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Evaluating the Interactive Effects of Traffic Volumes and Access Density on Crash Frequency

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EVALUATING THE INTERACTIVE EFFECTS OF TRAFFIC VOLUMES

AND ACCESS DENSITY ON CRASH FREQUENCY

BY

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AND ACCESS DENSITY ON CRASH FREQUENCY

This thesis is approved as a credible and independent investigation by a candidate for the Master of Science in Civil Engineering degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AD	Access Density
CMF	Crash Modification Factor
DOT	Department of Transportation
FHWA	Federal Highway Administration
HSIS	Highway Safety Information Safety
HSM	Highway Safety Manual
ITE	Institute of Transportation Engineers
MnDOT	Minnesota Department of Transportation
NB	Negative Binomial Regression
QRI	Qualitative Reading Inventory
RPNB	Random Parameter Negative Binomial
TRB	Transportation Research Boards
US	United States of America

ABSTRACT

EVALUATING THE INTERACTIVE EFFECTS OF TRAFFIC VOLUMES AND ACCESS DENSITY ON CRASH FREQUENCY

ALI ALSUBEAI

2017

Control of access points (e.g., driveway density) is an important consideration in roadway access management. Research has shown that by limiting the number of access points, there is a reduction in the number of conflict points along a roadway, resulting in improved safety. The effects of managing access points on crash frequency are documented as Crash Modification Factors/Functions (CMF) in the Highway Safety Manual (HSM) and the federal Highway Administration's CMF Clearinghouse. The CMFs from the HSM indicate that the impacts of Access Density (AD) on crash frequency are a function of both AD and traffic volume (for rural roads). It does not include traffic volume in the CMFs for urban roads. Although the function could be calculated manually, both AD and traffic volume data from research in this thesis were compared to the ranges provided on the CMF Clearinghouse website. The function is available from the CMF Clearinghouse website, but it does not show the interactive effects of AD and traffic volume, and the majority of CMFs do not provide associated confidence intervals. The objectives of the current research were to develop CMFs for

AD, as well as associated confidence intervals through time for various towns and cities in Minnesota. The data used was collected and provided by the following: (1) Highway Safety Information Systems (HSIS) over a period of five years at the same sites, (2) the Institute of Transportation Engineers (ITE), (3) and Google Earth. The methodology used in this study was cross-sectional longitudinal with multivariate statistical analysis. Multiple functional classifications of urban roadways were considered, with a focus on major/minor collectors and minor arterials. The CMFs were developed for total number of crashes, fatal, injury, rear-end, and side-swipe crashes. The interaction between AD and traffic volume was considered. Confidence intervals for the resulting CMFs were determined. The results of this research will be useful for engineers and planners in determining when AD should be changed or limited.

CHAPTER 1: INTRODUCTION

1.1 Background

According to the Institute of Transportation Engineers, access management may be described as follows:

> *. . . the process or development of a program intended to ensure that the major arterials, intersections and freeway systems serving a community or region will operate safely and efficiently while adequately meeting the access needs of the abutting land uses along the roadway. The use of access management techniques is designed to increase roadway capacity, manage congestion and reduce crashes.* (Institute of Transportation Engineers, 2004, p. 1)

Access management is a proven method for maintaining and improving roadway capacity; traffic flow; and the safety of traffic, pedestrians, and bicyclists on rural and urban highways and streets (Gluck & Lorenz, 2010). Improvements to operational efficiency and safety lead to reductions in transportation costs. Reductions in delay and improvements to traffic flow also reduce vehicle emissions, reducing the environmental impacts of transportation. Research has shown that access management related improvements to traffic operations and safety have a positive impact on the local economy (Benz, et al., 2015). One of the most basic access management methods is controlling access density. This can be accomplished by the following.

1. Managing access ingress and egress to driveways (Figure 1.1)

2. Using frontage roads (Figure 1.2)

3. Requiring driveways to access side roads or alleys

4. Using combined/shared driveways.

These methods can be applied in both urban and rural settings. The ability of engineers and planners to predict safety outcomes related to access density is essential in determining when control of access points should be implemented. It is also important in communicating the benefits of access management to stakeholders including local governments, businesses, and property owners.

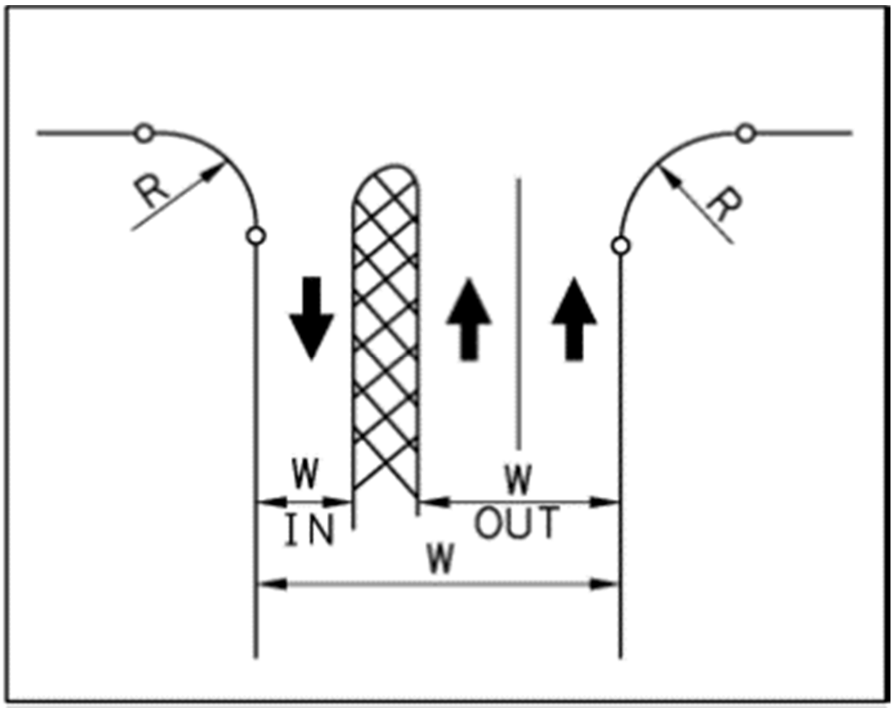


Figure 1.1. Managing ingress and egress to roadways
(after Garcia, 2014, p. 91)

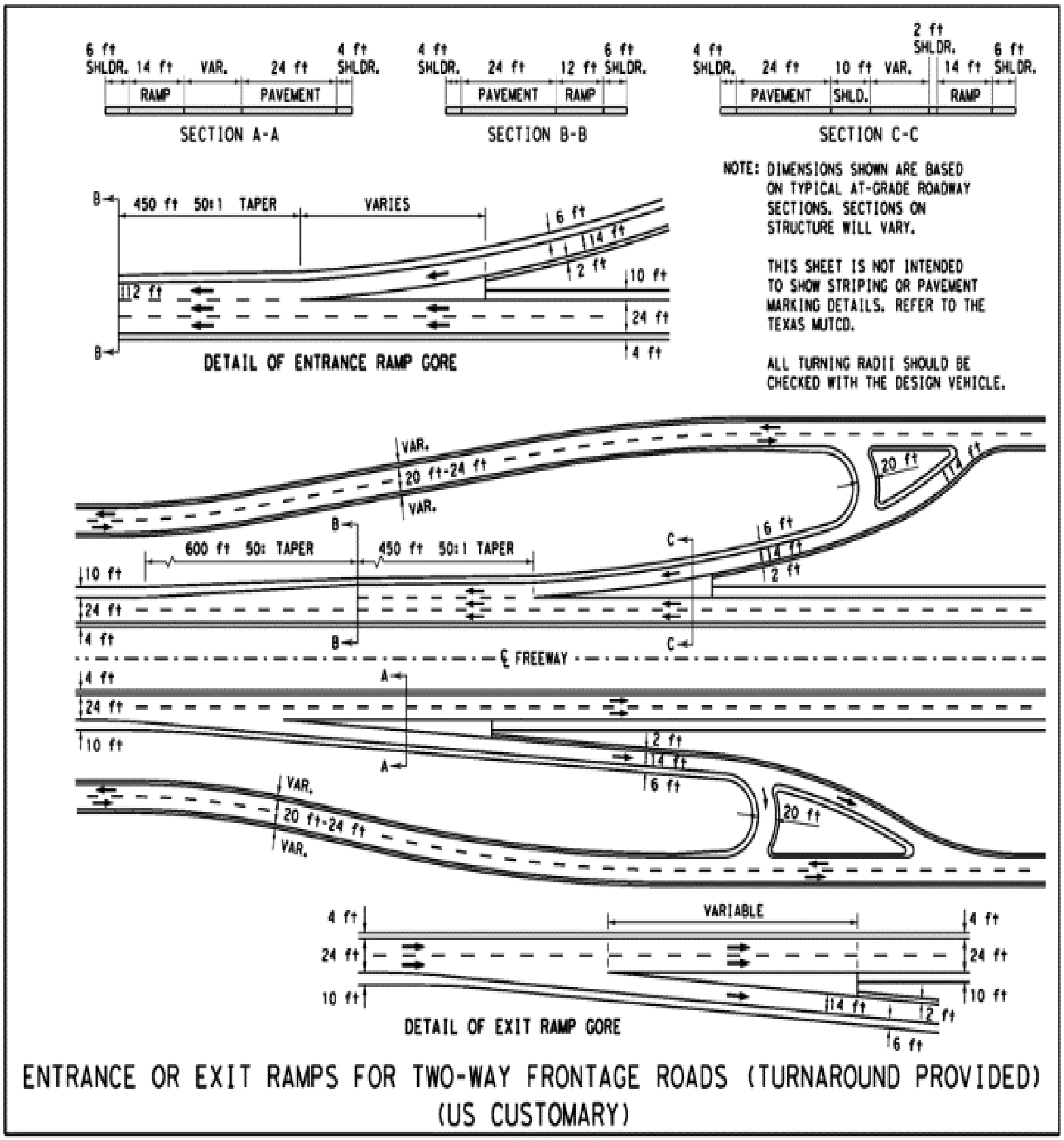


Figure 1.2. Using frontage roads adjacent to freeways
(after Garcia, 2014, p.137)

1.2 Scope and Objectives

The objective of this research is to develop CMFS for AD using data from Minnesota over a five-year period. Multiple functional classifications of urban roadways will be considered with a focus on major/minor collectors and minor arterials. CMFS will be developed for total, fatal and injury, multiple vehicle collision, and traffic Crash occurrences on a driveway access. The interaction between AD and traffic volume will be considered. Confidence intervals for the resulting CMF will also be provided. It is anticipated that the results of this research will be useful for engineers and planners in determining when AD should be changed or limited.

CHAPTER 2: LITERATURE REVIEW

2.1 General Review

It is important to understand how transportation engineers use the concept of Crash Modification Factors/Functions (CMFs), and that information is presented first in this section. Presented next are other important concepts: the impact of traffic volume on crash frequency and the importance of access density. That is followed by research sources that recognize increasing traffic density and volume that is becoming a worldwide problem, with some examples in the United States (US). This section concludes with results of a traffic volume study that was similar to the research that is the subject of this thesis, although that study and the current study each have slightly different variables.

2.1.1 CMFs

The effects of several access management methods on crash frequency are documented as Crash Modification Factors/Functions (CMFs) in the Highway Safety Manual (Gluck & Lorenz, 2010) and in the Federal Highway Administration's (2017) CMF Clearinghouse. The CMFs indicate the relative change in crash frequencies compared to base conditions with a value of 1 indicating no change, a value smaller than 1 indicating a crash reduction, and a value larger than 1 indicating an increase in crash frequency. The CMF Clearinghouse provides a quality rating of CMFs based on evaluations of the study design, sample size, standard error, potential bias, and the diversity of the data (i.e., if the data includes locations from more than a single state). The ratings range from one-star (the lowest rating) to Five-stars (the highest rating). The

CMFs from the CMF Clearinghouse include the following treatments related to driveway density:

1. Closure or relocation of all driveways from the functional area of an intersection (CMFs of 0.93-1.17 for total crashes and 1.41-1.67 for fatal and injury crashes, with one-star quality ratings) (Lall, 1995); and
2. Modifying access point density (a function of access point density and traffic volume, the quality is typically unrated) (Mauga & Kaseko, 2010).

The majority of CMFs are available in the CMF Clearinghouse (Federal Highway Administration, 2017) for predicting changes in safety related to driveway density, are low quality or are unrated. A search for literature related to the safety impacts of rural access control found research that used crash rate analysis (Gattis et al., 2005), which is known to result in biased estimates (Hauer, 1995). Other evaluations of the safety impacts of access management in the literature, with the majority focusing on the density of access points (Gross, et al., 2013), also used crash rate analysis. Overall, managing driveway access density reduces both the number and severity of crashes. There is a gap in the literature for research into the interaction between access density and traffic volume related to crash frequency.

2.1.2 Research sources that recognize increasing traffic density and volume that is becoming a worldwide problem

The impacts of driveway access management on traffic operations has been shown to have several benefits in most cases within two major categories: 1) reductions in speed variation and 2) total network travel timesaving (Gluck & Lorenz, 2010). While access management treatments may result in increased travel distances, the increase in overall traffic speeds and decreased variation in traffic speeds typically lead to lower overall travel times, although not true in every case. The specific benefits related to differences in total network travel time are specific to each application and local traffic conditions. The majority of such research is based on case studies that use simulation software to analyze specific conditions (Du, et al. 2015). For example, Shadewald and Prem (2004) conducted speed variation research of taxis in Shanghai, China, equipped with GPS to collect data, with speeds at specific locations allowing for comparison of access density and variation in taxi speeds.

2.1.3 The impact of traffic volume on crash frequency and the importance of access density

Traffic volumes have increased in the last decade throughout the world. Traffic volume increase impacts safety, a problem that needs to be addressed. For example, in Utah (Grant, 2010), reported that traffic volumes have been growing, especially in arterial roadways which often have high traffic volume in peak hours. Grant and others (2010) conducted research designed to improve highway safety in areas with high traffic volume. Their data was derived from a geographic information system–enabled, web-delivered data almanac. Their results showed locations of high crash impacts in dense traffic and provided some statistics of which lane was the most dangerous in the roadway. Data from the MnDOT generally confirms that high traffic volume increases the probability of crash occurrences from 1999-2001 and 2003-2004 in Sarasota, FL shown in (Table 2.1).

Table 2.1. Crash data and access point density for University Parkway in Sarasota, FL (after Schultz et al., 2007, p. 80)

	Before (1999-2001)	After (2003-2004)
Crashes Per Year	62.7	97.5
Crash Rate (Crashes/MVMT[1])	6.37	9.13
Fatality Rate (Fatalities/100 MVMT[1])	4.75	0.00
Access Points	18	14
Length of Section (mi.)	0.77	0.77
Access Points per Mile	23.4	18.2
AADT[2]	34,978	37,985

[1]MVMT = Million Vehicle Miles Traveled

[2]AADT is a weighted average calculated using Equation 4-4

AADT = (Total volume of vehicle traffic for 1 year) / 365 days

Where:

AADT = Annual Average Daily Traffic

Table 2.2. Traffic safety statistics summary, 1965-2014 from MnDOT (2014, p.9)

Year (a)	Total Crashes (b)	Persons Killed (c)	Persons Injured (d)	Licensed Drivers (million) (e)	Motor Vehicles (MV) (million) (f)	State Popu-lation (million) (g)	Vehicle Miles Traveled (VMT) (billion) (h)	Crash Rates Per 100,000 MV (i)	Crash Rates Per 100,000 Popu-lation (j)	Crash Rates Per 100 Mil VMT (k)	Fatality Rates Per 100,000 MV (l)	Fatality Rates Per 100,000 Popu-lation (m)	Fatality Rates Per100 Mil VMT (n)
1965	83,329	875	50,847	1.85	1.86	3.57	16.8	4,480	2,334	496	47.0	24.5	5.20
1970	99,404	987	38,538	2.05	2.24	3.80	22.4	4,438	2,616	444	44.1	26.0	4.40
1975	123,206	777	41,931	2.51	2.69	3.92	25.6	4,580	3,143	481	28.9	19.8	3.00
1980	103,612	863	45,227	2.77	3.01	4.08	28.5	3,446	2,546	364	28.7	21.2	3.03
1981	97,879	763	43,739	2.83	3.09	4.10	28.6	3,163	2,387	342	24.7	18.6	2.67
1982	89,443	581	38,692	2.87	3.01	4.13	29.2	2,972	2,181	304	19.3	14.2	1.98
1983	97,371	558	41,086	2.90	3.03	4.15	30.5	3,214	2,356	319	18.4	13.5	1.83
1984	93,741	584	41,808	2.91	3.13	4.16	32.2	2,995	2,262	291	18.7	14.1	1.81
1985	99,168	610	44,316	3.04	3.22	4.19	33.1	3,080	2,380	300	18.9	14.7	1.84
1986	95,460	572	42,130	3.07	3.25	4.21	34.2	2,937	2,266	279	17.6	13.6	1.67
1987	94,095	530	42,091	3.10	3.31	4.25	35.1	2,840	2,233	268	16.0	12.6	1.51
1988	102,094	615	44,415	3.13	3.39	4.31	36.4	3,012	2,371	280	18.1	14.3	1.69
1989	105,996	605	45,404	3.16	3.46	4.35	37.6	3,060	2,435	282	17.5	13.9	1.61
1990	99,236	568	44,634	3.18	3.52	4.38	38.8	2,817	2,268	256	16.1	13.0	1.47
1991	101,419	531	42,748	3.22	3.51	4.43	39.3	2,890	2,288	258	15.1	12.0	1.35
1992	96,808	581	43,249	3.27	3.55	4.48	41.3	2,730	2,161	235	16.4	13.0	1.41
1993	100,907	538	44,987	3.28	3.48	4.52	42.3	2,899	2,234	239	15.5	11.9	1.27
1994	99,701	644	46,403	3.34	3.67	4.57	43.4	2,720	2,183	230	17.6	14.1	1.48
1995	96,022	597	47,161	3.39	3.68	4.61	44.1	2,606	2,083	218	16.2	13.0	1.35
1996	105,332	576	48,963	3.46	3.70	4.66	45.9	2,845	2,261	230	15.6	12.4	1.26
1997	98,625	600	46,064	3.49	3.77	4.69	46.9	2,065	2,105	210	12.6	12.8	1.28
1998	92,926	650	45,115	3.53	3.90	4.74	48.5	2,380	1,962	192	16.6	13.7	1.34
1999	96,813	626	44,538	3.54	3.92	4.78	50.7	2,470	2,027	191	16.0	13.1	1.24
2000	103,591	625	44,740	3.65	4.20	4.92	52.4	2,469	2,106	198	14.9	12.7	1.19
2001	98,984	568	42,223	3.69	4.38	4.97	53.2	2,262	1,991	186	13.0	11.4	1.07
2002	94,969	657	40,677	3.76	4.49	5.02	54.4	2,115	1,892	175	14.6	13.1	1.21
2003	N/A	655	N/A	3.79	4.56	5.09	55.4	N/A	N/A	N/A	14.4	12.9	1.18
2004	91,274	567	40,073	3.85	4.63	5.14	56.5	1,971	1,774	162	12.2	11.0	1.00
2005	87,813	559	37,686	3.87	4.69	5.21	56.5	1,873	1,687	155	11.9	10.7	0.99
2006	78,745	494	35,025	3.87	4.76	5.23	56.6	1,654	1,505	139	10.4	9.4	0.87
2007	81,505	510	35,318	3.91	4.82	5.26	57.4	1,691	1,548	142	10.6	9.7	0.89
2008	79,095	455	33,379	3.94	4.86	5.29	57.3	1,628	1,494	138	9.4	8.6	0.79
2009	73,498	421	31,074	3.95	4.87	5.30	57.0	1,510	1,387	129	8.7	7.9	0.74
2010	74,073	411	31,176	4.00	4.92	5.30	56.8	1,507	1,397	130	8.4	7.5	0.72
2011	72,117	368	30,295	4.01	4.98	5.33	56.7	1,450	1,352	127	7.4	6.9	0.65
2012	69,236	395	29,314	4.04	5.02	5.37	57.0	1,378	1,290	122	7.9	7.4	0.69
2013	77,707	387	30,653	4.07	5.09	5.40	57.0	1,527	1,439	136	7.6	7.2	0.68
2014	78,396	361	29,439	4.12	5.14	5.42	57.0	1,525	1,446	138	7.0	6.7	0.63

Table 2.3. Traffic crash trends, 2009-2014 from MnDOT (2014, p.10)

	2009	2010	2011	2012	2013	2014	Record High	
Fatal Crashes	**371**	**364**	**334**	**349**	**357**	**324**	**878**	**(1973)**
Injury Crashes	**22,159**	**22,013**	**21,662**	**20,972**	**21,960**	**21,257**	**33,686**	**(1978)**
Severe	1,036	974	954	1,044	981	862	5,109	(1984)[1]
Moderate	5,942	5,792	5,581	5,423	5,563	5,302	12,326	(1985)[1]
Minor	15,181	15,247	15,127	14,505	15,416	15,093	18,578	(1996)[1]
PDO Crashes	**50,968**	**51,696**	**50,121**	**47,915**	**55,390**	**56,815**	**94,810**	**(1975)**
Total Crashes	**73,498**	**74,073**	**72,117**	**69,236**	**77,707**	**78,396**	**123,106**	**(1975)**
Total Injuries	**31,074**	**31,176**	**30,295**	**29,314**	**30,653**	**29,439**	**50,332**	**(1978)**
Severe	1,271	1,191	1,159	1,268	1,216	1,044	6,573	(1984)[1]
Moderate	7,714	7,445	7,110	6,902	7,109	6,712	17,670	(1985)[1]
Minor	22,089	22,540	22,026	21,144	22,328	21,683	28,631	(1996)[1]
Total Fatalities	**421**	**411**	**368**	**395**	**387**	**361**	**1,060**	**(1968)**
Motor Vehicle Occupant	302	305	271	276	269	278	544	(2002)[1]
Motorcycle	53	45	42	55	60	46	121	(1980)
Pedestrian	41	36	40	40	35	17	157	(1971)
Bicycle	10	9	5	7	6	5	24	(1977)
All Terrain Vehicle	9	8	8	9	7	7	10	(2008)
Snowmobile	0	3	0	1	2	4	9	(1984)
Farm Equipment	3	2	2	2	5	1	N/A	N/A
Other Vehicle Type	3	3	0	5	3	3	N/A	N/A
Minnesota Fatality Rate[3]	0.74	0.72	0.65	0.69	0.68	0.63	23.6	(1934)
U.S. Fatality Rate[3]	1.15	1.11	1.10	1.14	1.11	1.10	18.0	(1925)
Minnesota Economic Loss (millions)	$1,496	$1,477	$1,481	$1,514	$1,588	$1,604	$1,769	(2004)[4]

CHAPTER 3: RESEARCH METHODOLOGY

The methodology used in this study was cross-sectional longitudinal with multivariate statistical analysis. The methodology is described in this chapter.

3.1 Cross-Sectional

Cross sectional study, design is a methodology to assess diverse types of observational data. Cross sectional method is used to evaluate a data that gathered at a particular point in time across many entities. The outcome of the comparison group is assumed a good indication of 'what would have been' for the treatment group if the treatment had not been implemented. In order to illustrate the effects of the treatment, using the regression is an efficient method after comparing the two groups of the outcomes. Regression adjustments are assumed to account for differences impacting the outcome between the treated and comparison groups. The effects of the treatment can be estimated via use of continuous variables in the regression models. Cross sectional study is sensitive to issues such as measurement error, selection bias, and omitted variable bias. To illustrate, measurement error is simply error in the measurements of different observations. Omitted variables bias happens when the important variables are removed from the model. That would lead to incorrect results because there will be biased parameters in the model.

3.2 Longitudinal Studies

In contrast, of cross sectional method, longitudinal study is a method, which observes the data in long period (i.e., repeated measurements over time). Longitudinal study is used to detect the correlations between variables that are in the data. Also, this methodology has two types panel and cohort. The panel data used in this research, were collected over five years. These data are defined and identified based on route number, beginning point, end point, urban code, county name, city name and others. The major benefit of using longitudinal study are providing a clear vision for the researchers to observe the difference that might happen on the data over time.

3.3 Multivariate Statistical Analysis

Three statistical models were considered for this study: (1) Negative Binomial (NB), (2) Random Parameter Negative Binomial (RPNB), and (3) Poisson Regression, although only NB And RPNB were used for the thesis. Both NB and RPNB regression models were applied on the four types of crashes (Total, Fi, Mc, and Access).

CHAPTER 4: DATA COLLECTION

4.1 Data sources and collection

The data were provided by the Highway Safety Information System (HSIS). The HSIS provides data with quality that meets FHWA requirements. Data were collected in Minnesota State in the years 2009 through 2014. Route number, AADT, number of lanes, right shoulder widths, left shoulder widths, lane width, and beginning and ending milepost were included in the database for this project. A total of 413 road segments were checked in 2009 through 2014 using Google Earth. The reason of collecting data in five years was to deal with the changing in the traffic regulations such as changing in speed limit, signal light, stop sign and other variables might existed by the time and test the system in different situations.

In addition, HSIS provides data with route ID, county name, city name, and the type of the roadway. The pervious information are effective to locate the segment accurately and account the number of access points from the intersections, the number of access points from the minor roadways/driveways and the horizontal curves. Google Earth and Google street view are used to find the total number of access points and the horizontal curves. However, Google Earth does not show the start and end point of the segment. Therefore, using MnDOT Base Map is an assistant tool beside Google Earth to locate the segment and find the required information. This data was collected on urban roadways (principal arterials, minor arterials, and urban collectors). The descriptive statistics for the data shown in Table 4.1 and 4.2 respectively (after Nujjetty & Sharma, 2015). Table 4.3 provides mean, standard deviation, minimum, and maximum value for each estimated variable in this research.

Table 4.1. Variable descriptions

Variable Notation	Variable Description
ID.	Site number
Year	The respective year for the data
RTSYSNBR	Combined route system/route number
Route	Route number
LENGTH	Segment length (miles)
Access	Control of access (1=Yes, 0=No)
LSHLDWID	Left shoulder width (ft)
RSHLDWID	Right shoulder width (ft)
FUNC_CLS	Functional class
FED_AID	Federal Aid System (1=Yes, 0=No)
NO_LANES	Total Number of Lanes
LANEWID	Lane Width (ft)
RODWYCLS	Roadway Classification
Start_MP	Beginning milepost of segment
End_MP	Ending milepost of segment
NO_INTS	Number of intersections
NO_ACCES	Number of Access Points

Table 4.2 Variable descriptions (continued)

Variable Notation	**Variable Description**
NO_HC	Number of Horizontal Curves
INT_DENS	Intersection density (intersections per mile)
ACC_DENS	Access density (points per mile)
HC_DENS	Horizontal curve density (curves per mile)
AADT	Annual Average Daily Traffic
Total Crash	The Total Number of Crashes
Fi Crash	The Number of fatal and injury crashes
Mc Crash	Multiple Vehicle Collision (i.e., crash involves more than one vehicle)
Access Crash	Traffic Crash occurs on a driveway access
LN_AADT	Natural logarithm of AVE_AADT
LN_LEN	Natural logarithm of Length
Access_Daily_Trips_wkdy	Average Number of Vehicle Trips from the Access Points During the Weekdays
Access_Daily_Trips_wkend	Average Vehicle Trips from the Access Points During the Weekend
Post- Speed MPH	Post speed MPH

Table 4.3. Descriptive statistics for urban roadways data

	urban roadways (N= 413)			
Variable	Mean	Std. Dev.	Min	Max
LSHLDWID	2.14	3.37	0.00	12.00
RSHLDWID	2.20	3.50	0.00	22.00
FUNC_CLS	17.05	1.75	14.00	19.00
AADT	4457.00	5193.40	64.00	32310.00
Length	0.27	0.19	0.01	0.99
Access	1.00	0.05	1.00	2.00
LN_LEN	-1.50	0.70	-4.60	-0.003
LN_AADT	7.68	1.29	4.15	10.38
PRINC_AT	0.16	0.36	0.00	1.00
MINOR_AR	0.18	0.39	0.00	1.00
URBAN_CO	0.65	0.47	0.00	1.00
Fed_aid	16335.00	NA	0.00	16666.00
Rodwycls	3.00	26.39	3.00	99.00
NO_LANES	2.0	0.00	2.00	2.00
LANEWID	11.88	0.62	10.00	13.00
NO_INTS	1.24	1.38	0.00	6.00
NO_ACCES	9.92	6.40	1.00	39.00
NO_HC	0.33	0.56	0.00	3.00
INT_DENS	6.45	10.25	0.00	105.26
ACC_DENS	51.29	52.35	1.36	615.38
HC_DENS	1.89	5.92	0.00	100.00
TOTAL	1.16	2.35	0.00	22.00
FI	0.02	0.17	0.00	3.00

Mc_crash	0.90	2.01	0.00	23.00
Access_crash	0.04	0.26	0.00	3.00
Access_Daily_Trips_wkdy	2317.84	1311.46	144.00	4967.00
Access_Daily_Trips_wkend	1524.82	842.72	113.00	3200.00
Post- Speed MPH	40.00	9.37	25.00	65.00

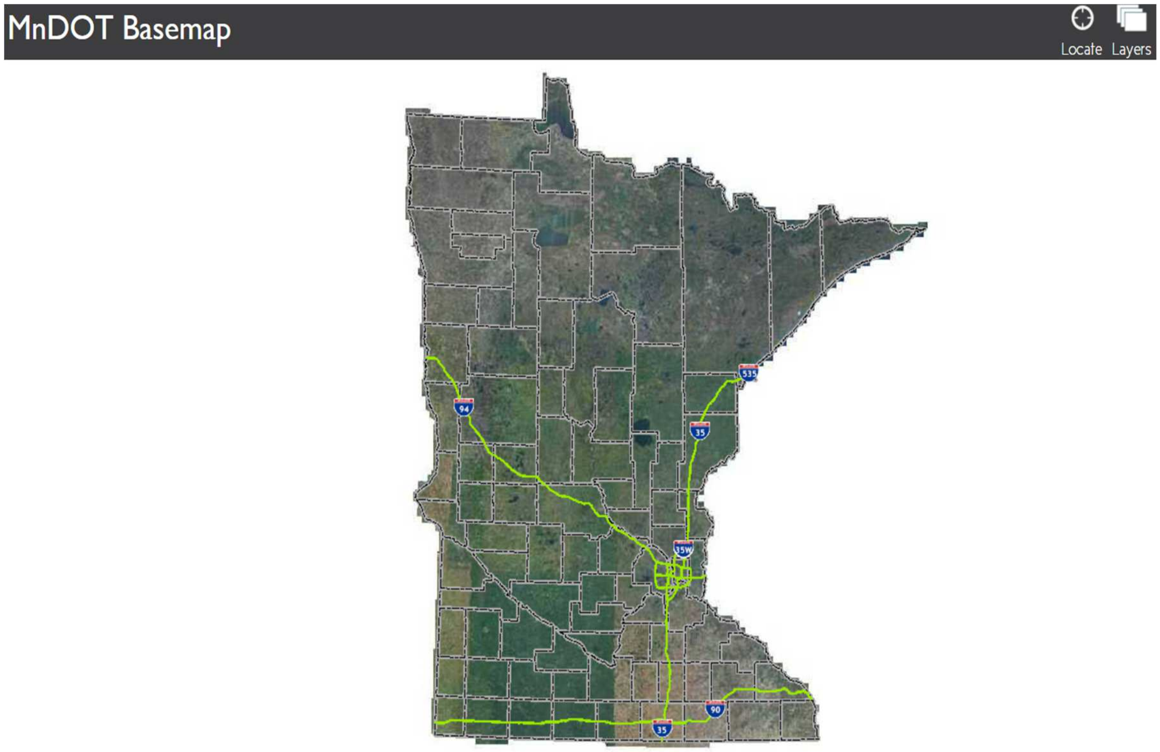


Figure 4.1. A screenshot of MnDOT basemap (after MnDOT, 2017, n.p.)

4.2 Access Density

Access density is defined as the number of access points per mile. Access density impacts safety on roadways. Safety impacts could exist as crashes. Increasing the access density in a particular area could either affect the operational performance on roadways in the short or long term by increasing travel times, fuel consumption, and vehicular emissions. Access point counts were collected using Google Earth for each segment in this study. By knowing the access points and the segment length, access density was measured as:

Access Density = access points / segment length (mile)

Overall, the minimum access density is 2.133 and the maximum is 34.55

In table 4.4, the access density is the term most often used in comparisons including signal density, median density, and driveway density.

Table 4.4. Number of online hits in 2009 for access related terms from the TRB (after Saxena, 2010, p. 3.)

No	Term	Number of hits in TRR (TRB)
1	Access Density	1039
2	Signal Density	767
3	Median Density	458
4	Driveway Density	108

4.3 Comparison between Access Density before – after rechecking locations

After calculating access density based on the data derived from HSIS, 145 locations out of 413 locations had high density (greater than 50 points per mile) according to locations on the Google Earth. These were re-checked for errors. It was found that these locations had counted access points on both sides of the street. To correct these measurements, the distances between access points were measured and the average value was calculated for each segment.

Table 4.5. The variance in density before and after checking

	Access Density Before Rechecking	**Access Density After Rechecking**
Mean	51.29	20.67
Standard Deviation	52.35	7.75
Min	1.36	2.13
Max	615.38	34.55

4.4 Traffic volume

Traffic volume is the number of vehicles crossing a section of road per unit time at any selected period. In this research, traffic volume is represented in two variables: Annual Average Daily Traffic (AADT) and the annual daily trips. The AADT was provided by HSIS in this study. The AADT is estimated using permanent counting stations, temporary coverage counts (i.e., counts taken on different segments for a few days once every couple of years), and adjustment factors. The ITE trip generation manual is used to predict the number of trips generated by specific land use types. This is used when it is not possible to collect trip generation data, which is different from AADT and road traffic volumes. For instance, to calculate the annual daily trips for a general light industrial, the manual provides the number of studies that have been creating in the same category, average number of users, and the directional distribution. It provides an equation in order to get a specific number of annual daily trips based on the situation that shall be studies. Figure 4.2 shows the evolution of the traffic volume in 1970- 2015 provided by MnDOT.

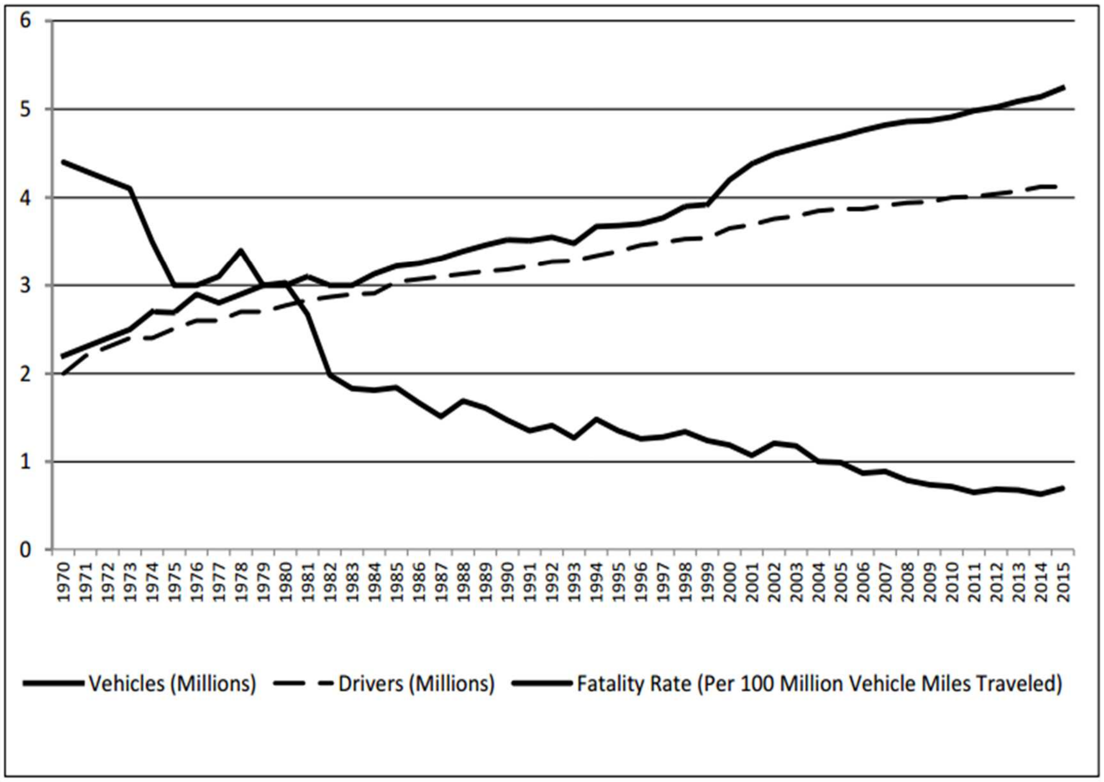


Figure 4.2. The evolution of traffic volume from 1970 to 2015
(after MnDOT, 2014, p.3)

4.5 Crash Data

Each state in the USA maintains a crash database. For the states that participate in the HSIS system, these data are provided and stored in a data repository. The data is gathered from multiple sources of information and assists in the planning of safety programs and projects. It is important that the data is accurate and timely. According to MnDOT (2017) , the basic components in the hazard identification process are as follows.

1. Establish a crash records database and safety objectives.
2. Review the crash records.
3. Identify crash frequencies/rates.
4. Compare to safety objectives and identify potential problem locations.
5. Develop alternative mitigation strategies.
6. Implement safety projects.
7. Evaluate the effectiveness of safety projects through a before/after or other appropriate study.

In 2014, there were about 32,675 traffic fatalities throughout the country (based on the most recent available data from 2014) and 411 in Minnesota (MnDOT, 2015, p.1). The respective fatality rates per hundred million miles of travel were 1.07 and 0.70. The MnDOT and the HSIS provided an overview of historical and recent data describing the overall situation for the state of Minnesota traffic system (Tables 4.5 through 4.6) as a starting point for the research in this thesis. Table 4.6 provides the number of fatalities per year since 1910 until 2015 retrieved from MnDOT and the following figure shows trend of traffic deaths, vehicle miles traveled, and fatality rate respectively. Also, Table

4.7 describes roadway categories and mileage numbers of each type in the state of Minnesota (Nujjetty & Sharma, 2015). The remarkable types for this research are urban multilane divided non-freeways which covers 1,012.572 miles and urban multilane undivided non- freeways which covers 542.74 miles. The total mileage of Minnesota roadways is 142,977.1 and the urban freeways represent 1,555.312 miles, which is 1.00% of the total number.

Table 4.6. The number of Minnesota traffic fatalities from 1910-2015 (after MnDOT, 2015, p. 4)

MINNESOTA TRAFFIC FATALITIES, 1910 - 2015
Since 1961: Vehicle Miles Traveled (Billions) and Fatality Rates (Per 100 Million VMT)

YEAR (1)	Fatal-ities (2)	YEAR (3)	Fatal-ities (4)	YEAR (5)	Fatal-ities (6)	YEAR (7)	Fatal-ities (8)	Vehicle Miles (9)	Fatal Rate (10)	YEAR (11)	Fatal-ities (12)	Vehicle Miles (13)	Fatal Rate (14)	YEAR (15)	Fatal-ities (16)	Vehicle Miles (17)	Fatal Rate (18)
1910	23	**1929**	505	**1948**	552	**1961**	724	14.5	4.99	**1980**	863	28.5	3.03	**1999**	626	50.7	1.24
1911	26	**1930**	561	**1949**	**540**	**1962**	692	15.1	4.58	**1981**	763	28.6	2.67	**2000**	**625**	**52.4**	**1.19**
1912	39	**1931**	**622**	**1950**	532	**1963**	798	15.3	5.22	**1982**	581	29.2	1.98	**2001**	568	53.2	1.07
1913	**46**	**1932**	486	**1951**	610	**1964**	841	16.2	5.19	**1983**	558	30.5	1.83	**2002**	657	54.4	1.21
1914	88	**1933**	525	**1952**	534	**1965**	875	16.8	5.21	**1984**	584	32.2	1.81	**2003**	655	55.4	1.18
1915	85	**1934**	641	**1953**	637	**1966**	977	17.7	5.52	**1985**	610	33.1	1.84	**2004**	567	56.5	1.00
1916	143	**1935**	596	**1954**	639	**1967**	965	18.7	5.16	**1986**	572	34.2	1.67	**2005**	559	56.5	0.99
1917	161	**1936**	649	**1955**	577	**1968**	1,060	19.9	5.33	**1987**	530	35.1	1.51	**2006**	494	56.6	0.87
1918	183	**1937**	630	**1956**	637	**1969**	988	20.8	4.75	**1988**	615	36.4	1.69	**2007**	510	57.4	0.89
1919	171	**1938**	609	**1957**	684	**1970**	987	22.4	4.41	**1989**	605	37.6	1.61	**2008**	455	57.3	0.79
1920	178	**1939**	576	**1958**	708	**1971**	1,024	23.4	4.38	**1990**	568	38.8	1.47	**2009**	421	56.9	0.74
1921	216	**1940**	577	**1959**	662	**1972**	1,031	24.9	4.14	**1991**	531	39.3	1.35	**2010**	411	56.8	0.72
1922	260	**1941**	626	**1960**	724	**1973**	1,024	25.2	4.06	**1992**	581	41.3	1.41	**2011**	368	56.7	0.65
1923	328	**1942**	439			**1974**	852	24.6	3.46	**1993**	538	42.3	1.27	**2012**	395	57.0	0.69
1924	366	**1943**	274			**1975**	777	25.6	3.04	**1994**	644	43.4	1.48	**2013**	387	57.0	0.68
1925	361	**1944**	356			**1976**	809	27.0	3.00	**1995**	597	44.1	1.35	**2014**	361	57.0	0.63
1926	326	**1945**	449			**1977**	856	28.1	3.05	**1996**	576	45.9	1.26	**2015**	411	59.1	0.70
1927	369	**1946**	536			**1978**	980	28.8	3.40	**1997**	600	46.9	1.28				
1928	435	**1947**	572			**1979**	881	29.0	3.04	**1998**	650	48.5	1.34				

NOTE: VMT data provided by the Minnesota Department of Transportation

MINNESOTA TRAFFIC FATALITIES, 1910 - 2015

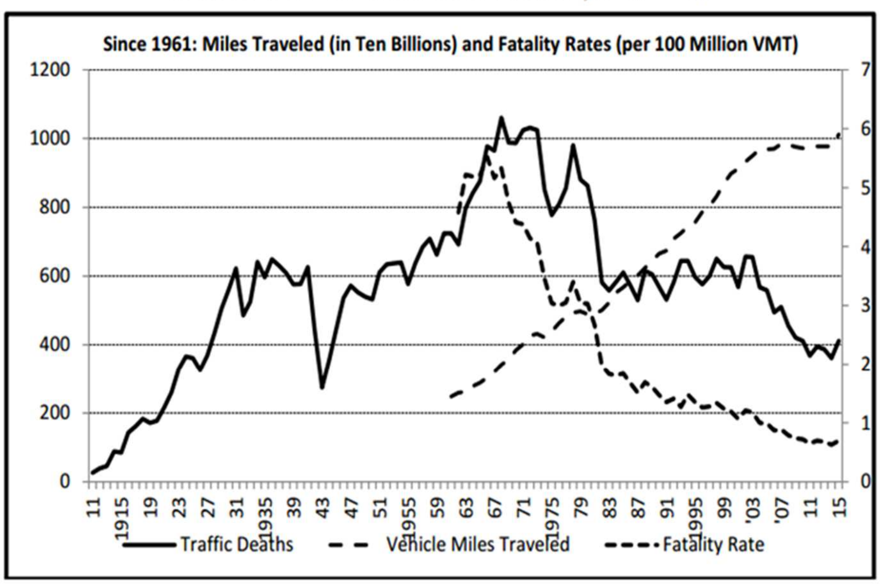


Table 4.7. The HSIS roadway mileage by roadway category for the state of Minnesota, 2012 data (Nujjetty & Sharma, 2015, p.8)

Roadway Category	**Mileage**
Urban freeways>= 4 Lanes	409.905
Urban freeways < 4 Lanes	2.28
Urban multilane divided non-freeways	1,012.572
Urban multilane undivided non- freeways	542.74
Urban 2 In highways	15,948.9
Rural freeways>= 4 Lanes	662.84
Rural freeways < 4 Ins	0.00
Rural multilane divided non-freeways	912.173
Rural multilane undivided non-freeways	85.447
Rural 2 In highways	39,053.78
Other	84,775.09
Total	142,977.1

CHAPTER 5. STATISTICAL REGRESSION MODELS

Three statistical models were considered for this thesis: (1) Negative Binomial (NB), (2) Random Parameter Negative Binomial (RPNB), and (3) Poisson Regression, although only NB and RPNB were used.

5.1 Poisson Regression Model

Theoretically, Poisson Regression consider as a nonlinear regression model in case the response outcomes are discrete (Kutner et al., 2008). Poisson Regression is useful when the outcome is a count. The general model of Poisson regression can be stated as follows:

$$Y_j = E\{Y_i\} + \sum_I \qquad i = 1,2,\ldots, n$$

And there are some commonly used functions for Poisson regression:

$$\mu_j = \mu(X_i, \beta) = X_i \beta$$

$$\mu_j = \mu(X_i, \beta) = \exp(X_i, \beta)$$

$$\mu_j = \mu(X_i, \beta) = \log(X_i, \beta)$$

The mean responses μ_i must be nonnegative in all three cases.

Poisson Regression is valuable if the mean approximately equal to the variance otherwise there are another models could be used in order to mitigate the “over dispersion”.

In this case, the independent variable appears as the expected number of crashes of type i on segment j represented as $\boldsymbol{\mu_j}$. The other variables represent the dependent variables where:

Xj = a set of traffic and geometric variables characterizing segment j;

β= regression coefficients estimated with maximum likelihood that quantify the relationship between E(Yij) and variables in X;

The following Figure describes the relationship between the variance and the mean.

5.2 Negative Binomial Model

Clearly, NB has many features as same as Poisson only if the variance is identical to the mean. In other words, in Poisson regression, the variance and mean are equal that means there are no over-dispersion in the data, which fit is the Poisson model. In the other hand, negative binomial could account for that added dispersion in the data (Wood et al. 2016). The NB is the essential statistical method applied in this research in order to detect the frequency of crashes in different segment and locations.

The following parameters describe the model:

$\mu ij = E(Yij) = \exp(Xj\beta + \ln Lj)$

Where:

$\mu ij = E(Yij)$ = the expected number of crashes of type i on segment j;

Xj = a set of traffic and geometric variables characterizing segment j;

β= regression coefficients estimated with maximum likelihood that quantify the relationship between $E(Yij)$ and variables in X;

Lj = length of segment j; and,

$\ln Lj$ = the natural logarithm of segment length.

The mean-variance relationship of the negative binomial regression model is expressed as:

$VAR(Yij) = E(Yij) + \alpha[E(Yij)]2$

Where:

$E(Yij)$ = the expected number of crashes of type i on segment j;

$VAR(Yij)$ = variance of crashes of type i on segment j; and

α = over dispersion parameter.

5.3 Comparison between Poisson and Negative Binomial Models

Poisson and NB Models have been the preferred tools to evaluate traffic accident in the years 1980-2000. As with any tool, there are limitations in use and strategy, which give an incentive to develop the idea and performance. In Poisson case, the variance-to-mean ration of the accident data requires to be about 1, which is not possible in many cases. In addition, accident data needs to be uncorrelated in time in both Poisson and negative binomial models (Lawless, J., 1987). The NB regression models have more options to illustrate clearly the correlation between accident occurrence and the site geometric characteristics. Therefore, in order to reach to high level of accuracy, the data needs to be assessed and evaluated by another type of regression model that would be more suitable.

5.4 Random Parameter Negative Binomial (RPNB) Model

The previous comparison between Poisson and NB shows some weak points that need to be treated in a proper way in order to get accurate estimates. Therefore, the RPNB is the appropriate model with the variety of properties that provided in analyzing accident frequency and the effects of the interaction of different variables (Chin &

Quddus, 2003). In addition, the random parameters allows correcting for heterogeneity that can appear from a number of different elements interacts in the model (Venkataraman et al., 2013). However, the RPNB is the primary model besides the standard negative binomial in this research.

CHAPTER 6. DATA ANALYSIS AND RESULTS

6.1 Data analysis and results for the Negative Binomial Regression Model

The output of NB Regression Model determines the interactive variables that have impacts on crash frequency are presented in this section. All segments were assessed using data from urban roads. Negative binomial models to detect the influences on crash frequency tested three major variables. Traffic volume has an impact on crash occurrence in this model and it is calculated by monitoring two factors, which are the Annual Average Daily Traffic (AADT) and the access daily trips. Also, access density has an essential impact on crash frequency and it is represented in the model by access density. Negative binomial regression models were applied on four types of crashes. Total crash, Fi crash, Mc crash, and Access crash are the crash types were evaluated in this research. In Total crash, Fi crash, Mc crash, and Access crash models, the regression parameters associated with the natural logarithm of AADT and with length, include the following variables: access density, lane width, intersection density, and access daily trips. The coefficients of the regression are very important in order to make a decision whether positive effect or impact. The negative coefficient represents that there is a decreasing crash frequency rate, and the variable has a positive impact on the model. On the other hand, the positive coefficients represent that the crash rate will grow because of these variables, which interact in the model, and require appropriate adjustment. The standard negative binomial regression model was used on four types of crashes (1=Total, 2= Fi, 3= Mc, 4=Access) with the following results by type (Tables 10-21).

6.1.1. Total crash results

There were four types of crashes examined in the NB model in this thesis: (1) Total crash, (2) Fi crash, (3) Mc crash, and (4) Access crash. The assumption was that most of variables that were tested would increase total crashes. That was the case throughout the results; however, two variables would decrease total crashes. In the case of total crash results, however, the responses obtained do not make sense and were not logically predictable. For example, in Table 6.1.1.1, the Intercept and the AD interacting with AADT are two negative values. That means that the increase in crash frequency is smaller (from the main effect of each variable) at larger values of the variables than at small values. The other variables in Table 6.1.1.1 will likely have effects to increase total crashes.

Table 6.1.1.1. NB effects of access density on total crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.4546						
Associated standard error for Alpha = 0.0277						
t-statistic for the alpha value = 16.41						
Log likelihood = -5566.8000						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-7.047*	1.05	-6.70	<0.0001	-9.14	-4.96
lnaadt	**0.4448**	0.07	6.30	<0.0001	0.30	-0.58
lnlength	**0.8818**	0.07	11.95	<0.0001	0.73	1.02
access_dens	**0.02207**	0.007	3.15	0.001588	0.01	0.03
lanewid	**0.3572**	0.07	4.78	<0.0001	0.20	0.51
Divaadt = 1/aadt	**109.1**	29.20	3.73	0.000187	53.57	166
int_dens	**0.01914**	0.004	4.40	<0.0001	0.01	0.03
access_daily_trips_wkdy	**0.0003124**	<0.0001	0.97	0.33	<0.0001	<0.0001
access_dens:aadt	*-0.0000003*	<0.0001	-0.37	0.71	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.1.1.2. NB effects of Access Density on total crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.4539						
Associated standard error for Alpha = 0.0276						
t-statistic for the alpha value = 16.44						
Log likelihood = -5567.7130						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-6.99*	1.04	-6.70	<0.0001	-9.08	-4.91
lnaadt	**0.43**	0.07	6.25	<0.0001	0.29	0.57
lnlength	**0.88**	0.07	11.93	<0.0001	0.73	1.02
access_dens	**0.02**	0.007	3.24	0.001	0.009	0.03
lanewid	**0.36**	0.07	4.88	<0.0001	0.21	0.51
Divaadt = 1/aadt	**108.00**	29.10	3.72	0.0001	52.80	165
int_dens	**0.02**	0.004	4.32	<0.0001	0.009	0.03
access_dens:aadt	<0.0001	<0.0001	-0.23	0.81	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.1.1.3. NB effects of access density on total crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.4546						
Associated standard error for Alpha = 0.0277						
t-statistic for the alpha value = 16.41						
Log likelihood = -5566.9460						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-6.88*	0.95	-7.24	<0.0001	-8.80	-4.98
lnaadt	**0.42**	0.04	9.72	<0.0001	0.33	0.50
lnlength	**0.88**	0.07	11.98	<0.0001	0.74	1.02
access_dens	**0.02**	0.006	3.50	0.0004	0.009	0.03
lanewid	**0.35**	0.07	4.80	<0.0001	0.21	0.51
Divaadt = 1/aadt	**104.00**	26.80	3.90	<0.0001	54.00	157.00
int_dens	**0.02**	0.004	4.42	<0.0001	0.01	0.02
access_daily_trips_wkdy	<0.0001	<0.0001	0.92	0.35	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

6.1.2 Fi Crashes

In the case of Fi crash results, the estimates made sense and were logically predictable. For example, in Table 6.1.2.1, the Intercept is a negative value. The variable of AD interacting with AADT is a positive value, which means that it has a negative effect on the model (increasing the Fi crash frequency).

Table 6.1.2.1. NB effects of access density on Fi Crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.1576						
Associated standard error for Alpha = 0.0786						
t-statistic for the alpha value = 2.00						
Log likelihood = -397.7030						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*10.70*	4.64	-2.32	0.02	-20.50	-2.09
lnaadt	**0.55**	0.28	1.93	0.05	0.01	1.12
lnlength	**1.28**	0.31	4.13	<0.0001	0.67	1.94
access_dens	**0.02**	0.03	0.60	0.54	-0.04	0.08
lanewid	**0.25**	0.34	0.73	0.46	-0.38	0.96
Divaadt = 1/aadt	**173.00**	119.00	1.45	0.14	-94.10	383
int_dens	**0.02**	0.01	1.15	0.24	-0.02	0.05
access_daily_trips_wkdy	<0.0001	<0.0001	1.26	0.20	<0.0001	<0.0001
access_dens:aadt	<0.0001	<0.0001	0.97	0.32	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.1.2.2. NB effects of access density on Fi Crashes

Number of obs = 2065

Prob > chi2 =0.0000

Alpha = 0.1515

Associated standard error for Alpha = 0.0759

t-statistic for the alpha value = 1.99

Log likelihood = -399.2770

Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*10.22*	4.65	-2.19	0.02	-20.10	-1.50
lnaadt	**0.52**	0.28	1.83	0.06	-0.02	1.09
lnlength	**1.28**	0.31	4.15	<0.0001	0.68	1.94
access_dens	**0.02**	0.03	0.79	0.42	-0.03	0.08
lanewid	**0.25**	0.34	0.74	0.45	-0.38	0.98
Divaadt = 1/aadt	**165.00**	119.00	1.38	0.16	-101.00	375.00
int_dens	**0.02**	0.02	1.08	0.27	-0.02	0.05
access_dens:aadt	<0.0001	<0.0001	0.957	0.33	<0.0001	<0.0001

Variables have impact of increasing the crash frequency are shown in **bold**.
Variables have impact of decreasing the crash frequency are shown in *italics*.

Table 6.1.2.3. NB effects of access density on Fi Crashes

<table>
<tr><td colspan="7">Number of obs = 2065</td></tr>
<tr><td colspan="7">Prob > chi2 =0.0000</td></tr>
<tr><td colspan="7">Alpha = 0.1545</td></tr>
<tr><td colspan="7">Associated standard error for Alpha = 0.0777</td></tr>
<tr><td colspan="7">t-statistic for the alpha value = 1.98</td></tr>
<tr><td colspan="7">Log likelihood = -398.6170</td></tr>
<tr><td>Variables</td><td>Coef</td><td>Std. Error</td><td>z value</td><td>Pr(>|z|)</td><td colspan="2">[95% Conf. Interval]</td></tr>
<tr><td>(Intercept)</td><td>12.50</td><td>4.29</td><td>-2.92</td><td>0.003</td><td>-21.70</td><td>-4.53</td></tr>
<tr><td>lnaadt</td><td>0.76</td><td>0.18</td><td>4.11</td><td><0.0001</td><td>0.41</td><td>1.13</td></tr>
<tr><td>lnlength</td><td>1.25</td><td>0.31</td><td>4.06</td><td><0.0001</td><td>0.65</td><td>1.91</td></tr>
<tr><td>access_dens</td><td>0.03</td><td>0.02</td><td>1.48</td><td>0.13</td><td>-0.01</td><td>0.08</td></tr>
<tr><td>lanewid</td><td>0.24</td><td>0.33</td><td>0.73</td><td>0.46</td><td>-0.38</td><td>0.96</td></tr>
<tr><td>Divaadt = 1/aadt</td><td>220.00</td><td>106.00</td><td>2.07</td><td>0.03</td><td>-21.80</td><td>406.00</td></tr>
<tr><td>int_dens</td><td>0.02</td><td>0.01</td><td>1.26</td><td>0.20</td><td>-0.02</td><td>0.06</td></tr>
<tr><td>access_daily _trips_wkdy</td><td><0.0001</td><td><0.0001</td><td>1.25</td><td>0.20</td><td><0.0001</td><td><0.0001</td></tr>
<tr><td colspan="7">Variables have impact of increasing the crash frequency are shown in bold.
Variables have impact of decreasing the crash frequency are shown in italics.</td></tr>
</table>

6.1.3 Mc crash

In the case of Mc crash results, the largest impact came from the variable (Divaadt). The following variables lnlength, lnaadt, and lanewid have significant impacts on the model based on the variables signs and magnitudes.

Table 6.1.3.1 NB effects of access density on MC Crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.3847						
Associated standard error for Alpha = 0.0253						
t-statistic for the alpha value = 15.20						
Log likelihood = -4863.8390						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-7.84*	1.17	-6.68	<0.0001	-10.20	-55.30
lnaadt	**0.42**	0.07	5.41	<0.0001	0.26	0.57
lnlength	**0.89**	0.08	10.97	<0.0001	0.73	1.05
access_dens	**0.02**	0.007	2.93	0.003	0.007	0.03
lanewid	**0.41**	0.08	4.98	<0.0001	0.24	0.58
Divaadt = 1/aadt	**103.00**	32.40	3.18	0.001	41.90	166.00
int_dens	**0.02**	0.02	4.91	<0.0001	0.01	0.03
access_daily_trips_wkdy	<0.0001	<0.0001	1.18	0.23	<0.0001	<0.0001
access_dens:aadt	<0.0001	<0.0001	-0.42	0.67	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.1.3.2. NB effects of access density on MC crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.3836						
Associated standard error for Alpha = 0.0252						
t-statistic for the alpha value = 15.20						
Log likelihood = -4865.1880						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-7.79*	1.16	-6.68	<0.0001	-10.10	-5.47
lnaadt	**0.40**	0.07	5.33	<0.0001	0.25	0.56
lnlength	**0.89**	0.08	10.94	<0.0001	0.73	1.05
access_dens	**0.02**	0.007	3.04	0.002	0.008	0.03
lanewid	**0.42**	0.08	5.09	<0.0001	0.25	0.59
Divaadt = 1/aadt	**102.00**	32.20	3.17	0.001	41.20	165.00
int_dens	**0.02**	0.003	4.82	<0.0001	0.01	0.03
access_dens:aadt	<0.0001	<0.0001	-0.28	0.77	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italic*.						

Table 6.1.3.3. NB effects of access density on MC crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.3847						
Associated standard error for Alpha = 0.0253						
t-statistic for the alpha value = 15.20						
Log likelihood = -4864.0310						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-7.64*	1.06	-7.17	<0.0001	-9.80	-5.51
lnaadt	**0.39**	0.04	8.21	<0.0001	0.29	0.48
lnlength	**0.89**	0.08	11.01	<0.0001	0.74	1.05
access_dens	**0.02**	0.006	3.20	0.001	0.008	0.03
lanewid	**0.42**	0.08	5.00	<0.0001	0.24	0.59
Divaadt = 1/aadt	**97.30**	29.80	3.26	0.001	41.86	155.00
int_dens	**0.02**	0.004	4.94	<0.0001	0.01	0.03
access_daily_trips_wkdy	<0.0001	<0.0001	1.13	0.25	<0.0001	1.09
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

6.1.4 Access crash

In the case of Access crash results, the largest impact on the model came from the (Divaadt) variable. The following variables lnlength, lnaadt, and lanewid have significant impacts on the model based on the variables signs and magnitudes.

Table 6.1.4.1. NB effects of access density on Access crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.2050						
Associated standard error for Alpha = 0.0673						
t-statistic for the alpha value = 3.04						
Log likelihood = -758.8470						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*17.40*	3.41	-5.10	<0.0001	-24.90	-10.60
lnaadt	**0.62**	0.20	2.97	0.002	0.21	1.05
lnlength	**0.73**	0.20	3.53	0.0004	0.36	1.12
access_dens	**0.04**	0.02	1.98	0.04	0.001	0.08
lanewid	**0.77**	0.24	3.15	0.001	0.29	1.30
Divaadt = 1/aadt	**224.00**	70.40	3.17	0.001	74.60	369.00
int_dens	**0.02**	0.01	1.50	0.13	-0.008	0.04
access_daily _trips_wkdy	<0.0001	<0.0001	2.25	0.02	<0.0001	<0.0001
access_dens: aadt	<0.0001	<0.0001	-1.29	0.19	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.1.4.2. NB effects of access density on Access crashes

<table>
<tr><td colspan="7">Number of obs = 2065</td></tr>
<tr><td colspan="7">Prob > chi2 =0.0000</td></tr>
<tr><td colspan="7">Alpha = 0.1992</td></tr>
<tr><td colspan="7">Associated standard error for Alpha = 0.0662</td></tr>
<tr><td colspan="7">t-statistic for the alpha value = 3.00</td></tr>
<tr><td colspan="7">Log likelihood = -763.7940</td></tr>
<tr><td>Variables</td><td>Coef</td><td>Std. Error</td><td>z value</td><td>Pr(>|z|)</td><td colspan="2">[95% Conf. Interval]</td></tr>
<tr><td>(Intercept)</td><td>16.10</td><td>3.37</td><td>-4.77</td><td><0.0001</td><td>-23.30</td><td>-9.47</td></tr>
<tr><td>lnaadt</td><td>0.52</td><td>0.20</td><td>2.56</td><td>0.01</td><td>0.12</td><td>0.93</td></tr>
<tr><td>lnlength</td><td>0.74</td><td>0.20</td><td>3.53</td><td>0.0004</td><td>0.36</td><td>1.13</td></tr>
<tr><td>access_dens</td><td>0.04</td><td>0.02</td><td>2.07</td><td>0.03</td><td>.003</td><td>0.08</td></tr>
<tr><td>lanewid</td><td>0.76</td><td>0.24</td><td>3.13</td><td>0.001</td><td>0.28</td><td>1.29</td></tr>
<tr><td>Divaadt = 1/aadt</td><td>206.60</td><td>70.00</td><td>2.95</td><td>0.003</td><td>59.30</td><td>350.00</td></tr>
<tr><td>int_dens</td><td>0.01</td><td>0.01</td><td>1.44</td><td>0.14</td><td>-0.009</td><td>0.04</td></tr>
<tr><td>access_dens:aadt</td><td><0.0001</td><td><0.0001</td><td>-1.00</td><td>0.31</td><td><0.0001</td><td><0.0001</td></tr>
<tr><td colspan="7">Variables have impact of increasing the crash frequency are shown in bold.
Variables have impact of decreasing the crash frequency are shown in italics.</td></tr>
</table>

Table 6.14.3. NB effects of access density on Access crashes

Number of obs = 2065						
Prob > chi2 =0.0000						
Alpha = 0.2032						
Associated standard error for Alpha = 0.0668						
t-statistic for the alpha value = 3.04						
Log likelihood = -760.6270						
Variables	Coef	Std. Error	z value	Pr(>|z|)	[95% Conf. Interval]	
(Intercept)	*-15.60*	3.14	-4.97	<0.0001	-22.40	-9.40
lnaadt	**0.39**	0.12	3.23	0.001	0.15	0.63
lnlength	**0.76**	0.20	3.65	0.0002	0.38	1.14
access_dens	**0.02**	0.01	1.49	0.13	-0.006	0.05
lanewid	**0.78**	0.24	3.17	0.001	0.29	1.31
Divaadt = 1/aadt	**177.10**	60.39	2.76	0.005	43.68	304.55
int_dens	**0.01**	0.01	1.43	0.15	-0.009	0.04
access_daily_trips_wkdy	<0.0001	<0.0001	2.07	0.03	<0.0001	<0.0001
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

6.2. Data analysis and results for the Random Parameter Negative Binomial (RPNB) Model results and discussion

The output of the Random Parameter Negative Binomial (RPNB) regression model determines the interactive variables that have impacts on crash frequency and safety, and they are presented in this section. All segments were estimated using urban road data. The random parameter negative binomial model to detect their influences on crash frequency tested two major variables. Traffic volume has an impact on crash occurrence in this model and it is calculated by monitoring two factors, which are the AADT and the access daily trips. Also, access density has an essential impact on crash frequency and it is represented in the model by access density, intersection density, and horizontal density. Random parameter negative binomial regression model were applied on four types of crashes. Total crash, Fi crash, Mc crash, and Access crash are the crash types were evaluated in this research. In Total crash, Fi crash, Mc crash, and Access crash models, the regression parameters associated with natural logarithm of the AADT and length in addition to access density, lane width, intersection density and access daily trips. The essential indicator is the coefficients of the regression. The negative coefficient represents that there is a decreasing on the crash frequency and the variable has a positive impact on the model. On the other hand, the positive coefficients represent that the crash rate will grow because of these variables, which needs to be taken into consideration when using this model. The standard negative binomial regression models were used on the different types of crashes (Total, Fi, Mc, and Access), and the results are shown in Tables 22-33.

6.2.1. Total crashes

There were four types of crashes examined in the RPNB model in this thesis: (1) Total crash, (2) Fi crash, (3) Mc crash, and (4) Access crash. The assumption was that most of variables that were tested would increase total crashes. That was the case throughout the results; however, three variables would decrease total crashes. In the case of total crash results, however, the responses obtained do not make sense and were not logically predictable. For example, in Table 6.2.1.1, the Intercept, the AD interacting with AADT, and the access daily trips in week days are three negative values. That means that they have an effect on the model beside their magnitudes. The other variables in Table 6.2.1.1 will likely increase total crashes.

Table 6.2.1.1. RPNB on Total crashes

<table>
<tr><td colspan="7">Number of obs = 2065</td></tr>
<tr><td colspan="7">Id: 413</td></tr>
<tr><td colspan="7">Alpha = 0.101</td></tr>
<tr><td colspan="7">Associated standard error for Alpha = 0.026</td></tr>
<tr><td colspan="7">t-statistic for the alpha value = 3.88</td></tr>
<tr><td colspan="7">Log likelihood = -2368.75</td></tr>
<tr><th>Variables</th><th>Coef</th><th>Std. Error</th><th>z value</th><th>Pr(>|z|)</th><th>Variance</th><th>StdDev</th></tr>
<tr><td>(Intercept)</td><td>-3.59</td><td>0.83</td><td>-4.29</td><td><0.0001</td><td>1.97</td><td>1.40</td></tr>
<tr><td>lnaadt</td><td>0.46</td><td>0.09</td><td>4.79</td><td><0.0001</td><td></td><td></td></tr>
<tr><td>lnlength</td><td>0.95</td><td>0.14</td><td>6.53</td><td><0.0001</td><td></td><td></td></tr>
<tr><td>access_dens</td><td>0.02</td><td>0.01</td><td>2.25</td><td>0.02</td><td></td><td></td></tr>
<tr><td>Divaadt = 1/aadt</td><td>57.50</td><td>34.80</td><td>1.65</td><td>0.09</td><td></td><td></td></tr>
<tr><td>int_dens</td><td>0.02</td><td>0.008</td><td>2.78</td><td>0.005</td><td></td><td></td></tr>
<tr><td>access_daily_trips_wkdy</td><td><0.0001</td><td><0.0001</td><td>-0.33</td><td>0.73</td><td></td><td></td></tr>
<tr><td>access_dens:aadt</td><td><0.0001</td><td><0.0001</td><td>-1.94</td><td>0.05</td><td></td><td></td></tr>
<tr><td colspan="7">Variables have impact of increasing the crash frequency are shown in bold.
Variables have impact of decreasing the crash frequency are shown in italics.</td></tr>
</table>

Table 6.2.1.2. RPNB on Total crashes

Number of obs = 2065

Id: 413

Alpha = 0.10

Associated standard error for Alpha = 0.025

t-statistic for the alpha value = 4.00

Log likelihood = -2370.63

Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-2.46*	0.59	-4.13	<0.0001	1.97	1.40
lnaadt	**0.32**	0.06	4.98	<0.0001		
lnlength	**0.96**	0.14	6.57	<0.0001		
access_dens	**0.02**	.01	1.69	0.09		
Divaadt = 1/aadt	**31.50**	32.00	0.98	0.32		
int_dens	**0.02**	0.008	2.67	0.007		
access_daily_trips_wkdy	<0.0001	<0.0001	-0.48	0.63		

Variables have impact of increasing the crash frequency are shown in **bold**.
Variables have impact of decreasing the crash frequency are shown in *italics*.

Table 6.2.1.3. RPNB on Total crashes

<table>
<tr><td colspan="7">Number of obs = 2065</td></tr>
<tr><td colspan="7">Id: 413</td></tr>
<tr><td colspan="7">Alpha = 0.10</td></tr>
<tr><td colspan="7">Associated standard error for Alpha = 0.025</td></tr>
<tr><td colspan="7">t-statistic for the alpha value = 4.00</td></tr>
<tr><td colspan="7">Log likelihood = -2368.81</td></tr>
<tr><th>Variables</th><th>Coef</th><th>Std. Error</th><th>z value</th><th>Pr(>|z|)</th><th>Variance</th><th>StdDev</th></tr>
<tr><td>(Intercept)</td><td>-3.67</td><td>0.80</td><td>-4.56</td><td><0.0001</td><td>1.97</td><td>1.40</td></tr>
<tr><td>lnaadt</td><td>0.46</td><td>.09</td><td>4.89</td><td><0.0001</td><td></td><td></td></tr>
<tr><td>lnlength</td><td>0.95</td><td>0.14</td><td>6.53</td><td><0.0001</td><td></td><td></td></tr>
<tr><td>access_dens</td><td>0.02</td><td>0.01</td><td>2.23</td><td>0.02</td><td></td><td></td></tr>
<tr><td>Divaadt = 1/aadt</td><td>58.10</td><td>34.80</td><td>1.67</td><td>0.09</td><td></td><td></td></tr>
<tr><td>int_dens</td><td>0.02</td><td>0.008</td><td>2.80</td><td>0.005</td><td></td><td></td></tr>
<tr><td>access_dens:aadt</td><td><0.0001</td><td><0.0001</td><td>-1.97</td><td>0.04</td><td></td><td></td></tr>
<tr><td colspan="7">Variables have impact of increasing the crash frequency are shown in bold.
Variables have impact of decreasing the crash frequency are shown in italics.</td></tr>
</table>

6.2.2. Fi Crash

In the case of Fi crash results, all variables are positive which means that crash occurrence is likely to increase which is predictable and logical. For example, in Table 6.2.2.1, the Intercept, the AD interacting with AADT, and the access daily trips in week days, and the other variables are positive values. That means that they have a negative effect on the model, which based on the variables sign and magnitude.

Table 6.2.2.1. RPNB on Fi crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.15						
Associated standard error for Alpha = 0.001						
t-statistic for the alpha value = 150.00						
Log likelihood = -199.134						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-7.89*	2.48	-3.18	0.001	<0.0001	0.002
lnaadt	**0.56**	0.28	2.02	0.04		
lnlength	**1.30**	0.32	4.01	<0.0001		
access_dens	**0.02**	.03	0.65	0.51		
Divaadt = 1/aadt	**168.00**	114.00	1.47	0.14		
int_dens	**0.02**	0.02	1.10	0.27		
access_daily_trips_wkdy	<0.0001	<0.0001	1.26	0.20		
access_dens:aadt	<0.0001	<0.0001	0.95	0.34		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.2.2.2. RPNB on Fi crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.15						
Associated standard error for Alpha = 0.001						
t-statistic for the alpha value = 150.00						
Log likelihood = -199.579						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-9.67*	1.69	-5.72	<0.0001	<0.0001	0.003
lnaadt	**0.75**	0.18	4.27	<0.0001		
lnlength	**1.28**	0.32	3.95	<0.0001		
access_dens	**0.03**	0.02	1.49	0.13		
Divaadt = 1/aadt	**214.00**	102.00	2.11	0.03		
int_dens	**0.02**	0.02	1.21	0.22		
access_daily_trips_wkdy	<0.0001	<0.0001	1.24	0.21		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.2.2.3. RPNB on Fi crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.15						
Associated standard error for Alpha = 0.001						
t-statistic for the alpha value = 150.00						
Log likelihood = -199.923						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-7.27*	2.45	-2.97	0.003	<0.0001	0.005
lnaadt	**0.53**	0.28	1.90	0.05		
lnlength	**1.31**	0.32	4.05	<0.0001		
access_dens	**0.02**	0.03	0.83	0.40		
Divaadt = 1/aadt	**159.00**	114.00	1.39	0.16		
int_dens	**0.02**	0.01	1.03	0.30		
access_dens:aadt	<0.0001	<0.0001	0.93	0.35		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italic*.						

6.2.3. Mc crash

In the case of Mc crash results, however, the responses obtained do not make sense and were not logically predictable. For example, in Table 6.2.3.1, the Intercept, the AD interacting with AADT, and the access daily trips in week days are three negative values. That means that they have a positive effect on the model based on the variables sign and magnitude. The other variables in Table 6.2.3.1 will likely increase total crashes.

Table 6.2.3.1. RPNB on Mc crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.12						
Associated standard error for Alpha = 0.006						
t-statistic for the alpha value = 20.00						
Log likelihood = -2064.37						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-3.97*	0.93	-4.24	<0.0001	2.31	1.52
lnaadt	**0.45**	0.10	4.19	<0.0001		
lnlength	**0.99**	0.16	6.09	<0.0001		
access_dens	**0.03**	0.01	2.43	0.01		
Divaadt = 1/aadt	**57.80**	39.10	1.48	0.13		
int_dens	**0.03**	0.009	3.21	0.001		
access_daily_trips_wkdy	<0.0001	<0.0001	-0.34	0.73		
access_dens:aadt	<0.0001	<0.0001	-1.71	0.08		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.2.3.2. RPNB on Mc crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.13						
Associated standard error for Alpha = 0.008						
t-statistic for the alpha value = 16.25						
Log likelihood = -2065.84						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-2.85*	0.66	-4.31	<0.0001	2.31	1.52
lnaadt	**0.31**	0.07	4.34	<0.0001		
lnlength	**0.99**	0.16	6.13	<0.0001		
access_dens	**0.02**	0.01	1.96	0.05		
Divaadt = 1/aadt	**32.30**	36.10	0.89	0.37		
int_dens	**0.03**	0.009	3.10	0.001		
access_daily_trips_wkdy	<0.0001	<0.0001	-0.46	0.64		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.2.3.3. RPNB on Mc crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.13						
Associated standard error for Alpha = 0.008						
t-statistic for the alpha value = 16.25						
Log likelihood = -2064.43						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-4.06*	0.90	-4.50	<0.0001	2.31	1.52
lnaadt	**0.45**	0.10	4.27	<0.0001		
lnlength	**0.99**	0.16	6.10	<0.0001		
access_dens	**0.03**	0.01	2.42	0.01		
Divaadt = 1/aadt	**58.40**	39.00	1.50	0.13		
int_dens	**0.03**	0.009	3.23	0.001		
access_dens:aadt	<0.0001	<0.0001	-1.74	0.08		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

6.2.4 Access crash

In the case of Access crash results, however, the responses obtained do not make sense and were not logically predictable. For example, in Table 6.2.4.1, the Intercept and the AD interacting with AADT are two negative values. That means that they have a positive effect on the model based on the variables sign and magnitude. The other variables in Table 6.2.4.1 will likely increase total crashes.

Table 6.2.4.1. RPNB on Access crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.002						
Associated standard error for Alpha = <0.0001						
t-statistic for the alpha value = 4166.60						
Log likelihood = -337.113						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-9.30*	2.40	-3.87	0.0001	3.57	1.89
lnaadt	**0.57**	0.27	2.11	0.03		
lnlength	**0.81**	0.30	2.64	0.008		
access_dens	**0.03**	0.02	1.22	0.22		
Divaadt = 1/aadt	**192.00**	94.50	2.03	0.04		
int_dens	**0.01**	0.01	0.94	0.34		
access_daily_trips_wkdy	<0.0001	<0.0001	1.57	0.11		
access_dens:aadt	<0.0001	<0.0001	-0.29	0.77		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.2.4.2. RPNB on Access crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.002						
Associated standard error for Alpha = <0.0001						
t-statistic for the alpha value = 500,000.00						
Log likelihood = -337.155						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-8.77*	1.56	-5.61	<0.0001	3.61	1.90
lnaadt	**0.51**	0.16	3.10	0.001		
lnlength	**0.81**	0.31	2.66	0.007		
access_dens	**0.03**	0.02	1.25	0.21		
Divaadt = 1/aadt	**180.00**	84.00	2.14	0.03		
int_dens	**0.01**	0.01	0.92	0.35		
access_daily_trips_wkdy	<0.0001	<0.0001	1.55	0.12		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

Table 6.2.4.3. RPNB on Access crashes

Number of obs = 2065						
Id: 413						
Alpha = 0.002						
Associated standard error for Alpha = <0.0001						
t-statistic for the alpha value = 609.75						
Log likelihood = -338.34						
Variables	Coef	Std. Error	z value	Pr(>|z|)	Variance	StdDev
(Intercept)	*-8.36*	2.32	-3.61	0.0003	3.75	1.93
lnaadt	**0.51**	0.27	1.88	0.06		
lnlength	**0.81**	0.31	2.63	0.008		
access_dens	**0.03**	0.02	1.32	0.18		
Divaadt = 1/aadt	**179.00**	94.20	1.90	0.05		
int_dens	**0.01**	0.01	0.87	0.38		
access_dens:aadt	<0.0001	<0.0001	-0.11	0.90		
Variables have impact of increasing the crash frequency are shown in **bold**. Variables have impact of decreasing the crash frequency are shown in *italics*.						

6.3 Limitations of the study

Access traffic volume numbers (daily trips) were estimated using the Institute of Transportation Engineers (ITE) Trip Generation Manual (Institute of Transportation Engineers, 2004). These are simple estimates and may be associated with measurement error and unobserved heterogeneity. However, the random parameters models all indicated that the access daily trips was not random, providing evidence that either the access daily trips were not a practically significant predictor of crash frequency and/or that the estimates are close enough for the predictions in the regression models. The RPNB results are also more accurate because variables are correlated with time of crash occurrence, compared to NB data, Poisson and other statistic regression models.

CHAPTER 7. SUMMARY AND CONCLUSIONS

Access control is of major importance in roadway management throughout the US. By limiting access points on roadways, there are fewer points of potential conflict, resulting in improved safety and reduction in property loss. The Highway Safety Information System (HSIS), Institute of Transportation Engineers (ITE) Trip Generation Manual, and Google Earth were used to develop the database for the state of Minnesota used in this thesis. The methodology was cross-sectional longitudinal with multivariate statistical analysis. Multiple functional classifications of urban roadways were considered, with a focus on major/minor collectors and minor arterials. The CMFs were developed for Total number of crashes, Fi, Mc, and Access. The NB Regression models and RPNB Regression models were developed. Independent variables were Total crashes, Fi, Mc, and Access-related. Dependent variables were AD, annual daily trips, lane width, length, AADT, and others. Results indicated that AD and traffic volume (represented in this thesis as annual daily trips) influenced crash frequency over the period 2009-2014 throughout the roadway system in Minnesota. The results of this research may be useful for transportation engineers and roadway planners in determining when AD should be reconsidered and controlled.

CHAPTER 8. RECOMMENDATIONS FOR FUTURE WORK

Future studies could include in both statistical models, more variables such as, limiting access by vehicle types, pedestrian safety, and bicycle lanes. All those data are available from the MnDOT and are easily accessible.

APPENDIX

APPENDIX FIGURES

Figure 1. A screenshot of the data that was used in this thesis

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
1	rtsysnbr	aadt	length	access	rshl_wd2	rshl_ty2	surf_wd2	surf_ty2	lshl_wd2	lshl_ty2	medwid	med_type	lshldwid	lshl_typ	surf_wid	surf_typ	rshldwid	rshl_typ	oneway	curb2	curb1	func_cls	fed_aid	no_lanes	lanewid
2	0300000001	6419	0.249	1									3	G2	24	G2	3	G2	U		N	14	P	2	12
3	0455000002	6500	0.22	1									2	E	24	G	2	E	U		N	16	U	2	12
4	0409000002	3000	0.75	1									4	I	24	I	4	I	U		N	17	U	2	12
5	0300000003	8500	0.102	1									8	G2	24	G2	8	G2	U		N	14	P	2	12
6	0405000003	8331	0.5	1									8	G	38	G	8	G	U		B	16	U	2	12
7	0409000003	5900	0.13	1									0	00	24	G	0	00	U		B	16	U	2	12
8	0414000003	4459	0.24	1									0	00	44	G2	0	00	U		B	16	U	2	12
9	300000003	8500	0.092	1									6	G2	24	G3	6	G2	U		N	14	P	2	12
10	0402000004	2470	0.3	1									0	00	44	I	0	00	U		B	16	U	2	12
11	0455000004	3950	0.23	1									3	G	24	J	3	G	U		N	16	U	2	12
12	0407000005	4595	0.16	1									0	00	48	G	0	00	U		B	16	U	2	12
13	0482000006	4954	0.308	1									10	I	24	I	10	I	U		B	17	N	2	12
14	0300000007	13300	0.175	1									8	G2	24	G2	8	G2	U		N	14	P	2	12
15	0409000007	9079	0.7	1									10	G	48	G	10	G	U		B	16	U	2	12
16	0402000007	14200	0.32	1									0	00	52	G	0	00	U		B	16	U	2	12
17	300000007	13300	0.089	1									8	G2	24	I	8	G2	U		N	14	P	2	12
18	300000007	6200	0.229	1									8	I	24	I3	8	I	U		N	14	P	2	12
19	300000007	14056	0.307	1									7	E	24	G2	7	E	U		N	14	P	2	12
20	300000007	14056	0.566	1									6	E	24	G2	6	E	U		N	14	P	2	12
21	300000007	14056	0.095	1									6	E	24	G2	6	E	U		N	14	P	2	12
22	300000007	13253	0.01	1									9	E	24	G2	9	E	U		N	14	P	2	12
23	0407000008	10889	0.1	1									8	00	48	G	8	00	U		B	16	U	2	12
24	0427000008	5812	0.77	1									4	G	24	I	4	G	U		N	17	N	2	12
25	0474000009	2189	0.425	1									5	E	22	G	5	E	U		N	17	N	2	11
26	0419000009	12346	0.917	1									2	E	24	G	2	E	U		N	17	N	2	12
27	300000009	7437	0.141	1									0	0	49	G3	0	0	U		B	14	P	2	12
28	0482000010	5156	0.26	1									10	S	24	G	10	S	U		N	16	N	2	12

Figure 2. A screenshot of the data that was used in this thesis (continued)

AG89 | f_x | 0

	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG
1	surf_wd2	surf_ty2	lshl_wd2	lshl_ty2	medwid	med_type	lshldwid	lshl_typ	surf_wid	surf_typ	rshldwid	rshl_typ	oneway	curb2	curb1	func_cls	fed_aid	no_lanes	lanewid	rodwycls	year	route	begmp	endmp	No_Ints	no_access	No_HC
2							3	G2	24	G2	3	G2	U		N	14	P	2	12	3	2014	1	47.184	47.433	0	7	0
3							2	E	24	G	2	E	U		N	16	U	2	12	3	2014	2	0.814	1.034	2	5	0
4							4	I	24	I	4	I	U		N	17	U	2	12	3	2014	2	1.14	1.89	0	8	0
5							8	G2	24	G2	8	G2	U		N	14	P	2	12	3	2014	3	1.076	1.178	4	9	0
6							8	G	38	G	8	G	U		B	16	U	2	12	3	2014	3	0.15	0.65	4	12	2
7							0	00	24	G	0	00	U		B	16	U	2	12	3	2014	3	13.63	13.76	1	5	0
8							0	00	44	G2	0	00	U		B	16	U	2	12	3	2014	3	1.07	1.31	0	11	0
9							6	G2	24	G3	6	G2	U		N	14	P	2	12	3	2014	3	1.368	1.46	0	15	0
10							0	00	44	I	0	00	U		B	16	U	2	12	3	2014	4	1.27	1.57	0	24	2
11							3	G	24	J	3	G	U		N	16	U	2	12	3	2014	4	6.057	6.287	0	5	0
12							0	00	48	G	0	00	U		B	16	U	2	12	3	2014	5	0.25	0.41	4	9	0
13							10	I	24	I	10	I	U		B	17	N	2	12	3	2014	6	1.347	1.655	1	14	1
14							8	G2	24	G2	8	G2	U		N	14	P	2	12	3	2014	7	173.519	173.694	0	3	1
15							10	G	48	G	10	G	U		B	16	U	2	12	3	2014	7	18.21	18.91	4	33	0
16							0	00	52	G	0	00	U		B	16	U	2	12	3	2014	7	1.73	2.05	0	16	0
17							8	G2	24	I	8	G2	U		N	14	P	2	12	3	2014	7	173.02	173.109	0	6	0
18							8	I	24	I3	8	I	U		N	14	P	2	12	3	2014	7	75.074	75.303	0	4	0
19							7	E	24	G2	7	E	U		N	14	P	2	12	3	2014	7	179.662	179.969	0	2	1
20							6	E	24	G2	6	E	U		N	14	P	2	12	3	2014	7	178.596	179.162	1	2	1
21							6	E	24	G2	6	E	U		N	14	P	2	12	3	2014	7	178.501	178.596	0	2	1
22							9	E	24	G2	9	E	U		N	14	P	2	12	3	2014	7	175.347	175.357	0	4	1
23							8	00	48	G	8	00	U		B	16	U	2	12	3	2014	8	6.26	6.36	0	3	1
24							4	G	24	I	4	G	U		N	17	N	2	12	3	2014	8	2.96	3.73	0	5	0
25							5	E	22	G	5	E	U		N	17	N	2	11	3	2014	9	2.562	2.987	1	7	0
26							2	E	24	G	2	E	U		N	17	N	2	12	3	2014	9	9.742	10.659	0	11	1
27							0	0	49	G3	0	0	U		B	14	P	2	12	3	2014	9	60.508	60.649	3	5	0
28							10	S	24	G	10	S	U		N	16	N	2	12	3	2014	10	7.01	7.27	0	6	1

Figure 3. A screenshot of Rstudio that was used for analyzing in this thesis

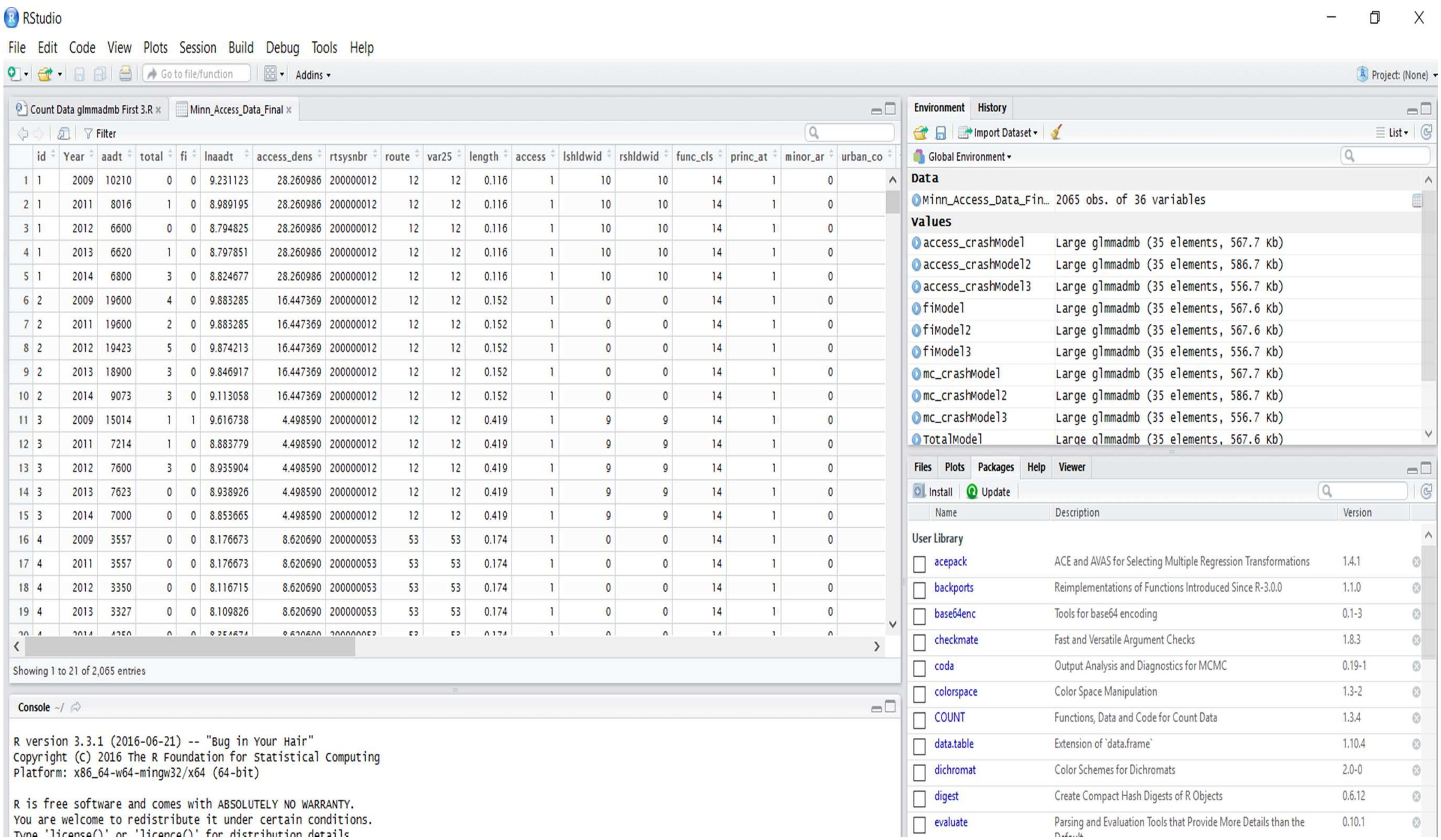


Figure 4. A screenshot of Google Earth that was used for gathering data in this thesis.

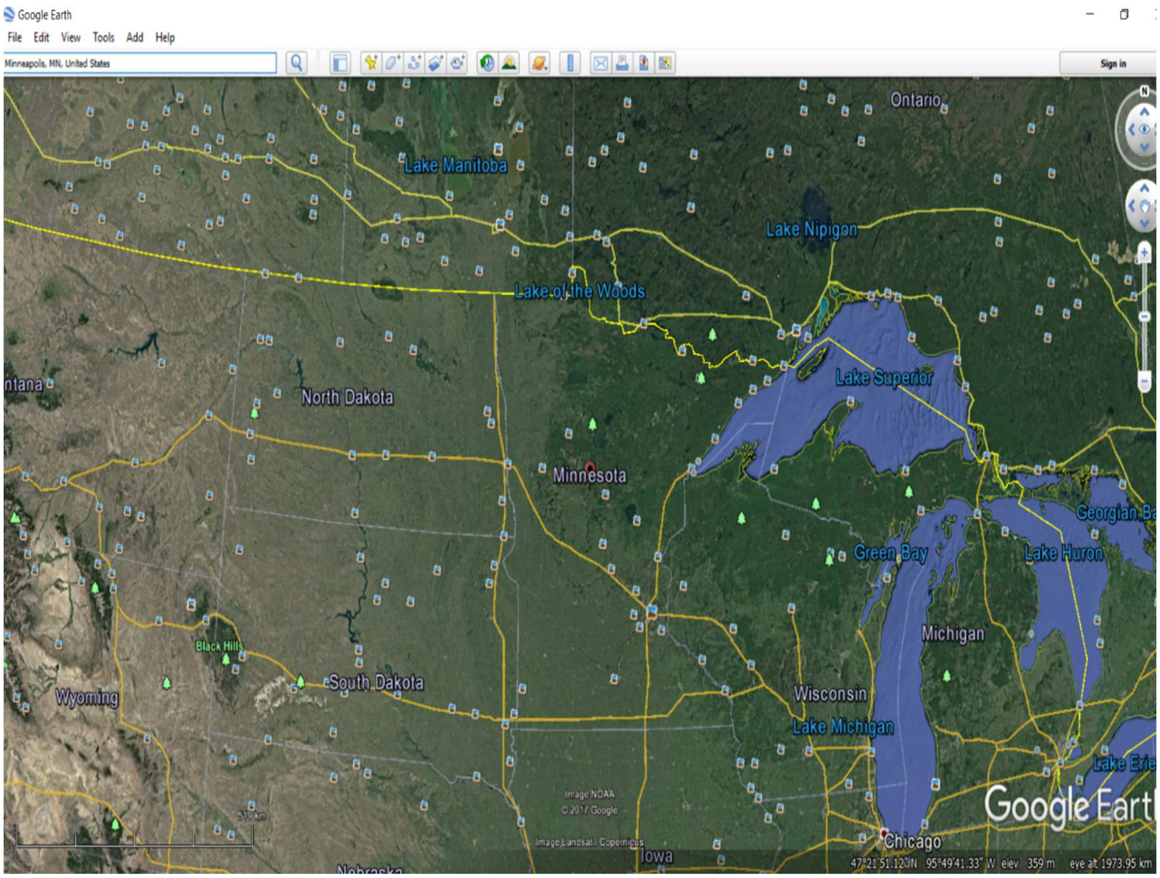


Figure 5. A plot compares between the residual and the leverage of the Total crash NB regression model

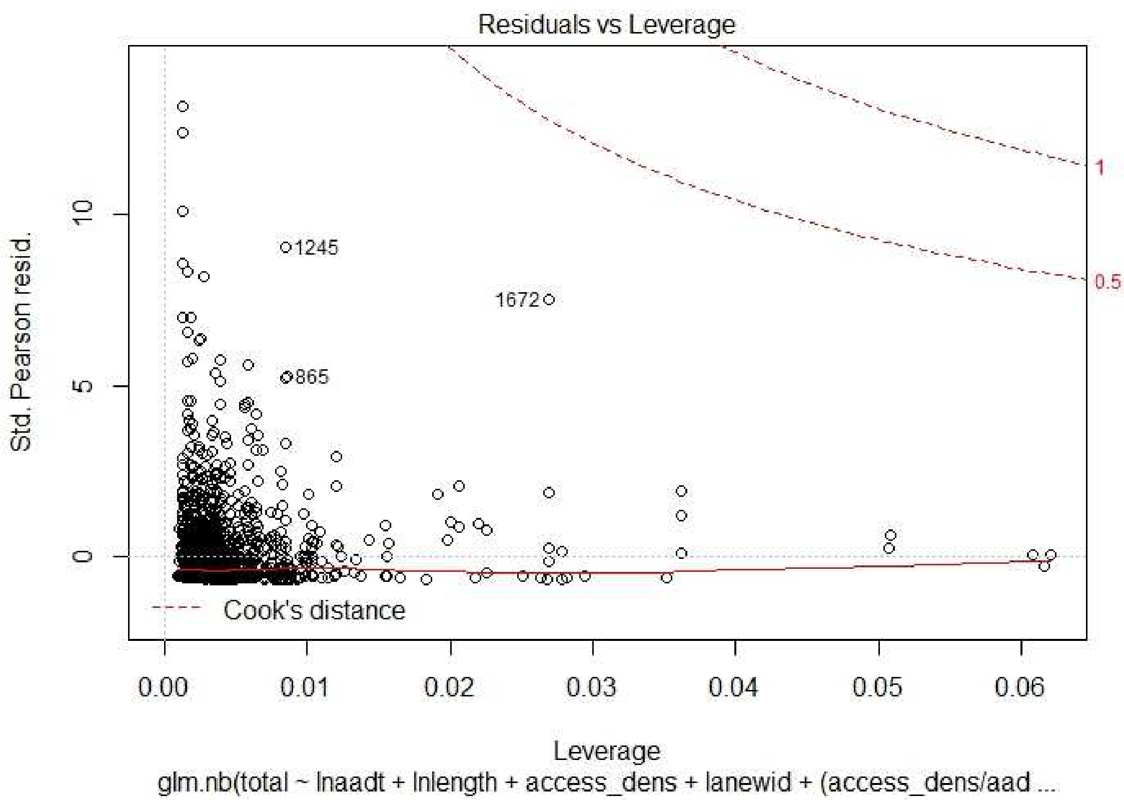


Figure 6. A plot compares between the residual and the fitted of the Total crash NB regression model

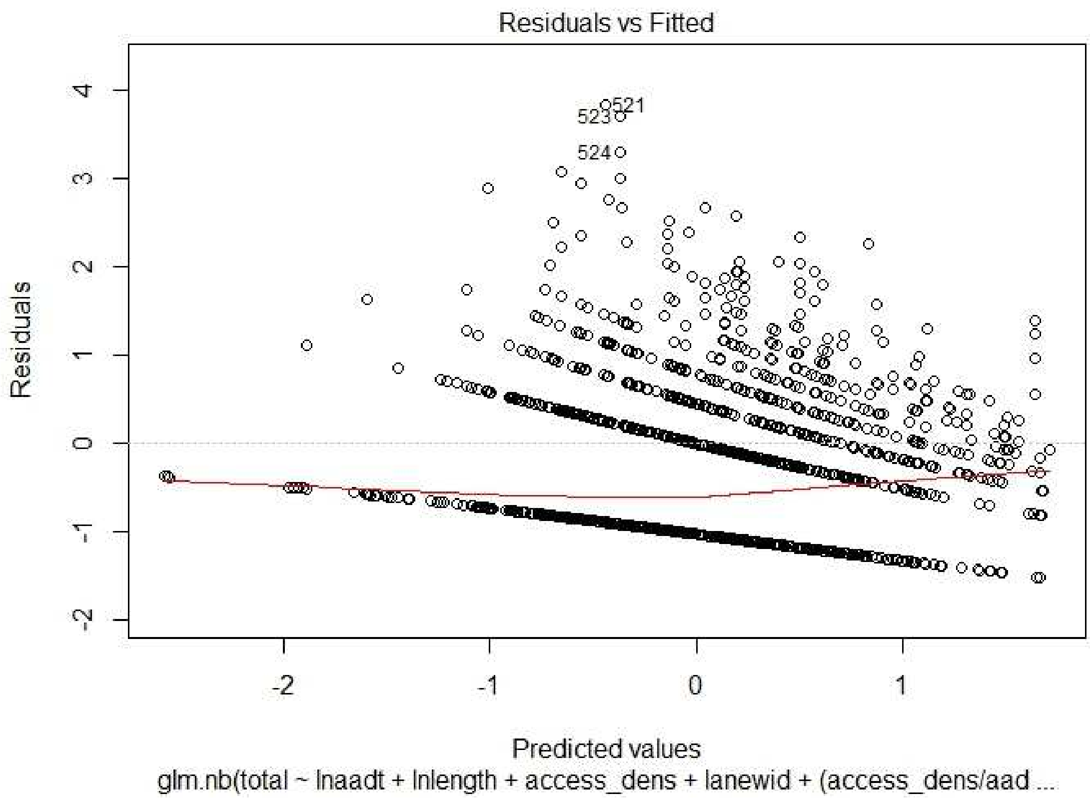


Figure 7. A plot shows the normal Q-Q of the Total crash NB regression model

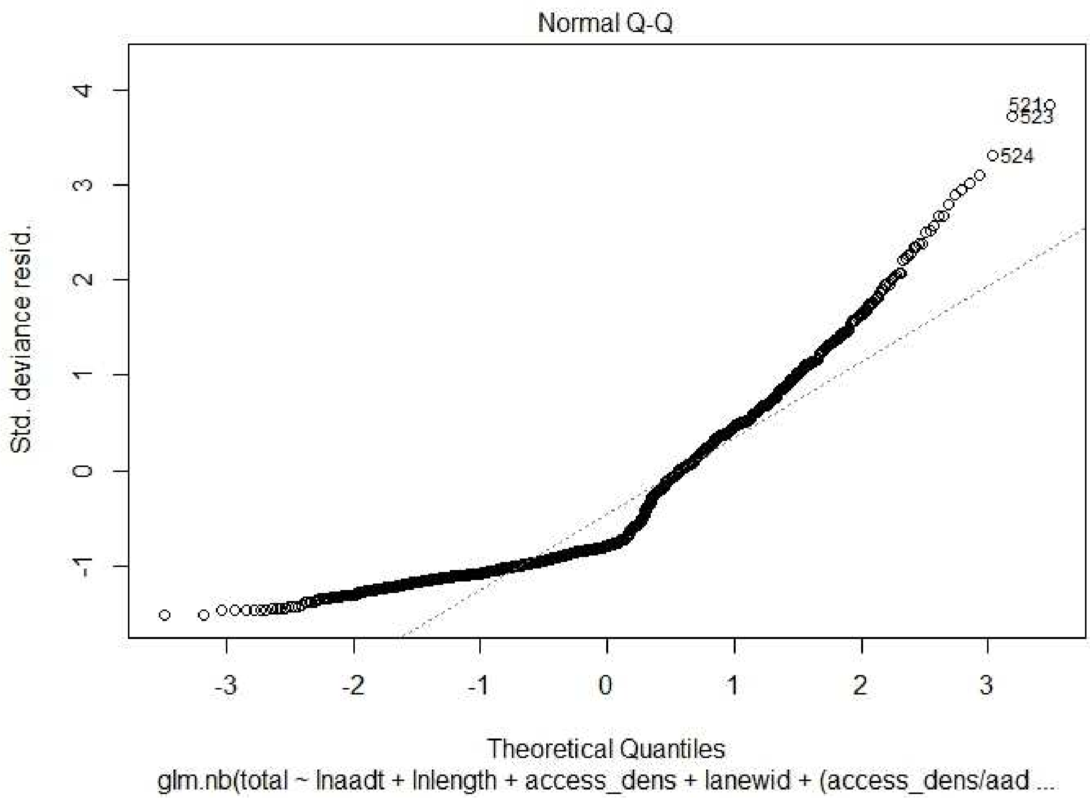
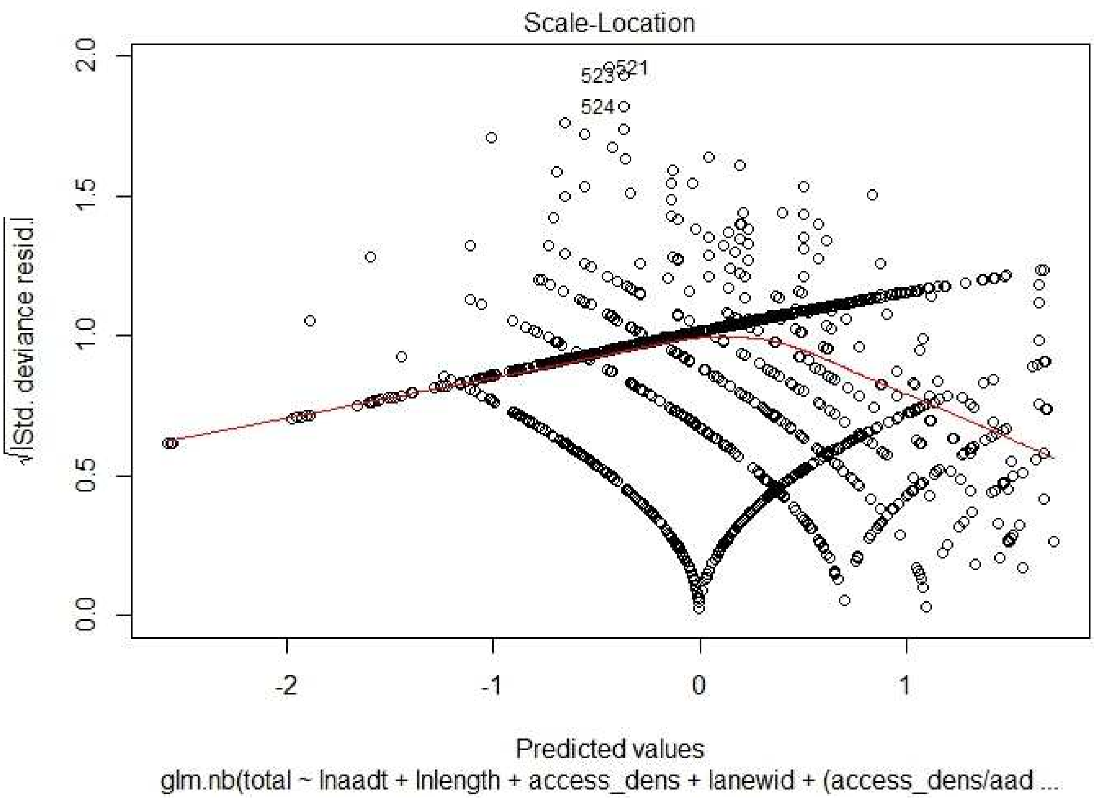


Figure 8. A plot shows the scale location of the Total crash NB regression model



REFERENCES

Benz, R. J., Norboge, N., Voigt, A., & Gage, S. (2015). Economic assessment of access management projects in the Houston, Texas, Region. *Transportation Research Record: Journal of the Transportation Research Board,* (2486), pp.80-89. doi: 10.3141/2486-10

Chin, H. & Quddus, M. (2003). Applying the random effect negative binomial model to examine traffic accident occurrence at signalized intersections. *Accident Analysis & Prevention, 35*(2), pp. 253-259. doi:10.1016/s0001-4575(02)00003-9

Du, Y., Zhao, C., Zhang, X., & Sun, L. (2015). Microscopic simulation evaluation method on access traffic operation. *Simulation Modelling Practice and Theory, 53*, pp. 139-148. doi:10.1016/j.simpat.2015.02.004

Federal Highway Administration (2017). Crash Modification Factors Clearinghouse. U. S. Department of Transportation. Retrieved from http://www.cmfclearinghouse.org/

Gattis, J. L., Balakumar, R, & Duncan, L.K. (2005). Effects of rural highway median treatments and access. *Journal of the Transportation Research Board*, *1931*, pp. 99–107. doi: 10.3141/1931-13

Garcia, R. (2014). Roadway Design Manual. Texas Department of Transportation. Austin, TX.

Gluck, J., & Lorenz, M. (2010). *State of the practice in highway access management*. Washington, D.C.: Transportation Research Board. doi: 10.17226/14419

Gross, F., Lyon, C., Persaud, B., & Gluck, J. (2013). Safety evaluation of access management policies and techniques. TRB 92nd Annual Meeting, Washington, DC.

Hauer, E. On exposure and accident rate. (1995). *Traffic engineering & control, 36* (3), pp. 134–138. London, England.

Institute of Transportation Engineers (2004). Access management. Issue Brief 13. U. S. Department of Transportation, Federal Highway Administration, Washington, DC. Retrieved from http://library.ite.org/pub/e26c5400-2354-d714-51b2-432d8f3da94d

Kutner, M., Nachtsheim, C., & Neter, J. (2008). Applied linear regression models. Boston: McGraw-Hill.

Lall, B. (1995). Analysis of traffic accidents within the functional area of intersections and driveways. Report No. TRANS-1-96. Portland State University, Portland, OR.

Lawless, J. (1987). Negative binomial and mixed Poisson regression. *Canadian Journal of Statistics, 15*(3), pp. 209-225. University of Waterloo, Waterloo, ON, Canada.

Mauga, T. & Kaseko, M. (2010). Modeling and evaluating the safety impacts of Access Management (AM) features in the Las Vegas valley. *Transportation Research Record: Journal of the Transportation Research Board, 2171*, pp. 57–65.

MnDOT (2015). Minnesota motor vehicle crash facts: *A summary of crashes occurring on Minnesota roadways based on crash reports submitted to the Minnesota Department of Public Safety by investigating police officers and drivers*. MnDOT, St. Paul, MN.

MnDOT (2017). Traffic Engineering. U. S. Department of Transportation. Retrieved from http://www.dot.state.mn.us/trafficeng/safety/crashdata.html

Nujjetty, A. & Sharma, S. (2015). Guidebook for data files Minnesota. Highway Safety Information system. Washington, DC.

Saxena, M. (2010). Comparison of various methods to compute access density and proposing a weighted methodology. University Of South Florida.

Shadewald, J. & Prem, C. (2004) Quantifying access management benefits using traffic simulation. Proceedings of the ninth TRB conference on the application of transportation planning methods. Baton Rouge, Louisiana.

Schultz, G., Lewis, J., & Boschert, T. (2007). Safety impacts of access management techniques in Utah. *Transportation Research Record: Journal of the Transportation Research Board, 1994*, pp. 35-42. doi:10.3141/1994-05

Venkataraman, N., Ulfarsson, G., & Shankar, V. N. (2013). Random parameter models of interstate crash frequencies by severity, number of vehicles involved, collision and location type. *Accident Analysis & Prevention, 59*, pp. 309-318. doi:10.1016/j.aap.2013.06.021

Wood, J., Donnell, E., & Fariss, C. (2016). A method to account for and estimate underreporting in crash frequency research. Accident Analysis & Prevention, 95, 57-66. doi:10.1016/j.aap.2016.06.013