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Effects of Geometric Design Features on Truck Crashes on Limited-Access Highways

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16. Abstract

Freight can be transported between most points in the country quite efficiently using trucks. However, involvement of large trucks in crashes can cause much damage and serious injuries, due to their large sizes and heavy weights. Large truck crashes occurring on limited-access highways may be more severe than crashes occurring on other roadways due to high speed limits, and traffic- and geometric-related characteristics. The purpose of this study is to describe the relationships between large truck crash probability, and traffic and geometric characteristics. Crash data from 2005 to 2010 were obtained from the Kansas Department of Transportation (KDOT), which included 5,378 large track crashes that occurred on Kansas limited-access highway sections. The traffic- and geometric-related details of highways were obtained from the Control Section Analysis System (CANSYS) database, which is maintained by KDOT as a highway inventory system. Homogeneous road sections in terms of speed limit, AADT, percent of trucks, horizontal curvature, horizontal grade, lane width, shoulder width, median width, and existence of rumble strips were identified. The total number of crashes occurring within each segment from 2005 to 2010 was determined, resulting in 7,273 analysis segments used in the modeling. A Poisson regression model and a negative binomial regression model were developed for identifying the relationships between the occurrence of truck crashes, and traffic and geometric characteristics. According to the models, highway design features such as horizontal curvature, vertical grade, lane width, and shoulder width are factors which can be used to change the occurrence of large truck crashes. Identifying the effect of traffic and geometric characteristics is important to promote safety treatments through engineering improvements.

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Abstract

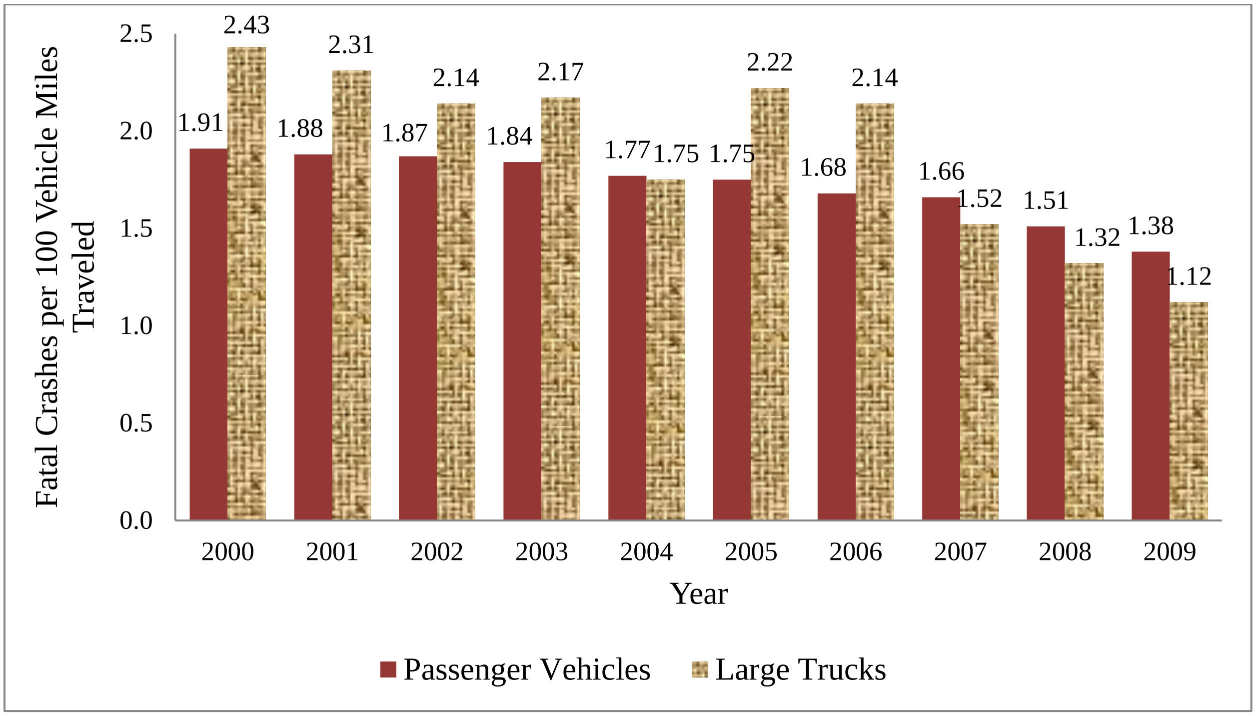
Freight can be transported between most points in the country quite efficiently using trucks. However, involvement of large trucks in crashes can cause much damage and serious injuries, due to their large sizes and heavy weights. Large truck crashes occurring on limited-access highways may be more severe than crashes occurring on other roadways due to high speed limits, as well as traffic- and geometric-related characteristics. The purpose of this study was to describe the relationships between large truck crash probability and traffic and geometric characteristics. Crash data from 2005 to 2010 were obtained from the Kansas Department of Transportation (KDOT), which included 5,378 large truck crashes that occurred on Kansas limited-access highway sections. The traffic- and geometric-related details of the highways were obtained from the Control Section Analysis System (CANSYS) database, which is maintained by KDOT as a highway inventory system. Homogeneous road sections—in terms of speed limit, Average Annual Daily Traffic (AADT), percent of trucks, horizontal curvature, horizontal grade, lane width, shoulder width, median width, and existence of rumble strips—were identified. The total number of crashes occurring within each segment from 2005 to 2010 was determined, resulting in 7,273 analysis segments used in the modeling. A Poisson regression model and a negative binomial regression model were developed for identifying the relationships between the occurrence of truck crashes and traffic and geometric characteristics. According to the models, highway design features such as a horizontal curvature, vertical grade, lane width, and shoulder width are factors which can be used to change the occurrence of large truck crashes. Identifying the effect of traffic and geometric characteristics is important to promote safety treatments through engineering improvements.

Chapter 1 Introduction

1.1 Background

Along with increased global economic integration, total transport and trade between countries and cities have also increased. The volume of freight in the United States (U.S.) has grown significantly over the past few decades. According to the Freight Analysis Framework, freight volumes are expected to increase by 70% from 2004 to 2020 (1). Trucks are one of the convenient modes that can be used for the movement of freight during the journey from origin to destination. Freight can be transported between most points in the country quite efficiently using trucks. Perhaps because of these advantages, the use of truck transport has increased. The American Trucking Association reported a 47% increase in registered trucks and a 65% increase in miles traveled by large trucks from 1988 to 2008 (2). In 2009, large trucks accounted for 4% of all registered vehicles and 10% of total vehicle miles traveled in the U.S. (3). As truck transport has become more common, the issues associated with the presence of large trucks have become more evident. Trucks with gross vehicle weight greater than 10,000 lbs are typically considered large trucks, and 296,000 of such large trucks were involved in traffic crashes on U.S. roadways during 2009 (3). There were 3,380 fatalities and 74,000 injuries reported due to large truck crashes that year (3). In motor vehicle crashes, large truck crashes represented about 7% of vehicles in fatal crashes, 2% of vehicles in injury crashes, and 3% of vehicles in crashes involving property damage only.

Involvement of trucks in crashes can cause much damage and serious injuries, due to their large sizes and heavy weights. According to figure 1.1, fatal crashes involving large trucks per 100 million vehicle miles traveled were close to fatal crashes involving passenger vehicles per 100 million vehicle miles traveled. However, total fatal crashes involving large trucks accounted for around 7% of total vehicles in fatal crashes, and large trucks accounted for 10% of total vehicle miles traveled.



Note: The Federal Highway Administration (FHWA) implemented an enhanced methodology for estimating registered vehicles and vehicle miles traveled by vehicle type for the years 2007-2009. As a result, involvement rates may differ from previously published rates.

Source: FHWA (4)

Figure 1.1 Vehicles Involved in Fatal Crashes per 100 Million Vehicle Miles Traveled

Large trucks seem more likely to be involved in fatal multiple-vehicle crashes as compared to fatal single-vehicle crashes. In 2009, about 81% of fatal crashes involving large trucks were multiple-vehicle crashes, compared to 58% for crashes involving passenger vehicles (3). Occupants of large trucks compose only 22% of fatalities resulting from fatal truck crashes, and 78% of the fatalities occur outside the truck and instead include pedestrians, cyclists, and—

primarily—the occupants of passenger vehicles (3). The disproportionate crash severities of passenger vehicles and large trucks are a reflection of a fundamental law of physics, which is expressed by the following equation 1.1 (5):

$$Kinetic\ Energy = 0.5\ \times Mass\ \times (velocity)^2 \tag{1.1}$$

Trucks typically weigh about 20 to 30 times as much as passenger vehicles and dissipate more kinetic energy in a crash (5). Kinetic energy can be dissipated in a crash by friction, heat, and the deformation of mass. If more kinetic energy is dissipated in a collision, the potential for injury to vehicle occupants will be greater. The greater mass and structural properties of trucks easily absorb the kinetic energy generated by collisions, which places the occupants of trucks at lower risk of injuries. However, similar amount of dissipated kinetic energy cannot be absorbed by passenger vehicles and the occupants of those vehicles are at risk of considerable severe injuries in the case of the collision. This indicates that truck crashes, in general, tend to be more severe than other crashes.

Because kinetic energy is determined by the square of the vehicle's speed, the probability of injury and severity of injuries that occur in a crash increase exponentially with vehicle speed. However, freight transport requires heavy trucks to have access to all—or at least major portions of—interstate and state highways and to operate at higher speeds. Also, drivers may face vehicle control challenges or difficulties while driving large trucks on interstate or state highways at high speeds compared to those while driving on typical streets. As a result, interstate and urban highways serve a diverse combination of passenger vehicle traffic, local delivery truck traffic, and long-haul truck traffic. While traffic disproportionately increases, traffic delays, traffic congestion, and crashes involving large trucks also increase.

1.2 Large Truck Crashes in Kansas

In 2009, about 45,435 fatal crashes involving large trucks occurred on U.S. roadways (3). Of these fatal large truck crashes, 1.6% occurred on Kansas roadways. Within Kansas crash data, the frequency of truck crashes varied between 3,007 and 4,830 crashes per year between year 2001 and 2010, with an average of 3,948 per year as shown in table 1.1. These data were found in Kansas crash database which was obtained from KDOT.

Table 1.1 Crashes Involving Large Trucks in Kansas by Crash Severity

Year	**Fatal Crashes**		**Injury Crashes**		**Property Damage Only (PDO) Crashes**		**Total**	
	Number	% among All Fatal Crashes	Number	% among All Injury Crashes	Number	% among All PDO Crashes	Number	% among All Crashes
2001	80	12.35	1,162	3.46	3,588	3.83	4,830	3.77
2002	81	11.88	973	3.04	3,315	3.50	4,369	3.43
2003	73	11.28	903	3.08	3,376	3.70	4,352	3.59
2004	83	13.26	897	3.14	3,203	3.54	4,183	3.49
2005	73	12.48	937	3.42	3,073	3.71	4,083	3.69
2006	65	10.20	785	2.93	2,741	3.51	3,591	3.40
2007	79	12.52	912	3.30	3,039	3.61	4,030	3.59
2008	56	11.16	880	3.49	2,930	3.72	3,866	3.70
2009	51	10.20	633	2.70	2,323	3.22	3,007	3.13
2010	71	12.26	685	3.02	2,411	3.35	3,167	3.33
Total	712	11.79	8,767	3.17	29,999	3.58	39,478	3.52
10-year Average	71	11.76	877	3.16	3,000	3.57	3,948	3.51

According to Kansas crash data, crashes involving large trucks showed a 5% increase from 3,007 in 2009 to 3,167 in 2010. The following national data were found from traffic safety facts report published by National Highway Safety Administration (3). In 2009, large trucks in Kansas accounted for 10.2% of all vehicles involved in fatal crashes, which is slightly higher than the national rate of 7%. Large trucks were involved in about 3.3% of all police-reported crashes in Kansas, but accounted for 12.3% of all fatal crashes in 2010. About 25% of these crashes occurred on limited-access highways each year, regardless of truck configuration and crash severity type, as shown in figure 1.2. In 2008, 1,023 large truck crashes occurred on

Kansas limited-access highways, which comprised 26% of crashes involving large trucks in Kansas.

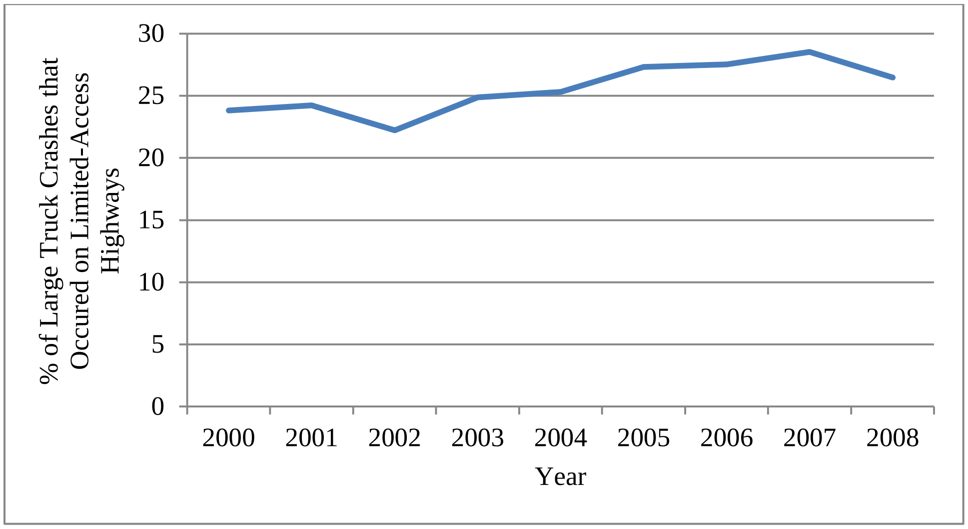


Figure 1.2 Percentages of Large Truck Crashes on Limited-Access Highways in Kansas

According to data from 2000 to 2008, the annual average of 14,047 all-vehicle crashes occurred on Kansas limited-access highways and about 7% out of these crashes involved large trucks, as shown in table 1.2. Due to high speed limits, these crashes may have been more severe than crashes that occurred on other roadways. Before 2005, fatal crashes involving large trucks on limited-access highways accounted for more than 10% of all vehicles involved in fatal crashes. However, in 2008, only 8% of fatal crashes involving large trucks out of all vehicles involved in fatal crashes were reported. Each year, injury crashes involving large trucks on limited-access highways accounted for more than 7% of all vehicles involved in injury crashes.

Table 1.2 Crashes Involving Large Trucks on Kansas Limited-Access Highways

Year	Fatal Crashes		Injury Crashes		Property Damage Only (PDO) Crashes		Total	
	No	% out of All Fatal Crashes	No	% out of All Injury Crashes	No	% Out of All PDO Crashes	No	% out of All Crashes
2000	17	17.00	284	7.38	819	8.22	1,120	8.05
2001	16	18.60	287	7.74	867	8.82	1,170	8.59
2002	11	12.36	267	7.53	693	6.89	971	7.09
2003	10	11.36	237	7.07	835	7.83	1,082	7.67
2004	9	11.54	281	8.19	769	7.16	1,059	7.44
2005	11	16.67	273	8.25	831	7.72	1,115	7.89
2006	8	9.41	236	7.14	744	7.66	988	7.54
2007	12	10.43	290	7.61	848	7.14	1,150	7.28
2008	5	8.77	220	7.11	798	7.48	1,023	7.40

1.3 Problem Statement

The analysis of large truck crash data indicates that certain traffic and highway geometric characteristics may be associated with the occurrence of large truck crashes (6, 7). Highway geometric design features such as a horizontal curvature, vertical grade, lane width, lane type, shoulder width, shoulder type, and median are engineering factors which might be used to change the occurrence of large truck crashes. The geometric design standard utilized in some cases may not always be adequate for large trucks. One of many important aspects of highway safety research is developing crash prediction models to quantify the relationship between geometric characteristics and the number of crashes observed.

Identifying the effect of traffic and geometric characteristics is also important to promote safety treatments by introducing engineering improvements. However, knowledge of the quantitative relationship between the probability of occurrence of large truck crashes on Kansas highways and these traffic and geometric variables is limited. The focus of this research was to understand and evaluate the effects of both traffic conditions and site characteristics on the occurrence of large truck crashes.

1.4 Objectives of the Study

The purpose of this study was to describe the relationships between large truck crash probability and traffic and geometric characteristics. Specific objectives of this study included the following:

- to examine relationships between the occurrence of crashes and related causal factors, including traffic and geometric variables;
- to apply existing crash modeling methods for Kansas limited-highway large truck crashes; and
- to quantify how various traffic and geometric variables affect occurrence of crashes based on the obtained models.

1.5 Organization of the Report

This report consists of five chapters. Chapter 1 contains background information and objectives of this study. Chapter 2 provides a summary of previous studies conducted in relation to the topic. Chapter 3 presents details of the data and methodologies used in achieving objectives of this study. The results, which were obtained by applying those methodologies, are presented in Chapter 4. Chapter 5 details the summary, conclusions, and recommendations for improving truck safety.

Chapter 2 Literature Review

Several studies have been conducted to explore the relationship between crash rates and traffic and geometric design features. In this section, more focus was given to previous findings on the relationship between truck crash rates and traffic and geometric design features.

A number of crash-frequency models have been developed for truck crashes exclusively. Mohamedshan et al. investigated traffic- and geometric-related variables that affect truck crashes using data from the Highway Safety Information System (HSIS), which is a highway safety database administrated by Federal Highway Administration (8). Multivariate logistic models for truck crashes on interstates and two-lane rural roads were developed considering truck crashes occurring in Utah from 1980 to 1989. The variables considered for model development were non-truck Average Annual Daily Traffic (AADT) per lane, truck Annual Daily Traffic (ADT) per lane, shoulder width, horizontal curvature, and vertical gradient as independent variables, and truck involvement rate/km/year as the dependent variable. The truck involvement rate is defined as the total number of trucks involved in a crash divided by truck ADT. However, median width, median type, shoulder type, and pavement type were not included in the model, as data were not available. The interstate model indicated that truck crashes were primarily affected by horizontal curvature and vertical gradient. For two-lane rural roads, the model indicated that truck crashes were affected by shoulder width and horizontal curvature.

Poisson regression models were developed by Miaou and Lum to evaluate the effect of geometric design features on truck crash involvement and the uncertainties of the expected reduction of truck crash involvement from various highway geometric improvements (6). The data were obtained from the HSIS. Data from Utah were considered for this analysis because this included a historical road inventory file in which year-to-year changes to the highway geometric features and traffic conditions were recorded. The database consisted of six files which were called roadlog, accident, vehicle, occupant, horizontal curvature, and vertical grade. Each record in the roadlog represented a homogeneous section in terms of lanes, lane width, shoulder width, median type and width, AADT, and percent of trucks. However, road sections were not homogenous in terms of horizontal curvature or vertical grade. Seven different Poisson regression models were developed considering different independent variables, and different observations were made investigating the estimated coefficients. The computations were explained, and it was concluded that Poisson models can be developed and tested for other states in a similar manner.

More details of this study, such as the variable selections and findings from the model, were documented in the report titled "Development of Relationship between Truck Accidents and Geometric Design" (9). Since the road sections were not homogenous in terms of horizontal curvature or vertical grade and one section may have had more than one horizontal curvature or vertical grade, surrogate measures were used and road sections were disaggregated into smaller subsections. Section length, horizontal curvature, vertical grade, lane width, shoulder width, shoulder type, median type, median width, number of lanes, pavement condition, speed limit, AADT, and percent trucks were the variables which were included into the model. Variables such as driver alcohol percent, light conditions, and weather were relevant to this study, but the associated truck exposure information was not available. Roadway design data such as side slope, ditch width, and roadside objects were not available for the analysis. The final Poisson regression model included AADT per lane, horizontal curvature, length of curve, stabilized outside shoulder width, and percent of trucks as independent variables. According to the developed model, the truck crash involvement rate increased by 10.8% as AADT per lane increased by 1,000 vehicles per direction. As the horizontal curvature increased or the length of curve increased, the truck crash involvement rate increased. As stabilized outside width increased by 1 ft per direction, the truck crash involvement decreased by about 3.3%. Researchers noted that the relationships developed at one time may no longer be representative in later years because of changes in vehicle performance, and that socioeconomic, legislative, and law enforcement conditions over the years could change the geometric design effect on truck crashes.

Miaou evaluated the relationship between truck crashes and geometric design of the road sections using Poisson regression, Zero-Inflated Poisson (ZIP) regression, and negative binomial regression models (7). Also, two other feasible estimators for determining the dispersion parameter in negative binomial regression models were examined. Data were obtained from the HSIS, which included 1,643 large track crashes occurring on Utah highway sections within the five-year period from 1985 to 1989. Estimated regression parameters from all three models were quite consistent in terms of the estimated relative frequencies of truck crash involvement across road sections. The developed models and estimators were then evaluated based on estimated regression parameters, overall goodness-of-fit, predicted relative frequency of truck crash involvement, severity of short road sections, and estimated total number of truck crashes. Evaluation results showed that Poisson regression models were best to use as the initial model for developing the relationship. If the overdispersion of crash data were found to be high or medium, then negative binomial regression and ZIP models could be used.

Schneider et al. developed a negative binomial regression model using crash data from Ohio to investigate the effect of rural two-lane horizontal curves on non-intersection truck crashes (10). Data were obtained from the Ohio Department of Public Safety and Ohio

Department of Transportation's Roadway Inventory files. This data set included all heavy-duty truck crashes related to single- and multiple-vehicle crashes on horizontal curves. This study further investigated implementation of Bayesian methods on model performance. Impact on shoulder width, curve radius, curve length, other traffic parameters, and evaluation of improved predictive capabilities were investigated using Bayesian methods. The developed model was used to target improvements to specific roadways. The model could also be used to identify truck crash problems due to volume increases. The authors noted the need for improved models that can accommodate factors not related to volume that contribute to truck crashes, in order to improve the truck crash-frequency prediction.

A study was conducted in Virginia to find the quantitative relationship between traffic and geometric variables and probability of occurrence of large truck crashes (11). Crash data were obtained from the Virginia Department of Transportation, and geometric data were collected directly from the sites. Selection of sites was based on the length of highway segment, mobility type, pattern of crash occurrence, and feasibility of data collection. The investigation in this study included interstate highways, divided highways with four or more lanes, undivided highways with four or more lanes, and two-lane highways. Geometric and traffic data collected from the site included 24-hour vehicular volume, vehicular classification, vehicular speed, speed samples for truck and non-trucks, speed limit, advisory speed limits, highway type, number of lanes, lane and shoulder width, and vertical and horizontal alignments. Multiple linear and Poisson regression analyses were done in order to predict the number of truck crashes. These models showed that slope-change rate (i.e., absolute slope), change in the vertical direction divided by length of highway segment, average daily traffic, percent of trucks, and speed differential between trucks and non-trucks that had influenced the number of truck-involved crashes.

Daniel et al. developed a crash-prediction model for truck crashes on route sections with signalized intersections (12). Crash data were obtained from New Jersey accident records, and volume and geometric data were obtained by reviewing straight-line diagrams and contract drawings of the roadway. About 37% of all truck crashes occurred at intersections during 1998 and 1999. Variables such as segment length, AADT, degree of curve for horizontal curves, length of horizontal curve, crest-curve grade rate in percent per 100 ft, length of vertical curve, posted speed limit, number of lanes, number of traffic signals within the segment, number of interchanges in the segment, and pavement width were used to develop a Poisson regression model and a negative binomial regression model. Coefficients of the developed models showed impact of segment length, AADT, length of horizontal curve, number of lanes, number of signals within the segment, and pavement width on truck crash frequency on selected roadways. The models also showed the number of signalized intersections along a route can be used as a variable in crash prediction models.

Ivan et al. investigated the relationship between traffic intensity, level of service, site characteristics, and highway crash rates by estimating Poisson regression models for predicting single- and multiple-vehicle crashes separately on rural two-lane highways (13). Crash rates were defined as number of crashes per million vehicle miles travelled per year. Hourly traffic volumes were obtained from the continuous-count stations maintained by the Connecticut Department of Transportation (ConnDOT). Geometric conditions as well as environmental and traffic factors were obtained from ConnDOT's Highway Performance Monitoring sites. These data were related to randomly selected roadway segments with uniform geometric characteristics. This data set contained sunrise and sunset times for each site on every day of the period considered, based on which light condition was obtained. The number of crashes occurring in a given 12-month period on a particular highway segment under given combinations of light conditions and level of service was taken as the dependent variable. Prior to developing the crash models, including all independent variables, preliminary models for crash rates were developed with site location, level of service, and light conditions as independent variables. Poisson regression models were then developed with hourly levels of service, traffic composition, and geometric characteristics as independent variables. Results showed that single-vehicle crash rates decreased with increasing traffic intensity, shoulder width, and sight distance. Multiple-vehicle crash rates increased with increasing number of signals, shoulder width, and the daily single-unit truck percentage. Single-vehicle crashes seemed to occur when traffic volume was low and on roads with less forgiving geometry, such as sharp horizontal curves and narrow shoulders.

In a more recent study, Venkataraman et al. proposed the random parameter negative binomial regression model for the analysis of crash counts (14). Nine-year historical crash data, geometrical characteristics, and traffic volume data were obtained from the Washington State Department of Transportation's annual records. Segments were assembled based on interchange and non-interchange definitions. Interchange segments were defined by the farthest merge/diverge ramp limits for each direction. Non-interchange sections were defined as continuous-travel segments between two interchanges. Interstate geometric variables such as lighting type, shoulder width, lane cross section, and horizontal and vertical curve parameters were used in the model specifications. Results showed several curvature effects such as largest degree of curvature, smallest and largest vertical curve gradient, and number of horizontal and vertical curves in a segment were significant variables. The logarithm of ADT, median, no lighting and lighting, and proportions were also found to have significant effect.

The effect of roadway geometric features on the incidence of head-on crashes on two-lane rural roadways in Connecticut was investigated using negative binomial regression models by Zhang and Ivan (15). Highway segments, each with a uniform length of 1 km and no intersections, with signals and stop controls, were taken for the analysis. Geometric variables of each segment were obtained from photolog and horizontal- and vertical-curve classification system software maintained by the Connecticut Department of Transportation. Significant variables in predicting the incidence of head-on crashes were speed limit, sum of absolute rate of change of horizontal curvature, maximum degree of horizontal curve, and sum of absolute rate of change of vertical curvature. The number of crashes increased with each of these variables except speed limit. Variables such as roadway width, lane width, and shoulder width were not significant in the predictive models. According to the results, the best way to improve the geometric features was to have a lesser number of medium and sharp horizontal curves. This study also showed that widening of the roadway was not as effective as curve straightening for reducing head-on crashes on two-lane roadways.

Dissanayake and Rathnayake investigated the effect of highway geometric design and other related factors on frequency of rural highway crashes (16). Crash data were obtained from the Kansas Accident Reporting System database, while highway geometric data were obtained from the CANSYS database from 1998 to 2002. Two separate negative binomial regression models for two-lane highways and freeways were developed using 71,281 crashes occurring on rural highways. The dependent variable—crash frequency—was considered in two different ways: total crash frequency and Equivalent Property Damage Only crashes. According to the goodness-of-fit statistics, the negative binomial regression models provided a satisfactory method for crash-frequency modeling. Results showed factors related to traffic conditions, posted speed limits, and highway geometric characteristics such as horizontal and vertical alignment, shoulder width, and slope were significant in predicting crash frequencies for two-lane highways and freeways.

Milton and Mannering explained the crash-frequency model can eventually be used as part of a proactive program to allocate highway improvement funds (17). In this study, negative binomial regression models were developed using crash data from Washington State. Various highway geometric and traffic characteristics were used as independent variables in modeling the annual crash frequencies on specified highway sections for principle arterials. Models showed significant differences between principle arterials in western and eastern Washington. It was concluded that negative binomial regression models were a powerful predictive tool for crash-frequency analysis research.

Chapter 3 Data and Methodologies

This chapter provides detailed discussion of data used in this study and relevant methodologies used to model truck crash frequencies. This study used methodologies of the Poisson regression model and negative binomial regression model to predict truck crash frequencies.

3.1 Data

3.1.1 KARS Database

Crash data from 2005 to 2010 were obtained from the Kansas Department of Transportation (KDOT). This data set, the Kansas Accident Reporting System (KARS) database, is comprised of all police-reported crashes that occurred in Kansas. On limited-access highways, access is fully controlled, which means ramps were the only points of exit and entry. These highways include road segments in the interstate system, U.S. highway system, and Kansas highway system. For this study, large truck crash records on limited-access highways were extracted by making the query include all crashes involving large trucks from 2005–2010 for the state of Kansas. Types of trucks included in the analysis were vehicles whose classification on the crash database was one of the following: single heavy truck, truck and trailer(s), or tractor-trailer(s). All those trucks had weight greater than 10,000 lbs. A single heavy truck might have not only two axles, but even three or more axles and more than six tires. A single truck could also indicate a bus converted into a recreational vehicle with less than nine seats used for commercial business. Truck and trailer indicates a single-unit truck pulling a trailer. This also includes truck-trailer combinations converted into recreational vehicles and used for commercial business. The tractor-trailer(s) label suggests a bobtail and one or more attached trailers. Table 3.1 provides details of the number of crashes involving large trucks in Kansas by truck type.

During the six-year period, 5,392 large trucks were reported to be involved in crashes on limited-access highways, regardless of severity. This accounted for 24% of all truck crashes occurring on Kansas highways during the six-year period.

Table 3.1 Crashes Involving Large Trucks on Kansas Limited-Access Highways by Truck Type

Year	Single heavy truck	Truck and trailer(s)	Tractor-trailer(s)	Total
2005	253	50	716	1,019
2006	205	60	635	900
2007	186	110	666	962
2008	183	192	573	948
2009	142	141	438	721
2010	156	120	566	842
Total	1,125	673	3,594	5,392

After identifying crashes involving large trucks on limited-access highways, information to locate each crash on the highway was obtained from the CANSYS database. Crashes involving large trucks can be located in a roadway map on Kansas as shown in figure 3.1.

Note: A dot indicates a crash

Figure 3.1 Crashes Involving Large Trucks on Limited-Access Highways (Source: KDOT)

3.1.2 CANSYS Database

The CANSYS database is maintained by KDOT as a highway inventory system and includes many traffic- and geometric-related details of national and state highways in Kansas. Data from 2005 to 2010 were obtained for limited-access highways, and sections were defined based on homogeneity of road segments and data available. The sections were homogenous in terms of number of lanes, horizontal curvature, median width, AADT, truck AADT percent, lane width, shoulder width, and existence of rumble strips.

Additionally, variables such as functional class, section length, and year were considered for the analysis. It should be noted some information—such as vertical grades—was not frequently updated in the CANSYS database. For this study, data on vertical grade were provided by KDOT from construction drawings and a Global Positioning System (GPS). However, GPS data were available for only 2009 and 2010. Hence, data obtained from construction drawings were used for the modeling.

A total of 16,853 roadway segments were identified for the period from 2005 to 2010. These segments ranged in length from 0.10 mi to 19.87 mi, with an average segment length of 0.81 mi. Data were reviewed, and irrelevant segments such as sections with speed limits lower than 55 mph and lengths shorter than 0.25 mi were discarded. A total of 7,273 roadway segments were considered for further analysis. Table 3.2 shows characteristics of individual road segments used for the analysis. All roadway sections were divided-roadway sections, as the focus of this study was limited-access roads. Shoulder widths and rumble strips were recorded separately for inside (or left) and outside (or right) lanes in a given direction. Absolute values of horizontal curvature and vertical grade on each homogeneous section were used for the modeling. The total number of crashes occurring within each segment was determined by combining crash data and

CANSYS data. About 35% of the road segments had at least one truck crash, regardless of truck configurations and crash-severity type, while the remaining segments were free of truck crashes.

Table 3.2 Traffic- and Geometric-Related Characteristics of Limited-Access Highway Sections Considered

Variable	Description	Sections No.	Sections %	Variable	Description	Sections No.	Sections %
Section Length (SL, in mi)	$0.25 \leq SL < 0.50$	2,466	33.91	*Right Rumble Strips*	Rectangle	4,492	61.76
	$0.50 \leq SL < 1.00$	2,053	28.23		Not applicable	2,781	38.24
	$1.00 \leq SL < 2.00$	1,302	17.90	*Inside Rumble Strips*	Rectangle	4,200	57.75
	$2.00 \leq SL < 3.00$	522	7.18		Not applicable	3,073	42.25
	$3.00 \leq SL < 4.00$	265	3.64	*Right Shoulder Width (ft)*	0	68	0.93
	$4.00 \leq SL$	665	9.14		2	24	0.33
Speed Limit (mph)	55	122	1.68		6	46	0.63
	60	769	10.57		8	195	2.68
	65	1,486	20.43		9	8	0.11
	70	4,896	67.32		10	6,838	94.02
Median Width (MW, in ft)	$MW < 10$	92	1.26		12	94	1.29
	$10 \leq MW < 20$	2,087	28.70	*Inside Shoulder Width (ft)*	0	2,845	39.12
	$20 \leq MW < 30$	349	4.80		2	41	0.56
	$30 \leq MW < 40$	3,997	54.96		3	8	0.11
	$40 \leq MW$	748	10.28		4	32	0.44
Functional Class	Expressways	1,211	16.65		6	2,970	40.84
	Rural interstate	3,351	46.07		7	16	0.22
	Urban interstate	2,711	37.27		8	126	1.73
AADT per lane	Less than 1,000	302	4.15		9	511	7.03
	1,000–1,999	2,965	40.77		10	696	9.57
	2,000–2,999	1,224	16.83		12	28	0.38
	3,000–3,999	629	8.65	*Horizontal Curve*	Straight	660	9.07
	4,000–4,999	437	6.01		Curve	6,613	90.93
	More than 5,000	1,716	23.59	*Vertical Grade*	Grade	6,795	93.43
AADT of Heavy Truck Count	Less than 1,000	1,549	21.30		Level	478	6.57
	1,000–2,000	4,728	65.01	*Number of Lanes*	4	5,855	80.50
	2,000–3,000	768	10.56		6	1,220	16.77
	More than 3,000	228	3.13		8	198	2.72

3.2 Methodologies

Various statistical models could be considered for identifying relationships between the occurrence of truck crashes and geometric and traffic characteristics. Because of the random, discrete, and non-negative nature of crashes, multiple-regression models could not be considered as appropriate. A Poisson regression was a good starting point for modeling, as crash data have been found to be approximately Poisson distributed.

3.2.1. Poisson Regression Model

Poisson regression belongs to a class of generalized linear models, which is an extension of traditional linear models that allows the mean of a population to depend on a linear predictor through a nonlinear link function (18). It allows the response probability distribution to be any member of an exponential family of distributions. This model is appropriate for dependent variables that have non-negative integer values such as 0, 1, 2, and so on. Hence, in most cases, count data could be precisely analyzed by Poisson regression. More details of Poisson regression analysis can be found in Long's "Regression Models for Categorical and Limited Dependent Variables" (19). The Poisson regression model was proposed by Miaou to find the relationship between vehicle crashes and geometric design features of road sections, such as lane width, shoulder width, horizontal curvature, and lane width (6). The Poisson regression model proposed by Miaou is given by

$$P(Y_i = y_i) = p(y_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!}, \; (i = 1,2,3, \ldots . n; \; y_i = 0,1,2,3, \ldots .) \quad (3.1)$$

where

i = a roadway segment. The same roadway segments in different sample periods are considered as separate roadway segments.

Y_i = the number of truck crashes for a given time period for roadway segment i.

y_i = the actual number of truck crashes for given time period for roadway segment i.

$P(y_i)$ = probability of the occurrence of y_i truck crashes for a given time period on roadway segment i.

μ_i = mean value of truck crashes occurring for a given time period as

$$\mu_i = E(Y_i) = \vartheta_i[e^{\sum_{j=1}^{k} x_{ij}\beta_j}] \tag{3.2}$$

where

x_{ij} = the j^{th} independent variable for roadway segment i,

β_j = the coefficient for the j^{th} independent variable, and

ϑ_i = traffic exposure for roadway segment i.

Associated with each roadway segment i, x_i independent variables describe geometric characteristics, traffic conditions, and other relevant attributes. Traffic exposure, which is the amount of truck travel during the sample year, can be computed as

$$\vartheta_i = 365 \times AADT_i \times T\%_i \times l_i \tag{3.3}$$

where

$AADT_i$ = annual average daily traffic (in number of vehicles),

$T\%_i$ = percentage of trucks in traffic stream, and

l_i = length of road section.

This model assumes the truck crash numbers for a given time period for roadway segment ($Y_i;\ i = 1,2,\dots n$) are independent of each other and Poisson distributed with mean μ_i. The expected number of truck-involved crashes $E(Y_i)$ is proportional to truck travel ϑ_i. The model ensures the crash frequency is positive, using an exponential function which is given by

$$\lambda_i = \frac{E(Y_i)}{\vartheta_i} = \exp(x_i'\beta) \tag{3.4}$$

where

λ_i = truck-crash-involvement,

$E(Y_i)$ = expected number of truck crashes,

x_i' = transpose of covariate vector x_i, and

β = vector of unknown regression parameter.

The maximum likelihood method in the SAS GENMOD procedure is used to estimate the parameters of the Poisson regression model for log(μ). One important property of Poisson regression is that it restricts the mean and variance of the distribution to be equal. This can be written as

$$Var(y_i) = E(y_i) = \mu_i \tag{3.5}$$

where

μ_i = mean of the response variable y_i,

$E(y_i)$ = expected number of response variable y_i , and

$Var(y_i)$ = variance of response variable y_i .

If this equality does not hold, the data are said to be either underdispersed or overdispersed, and the resulting parameter estimates will be biased. If the overdispersion is not captured in the analysis, the standard errors are underestimated and hence, the coefficients become an overstatement of significance in hypothesis testing (18). Consequently, using an inappropriate frequency model can affect the statistical inference and resulting conclusions. Deviance and a Pearson chi-square statistic divided by degrees of freedom can be used to detect whether overdispersion or underdispersion exists in the data. The degree of freedom can be obtained by reducing the number of parameters estimated in the model from the total number of road sections considered for truck-crash modeling. As explained later in section 3.2.3, the deviance is the likelihood-ratio statistic for comparing the model to the saturated model. Larger deviance values indicate a poor model fit to the data. If the model fits the data, both deviance and Pearson chi-square statistic divided by the degrees of freedom are approximately equal to one. Values greater than one indicate the variance is an overdispersion, while values smaller than one indicate the underdispersion.

With respect to crash-frequency data, the variance of crash frequency is commonly found to exceed the mean, resulting in overdispersion. According to Miaou and Lum, overdispersion could come from several possible sources, such as uncertainty of truck exposure or omitted variables (6). Also, it could results from a highway environment that is not homogeneous; for example, truck involvement during the daytime and nighttime could be different. However, it is possible to account for overdispersion with respect to the Poisson model by introducing a scale (dispersion) parameter into the relationship between the variance and the mean (18). This is a quasi-likelihood, approach-based method that permits estimations of parameters without full knowledge of data. The parameter estimates are not affected by the scale parameter, but the estimated covariance matrix is affected by this factor. That means the parameter estimates are not changed, but their standard errors are inflated by the value of scale parameter. Hence, the confidence intervals are wider, p-values are higher, and significance tests are more conservative than the Poisson distribution before the adjustment. Introduction of scale parameter gives a correction term for testing the parameter estimates under Poisson distribution but not a different probability distribution.

Another way to address this problem of overdispersion, if it exists, is the consideration of a distribution that permits more flexible modeling of the variance. Hence, use of negative binomial regression modeling would be the next step in the analysis. The negative binomial regression model is more appropriate for overdispersed data because it relaxes the constraint of equal mean and variance. The negative binomial regression model was proposed by Miaou to find the relationship between vehicle crashes and geometric design of road segments, such as lane width, shoulder width, horizontal curvature, lane width, and traffic-related variables (6).

3.2.2. Negative Binomial Regression Model

Theoretical details of the negative binominal regression model can be found in Long's "Regression Models for Categorical and Limited Dependent Variables" (19). The following details of negative binomial regression models related to highway truck crashes were described in many studies (6, 9, 10, and 12). Consider a set of n highway sections of a limited-access highway. Let Y_i be a random variable representing the number of trucks involved in crashes on highway section i during the analysis period. Further, assume the amount of truck travel or truck exposure on this highway section, V_i, is also a random variable estimated through a highway sampling system. Associated with each highway section i is a $k \times 1$ vector of explanatory variables, denoted by $\underline{x}_i = (x_{i1} = 1, x_{i2}, \dots \dots x_{ik})'$, describing its geometric characteristics, traffic conditions, and other relevant attributors. Given V_i, and x_i, truck crash involvements $Y_i, i = 1,2,3, \dots \dots, n$, are postulated to be independent, and each is Poisson distributed as (9)

$$P(\,Y_i = y_i) = \frac{(\lambda_i \vartheta_i)^{y_i} e^{-\lambda_i \vartheta_i}}{y_i!} \tag{3.6}$$

where

λ_i = truck crash involvement and

ϑ_i = exponential of random error.

If the log-linear rate function is used as follows, the model becomes the negative binomial regression model that gives the relationship between the expected number of crashes occurring at the ith sections and K number of parameters.

$$\lambda_i = \exp(\beta_0 X_{i0} + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{iK} + \varepsilon_i) \tag{3.7}$$

where

λ_i = number of truck crashes on limited-access highway section i, with negative binomial distribution conditional on ε_i,

β_0 = constant term,

$\beta_1, \dots \dots, \beta_n$ = estimated parameters in vector form,

$x_1, \dots \dots, x_n$ = explanatory variables in vector form, and

ϵ_i = random error; exponential of ϵ_i is distributed as gamma with mean 1 and variance α^2.

The negative binomial distribution arises as a consequence of gamma heterogeneity in Poisson means. The effect of the error term in the negative binomial regression model allows for overdispersion of the variance, such that (18, 19)

$$Var(y_i) = E(y_i) + \alpha E(y_i)^2 \tag{3.8}$$

where

α = the overdispersion parameter,

$E(y_i)$ = expected mean number of truck crashes on limited-access highway section i, and

$Var(y_i)$ = variance of number of truck crashes y_i.

Variance over the mean is called the overdispersion rate, and equation 3.8 can be given as (19)

$$\frac{Var(y_i)}{E(y_i)} = 1 + \alpha E(y_i) \tag{3.9}$$

where

α = the overdispersion parameter,

$E(y_i)$ = expected mean number of truck crashes on limited-access highway section i, and

$Var(y_i)$ = variance of number of truck crashes y_i.

If overdispersion, α, is equal to zero, the negative binomial reduces to the Poisson model (19). The larger the value of α, the more variability there is in the data over and above that associated with mean $E(y_i)$. As in the case for the Poisson regression model, coefficients β_i are estimated by maximizing the log likelihood $\log_e L(\beta)$. The maximum likelihood method in the SAS GENMOD procedure is used to estimate the parameters of the negative binomial regression model for log(μ) and the overdispersion parameter α.

3.2.3. Assessment of the Models

In order to assess the adequacy of the Poisson regression model, the basic descriptive statistics for the event count data first need to be investigated (18). If the count mean and variance are very different then the model is likely to be overdispersed. The models developed using the relevant statistically significant variables are further tested for the goodness-of-fit, which includes deviance statistics and Pearson chi-square statistics.

Deviance statistics are used to assess the fit of the model and overdispersion. These statistics are sometimes referred to as the likelihood ratio test or G-squared value. The G-squared value is the sum of deviance and is defined as the change in deviance between the fitted model and the model with a constant term and no covariates. The G-squared statistics is given by (20)

$$G^2 = 2\sum_{=1}^{n} y_i \ln(y_i/E(y_i)) \tag{3.10}$$

where

G^2 = deviance,

y_i = observed number of truck crashes,

$E(y_i)$ = expected number of truck crashes, and

n = number of road sections.

If this test is significant, then the covariates contribute significantly to the model. If not, other covariates and/or other error distributions need to be considered. Deviance is approximately a chi-square random variable with degrees of freedom equal to the number n of observations minus the number p of parameters. A value of the deviance over $n - p$ (degrees of freedom) suggests the model is overdispersed due to missing variables and/or a non-Poisson form. Thus, deviance divided by degrees of freedom that is significantly larger than 1 indicates overdispersion.

Pearson chi-square statistics are used to assess the presence of overdispersion in the model and is given in equation (20):

$$\mathrm{x}^2 = \sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{(\mathrm{y_i} - \lambda_\mathrm{i})^2}{\lambda_\mathrm{i}} \tag{3.11}$$

where

y_i = observed number of truck crashes,

λ_i = expected number of truck crashes, and

n = number of road sections.

If the value of the chi-square statistics over degrees of freedom is larger than one, overdispersion is also indicated. If deviance and Pearson chi-square divided by their respective degrees of freedom are nearly equal to one, overdispersion does not exist. Pearson chi-square statistics divided by degree of freedom and deviance statistics divided by degree of freedom closer to one indicate a better model fit.

Chapter 4 Results and Discussion

This chapter discusses the variables chosen for consideration in large truck crash-frequency models and developed truck crash-frequency models. Results of both the Poisson model and negative binomial regression models were discussed in identifying the effect of traffic- and geometric-related variables on large truck crashes.

4.1 Variable Definitions

The selection of variables for modeling the occurrence of truck crashes was based on the available attributes of individual road segments, previous findings, and engineering judgments. The objective was to consider the many variables in order to obtain a realistic model. However, environmental, human, and vehicle factors were not available for individual road sections to investigate the effect of these factors. Miaou et al. explained that analysts should be careful in interpreting the estimated models with omitted variables (9). For example, changes in vehicle performance, socioeconomics, and legislation over the years would affect the occurrence of the truck crashes, even if nothing had changed in the geometric design features of the roads.

With consideration given to variables used in past models and data availability, candidate variables were selected: the definitions of variables considered for individual road sections, along with the descriptive statistics, are presented in table 4.1. As explained in section 3.1, all roadway sections were homogeneous in terms of number of lanes, horizontal curvature, median width, AADT, truck AADT percent, lane width, shoulder width, and existence of rumble strips. A total of 17 explanatory variables were selected to be considered for the model. The existence of right rumble strip and inside rumble strip were taken as categorical variables.

Table 4.1 Variable Definitions for Limited-Access Highway Truck Frequency Modeling

Variable	Description	Notation and Definition	Min.	Max.	Mean	Std. Dev.
TRUCK_NUM	Number of trucks crashes in a section	y_i	0	32	0.66	1.34
SEC_LEN	Section length (in m)	l_i	0.25	19.87	1.51	2.20
TR_EXPO	Truck miles or truck exposure (log scale)	$\vartheta_i = (365 \times AADT_i \times T\%_i \times l_i)\ /\ 1000$	6.10	14.04	10.63	1.12
Y_2005	Dummy variable for year 2005	x_{i1} = 1, if road section is in year 2005; 0 otherwise	0	1	0.15	0.35
Y_2006	Dummy variable for year 2006	x_{i2} = 1, if road section is in year 2006; 0 otherwise	0	1	0.15	0.36
Y_2007	Dummy variable for year 2007	x_{i3} = 1, if road section is in year 2007; 0 otherwise	0	1	0.15	0.36
Y_2008	Dummy variable for year 2008	x_{i4} = 1, if road section is in year 2008; 0 otherwise	0	1	0.15	0.36
Y_2009	Dummy variable for year 2009	x_{i5} = 1, if road section is in year 2009; 0 otherwise	0	1	0.18	0.38
Y_2010	Dummy variable for year 2010	x_{i6} = 1, if road section is in year 2010;0 otherwise	0	1	0.20	0.40
AADT	A surrogate variable to indicate traffic conditions or traffic density	$x_{i7} = (AADT_i / no.of\ lanes_i)/1000$	0.15	13.83	3.35	2.48
HC	Horizontal curvature (absolute value in degrees per 100 ft arc)	x_{i8}	0	4	0.11	0.43
VG	Vertical grade (absolute value in percent)	x_{i10}	0	3.35	0.23	0.58
IN_SHOU	Inside shoulder width	x_{i12}	0	12	9.83	1.17
OUT_SHOU	Right-side shoulder width	x_{i13}	0	12	6.99	1.88
TRUCK	Percent truck in the traffic stream (log scale)	x_{i14}	1.42	39.16	10.63	1.12
IN_RUM	Dummy variable for inside rumble strip	x_{i5} = 1, if inside rumble strip exists; 0 otherwise	0	1	0.61	0.48
OUT_RUM	Dummy variable for right rumble strip	x_{i5} = 1, if right rumble strip exists; 0 otherwise	0	1	0.57	0.49
SPEED	Speed limit (in mph)	x_{i16}	55	70	67.67	3.75
L_WIDTH	Lane width (in ft)	x_{i17}	12	20	12.06	0.53

As the number of lanes varies from section to section, AADT per lane—which gives the average of the vehicle flow in an average day—was considered in this modeling. The maximum horizontal curvature was 4° per 100 ft of arc (degrees of curvature) for the limited-access highways, while the corresponding maximum grade was 3.35%. Considerable variation of risk was found across the years due to long-term trends and changes in omitted variables such as road surface condition and weather. Year-to-year changes in the overall truck crashes were captured using yearly dummy variables in the model.

4.2 Poisson Regression Model

A Poisson regression model was developed, taking into account the above explained variables and estimated coefficients shown in table 4.2. The coefficient of each independent variable influencing the large truck crashes in the model gave the size of the exponential effect of a particular variable on the number of truck crashes. Coefficients bearing a positive sign indicated an increase in truck crashes with an increase of the variable, while a negative sign indicated a decrease in truck crashes with an increase of the variable. A unit change in the variable would affect the truck crashes by an exponential power of that variable coefficient, if all other variables were kept constant.

Table 4.2 Estimated Coefficients of the Poisson Regression Model and Associated Statistics

Variable	**Description**	**Estimate**	**P-value**
Intercept		-14.260	<0.0001
*SEC_LEN**	*Section length (in mi)*	*0.1738*	*<0.0001*
*L_WIDTH**	*Lane width (in ft)*	*0.1363*	*0.0105*
SPEED	Posted speed limit (in mph)	-0.0068	0.3018
*NUM_LANE**	*Number of lanes*	*0.0927*	*<0.0001*
*HC**	*Horizontal curvature (in degree per 100 ft arc)*	*-0.6097*	*<0.0001*
*VG**	*Vertical grade*	*-0.4348*	*<0.0001*
*AADT**	*AADT of the traffic stream per lane*	*0.1592*	*<0.0001*
R_SHOULD	Right shoulder width (in ft)	0.0360	0.2176
IN_SHOULD	*Inside shoulder width (in ft)*	*0.0697*	*<0.0001*
*Y_2005**	*Dummy variable for year 2005*	*0.3706*	*<0.0001*
*Y_2006**	*Dummy variable for year 2006*	*0.2289*	*<0.0001*
*Y_2007**	*Dummy variable for year 2007*	*0.1915*	*0.0010*
*Y_2008**	*Dummy variable for year 2008*	*0.1546*	*0.0020*
Y_2009	Dummy variable for year 2009	-0.1209	0.0708
MD_SHOULD	Median width (in ft)	-0.0017	0.2176
R_RUMBLE	Dummy variable for inside rumble strip	0.0501	0.4699
*IN_RUMBLE**	*Dummy variable for right rumble strip*	*-0.2532*	*0.0010*
Scale		1.2145	
Goodness-of-Fit Statistics			
Criterion		**Value**	**Value/DF****
Deviance		8,256	1.1381
Pearson chi-square		10,701	1.4751
Scaled deviance		5,597	0.7715
Scaled Pearson chi-square		7,255	1.0000
Number of observations (road sections)		7,273	
Note: * *Significant variables in italics,* ** DF-degrees of freedom			

However, the data displayed in table 4.1 showed the mean number of crashes in a section was 0.66 with a variance of 1.34, indicating the crash data were highly overdispersed. Also, goodness-of-fit statistics showed that value over degrees of freedom for both deviance and Pearson chi-square statistics was slightly higher than 1.00. It also suggested that more variability existed among counts than would be expected for Poisson distribution. Such increased variability may arise because repeated crashes on a road section might not be independent (18). One of the most common reasons for data being overdispersed was that μi parameters vary not only with measured covariates, but with latent and uncontrolled factors (18). This extra variation might be reduced by including many dependent parameters, more truck exposure data by time of day, weather conditions, and human factors (7). These data were not, however, available for individual road sections considered in this study. Statistically, limiting the study by truck crashes and limited-access highways was meant to create a relatively homogenous highway environment; thus, the crashes occurring in this specific environment and involving this specific vehicle type had relatively less variation. However, as the number of crashes available for analysis decreases, the uncertainty of analysis results increases (9). Hence, without any adjustment for overdispersion, the Poisson model was not quite adequate to describe the occurrence of large truck crashes on limited-access highways in Kansas. The model presented in table 4.2 was adjusted for overdispersion by including a scale (dispersion) parameter. The scale parameter was estimated by considering a ratio of the Pearson chi-square to its associated degree of freedom. The estimated scale parameter was 1.23 and the scaled Pearson chi-square was fixed to 1. The significant variables in the model were section length, number of lanes, horizontal curvature, vertical grade, AADT per lane, inside shoulder width, inside rumble strip, and yearly dummy variables for 2005, 2006, 2007, and 2008.

4.3 Negative Binomial Regression Model

The negative binomial regression model naturally accounts for the overdispersion, as its variance is greater than the variance of a Poisson distribution (9). Hence, the model developed in the previous section was reinvestigated using negative binomial assumptions. The maximum likelihood estimates of negative binomial regression model parameters, including dispersion parameter and goodness-of-fit statistics, are given in table 4.3. The dispersion parameter of the estimated negative binomial regression model was 0.5596. Since the dispersion parameter was greater than 0, the response variable was overdispersed. If the deviance value was equal to 0, the model was considered to be a perfect-fit model. Thus, the lowest deviance value was considered to have a better fit. Pearson chi-square statistics divided by degree of freedom and deviance statistics divided by degree of freedom closer to 1 indicated a better model fit. Scaled deviance statistics divided by degree of freedom (0.8140) were closer to 1 in the developed negative binomial regression than that value (0.7715) of the Poisson regression model.

Table 4.3 Estimated Coefficients of the Negative Binomial Regression Model and Associated Statistics

Variable	**Description**	**Estimate**	**P-value**
Intercept		-3.5407	0.0003
*SEC_LENGTH**	*Section length (in mi)*	*0.2144*	*<0.0001*
LANE_WIDTH	Lane width (in ft)	0.0464	0.3740
SPEED	Posted speed limit (in mph)	0.0006	0.9311
*NUM_LANE**	*Number of lanes*	*0.0568*	*0.0295*
*HC**	*Horizontal curvature (in degrees per 100 ft arc)*	*-0.5661*	*<0.0001*
*VG**	*Vertical grade*	*-0.3819*	*<0.0001*
*AADT**	*AADT in the traffic stream per lane*	*0.2278*	*<0.0001*
*TRUCK**	*Truck percent*	*0.0141*	*<0.0001*
R_SHOULD	Right shoulder width (in ft)	0.0006	0.9812
IN_SHOULD	*Inside shoulder width (in ft)*	*0.0915*	*<0.0001*
*Y_2005**	*Dummy variable for year 2005*	*0.3528*	*<0.0001*
*Y_2006**	*Dummy variable for year 2006*	*0.2019*	*0.0500*
*Y_2007**	*Dummy variable for year 2007*	*0.2653*	*<0.0001*
*Y_2008**	*Dummy variable for year 2008*	*0.2020*	*0.0017*
Y_2009	Dummy variable for year 2009	-0.1036	0.1194
MD_WIDTH	Median width (in ft)	-0.0000	0.9786
R_RUMBLE	Dummy variable for inside rumble strip	-0.0207	0.7614
IN_RUMBLE	Dummy variable for right rumble strip	-0.1091	0.2058
Dispersion		0.5596	
Goodness-of-Fit Statistics			
Criterion		**Value**	**Value/DF****
Deviance		5,905	0.8140
Pearson chi-square		7,310	1.0077
Scaled deviance		5,859	0.8040
Scaled Pearson chi-square		7,254	1.0000
Number of observations (road sections)		7,273	
Note: * *Significant variables in italics,* ** DF-degrees of freedom			

The significant variables in the model were section length, number of lanes, horizontal curvature, vertical grade, AADT per lane, truck percent, and inside shoulder width. Each significant variable influenced truck crash occurrence, and the coefficient gave the size of the exponential effect of a particular variable on the number of truck crashes, just as in the Poisson regression model. The positive coefficients indicate an increase in truck crashes, while a minus sign indicates a decrease in truck crashes with an increase in the variable coefficient.

4.3.1 Length of Section

The model showed that section length had a positive sign, signifying that for a unit increase in length of a section, crash frequency increases if all other variables are kept constant. The effect of section length on expected crash frequency was consistent with the logit function, which suggested that shorter sections were less likely to experience crashes than longer sections, due to decreased exposure.

4.3.2 Number of Lanes

The variable for number of lanes was significant with a positive coefficient. This means as the number of lanes increases, opportunities for conflicts related to lane changes also increase. Increased maneuverability associated with availability of more lanes tended to increase the average speed of traffic and speed differential. This variable was capturing some traffic operational effects associated with multilane roadways.

4.3.3 Horizontal Curvature

The horizontal curvature variable indicated crashes were less likely on curves with a high degree of curvature. This finding was compatible with some of previous findings such as Daniel et al. (12). The variable, horizontal curve, works in conjunction with the length of section variable; hence, the net effect of a sharp horizontal curve on truck crash frequencies is not clear. That is why some of researchers found the positive relationship between the truck frequencies and horizontal curvature (6).

4.3.4 Vertical Grades

Vertical grades were significantly negatively correlated with truck-crash frequency. One possible explanation was that vertical curves on a limited-access highway consist of minor initial grades and adequate sight distances.

4.3.5 AADT per Lane

AADT was divided by the number of lanes in both directions of a section of highway in order to obtain the AADT per lane. This gave an average volume per lane over the entire section. Positive coefficients of the AADT in the model indicated that as the number of vehicles through a section increases, the number of crashes increases. The explanation for this was that as the number of vehicles increase through a section, exposure to potential crashes and number of conflicts also increases.

4.3.6 Truck Percent

An increase in AADT per lane tended to increase large truck crash frequency. An increase in the percentage of trucks tended to increase large truck crash frequency. This is consistent with the expectation that crash occurrence should increase with an increase in truck percentage.

4.3.7 Inside Shoulder Width

Inside shoulder width had a positive correlation with the number of truck crashes, meaning the number of crashes increases when inside shoulder width increases.

4.3.8 Yearly Dummy Variables

The coefficient of the year variable for years 2005, 2006, 2007, and 2008 was positive and significant. This means that over time, the overall number of truck crashes was increasing due to unmeasured factors not included in the model.

Based on the developed model, the relationship between truck-crash occurrence and geometric design features, traffic, and other characteristics was identified. The identified effective parameters in truck crashes can be considered as the criteria for highway safety. Developed models can be used to identify target improvements to limited-access highways to reduce truck crashes. Also, it can be used to inform public policy and highway design criteria. This understanding offers important insight into the relationship between safety and mobility that will improve the quality of decisions made by practicing engineers and planners.

4.4 Discussion

In roadway design, features normally considered include cross section elements, sight-distance considerations, and horizontal curvature as per the design guides. The most important factor in design of a limited-access highway facility is design speed. For urban areas, the designer needs to select a reasonable design speed, considering access restrictions and type of access control that can be achieved. Limited-access roadways need to be designed with smooth-flowing horizontal and vertical alignments. Proper combination of curvature, tangents, grades, and median types provides safety and aesthetics for the roadway. The dimensions, weight per axle, and operating characteristics of a vehicle influence design aspects such as width of the lane and curvature. Additionally, consideration of human, traffic, and environmental factors is important in designing roadways (21). Major design features of a roadway are defined during the preliminary design stage. At this stage, it is necessary to ensure reasonable balance between cost and effectiveness of the proposed design. Evaluation during the preliminary design stage usually considers the environmental impact, operational performance, right-of-way requirements, and construction cost of various alternatives (21). Limited attention is given for safety evaluation in this stage because a safety evaluation is usually limited to the examination of crash history.

However, at the preliminary design stage, researchers must consider the balance among safety, mobility, economics, and the protection and enhancement of the natural environment.

In recent years, a number of studies have been conducted on geometric design features, including their effects on safety, operations, and other activities. The National Cooperative Highway Research Program has reported those findings in the report Synthesis 432 (22). According to the report, trucks are given important consideration in geometric design. Some research has given several recommendations for updating existing design guides. As the dimensions of trucks have changed in the recent past, a revision of design guides might be needed. Lamm et al have developed a process to evaluate the safety of horizontal alignment on two-lane rural roads (23). This methodology allows designers to predict potential crash risks and safety-related concerns of an alignment, and to make changes or develop countermeasures. The occurrence of crashes on two-lane highways is different than that on multilane divided highways, but a similar process for evaluating the safety of horizontal alignment on multilane highways may be developed.

According to results of this study, increased traffic volume showed an increased number of truck crashes. Also, practicing engineers and planners may believe that decreased traffic is associated with some degree of improved safety and make decisions to add travel lanes on a freeway when they find the capacity of the road needs to increase. However, results also showed that crashes increase with an increase in the number of lanes. Hence, the introduction of barrier-separated lanes, express lanes, and managed lanes such as toll roadways and dual-dual lanes are effective strategies to offset the increase of conflict opportunities associated with an increase in the number of lanes (24). Dual-dual lanes are managed lanes that have physically separated inner and outer lanes in each direction. The following explanation on managed lanes was giving in managed lane handbook (25). The outer roadway is open to all vehicles, while the inner lane is reserved for light vehicles. These lane strategies are a treatment for a specific section of roadway that has a unique set of characteristics such as vertical grades, weaving area, and high percentage of truck traffic. During the design phase, however, it is critical to ensure that the interface between managed and general purpose lanes is carefully coordinated to minimize turbulence related to merging and diverging. In particular, trucks limit the visibility and maneuverability of smaller vehicles attempting to enter and exit freeways. Hence, the effect of barriers is an over-involvement of trucks in weaving area crashes, rear-end collisions, and side collisions (25). In an effort to determine potentially effective countermeasures to reduce crashes, past knowledge of countermeasure effectiveness can be used.

The percent increase of truck traffic is increasing the number of truck crashes. This is an important matter for drivers because it affects speed of travel, safety, comfort, and convenience. Hence, many transportation agencies have implemented a variety of countermeasures for trucks in an attempt to mitigate the effects of increasing truck traffic. One such example is exclusive truck lanes (25). As shown in figure 4.1, California operates an exclusive truck roadway on IH-5 in the Los Angeles area. While other vehicles are allowed to use the roadway, trucks are the primary users. This limited-access road section that includes vertical grades allows slower truck speeds than the free-flow speed of other vehicles, especially in the uphill direction. At the end of the truck lane, trucks are allowed to regain speed at the top of the hill before merging with other traffic. The Managed Lanes Handbook suggests exclusive barrier-separated truck lanes if truck volumes exceed 30% of the vehicle mix, peak-hour volumes exceed 1,800 vehicles per lane-hour, and off-peak volumes exceed 1,200 vehicles per lane-hour (25).

Source: Managed Lanes Handbook (23)
Figure 4.1 An Exclusive Truck Roadway, Los Angeles, California

The focus of this study was limited to the investigation of the relationship between roadway geometric characteristics and truck crashes. However, countermeasures for improving safety are not only limited for geometric improvements but also improvements in pavement markings, traffic signs, roadside improvements, lighting, and changing regulations. Table 4.4 shows a general countermeasure list that could be used to improve the safety of roadways focusing on all possible areas (26). For example, if the case of sharper horizontal curves cannot be avoided, countermeasures such as warning signs can be used. Widening and improving clear zones is an alternative countermeasure, which also helps to reduce run-off-road crashes. This may include flattening side slopes, removal of roadside obstacles, and increasing available stopping distance adjacent to the road (26). As identified in this study, geometric changes such as horizontal alignments decrease truck crash frequency. Geometric alternations may be considered when other less costly countermeasures are not effective and when the current roadway geometry designs can significantly benefit from improvements.

Table 4.4 A General Countermeasure List for Improving the Roadway Safety
Source: Washington et al. (25)

<table>
<tr><th>Category</th><th colspan="2">Countermeasure</th></tr>
<tr><td rowspan="2">Pavement Markings</td><td colspan="2">Add/Upgrade Edgeline</td></tr>
<tr><td colspan="2">Add Raised Pavement Markings (RPMs)</td></tr>
<tr><td rowspan="4">Traffic Signs</td><td colspan="2">Warning Signs</td></tr>
<tr><td colspan="2">Advisory Speed Signs</td></tr>
<tr><td colspan="2">Chevron Alignment Sign</td></tr>
<tr><td colspan="2">Post Delineator</td></tr>
<tr><td rowspan="7">Roadway Improvements</td><td colspan="2">Modify Geometric Alignment</td></tr>
<tr><td colspan="2">Improve Sight Distance without Geometric Realignment</td></tr>
<tr><td colspan="2">Add Turn Lanes/ Barrier-Separated Lanes/Managed Lanes</td></tr>
<tr><td rowspan="3">Improve Longitudinal Shoulder</td><td>Add/Widen Graded/Stabilized Shoulder</td></tr>
<tr><td>Pave Existing Graded Shoulder of Suitable Width</td></tr>
<tr><td>Widen and Pave Existing Paved Shoulder</td></tr>
<tr><td colspan="2">Add Rumble Strips</td></tr>
<tr><td rowspan="8">Roadside Improvements</td><td colspan="2">Install/Upgrade Guardrail</td></tr>
<tr><td colspan="2">Upgrade Guardrail End Treatment/Add Impact Attenuator</td></tr>
<tr><td rowspan="6">Clear Zone Improvements</td><td>Widen Clear Zone</td></tr>
<tr><td>Flatten Side Slope</td></tr>
<tr><td>Relocate Fixed Object</td></tr>
<tr><td>Remove Fixed Object</td></tr>
<tr><td>Convert Object to Breakaway</td></tr>
<tr><td>Construct Traversable Drainage Structure</td></tr>
<tr><td rowspan="2">Lighting</td><td colspan="2">Add Segment Lighting</td></tr>
<tr><td colspan="2">Add Intersection Lighting</td></tr>
<tr><td>Regulations</td><td colspan="2">Enforcement Speed Limits</td></tr>
</table>

Before implementing countermeasures, the most effective countermeasures and specific conditions for which they are effective need to be identified. Not all countermeasures can be implemented simultaneously. Also, some countermeasures are less effective when introduced in isolation.

Chapter 5 Summary, Conclusions, and Recommendations

Due to their large sizes and heavy weights, large trucks can cause more damage and serious injuries in crashes than other vehicles can. In 2009, about 3,380 people were killed and another 74,000 were injured in large truck crashes in the U.S. Occupants of large trucks compose only 22% of the fatalities resulting from fatal truck crashes, while 78% of the fatalities occur outside the truck to pedestrians, cyclists, and, primarily, occupants of passenger vehicles. In addition, the probability of injury and severity of injuries that occur in a crash increase exponentially with vehicle speed, because kinetic energy is determined by the square of the vehicle's speed. As a result, large truck crashes that occurred on limited-access highways were much more severe than crashes on low-speed roadways. When looking for ways of improving situations related to truck safety, understanding the effects of geometric design features on truck crashes can bring significant benefits, as this is the area where transportation engineers have the highest level of influence. Thus, the objective of this study was to investigate the safety effects of traffic- and geometric-related features on limited-access highways.

Traffic- and geometric-related data from 2005 to 2010 were obtained from the CANSYS database maintained by the KDOT, while crash data were also obtained from the KDOT-maintained KARS database. Data available for use in the evaluation included 7,273 homogeneous, limited-access roadway segments which had speed limits of more than 55 mph, and length more than 0.25 mi. About 35% of road sections had at least one truck crash regardless of truck configurations and crash-severity type, while the remaining sections were free of truck crashes. Poisson and negative binomial regression models were used to estimate the effects of independent variables. Independent variables considered in developing the models included section length, lane width, posted speed limit, number of lanes, horizontal curvature, vertical grade, AADT per lane, truck percent, right shoulder width, inside shoulder width, median width, and the existence of rumble strips. Additionally, yearly dummy variables were used to capture variation in overall truck crashes across the years due to long-term trends and changes in omitted variables such as road surface conditions and weather.

According to the coefficients of the developed models, truck crash frequency increased with the length of a section as one could have expected. If the number of lanes increased, the number of truck crashes also increased. Horizontal curvature variable indicated crashes were less likely on curves with a high degree of curvature. Vertical grades were significantly negatively correlated with truck crash frequency. An increase in AADT per lane and percentage of trucks tended to increase large truck crash frequency. Inside shoulder width had a positive correlation with the number of truck crashes, meaning the number of crashes increased when inside shoulder width increased. The variables of years 2005, 2006, 2007, and 2008, which represent time trend, were significant in showing the overall number of truck crashes increasing over time due to unmeasured factors not included in the model.

Trucks need to be given important consideration during geometric design. Revision of existing design guides needs to take into account current dimensions of trucks and vertical curvature considerations. A process for evaluating the safety of horizontal alignment on multilane highways can be an effective countermeasure. This process allows designers to predict potential crash risks and safety-related concerns of an alignment, and make changes or develop countermeasures.

Exclusive truck lanes are one countermeasure to mitigate effects of increasing truck traffic. Introduction of barrier-separated lanes, express lanes, and managed lanes such as dual-dual lanes and toll roadways are effective strategies to offset the increase of conflict opportunities associated with an increase in the number of lanes. Warning signs on approaching curves and widening and improving clear zones are countermeasures for decreasing truck crash involvement. Before implementing countermeasures, the most effective countermeasures and specific conditions in which they are effective need to be identified.

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