2018

Examining the spatial and temporal transferability of safety performance functions: A case study for the Iowa interstate system

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Examining the spatial and temporal transferability of safety performance functions: A case study for the Iowa interstate system

by

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A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Civil Engineering (Transportation Engineering)

Program of Study Committee:
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Peter Savolainen, Co-major Professor
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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2018

DEDICATION

This thesis is dedicated to my parents, for their endless support and devotion throughout my life. My mother is always the person who supports my decisions, she helped me with the transfer program and encourage me to study abroad. If you ask me who my role model is, I will answer without any hesitation that my mother is. She is a woman with a strong heart and independent spirit, who inspires me and guides me towards the right path. Thank you, my parents, for giving the sweetest love of the world and the happiest family on earth, which make me as a positive person. Without their love and support, I would not get the chance to see the big world, to learn what I want to learn, to be what I want to be.

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NOMENCLATURE

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AIC	Akaike Information Criterion
CMF	Calibration Modification Factor
DOT	Department of Transportation
FHWA	Federal Highway Administration
GIMS	Geographic Information Management System
GLM	Generalized Linear Model
GOF	Goodness-of-Fit
HSM	Highway Safety Manual
HSIS	Highway Safety Information System
MAD	Mean Absolute Deviation
MSE	Mean Squared Error
MPE	Mean Percentage Error
NCHRP	National Cooperative Highway Research Program
QA/QC	Quality Assurance/ Quality Control
RMSE	Root Mean Square Error
SPF	Safety Performance Function
Std.Dev	Standard Deviation
Std.Err	Standard Error

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my major professor, Dr. Peter Savolainen, for his endless support and guidance these past two years. I would like to thank my committee members, Dr. Christopher Day and Dr. Ashley Buss for their guidance and support throughout the course of this research.

In addition, I would also like to thank my friends, co-workers, Qiuqi Cai, Megat Usamah Bin Megat Johari, Trevor Kirsch, Chao Zhou, Justin Cyr, Jacob Warner, Hitesh Chawla for making my time at Iowa State University a wonderful experience.

And last, but not least, Wenjing Cai, Lin Ma, Mengguo Yan, thank you for all support and help, and thank you for always standing by my side.

ABSTRACT

This case study aimed to examine the spatial and temporal transferability of safety performance functions (SPFs), which were developed for the Iowa interstate system in the form of negative binomial regression models. Four years of crash data were integrated with geometric and traffic information over a four-year period for the entire interstate system. The segments were randomly split into two groups and these groups were also split into a pair of two-year time periods. This allowed for an assessment of model transferability across space, time and both dimensions. Separate models were estimated for each of the four datasets and these models were used in cross-validation exercises. The predicted values were directly compared to actual observed values to assess predictive accuracy. In this setting, less spatial variability was shown as compared to temporal variability, which was largely reflective of significant reductions in crashes that occurred over the course of the study period. In all settings, temporal transferability was relatively poor. The results improved when calibration exercises were conducted. Ultimately, the results support prior research, which suggests state-specific SPFs are recommended in order to obtain better predictive capabilities. Full models, which considered numerous predictor variables, performed better than simple models considering only annual average daily traffic. Additional research is suggested in this area in order to better understand how spatial and temporal transferability compares across different empirical settings.

CHAPTER 1. INTRODUCTION

1.1 Background

The state of Iowa serves as a major freight thoroughfare in the Midwestern United States, particularly along Interstate 80 and Interstate 35, which are major transport corridors serving east-to-west and south-to-north traffic, respectively. Figure 1-1 shows the layout of the Iowa Interstate network system. Besides, I-80 and I-35, other interstates include I-235, I-280, I-380, I-480, I-680, I-29, and I-74. These routes cover a total length of 825 miles across the state. In addition to providing for efficient goods movement, another objective of the Iowa Department of Transportation (DOT) is to provide safe roadway conditions and facilitate progress toward the overarching goal of experiencing zero traffic fatalities. Figure 1-2 presents the history of crashes that have occurred on the Iowa interstate system from 2008 to 2017, including the numbers of total crashes and injuries, as well as the number of fatalities. It can be seen that fatalities have generally been decreasing while injuries and total crashes have largely plateaued. In order to facilitate further reductions in traffic crashes, injuries, and fatalities, an important objective is to allow for proactive design and the implementation of countermeasures that reduce the frequency and severity of crashes. One important tool in support of this objective is the use of safety performance functions (SPFs), which are mathematical models that can be used to predict the number of crashes that would be experienced for specific roadway geometry characteristics and traffic volumes.

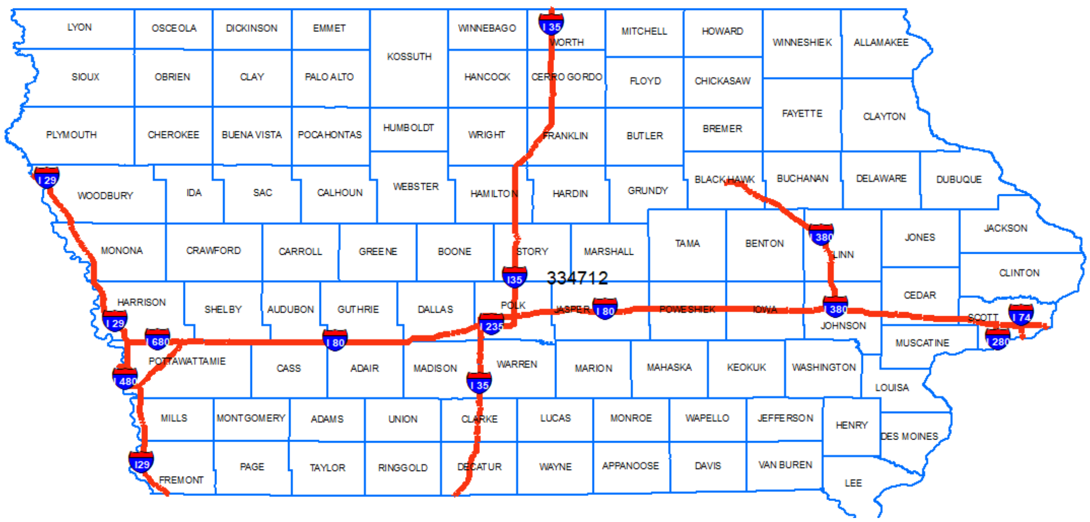


Figure 1-1: Iowa Interstate highway system network map

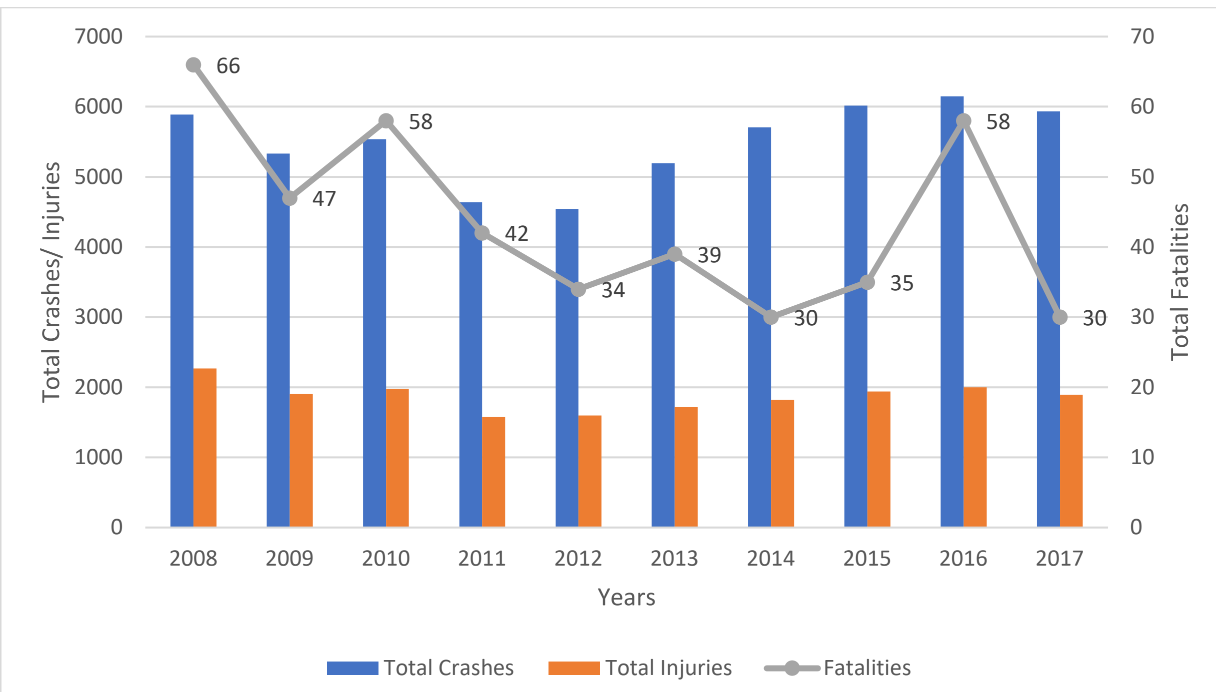


Figure 1-2: Iowa Interstate crashes from 2008-2017 source from Iowa SAVER

These SPFs are provided in the *Highway Safety Manual* (HSM) (American Association of State Highway and Transportation Officials (AASHTO), 2010), which provides guidance and best practices for safety management. The HSM is published by the American Association of State Highway and Transportation Officials (AASHTO). It provides analytical tools and techniques for quantifying the safety performance of various types of road facilities. The first edition of the HSM provides initially predictive methods for rural two-lane, two-way roads, rural multilane highways, and urban and suburban arterials. Subsequently, additional research has led to the development of SPFs for freeways and interchanges. These models were developed as a part of National Cooperative Highway Research Program (NCHRP) Project 17-45 and the content comprise supplementary Chapter 18 of the first edition of the HSM.

The primary data used for model calibration and validation were obtained from the Highway Safety Information System (HSIS) for the states of California, Maine, and Washington. It is important to note that research suggests the use of the SPFs from the HSM require local calibration or estimation of state-specific models in consideration of the fact that each state may have different features that are representative of the data from those three states. Concerns have been raised about the applicability, transferability, and accuracy of the SPFs. Studies of the calibration and development of jurisdiction-specific safety performance function were conducted for Alabama, Utah, Oregon and Michigan (Brimley et al, 2012;Mehta and Lou, 2013;Dixon and Avelar, 2015;Savolainen et al, 2015). A study in Utah developed new models for rural two-lane two-way highways and the results showed that the original HSM models under-predicted crashes. Moreover, the study in Alabama developed state-specific statistical models for two-lane two-way rural roads, as well as four-lane divided highways and found that the HSM-recommended method for calibration estimation performs well. A study to assess the transferability of the HSM predictive method using data for a two-lane rural road network in the province of Salerno in Italy (Russo et. al, 2014). The results suggested that local safety performance functions and crash modification factors (i.e. CMF) should be developed to more effectively implement the HSM techniques.

It is necessary to conduct state-specific SPFs and validate the HSM predictive methods. The HSM recommends each state to have its own SPFs, and the manual outlines three different ways for states to use and apply SPFs to make better decisions: (1) network screening to identify potential improvement; (2) determining effects of safety treatments or countermeasures; and (3) determining safety impacts of changed design on project level.

The Federal Highway Administration (FHWA) sponsored a project focused on developing state-specific SPFs (Srinivasan, Bauer, 2013). The project report provides guidance on how to develop local SPFs. Various forms of nonlinear regression models were considered, including power, sigmoidal, and negative binomial functional forms. There are a few studies conducted the statistical model comparison, thus, based on a state-specific database, model selection may result in different coefficients when forming the SPFs which will be introduced under the literature review chapter.

Iowa generated its first version of Iowa DOT Data Driven Safety Guidance (Iowa Department of Transportation (Iowa DOT) , 2017) in October 2017. The intent of the document is to provide guidance on safety analyses for Iowa DOT interchange projects. This guidance concerns CMFs for use in crash frequency prediction, based on information from the CMF clearinghouse. Calibration factors developed by Iowa DOT's Office of Traffic and Safety are included, which can be used to adjust the HSM SPFs to Iowa conditions. Table 1-1 provides segment calibration factors developed by the Iowa DOT for urban and rural freeway segments, as well as two-lane highway segments. These calibration factors represent the average rate by which the base models from the HSM tend to over- or under-estimate crashes of various types on Iowa highways. Calibration factors greater than one are reflective of cases where the HSM models under predict actual (observed) crashes based on Iowa data while calibration factors less than one correspond to cases where the HSM models tend to over predict. At this moment, the Iowa DOT has not developed state-specific safety performance functions using data from Iowa.

Table 1-1: Iowa SPF Segment Calibration Factors (Iowa Department of Transportation (Iowa DOT) , 2017)

Crash Type	Calibration Factor
Urban Freeway	
Multiple-Vehicle Fatal and Injury	1.26
Multiple-Vehicle Property Damage Only	1.79
Single-Vehicle Fatal and Injury	0.85
Single-Vehicle Property Damage Only	1.17
Rural Freeway	
Multiple-Vehicle Fatal and Injury	1.08
Multiple-Vehicle Property Damage Only	1.67
Single-Vehicle Fatal and Injury	0.64
Single-Vehicle Property Damage Only	1.16
Rural, Primary, Two-Lane Road Segments	
All crashes	0.84

1.2 Research Objective

The initial objective of this study aims to see if follow the HSM predictive method, will the model well-transferred and suit Iowa data. With regards of this objective, a series of SPFs are developed. Negative binomial regression models were estimated, as recommended by the HSM. An Interstate database was assembled to examine the safety performance of the mainline system, wherein segments are comprised of uniform characteristics and are exclusive of interchange and ramp sections. Segments with lengths shorter than 0.1 miles were combined with adjacent segments in ArcMap, as the HSM suggests a minimum segment length of 0.1 miles. The final analysis database includes segment-level traffic information, geometric characteristics, and roadside data, along with crash counts during the analysis period from 2012 to 2016.

A series of SPFs were estimated using subsets of these data with the intent of validating the accuracy of the predictive models separately across space and time, as well as with respect to both dimensions. Goodness-of-fit is compared using metrics that include mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE). Ultimately, the results provide guidance as to the relative issues posed by temporal and spatial transferability.

1.3 Thesis Structure

This thesis consists of six chapters in total. This introductory chapter provided the motivation for the present study. The remaining chapters are briefly described below:

- Chapter 1: Introduction- This chapter introduces the background on general information related to the documentation of safety predictive method. The main reference is mentioned as well as the necessity of current research objective. The following sections under this chapter are stating the detail information of the research objective.
- Chapter 2: Literature Review- This chapter is structured into three parts to summarize the existing papers established in the related area. This chapter begins by examining previous studies on a validation techniques that inspired the present study. Those techniques gave insights on how to compare and identify function performance, and how to assess transferability of models by focusing on data sample design. Additional work on analytic methods involving before-after and cross-sectional as well as Empirical Bayes are discussed. The second section examines state practices on SPFs development. The last section briefly introduces the negative binomial model and talks about the applied examples in similar studies.

- Chapter 3: Data Description- This chapter describes the data used in this study, including databases from Iowa DOT and manually combined segments. A data integration process using ArcMap is presented. All variables used in data analyses are summarized statistically including crash data, traffic data and roadway characteristics.
- Chapter 4: Methodology- This chapter states the statistical methods and validation techniques used in this study, including the general formulas, coefficient descriptions, and reasons for selecting those methods. A detailed study design is presented to talk through how to validate the model across time, space and both dimensions, and how to examine transferability by designing the sub-datasets.
- Chapter 5: Results and Discussion- This chapter presents the results of the statistical models developed for this study under each validation purpose and examines why those results were obtained.
- Chapter 6: Conclusion and limitation- This chapter concludes this study with a concise summary of key findings. Limitations and expectations for future work are presented.

CHAPTER 2. LITERATURE REVIEW

This chapter is organized into three sections to introduce previous work on safety model transferability. The first section introduces two study cases on applying validation techniques and comparing SPF models, which inspired the present study. The second section examines how various states have either developed their own SPFs or calibrated HSM predictive methods. The third part examines previous studies on the development of negative binomial models for safety performance prediction.

2.1 Validation technique and analytic method

There were two validation cases in recent years on safety performance functions which inspired the methodology of the present study. This research (Dixon and Avelar, 2015) applied a validation technique to safety performance functions developed by the Oregon DOT for arterial segments. The Oregon DOT previously developed its own SPFs for arterial segments, and the validation activities were assessed within three technique approaches: spatial transferability, spatial-temporal transferability, and individual coefficient stability and significance of the models.

To examine spatial transferability, the researchers reviewed the model results for the same year in the original analysis at a different group of sites. The direct comparison results are shown in Figure 2-1. The predicted values are not statistically different from the observed values because the p-value of goodness-of-fit (GOF) was 0.0828 but should at least equal to 0.05 when achieve a 95% confidence interval.

For the spatial-temporal transferability approach, the predictive power of the model was verified for a different time period. The sites were controlled, the spatial analysis was designed into two time-base cases: (1) only crashes occurring from 2009 to 2011; and (1) all crash data from 2004 to 2011. The direct comparison results are shown in Figure 2-2. The paper pointed out that it was reasonable to expect the variability of crash frequency to increase when the number of crashes increased. The authors constructed the plot to compare observed crashes versus predicted crashes graphically, as shown in Figure 2-3 and 2-4 respectively for the two time-base cases. The analysis indicated that the predictive power of the urban model was generally suitable, and the predictive model tended to deviate from the observed crash frequencies more than expected.

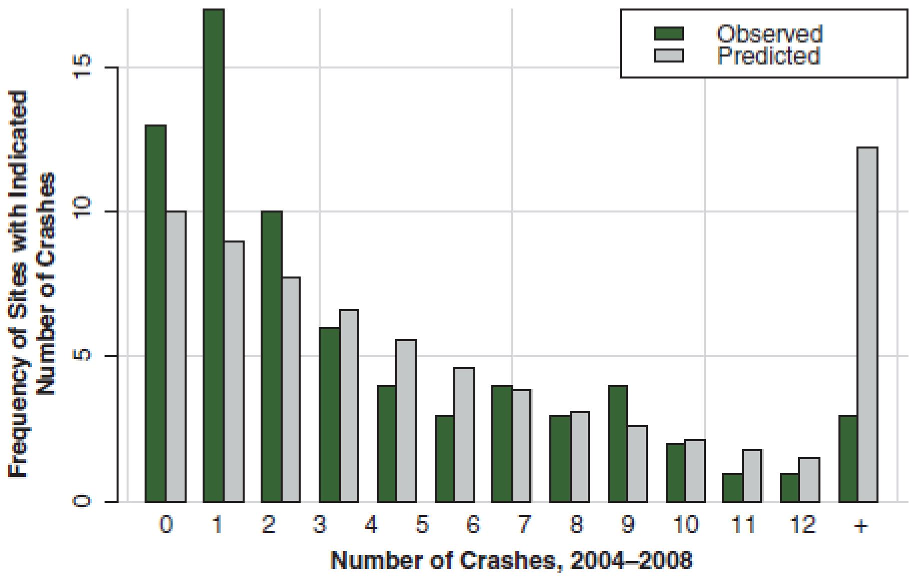
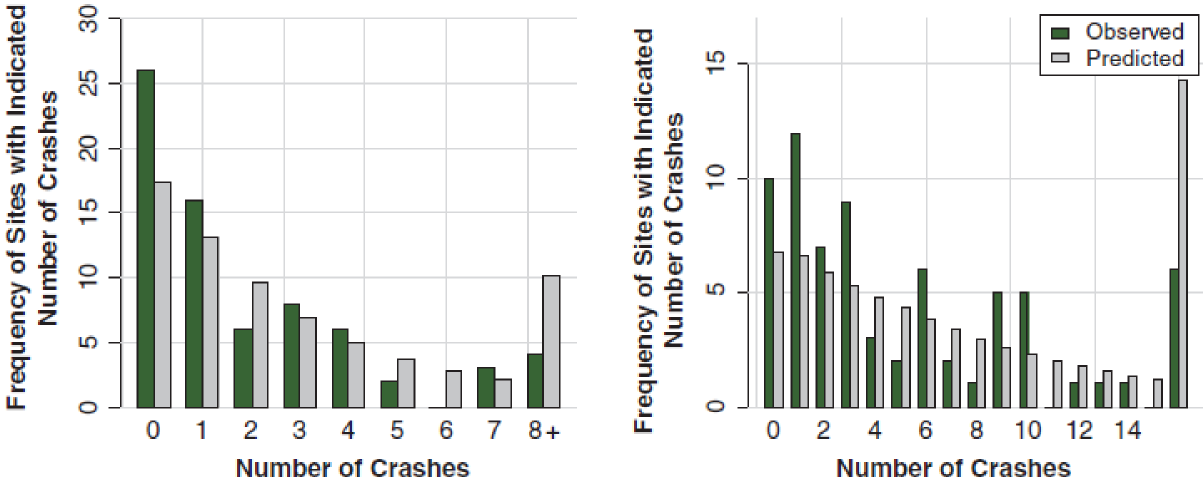


Figure 2-1: Original model predictions versus observed validation crashes (urban) p-value= 0.0828 (Dixon and Avelar, 2015)



(a) (b)

Figure 2-2: Crash distributions associated with time for (a) 2009-2011 and (b) 2004-2011 (Dixon and Avelar, 2015)

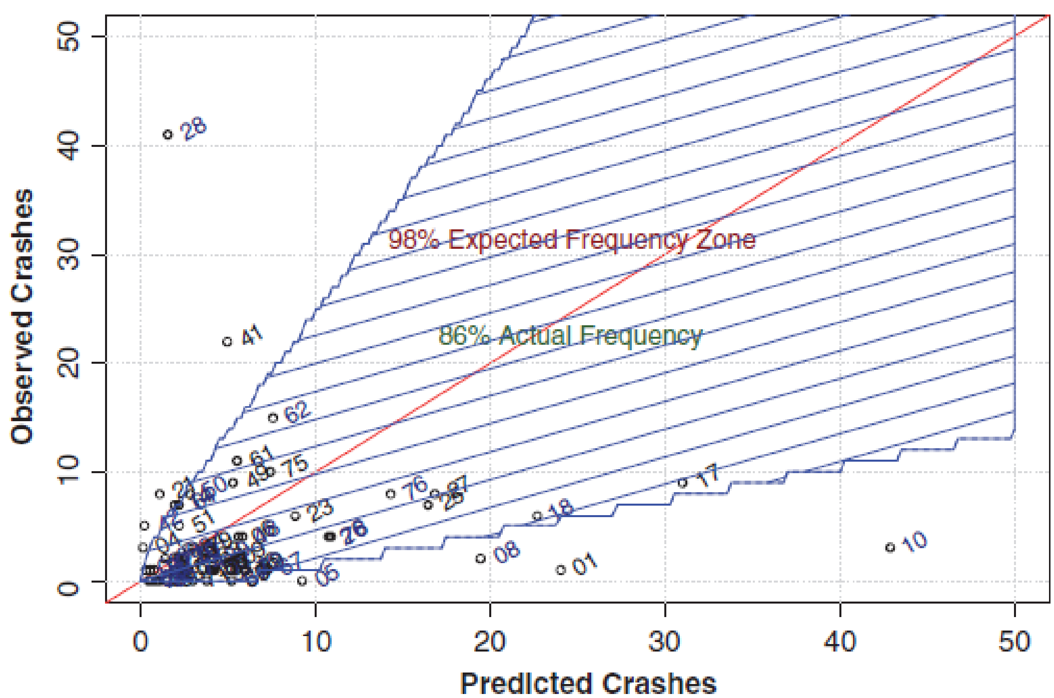


Figure 2-3: Predicted and observed urban crash frequencies for 2004-2008 (sites are identified by a number) (Dixon and Avelar, 2015)

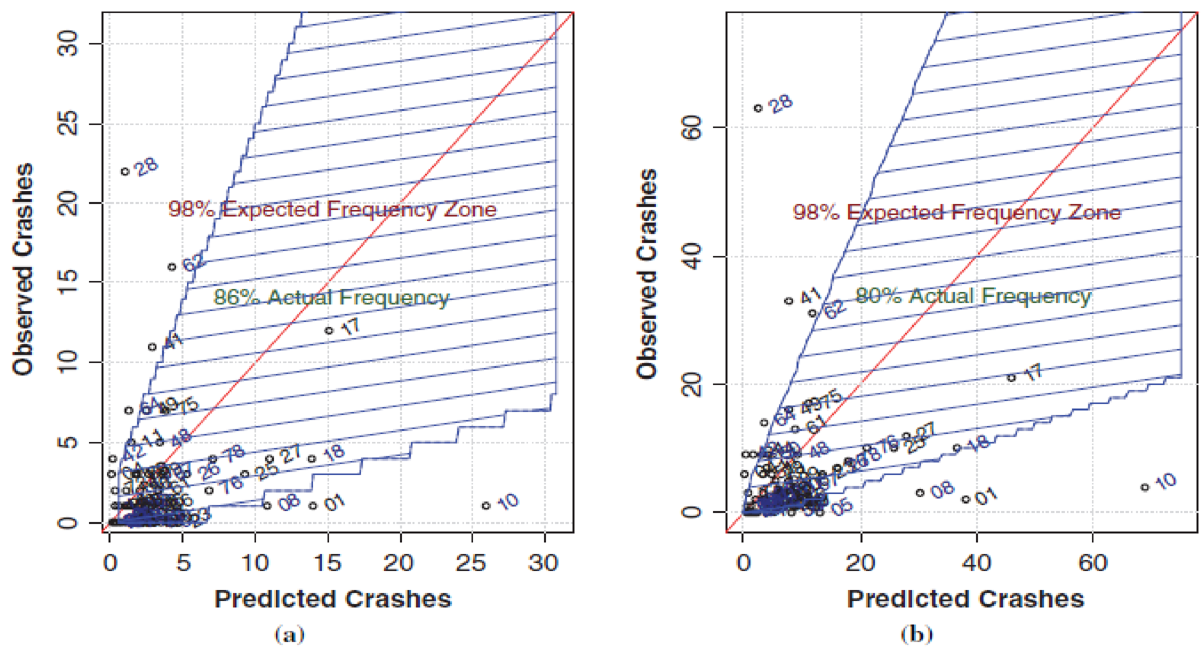


Figure 2-4: Site expected frequencies for (a) 2009-2011 and (b) 2004-2011 (Dixon and Avelar, 2015)

As noted in the final guidance report, temporal correlation could result in incorrect estimations of coefficients' standard errors. The guidance provided methods for addressing this issue by estimating generalized equations or using random effect negative multinomial models (Srinivasan, Bauer, 2013).

Regarding the approach of equivalent model coefficients, the accuracy of coefficient values of the original model was analyzed and verified. In addition, a study examined the theoretical characteristics of the modeling approach and compared them using two different datasets. The results showed that these methods had very similar performance. A sensitivity analysis was conducted to explore how the performance of these techniques vary by degree of dispersion and observed correlation levels of total and severe injury crashes with potential explanatory variables (Avelar, Veronika, Jirˇí, 2018).

Another study validated FHWA crash models for rural intersections. The validation was conducted using internal validation and external validation approaches. Internal validation took care of the underlying phenomenon explanation, and external validation was concerned with the temporal and spatial transferability of the predictive model. It also focused on GOF, using mean prediction bias, Mean Absolute Deviation (MAD), Mean Squared Prediction Error (MSPE) and Pearson product moment correlation coefficients between observed value and predicted values. The preliminary validation consisted of running models for different years for the same intersection. This aimed to assess the ability of models to forecast crashes across time. Data from Minnesota was used to provide multiple years of accident data, and data from Georgia was used for model validation across jurisdictions. The external validation used GOF of the statistical models to compare independent data (Oh et al., 2003).

The NCHRP 17-45 report (Bonneson et al., 2012) provided a two-step process for model validation. The first step required predicting the crash frequency using calibrated models from a third database which was not utilized for the development of SPFs as known as the calibrated models. The second step required comparing CMFs between calibrated CMFs and similar CMFs mentioned in previous literature to ensure that the calibrated CMFs were consistent with previous research results. As mentioned previously, data from three states were included in the HSIS database. The models were developed using data from California and Washington, with data from Marine excluded for validation purposes. A study came to reference which applied geographically weighted regressions to account for spatial heterogeneity to evaluate whether SPFs would vary across space. This study identified better performance between two different negative binomial regression models through the comparisons based-on time and space basis: (1) geographically weighted negative binomial regression and: (2) traditional negative binomial regression. The log likelihood, Pseudo-R^2 and AIC (Akaike Information Criterion) were used to compare model performance (Liu, Khattak, Wali, 2017).

To validate models across time, the before-and-after method could be used, while cross-sectional study are commonly used for assessing space bias throughout samples. In addition, Empirical Bayes and full Bayes methodology are often used for road safety studies. An article (MacNab and Ying C., 2003) illustrated modelling technique implementation in accident and injury surveillance and prevention system which could be utilized by transportation or health agency to examine routine on accidents, injuries, and hospitalizations and target high-risk regions. An empirical Bayes inference technique using penalized quasi-likelihood estimation was implemented to model both rates and counts, with spline smoothing accommodating non-linear temporal effects. The technique introduced in this article providing application and illustration on spatial-temporal modelling framework as part of accident surveillance and prevention system to identify the high-risk regions. A Bayesian hierarchical Poisson random effects spline model incorporated both spatial and temporal components into a unified framework to space and time surveillance. A validation study (Wang, Abdek-Aty, Lee, 2016) for a Full Bayes methodology for observational before-after studies was conducted and the results supported that the Full Bayes could provide similar results as Empirical Bayes. To examine SPFs' transferability for developing CMFs, a study modified before-after study with EB adjustment which was a method combining before-after and traditional EB to strengthen on case control techniques when using regression models. The paper pointed out that this combo method could make the estimations more precise and correct the bias of regression to mean.

In a word, the validation should be designed and conducted either across time or across space or both dimensions. A few studies were conducted using data from outside of the U.S. that to examine international transferability in other countries such like Italy and Canada (Russo et al., 2014; Martinelli et al., 2009; Persaud et al., 2012)

2.2 HSM predictive method calibration and state-specific SPFs examples

Researchers and state DOTs have been working on the calibration of HSM and developing customized SPFs. In 2010, a study (Garber, Haas, Gosse, 2010) examined SPFs provided by SafetyAnalyst, a software tool that provides SPFs for two-lane roads in Virginia but which was based on data from Ohio. The study developed separate models for urban and rural areas through generalized linear modeling with negative binomial distribution assumed crashes. The results indicated that the SPFs developed using local data fit better than the results obtained from SafetyAnalyst.

The state of Illinois completed a project and established a report (Robert, Jang, Ouyang, 2010) on development of state-specific SPFs. In this report, predicted SPFs were applied for roadway segments and intersections under Illinois DOT's jurisdiction by modeling the relationship among traffic, geometric conditions and crash density. The developed SPFs were used to identify high potential locations for safety improvements. Florida also established a report (Srinivasan and Bauer, 2011) on developing and calibrating HSM predictive methods for Florida conditions both on segment-level and intersection-level. The study suggested that the models should be developed at a lower level to obtain better results, because district-level or population-group-level calibration factors tend to achieve more adequate results than state-level.

In 2012, two papers talked about development jurisdiction-specific SPFs both using negative binomial regression models. One was the city of Regina, Saskatchewan, using five-year crash data from 2005-2009 (Young and Park, 2012), and another was the State of Utah (Brimley et al., 2012). They both concluded that state-specific SPFs provided the best fit to the data.

In 2014, a research (Kweon, Lim, Turpin, Read, 2014) was conducted on a customized SPF development procedure for Virginia DOT by using empirical data on four-leg signalized intersections of rural multilane highways. Within the same year, another study (Islam, Ivan, Lownes, Ammar, Rajasekaran, 2014) conducted SPFs development for Connecticut's Interstate highways separately on single-vehicle and multivehicle crashes. All geometric variables were used to estimate SPFs in form of negative binomial, and the best fit model was identified by comparing goodness-of-fit metrics. The results suggested that it was important to incorporate the interaction effect between the speed limit and geometric variables.

Internationally, SPFs calibrations were conducted based on HSM predictive method for urban four-lane divided roadway with angle parking in Riyadh, Saudi Arabia (Khalid and Mohamed, 2015). The study developed new SPFs using negative binomial regression models. The datasets contained fatal and injury crashes with AADT, geometric design feature data for undivided four-lane roadway (U4D) to calibrate HSM predictive method, and the resulted showed that the new SPFs performed better than the calibrated model in crash prediction.

Recently, Pennsylvania developed regionalized SPFs for two-lane rural roads by modelling three regional levels: statewide, engineering district and individual countries. Negative binomial models were utilized to form the SPFs, the statewide database consisted of large size data more than 10,106 miles and over 113,600 reported crashes. Three methods were used to compare different regionalized SPFs using GOF, cumulative residuals plots, and RMSE. The predicted values were compared to observed values based on 8 years' data. The results indicated that the district-level SPFs with county-level adjustment factors had a better performance in predicting crashes than other regional SPFs. It was necessary to develop an analytical method which can combine the results of before-and- after studies with cross-sectional studies in a meaningful and useful way (Li, Gayah, Donnell., 2017; Oh et al., 2003).

2.3 Negative binomial model election

To develop state-specific safety performance functions, statistical models need to be considered. The HSM recommends using the negative binomial model to develop state-specific safety performance functions. This section did provide a wide range reviews of paper relate to or involve negative binomial in studies.

Traditional Poisson and Poisson–gamma (or negative binomial) distributions were mentioned as the most common and popular statistical models for transportation safety analysts for modeling motor vehicle crashes (Srinivas and Dominique, 2008). There were some previous studies conducting the comparison between commonly used statistical models. When selecting models, their advantages and disadvantages should be known. For example, since panel data became available and popular in the safety area, heterogeneity may bias the results and the issue needs to be addressed. Study results (Karlaftis and Tarko, 1998; Ambros et al., 2016) indicated that significant differences existed among the developments of modeling. It was shown that separate models were more efficient than the joint model, and simple crash prediction models were found sufficient for network screening.

In 2007, a paper published on crash prediction model focusing on multilane rural roads in Italian. The Poisson, negative binomial and negative multinomial regression models were used to form the models and predicted the frequency of accident occurrence. Besides the common variables, safety effects such as stopping sight distance and pavement surface characteristic were taken into consideration. Moreover, separately analysis models were developed for tangents and curves. Regarding the model comparison, negative multinomial distribution was suggested as the most appropriate statistical regression tool for longitudinal crash data analysis. Because both Poisson and negative binomial models required the accident data to be uncorrelated in time, the random effect negative binomial model became more suitable due to the unobserved heterogeneity and serial correlation in the accident data (Caliendo, Guida, Parisi, 2007).

A different study evaluated the performance of Poisson and negative binomial regression models for analyzing the relationship between truck accidents and geometric design of road sections. The unknown parameters were estimated using the maximum likelihood method and results showed that negative binomial regression models using moment and regression-based methods should be used with caution (Miaou, 1994).

A similar study was conducted to examine impacts of roadway geometric features on rural two-lane highway crash severity using data from Illinois from 2007-2009. This analysis used standard ordered logit and multilevel ordered logit as statistical models. The results showed that the multilevel ordered logit model provided greater consistency with the data generating mechanism and could be utilized to evaluate the safety effects of geometric design improvement projects (Haghighi, Liu, Zhang, Porter, 2018).

Another study sought to document a new type of model, using the Generalized Waring (GW) distribution. The GW model could yield more information about the observed variance in datasets by separating it into three parts: *randomness* (explaining the model's uncertainty), proneness (the internal differences between entities or observations), and *liability* (variance caused by other external factors that are difficult to identify and which were not included as explanatory variables). The results showed that the GW model could provide meaningful information about the source of variance in crash data, and yielded a fit better than the negative binomial model for both empirical datasets (Peng, Lord, Zou, 2014).

A Bayesian hierarchical Poisson random effects spline model incorporated both spatial and temporal components into a unified framework for space and time surveillance. The tool might be used for routine monitoring focusing on visually describing the spatial distribution of accident rates/ratios over regions and time in order to link critical factors for further investigation (MacNab and Ying C., 2003). A project (Wang et al., 2016) used 36 safety-related parameters for three- and four-legged non-signalized intersections in Alabama, aiming to explore the influence on intersection characteristic scores while choosing statistical models for estimating SPFs. Poisson regression, negative binomial regression, regularized generalized linear model (GLM) and boosted regression trees (BRT) were used to evaluate SPFs. The results are shown in Figure 2-5. The figure shows the error for each type of model at different levels of complexity. The BRT model had substantially lower prediction error and relatively stable performance than the other three models. The Poisson regression model is the one most used to generate SPFs, as it captures the discrete nature of count data. However, negative binomial was considered better than Poisson since count data is often overdispersed in Poisson models. The traditional GLM models form the linear structures which could only assign the importance to the linear relationship between some intersection characteristics and crash rate.

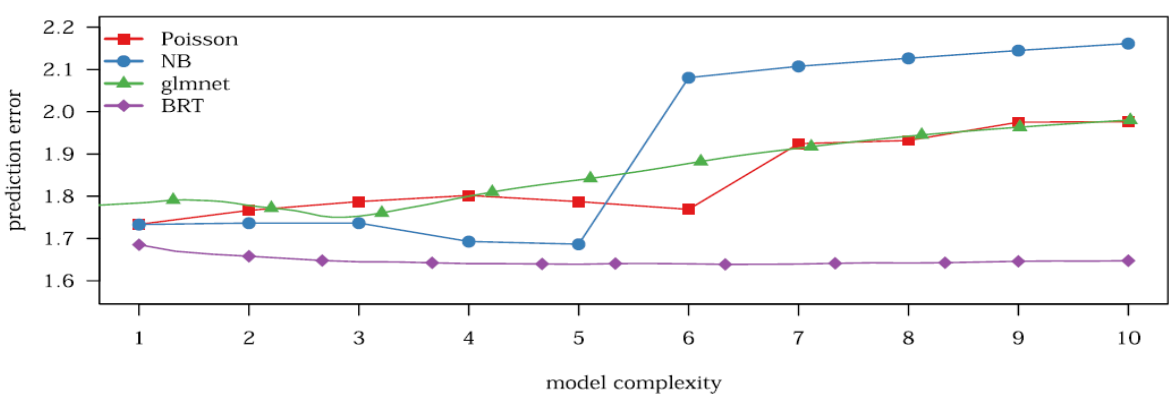


Figure 2-5 Cross-validated prediction error measured by the negative mean log-likelihood (Wang et al., 2016).

CHAPTER 3. DATA DESCRIPTION

3.1 Overview of Data Description

The main purpose of this study is to examine the spatial and temporal transferability of crash prediction models which are generated to obtain SPFs. The models were estimated using subsets of the data and a validation process was conducted to evaluate the predictive ability and performance of each model over space, time and both dimensions. Two databases were the primary source of data: the Geographic Information Management System (GIMS) database and the Iowa Crash database. GIMS contains traffic information as well as roadway geometric characteristics, and the Iowa Crash database compiles all reported crashes within the state of Iowa from police reports. Manual segment combination was conducted in order to achieve Highway Safety Manual (HSM) minimum segment length suggestion, and all involved segments' lengths were greater than 0.1 miles. ArcGIS and Microsoft Excel were used for data integration

3.2 Iowa DOT Geographic Information Management System

The Iowa DOT GIMS database contains georeferenced data describing numerous aspects of roadway information. The database is updated every other year to incorporate changes due to highway construction or maintenance activities. Each segment is assigned a link number called MSLINK which is an auto-incrementing variable assigned by the Modular GIS Environment software. MSLINK is the key reference for assembling and joining data in ArcGIS. There are 13 different datasets in GIMS that cover almost all information for a specific roadway segment location, such as traffic information, roadway geometric design characteristic, etc. Among those datasets, Traffic, Road Info, and Direct Lane were mainly utilized in this study.

The Traffic dataset provides information on traffic parameters, such as annual average daily traffic (AADT) and vehicle type distribution (i.e., the proportions of different classes of vehicles in mixed traffic volume). The Road Info dataset contains geometric information of roadway segments including surface type/width, median type/width, lane numbers and types (i.e., through lanes, turning lanes, two-way left turn lanes, etc.), etc. The Direct Lane dataset gives various characteristics related to roadway infrastructure or countermeasures, such as posted speed limit, shoulder type/width, curb presence, rumble strip installation conditions, etc.

3.3 Iowa DOT Crash Database

The Iowa DOT crash database records all reported crashes occurring in the State of Iowa. There are three subsets at the person level, vehicle level, and crash level. The database provides the crash date, location, and manner of collision, weather/light condition, crash severity, first harmful event, crash types, driver age, sex, and other crash information, integrated from police reports. For this study, only the crash-level dataset was used.

Five years of crash data from 2012 to 2016 were integrated using ArcGIS and Microsoft Excel for this study. Crashes occurring along mainline Interstate highways (i.e., on through-lane sections) were identified and intercepted by applying a 50 feet buffer distance from the roadway mainline. QA/QC procedures were conducted to ensure the buffer width was selected correctly to contain relevant crashes.

3.4 Segment Combination

Loading GIMS geodatabase in ArcGIS, all segments under Iowa DOT jurisdiction could be filtered out by using ‘select by attribute’ and making queries ‘Justice=1.’ Figure 3-1 shows the overview roadway layout under Iowa DOT jurisdiction. In order to get the interstate mainline system, new queries were made through ‘select by attribute' function as ‘syscode=1’ (i.e. Interstate highway classification code), ‘NINEONEONE' involving RAMP, LOOP, ST, SPE CASE, US20, etc. to clean current layout and show interstate mainline system only. Besides using queries for filtering, a column indicating roadway function was used as an additional check. Further checking was conducted while was doing the segment combination. After preliminary assembly, there were 4,153 segments under the interstate system and each segment owned unique MSLINK. Of these, 2,109 segments were shorter than 0.1 miles, which could not be used in model analysis according to the HSM. In Figure 3-2 below, the Iowa interstate mainline system is shown and shorter segments which needed to be combined to nearest longer segment are highlighted in red.

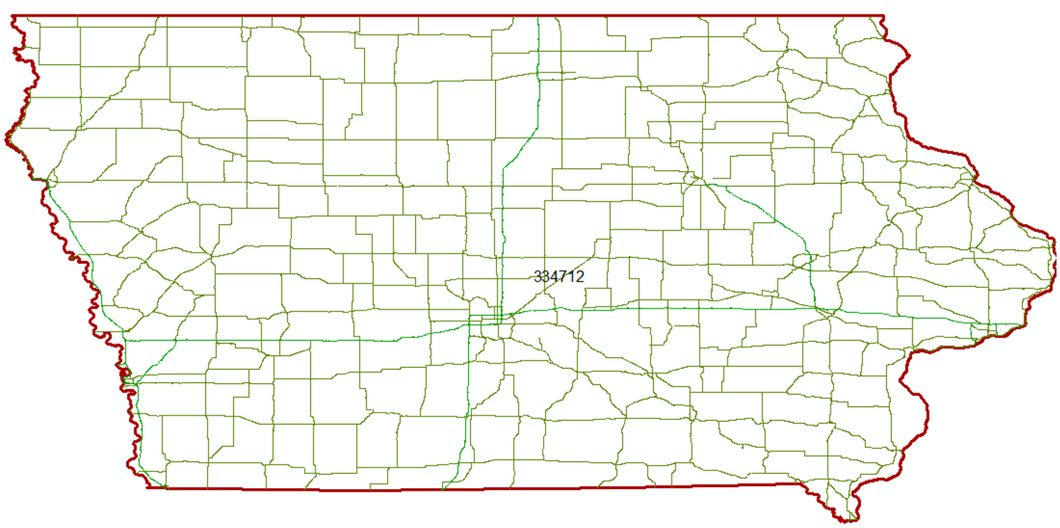


Figure 3-1 Roadway layout under IowaDOT jurisdiction in GIMS

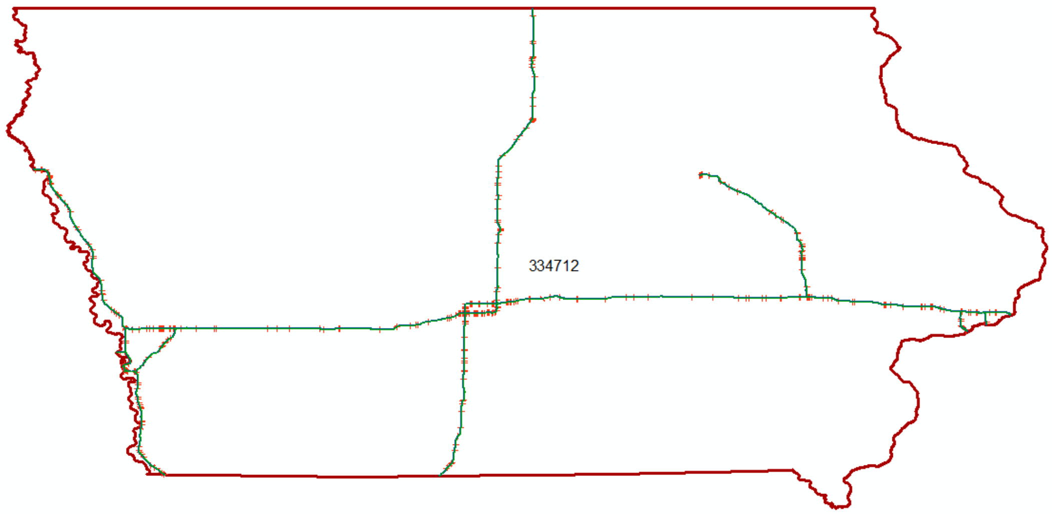


Figure 3-2 Interstate Highways layout with shorter segments highlighted

Segment combination was conducted by adding a new column called 'NewID'. The idea was to combine segments with lengths shorter than 0.1 miles to their nearest segments with lengths greater than 0.1. Manual combination was done because shorter segments were often located next to each other, making automated combination unreliable as engineering judgment was required to arrange the combination. After this process, the shorter segment's MSLINK was changed to the MSLINK of the nearest longer segment under the NewID column, and the longer segment MSLINK remained the same. As mentioned previously, QA/QC was conducted during combination. Leftover ramp sections and very short isolated segments were removed. The final step of the combination used the 'Dissolve' function to spatially combine the segments based on NewID. New segment lengths were calculated for the combined segments. At the end of this process, there were 2050 segments with lengths ranging from 0.1 to 1.6 miles on the interstate mainline system.

3.5 Data Integration Process

With segment combination accomplished, roadway geometry, direct lane, and traffic info were joined to assemble a comprehensive database using the new segment definitions. Concerns arose at this point that the geometric information used data from 2015 rather than individual geometric datasets for different years. For this study, an important assumption was made that the geometric information was consistent throughout the five-year period. The shorter segments were assumed to have the same characteristics with the nearest longer segments. For this study, the roadway and roadside features were all transferred into binary indicators for analysis. Crashes were spatially identified by making a 50ft buffer around the roadway centerlines as defined in the shapefiles. The 50-ft distance was determined from trial and error. Several attempts were made using values from 20ft to 150ft to obtain interstate crashes without involving nearby crashes on local streets or ramp sections. A 50-ft distance achieved the best performance in this regard.

To export the attribute table from ArcGIS, some dataset restructuring and recoding was necessary. There were a few segments missing AADT data. To solve this issue, the AADT of the nearest segment was applied. This was done manually in ArcMap. During the column check, surface width, as well as median width, were excluded from analysis due to apparent measurement bias. The surface width definition was not officially defined, while median width and surface width were confused when approaching interchange areas. Binary indicator variables would be used to minimize the bias. The surface type was recoded based on material (either asphalt or concrete), which is shown in Table 3-1. The median type was recoded into two binary categories which indicated whether a barrier installed or not, and whether the median surface was paved or grassy. The median barrier determination was made by comparison with Iowa DOT Cable Median Barrier Project Geodatabase records. Each column was checked before integration with the analysis tool; 42 out of 2050 records showed two lanes under the "number of lanes" column, but this did not match lane type records which had been corrected. Regarding the lane number and lane type data, the new column called 'Transition_zone' was recoded which indicated current segment located within transition area (i.e. lane type record involves number 6_exit lane, 7_entrance lane, 9_other).

Table 3-1 Recoding summary for Surface_Type

Surface_Type_Code	Description	Count	Surface_Asphalt	Amount
60	Generic asphalt	88	1	950
65	Asphalt on old Portland cement concrete	745	1	
69	Asphalt on asphalt	66	1	
92	Combination surface-asphalt and asphalt	51	1	
70	Generic concrete	6	0	1100
74	New type Portland cement concrete(not reinforced)	894	0	
76	New type Portland cement concrete(fully reinforced)	190	0	
79	Portland cement concrete on asphalt	10	0	

3.6 Data Summary

To obtain a better fit crash prediction model for a segment group, 10 different predictor variables were included to generate safety performance functions including segment length, AADT, and binary indictor variables covering surface type, and roadside/roadway features. Those variables could be used in SPFs to predict crash frequency. The descriptive statistics of the predictor variables are shown in Table 3-2. Segment lengths ranged from 0.10 to 1.61 miles, with a total length for all analysis segments of 779.97 miles. The presence of rumble strips, median features, and speed limits are treated as binary indicators in the models, following the HSM recommendations. In addition, each segment's yearly crashes were counted. There were 2050 segments in the Interstate database, and 24,617 crashes were reported on Interstate segments from 2012 to 2016, as shown in Table 3-3.

Table 3-2 Interstate database descriptive statistic summary

Variables	Min	Max	Sum	Median	Mean	Std. Dev
Segment_Length	0.100	1.609		0.267	0.380	0.2813
AADT_2012	5700	118300		21400	26690	18471.15
AADT_2013	5700	119500		21500	26832	18634.21
AADT_2014	5400	127100		22100	27988	19278.91
AADT_2015	5600	130800		23000	28977	19895.29
AADT_2016	5500	135300		23400	29305	20105.98
Surface Type (1 if asphalt; 0 if concrete)	0	1	899	0	0.439	0.4963
Shoulder_present_L (1 if yes; 0 otherwise)	0	1	2015	1	0.983	0.1296
Shoulder_present_R (1 if yes; 0 otherwise)	0	1	2034	1	0.992	0.0880
Rumble_Installed_ L (1 if yes; 0 otherwise)	0	1	1803	1	0.880	0.3256
Rumble_Installed_ R (1 if yes; 0 otherwise)	0	1	1830	1	0.893	0.3096
Speed Limit	55	70		70	68.080	3.8341
Speed limit_55 (1 if yes; 0 otherwise)	0	1	102	0	0.050	0.2175
Speed limit_60(1 if yes; 0 otherwise)	0	1	54	0	0.026	0.1602
Speed limit_65(1 if yes; 0 otherwise)	0	1	373	0	0.182	0.3859
Speed limit_70(1 if yes; 0 otherwise)	0	1	1521	1	0.742	0.4377
Median_surface_hard(1 if hard surface; 0 if grass surface)	0	1	176	0	0.086	0.2802
Transition_zone(1 if contains exit/entrance lane; 0 if through lane only)	0	1	450	0	0.220	0.4140
Cable_Barrier_Installed(1 if yes; 0 otherwise)	0	1	735	0	0.359	0.4797

Table 3-3: Crash data summary

	Min	Max	Sum	Median	Mean	SE.Mean	CI.Mean.95%	Std.Dev
Crash_2012	0	63	5578	1	2.721	0.0917	0.1798	4.1502
Crash_2013	0	60	5472	1.5	2.669	0.0853	0.1673	3.8618
Crash_2015	0	33	4693	1	2.289	0.0735	0.1442	3.3296
Crash_2016	0	55	3750	1	1.829	0.0651	0.1276	2.9463

CHAPTER 4. METHODOLOGY

Under this section, the detailed methodology used as a part of this study is discussed, including a description of the statistical methods, validation techniques and goodness-of-fit tests. As the primary purpose of this study is to examine the spatial and temporal transferability of SPFs, a description of how the analysis datasets prepared is first presented.

4.1 Data Preparation and Summary

The full database described in the previous chapter is comprised of 2,050 segments. For each segment, geometry, traffic volume, and crash data are obtained for two-time periods: (1) 2012 to 2013; and (2) 2015 to 2016.

After the original database was developed, random selection was conducted in R studio. The original database was divided into two equal size subsets named Group_A and Group_B respectively. Ultimately, Group A and B from random selection used in this study had similar total segment length, and the differences among total crashes for each year were smallest. The descriptive summary of Group A and B can be found in Table 4-1. From the summary, the total length of segments of Group_A was 389.548 miles, and Group_B had similar total segment length as 390.424 miles. It could be seen that Group A and B had similar feature distributions. For example, the groups are well balanced with respect to traffic volumes, surface type, speed limit, and other geometric characteristics.

Table 4-1: Subset descriptive statistic summary

	Group_A			Group_B		
	Sum	Mean	Std.Dev	Sum	Mean	Std.Dev
Segment_Length	389.548	0.38	0.28	390.424	0.38	0.29
Average AADT of 2012-2013	27389600	26721.56	18069.62	27470115	26800.11	19029.48
Average AADT of 2015-2016	29806950	29079.95	19369.29	29931800	29201.76	20561.03
Surface Type (1 if asphalt; 0 if concrete)	455	0.44	0.50	444	0.43	0.5
Shoulder_present_L (1 if yes; 0 otherwise)	1008	0.98	0.13	1007	0.98	0.13
Shoulder_present_R (1 if yes; 0 otherwise)	1016	0.99	0.09	1018	0.99	0.08
Rumble_Installed_ L (1 if yes; 0 otherwise)	912	0.89	0.31	891	0.87	0.34
Rumble_installed_R (1 if yes; 0 otherwise)	921	0.90	0.30	909	0.89	0.32
Speed limit_55 (1 if yes; 0 otherwise)	49	0.05	0.21	53	0.05	0.22
Speed limit_60(1 if yes; 0 otherwise)	20	0.02	0.14	34	0.03	0.18
Speed limit_65(1 if yes; 0 otherwise)	195	0.19	0.39	178	0.17	0.38
Speed limit_70(1 if yes; 0 otherwise)	761	0.74	0.44	760	0.74	0.44
Median_surface_hard(1 if hard surface; 0 if grass surface)	78	0.08	0.27	98	0.1	0.29
Transition_zone(1 if contain deceleration/acceleration lane; 0 if through lane only)	213	0.21	0.41	237	0.23	0.42
Cable_Barrier_Installed(1 if yes; 0 otherwise)	387	0.38	0.49	348	0.34	0.47
Total Crash of 2012-2013	5457	5.32	7.64	5593	5.46	7.56
Total Crash of 2015-2016	4184	4.08	5.62	4259	4.16	5.96

4.2 Statistical methodology of SPF development

Safety Performance Functions are crash prediction models developed from past observed crash data, site characteristics, and roadway traffic information. For developing segment-level SPFs, the total crashes for analysis period would be used as the exposure variable. In this study, negative binomial regression model was run in R studio to obtain the SPFs, the accuracy and transferability of the models was examined.

4.2.1 Generalized Linear models

Crashes are randomly occurring events; crash data is nonnegative and discrete in nature. Consequently, some segments have minimal or zero crashes. This means that crash distributions do not follow the normal distribution. In this case, in NCHRP 17-45, the researchers used nonlinear regression to develop SPFs. The traditional generalized linear models (GLM) models form the linear structures which assign the importance to the linear relationship between roadway characteristics and crash rates, and the models allow the predictor variables to have error distributions other than normal distributions. Also, the models can fit maximizing the likelihood or log-likelihood of the observed parameters

In a generalized linear model, the dependent variable Y is assumed to be generated from a specific distribution: usually either the normal, binomial, Poisson or Gamma distributions are used. The distribution of mean, μ, depends on the independent variables, X_i. The equation can be written as:

$$P(y_i) = \mu_i = g^{-1} * (\beta_i X_i) \quad (3)$$

Where $P(y_i)$ is the expected value, $\beta_i X_i$ is the linear predictor, and g is the link function. Under this framework, the variable can be expressed as:

$$Var(y_i) = V(\mu) = V\left(g^{-1}(\beta X)\right) \quad (4)$$

4.2.2 Negative Binomial Regression Models

There are two types of commonly used count models. As mentioned previously these are the Poisson and negative binomial (also known as Poisson-gamma models) regression models. The negative binomial regression is a type of generalized linear model where the dependent variable Y is count data for events occurring within a defined time period. The probability of the number of crashes occurring within dataset during a specific time period is given by:

$$p(y_i) = P(Y = y_i) = \frac{e^{-\lambda} * \lambda_i^{y_i}}{y_i!} \tag{5}$$

where y_i is the number of crashes for segment i, and λ_i is the Poisson parameter for segment i. For this study, λ_i will be the expected number of crashes at segment i for a given time period. The expected number of crashes can be expressed as:

$$\lambda_i = \mathrm{EXP}(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n) \tag{6}$$

where X_1 through X_n are explanatory variables which represent site characteristics such as traffic volumes, speed limit, roadside and cross-section features; β_1 through β_n are the estimate coefficients obtained from the regression analysis. The mean number of crashes was assumed to be equal to the variance. However crashes occurred randomly, and crash data in nature therefore naturally have greater variances. This is known as overdispersion. Overdispersion can be handled by adding an additional term to the expression for λ_i, as shown below:

$$\lambda_i = EXP(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon_i) \tag{7}$$

Here, the new term ε_i is a gamma-distributed error term with a mean equal to one and variance α (also known as the overdispersion parameter). The inclusion of the overdispersion parameter allows the variance to differ from the mean, as demonstrated in the equation below:

$$Var(y_i) = E(y_i) + \alpha E(y_i)^2 \tag{8}$$

This can be interpreted as follows. A positive estimated coefficient represents an increased effect in the total number of crashes, while a negative sign indicates a decreased effect in the total number of crashes. To obtain the marginal effect which represents the percentage increase or decrease in the number of total crashes, the equation can be expressed as:

$$\Delta\lambda = 100 * \left(e^{\beta_n X_n} - 1\right) \qquad (9)$$

Where $\Delta\lambda$ is the percentage change in the number of crashes.

4.3 Validation study design procedure and methods

Eight statistical models were developed using the negative binomial regression in R studio to fully examine the transferability of SPFs. Cross-validation was conducted using the results from those eight models and a validation technique was applied to examine the spatial and temporal transferability of SPFs as well as the predictive abilities.

The transferability of a model refers to the degree to transfer the results can be generalized from a research setting to other contexts or settings (Trochim, 2006). In this case study, negative binomial regression is used to develop local SPFs and examine whether the method could be transferred and fit well to Iowa data as recommended by the HSM. The transferability is examined across space, time and both dimensions.

Ultimately, eight models were developed, including four simple models (i.e. using a subset of available variables) and four full models (i.e. containing all significant variables). The models were developed using two data subsets, Group_A and Group_B, during different analyzed time periods: 2012-2013 and 2015-2016. Four parts of these two subsets were used to develop SPFs and the results were utilized further to examine spatial and temporal transferability. Four cohorts of data were organized as follows:

- Group_A during 2012-2013(Group_A_{1213})
- Group_A during 2015-2016(Group_A_{1516})
- Group_B during 2012-2013(Group_B_{1213})
- Group_B during 2015-2016(Group_A_{1516})

The models were then used to develop SPFs. For each of these four cohorts, a "simple" and a "full" model were generated, making eight models in total. These are referred to as, for example, SPF_A_{1213_simple} and SPF_A_{1213_full} respectively representing the simple and full models for Group_A_{1213} data.

The transferability was examined among the models as well as across the models. SPFs developed using same subset were compared to each other by goodness-of-fit statistics to assess how well the model fit the data. The predictive ability and accuracy of prediction were evaluated by applying the SPFs to different validation sites. These sites were excluded from the model development. Next, the predicted values were directly compared to the actual observed values. The validation approaches are introduced subsequently and summarized in Table 4-2.

To examine the spatial transferability, the locations were changed. SPF_A_{1213_simple} and SPF_A_{1213_full} were applied to Group_B_{1213} data, while, SPF_B_{1516_simple} and SPF_B_{1516_full} were applied to Group_A_{1516} data. Under this experiment design, the predictive ability across space was assessed. Group A and B contain mutually exclusive groups of roadway segments randomly selected from the full segment set. The time periods used for developing SPFs and validation were the same (2012-2013 or 2015-2016).

To examine the temporal transferability, models developed under the earlier time series were applied to the later time series. Under this approach, SPF_A_{1213_simple} and SPF_A_{1213_full} were used to predict crash frequency of Group_A_{1516} data. Then SPF_B_{1213_simple} and

$SPF\_B_{1213\_full}$ were applied to $Group\_B_{1516}$ data. Thus, the locations were the same but the time periods were changed. The SPFs were developed using data from 2012-2013 and used to predict crashes expected to occur in year 2015-2016.

Spatial-temporal transferability was also examined using cross validation.$SPF\_A_{1516\_simple}$ and $SPF\_A_{1516\_full}$ were used to predict the crash frequency of $Group\_B_{1213}$ data; $SPF\_B_{1516\_simple}$ and $SPF\_B_{1516\_full}$ were applied to $Group\_A_{1213}$ data. This approach controlled the location and time period at the same time to examine the model performance using completely different datasets across both time and space. This is the most common situation encountered when using the HSM method for local SPF development.

Table 4-2: Transferability examination study approach design summary

Spatial transferability		
SPFs developed data	**Validated data**	**Model type**
Group_A during 2012-2013	Group_B during 2012-2013	Simple
Group_A during 2012-2013	Group_B during 2012-2013	Full
Group_B during 2015-2016	Group_A during 2015-2016	Simple
Group_B during 2015-2016	Group_A during 2015-2016	Full
Temporal transferability		
Group_A during 2012-2013	Group_A during 2015-2016	Simple
Group_A during 2012-2013	Group_A during 2015-2016	Full
Group_B during 2012-2013	Group_B during 2015-2016	Simple
Group_B during 2012-2013	Group_B during 2015-2016	Full
Spatial-temporal transferability		
Group_A during 2015-2016	Group_B during 2012-2013	Simple
Group_A during 2015-2016	Group_B during 2012-2013	Full
Group_B during 2015-2016	Group_A during 2012-2013	Simple
Group_B during 2015-2016	Group_A during 2012-2013	Full

This experiment design excludes the year 2014. On one hand, traffic information from 2017 was missing, so only five years of data could be obtained for this case study. On the other hand, considering the nature of SPF, when SPFs were generated using two-year periods of crash count data, the units would be crashes per mile per two years.

As recommended by the HSM, the standard form of an SPF for roadway segments can be expressed using one of the three following forms (American Association of State Highway and Transportation Officials (AASHTO), 2010) (Srinivasan et al., 2011):

$$N_{SPF} = L * e^{a+b*\ln(AADT)}$$

$$N_{SPF} = e^{a+b*\ln(AADT)+\ln(L)}$$

$$N_{SPF} = e^{a+b*\ln(AADT)+c*\ln(L)}$$

It can be expected that driving on longer segments results in longer exposure time than the shorter segment. In this case, the number of crashes can be expected to increase while driving on the roadway. Therefore, the third equation was an adjusted form of SPFs which was suggested in the study received acknowledge from transportation professionals where a and b are regression coefficients to be estimated using crash data, c is a parameter indicating the relationship between crash frequency and segment length. In this study, the length of the segment had been offset in log form, which meant that the crash frequency was predicted as crashes occurred on unit mile which was crash per mile per analyzed year period, and the equations can be simplified as follow:

Simple model: $N_{SPF} = e^{a+b*\ln(AADT)}$ (10)

Full model: $N_{SPF} = Exp(a + b * ln(AADT) + \sum_{\forall i} c_i * x_i)$ (11)

where c_i is the parameter estimate for variable x_i.

Goodness-of-fit measures are used to evaluate the ability of the models to represent the observed data. McFadden's pseudo R^2 was used that the intercept model's log likelihood was treated as squares total, and the full model's log likelihood was treated as total squared errors.

When comparing models on the same data, the McFadden R^2 would be higher for the model with the greater log likelihood. The likelihood is the occurrence probability resulted in given parameter estimates. The higher the likelihood is, the better the model. The Akaike Information Criterion (AIC) was used to evaluate the suitability of the models using the maximum likelihood concept. AIC describes the trade-off between variance and bias, and is calculated by:

$$AIC = -2LL + 2 \times N_P \tag{12}$$

where N_P is the number of parameters. The lower the AIC value, the better the model is because the number of parameters is a factor affecting the AIC, and effectively discourages overfitting of data by penalizing the addition of parameters. So the AIC can be used for comparing models with the same number of variables.

Because the analyzed facility was an Interstate highway system, the estimated models in this study may not capture the features as accurately as possible. In this case, simple model was necessary because the inclusion of more variables may increase the prediction errors. Previous studies suggest that simple models could be more effective for prediction. Better fit models were identified by seeking smaller AIC, higher McFadden R^2, and higher log likelihood.

Cross-validation is the process for out-of-example evaluation which can assess how the fit of a statistical analysis developed based on the independent dataset. The predictive accuracy of each model would be evaluated. In order to assess how good a prediction is that can be either measure the predictive accuracy per se or compare various predicted models. The process can validate the models through analyze the goodness of fit of the regression, check regression residuals, and check the predictive performance of models by being applied on the data which is not used in model development.

Mean absolute error (MAE) is a measure of difference between two continuous variables. It is an average of the absolute errors where μ_i is the actual observed crash count and y_i is the predicted value from developed SPFs. The equation is:

$$MAE = \frac{\sum_{i=1}^{n} |\mu_i - y_i|}{n}$$

Mean square error (MSE) is probably the most commonly used error metric. It penalizes larger errors because squaring larger numbers has a greater impact than squaring smaller numbers. The MSE is the sum of the squared errors divided by the number of observations. The equation is:

$$MSE = \frac{\sum_{i=1}^{n} (\hat{\mu}_i - y_i)^2}{n}$$

The Root Mean Square Error (RMSE) is simply the square root of the MSE.

These three metrics can be used for model validation. The MAE measures the average magnitude of the errors in a set of predictions, and it is the average over the test sample of the absolute differences between prediction and actual observed crash count where all individual differences have equal weight. The MSE is a measure of how close the predicted value fit the actual observed data. The smaller the MSE, the closer the fit is to the observed data. Additional, RMSE is the square root of the MSE which can be expressed as the average distance of a data point from the fitted point measuring along vertical axis. Both metrics can range from zero to infinite and the direction of errors are different. They ate negatively-oriented scores, which means the lower values are better.

CHAPTER 5. RESULTS AND DISCUSSION

5.1 Model results of developed SPFs

To examine the transferability of safety performance functions, SPFs first needed to be developed. As mentioned in the previous chapter, four "simple" SPFs were generated using SPFs which included only AADT and segment length as their variables. Four "full" SPFs were developed by including all of the significant variables. In this study, variables achieved at least 95% confidence were retained in the SPFs.

Table 5-1 and 5-2 show the model results using Group_A_{1213}. Treating segment length as offset, the units of were crashes per mile per analysis period. The estimated number of crashes from SPF_A_{1213_simple} was higher than SPF_$A_{1213_full.}$ The simple model showed that the crashes would increase by 1.36% if AADT increased by 1.0% and the full model presented an increase of 1.08% if AADT increased by 1.0%. When treating length as offset, the estimates of log (AADT) are generally close to 1, but the simple model had slightly higher estimates on log (AADT) and the full model estimate of log (AADT) was dropped within general range usually closed to 1.0. This was reasonable given that that simple model only includes length and AADT, and the full model contained all other potential variables which would tend to weaken and distribute the effect of AADT. In the full model, speed limit at 55 mph and 65 mph had positive estimates compared to the base condition with speed limit at 70 mph. The positive estimates indicated that those variables would increase the crash frequency. Since this study did not separate urban and rural areas, the results more likely implied the effect of the area where the segments were located. Urban areas usually have speed limits below 70 mph (a posted speed limit of 55 mph is common). Variables regarding asphalt surface and hard median also indicated urban locations, higher volume demand and more complex traffic transit situations resulting in higher crash frequency. In addition, segments with cable median barriers had positive value of coefficient estimates which indicated those segments had higher crash frequencies. Cable median barriers were installed on those segments as a countermeasure to decrease crash severity, and drivers driving on those segments with cable median barriers installed were more likely to occur crashes. To identify the better fit model between these two models, the higher McFadden R^2 of 0.163, and the higher values of log-likelihood and lower AIC indicate that the full model performs better than the simple model.

Table 5-1: Model results using Group_A_{1213}

SPF_A_{1213_simple}					
Coefficients:	**Estimate**	**Std. Error**	**Z value**	**Pr(>|z|)**	
(Intercept)	-11.249	0.44836	-25.09	<2e-16	***
log(Ave_AADT_1213)	1.36425	0.04391	31.07	<2e-16	***

AIC	4806.5	Std.Err	0.268		
Theta	3.229	McFadden R^2		0.150934	
2 x log-likelihood	-4800.52				
SPF_A_{1213_full}					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-8.8128	0.73787	-11.94	< 2e-16	***
log(Ave_AADT_1213)	1.08255	0.07248	14.936	< 2e-16	***
Speed limit_55	0.73308	0.11559	6.342	2.27E-10	***
Speed limit_60	0.34223	0.18001	1.901	0.057275	.
Speed limit_65	0.25781	0.0721	3.576	0.000349	***
Speed limit_70 (base condition)	N/A	N/A	N/A	N/A	
Surface_Asphalt	0.16571	0.04947	3.35	0.000809	***
Rumble_installed_R	0.19655	0.14411	1.364	0.172593	
Rumble_installed_L	0.03747	0.1446	0.259	0.795558	
Shoulder_present_R	-0.16185	0.26717	-0.606	0.544637	
Shoulder_present_L	0.05065	0.21714	0.233	0.815572	
Cable_barrier_Installed	0.19147	0.06174	3.101	0.001928	**
Median_surface_hard	0.29576	0.11712	2.525	0.01156	*
Transition_zone	0.12148	0.06284	1.933	0.053241	.

Table 5-2: Model results using Group_A1213 (Continued)

AIC	4759	Std.Err	0.329	
Theta	3.729	McFadden R^2		0.163234
2 x log-likelihood	-4730.98			
*p<0.05, **p<.01, ***p<.001				

$SPF\_A_{1516\_simple}$ and $SPF\_A_{1516\_full}$ are presented in Table 5-3. In addition to the variables mentioned previously such as speed limit at 55 mph and 65 mph, asphalt surface and concrete median surface were associated with higher crash frequency. Cable median barrier installation was also associated with higher crash frequency. Right side rumble strip installation was captured with a positive estimate, implying that they also have an increasing effect on crash frequency. The rumble strips installed along the edges of the roadway can inform fatigued or distracted drivers when they are about to leave the travel lanes. The positive estimate here is still reasonable, since drivers on those particular segments are more likely to drive off the roadway, and rumble strips were installed as a countermeasure. Within these two models, the full model still had better performance with better GOF results. Recall the database was assembled at segment level, and geometric features were assumed unchanged throughout analyzed five years. SPF_A_{1213} and SPF_A_{1516} all used Group_A data and this meant the sample size of these four models were the same, and changed variables were average AADT values and actual crashes observed on those segments. The McFadden R^2 values for the 2015-2016 models are similar to the 2012-2013 models, but the AIC and log-likelihood of $SPF\_A_{1516\_full}$ was much higher than model $SPF\_A_{1213\_full}$. The model results were different because of the model complexity as well as the different exposure even using the same data group.

Table 5-3: Model results using Group_A_{1516}

SPF_A_{1516_simple}					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-11.363	0.48022	-23.66	<2e-16	***
log(Ave_AADT_1516)	1.33759	0.04657	28.72	<2e-16	***

AIC	4390.7	Std.Err	0.304		
Theta	3.228	McFadden R^2		0.1498	
2 x log-likelihood	-4386.7				
SPF_A_{1516_full}					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-8.2094	0.78312	-10.483	< 2e-16	***
log(Ave_AADT_1516)	1.02836	0.07643	13.455	< 2e-16	***
Speed limit_55	0.47348	0.12463	3.799	0.00015	***
Speed limit_60	0.08094	0.19267	0.42	0.67441	
Speed limit_65	0.3423	0.07531	4.545	5.48E-06	***
Speed limit_70 (base condition)	N/A	N/A	N/A	N/A	
Surface_Asphalt	0.13734	0.05255	2.614	0.00896	**
Rumble_installed_R	0.33705	0.14755	2.284	0.02235	*
Rumble_installed_L	-0.2017	0.14726	-1.37	0.17068	
Shoulder_present_R	-0.3955	0.27197	-1.454	0.14589	
Shoulder_present_L	-0.0331	0.22516	-0.147	0.88331	
Cable_barrier_Installed	0.19294	0.0658	2.932	0.00337	**
Median_surface_hard	0.29175	0.12158	2.4	0.01641	*
Transition_zone	0.142	0.06687	2.124	0.03369	*

AIC	4358	Std.Err	0.379		
Theta	3.738	McFadden R^2		0.16039	
2 x log-likelihood	-4330				
*p<0.05, **p<.01, ***p<.001					

SPF_B_{1213_simple} and SPF_B_{1213_full} used data from Group_B_{1213} and the results are shown in Table 5-4. The full model captured more variables, achieving 95% confidence, and the estimate of AADT and intercept had larger differences from the simple model's estimates. The estimate of intercept was -11.09 in the simple model and -6.23 in the full model. In addition, if the AADT increased by 1.0%, the crashes are predicted by the simple model to increase by 1.35% and are predicted by the full model to increase by 0.95%. Compared to the base condition, speed limit at 70 mph and speed limit at 60 had positive estimates which indicted an increasing effect on crash frequency. Right shoulder presence had a negative estimate and p-value smaller than 0.001 which indicated that the segments with right shoulders had significantly lower crash frequencies. This makes sense considering that right shoulders increase the clear zone for errant vehicles and can thus prevent crashes from occurring. The transition zone obtained a positive estimate, indicating an increasing effect on crash frequency. Transition zones include exit and entrance lanes. Thus, there are more complex driving activities and traffic conditions occurring in those sections, leading to higher crash frequencies. SPF_B_{1213_simple} performed the weakest among all eight models and fit the data with the highest AIC and lowest log-likelihood.

Table 5-4: Model results using Group_B_{1213}

SPF_B_{1213_simple}					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-11.09	0.4527	-24.5	<2e-16	***
log(Ave_AADT_1213)	1.3544	0.0444	30.5	<2e-16	***

AIC	4917.5	Std.Err	0.217		
Theta	2.676	McFadden R^2		0.13804	
2 x log-likelihood	-4911.5				

SPF_B_{1213_full}					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-6.2357	0.68798	-9.064	< 2e-16	***
log(Ave_AADT_1213)	0.95995	0.06904	13.904	< 2e-16	***
Speed limit_55	0.65527	0.1088	6.023	1.72E-09	***
Speed limit_60	0.3304	0.13942	2.37	0.0178	*
Speed limit_65	0.38392	0.07267	5.283	1.27E-07	***
Speed limit_70 (base condition)	N/A	N/A	N/A	N/A	
Surface_Asphalt	0.11484	0.04959	2.316	0.0206	*
Rumble_installed_R	0.23489	0.1446	1.624	0.1043	
Rumble_installed_L	-0.2637	0.14218	-1.855	0.0636	.
Shoulder_present_R	-1.0522	0.26433	-3.981	6.88E-05	***
Shoulder_present_L	-0.2033	0.19153	-1.061	0.2885	
Cable_barrier_Installed	0.3034	0.06136	4.945	7.63E-07	***
Median_surface_hard	0.17863	0.11069	1.614	0.1066	
Transition_zone	0.24262	0.05928	4.093	4.26E-05	***

AIC	4757.24	Std.Err	0.324		
Theta	3.704	McFadden R^2		0.16511	
2 x log-likelihood	-4757.2				

*p<0.05, **p<.01, ***p<.001

The last two model results developed by using Group_B_{1516} are summarized in Table 5-5 and 5-6. Similar to the previous models, speed limit at 55 mph and speed limit at 65 mph also were found to increase crash frequency. Similar results were also seen for cable median barrier installation and transition zone indicator variables. In this model, the presence of a left shoulder was found to be significant, with a negative estimate indicating that a left shoulder decreased the number of crashes. This can be attributed to a greater clear zone, similar to a right shoulder. SPF_B_{1516_simple} and SPF_B_{1516_full} indicated better fits of data by obtaining higher values of McFadden's R^2. Models developed using data from 2015-2016 performed better than models based on data during 2012-2013. That could be identified from the values of AICs and log-likelihoods. Although the goodness-of-fit values were similar, the full model still performed slightly better than simple model. Finally, Table 5-5 summarizes the results of estimates from model to model. The differences of each variable's estimate among all eight SPFs can compared.

Table 5-5: Model results using Group_B_{1516}

SPF_B_{1516_simple}					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-12.372	0.443	-27.93	<2e-16	***
log(Ave_AADT_1516)	1.43573	0.04282	33.53	<2e-16	***

AIC	4287.1	Std.Err	0.384		
Theta	3.901	McFadden R^2		0.17484	
2 x log-likelihood	-4281.1				

Table 5-6: Model results using Group_B1516 (Continued)

SPF_B1516_full					
Coefficients:	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	
(Intercept)	-8.5701	0.71808	-11.935	< 2e-16	***
log(Ave_AADT_1213)	1.10889	0.06994	15.855	< 2e-16	***
Speed limit_55	0.44134	0.10781	4.094	4.25E-05	***
Speed limit_60	0.0424	0.14061	0.302	0.76299	
Speed limit_65	0.46585	0.07195	6.474	9.54E-11	***
Speed limit_70 (base condition)	N/A	N/A	N/A	N/A	
Surface_Asphalt	0.09402	0.04977	1.889	0.05887	.
Rumble_installed_R	0.09833	0.13776	0.714	0.47537	
Rumble_installed_L	-0.1939	0.13672	-1.418	0.15621	
Shoulder_present_R	-0.311	0.24896	-1.249	0.21156	
Shoulder_present_L	-0.3645	0.1847	-1.973	0.04845	*
Cable_barrier_Installed	0.15996	0.06214	2.574	0.01004	*
Median_surface_hard	0.08009	0.10775	0.743	0.45728	
Transition_zone	0.18607	0.06042	3.08	0.00207	**

AIC	4217.3	Std.Err	0.516		
Theta	4.802	McFadden R^2		0.19253	
2 x log-likelihood	-4189.3				
*p<0.05, **p<.01, ***p<.001					

Table 5-7: Model to model estimate results summary table

	$SPF\_A_{1213\_simple}$	$SPF\_A_{1516\_simple}$	$SPF\_B_{1213\_simple}$	$SPF\_B_{1516\_simple}$
Coefficients:	**Estimate**	**Estimate**	**Estimate**	**Estimate**
(Intercept)	-11.24904	-11.36313	-11.0904	-12.37243
log(Ave_AADT_1213)	1.36425	1.33759	1.3544	1.43573

	$SPF\_A_{1213\_full}$	$SPF\_A_{1516\_full}$	$SPF\_B_{1213\_full}$	$SPF\_B_{1516\_full}$
Coefficients:	**Estimate**	**Estimate**	**Estimate**	**Estimate**
(Intercept)	-8.8128	-8.20942	-6.23572	-8.57009
log(Ave_AADT_1213)	1.08255	1.02836	0.95995	1.10889
Speed limit_55	0.73308	0.47348	0.65527	0.44134
Speed limit_60	0.34223	0.08094	0.3304	0.0424
Speed limit_65	0.25781	0.3423	0.38392	0.46585
Speed limit_70 (base condition)	N/A	N/A	N/A	N/A
Surface_Asphalt	0.16571	0.13734	0.11484	0.09402
Rumble_installed_R	0.19655	0.33705	0.23489	0.09833
Rumble_installed_L	0.03747	-0.20174	-0.26371	-0.19386
Shoulder_present_R	-0.16185	-0.39549	-1.05216	-0.31103
Shoulder_present_L	0.05065	-0.03305	-0.2033	-0.36449
Cable_barrier_Installed	0.19147	0.19294	0.3034	0.15996
Median_surface_hard	0.29576	0.29175	0.17863	0.08009
Transition_zone	0.12148	0.142	0.24262	0.18607

5.2 Validation analysis

The validation results are shown and summarized in Table 5-6 below. The three approaches were conducted to examine the transferability of SPFs across time and space and both dimensions. After developing SPFs using different datasets, the coefficients were used to form the standard SPF equations using either equation 10 or 11. The predicted results were directly compared to the actual observed results. Since segment length was treated as offset, the actual predicted value for each analyzed segment should use the calculation results from either equation 10 or 11 and then multiply its actual segment length. $SPF\_A_{1213\_simple}$ was used as an example, the equation 10 was used as the basic form of SPF, and the expression could be expressed as:

N_{SPF}= [exp (-11.249+1.36425*ln ($AADT_{avg}$))] × *L*,

where $AADT_{avg}$ is the average AADT of the individual AADTs over the analysis period and *L* is the segment length. Where two years of data was used to generate SPF, the units of the predicted results after multiplying in the segment length work out to be crashes per analysis period per segment (rather than per mile). To assess the predictive power and prediction accuracy, MAE, MSE, RMSE were calculated. These metrics were introduced in the previous chapter.

To examine the models' spatial transferability, $SPF\_A_{1213\_simple}$ and $SPF\_A_{1213\_full}$ were applied to $Group\_B_{1213}$ data and directly compared to the observed number of crashes. Similarly, $SPF\_B_{1516\_simple}$ and $SPF\_B_{1516\_full}$ were applied to $Group\_A_{1516}$ data.

$SPF\_A_{1213\_simple}$ had the closest predicted result of 5818.88 compared to an observed number of crashes of 5593. Meanwhile, $SPF\_B_{1516\_simple}$ resulted in the smallest MAE and RMSE values. Among the four model results, full models obtained better performance than simple model in terms of their GOF coefficients (i.e. higher McFadden R^2) , but in validations across space series data, the predicted ability of simple models performed better.

Next, the temporal transferability was examined. The locations of the sites were controlled and the predicative ability was assessed by applying models to different time series. $SPF\_A_{1213\_simple}$ and $SPF\_A_{1213\_full}$ were used to predict the crash frequency for 2015-2016 for Group_A data, while $SPF\_B_{1213\_simple}$ and $SPF\_B_{1213\_full}$ were applied to predict the crash frequency of Group_B data for 2015-2016. Zooming in to the individual segment relationships, MAE and MSE were generally higher than those observed for the spatial validation tests. The predicted results of Group_B_{1516} were more spread out that Group A_{1516}. Also, all four models overpredicted the crash frequency, and resulted in higher predictive errors.

Finally, spatial-temporal transferability was examined by controlling site locations and predictive year periods. For this activity, cross-validation process was used. SPF_A_{1516_simple} and SPF_A_{1516_full} were applied to Group_B_{1213} data, and SPF_B_{1516_simple} and SPF_B_{1516_full} were applied to Group_A_{1213} data. The simple models tended to under-predict the values, and the full models were more likely to over-predict the values. SPF_B_{1516_simple} had the closest predicted value at 4030.71 compared to the observed value of 4184. The full models had better performance in fitting the data, but their predictive accuracy was not better than the simple models. Interestingly, the simple models had smaller MAEs but higher MSEs/RMSEs. Overall, SPF_B_{1516_full} obtained the best results with relatively small predictive coefficients.

To further compare the models, a calibration process was conducted. This is a reverse process to regression where the observation values of the dependent variables are known and used to predict a corresponding explanatory variable (Upton and Cook, 2006) Table 5-7 provides the calibrated validation results; the predicted value of each segment was calibrated by multiplying a calibration factor. The calibration factor was the ratio of the observed and predicted values. In this case, the total predicted value equaled the observed value.

After calibration, the MAEs of predicted results using the same dataset became the same when examining spatial transferability. Also, MAEs and RMSEs were close to each other under the same settings. The full models obtained better performance in both data fitting and prediction. Regarding the temporal transferability, the MAEs were similar, and RMSEs occurred minor differences. When transferred the model across time in this case study. This might be attributable to the increase in AADT from 2012-2013 to 2015-2016 (see Table 5). The mean difference of AADT between these two periods was almost 3000 per segment. The calibrated results of spatial-temporal transferability were not uniform. Both metrics existed differences between simple and full models using the same subset. Compared uncalibrated results to calibrated results, similar MAEs between estimation and validation sites indicated a strong support for transferability. The MAEs obtained from spatial transferability analysis were relatively similar compared to temporal transferability. Simple models more likely to be transferred because of the small differences between MAEs. Besides, the difference of MAEs more likely depend on how well the models fitting the data. Like mentioned previously, the models fit data during 2015-2016 better than data during 2012-2013.

Overall, these three approaches examined the model transferability. The default assumption of this case study was the geometric features remained the same through these five years. Consequently, the spatial transferability was the most stable, and the spatial-temporal transferability came to the second. In contrast, temporal transferability became stable after calibration. The subject of spatial and temporal correlation was discussed in previous research, and it was observed that temporal correlation could result in incorrect estimation. This examination could be improved, and the issue could be addressed in the future study by improving the models.

Table 5-8: Validation results for uncalibrated models

Spatial transferability				
	SPF_A$_{1213_simple}$	SPF_A$_{1213_full}$	SPF_B$_{1516_simple}$	SPF_B$_{1516_full}$
Validated sites	Group_B$_{1213}$	Group_B$_{1213}$	Group_A$_{1516}$	Group_A$_{1516}$
Actual observed	5593	5593	4184	4184
Total predicted	5818.88	5028.63	4556.51	6256.91
MAE	2.93	2.74	2.29	3.05
MSE	24.88	23.52	14.64	27.23
RMSE	4.99	4.85	3.83	5.22
Temporal transferability				
	SPF_A$_{1213_simple}$	SPF_A$_{1213_full}$	SPF_B$_{1213_simple}$	SPF_B$_{1213_full}$
Validated sites	Group_A$_{1516}$	Group_A$_{1516}$	Group_B$_{1516}$	Group_B$_{1516}$
Actual observed	4184	4184	4259	4259
Total predicted	6583.10	5605.58	6925.74	7661.40
MAE	3.35	2.70	3.48	3.99
MSE	31.20	21.78	32.60	43.57
RMSE	5.59	4.67	5.71	6.60
Spatial-temporal transferability				
	SPF_A$_{1516_simple}$	SPF_A$_{1516_full}$	SPF_B$_{1516_simple}$	SPF_B$_{1516_full}$
Validated sites	Group_B$_{1213}$	Group_B$_{1213}$	Group_A$_{1213}$	Group_A$_{1213}$
Actual observed	4259	4259	4184	4184
Total predicted	3927.88	7003.54	4030.71	5698.72
MAE	2.84	3.37	2.63	2.68
MSE	27.25	35.49	23.65	19.46
RMSE	5.22	5.96	4.86	4.41

Table 5-9: Validation results for calibrated models

Spatial transferability				
	SPF_A$_{1213_simple}$	SPF_A$_{1213_full}$	SPF_B$_{1516_simple}$	SPF_B$_{1516_full}$
Validated sites	Group_B$_{1213}$	Group_B$_{1213}$	Group_A$_{1516}$	Group_A1516
Actual observed	5593	5593	4184	4184
Calibration factor	0.961	1.112	0.918	0.669
MAE	2.882	2.836	2.184	2.143
MSE	24.215	24.079	13.338	11.900
RMSE	4.921	4.907	3.652	3.450
Temporal transferability				
	SPF_A$_{1213_simple}$	SPF_A$_{1213_full}$	SPF_B$_{1213_simple}$	SPF_B$_{1213_full}$
Validated sites	Group_A$_{1516}$	Group_A$_{1516}$	Group_B$_{1516}$	Group_B$_{1516}$
Actual observed	4184	4184	4259	4259
Calibration factor	0.636	0.746	0.615	0.556
MAE	2.172	2.171	2.170	2.181
MSE	12.906	12.906	13.148	14.634
RMSE	3.593	3.592	3.626	3.825
Spatial-temporal transferability				
	SPF_A$_{1516_simple}$	SPF_A$_{1516_full}$	SPF_B$_{1516_simple}$	SPF_B$_{1516_full}$
Validated sites	Group_B$_{1213}$	Group_B$_{1213}$	Group_A$_{1213}$	Group_A$_{1213}$
Actual observed	4259	4259	4184	4184
Calibration factor	1.084	0.608	1.038	0.734
MAE	2.796	2.845	2.601	2.626
MSE	25.582	29.011	22.929	21.014
RMSE	5.058	5.386	4.788	4.584

CHAPTER 6. CONCLUSIONS AND LIMITATIONS

6.1 Summary of Findings

This study utilized negative binomial regression models to develop safety performance functions for the Iowa interstate system. Data for the entire system were collected for calendar years 2012-2013 and 2015-2016. These data were randomly halved and disaggregated into these two-year periods, resulting in four datasets of equal size. Separate models were then estimated for each dataset and a cross-validation approach was used to examine the model transferability over time, across space, and with respect to both dimensions. The predictive ability of each developed SPF was evaluated as a part of model validation. Each segment contained traffic information, basic roadway and roadside features and crash counts. The total crash counts for each two-year period were used as the dependent variable, segment length was treated as an offset (implying that crashes increase proportionately with respect to segment length), and annual average daily traffic (AADT) was log-transformed. All other included variables were converted into binary indicators. The roadway and roadside features were assumed to be the same during the analysis period from 2012 to 2016. Two different models were estimated for each of the four datasets. This included a simple model, which considered only segment length and AADT, as well as full models that included a range of geometric variables, as well.

Overall, among these eight models, the performance of full models was generally better than simple model, as indicated by a lower Akaike Information Criterion (AIC) and higher log-likelihood and R^2 values. Although the temporal comparison assessed models generated using the same predictors, aside from changes in crashes and traffic volumes, the goodness-of-fit was markedly different between the two models. For example, for the four models derived using data from Group_A, although the intercepts and estimates were similar, the AIC for the models estimated from data during 2015-2016 was significantly better than the models estimated using 2012-2013 data. Regarding the full models, the common significant variables were speed limit at 55 and 65 mph, asphalt surface, and transition zones. Segments with cable median barrier installed also showed higher crash frequencies. The model results were slightly different among these four full models based on different exposures, some roadside features such like shoulder presence and rumble strip installation were captured in the models.

Three approaches were used to examine the model transferability across space, time, and both dimensions simultaneously. To examine the spatial transferability, SPFs were estimated for each subset of the data over the same two-year periods (i.e., 2012-2013 and 2015-2016). The results from each SPF were then used to assess the predictive ability on the other sample (i.e., across different spatial locations). The predicted values were directly compared to actual observed values, and mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) were calculated to assess the predictive ability and goodness-of-fit on the validated dataset. Similarly, temporal transferability was examined by estimating SPFs within the same half of the dataset for each of the two time intervals. These models were then used to predict the crash frequency for the same data subset under the other two-year analysis period. This allowed for an examination of the transferability of the parameter estimates over time (i.e., the temporal stability of the parameters).

When considering spatial transferability, it is interesting to note that simple models, which considered only AADT, showed better prediction capabilities as evidenced by smaller MAE, MSE, and RMSE values when applied to the other (validation) dataset. This may be due in part to the fact that the roadway geometry was uniform across the two periods. Overall, transferability across space showed relatively stable estimates.

However, performance was much poorer when considering temporal transferability. When conducting model validation, all the model results tended to significantly over predict when applied to the other subsample. Ultimately, the results of the calibration exercise showed significant variables in the estimates between and among groups. This is largely reflective of the fact that crashes declined considerably between 2012-2013 and 2015-2016.

It was surprising to see that the comparison of spatial-temporal transferability showed better predictive capability than when considering only temporal transferability. However, the converse was true when the models were calibrated to adjust for the degree of overall over (under) prediction of the respective models.

These results provide several important insights that reinforce the broader literature in this area. When applying SPFs, agencies are strongly recommended to either develop their own state-specific models or, at minimum, to calibrate the existing models from the Highway Safety Manual. In either case, it is critical that the underlying dataset is designed carefully and is representative of the broader set of locations to which the SPFs are to be applied. There is a strong argument to be made for simpler models. As design standards on interstate facilities are relatively stable and the geometric design features are typically quite uniform, applying simple AADT-only models is likely to provide acceptable performance when applying the results to other locations based upon the assessment of spatial transferability.

Ultimately, agencies are encouraged to conduct these types of validation exercises across both space and time in order to obtain more accurate and stable predicted values. Although outside the scope of this study, potential concerns exist as to correlation of the spatial and temporal dimensions, and further explorations of the effects of time should be conducted to address the issue.

In conclusion, the transferability of SPFs was not found to be consistent across time and space. Overall, the predictive capability was different across each of the validation scenarios. From the eight developed SPFs and the validation results, agencies are recommended to carefully consider the application of existing SPFs when conducting planning level or network screening analyses.

6.2 Limitations and Future Research

This section discusses the limitations of this study and the potential improvements that could be done in future. Data quality is a principal limitation when developing and applying SPFs. This study leveraged information from the Geographic Information Management System (GIMS) database. This database is being phased out by the Iowa DOT and replaced by the Roadway Asset Management System (RAMS). As a consequence, it is possible that higher fidelity and more timely geometric information in RAMS would allow for a more meaningful examination of performance differences between a simple, AADT-only model and a more complex model that considers a range of other important predictors.

Even with the new database, quality assurance and quality control procedures are critically important. For example, over the course of this study, issues were identified with various pieces of information, including data on median widths and surface widths, each of which are particularly important. There were various instances of erroneous data, which were ultimately filtered out prior to conducting the analysis. There were a variety of potentially interesting relationships that could not explored given the difficulty in integrating information from various data sources. Cases like interchanges or ramps could be considered separately when assembling the database. A previous study (Oh et al., 2003) discussed internal validation for a rural intersection that indicated the crash models potentially experience omitting variables that would affect safety （i.e. potential correlations between variables) Data standardization as well as collection practices needed to be improved. This issue could be addressed by using smaller scale (i.e., more precise) data. Regarding the sample size, currently, the database contained all segments of Iowa interstate system (2050 segments). For this study, Group_A and Group_B were randomly divided into groups of 1025 segments each. Instead of randomly selecting 50%, smaller percentages could be used to narrow down the sample size to assess how goodness-of-fit varies when considering smaller subsets of the data. Transferability could also be compared across smaller geographic regions, such as Iowa DOT districts. Additional areas of exploration could include assessing appropriate sample size recommendations, including determining lower bounds of sample size to obtain certain levels of precision. This would also require consideration of related issues, such as minimum segment length, and the degree to which features on each segment are homogeneous.

Refinements of segment definitions are recommended for some applications. For example, instead of conducting an analysis on the entire Interstate system, the study could focus on particular highways (e.g., I-80 and I-35), segments in urban areas, corridors located in specific counties, and so on. This would allow for a comparison of how sensitive model results are at a finer spatial level.

Also, the site selection process could be improved. Instead of using R studio code to randomly select samples in consideration of various descriptive statistics for each group, group selection could be conducted spatially using tools like ArcGIS to ensure the sites were located within similar regions.

Lastly, this case study used only negative binomial regression model as its statistical model for developing SPFs. As seen in related research in the literature review, additional models could be considered besides negative binomial regression. Some of these, such as random effects models, may result in models with better spatial and temporal transferability.

CHAPTER 7. REFERENCES

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