Developing Safety Risk Index for Truck Preferred Arterial Corridors

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16. Abstract

Truck safety has been of great interest to transportation officials, engineers and researchers for many years because of the amount of freight transported by trucks, the safety impact of trucks in traffic, and trucks' invaluable contribution to the country's economic growth. Connecting between traffic generators, arterial streets are key links for door-to-door deliveries. It is imperative to study and evaluate truck safety impact on arterial streets in response to the continued strong growth of truck traffic. This project provided a comprehensive analysis of truck-related crashes that occurred on arterial streets.

By collecting extensive roadway geometries, pavement conditions, traffic data on selected arterial corridors heavily traveled by trucks, truck crash frequency and injury severity contributing factors have been identified. Statistical models have been tested with different combinations of datasets, with and without access parameters. Without the access related variables, truck miles traveled, annual average daily traffic (AADT), signal density, shoulder width, pavement service index (PSI) and its standard deviation are statistically significant factors for predicting the crash frequency. After incorporating access information, commercial driveway design related variables exhibit statistical significance while the previously significant variables such as AADT, PSI and its standard deviation are no longer statistically significant. This noticeable change of the statistical models warns that a spurious relationship may be formed if a causal relationship cannot be sufficiently supported via the data collected. For crash severity prediction, twelve contributing factors such as posted speed limit, lane width, number of lanes, pavement condition index, and undivided roadway portion were identified. Subsequently, the corridors safety performance measured by a truck crash severity index (CSI) as a function of crash frequency and injury severity has been established. It is anticipated that the findings in the study will not only benefit state and local agencies in planning, designing, and managing a safe arterial corridor for trucks and other motorists, but also help motor carriers to optimize their routes from a safety perspective.

17. Key Words
arterial corridor, truck safety, crash frequency, crash severity, crash severity index.

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EXECUTIVE SUMMARY

The inevitable contribution of the truck's transport services on the country's economic growth has made transportation personnel and researchers to think truck related safety issues deeply. According to the National Highway Traffic Safety Administration (NHTSA), over 400,000 truck-related crashes occurred in 2009 with approximately 7,800 of those being fatal. Truck related crashes undermine their remarkable contribution to the US economy. Compared to the extensive studies conducted on freeway truck safety, research on arterial streets is considerably negligible. Connecting between traffic generators, arterial streets are key links for door-to-door deliveries. Identifying critical factors contributing to truck related crashes and developing remedial and preventive strategies to reduce truck crashes and their consequences is imperative. This study closes the gap by providing a comprehensive analysis of truck-related crashes on arterial roads.

Previous research identified roadway geometric features, traffic operational, access management, human factors and pavement characteristics that contribute to truck crashes. The project team conducted a comprehensive literature review to acquire a thorough understanding of the truck crash contributing factors, safety analysis from a corridor perspective and currently available safety indexes.

Five year (2005-2009) safety and crash data were collected from WisTransportal, an online Wisconsin crash database. Crash data belongs to two different sources, Meta-manager and State Trunk Network. In general, seventeen geometric, traffic and pavement variables, namely annual average daily traffic (AADT), annual average daily truck traffic (AATT), truck percentage, number of bridges, signal density, access point density, posted speed limit, lane width, median width, left and right shoulder width, divided and undivided portion of roadways, number of lanes, horizontal curvature speed, pavement serviceability index, international roughness index and pavement condition index data were used to model truck crashes. Most of the access related variables are not readily available in any geographic information system (GIS) or table format. The reliable source for collecting this is aerial photographs, but measurements must be taken manually. Considerable effort was made to collect access related variables. Fifteen access parameters were collected, such as median opening width, median opening density, length of left turn bay, minimum distance of a driveway to a signalized intersection, two-way left-turn lane (TWLTL) length, several driveway design features both for commercial and residential driveways etc.

The scope of the research was to analyze truck crashes on arterial corridors including principal and minor arterials. An arterial corridor is defined as a section of a roadway connecting interstate and freeways and providing access to properties at the same time provides mobility. The corridor selection criteria were

- Corridor length is no less than one mile
- Annual Average Daily Truck Traffic is at least 800 or more, and
- corridors located within five miles of an Interstate highway or a freeway

Short roadway segments were dissolved with similar or same annual average daily truck traffic (ADTT). Finally 100 corridors were selected that served the study purpose.

Crash prediction models have been focused on either crash frequency or injury severity given a crash occurrence. Knowing the number of crashes and the consequences of the crashes, a safety index can be built. Negative binomial (NB) model and multinomial logit (MNL)/ordered probit (OP) model have been employed to predict crash frequency and injury severity, respectively. Crash severity index (CSI) was estimated based on the concept of HSM's "Relative Severity Index". The expected number of crashes can be modeled as the product of traffic exposure and the crash rate which may be a function of truck volume, AADT and other factors. Based on the Akaike information criteria (AIC) value, a measure of statistical goodness-of-fit, the final model was chosen.

Along with the intercept, million truck miles traveled (TMT), AADT, signal density and standard deviation of Pavement Serviceability Index (PSI) are positively associated with the number of truck crashes. Shoulder width and average PSI are negatively associated with the number of truck crashes. The model results imply that the corridor-based safety performance could be improved by better pavement conditions, wider shoulder widths, and more consistent signal spacing. Given the importance of access data on arterial street traffic safety, newly collected data elements were added to the model link function. The augmented data was expected to offer more explanation and prediction power to truck crashes. Some previously significant variables (AADT, PSI, standard deviation (PSI)) become insignificant after adding access related variables such as median, driveway and left turn lane. Commercial driveways which are frequently used by trucks apparently affect the safety performance of a corridor.

In order to overcome the canonical negative binomial model's fixed overdispersion parameterization, generalized negative binomial (GNB) regression method had been used for assessing the source of overdispersion. It was assumed that AADT, TMT, signalized intersection density, driveway density etc. may be the contributing factors to overdispersion. Same variables are statistically significant for the truck crash prediction. Though the magnitude changed the signs are consistent and interpretations are also same. Finally the variables that caused the overdispersion of the study data are the million miles traveled by truck, signal density and proportion of divided commercial driveways. The AIC indicates that GNB yields a better goodness of fit than the NB model.

MNL and OP model results were compared with the observed proportion using the sum of absolute difference (SAD). Based on the SAD analysis, the MNL model was chosen for predicting injury severity. There were five levels for the dependent variable: crash severity, coded as fatal (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C) and property damage only (PDO). When estimating the MNL model, the property damage only crash was treated as the base category. MNL model results show the posted speed limit, shoulder width, pavement serviceability index, standard deviation of PSI, pavement condition index, number of lanes, lane width, ADTT, AADT and undivided portion of roadway are statistically significant variables for predicting different levels of injury severity at the 10% significance level. In the MNL model, the coefficient estimates are explained as the comparison between injury level *i* with the base level PDO.

Finally, a worksheet was designed to facilitate the calculation of CSI, based on the statistical results. Some corridors were overestimated in the predicted CSI compared to observed CSI. For those overestimated corridors, some common characteristics such as narrower shoulder width, higher standard deviation of truck volume, lower pavement serviceability index, and narrower lane width were observed, which seem to contribute considerably to the predicted crash frequency and severity. Nevertheless, the overestimated corridors are the ones with low CSI, suggesting very few serious injury crashes.

In conclusion, crash severity index (CSI) developed in this research will provide a holistic measurement of truck crash risk and help to develop more proactive, corridor-based truck safety strategies.

1 INTRODUCTION

1.1 Background

Freight transportation is extremely critical to the economic development of a nation. The United States economy depends on trucks to deliver nearly 70% of all freight transported annually, accounting for $671 billion worth of manufactured and retail goods in the U.S., along with $295 billion in trade with Canada and $195.6 billion in trade with Mexico (1). Trucking revenues totaled $610 billion in 2011, and revenues are estimated to nearly double by 2015 (2). While the rapid commercial trucking growth is great news for the country's economy, the increasing truck traffic may negatively impact cars, vans, SUVs and other vehicles that share the road. In 2010, large trucks accounted for 4 percent of all registered vehicles and 10 percent of the total vehicle miles traveled and accounted for 8 percent of all vehicles involved in fatal crashes and 3 percent of all vehicles involved in injury and 2 percent property-damage-only crashes. Of the fatalities in crashes involving large trucks during that year, 76 percent were occupants of other vehicles (3). Figure 1-1 shows the fatal crash rate by vehicle type (4). In fact, one person is injured or killed in a truck accident every 16 minutes and one out of every eight traffic fatalities involves a trucking collision (2). The National Highway Traffic Safety Administration (NHTSA) has estimated that over 400,000 truck accidents occurred in 2009 with approximately 7,800 of those being fatal crashes (5). Therefore, it is vital to improve truck safety and reduce truck-related crashes.

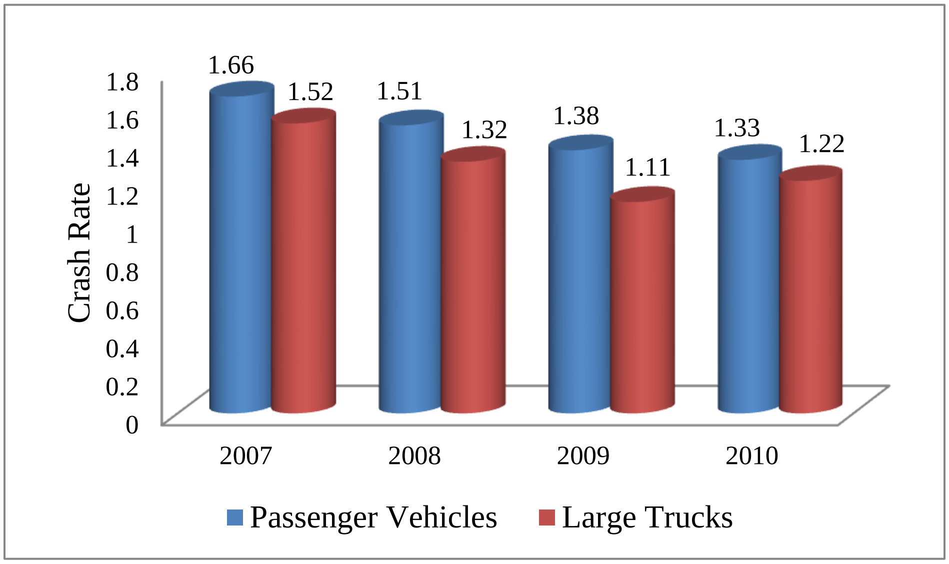


Figure 1-1: Vehicles Involved in Fatal Crashes per 100 Million Vehicle Miles Traveled by Vehicle Type

Truck safety on arterial roads is crucial because the dual role (moving passengers and goods and providing access to the local businesses and residences) played by the arterial roads often conflict with each other. Arterials collect traffic from local roads and channel it to interstate highways, providing both mobility and accessibility. An arterial can be designed with infrequent access points accompanied by access control measures such as raised medians to prevent left-turns and crossing maneuvers. An arterial can also be designed with a low level of access control with many commercial and residential driveways having direct access to the arterial street. Arterials with low levels of access control have more conflicts points when compared to high access controlled roads. So, it becomes clear that there is a trade-off between mobility and access which may compromise safety.

According to a study conducted in Iowa, nearly 10 percent of all crashes occurred at commercial driveways, primarily on city arterial streets (6). In a Michigan study, there were nearly 318,000 crashes (excluding limited access facilities) in the three-year period from January 1, 1992 to December 31, 1994, among which 33,000 crashes (9.63 percent) were driveway related, accounting for 69 fatalities and nearly 13,900 injuries (7). In Texas, driveway accidents accounted for 13.95% of the total number of accidents in four years on 100 selected roadway sections (8). In Maine, 1 in 6 crashes occurred at driveways or entrances; 1 in 5 people involved in crashes were engaged in driveway or entrance related crashes in 1996 (9). The proportion of driveway related accidents to the overall accident numbers seen in these states illustrates the magnitude of the problem. However, the solution to the problem is not simply limiting, reducing or closing all the accesses, but rather providing access at proper locations and designing them in a safer manner is more effective.

Extensive research has been conducted on site-specific characteristics and their effects on truck crashes, either at intersections or on segments (10-17). Moreover, truck safety on freeways and interstate highways has usually been a focus of research because of the high speed and high truck percentage (13-22). Studies have shown that full access controlled roads have a safer traffic record, accounting for only 24 percent of crashes, while the remainder occurs on arterial or local roadways (12). In contrast, limited research has been conducted on arterial streets, especially from a corridor perspective. Arterial streets connect freeway corridors to the distributors, carriers, vendors and customers. They are the “last miles” for commercial motor vehicles to deliver the freight to destinations or enter the interstate highway system. Analyzing safety from an arterial corridor perspective is important as there are more opportunities for conflicts with passenger vehicles at signalized intersections and it is valuable for developing system-wide, corridor-based and more importantly, proactive safety improvement strategies.

There are some key factors commonly identified in the literature that are known to directly influence safety performance of arterial highways: driveway spacing, signal density, driveway design, driveway proximity to intersections and interchanges, median configuration, geometric design elements, land use and signal timing plan. Safety conditions are certainly critical on the arterials because of numerous access points, turning movements, and mixture of transportation modes. It can be further complicated by various traffic control devices and strategies. For arterial mobility, roadway characteristics such as lane width, shoulder width, posted speed limit, median width, horizontal/vertical curvature and pavement surface conditions are important determinants to safety as each of these components ensures a certain level of service when the arterials act as a thoroughfare. From the accessibility perspective, driveways and median opening densities are important for safety as each of them adds to the number of conflicts for vehicles along a roadway during egresses and ingresses. While it is certainly necessary to ensure mobility, it is also important to accommodate access to commercial and residential properties; thus the number, type, spacing and location of driveways and median openings need to be planned carefully. So it is important for local governments, road authorities and land developers to coordinate access decisions based on the expected level of the arterial performance in safety, mobility and accessibility.

Due to the substantial truck-passenger vehicle interactions occurring on arterial streets, there is an urgent need to study the relationship between truck safety and arterial access management, geometric characteristics and traffic control.

1.2 Objectives

The goal of this project is to identify the causal truck crash factors on arterial corridors and develop a cost-based safety risk index for these corridors heavily used by trucks with the emphasis on access management, geometric design and traffic control. The truck routes/corridors were selected based on their designation for existing truck use (Annual Average Daily Truck Traffic) and their distance from nearby Interstate highways and freeways. The findings from the study not only directly benefit state and local agencies in planning, designing and managing a safer truck arterial corridor, but also help motor carriers to optimize their routes from a safety perspective. The study also reviews the state-of-the-practice access design such as median treatments, signalized intersection density, commercial/private driveways – all of which are crucial to design consistency on arterials. In summary, the objectives of the study are to:

1. Select critical truck arterial corridors;
2. Conduct comprehensive data collection in relation to truck safety;
3. Identify causal factors for heavy vehicle involved crashes;
4. Develop a cost-based arterial corridor safety risk index.

1.3 Organization of the Report

This report is organized in the following manner: Chapter 2 is the endeavor to synthesize the related research on arterial safety. Chapter 3 is composed of statistical and mathematical methodologies for crash frequency, injury severity and risk index calculation. The detailed description of data sources, data processing, variable preparation and corridor identification procedure is presented in Chapter 4. Chapter 5 consists of exploratory data analysis of the safety data used in this research. Chapter 6 presents the results of statistical modeling in this study. In particular, several model forms are evaluated based on assumptions, limitations and goodness of fit. Chapter 7 concludes the results of this report as well as suggests future plans that can be continued from this research.

2 REVIEW OF LITERATURE

A crash is a complicated event because many factors may be involved.. Roadway crashes have been analyzed from geometric characteristics, traffic, pavement and access management perspective. Looking beyond highway geometric data and access related issues, Wang et al. developed multi-level estimation models by using freeway traffic data (flow, ramp volume, and shoulder width), economic activity data (shipment, county unemployment rate, income) and safety performance data to identify any contributing factors that may increase crash rates (13). They found that factors such as the number of shipments, county unemployment rate, truck and ramp AADT and lane width significantly affect the number of truck crashes. This chapter provides an overview of all the contemporary studies that have been approached for highway safety.

2.1 Arterial Safety from Geometric Design Perspective

Of prime interest to transportation agencies is the impact of roadway geometric design on truck crashes. Several studies have focused on identifying roadway geometric features, traffic operational and pavement characteristics that contribute to truck crashes (10-19, 22). Many of the preceding studies were based on either individual intersections or segments, while few studies approached safety issues from a corridor perspective (25-28). Sayed and El-Basyouny assessed the corridor effects with alternate specifications (25). They compared the traditional Poisson Log Normal (PLN) model with two extended PLN models using a data set from 392 urban arterials in the city of Vancouver, BC, and grouped the data into 58 corridors. The results of their paper provided some strong evidence of the benefit of clustering road segments into rather homogeneous groups (e.g., corridors) and incorporating random corridor parameters in accident prediction models. Lee et al. examined factors that affected urban divided arterial road mid-block crashes on a 5.3-km section of urban arterial and concluded that the number of access points on urban arterial roadways should be reduced to minimize the number of mid-block crashes (26). Abdel-Aty and Wang emphasized the fact that signalized intersections within a corridor have a correlated influence on the occurrence of crashes if the intersections are placed closely (27). To account for the correlated data problem, they used generalized estimating equations (GEE) to estimate the coefficients and their statistical inferences assuming crash count follows a NB distribution. Milton et al. used corridor specific and weather related variables to predict injury severity proportions using a mixed logistic model (28). Within these results, the parameters for average daily traffic (ADT), snowfall, truck average daily traffic, truck percentage, and the number of interchanges per mile were found to be statistically significant variables for predicting different levels of injury severity. Pavement friction, horizontal curvature per mile and number of grade breaks per mile had a fixed effect across all injury levels. These studies demonstrate the importance of corridor effects or corridor-level variables on crash occurrence and injury severities.

2.2 Arterial Safety from Access Management Perspective

Arterial streets are the “last miles” for trucks to deliver the freight to commercial and residential destinations or enter the Interstate highway system. Frequent and direct access from commercial and residential driveways to an arterial reduces capacity and creates substantial potential for crashes. Increasing the spacing between access points helps reduce the number and variety of events to which drivers must respond. In addition, wide access spacing gives drivers more time to perceive potential incidents, react accordingly and navigate safely. Recent truck crashes in many of the counties of Wisconsin have increased following the historical trend that has continued to increase in recent years, particularly on arterial streets (29). The increased truck crashes have become a major topic for the researchers and transport officials who frequently debate on the cost effectiveness of implementing access management techniques (i.e., raised medians, coordinated signal timing plan or driveway consolidation) to alleviate some of the safety concerns associated with access on arterial streets. Application of access management best practices has benefits for motorists, transit riders, planning and government agencies, and also for communities. Numerous studies have been conducted on the safety relationship of access management techniques as a function of access spacing, corner clearance and medians (30-35).

Schultz et al. (33-35) undertook several studies on urban arterial access management and safety in order to determine the safety benefits provided by access management techniques (corner clearance, raised medians and driveway consolidation) in Utah. Statistical analyses showed that roadways which included high access density, numerous signals per unit length and lack of medians were positively related with increased crash rate and severity (33). In particular, crash totals, crash rates and rear-end crashes in intersection functional areas increase with increase in commercial access density. In a follow-up study, the researchers proved that raised medians and driveway consolidation can change the crash pattern (manner of collision) and injury severity (35). Gluck, Levinson and Stover (36) stated that doubling the access frequency from 10 to 20 access points per mile would increase accident rates by 40 percent. A road with 60 access points per mile would have tripled the accident rate (200% increase) as compared with a spacing of 10 access points per mile. Each additional access point increases the accident rate by about 4%. Their research results suggest a generally consistent relationship the greater the frequency of driveways and intersections, the greater the number of accidents. Gattis et al. (37) presented six major considerations for driveway design; including maintaining or improving the efficiency and safety of the intersecting roadway, and providing adequate sight distance for road and sidewalk users. Stover and Koepke (38) indicated that two-way driveways should allow for simultaneous two-way operations and thus it is better to have separate entrance and exit lanes.

Adequate spacing and design of access to crossroads in the vicinity of freeway ramps avoids traffic backups and preserves safe and efficient traffic operation (39). A methodology was developed by Rakha et al. (31) to evaluate, quantitatively, the safety impacts of different access-spacing standards in Virginia. According to their analysis, shortcomings exist in the AASHTO standards and there are significant safety benefits which can be realized by increasing these values to stricter standards like those recommended in the TRB Access Management Manual. For example an increase in the minimum access spacing from 300 ft to 600 ft results in a 50% reduction in the crash rate.

In recent years, access management in arterial streets started to gain attention from different researchers (30, 40, 41). Using microscopic traffic simulation models for 11 arterial corridors, Eisele and Frawley estimated the relationships between crash rates and access point (driveways and public street intersections) densities, with or without the presence of raised medians or two-way left-turn lanes (30). They concluded that as access point density increases, there is an increase in crash rates, irrespective of the median type. Although, the researchers found that the relationship between access density and crash rate is higher on roadways without raised medians. Lee et al. (41) analyzed crashes that occurred at midblocks of an urban arterial road using log-linear models to show that midblock crashes are more likely to occur on road sections with access points and high percentage of trucks (>20%). The results show that median opening, driver age/gender, lighting, time of day and day of week are associated with different types of crashes classified by the vehicles involved in crashes. The study shows the importance of analyzing midblock crashes using the urban divided arterial roads with high truck volume by vehicle type and by travel direction because the complex interaction among cars and trucks is influenced by more frequent egressing and ingressing driveway traffic.

2.3 Safety Risk Index

Relationships between crash frequency, severity and any contributory factors can be applied in a proactive safety analysis. De Leur and Sayed worked on the development of a systematic framework for proactive road safety planning in which they assumed road risk was a function of exposure, collision probability of a vehicle and consequence of a potential collision (42). They also provided planning recommendations regarding land use shape, road network shape, geometric design elements, roadway functionality and friction, speed at crash prone areas and road side environment in an effort to improve the safety of a roadway segment. Furthermore, De Leur and Sayed developed two types of road safety risk index: $RSRI_{specific}$ and $RSRI_{combined}$, based on the risk score of a particular road feature (43). $RSRI_{specific}$ defines the risk associated with each road feature, obtained by combining the scores for the three components of risk namely exposure, probability and consequences., While $RSRI_{combined}$ defines overall risk by combining the $RSRI_{specific}$ scores for all road features. The formulations are as follows in equation 2-1 and 2-2.

$$RSRI_{specific} = E_i P_i C_i \quad \text{2-1}$$

$$RSRI_{combined} = \sum_{i=1}^{n} E_i P_i C_i \quad \text{2-2}$$

where,

E_i= risk score due to exposure for road feature *i,*

P_i= risk score due to probability for road feature *i,*

C_i= risk score due to consequence for road feature *i*, and

n= number of road features investigated.

In a recent study, Wu and Zhang proposed a framework for developing a composite Road Risk Index using a logistic function based on exposure, crash rate and crash severity (44). They showed risk index as a function of a predicted number of different crash types multiplied by a relative level of cost due to a particular type of crash using the HSM crash severity distribution and associated crash unit costs.

$$RRI_{Ind}(i) = f\left(\sum_j N_{ij} * AS_{ij}\right) \quad \text{2-3}$$

Where i = roadway segment

j = 1 to 3, which indicates crash types

N_{ij}= predicted number of type j crash on roadway segment i

ASj= relative level of cost due to type j crash

f (.) = a transformation function which maps the input to a desired range.

And the road risk index for a road way segment is as follows:

$$RRI_{ACU}(i) = g(RRI_{Ind}(i) * EXPO_i) \quad 2\text{-}4$$

where $EXPO_i$ exposure in million vehicle-miles of travel per year on roadway section i and calculate as

$$EXPO_i = AADT * L_i * 10^{-6} * 365 \quad 2\text{-}5$$

here L_i = length of the segment i

and g (.) = a transformation function which maps the input to a desired range.

RRI $_{\text{Ind}}$ and RRI are defined on a scale of 0 to 10, with 0 presenting the lowest road risk and 10 the highest. The transformation functions f (.) and g (.) are defined as generalized logistic functions:

$$f(x) \text{ or } g(x) = A + \frac{C}{1 + T * e^{(-B*(x-M))^{1/T}}} \quad 2\text{-}6$$

where A= Lower asymptote

C= Upper asymptote

M= the time of maximum growth

B= the growth rate

T= near which the asymptote maximum growth occurs.

In the HSM network screening process, a site-specific relative severity index (RSI) is calculated by multiplying the observed or predicted average crash frequency for each crash severity with their respective comprehensive crash costs. An average RSI is then obtained by dividing the overall RSI by the total number of observed crashes that occurred at the site as shown in equation 2-7 and 2-8 (23).The average RSI per site is then compared to the average RSI cost for its respective population.

$$RSI_i = \frac{\sum_{j=1}^{n} RSI_j}{N_{observed,i}} \quad 2\text{-}7$$

where, RSI_i= Average RSI cost for the intersection, i

RSI_j=RSI cost for each crash type, j

$N_{observed,i}$= Number of observed crashes at the site, i

and

$$RSI_{av(control)} = \frac{\sum_{j=1}^{n} RSI_i}{\sum_{i=1}^{n} N_{observed,i}} \quad 2\text{-}8$$

where, $RSI_{av(control)}$= Average RSI cost for the reference population (control group)

RSI_i= Total RSI cost for site i

$N_{observed,i}$ = Number of observed crashes at the site, i

For the sake of proactive safety management, different researchers developed different types of indexes in order to quantify the risk associated with a roadway section. Regardless of the differences in the methods that have been examined, these methodologies can provide valuable clues for informed decision-making.

3 METHODOLOGIES

Crash prediction models have focused on either crash frequency or injury severity given a crash occurrence. The statistical models commonly applied for the first category include Poisson, Negative Binomial, Zero-Inflated Poisson and Negative Binomial Models (ZIP and ZINB). Studies belonging to the latter category often apply the Ordered Probit (OP) model, Ordered Logit model, Multinomial Logit model, Mixed Logit model and artificial intelligence techniques. This section contains the theoretical concepts and mathematical equations necessary for the development of truck arterial corridor crash severity index (CSI). Methodologies of predictive methods for crash frequency and crash severity distribution are discussed.

3.1 Modeling Methods for Crash Frequency

3.1.1 Negative Binomial

Count-data modeling (Poisson, negative binomial) techniques are widely used for crash frequency as the number of accidents n_i on a roadway segment per unit of time is a non-negative integer. When the variance is larger than the mean, the data is said to be over dispersed. Over dispersed count data is usually modeled with a negative binomial distribution because the Poisson distribution has a restrictive assumption of equal variance and mean. In a Poisson model, the probability of the number of truck crashes for corridor i, n_i is as follows:

$$P(\mathrm{n_i}) = \frac{\exp(-\lambda_i){\lambda_i}^{n_i}}{n_i!} \quad 3\text{-}1$$

where $P(n_i)$ is the probability of a corridor i having n_i crashes and λ_i is the expected number of crashes in corridor i. The negative binomial model is an extension of the Poisson where the Poisson parameter λ follows a gamma probability distribution. The standard log link function for the negative binomial model can be expressed as a linear model of the covariates in Equation 3-2.

$$\lambda_i = \exp(\beta_0 + \beta_1 x_{1i} + \cdot\cdot\cdot + \beta_k x_{ki})\exp(\varepsilon_i) \quad 3\text{-}2$$

where βs are coefficients of explanatory variables and $\exp(\varepsilon_i)$ is the term adjusting for over-dispersion and is gamma distributed. In this Study the models were estimated by using maximum likelihood estimation. For this modeling, the SAS GENMOD procedure was used (45).

3.1.2 Generalized Negative Binomial

Generalized negative binomial is a generalization of the negative binomial mean-dispersion model; the shape parameter alpha (α) may also be parameterized more specifically it can treat the heterogeneity of the count data. The heterogeneous negative binomial extends the negative binomial model by allowing observation-specific parameterization of the ancillary parameter, α.

In other words, the value of α is partitioned by user specified predictors. The method is applicable to different structures of NB model such as NB1, NB-C, and NB2 . There are two uses of the heterogeneous model. First, parameterization of α provides information regarding which predictors influence overdispersion. Second, it is possible to determine whether over dispersion varies over the significant predictors of α by observing the differential values of its standard errors. If the standard errors vary only a little between parameters, then the over dispersion in the model can be regarded as constant (46).

The standard log link function for the over dispersion parameter of the negative binomial model can be expressed as a linear model of the covariates in Equation 3-3.

$$\text{Ln}(\alpha)=\mathbf{X}\boldsymbol{\beta} \tag{3-3}$$

3.2 Modeling Methods for Crash Severity

3.2.1 Ordered Probit (OP) Model

The consequence of a crash can be modeled as a discrete outcome. An extensive and detailed review of the discrete choice probabilistic models and their applications in predicting crash severities is discussed by Savolainen et al. (47). It has been accepted by many researchers that there is an ordinal nature to crash severities, i.e. injury severity can be ranked from high to low as fatal injury (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C), and property-damage-only (O). To model injury severities as the ordinal response, researchers most frequently used discrete choice models such as ordered Probit (OP) models (47). An OP model is a special case of the Probit model where more than two outcomes of an ordinal dependent variable is modeled, which is usually estimated using maximum likelihood. The underlying relationship to be characterized is shown in Equation 3-4.

$$y^* = \mathbf{X}'\boldsymbol{\beta} + \varepsilon \tag{3-4}$$

where y* is the exact but unobserved dependent variable; **X** is the vector of independent variables and **β** is the vector of regression coefficients which needs to be estimated. The ε is a random error term and assumed to follow a standard normal distribution. Furthermore y* cannot be observed, instead the categories of response can only be observed, as expressed in Equation 3-5.

$$y = \begin{cases} 1 & if\, y^* \leq 0 \\ 2 & if\, 0 < y^* \leq \mu \\ 3 & if\, \mu < y^* \end{cases} \tag{3-5}$$

μ represents thresholds to be estimated along with the parameter vector **β**.

3.2.2 Multinomial Logistic (MNL) Model

When modeling crash severities as an ordinal dependent variable, some restrictions can potentially affect the estimated results (47). The primary concern is the manner in which the explanatory variables affect the probabilities of the discrete outcome; the shift in the cutoff thresholds is constrained to move in the same direction. On the other hand, non-ordinal probabilistic models, such as multinomial logit (MNL) models, allow variables to have opposite effects regardless of the order of the injury severities. The MNL model is a regression model which generalizes logistic regression by allowing more than two discrete outcomes. MNL relies on the assumption of independence of irrelevant alternatives (IIA) - the odds of preferring one class over another do not depend on the presence or absence of other "irrelevant" alternatives. The mathematical model underlying MNL is to construct a linear predictor function that constructs the relationship between outcomes from a set of weights that are linearly combined with the explanatory variables of a given observation:

$$\mathrm{U_{ij}} = \mathbf{X}_\mathbf{i}'\boldsymbol{\beta}_j + \varepsilon_{\mathrm{ij}} \qquad 3\text{-}6$$

where $\mathbf{X_i}$ is the vector of explanatory variables describing observation i, $\boldsymbol{\beta}_\mathbf{j}$ is a vector of weights (or regression coefficients) corresponding to outcome j, and $\mathrm{U_{ij}}$ is the utility associated with assigning observation i to get category j. The $\varepsilon_{\mathrm{ij}}$ is an error term that accounts for the random noise and assumed to be independently and identically distributed with a Gumbel extreme value distribution, and its logistic formulation is given by:

$$P_i(j) = \frac{EXP[\boldsymbol{X}_i'\boldsymbol{\beta}_j]}{1+\sum_{j=1}^{K-1} EXP[\boldsymbol{X}_i'\boldsymbol{\beta}_j]} \quad \text{for j} = 1, \ldots, \mathrm{K}-1 \qquad 3\text{-}7$$

In a multinomial logit model, for K possible outcomes, running (K-1) independent binary logistic regression models, in which one outcome is chosen as a "pivot" and then the other (K-1) outcomes are separately regressed against the pivot outcome. If the last outcome K is chosen as the pivot, the estimated coefficients are usually presented as a log odds ratio between the probability of a given category and the reference one, resulting in (K-1) estimates for each independent variable if the response variable has K levels, as specified in Equation 3-8.

$$\log\left[\frac{P_i(j)}{P_i(K)}\right] = \boldsymbol{X}_i'\boldsymbol{\beta}_j \quad \text{for j} = 1, .. \mathrm{K}-1 \qquad 3\text{-}8$$

Note that $\boldsymbol{\beta}_\mathbf{j}$ is a vector of estimable parameters representing the log odds ratio between the probabilities of two alternatives.

In a similar attempt, Geedipally et al. applied MNL models for estimating the proportion of crashes by collision type and then multiplied by the total number of crashes estimated with a total crash model to obtain the crash counts for each crash type at a site (48). They concluded that it is a promising method based on comparisons with the fixed proportion method and the method of developing respective collision type models.

3.3 Crash Severity Index (CSI)

Truck corridor CSI was measured by the annual societal economic costs due to truck crashes which occurred along the specific corridor measured by unit length. Expected annual number of truck crashes as well as the proportion of crash by severity can be estimated via corridor geometric characteristics and traffic conditions. Combining annual crash frequency, severities, unit crash cost, and corridor length, the truck arterial corridor CSI is formulated in Equation 3-9.

$$CSI_i = \frac{\sum_{j=1}^{J} N_i P_j^i U_j}{L_i} \tag{3-9}$$

where:

CSI_i is the crash severity index for truck corridor i,

N_i is the annual expected number of truck crashes along corridor i,

P_j is the proportion of crash severity j with j=1, J for corridor i,

U_j is the unit crash cost for severity j and

L_i is the length of corridor i.

For any truck corridor under consideration, the CSI value can be estimated using the corridor characteristics and applied either as a ranking tool for truck safety performance or a proactive method for truck safety planning.

4 DATA COLLECTION AND PROCESSING

4.1 Data Source

The data used in this research consisted of five years' worth (2005 to 2009) of crash counts and geometric, pavement, and traffic volume data. Truck crashes were retrieved from the online Wisconsin crash database through the WisTransportal System (29). The crash data belongs to two different sources, Meta-manager (MM) and State Trunk Network (STN).

4.2 Data processing

Mobility, roadway, bridge and pavement data were found in five different files based on regions: North East, North West, North Central, South East and South West in the online document of WisTransportal System. Those five separate files were combined to make one single file for mobility, roadway, pavement and bridge data set for the whole state. There are many variables in each of the data sets and some variables are redundant across the data sets. So, based on the research query, three variables from Pavement table, seven variables from Roadway table, four variables from Mobility table and four variables (number of bridges, width of bridge, number of signalized intersection & number of un-signalized intersection) from STN were selected. Table 4-1 depicts the detailed description of the variable name, their description and source.

Table 4-1: Variable name, explanation and their source

Variable name	Variable definition	Source
Base Data		
PDP_ID	Meta-Manager Segment ID Number	M_M
PDP_FRM	Meta-Manager Segment "FROM Reference Point (RP)"	M_M
PDP_TO	Meta-Manager Segment "TO Reference Point (RP)"	M_M
PDP_MILE	Meta-Manager Segment Length	M_M
DIVUND	Divided/Undivided/1-Way Highway Segment (D / U / 1)	STHN INV
Roadway Data		
FCLASS	Federal Functional class	STHN INV
TRWAYWD M	Traveled way width (through lanes only)	STHN INV
RSHTOTWD M	Right shoulder total width	STHN INV

HCURLE40 1	Curves/mile posted 40 mph or less (Coded as Good, Fair & Poor)	DEF/M_M
HCURGT40 1	Curves/mile posted more than 40 mph (Coded as Good, Fair & Poor)	DEF/M_M
NUMLANES	Number of lanes (Directional when roadway is divided)	STHN INV
MEDNWD	Median Width	STHN INV
Mobility Data		
PTDSPEED	Posted speed	DEF
LSHTOTWD	Left shoulder width	STHN INV 2
AADTYR_1	Projected AADT for 1 year from the current year (both directions total)	Forecast file
TRKYR_1	Percentage of AADT as trucks for 1 year from the current year	Forecast file
Pavement Data		
PCI	Pavement Condition Index (base year and projected year where applicable)	PIF/M_M [1]
PSI	Pavement Serviceability Index (base year and projected year where applicable)	PIF/M_M [1]
IRI	International Roughness Index Rut (avg. mm) (base year and projected year where applicable)	PIF/M_M [1]

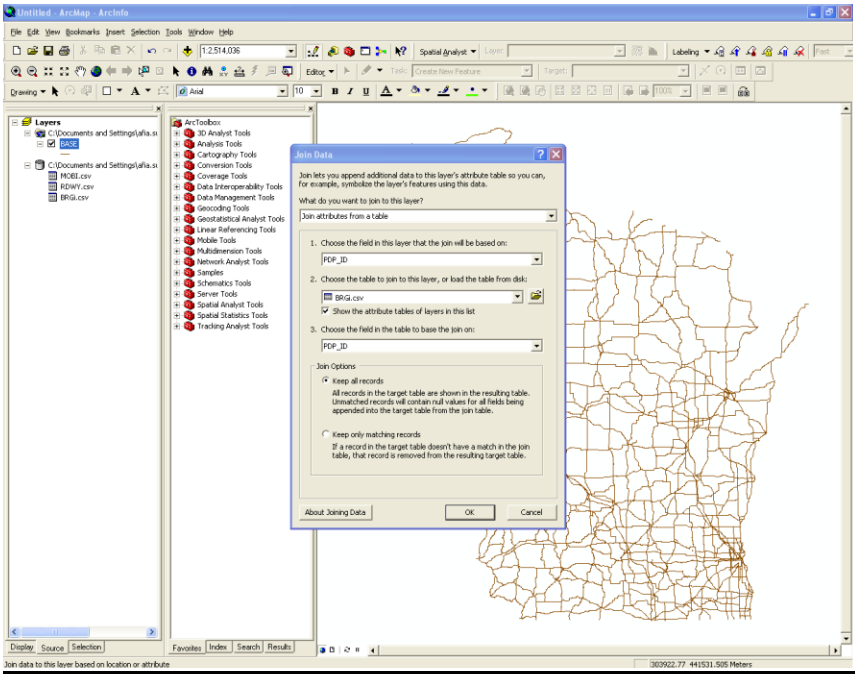
** STHN INV= State Trunk Highway Network Inventory Data

** DEF=Deficiency File

** PIF=Pavement Information File

** M_M [1]= Projected conditions using the PMDSS deterioration curves

Then the revised mobility, roadway and bridge data tables were joined with Meta-Manager 2011 based on the common field PDP_ID so that all the target variables can be found in one single spread sheet.



Join Data

Join lets you append additional data to this layer's attribute table so you can, for example, symbolize the layer's features using this data.

What do you want to join to this layer?

Join attributes from a table

1. Choose the field in this layer that the join will be based on:

PDP_ID

2. Choose the table to join to this layer, or load the table from disk:

BRGI.csv

☑ Show the attribute tables of layers in this list

3. Choose the field in the table to base the join on:

PDP_ID

Join Options

● Keep all records

All records in the target table are shown in the resulting table. Unmatched records will contain null values for all fields being appended into the target table from the join table.

○ Keep only matching records

If a record in the target table doesn't have a match in the join table, that record is removed from the resulting target table.

About Joining Data OK Cancel

Figure 4-1: Screen shot of table joining procedure in ArcGIS

The scope of the research was to analyze truck crashes on arterials including principal and minor arterials. To achieve the criteria principal and minor arterials from MM segments were selected based on the functional class (10, 20, 60, 61, 62, 70, 71, 72, and 73). The following SQL was used for that selection and exported as a separate shape file for ease of analysis.

"FCLASS" = '10' OR "FCLASS" ='20' OR "FCLASS" = '60' OR "FCLASS" = '61' OR "FCLASS" = '62' OR "FCLASS" = '70' OR "FCLASS" = ' 71' OR "FCLASS" = ' 72' OR "FCLASS" = '73'

Total number of resulting MM segments in this process is 10605 corresponding to 8327 miles of highway. After that, three fields named bin100, ADTT and LNWD were added to the newly formed shape file and the following values were calculated as

ADTT = AADT * percentage of trucks.

$$\text{LNWD} = \frac{\text{Travel−way width}}{\text{number of lanes}}$$

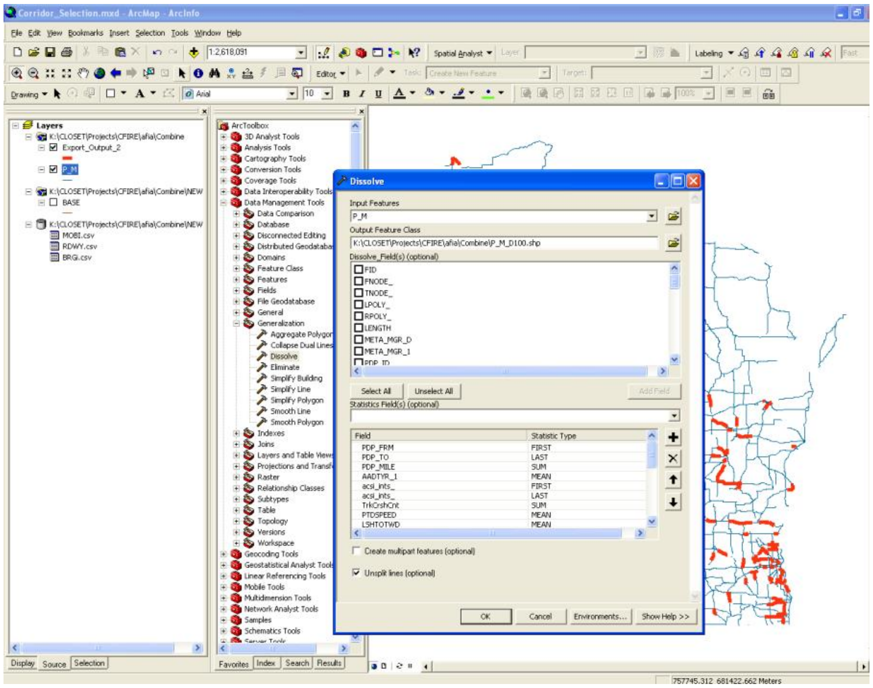
$$\text{Bin100} = \frac{\text{ADTT}}{100}$$

Before fixing the bin size, the following sensitivity analysis has been done to see how the bin size affects the total number of resulting Meta-Manager (MM) Segments.

Table 4-2: Sensitivity analysis of Bin size on the resulting MM segments

Formula	Resulting line segments after dissolution
AADTT/10	5,401
ADTT/20	5,243
ADTT/30	5,101
TADTT/40	4,964
ADTT/50	4,831
…	…
ADTT/100	4265

To maximize the effects of each variable in the statistical modeling of truck crashes, few variables (DIVUND, Number of lanes, Horizontal curvature) went through further transformation. For example, variable DIVUND was converted into two new variables: Divided portion of roadway and undivided portion of roadway. Two new columns have been added in the data set in order to accommodate the transformation. With the help of the Query tool, firstly divided portion of the segments were selected and corresponding segment length were put in one of the newly added columns and vice versa. The same procedure has been done for the other two; horizontal curvature and number of lanes. Recognizing the challenge of short (less than 1 mile) or very short segments (less than 0.1 mile) in the dataset, it was necessary to collapse short segments into longer ones so that it can be treated as a corridor. This was done by using a collapsing criterion to dissolve adjacent roadway segments with similar or same annual average daily truck traffic (ADTT). Dissolving the adjacent segments with similar or same ADTT based on bin100 essentially means a segment containing 700 to 799 trucks will have the same bin size 7. After the sensitivity analysis showed in Table 4-2, corridor length, it was determined to collapse the adjacent segments having ADTT differences within the range of 100 trucks per day in order to achieve a reasonable length. To accomplish this, the following process was involved:



Dissolve

Input Features: P_M

Output Feature Class: K:\CLOSET\Projects\CFIRE\afia\Combine\P_M_D100.shp

Dissolve_Field(s) (optional):
☐ FID
☐ FNODE_
☐ TNODE_
☐ LPOLY_
☐ RPOLY_
☐ LENGTH
☐ META_MGR_D
☐ META_MGR_1
☐ PDP_ID

Field	Statistic Type
PDP_FRM	FIRST
PDP_TO	LAST
PDP_MILE	SUM
AADTYR_1	MEAN
acsi_ints_	FIRST
acsi_ints_	LAST
TrkCrshCnt	SUM
PTDSPEED	MEAN
LSHTOTWD	MEAN

☐ Create multipart features (optional)

☑ Unsplit lines (optional)

Figure 4-2: Screen shot of dissolve procedure in ArcGIS

In the segment dissolve process each variable went through some transformation. Dissolving adjacent segments may cause loss of information contained in different segments because each segment may be different from each other. To preserve the information as much as possible and to reflect the scale of data heterogeneity after dissolving, for some variables mean (MEAN) and standard deviation (STD) were considered while sum (SUM) or count (NO) option was considered for others.

Table 4-3: Transformed Variable in the dissolving process

SUM	MEAN	STD	NO
SUM_PDP_MILE SUM_TrkCrsh SUM_DIVUND_U SUM_DIVUND_D SUM_HCL_G SUM_HCL_F SUM_HCL_P SUM_NL_2 SUM_NL_3 SUM_NL_4 SUM_HCG_G SUM_HCG_F SUM_HCG_P SUM_BRLNWD	MEAN_AADT MEAN_ADTT MEAN_PTDSPEED MEAN_LNWD MEAN_LSHTOTWD MEAN_RSHTOTWD MEAN_BRLNWD MEAN_PSI MEAN_PCI MEAN_IRI	STD_AADT STD_ ADTT STD_PTDSPEED STD_LNWD STD_LSHTOTTWD STD_RSHTOTTWD STD_PSI STD_PCI STD_IRI	NO_BR

The above mentioned dissolving process created 4265 longer segments for further research and the sample data table is as follows:

Table 4-4: Data format after the dissolve procedure

FIRST_PDP_ From	LAST_PDP_To	SUM_PDP _Mile	MEAN_ AADT	SUM_Trk Crashes	MEAN _ADTT	ST_NAME (IH)*
054E056 013	054E058M033	1.03	12720	11	1004	I-94
010E233M000	010E231K000	3.37	21020	54	1008	WIS 39
026N048 100	026N043M082	5.02	12780	29	1009	I-94
032N051G010	032N051G010	1.18	14605	4	1022	I-43
054E245 000	054E244K046	1.17	14537	29	1016	I-43

***** Here ST_NAME (IH) means the nearby Interstate highway of a MM segment.

4.3 Corridor Identification

After the dissolving process, three more criteria were applied on the resulting 4265 MM segments. They are as follows:

a) "SUM of Road miles" >=1 mile
b) "MEAN_ADTT" for each road segments >= V_T (Threshold ADTT)
c) Within certain distance of an interstate highway (IH) or freeway

Table 4-5 shows the sensitivity analysis that had been done against

"MEAN_ADTT" and distance from interstate highway (IH) or freeway on the resulting MM segments. The results are as follows:

Table 4-5: Bin=100, Mean ADTT >= VT and Length>=1 mile

ADTT (V_T)	Resulting segments	Max(mi)	Mean(mi)	Stdv(mi)	Sum(mi)
1000	161	5.02	1.59	.71	256
800	385	16.94	4.88	3.42	835
600	736	24.89	2.96	2.6	2180
400	1017	24.89	2.9	2.45	3001

Table 4-6: Road segments within 2 mile and 5 miles of IH and Freeway

ADTT	Search radius	Resulting segments	Max(mi)	Mean(mi)	Stdv(mi)	Sum(mi)
1000	2 mile	96	5.02	1.56	0.75	150.34
	5 mile	136	5.02	1.57	0.72	213.6
800	2 mile	156	10.5	1.85	1.25	290
	5 mile	252	16.94	4.88	3.88	488.77
600	2 mile	216	24.89	2.23	2.23	482.67
	5 mile	345	24.89	2.28	2	789.21
400	2 mile	284	24.89	2.40	2.23	683.83
	5 mile	456	24.89	2.40	2	1096.52

Based on the sensitivity analysis presented in table 4-5 and table 4-6, threshold for the three criteria were determined to identify the beginning and end of the study corridors: 1) threshold of the corridor length is no less than one mile, 2) threshold value of truck annual average daily traffic 800 or more, and 3) study segment must be within five miles of an Interstate highway or a freeway.

Still candidate corridors (blue color) were separated by short segments with lower truck ADT (called gaps). Following figures are the examples of this problem

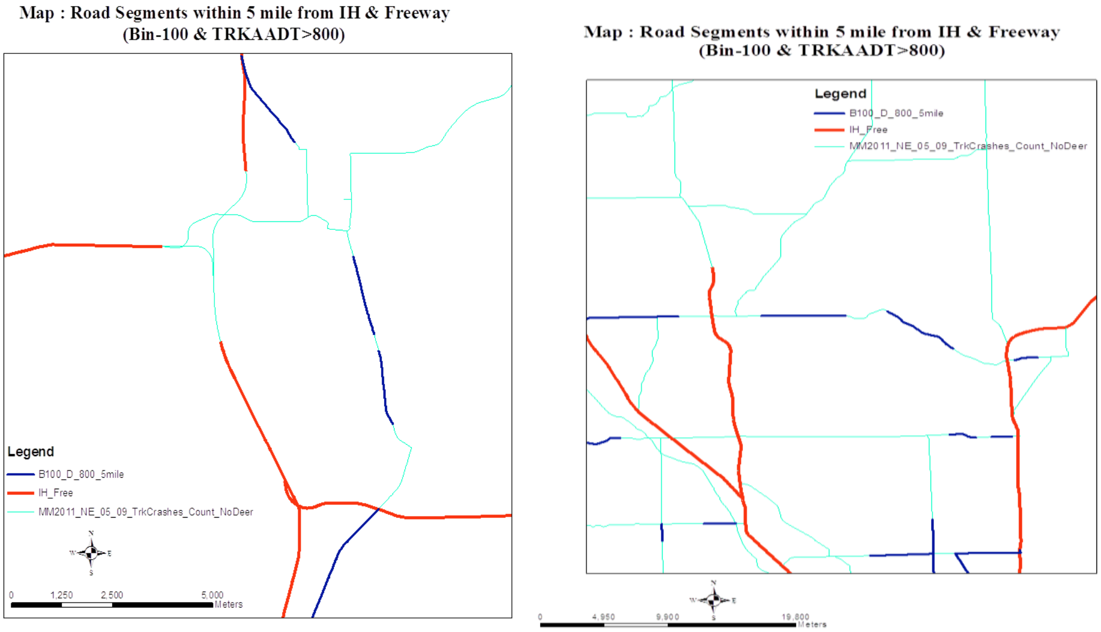


Figure 4-3: Screen shot of gaps within the Corridor

The gap within a corridor may create some confusion among the other researchers as the corridors lose the continuity. To avoid this problem the researchers decided to include the gap in the corridors. There were 720 Meta segments in total. Later on the dbf file was summarized in Microsoft Access to generate 100 corridors.

The number of signalized intersection and un-signalized intersection were counted from STN. Signal density and Access point density were calculated as follows

$$\text{Signal density} = \frac{\text{number of signalized intersection}}{\text{length of the corridor}}$$

$$\text{Access point density} = \frac{\text{number of un-signalized intersection}}{\text{length of the corridor}}$$

Selected corridors are not evenly distributed throughout the state due to the uneven distribution of truck traffic volume and Interstate Highways. The south-east region contains 41 corridors and more than 51% of crashes. The second highest crashes (19.56%) occurred in

North-east region which contains 20 corridors. South-west region also has 20 corridors. Figure 4-4 and 4-5 provide a clear notion of the location of the selected corridors.

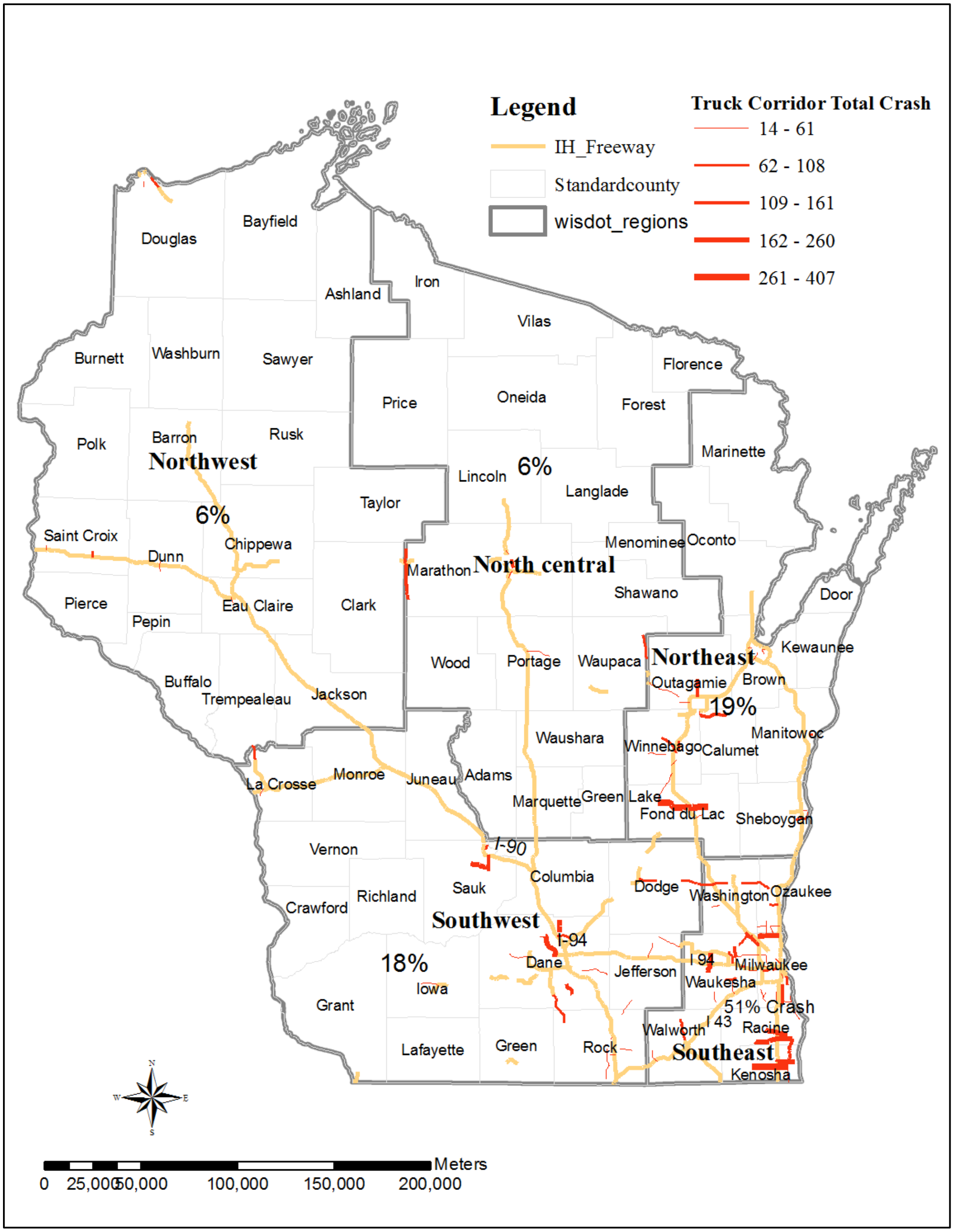


Figure 4-4: Truck Preferred arterial corridors in Wisconsin

Milwaukee County has the highest number of recorded crashes. During this five year period there were 17.28 % (1416 crashes) crashes that occurred in Milwaukee County and it contains 18 corridors. The second highest number of crashes took place in Waukesha County which contains 12.37% of crashes.

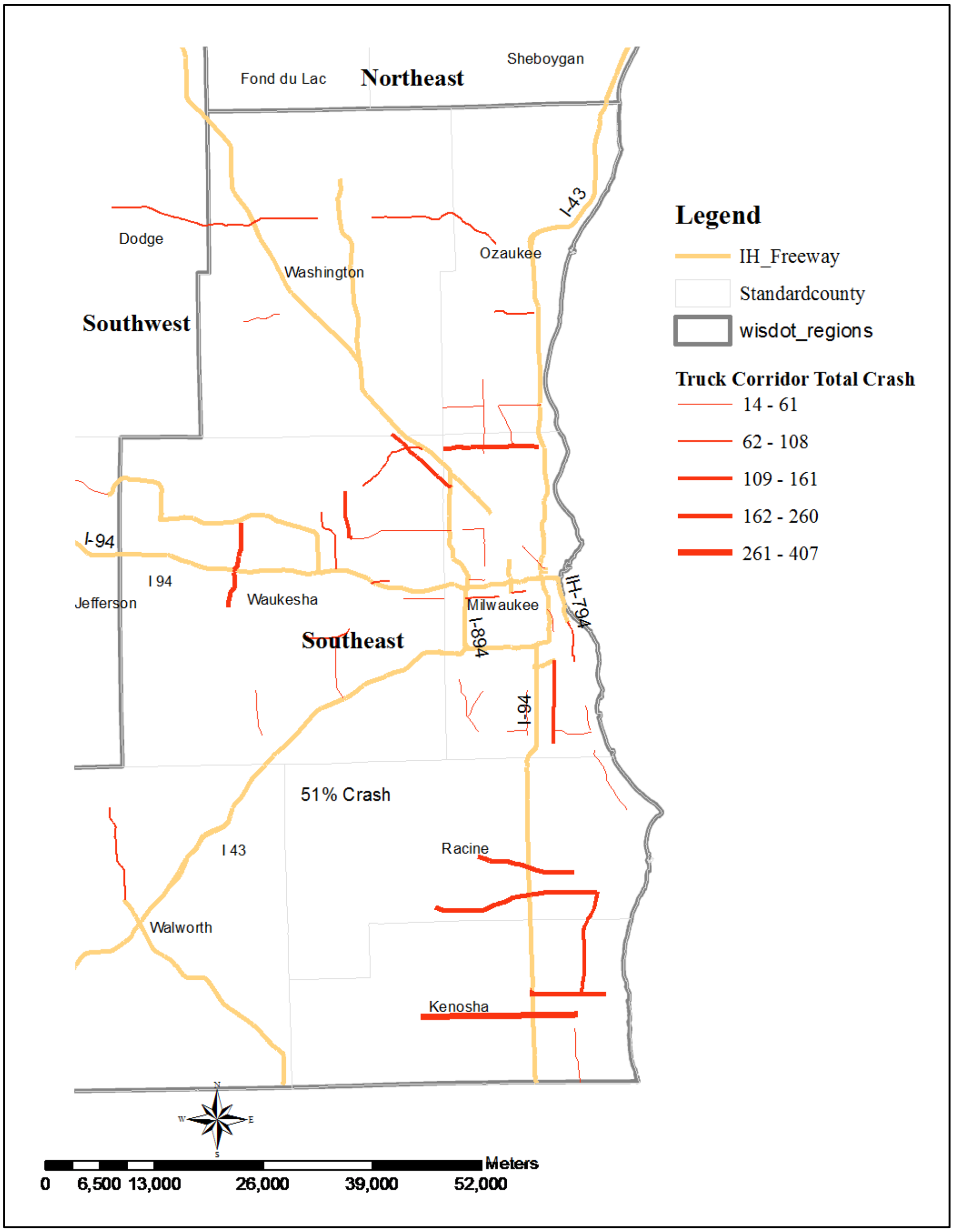


Figure 4-5: Truck Corridors in South-east Region of Wisconsin

4.4 Description of the Corridor Level Variable

The descriptive statistics for key variables used in the crash frequency and severity models can be seen in Table 4-7.

Table 4-7: Summary Statistics of Crash, Geometric and Traffic Variables for 100 Corridors

Variable	Description	Mean	STDV	Min	Max
Crash count	5 Year crash count for each corridor	82	71	14	407
	Property Damage Only (O)	54	49	9	276
	Possible Injury (C)	17	16	0	84
	Non Incapacitating Injury (B)	8	7	0	41
	Incapacitating Injury (A)	3	3	0	11
	Fatal (K)	1	2	0	6
L	Length of the corridor (miles)	4.88	3.42	1.03	16.94
AADT	Annual average daily traffic	16256	6107	8172	39435
ADTT	Annual average daily truck traffic	1077	211	800	1892
TRKPT	Truck percentage (%)	7.1	1.4	4.8	10.2
N_br	Number of bridges	1.01	1.38	0	8
Sigden	Signal density (signals/mile)	0.51	0.87	0	4.33
Accden	Access point density (access points/mile)	5.29	4.81	0	30.47
SPD	Posted speed limited in mph	45	9	30	60
Lnwd	Lane width in feet	12.3	0.8	10	18
Mednwd	Median width in feet	14	12.9	0	47.3
Lshwd	Left shoulder width in feet	3.8	3.4	0	10.9
Rshwd	Right shoulder width in feet	5.6	4.2	0	15
Divund_U	Portion of undivided segments within a corridor	0.48	0.4	0	1
Divund_D	Portion of divided segments within a corridor	0.52	0.4	0	1
NL_1	Portion of segment with one lane	0.01	0.06	0	0.47
NL_2	Portion of segment with two lane	0.81	0.3	0	1
NL_3	Portion of segment with three lane	0.06	0.2	0	1
NL_4	Portion of segment with four lane	0.12	0.25	0	1
Hcl_g	Portion of segment with Horizontal curve speed less than 40mph_Good	0.95	0.19	0	1
Hcl_f	Portion of segment with Horizontal curve speed less than 40mph _Fair	0.03	0.17	0	1
Hcl_p	Portion of segment with Horizontal curve speed less than 40mph _Poor	0.01	0.07	0	0.43

Hcg_g	Portion of segment with Horizontal curve speed greater than 40mph_Good	0.89	0.29	0	1
Hcg_f	Portion of segment with Horizontal curve speed greater than 40mph _Fair	0.09	0.26	0	1
Hcg_p	Portion of segment with Horizontal curve speed greater than 40mph _Poor	0.02	0.09	0	0.59
PSI	Pavement Serviceability Index(0-5)	3.05	0.92	0.88	4.75
STD(PSI)	Standard deviation of PSI	0.58	0.42	0	1.98
IRI	International Roughness Index in mm	0.08	0.08	0	0.427
PCI	Pavement Condition Index (0-100)	77.09	24.35	0	100

Corridor-level variables were created for each of the 100 corridors. As shown in Table 1, the total annual crash frequency had a mean of 82 and a standard deviation of 71, with a maximum of 407 crashes. The percentage of observations with more than 50 crashes within a corridor was found to be over 50%. Corridor lengths vary from relatively short (1.03 mi) to very long (16.94 mi) with an average segment length of 4.88 mi. The mean corridor AADT was 16,256 with a standard deviation of 6,107. Signal density and access point density were calculated by the ratio of the number of signalized intersections to corridor lengths and the number of un-signalized intersections to corridor lengths. The maximum access point density of 30.47 exists in a 2.56 mile corridor where a total of 78 access points were counted, including 60 residential and commercial driveways and 18 other types of access points. The maximum speed of 60 mph is because that corridor contains a portion of a principal arterial with the 65 mph posted speed limit. Similarly, the maximum average lane width of 18 feet is caused by a portion of a principal arterial corridor having very wide lane width, i.e., 22 feet. In addition, the proportion of corridor by the number of lanes, median presence and speed limits were calculated respectively. In particular, the corridor data was analyzed carefully for the good, fair, poor pavement condition of roadways with less than or greater than 40 mph horizontal curvature speed.

4.5 Description of the Access Related Variables

Most of the access related variables are not readily available in any GIS or table format. The reliable source for collecting this is aerial photographs but measurements must be taken manually. Considerable effort has been made to collect access related variables such as median opening width, length of left turn bay, length of two way left turn lane, driveway width and driveway width with flare. These variables were measured from Google Earth and Google Maps images and then the mean and standard deviation were calculated. Median opening width, left turn bay length, minimum distance to a signalized intersection and intersection functional area distances have been illustrated in Figure 4-7. The corridor start and end point were carefully identified by matching the attributes of these corridors in the GIS shapefile. Signal, median opening and driveway density were calculated by the count to corridor lengths.

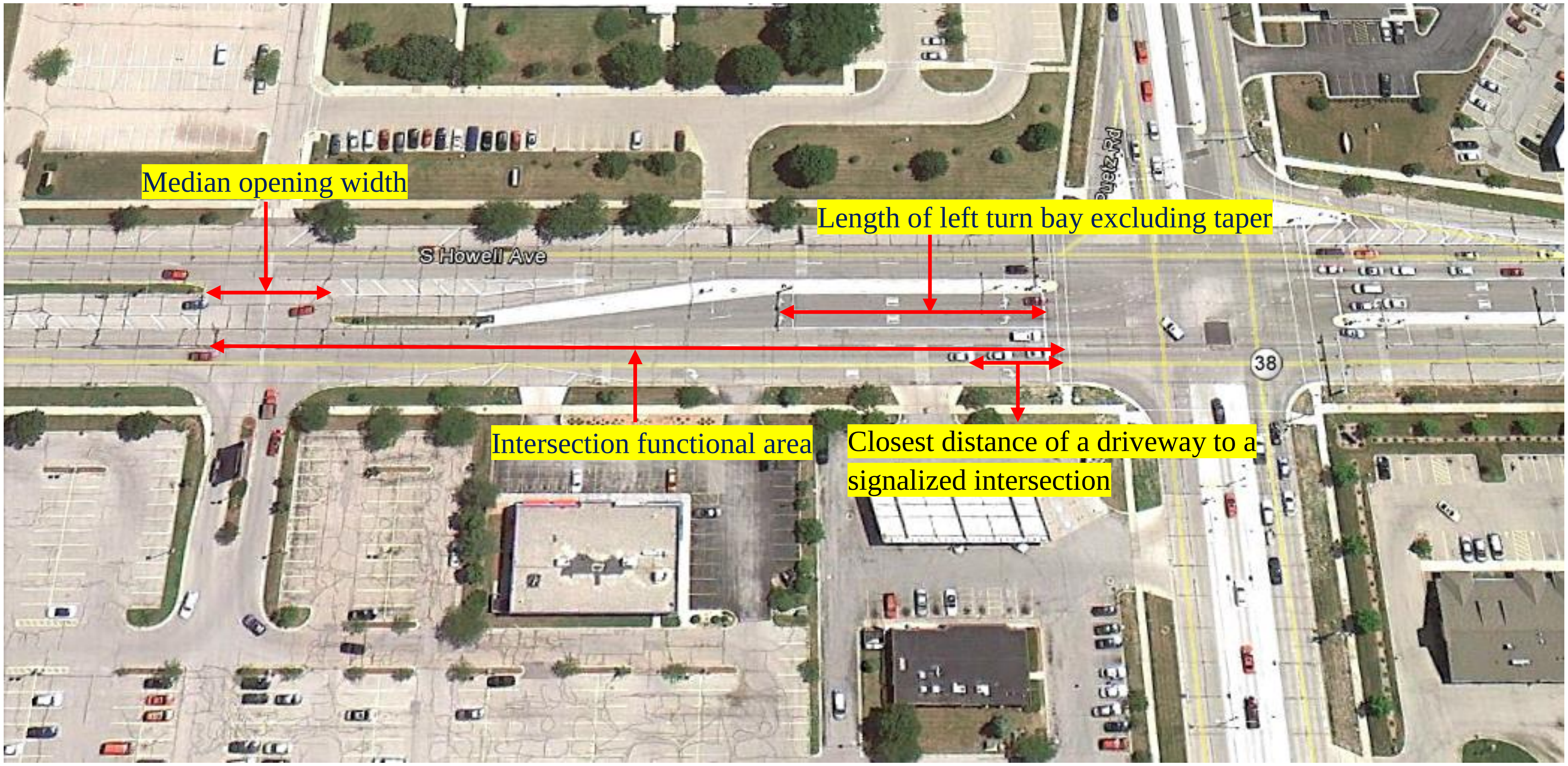
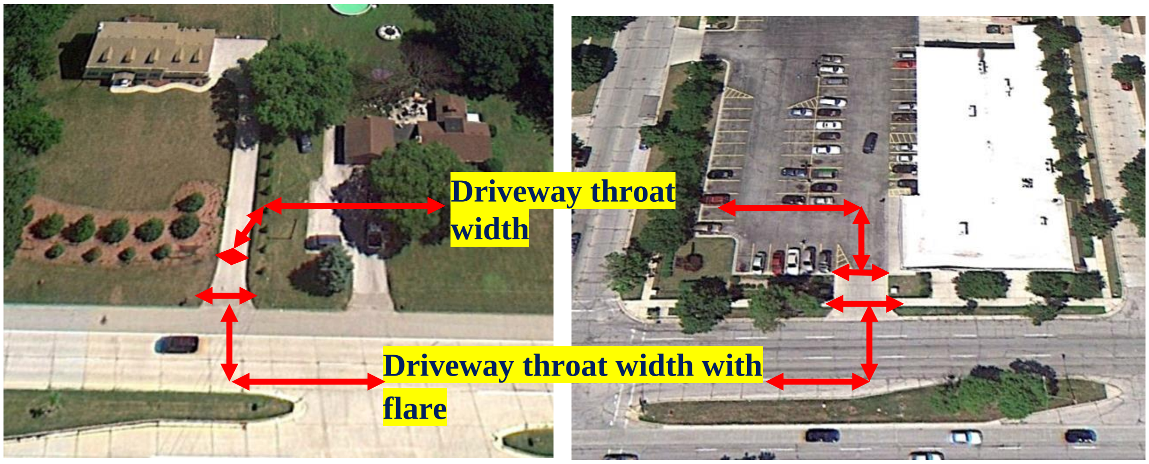


Figure 4-6: Different Access Related Components

The driveways were categorized under two types: residential and commercial (commercial driveway includes commercial, industrial, institutional etc.) by using photographs available in the “Street View” feature in Google Maps and the number of visible parking spots to distinguish the type of driveway. Primarily, driveway turn radius, driveway throat width, driveway throat length, driveway slope, existence of dedicated turn lanes, and length of sight distance (especially for drivers exiting driveways) were considered as the key driveway design factors. Later on, data collection was limited to three aspects due to time limitation and technical difficulties e.g. driveway slope. Figure 4-8 shows the measurement that has been taken for the throat width and throat width with flare.

The maximum driveway density 54.7 exists in a 1.17 mile long corridor where a total of 64 driveways were counted, including 30 commercial and 34 residential. Many researchers recommend 20 to 30 driveways per mile as a maximum driveway density standard above which, accident rates may become unacceptably high (6). This standard applies to commercial driveways on urban, multilane arterials with a posted speed limit of 35 miles per hour (6). In our data, 17 corridors with an average of 45 mph posted limit have more than 30 driveways per mile. High speed limits suggest lower driveway density if the roadway is primarily functioning toward through traffic, i.e. higher mobility demands are more important than the need for accessibility. Hence, some trucks preferred arterial corridors but may have safety compromises. Furthermore, the number of divided commercial driveways was counted and presented as a proportion of total commercial driveways.



(a) Residential (b) Commercial

Figure 4-7: Driveway configurations

The functional area of an intersection is that area beyond the physical junction of two roadways that comprises decision and maneuvering distance, plus any required vehicle storage length. Limiting or, where possible, eliminating driveways within the functional area of an intersection (upstream and downstream) helps reduce crashes while traveling through an intersection and reduce possible driver errors as well. In the vicinity of an intersection, corner properties typically attract businesses that generate higher volumes of traffic; such as convenience stores, gas stations and fast food restaurants. Vehicles stopped in the travel lanes waiting to turn into a corner property may, and often, block traffic on the roadway. It is important that the influence of any driveway access should be minimized at the functional area of an intersection because driveway traffic may result in higher crash rates and increased congestion. According to the definition of Manual of Uniform Traffic Control Devices (Federal Highway administration, 2009), the crashes that occur within 15 m to 152 m(50-500 feet) radius from the center point of an intersection are classified as intersection related crashes (49). In order to assess the safety impact of a driveway within the intersection functional area, two variables were collected: minimum distance of a driveway to a signalized intersection and the total number of residential and commercial driveways that are located within 500 feet of a signalized intersection. Figure 4-9 illustrates the number of driveways that are located within the intersection functional area.

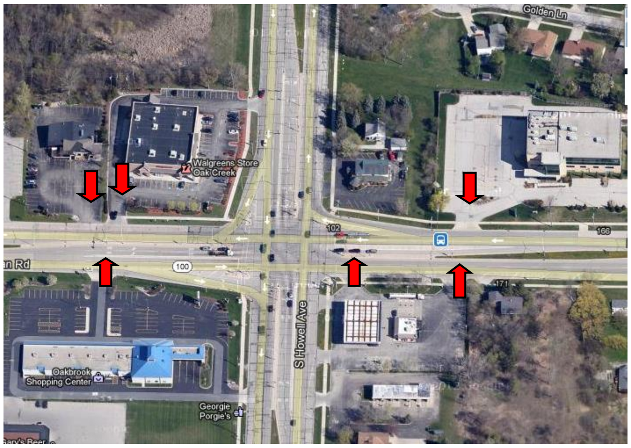


Figure 4-8: Functional area of an intersection

In general there are three median types, raised median, painted median and two way left turn lane (TWLTL), commonly used in practice. Continuous TWLTLs are a common access management treatment when combined with driveway consolidation and corner clearance. TWLTLs provide a separate lane for vehicles turning in to property access. In our study, only 23 out of 74 corridors have this kind of median treatment. Raised medians with left-turn lanes at intersections offer a cost-effective means for reducing accidents and improving operations at higher volume intersections. Continuous raised medians with well-designed median openings are among the most important features for managing access to create a safe and efficient highway system. Median openings should generally only be provided at public road intersections or at driveways shared by several businesses. They should generally not be provided for access to individual businesses or residences. The number of median openings should be kept to a minimum since they add conflict points and detract safety. In this study, data for median opening width and the number of median openings for a roadway segment with raised medians were collected. Summary statistics show that the average median opening is 1801 feet which is much higher than the standards of 660 feet for urban and 1320 feet for rural areas (50). The number of corridors changed from 100 to 74 because only the corridors with signalized intersections were considered in this stage.

Table 4-8: Summary Statistics of Crash, Traffic and Access Related Variables

Variable_Name	Description	Avg	Stdv	Min	Max
Crash count	5 year crash count for each corridor	93	79	14	407
L	Length of the corridor	4.80	3.40	1.03	16.90
AADT	Annual average daily traffic	16256	6107	8172	39435
ADTT	Annual average daily truck traffic	1077	211	800	1892
W_Med_Op	Average width of median opening within a corridor (ft)	71.20	14.40	36	97.10
Stdv_W_Med_Op	Standard deviation of median opening width (ft)	18.90	8.80	0	44.30
Med_den	Median opening density	4.40	3.50	0	17.60
Min_Dist	Minimum distance of a driveway to a signalized intersection	143.80	270.90	0	1920
TWLTL	Length of Two Way Left Turn Lane(mi)	0.70	0.80	0.06	3.50
L_LT	Average length of left turn bay within a corridor (ft)	178.90	72.90	60.30	451.80
Stdv_L_LT	Standard deviation of length left turn bay length (ft)	68.70	33.70	15.20	197
R_Throat_W	Average width of driveway (ft)	12.80	2.60	8	22
R_Stdv_Throat_W	Standard deviation of driveway width(ft)	3.90	2.30	0.70	15.80
R_Flare_W	Average width of driveway with flare (ft)	25.40	9.30	8	61
R_Stdv_Flare_W	Standard deviation of driveway width with flare (ft)	7.30	6.50	0.78	46.60
C_Throat_W	Average throat width of driveway (ft)	28.30	4.10	19.80	37.10
C_Stdv_Throat_W	Standard deviation of driveway throat width (ft)	9.20	3.10	4.10	17.80
C_Flare_W	Average width of driveway with flare	48.10	15.70	25.20	112.30

C_Stdv_Flare_W	Standard deviation of driveway width with flare	19.8	11	5.1	56.4
Drv_SigInt	Average number of driveways located within .1 mile from Signalized Intersection	17.30	14.30	0	60
C_Div_Drv	Proportion of divided driveway, Commercial	0.30	0.20	0	0.60
Drv_den	Driveway density for a corridor/ mile	17.10	11.50	1.10	54.70
C_Den	Number of Commercial driveway per mile	9.50	7.30	0.90	41.30
R_Den	Residential driveway density / mile	7.50	7.10	0	34.20
Sig_Den	Signal density (signals/mile)	1.50	1.0	0.10	4.80
PSI	Pavement Serviceability Index	2.80	0.80	0.80	4.30
STD(PSI)	Standard deviation of PSI	0.60	0.40	0	1.90
SHWD	Shoulder width	3.13	2.80	0	10

5 EXPLORATORY DATA ANALYSIS

During this (2005-2009) five year period, 8,196 truck related crashes occurred in the 100 selected corridors. They can be single truck, truck-truck and truck-passenger car crashes. Notably more than 50% of the crashes occurred in the South-East region and near the Milwaukee area where most truck activities occur. Among these truck crashes, 66% were property damage only (O); 21% were possible injuries (C); 9.3% were non-incapacitating injuries (B); 3% were incapacitating injuries (A); and 0.7% were fatal injuries (K).

5.1 General Trends

Figure 5.1 shows that there is a decreasing trend of crashes over the five year period with 2009 showing the lowest number of crashes. It can be noted that the total number of crashes decreased by 22.5 percent from 1790 in 2005 to 1388 in 2009. Although there exists downward trend in crashes, there were still more than 1000 truck crashes that occurred each year during this period and that is only on 100 corridors.

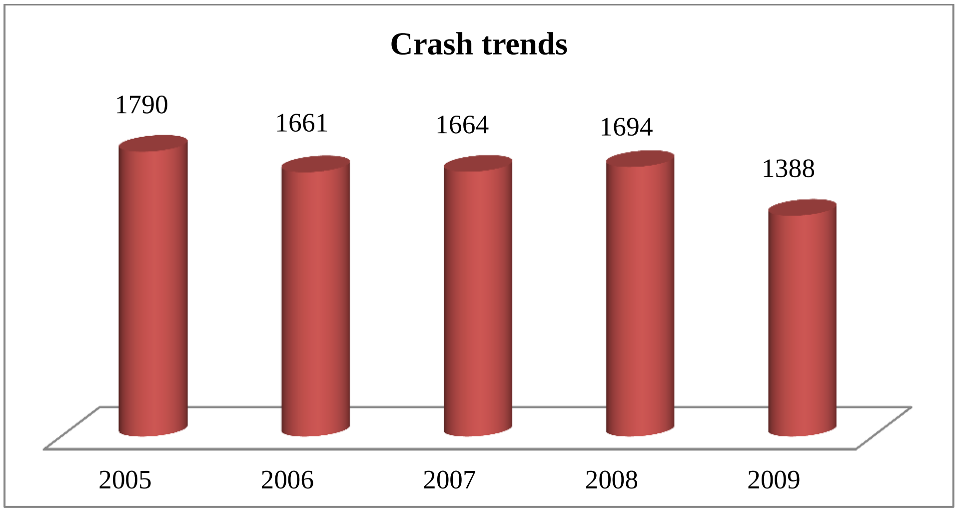


Figure 5-1: Truck crash trends in Wisconsin

The mean of the truck crashes in a corridor is 82 where 74% of corridors have less than 100 crashes. Very few corridors have high crash frequency and high fatality. Figure 5.2 and 5.3 depict the truck crash and fatality distribution by corridor. Sixty four% of corridors do not have any fatal crashes.

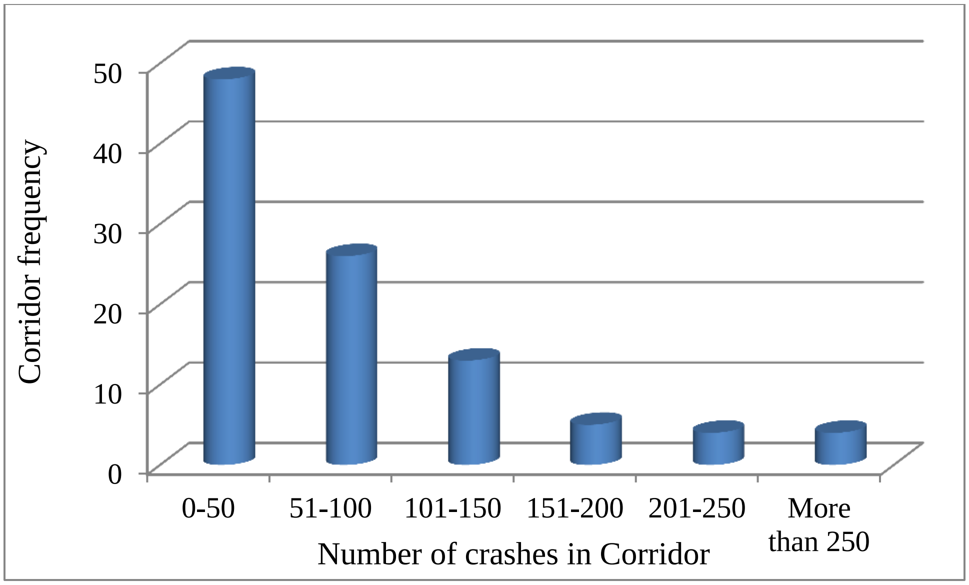


Figure 5-2**:** Truck crash frequency distribution

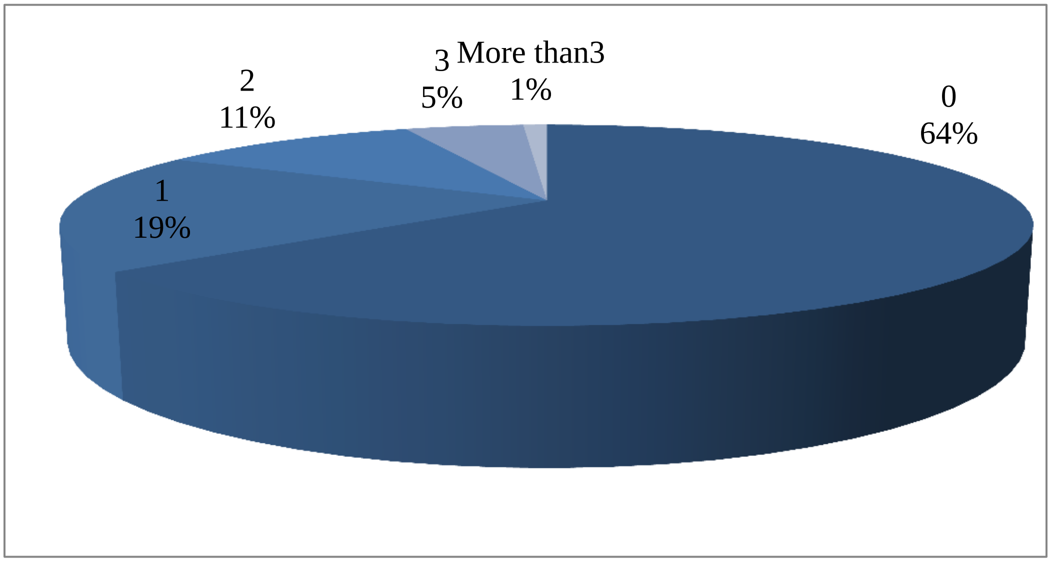


Figure 5-3: Truck crash fatality distribution by corridors

5.2 Crash rate & Crashes per mile

The crash rate for the corridor crashes is calculated as:

$$R = \frac{C*1000000}{V*N*L} \qquad 5\text{-}1$$

The variables in this equation are:

- R = Corridor crash rate expressed as crashes per million vehicle miles of travel
- C = Total number of corridor crashes in the study period
- V = ADTT

- N = Number of years of data
- L = Length of the corridor in miles

A "crashes per mile" or crash density (CD) for corridor crashes is calculated as:

$$CD = \frac{C}{N * L} \qquad 5\text{-}2$$

Where:

- CD = Crashes per mile for the road segment expressed as crashes per each 1 mile of roadway per year.
- C = Total number of crashes in the study period.
- N = Number of years of data.
- L = Length of the roadway segment in miles.

By using the above mentioned formulas, crash rate and crash density for the 100 corridors were calculated. The crash rate had a mean of 10.3 and a standard deviation of 7.7, with a maximum of 48.1 and minimum of 1.7. Crashes per mile for the selected 100 corridors had a mean of 4.2, a standard deviation of 3.5, with a maximum of 20.5 and minimum of 0.5.

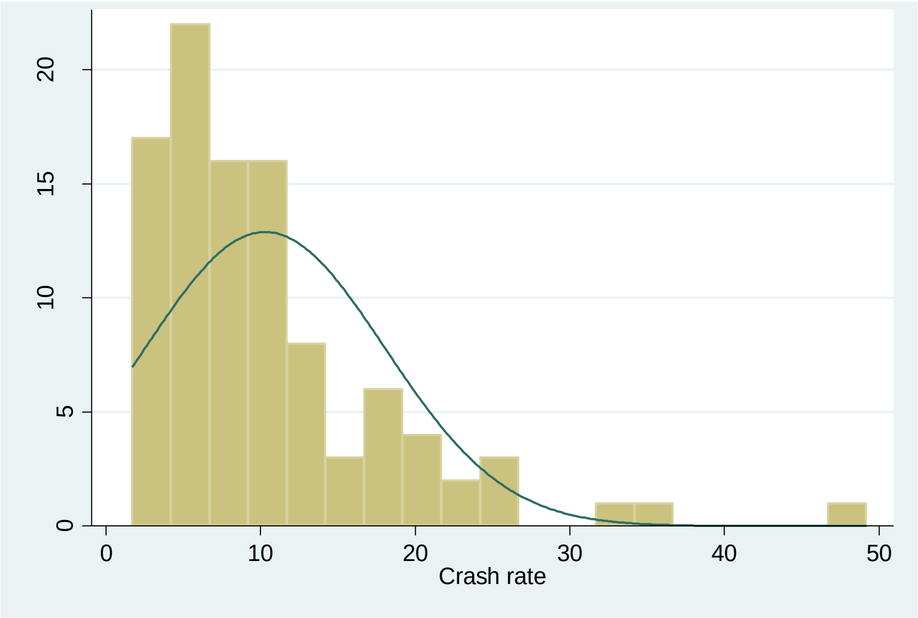


Figure 5-4: Distribution of crash rate for 100 corridors

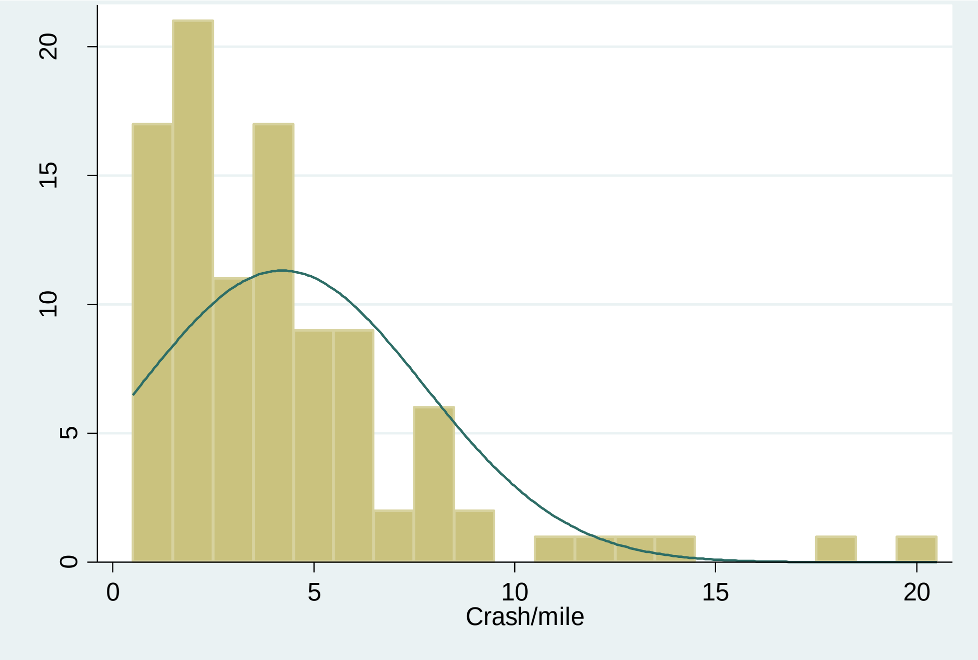


Figure 5-5: Distribution of crashes per mile for 100 corridors

Both single and multiple vehicle crashes were studied, where 88% of the crashes were multi-vehicle crashes. Two vehicle property damage (PDO) crashes are prominent (more than 50%).

Table 5-1: Crashes by number of vehicle and severity

No of vehicles	Injury severity										
	K		B		C		A		PDO		Total
	I	N	I	N	I	N	I	N	I	N	
1	0.0%	.1%	0.5%	0.7%	0.4%	0.7%	0.1%	0.2%	4.1%	5.0%	11.7%
2	0.3%	.3%	4.1%	2.0%	10.2%	5.1%	1.3%	0.7%	**32.9%**	**18.8%**	**75.7%**
3	0.1%	0.0%	1%	.5%	2.2%	1.4%	0.3%	0.2%	2.8%	2.1%	10.6%
>3	0%	0.0%	.2%	.3%	0.3%	0.4%	0.0%	0.1%	0.4%	0.3%	1.9%
Total	0.4%	0.4%	5.8%	3.5%	13.1%	7.5%	1.7%	1.2%	40.2%	26.2%	100. %

5.3 Severity distribution by crash location

As mentioned earlier, half of the crashes took place in the South East region where Milwaukee, Waukesha, Walworth, Washington, Kenosa, Ozaukee and Racine counties are located. Table 5-2 portraits a clear overview of the crash location by region.

Table 5-2: Crashes by region and severity

Regions	Injury severity					
	K	B	C	A	PDO	Total
NC	0.00%	0.50%	1.30%	0.20%	4.10%	6.10%
NE	**0.10%**	**1.90%**	**4.20%**	**0.50%**	**12.80%**	**19.60%**
NW	0.10%	0.60%	1.00%	0.20%	3.90%	5.70%
SE	**0.30%**	**4.10%**	**10.50%**	**1.40%**	**34.70%**	**50.90%**
SW	0.20%	2.30%	3.60%	0.70%	10.80%	17.70%
Total	0.70%	9.30%	20.60%	3.00%	66.40%	100.00%

The arterial corridors are divided into four categories of highway. Although, traffic volumes are denser in the city areas thereby chances of collision are higher in City Streets but the state highways contain 84% of all crashes. Fatal crashes mostly occurred on Rural State Highways.

Table 5-3: Crashes by highway class and severity

Highway Class	Injury severity					
	K	B	C	A	PDO	Total
County Trunk Rural	0.0%	0.1%	0.5%	0.0%	1.8%	2.4%
State Highway Rural	**0.5%**	4.4%	6.9%	1.6%	23.2%	**36.6%**
City Street Urban	0.0%	0.6%	2.2%	0.1%	9.5%	12.5%
State Highway Urban	0.2%	4.2%	11.0%	1.2%	31.9%	**48.5%**

Raised medians facilitate the movement of through traffic along a roadway. It is placed on major arterials in order to reduce the number of conflicting vehicle maneuvers at driveways. Table 5-4 shows that divided highways with traffic barriers have a lower percentage of crashes for all the injury severity levels.

Table 5-4: Crashes by motor vehicle operation area and severity

Motor vehicle Operation area		Injury severity				
	K	A	B	C	PDO	Total
Blank	0.0%	0.0%	0.0%	0.1%	0.2%	0.3%
Divided highway with traffic barrier	**0.0%**	**0.2%**	**0.6%**	**1.5%**	**5.1%**	**7.3%**
Divided highway without traffic barrier	0.2%	1.1%	3.4%	9.2%	28.7%	**42.7%**
Not physically divided	0.5%	1.6%	5.2%	9.5%	31.2%	**48.1%**
Other	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%
One-way Traffic	0.0%	0.0%	0.1%	0.3%	1.2%	1.6%
Grand Total	0.7%	3.0%	9.3%	20.6%	66.4%	100.0%

5.4 Crashes by Corridor Perspective

74.4 percent (4277.28 miles out of 5746.73 miles) of the highways consist of two lanes. Table 5-5 shows the fact that three fourths of the crashes took place on two lane corridors regardless of the injury severity level.

Table 5-5: Crashes by number of lanes and severity

Number of Lanes	Injury severity					
	A	B	C	K	PDO	Total
2	**2.3%**	**7.3%**	**14.9%**	**0.6%**	**49.6%**	**74.7%**
3	0.3%	0.8%	2.5%	0.1%	7.3%	11.0%
4	0.3%	1.2%	3.2%	0.1%	9.5%	14.3%
Total	3.0%	9.3%	20.6%	0.7%	66.4%	100.0%

Of all the accidents in these 100 corridors in Wisconsin, about 61% of the total, and 44% of the fatal accidents, occurred at intersections. For intersections, an in-depth and comprehensive analysis is needed based on signalized intersection density and spacing, access point density, type, design, median opening type and design, intersection turning lanes and traffic signal timing and coordination.

Table 5-6: Crashes by accident location and severity

Accident Location	Injury severity					
	K	B	C	A	PDO	Total
Intersection	0.35%	5.8%	13.1%	1.7%	40.2%	61.2%
Segment	0.35%	3.5%	7.5%	1.3%	26.2%	38.8%
Total	0.70%	9.3%	20.6%	3.0%	66.4%	100%

Speed differentials at an intersection have significant impact on crash occurrence process. Table 5-7 demonstrates the scenario of the speed differences in intersections wherein most of the cases speed limits for the approaching vehicles are the same.

Table 5-7: Crashes by speed limit at intersection

Speed limit 1(mph)	Speed limit 2 (mph)						
	<30	30-35	40-45	50-55	>55	Blank	Total
>30	**9.6%**	2.5%	0.8%	0.3%	0.1%	1.6%	15.0%
30-35	2.2%	**31.5%**	0.9%	0.5%	0.2%	2.8%	38.2%
40-45	1.1%	1.5%	**24.2%**	0.6%	0.1%	2.3%	29.9%
50-55	0.1%	0.3%	0.8%	**12.1%**	0.2%	0.9%	14.4%
< 55	0.1%	0.2%	0.2%	0.3%	**1.5%**	0.2%	2.5%
Total	13.1%	36.0%	27.1%	13.8%	2.3%	7.7%	100.0%

5.5 Crashes by Manner of Collision

Manner of collision is a very important aspect from which the root causes of a crash may be identified. Here, manner of collision is investigated with respect to accident location, number of vehicles involved in a crash situation, type of traffic control at the time of crash and number of lanes of a highway where the crash took place. Common factors that contribute to rear-end collisions include drivers’ inattention or distraction, tailgating, panic stops and reduced in traction due to weather or worn pavement.

Table 5-8: Crashes by Manner of Collision type and severity

Manner of Collision	Injury severity					
	K	B	C	A	PDO	Grand Total
Angle	**0.3%**	**3.8%**	**6.3%**	**1.3%**	**16.3%**	**28.2%**
Blank	0.0%	0.0%	0.2%	0.0%	0.5%	0.7%
Head	0.2%	0.5%	0.4%	0.2%	0.7%	2.0%
No Collision	0.1%	1.3%	1.2%	0.3%	11.2%	14.2%
Rear	**0.1%**	**2.9%**	**10.7%**	**0.7%**	**25.8%**	**40.1%**
Sideswipe (Opposite direction)	0.0%	0.4%	0.6%	0.2%	1.6%	2.8%
Sideswipe (same direction)	0.0%	0.3%	1.2%	0.2%	10.3%	12.0%

Angular and rear end are the most common type of manner of collision for which crashes occurred in these 100 sample corridors. Multi-vehicle rear-end accidents constitute a substantial portion of the accidents occurring at signalized intersections.

Table 5-9: Crashes by manner of collision and total vehicle involved in accident

Manner of collision	Total vehicles involved in accident				
	1	2	3	> 3	Total
Angle	**0.0%**	**25.5%**	**2.3%**	**0.3%**	**28.1%**
Blank	0.0%	0.6%	0.0%	0.0%	0.7%
Head	0.0%	1.6%	0.4%	0.0%	2.0%
No Collision	11.5%	2.1%	0.5%	0.1%	14.2%
Rear	**0.0%**	**32.5%**	**6.3%**	**1.3%**	**40.1%**
Sideswipe (opposite direction)	0.0%	2.3%	0.4%	0.1%	2.8%
Sideswipe (same direction)	0.0%	11.2%	0.7%	0.1%	12.0%
Total	11.7%	75.7%	10.6%	1.9%	100.0%

22.4% of the total crashes are intersection related angular crash involving left turning and opposing through vehicles. A properly timed, protected left-turn phase can also help reduce rear-end and sideswipe crashes between left-turning vehicles and the through vehicles behind them.

Table 5-10: Crashes by manner of collision and accident location

Manner of collision	Accident location		
	I	N	Grand Total
Angle	**22.4%**	**5.7%**	**28.1%**
Blank	0.5%	0.2%	0.7%
Head	1.1%	1.0%	2.0%
No Collision	5.7%	8.5%	14.2%
Rear	**24.3%**	**15.8%**	**40.1%**
Sideswipe (opposite direction)	1.3%	1.5%	2.8%
Sideswipe (same direction)	5.8%	6.1%	12.0%
Grand Total	61.2%	38.8%	100.0%

5.6 Crashes by Traffic Control

The timing of traffic signal clearance intervals (yellow and red phases) can affect accident occurrence at signalized intersections. When the clearance interval is not properly timed some drivers may be forced to choose between abruptly stopping or accelerating in order to cross the intersection. Rear-end accidents are the most common accident type at signalized intersections since the diversity of actions taken increases due to signal change. A proper space cushion is needed to provide a driver enough reaction time to recognize a hazardous situation and make a stop decision. Rear-end and angle type of accidents account for 40.1% and 28.1% of all truck accidents respectively. Here ‘None’ means an intersection without any type of traffic control.

Table 5-11: Crashes by traffic control at intersection and manner of collision

Manner of collision	Traffic Control					
	Four-way Stop	None	Signal	Two-way Stop	Yield	Total
Angle	1.8%	16.6%	13.6%	4.7%	0.7%	**36.6%**
Head	0.0%	0.8%	0.7%	0.1%	0.1%	1.7%
No Collision	0.6%	4.1%	3.3%	1.2%	0.2%	9.3%
Rear	2.2%	17.5%	14.5%	5.0%	0.6%	**39.8%**
Sideswipe (opposite direction)	0.2%	0.7%	0.9%	0.3%	0.1%	2.2%

Sideswipe (same direction)	0.6%	4.1%	3.6%	1.1%	0.1%	9.5%
Total	5.4%	43.8%	36.5%	12.4%	1.9%	100.0%

Arterial intersection without any type of traffic control has highest crash percentage for all injury severity levels. It is an interesting finding that crashes at the signalized intersections is also high.

Table 5-12: Crash severity by traffic control at the intersection

Traffic Control	K	A	B	C	PDO	Total
Four-way	0.0%	0.2%	0.3%	1.1%	3.8%	5.4%
None	0.2%	1.4%	4.2%	10.1%	27.9%	43.8%
Signal	0.2%	0.9%	3.5%	7.1%	24.8%	36.5%
Two-way	0.1%	0.4%	1.2%	2.7%	8.1%	12.4%
Yield	0.0%	0.1%	0.3%	0.4%	1.2%	1.9%
Total	0.5%	2.9%	9.5%	21.4%	65.7%	100.0%

Truck and passenger car are the most common type of crashes irrespective of the traffic control type. But intersections without any type of traffic control have more crashes than signal-controlled intersections.

Table 5-13: Crashes by type of vehicle and traffic control at the intersection

Vehicle type	Traffic control					
	Four-way	None	Signal	Two-way	Yield	Total
Trk-Car	4.4%	**33.6%**	**28.4%**	9.3%	1.3%	**77.0%**
Trk-Other	0.1%	0.7%	0.5%	0.3%	0.0%	1.6%
Trk-Trk	0.3%	3.8%	3.1%	1.0%	0.1%	8.4%
Truck Only	0.5%	3.5%	2.8%	1.0%	0.2%	8.1%
Grand Total	5.4%	**43.8%**	**36.5%**	12.4%	1.9%	100.0%

Pedestrian and bicycle crashes normally ended up with injury, of which 13 percent were fatal and a quarter of the crashes are incapacitating injury. Around 80% pedestrian and 90%

bicycle crashes occurred in intersection areas, which mean more safety efforts, are needed in these areas.

Table 5-14: Pedestrian and bicycle crashes by severity

Accident Type	K	A	B	C	PDO	Total
Pedestrian	12.5%	25.0%	12.5%	45.8%	4.2%	100.0%
Bicycle	4.0%	4.0%	44.0%	48.0%	0.0%	100.0%

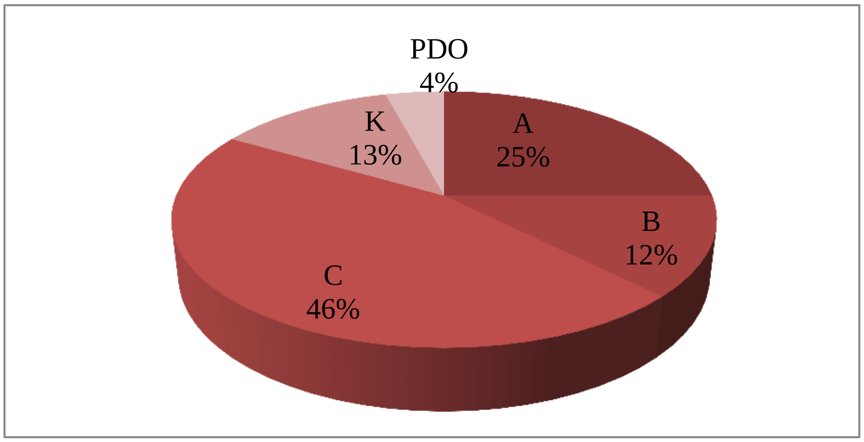


Figure 5-6: Pedestrian Crashes by severity

Arterials are prone to crashes as there are more access points due to connectors and different kinds of driveways such as industrial, commercial, residential, institutional, farm unit driveways, etc. Highlights of the crash data are as follows:

- Truck crashes in Wisconsin's arterial roads have decreased by 22.5%, going down from 1790 to 1388 between 2005 and 2009.
- Crash rate had a mean of 10.3 and a standard deviation of 7.7 with a maximum of 48.1 and minimum of 1.7 per million vehicle miles travel for the 100 corridors.
- 64% of corridors have zero traffic fatalities. High traffic crash frequency (more than 250 crashes) corridors are very few (only 8%).
- Both single and multi-vehicle truck crashes have been studied where two vehicles and intersection related crashes are prominent.
- Angle and rear end crashes are prominent, which drives attention to the proper management of intersection signal timing.

6 ANALYSIS AND DISCUSSION

This section presents the results based on crash count data and injury severity data from the selected arterial corridors that are heavily used by trucks. Truck crash frequency and severity contributing factors have been identified using various structures of a negative binomial model and a multinomial logit (MNL) model/ ordered probit model, respectively. The modeling results are subject to the following:

1) Probability distributional assumption
2) Model specification
3) Data availability

It is anticipated that improved safety data collection and appropriate assumptions for modeling crash count and injury severity improve the prediction accuracy and unravel the complex relationship between crash occurrence and travel conditions.

6.1 Negative Binomial Model Format

When traveling along an arterial corridor, truck drivers must adjust to varying highway and traffic conditions such as the posted speed limit, signal timing, and roadway geometric changes as well as heed the drivers of other motor vehicles to avoid any possible collisions. The expected number of truck crashes can be modeled as the product of traffic exposure and the truck crash rate which may be a function of truck volume, AADT and other factors. There is no fixed formula for measuring traffic exposure; different methods can be applicable depending on how the segment length and traffic volume were specified (15, 51, 52). For example, Miaou (15) used ADTT as an exposure variable and AADT as a surrogate variable to represent traffic conditions while modeling truck crashes. Whereas Venkataraman (51) used AADT and the length of a segment as exposure variables in modeling Interstate crash occurrences. Using vehicle miles traveled (VMT), the product of segment length, AADT and the number of days a year in the unit of million or 100 million, as the traffic exposure measurement is also common. Therefore, a variety of model specifications have been tested before the selection was narrowed down to the three representative ones.

The basic measure of vehicle exposure is the total amount of time that vehicles travel on the road. The other covariates, on the other hand, are intended to reflect the conditions to which these vehicles are exposed during the time of their travel. Different researchers define the exposure measure differently based on the assumptions they made. As shown in Table 6-1, Model 1 uses million VMT as the traffic exposure and truck percentage (TRKPT) as one of the explanatory variables in the crash rate function. Model 2 uses truck miles traveled (TMT) as the traffic exposure, assuming the number of truck crashes are proportional to the truck volume and segment length. AADT is then treated as one of the explanatory variables, representing traffic density. Model 3 uses both ADTT and AADT in the traffic exposure and treats segment length as an offset variable. This model structure emphasizes the interaction between trucks and other motor vehicles when assuming the number of crashes is proportional to the corridor length. Consequently, the statistically significant variables vary across three models due to different model specifications. For brevity, they are represented as $\mathbf{X\beta}$ in the model.

The final model was selected based on both the model statistical goodness-of-fit and the number of meaningful and statistically significant variables. The Akaike information criterion (AIC) is a measure of the statistical goodness-of-fit with the general formula of $AIC= 2k - 2\ln(L)$ where k is the number of parameters in the statistical model and L is the maximized value of the likelihood function for the estimated model. Model 2 is the preferred model with the smaller AIC value.

Table 6-1: NB Model Structures

Model	Equation	AIC value
Model 1	$\mu= (VMT)^{\alpha} EXP (\beta_0+\beta_1 TRKPT+\mathbf{X'\beta})$ where VMT is million VMT	968
Model 2	$\mu= (TMT)^{\alpha} EXP (\beta_0+\beta_1 AADT+\mathbf{X'\beta})$ where TMT is million truck miles traveled	966
Model 3	$\mu=length*ADTT^{\alpha1}AADT^{\alpha2}EXP (\beta_0+ \mathbf{X'\beta})$	982

6.2 NB model results

After the traffic exposure of the crash prediction model has been determined, the standard negative binomial model was run three times with different sets of variables. Firstly, the negative binomial was run using the readily available data from the existing roadway inventory (geometric, traffic and pavement variables). Then, access related variables collected for this study were added. Finally, the insignificant variables were removed and the final predictors for the arterial truck crash frequency were determined.

6.2.1 NB model results without access parameters

Table 6-2 summarizes the parameter estimates, standard deviation, t-statistics and variables that are statistically significant at the 95% confidence limit. Along with the intercept, million truck miles traveled (TMT), AADT, signal density and standard deviation of Pavement Serviceability Index (PSI) are positively associated with the number of truck crashes. The vehicle arrival rate and pattern, signal timing and phasing, and coordination, as well as the intersection capacity directly affect the traffic operations and safety at the intersection and the ones upstream and downstream. A corridor with closely spaced signalized intersections is particularly challenging because of limited storage area between intersections (27). Shoulder width and PSI are negatively associated with the number of truck crashes. PSI (0-5) value was calculated based on slope variance (profile), rut depth, cracking and patching. A PSI value of 5 means the perfect riding condition of a road surface and vice versa. The model results imply that corridor-based safety performance could be improved by better and more uniform pavement conditions, wider shoulder widths, and more consistent signal timing designs (presence of protected phases, longer clearance interval, etc.).

Table 6-2: NB Estimates for Accident Frequency Prediction without Access Parameters

Effect	Estimate	Std. Err.	t- Statistics	p-value
Constant	2.7523	0.255	11	0.0001
TMT	0.8404	0.08	10.2	0.0001
AADT in thousands	0.023	0.009	2.54	0.0366
Shoulder width	-0.042	0.02	-2.24	0.0283
Signal density	0.186	0.042	2.95	0.0036
PSI	-0.2115	0.061	-3.53	0.0009
STD(PSI)	0.26	0.112	2.27	0.0278
Dispersion	0.180	0.027	6.67	0.0001
AIC = 966; Pearson Chi-Square / DF=1.07				

6.2.2 *NB model results with access parameters*

Given the importance of access data on arterial street traffic safety, newly collected data elements were added to the model link function. At this stage of the analysis, 74 corridors were studied because these corridors contain signalized intersections. The augmented data was expected to offer more explanation and prediction power to truck crashes. Since many independent variables were added, it was necessary to reevaluate all the variables, existing and new, and pare down the variables to those with significant impact on safety of an arterial roadway. After several iterations, statistically significant variables were listed in Table 6-3. The design and location of commercial driveways, which are frequently used by trucks, apparently affects the safety performance of a corridor. Standard deviation of commercial driveway throat width, flared commercial driveway throat width and its standard deviation, proportion of divided commercial driveway, minimum distance of a driveway to a signalized intersection, signal density and shoulder width are significant factors for crash frequency prediction. Amongst all the statistically significant variables, flared commercial driveway throat width, shoulder width, minimum distance of a driveway to the signalized intersection and proportion of divided commercial driveway are negatively associated with frequency of truck crash prediction. These variables help to provide insightful, logical and meaningful explanation to the cause-effect relationship of truck crashes.

Table 6-3: NB Estimates for Crash Frequency Prediction with Access Parameters

Effect	Estimate	Std. Err.	t-value	Pr > l t l
Intercept	3.08142	0.30691	10.04	0.000
TMT	0.10294	0.00946	10.88	0.000
C_Stdv_Throat_W	0.04096	0.01855	2.21	0.027
C_Flare_W	-0.0098	0.0042	-2.34	0.019
C_Stdv_Flare_W	0.01558	0.00585	2.66	0.008
C_Div_Drv	-0.5987	0.29473	-2.03	0.042
SHWD	-0.0428	0.02124	-2.02	0.044
Min_Dist	-0.0004	0.00023	-1.69	0.091
Sig_den	0.31837	0.06912	4.61	0.000
Dispersion	.1611	0.028	5.72	0.000
AIC= 726				

When comparing with Table 6-2, it is not difficult to find out some previously significant variables (AADT. PSI, STD (PSI)) become insignificant after adding access related variables such as median, driveway and left turn lane. The plausible explanations are provided in the next section.

6.2.3 Discussion

Addition of access related variables led to different results (Table 6-3) using the same exposure - TMT. Interestingly, AADT, PSI and its standard deviation are no longer statistically significant for predicting truck crashes. It is one of the exciting findings in this study that the presence of more relevant variables can nullify the effect of statistically significant variables that are less relevant. Under the guided data collection, the new variables represent a relationship between truck crashes and access design and management. This strong relationship not only displays the statistically significant correlation, but also corrects the spurious causality between crashes and variables; a statistical artifact. The statistical artifact is a difficult issue to address because it can be caused by the choice of faulty variables or function misspecification. A well designed data collection guided by the appropriate knowledge of highway safety can mitigate the negative impact of statistical artifacts.

The negative sign of the PSI coefficient in the model without access parameters suggests that the probability of a crash occurrence becomes higher on distressed pavement. One may be able to argue that a poor pavement condition caused by rutting, potholes, failures and cracking forces drivers to be more wary and travel slower, resulting in fewer crashes or less severe injuries. Smoother pavements may allude to faster driving conditions and consequently end up higher driving speeds, which increase the probability of frequency and severity of a crash. One can also argue that poor pavement condition may constantly make drivers swerve or stop to avoid damage to the vehicle - acts that clearly compromise safety. The dilemma exists because the variable can be confounded with other unobserved or unavailable factors such as driver behavior. The solution can be difficult without a good understanding of how the variables interact with each other. And more difficult is that the data may not be available at all. The alternative is to seek the new variables without ambiguous influence on safety. In this study, the added commercial driveway design data gives more insight and logical explanation to truck crashes without comprising the statistical goodness-of-fit. Table 6-4 shows the standard negative binomial model results.

Table 6-4: Comparison of the NB model results

Effect	t-value	
	Combined*	New Model*
Intercept	7.6	10.04
TMT	9.36	10.88
AADT	1.74	-
SHWD	-1.67	-2.02
PSI	-0.44	-
STD(PSI)	1.37	-
Sig_den	3.72	4.61
C_Stdv_Throat_W	2.47	2.21
C_Flare_W	-2.48	-2.34
C_Stdv_Flare_W	2.59	2.66
C_Div_Drv	-2.14	-2.03
Min_Dist	-1.22	-1.69
Dispersion	5.68	5.72

AIC	728	726

* Combined model includes all the traffic, geometric pavement and access related variables

* New model includes only the significant variables

*- means variable is not significant in the model at 10% significance level.

6.3 Generalized Negative Binomial Model Results

The standard negative binomial model is often criticized because of its fixed overdispersion parameter α. Researchers are keen to find the source of this overdispersion (53, 54). Heterogeneous or generalized negative binomial (GNB) regression is a valuable method for assessing the source of overdispersion (46). GNB can be used to differentiate sources influencing the model parameter estimates from sources influencing overdispersion. Through overdispersion factor parameterization, predictors influencing α value can be determined by establishing a functional relation between them and estimated by including the function in the overall model estimation. It was hypothesized that AADT, TMT, signalized intersection density, driveway density may be the contributing factors to α. Table 6-5 is the attempt to formulate the parameters as the sources of overdispersion including signal density, proportion of divided commercial driveway, and truck million miles traveled. Other than that, the same variables are statistically significant for the truck crash prediction. The AIC indicates that GNB yields a better goodness of fit than the NB model.

Table 6-5: GNB Estimates for Accident Frequency Prediction

Effect	Estimate	Std. Err.	t-value	Pr > l t l
Equation	$\mu = TMTexp(\beta_0 + \boldsymbol{X\beta})exp(\varepsilon)$ where $exp(\varepsilon) \sim Gamma(\alpha)$			
Constant	2.7659	0.30204	9.16	0.000
TMT	0.12508	0.01644	7.61	0.000
c_stdv_throat_w	0.05526	0.0171	3.23	0.001
c_flare_w	-0.0086	0.00422	-2.03	0.042
c_stdv_flare_w	0.01638	0.00518	3.16	0.002
c_div_drv	-0.6893	0.29692	-2.32	0.020
shwd	-0.0588	0.01954	-3.01	0.003
sig_den	0.30074	0.06639	4.53	0.000
Overdispersion	Ln(α)=$\mathbf{X}\boldsymbol{\beta}$			

TMT	0.10707	0.04503	2.38	0.017
c_div_drv	-3.5114	1.43085	-2.45	0.014
sig_den	0.577	0.2546	2.27	0.023
Constant	-2.6737	0.63455	-4.21	0.000
AIC=718				

6.4 Discussion of Crash Contributing Factors

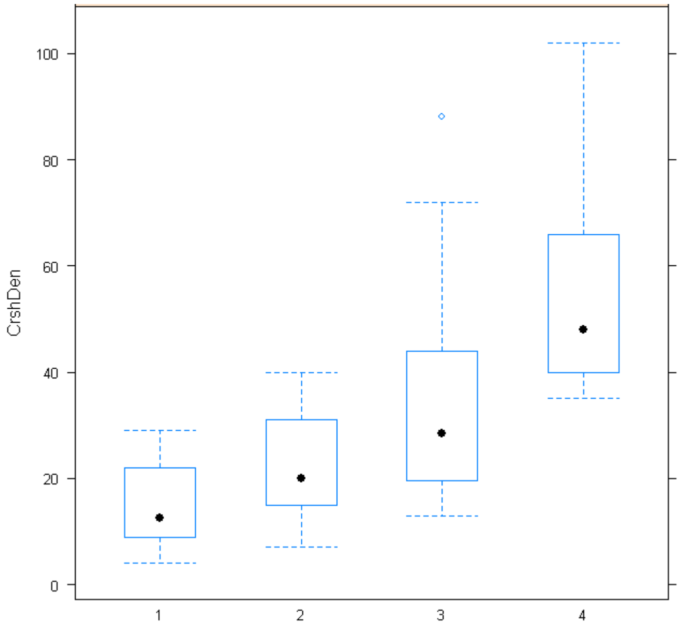
Based on the model results it is apparent that commercial driveway design components are a very intriguing issue for the truck preferred arterial corridors other than geometric features. The following section is the endeavor to enhance understanding of the factors that influence crash occurrence either positively or negatively.

6.4.1 Commercial Driveway Design

An important component of access management involves managing traffic movements into and out of commercial driveways. The reason for this is that a large number of crashes on arterial streets involve commercial driveways. Commercial driveway width is important because it has a significant impact on the ease of entry into the driveway (39). A larger radius results in easier egress and ingress for passenger cars as well as commercial motor vehicles so that the driveway movement can be performed without abruptly slowing down or substantially encroaching into other roadway lanes and driveway lanes. The more quickly a vehicle can enter a driveway, the less chance there is of a rear end collision (C_Flare_W has a negative impact). According to the TRB Access Management Manual (39), simultaneous entry and exit by a single unit truck must have a driveway throat width of 40 feet. Our estimate indicates that 18 percent of corridors have a higher number of crashes because they contain driveway throat width with flare less than 40 feet and 38 percent of corridors have a lower number of crashes because they contain driveway width with flare greater than 40 feet. Varying width (standard deviation of throat width and throat width with flare) leads to a situation where the driver is not guided to the best position for driveway movements. In this case, pavement marking becomes vital to guide the driver to entering the road.

6.4.2 Signalized Intersection Density

Although most discussions about access management focus on the management of private driveways, proper spacing of signalized intersections is an equally important issue. The importance of intersection spacing is similar to that of driveway spacing. As the number of intersections per mile increase, the opportunity for crashes increases. The existence of too many intersections per mile also increases delay and congestion. Stover and Gluck (56, 57) reported that crash rates increase as the number of signalized intersections per segment increases. The average crash rate can be increased by up to 200 percent when the signal density along a given segment is increased from two to four signals per mile, depending on the number of un-signalized access points along the same segment (39). To test the findings of the previous literature, a sensitivity analysis has been performed in order to capture the impact of the signalized intersection density. The graph shows that crash density increases exponentially with increase in signal density. So, for higher values of signal density, crash density will increase at a higher rate than for a lower value of signal density.



x axis represents signal density

1= signal density <=1 per mile

2= 1<signal density <=2 per mile

3= 2<signal density <=3 per mile

4= signal density >3 per mile

Figure 6-1**:** Crash density per million vehicle miles travel versus signal density

6.4.3 Intersection Functional Area

Crashes at intersections are about three times more frequent than those between intersections and crash rates increase dramatically as the number of driveways per mile increases (58). The integrity of functional areas of intersections can be protected through corner clearance, relocating driveways to the cross road or a frontage or backage road, installation of raised medians and intersection spacing requirements. Median openings should not be located within the functional area. The statistical analysis shows that, minimum distance of a driveway to a signalized intersection within a corridor has negative safety impact in the crash occurrence process.

6.5 Crash Severity Model results

Multivariate analysis and discrete-response models are often used to model the level of injury severity. Among them, the logistic model is a popular choice. The ordered probit model and the multinomial logit model were used for the purpose of injury severity prediction. There were five levels of dependent variables: crash severity, was coded as fatal, incapacitating injury, non-incapacitating injury, possible injury, and property damage only crash in the original crash dataset. When estimating the MNL model, the property damage only crashes variable was treated as the base category.

6.5.1 MNL Model Results

In the MNL model results shown in Table 6-6, posted speed limit, shoulder width, pavement serviceability index, standard deviation of PSI, pavement condition index, number of lanes, lane width, ADTT, AADT and undivided portion of roadway were all determined to be statistically significant variables for predicting different levels of injury severity at the 10% significance level. The coefficients of the estimated model can be interpreted as follows: a positive significant coefficient on a variable indicates that the variable is associated with a higher probability of being in that group choice relative to the reference group. The implication is that the probability of a crash at that level of severity is greater than the probability of placing it in the reference group. Negative sign means that the probability of a crash at that level of severity is smaller than the probability of placing it in the reference group. For example, the coefficient of one lane segment is a positive value of 1.38 for the severity level of B, indicating that the probability of a crash to be a B crash is higher than a PDO crash if the segment is one lane.

Table 6-6: Coefficient Estimates for MNL

Variable	C		B		A		K	
	Coef. (Std. Err.)	Z (p-value)	Coef. (Std. Err.)	Z (p-value)	Coef. (Std. Err.)	Z (p-value)	Coef. (Std. Err.)	Z (p-value)
Intercept	-	-	-2.44 (1.08)	-2.24 (.02)	-7.13 (2.0)	-3.40 (.001)	-12.51 (4.0)	-3.11 (.002)
AADT	-	-	-.043 (.024)	-1.83 (.06)	-	-	-	-
ADTT	-	-	.001 (.000)	1.99 (0.04)	-	-	-	-
SPD	-	-	-	-	.052 (.01)	3.22 (.001)	.059 (.03)	1.85 (.06)
Ln width	-.096 (.04)	-1.94 (.053)	-	-	-	-	.393 (.22)	1.76 (.07)
NL_1			1.38 (0.61)	2.25 (.02)	-	-	-	-
NL_2	-.378 (.17)	-2.21 (.02)	-	-	-	-	-	-
NL_3	-.480 (.19)	-2.41 (.01)	-	-	-	-	-	-
Shoulder width	-	-	-	-	.111 (.03)	2.87 (.004)	-	-
Divund_U	-	-	.348 (.18)	1.93 (.053)	-	-	-	-
PCI	-.003 (.001)	-1.69 (.09)	-.004 (.002)	-2.06 (.03)	-	-	-	-
PSI	-	-	.173 (.08)	2.15 (0.03)	-	-	-	-
STD(PSI)	-	-	-	-	-.735 (.20)	-3.61 (.000)	-1.25 (.42)	-2.89 (.003)

Note: Number of observation = 1986, Prob>chi-square=0; LL= -7755.43

"-" represents the variables that are not statistically significant at 10% level of significance.

6.5.2 OP Model Results

In the OP model results shown in Table 6-7, posted speed limit, shoulder width, pavement serviceability index (PSI), standard deviation of PSI, pavement condition index (PCI), ADTT and AADT were all determined to be statistically significant variables for predicting different levels of injury severity at the 10% significance level. Lane width, number of lanes and proportions of undivided roadway segments are not statistically significant predictors as it was in MNL model. A positive coefficient suggests the likelihood of less severe injuries with increasing value of the variable while a negative coefficient suggests otherwise. The value of the loglikelihood function of OP model is smaller than the MNL model, thereby the AIC value of the OP model is greater than the MNL model.

Table 6-7: Coefficient Estimates for OP model

Injury Severity	Coef.	Std. Err.	z	P>	[95%Conf. Interval]	
AADT	-2E-05	7.53E-06	-2.86	0.004	-4E-05	-6.76E-06
ADTTADTT	0.00053	0.00019	2.74	0.006	0.00015	0.000903
SPD	0.00666	0.00293	2.28	0.023	0.00092	0.012399
NL_2	-0.1896	0.07068	-2.68	0.007	-0.3282	-0.05111
NL_3	-0.1903	0.09082	-2.1	0.036	-0.3683	-0.01233
SHWD	0.01987	0.00682	2.91	0.004	0.0065	0.033249
PCI	-0.002	0.00072	-2.73	0.006	-0.0034	-0.00056
PSI	0.04476	0.02718	1.65	0.1	-0.0085	0.098033
STD(PSI)	-0.1598	0.03626	-4.41	0	-0.2309	-0.08877
/cut1	0.71104	0.12505			0.46595	0.956138
/cut2	1.4217	0.12558			1.17557	1.667836
/cut3	2.09131	0.12727			1.84187	2.340749
/cut4	2.74513	0.13318			2.48409	3.006165
Note: Number of observation = 8196, Prob>chi-square=0; LL= -7806.67						

6.5.3 Crash Severity Model Selection

Following the crash frequency prediction, the crash severity distribution was also estimated based on corridor-level variables. Both the MNL and OP models were used for prediction of probabilities for crash injury severity proportions for each corridor. The predicted probabilities were compared with the observed proportion using the sum of absolute difference (SAD) as follows:

$$SAD^j = \sum_{i=1}^{100} \left| P_i^j - O_i^j \right| \tag{10}$$

Where:

SAD^j is the sum of absolute difference for all 100 corridors for injury severity type j;

P_i^j is the predicted probability for injury severity type j on corridor i; and

O_i^j is the observed probability for injury severity type j on corridor i;

Table 6-8 shows the sum of absolute difference of injury severity proportions of MNL and OP models. The MNL model was chosen to calculate the predicted number of crashes for the five levels within a corridor because the sum of the absolute difference in MNL was smaller than OP model for all severity levels.

Table 6-8: Sum of Absolute Difference of Injury Severity Proportions

Model	O	C	B	A	K
OP	6.29	6.02	3.81	2.16	1.50
MNL	6.16	5.06	3.70	1.82	1.27

6.5.4 Discussion

Variables of every type were found to be informative in the final model. Speed limit, lane width, shoulder width and standard deviation of PSI were found to be highly crucial for the incapacitating injury (A) and for fatal crashes (K). Other things being constant: good pavement condition will help to reduce severity for crashes. Traffic volumes appear to have no significant effect on the high severity level for K & A, given that a crash has occurred. In the MNL model, the coefficient estimates are explained as the comparison between injury level *i* with the base level O. For example, if a road is undivided, a driver’s chance of getting injured increases significantly, with respective probabilities of level B being 1.42 ($e^{0.348}$) times that of O. Similarly, injury severity due to the effect of PSI for level B is 1.2 ($e.^{173}$) times that of the base level.

6.6 Crash Severity Index Development

In the final phase of the research, the predicted crash frequency and the predicted severity proportions for each corridor were employed to develop the truck corridor CSI using Equation 3-8. The total number of predicted crashes for a corridor was multiplied by the corresponding injury severity proportions in order to get the crash frequency for each severity type. Then those predicted injury severity frequencies were multiplied by the respective comprehensive crash cost provided in HSM for the estimation of total crash costs of each corridor (23). A worksheet was designed to facilitate the calculation as illustrated in Table 6-9.

Table 6-9: CSI Estimation Worksheet

<table>
<tr><td colspan="2">Corridor Location Information
Highway name:
From / To:
Nearby Interstate Highway:
Region:</td></tr>
<tr><td rowspan="2">Variables
AADT
ADTT
L
Shoulder width
Signal density
Ln width
NL_1
NL_2
NL_3
Divund_U
SPD
PCI
PSI
STD(PSI)</td><td>Calculation of expected number of crashes
$TMT = \frac{365 \times AATT \times L}{1000000}$
$\mathrm{N} = \mathrm{TMT}^{0.084} \exp^{(2.75 + 0.02 * \mathrm{AADT} - 0.042 * \text{Shoulder width} + 0.186 * \text{Signal density} - 0.212 * \mathrm{PSI} + .258 * \mathrm{STD(PSI)})}$</td></tr>
<tr><td>Calculation of predicted injury severity proportion
(coefficients refer to Table 5)
$\log\left[\frac{P_i(k-1)}{P_i(k)}\right] = \alpha_{k-1} X_{(k-1)}$
$P^k = P(O) * e^{\alpha_k X_k}$
$P^A = P(O) * e^{\alpha_A X_A}$
$P^B = P(O) * e^{\alpha_B X_B}$
$P^C = P(O) * e^{\alpha_C X_C}$
$P^O = \frac{1}{1 + \sum_{j=1}^{4} e^{\alpha_j * x}}$</td></tr>
</table>

Unit crash cost ($) (23)	**Calculation of corridor crash severity index (CSI)**
U_{PDO} = 7,400 U_C = 44,900 U_B = 79,000 U_A = 216,000 U_K = 4,008,900	$CSI = \frac{\sum_{j=1}^{J} NP^j U_j}{L}$
Glossary: Refer to Table 1	

The observed truck corridor CSIs were calculated and compared with the predicted ones. Figure 6-2 shows that both predicted CSI and observed CSI skewed to the left, suggesting the CSI is not symmetrically distributed. The average annual predicted CSI was found to be $239,830 per mile with a standard deviation of $190,269, which was higher than the actual average annual CSI of $202,850 per mile with a standard deviation of $198,751. In the endeavor for testing the mean of this predicted and observed CSI using t-test infers that they are not statistically different (critical t value is 1.35) at 5 percent significance level. Similarly the chi-square test result also confirms that the two distributions are same. In the predicted CSI some corridors are underestimated and some are overestimated. The overestimation was more apparent in the range of $200K~$300K than in other intervals. For those overestimated corridors, some common characteristics such as narrower shoulder width, higher standard deviation of ADTT, lower pavement serviceability index and narrower lane width were observed, which seem to contribute considerably to the predicted crash frequency and severity. Nevertheless, the overestimated corridors are the ones with low CSI, suggesting very few serious injury crashes.

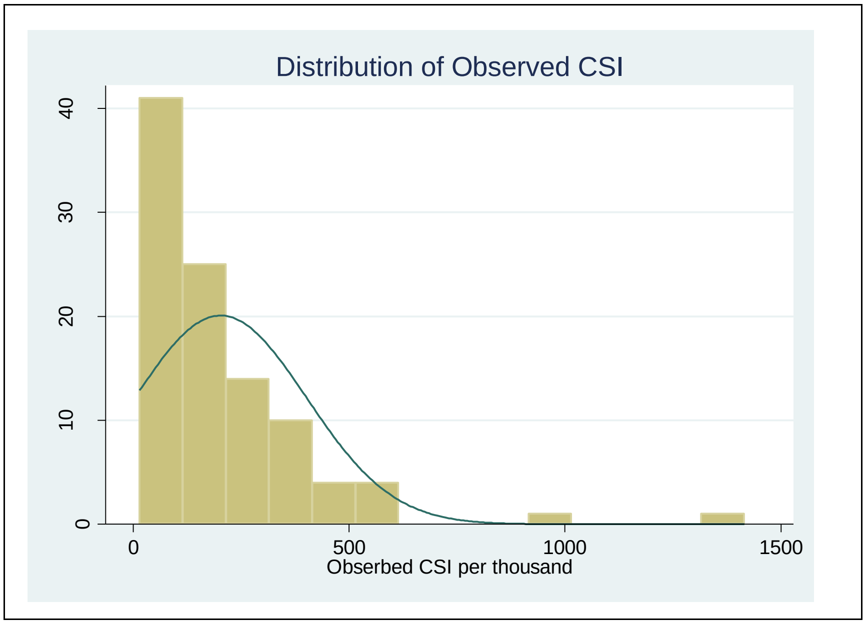


Figure 6-2: Histogram of observed CSI per thousand.

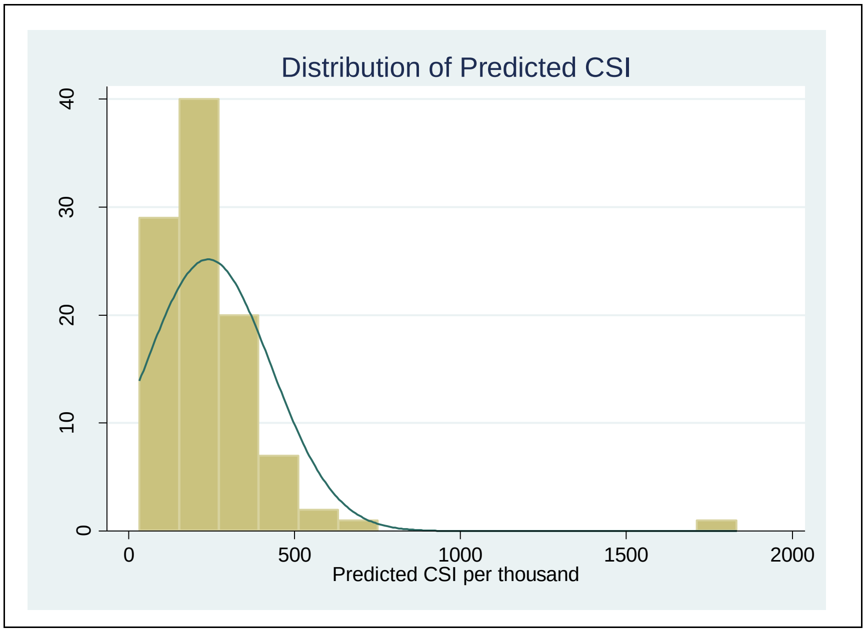


Figure 6-3: Histogram of observed and predicted CSI per thousand.

The developed CSI can play a vital role in quantifying the overall risk to the traveling public posed by each truck corridor. The CSI is designed to alert motor carriers and transportation agencies of potential safety issues so that preventive measures can be taken. The index could assist transportation agencies in allocating safety improvement funding and enhancing the identified geometric design components of arterials. By taking adequate measures based on CSI, road agencies can direct trucks to arterial roadways with adequate geometries and pavement conditions. The CSI can also be employed to a truck route network analysis so that highway safety can be incorporated into the route choice. Motor carriers can make informed decision based on not only logistics but also safety.

7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

Due to rapid growth in truck traffic in the country, concern amongst transportation agencies about truck related safety issues has increased. Although numerous studies have been conducted for truck safety on the Interstate highway system, research on truck crashes on arterial streets, especially from an arterial corridor perspective, is relatively limited. Arterial streets are the “last miles” for trucks to deliver freight to destinations or enter the Interstate highway system. Improving truck safety from an arterial corridor standpoint is crucial for developing more proactive, corridor-based safety strategies. This study set out to attain four objectives. First, is to establish criteria for identifying statewide critical truck arterial corridors. Second, is to design and conduct innovative data collection for access management. Third objective is to identify heavy vehicle involved crash causal factors. And lastly, fourth is to develop a cost-based arterial corridor safety risk index based on crash frequency and crash severity.

In this study, rigorous effort was made in the selection of truck corridors based on corridor length, truck volume and their proximity to interstate highways. In pursuit of the second objective, considerable effort was made to collect access related variables as most of the access related variables are not readily available in any GIS or table format.

In order to identify and quantify factors contributing to frequency and severity of truck crashes, it was decided to fit negative binomial and discrete choice models for crash count and severity data, respectively. The significance and magnitude of the coefficients have been estimated through the models. Negative binomial model was used to predict the total number of truck crashes in two stages - without and with access related variables. In the first phase(without access related variables), million truck miles traveled, AADT, signal density, shoulder width, pavement serviceability index and its standard deviation were identified as statistically significant variables. In the second phase (with access related variables), standard deviation of commercial driveway throat width, commercial driveway throat width with flare and its standard deviation, proportion of divided commercial driveway, minimum distance of a driveway to the signalized intersection, signal density and shoulder width were significant factors for crash frequency prediction. The addition of access related variables explains reasonably well the causal relationship of truck crashes and nullifies a few variables that were statistically correlated with the dependent variable, the number of crashes in previous models. The statistical inconsistency of these variables may be a statistical artifact which can be corrected by including more appropriate variables or improving model specification. One of the challenges facing the current crash model development is the data heterogeneity because crash data are usually obtained at different times across a wide range of geographical locations. In order to overcome the standard negative binomial model’s fixed overdispersion parameterization, generalized negative binomial (GNB) regression method had been used for assessing the source of overdispersion. Same variables are statistically significant for the truck crash prediction though the magnitude has been changed but the signs are consistent and interpretations are also same. Finally the variables that caused the overdispersion of the study data are the truck million miles traveled by truck, signal density and proportion of divided commercial driveways. The AIC indicates that GNB yields a better goodness of fit than the NB model. This study closes the gap by providing a comprehensive analysis of truck-related crashes on arterial roads by establishing a causal relationship with traffic, geometric, pavement and access parameters. Nevertheless, the use of the generalized negative binomial model better address the data heterogeneity and helped dentify the parameters that caused overdispersion.

For crash severity prediction, two discrete choice models were tested: the multinomial logit (MNL) model and the ordered probit (OP) model. MNL model was selected to estimate injury severity proportion based on sum of absolute difference (SAD). The MNL model results showed that AADT, ADTT, shoulder width, PSI and its standard deviation, posted speed limit, lane width and number of lanes, pavement condition index and undivided roadway portion contributed to truck crash severity without the presence of access parameters. The common factors that affect both are AADT, ADTT, shoulder width, PSI and its standard deviation.

In the final phase of this study, a quantifiable crash severity index (CSI) was developed to provide a holistic measurement of truck crash risk, based on the selected truck corridors. The mean and distribution of the predicted and observed CSI are not statistically different form each other. The truck corridor based CSI is defined as the annual societal economic costs due to truck crashes per unit length. It is a composite average of the truck crashes by severity with the weights determined by the crash unit cost. Therefore, when comparing different safety improvement strategies, any change to the value of the factors related to crash frequency, severity, and especially both should be comprehensively and carefully evaluated.

7.2 Future Work

- Data is crucial for safety analysis. The quality of the research is highly dependent on the availability and quality of data. In the next phase of the research, parameters related to intersection signal timing can be added to existing variables.
- Different negative binomial model structures can be incorporated, such as generalized negative binomial with endogenous stratification (GNBSTRAT) in the quest of better model results.
- Similar analysis can be done using Interstate or freeway data to develop Interstate highway CSI which can be compared with arterial CSI.
- Relationship between crash frequency and access, traffic, pavement and geometric factors was analyzed in this study. There is also a need to establish the relationship between crash severity and the access parameters.. The crash frequency and severity prediction

models may share some common contributing factors but will certainly have different ones as well. Even for those common factors, the magnitude of influence may not be the same.

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