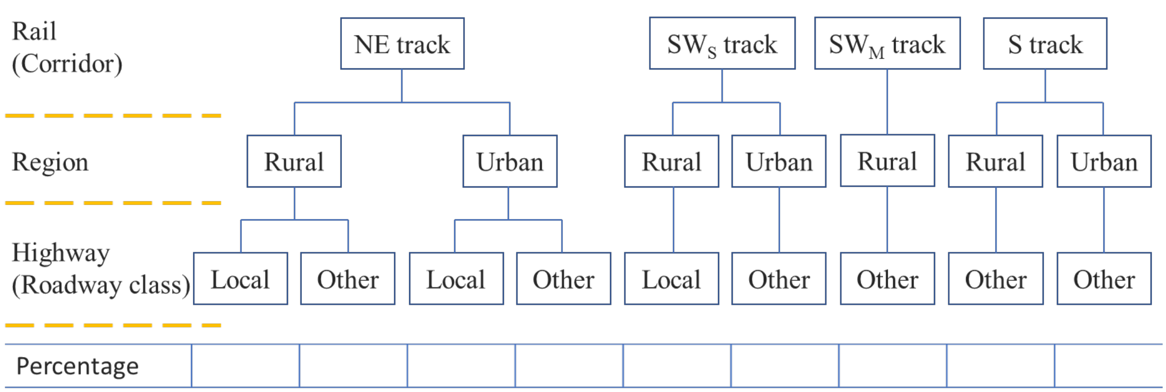


Figure 6.8 HRGC Categorization

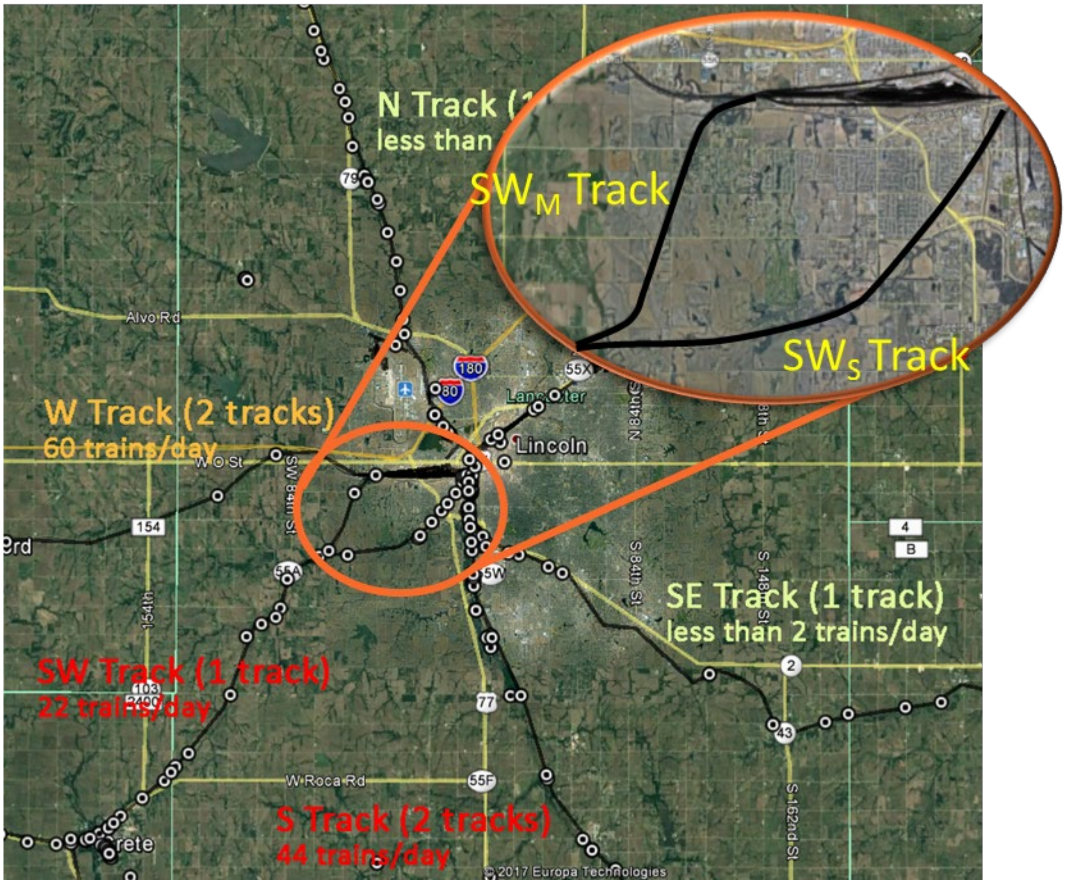


Figure 4.9 Sub-tracks SW$_S$ and SW$_M$ of SW Track

After the data is processed, the collected data are transferred to vehicle exposure (percentage of delayed vehicle). The final result is shown in Table 12 and Figure 16.

Table 4.7 Final Results

	NE Track 2 tracks				
Xing Type	Rural/ Local		Rural/Other	Urban/Local	Urban/Other
HRGC ID	098443J	074942G	074940T	074860A	064128X
Latitude	40.8775	40.9206	40.916136	40.848341	40.841021
Longitude	-96.6032	-96.5209	-96.529614	-96.658883	-96.67282
Location	N 84th St & Cornhusker Hwy	N 148th St & Cornhusker Hwy	N 141st St & Cornhusker Hwy	N 44th St & Cornhuskers Hwy	N 33rd St & Cornhusker Hwy
AADT	120	700	2350	2600	9250
Field AADT	211	1941	3825	1886	6702
Ave. DTT	53.2				
Percentage	12.56%	11.20%	7.06%	8.60%	9.85%
Exposure	27	216	268	162	668
	SW Track 1 track				
	SW_M Track		SW_S Track		
Xing Type	Rural/Other		Rural/Local	Urban/Other	
HRGC ID	073289S	073291T	083048F	064130Y	083044D
Latitude	40.7412643	40.733208	40.7768	40.799118	40.79391
Longitude	-96.8413297	-96.853846	-96.7494	-96.724688	-96.7302
Location	W Denton Rd & Front St	SW 98th St & Haley Lynn Ln	S Coddington Ave & W Calvert St	W A St & Salt Creek Levee Trail	S Folsom St & Folsom Ln
AADT	1515	1445	425	8500	4800
Field AADT	2079	2004	2111	8375	5208
Ave. DTT	5		17		
Percentage	1.74%	3.19%	0.62%	0.86%	0.91%
Exposure	36	64	13	72	47

	S track 1 track			
	Rural/Other	Urban/Other		
HRGC ID	083516X	074406N	064362N	064361G
Latitude	40.6973743	40.7556	40.788708	40.791812
Longitude	-96.6814059	-96.71278	-96.716345	-96.716675

Location	Saltillo Rd & S 27^{th} St	Old Cheney Rd & Jamaica North Trail	Park Blvd & S 4^{th} St	South St & S 3^{rd} St
AADT	9050	14560	8400	3300
Field AADT	9540	12610	2918	4491
Ave. DTT	27			
Percentage	9.37%	6.61%	6.07%	6.35%
Exposure	894	834	177	285

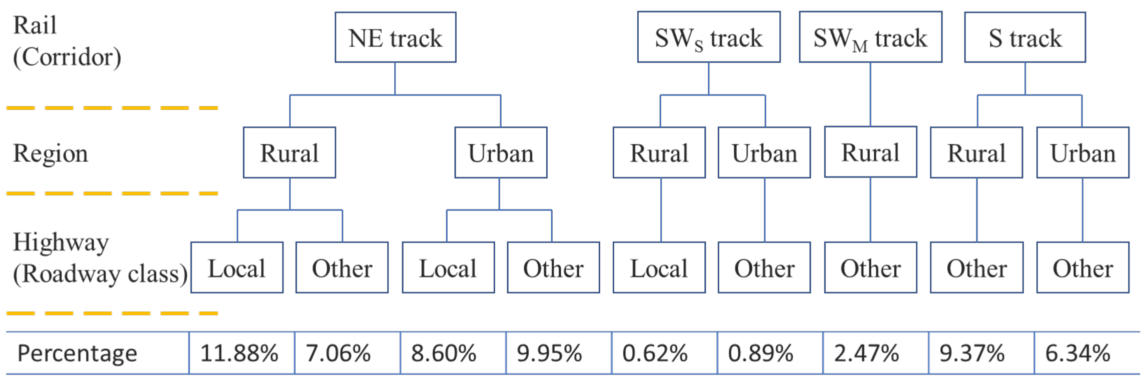


Figure 4.10 Vehicular Exposure Decision Tree

As can be seen from Table 12, most HRGCs at the same category have similar percentages of vehicles that are exposed to passing trains. The averaged percentage was calculated as the vehicular exposure rate for each HRGC category. The corresponding vehicular exposure can be calculated as exposure rate * AADT.

Chapter 5 Conclusions and Recommendations

Motor vehicle exposure to train-involved crashes at HRGCs is a key factor in safety models. However, existing models fail to take into account the actual vehicular exposure, thus presenting a muddy picture of real safety at these critical junctions in the transportation network. This study proposed $(AADT)_{TP}$ is a better measure of vehicular exposure to train-involved crashes and presented methods to estimate $(AADT)_{TP}$.

Simulation results showed that when the model is properly calibrated according to the vehicle and train speed profiles, vehicle headway, train length distribution, etc., it can simulate the operation of rail crossings and provide an accurate estimate of $(AADT)_{TP}$. A comparison among three HRGCs using different hazard index formulas revealed the underlying assumptions of those formulas that the proportion of delayed vehicles due to a passing train is the same for studied rail crossings. By using AADT and the number of daily trains to measure vehicular exposure, those formulas cannot provide accurate estimation or a correct ranking of HRGCs when that underlying assumption is not satisfied. Further, factors including AADT, train traffic, variation in hourly traffic volume, and train volume were identified as having an influence on $(AADT)_{TP}$.

Except simulation-based estimation, the study also provided a decision tree to give a rough estimation for HRGCs in the same category. The study first assumed that by grouping HRGCs according to vehicular exposure related factors, the exposure rate in each HRGC group would be similar. Field collected data verified the assumption. An implementable data collection method was proposed. A vehicle detection algorithm and program were developed to detect a vehicle from raw data and provide basic statistical analysis. The algorithm and program performed satisfactory with accuracy around 95%.

Transportation agencies often use crash predictions to identify deserving HRGCs amongst candidate locations for the expenditure of limited safety resources. The implication of using AADT in place of the more relevant $(AADT)_{TP}$ in HRGC crash prediction models is the possibility of missing deserving HRGCs. Therefore, $(AADT)_{TP}$ is recommended instead of AADT for use as a more appropriate measure of vehicular exposure in crash safety models. The contribution of this paper is the illustration of estimating $(AADT)_{TP}$ via simulation and validation of the results.

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Appendix 1

Veh #	Date	Time	Sys Delay	Real Time	Direction	Speed (MPH)	FHWA Class	Axles	Correctness	Real Time	Direction	Final Time	Final Direction	Gap	Incident Time	Incident	# of delayed vehicles	# of trains	Train duration
6	3/12/2018	18:05:47	6	18:05:53	South	32	6	3	1			18:05:53	South	2					
7															18:05:55	Train present		1	
8									2	18:08:15	North	18:08:15	North	142					
9									2	18:08:21	North	18:08:21	North	6					
10									2	18:08:24	North	18:08:24	North	3					
11	3/12/2018	18:08:20	6	18:08:26	South	36	4	4	1			18:08:26	South	2					
12	3/12/2018	18:08:22	6	18:08:28	North	19	2	2	1			18:08:28	North	2					
13	3/12/2018	18:08:24	6	18:08:30	North	19	2	2	1			18:08:30	North	2					
14	3/12/2018	18:08:28	6	18:08:34	South	24	4	4	1			18:08:34	South	4					
15	3/12/2018	18:08:30	6	18:08:36	South	20	2	2	1			18:08:36	South	2					
16									2	18:08:37	North	18:08:37	North	1					
17									2	18:08:38	North	18:08:38	North	1					
18	3/12/2018	18:08:32	6	18:08:38	South	24	6	3	1			18:08:38	South	0					
19	3/12/2018	18:08:34	6	18:08:40	North	17	2	2	1			18:08:40	North	2					
20	3/12/2018	18:08:37	6	18:08:43	South	23	3	2	1			18:08:43	South	3					
21	3/12/2018	18:08:37	6	18:08:43	North	18	4	4	1			18:08:43	North	0					
22	3/12/2018	18:08:39	6	18:08:45	South	25	3	3	1			18:08:45	South	2					
23	3/12/2018	18:08:41	6	18:08:47	South	23	4	4	1			18:08:47	South	2					
24	3/12/2018	18:08:41	6	18:08:47	South	93	4	2	0	18:08:47	North	18:08:47	North	0					
25	3/12/2018	18:08:44	6	18:08:50	South	22	4	4	1			18:08:50	South	3					
26	3/12/2018	18:08:44	6	18:08:50	South	95	4	2	0			18:08:50	South	0					
27															18:08:51	Train gone			
28	3/12/2018	18:08:46	6	18:08:52	South	26	4	4	1			18:08:52	South	2					
29	3/12/2018	18:08:49	6	18:08:55	South	18	1	2	1			18:08:55	South	3					
30	3/12/2018	18:08:52	6	18:08:58	South	24	4	4	1			18:08:58	South	3					
31	3/12/2018	18:08:54	6	18:09:00	South	22	4	4	1			18:09:00	South	2					
32															18:09:02	Queue dissipation	24		187
33	3/12/2018	18:09:28	6	18:09:34	North	34	2	2	1			18:09:34	North	34					