Highway Design Consistency and Safety: Individual and Overall Evaluation Criteria

Submitted by
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of the requirements for the degree of Master of Applied Science in Civil Engineering

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ABSTRACT

The concept of design consistency is one of several tools used by highway designers to improve roadway safety. The most promising consistency measures identified in previous research fall into four main categories, namely: operating speed, vehicle stability, alignment indices, and driver workload. Previous research has focused on the development of models that can estimate these consistency measures, while little research has considered their relationships to safety. The main objective of this thesis is to quantify the relationships of individual consistency measures to actual collision experience through regression analysis. A subsequent objective is to provide an overall safety-based model for consistency evaluation. Model development was based on a database consisting of 70 horizontal curves located on two-lane rural highways in Eastern Ontario. Several statistically significant models relating the consistency measures to safety were developed. These models provide a quantitative tool for evaluating the safety benefits of improving the consistency of design elements.

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DEDICATION

This thesis is dedicated to the two most important people in my life, my parents, Jamilla and Mahmoud Awatta. Without their love, support and encouragement throughout my studies, I would not be where I am today.

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LIST OF SYMBOLS

μ = Average number of successes

$\beta_0, \beta_1, \beta_2, \dots, \beta_n$ = Model parameters

χ^2 = Pearson chi-squared statistic

$\Delta_{85}V$ = 85th percentile of speed reduction

ΔV_{85} = Reduction of 85th percentile speeds

$85MSR$ = 85th percentile maximum speed reduction

$AADT$ = Average Annual Daily Traffic

AR = Average Radius

AVC = Average rate of vertical curvature

CCR = Curvature change rate

CRR = Curve Radius to Average Radius

DC = Degree of curve

D^m = Scaled deviance

e = Superelevation rate

$Expo$ = Single exposure term (million vehicle-km)

f_r = Side friction supply

f_{rd} = Side friction demand

f_{Rperm} = Maximum side friction factor

f_{Tperm} = Maximum tangent friction factor

G = Longitudinal grade

K = Over-dispersion parameter

K_{max} = Maximum over-dispersion parameter

k = Scaled deviance or Chi-Square dispersion measure

L = Length of curve

L^f = Log-likelihood achieved if the model gave a perfect fit

L^m = Log-likelihood of the model under study

n = Number of observations (curves)

N = Utilization ratio

p = Number of coefficients considered in model

R = Radius of curvature

R^2 = Coefficient of determination

R_k^2 = Goodness of fit measure

RR = Ratio of the maximum and minimum curve radii

V_{85} = 85th percentile operating speed

V_D = Design speed

VD_{LF} = Visual demand of familiar drivers

VD_{LU} = Visual demand of unfamiliar drivers

$X_1...X_n$ = Model predictor variables

Y = Expected three-year mean collision frequency

CHAPTER ONE

1.0 INTRODUCTION

The dramatic growth of motorization and highway construction in the past several decades has led to a remarkable increase in mobility and prosperity worldwide. However, this increased mobility has also resulted in hundreds of thousands of deaths and millions of injuries annually due to traffic collisions worldwide. In Canada, traffic collisions on the highway network have resulted in 2,917 deaths and 227,500 injuries in the year 2000 alone (*Canadian motor*, 2000). However, it is noteworthy that there has been a considerable improvement in Canadian roadway safety in the past few decades. For example, in 1971 Ontario roads experienced an unsurpassed fatality rate of 5.24 fatalities per 10,000 licensed drivers, which has since dropped to 1.02 fatalities per 10,000 licensed drivers in 2001, making Ontario roads the safest in North America (*Ontario road*, 2001).

Nonetheless, the current figures remain an indication that the highway safety problem still exists, and suggest the need for further research and advancements in the area of highway safety improvement. This chapter provides background information regarding highway safety and design consistency, describes the research problem that has motivated this study, defines the thesis objectives and scope, and presents an overview of the remaining chapters in this thesis.

1.1 BACKGROUND

Critical driving situations can be described as the result of inappropriate interactions between at least two of the three main elements in the roadway system: the road user, the vehicle, and the road itself. Collisions are complex events, which are rarely the result of only one of the roadway elements, and thus are very difficult to analyze.

However, when collisions occur there is a general tendency among roadway specialists to excessively hold the driver responsible. The tendency to focus on driver error as the main cause of collisions may reduce the designer's role in improving the design and safety of roadway features. Pasupathy et al. (2000, p.3) stated, "It is important to realize that crashes are generally the result of bad decisions by the driver made in an environment created by the engineer". Although it is undeniable that the road user is the main controlling element on the roadway and has the most significant impact on safety, research has shown that collisions tend to occur disproportionately at certain roadway segments. This implies that in addition to driver error, road characteristics play a major role in collision occurrence. A common estimate in literature is that road-related factors are associated with approximately 30% of crash causation (Lum and Reagan, 1995). Thus, designers carry a high degree of responsibility in the incidence of unsafe driver actions through their contribution to bad decisions made by the driver.

Collisions that are related to deficiencies in roadway geometry can be largely attributed to design inconsistency. Design consistency can be defined as the degree to which highway systems are designed and constructed to avoid critical manoeuvres that may lead to collision risk (Al-Masacid et al., 1995). Design consistency is also commonly defined as the roadway's conformance to driver expectancy. Driver expectancy is shaped by experience, which is largely dependent on: the number of times a driver has driven on a particular road, the similarity of the road to others in the driver's experience, and the accuracy of recent predictions that have been made about the road (Fitzpatrick et al., 2000a). Thus, a design inconsistency in a roadway segment implies a geometric feature or features that violate driver expectancy, such as an abrupt change in

roadway geometry. Surprising drivers by violating their expectancies increases the chance of delayed response times, speed errors, and unsafe driving manoeuvres that may lead to higher collision risk. To avoid these problems, designers should ensure that the roadway design complies with driver expectations through the evaluation of design consistency, and the redesign of inconsistent locations. The concept of design consistency is one of several promising tools being employed by highway designers to help improve roadway safety.

Although design consistency is an important factor affecting collision experience on highways, traditional North American highway geometric design guidelines provide little assistance for ensuring the design of consistent roadway features. North American design practice relies on the design speed concept to ensure safety, which has been applied since the 1930's in response to increasing collision rates (Fitzpatrick, 1994). The design speed concept is based on an arbitrary design speed value that is selected by the highway designer. This design speed is applied to the geometric design of highway elements including horizontal curve radius, superelevation, and vertical curve elements. Based on this approach, it is assumed that design consistency will be achieved since drivers are not expected to exceed either the speed limit or the design speed. Initially, the design speed concept allowed most drivers to drive consistently at their desired speed. However, as driver behaviour and vehicle designs evolved, it is argued that the design speed concept is no longer successful at producing consistent roadway alignments (Krammes, 2000).

Several research projects have shown that drivers adopt their speed according to the highway conditions ahead, and are not greatly impacted by the presence of posted

speed limits. For example, research conducted in the United States has shown that a noticeable disparity between the operating speed and design speed on two-lane rural highways exists, specifically on curves with design speeds less than 90 to 100 km/h (Krammes, 2000). This research indicated that the design speed concept tends to underestimate the desired speed of drivers. Furthermore, the design speed of a highway alignment is typically limited by a few horizontal curves, with the remaining highway segments allowing higher operating speeds. Harwood et al. (2000b, p.118) stated,

Most drivers have learned that there is minimal sensation of discomfort and minimal loss of control potential in traversing horizontal curves at speeds 16 to 32 km/h above the posted speed limit. This driver experience may lead to potential safety problems on the few curves that are posted with realistic advisory speeds.

Thus, drivers travelling at their desired speeds may have to reduce their speeds dramatically on these limiting curves, which may increase collision risk (Lamm et al., 1999). This implies that the application of the design speed concept may actually contribute to driver expectancy violations.

It is considered essential for highway designers to analyze design consistency in the design phase so that inconsistencies are not built into the roadway system. Yet, most researchers will agree that current North American design guidelines do not guarantee a consistent highway design. Furthermore, there is no method provided in guidelines for detecting inconsistencies, since the design speed concept assumes that they cannot take place (Voigt and Krammes, 1995). Two major flaws in the traditional design speed concept are particularly pointed out. Firstly, no quantitative guidance is provided to

establish maximum tangent lengths in order to control operating speeds. A study conducted by Fink and Krammes (1995) showed that sharp curves are more likely to have higher collision rates when preceded by a long tangent than by a moderate tangent. This is because drivers do not expect a sharp curve and are not mentally prepared to slow down. Current design guidelines centre on individual design elements only, and there is a clear lacking of a more system-wide approach for highway design. Secondly, the design speed concept only controls minimum design values, and encourages the use of above minimum values with the hypothesis that this will lead to a safer design (Krammes, 2000). The problem with this belief is that using above minimum design values for horizontal curve design may encourage operating speeds greater than the design speed of the element, thus leading to an adverse impact on safety (Brenac, 1996).

These weaknesses have led several countries to adopt the operating speed concept in order to help ensure highway design consistency and safety. Australia and several European countries including Germany, Switzerland, Britain, France, and Sweden have already enhanced their use of the design speed concept to include considerations of predicted operating speed rather than an arbitrary speed value selected by designers (Polus et al., 1995). Alternatively, the classical design speed concept is still applied for selecting geometric elements in Canada and the United States. Nevertheless, although the design policy in the United States is still based on the design speed concept, the Federal Highway Administration's (FHWA) newly released Interactive Highway Safety Design Model (IHSDM) includes a design consistency module based on operating speed reduction, and the difference between operating and design speeds. This module is expected to complement the design speed concept, and help improve two-lane rural

highway safety. In Canada, the 1999 Transportation Association of Canada (TAC) Geometric Design Guide made a modest effort to improve safety by including a chapter on design consistency based on cross-section, operating speed, and driver workload. Although this addition was mostly based on US research, it is still a promising indication of future improvements in the Canadian guide with respect to providing designers with tools for increasing roadway safety.

At this point, it should be noted that previous research regarding the evaluation of design consistency has focused on the horizontal curves of two-lane rural highways due to their overrepresentation of collisions. Two-lane rural highways are by far the most prevalent class of highways at the global level. In Canada, two-lane rural highways represent 82% of the Canadian highway network (*Transportation*, 1995). In addition, 63% of fatal vehicle collisions in Canada were found to occur on two-lane rural highways in the year 2000 (*Canadian motor*, 2000). This is mainly due to the high speeds and low attention levels that are common to this class of highways. Furthermore, numerous studies have shown that collisions are several times more likely to occur on horizontal curves than tangent sections. For example, based on a review of collisions that have occurred on two-lane rural highways in the United States and Europe, over 70% of fatal and injury collisions were found to occur on the horizontal curve segments (Lamm et al., 1999).

Since the 1970's, the concept of design consistency has been achieving greater and greater awareness, resulting in the availability of a considerable amount of research related to the design consistency of two-lane rural highways. There are a variety of approaches and models that have been suggested for consistency evaluation worldwide.

Based on a review of the state of the art of design consistency research in North America and Europe, Gibreel et al. (1999) categorized design consistency research and practice into three main areas: (1) Operating speed considerations, which include the speed reduction at successive elements, and the difference between operating speed and design speed at single elements; (2) Safety considerations, which address the impacts of highway/traffic elements, vehicle stability and low-cost improvements on safety; and (3) Performance considerations, which include driver workload, driver anticipation and highway aesthetics. Of the previously mentioned design consistency considerations, Hassan et al. (2001) identified the measures considered the most viable candidates in rating the design consistency of two-lane rural highways. These measures or models fall into four main approaches that are based on: operating speed, vehicle stability, alignment indices, and driver workload.

Most research in the area of highway design consistency has been dedicated to the development of models that estimate individual consistency measures based on different design dimensions. At the mean time, little research has considered the relationship of these measures to actual collisions in order to quantify their safety benefits. The 1999 TAC Geometric Design Guide stated, "The most valuable tool for evaluating geometric design consistency is actual collision experience, which should, for any existing facility, be used as a basis for design consistency evaluation". Studying the safety benefits of applying these consistency measures is very important in establishing their validity and helping to further advance their application in the design process.

Furthermore, a major area in current design consistency research that is lacking attention is the establishment of an overall model for highway design consistency

evaluation based on safety research. Occasionally, alternative consistency measures will provide conflicting consistency levels, for example, one measure may identify the design as “Good”, while another identifies it as “Fair” or “Poor”, and so forth. This is because these measures are based on differing assumptions and focus on somewhat different aspects of the roadway design. Relying on only one measure for consistency evaluation could be a possible solution to this problem; however, this may lead to the loss of valuable insight provided by the eliminated measures of consistency. Particularly, since it is not expected that the use of one single consistency measure will provide a comprehensive evaluation of design elements. On the other hand, combining the different evaluations provided by each measure with the assumption that they have equally important relationships to safety is not considered accurate. Thus, the availability of an overall model that reflects the varying relationships of alternative consistency measures to safety would provide a more accurate approach for assessing the tradeoffs between results provided by different consistency measures.

1.2 OBJECTIVES AND SCOPE

Following from the research needs identified in the previous section, and the above recommendation by TAC (1999), the objectives of this research project are described as follows:

1. To study the relationships of the individual design consistency measures to actual collision experience in order to establish their validity, and provide a ranking system in terms of their importance to safety; and
2. To provide an overall approach for design consistency evaluation based on collision analysis, to serve as a tool for helping designers maximize highway safety.

The scope of this study is limited to the horizontal curves of two-lane rural highways. The model database is based on actual collision records, traffic volume and geometric alignment data, and consists of 70 horizontal curves located on two-lane rural highways in the Eastern Ontario region. It is important to note that the above objectives were achieved through the implementation of regression analysis techniques. It is also important to clarify that the purpose of the regression models developed in this study is not to predict collisions, but rather to provide a better understanding of the relative impact of each consistency measure on safety. The results of this research project are considered a vital contribution to the limited Canadian research related to highway design consistency evaluation.

1.3 THESIS ORGANIZATION

The organization of the remaining chapters is briefly outlined as follows:

- Chapter 2 contains a comprehensive review of previous research related to the main consistency evaluation categories identified, namely: operating speed, vehicle stability, alignment indices, and driver workload.
- Chapter 3 provides a detailed description of the data collection process, including site selection, and the collection of collision history, traffic volume, and geometric alignment data.
- Chapter 4 explains the analysis methodology applied in this study including the regression technique, model form, modelling approach, selection of predictor variables, and goodness of fit measures.
- Chapter 5 discusses the results of the regression models developed in this study, which relate each of the individual consistency measures to safety, and the attempt to

fit an overall consistency model based on regression analysis.

- Chapter 6 presents the results of the sensitivity analysis conducted, and ranks the consistency measures in terms of their importance to safety in order to provide an alternative system for overall safety-based consistency evaluation.
- Finally, Chapter 7 provides a brief summary of this thesis, and presents the main conclusions and recommendations of the research results.

CHAPTER TWO

2.0 LITERATURE REVIEW

A comprehensive review of previous research related to design consistency measures has been conducted. This review allows a deeper understanding of the potential capabilities and limitations of safety based consistency models, since their performance will depend heavily on the reliability of the consistency measures applied. Sections 2.1 to 2.4 provide a review of the four main categories of design consistency measures identified. Section 2.2 also describes a subjective method of overall consistency evaluation that has been recommended by Lamm et al. (1999). Finally, Section 2.5 summarizes available research regarding the relationships of consistency measures to safety.

2.1 OPERATING SPEED

Inappropriate vehicle speeds and high variations in speed are widespread manifestations of design inconsistencies in the highway alignment. Accordingly, the examination of vehicle operating speeds along a highway alignment has become the most common approach for consistency evaluation. Operating speed is defined as the speed selected by drivers under free-flow conditions. This speed can be used in both highway safety evaluations, and in the design of highway elements such as sight distance, superelevation rates, and minimum curve radii. Operating speed is commonly taken as the 85th percentile speed, i.e. the speed that 85% of drivers will not exceed. Most researchers will agree that the 85th percentile speed provides a satisfactory representation of the driver population, while the use of higher percentile speeds may not be considered practical.

Lamm et al. (1999) established the following two main operating speed based consistency measures: (1) design speed consistency, referred to as Safety Criterion I; and (2) operating speed consistency, referred to as Safety Criterion II. Although these two measures are independent techniques for design consistency evaluation, they are often grouped together in literature due to their mutual dependence on operating speed.

In addition, Collins et al. (1999) investigated the suitability of operating speed based distribution measures for design consistency evaluation, including speed variance measured as standard deviation, and mean speed. However, the statistical analysis of these speed distribution measures showed very low correlation to alignment features, and was thus found to be inappropriate for the evaluation of highway design consistency.

2.1.1 Design Speed Consistency

Design speed consistency (Safety Criterion I) is evaluated based on the difference between the 85th percentile operating speed (V_{85}) and the design speed (V_D) for individual curve segments as $|V_{85} - V_D|$. This measure aims to ensure that the design speed is in balance with actual driver speeds and behaviour, and that the safety problems resulting from operating speeds that are excessively higher than design speeds are avoided (Lamm et al., 1999). Safety studies have shown that two-lane rural highway sections with design speeds in excess of 80 km/h are associated with higher collision experience, since higher design speeds also encourage higher operating speeds that may exceed both the posted speed limit and the design speed. It is noteworthy that since safety evaluation is based on the absolute value of this measure, it is not biased towards flatter curves. In other words, locations with operating speeds that are excessively lower than the design speed, such as extremely flat curves, may also be rated as “Poor” from the consistency point of view.

Although a flat curve generally experiences operating speed values far less the design speed of the curve, thus leading to the impression of a safe design, it also encourages generally higher operating speeds on the highway alignment. This may lead to safety problems on other more restrictive highway segments.

The operating speed in Safety Criterion I can be estimated using one of several operating speed prediction models that are currently available. A review of several speed prediction models developed in previous studies is provided in Section 2.1.4. On the other hand, the design speed is simply taken as the design speed of the whole highway alignment (Lamm et al., 1999). Hassan et al. (2001) has also suggested the possibility of using the estimated limiting speed of the individual curves under study. To estimate the limiting speed at each curve, the point mass formula discussed in Section 2.2 is applied.

Furthermore, it is noteworthy that the operating speed reduction experienced on curves (Safety Criterion II), which is the second operating speed-based measure recommended, is also influenced by the design speed. One would not expect to find high operating speed reductions on curves unless the design speed was also greatly reduced (Anderson and Krammes, 2000). Thus, design speeds that are constant along longer sections of the roadway are recommended since they help reduce operating speed fluctuations and promote a greater level of highway consistency (Lamm et al., 1999).

Finally, it is important to clarify that this measure is used to evaluate the consistency of individual design elements only, which are usually horizontal curve segments. Theoretically, it could be applied to independent tangents as well, taking the design speed of the tangent as that of the entire highway alignment. However, the use of

this measure for evaluating the consistency of tangent sections is not currently possible since a successful model for predicting operating speed on tangents is not yet available.

2.1.2 Operating Speed Consistency

Operating speed consistency (Safety Criterion II) is based on the speed reduction between two consecutive elements; either an independent tangent followed by a curve, or two curves separated by a non-independent tangent. Thus, this safety measure provides a consistency evaluation for successive elements along a roadway rather than individual elements. The evaluation of successive elements on a highway alignment is one of the basic principles of consistency evaluation that is not covered in traditional North American design practices. Operating speed consistency is by far the most common method of consistency evaluation, since large changes in vehicle speed are a frequent and observable indicator of driver expectancy violation. In fact, many road specialists believe that speed variation is more important to safety than the value of speed.

To calculate speed reduction, the 85th percentile speeds on a curve and its preceding independent tangent, or on two successive curves separated by a non-independent tangent are first predicted. The difference between these values represents the 85th percentile of speed reduction ($\Delta V_{85} = |V_{85i} - V_{85i+1}|$). Independent tangents are those tangents long enough to permit acceleration to and deceleration from the free-flow speed. On the other hand, non-independent tangents are those tangents that are too short to permit acceleration and have speeds similar to their preceding curve. Based on the relationship between tangent lengths and operating speed provided in Lamm et al. (1999), tangents less than approximately 180 m in length were considered to be non-independent

in this study. To achieve a consistent design, designers should try to minimize the changes in operating speed induced by curve radius and tangent length.

Some road specialists have raised the concern that ΔV_{85} may not provide an accurate representation of individual speed reductions experienced by drivers. It was hypothesized that this measure underestimates the actual speed reduction since it is based on independent speed distributions at each location. This is a considerable concern, since it implies that the evaluations provided by this measure overrate the consistency level of alignments. Motivated by this hypothesis, McFadden and Elefteriadou (2000) studied the implications of using ΔV_{85} for consistency evaluation. The results of their study confirmed that ΔV_{85} significantly underestimates speed reduction.

A new potential measure for quantifying speed variability, named the 85th percentile maximum speed reduction (*85MSR*) was suggested by McFadden and Elefteriadou (2000). This measure is computed using the speed profiles from approach tangent to curve for each driver to determine the maximum speed reduction each driver experiences. These maximum speed reductions are then sorted to determine the value of *85MSR*. This new measure was believed to be a more logical and accurate approach for predicting the reduction in operating speeds. McFadden and Elefteriadou (2000) also conducted a comparison between *85MSR* and ΔV_{85} and it was found that *85MSR* values were typically two times larger than the values of ΔV_{85} . This would suggest that if one were evaluating design consistency based on the ΔV_{85} speeds, this value would have to be multiplied by two to obtain a more accurate result of the actual speed reduction experienced by drivers. However, research relating this measure to safety has not been found in the literature. Further studies were recently conducted by Misaghi (2003) to

develop a speed prediction model based on this concept, and determine whether it should replace the traditional method of calculating operating speed reduction. The results of this study are presented in Section 2.1.4.

2.1.3 Operating Speed Safety Criteria

Lamm et al. (1999) recommended two sets of criteria for operating speed and design speed consistency evaluation (Table 2.1), that were based on the following foundation:

1. The experience that the values for Safety Criteria I and II should fall within certain ranges.
2. Accident analysis and comparative evaluations, indicating the permissible and non-permissible changes in speed for the assessment of “Good”, “Fair” and “Poor” consistency levels for Safety Criteria I and II.

Table 2.1 illustrates the cut-off points for “Good”, “Fair” and “Poor” designs applicable to operating speed-based consistency measures. Experience has shown that the collision rates corresponding to “Fair” design levels are at least twice as high as the collision rates for “Good” design levels, while collision rates on curves classified at the “Poor” design level were found to be four to five times as high as the “Good” design level. It is recommended that new designs of two-lane rural roads should satisfy the “Good” design level. Although the “Fair” design level can be acceptable in redesign, and Reconstruction, Rehabilitation and Restoration (RRR) projects, it is recommended that additional guidance, such as traffic warning signals, be given to drivers in these areas (Lamm et al., 1999).

Table 2.1: Operating Speed Based Consistency Criteria (Lamm et al., 1999).

Evaluation	Safety Criterion I:	Safety Criterion II:
Good	$ V_{85} - V_D \leq 10 \text{ km/h}$	$\Delta V_{85} = V_{85i} - V_{85i+1} \leq 10 \text{ km/h}$
Fair	$10 \text{ km/h} < V_{85} - V_D \leq 20 \text{ km/h}$	$10 < \Delta V_{85} \leq 20 \text{ km/h}$
Poor	$ V_{85} - V_D > 20 \text{ km/h}$	$\Delta V_{85} > 20 \text{ km/h}$

Where: V_{85} = operating speed; V_D = design speed; and V_{85i} and V_{85i+1} = operating speed on elements i and $i+1$.

Table 2.1 shows that speed differentials in excess of 20 km/h reflect a “Poor” design. Considering the limits provided for Safety Criterion I, it is interesting that the curve design can tolerate an operating speed of up to 20 km/h in excess of the design speed. This is due to the fact that roadway design is based on design speed values for near worst-case road conditions, while operating speed prediction models are based on normal driving conditions.

Upon a review of the criteria development process presented in Lamm et al. (1988), it was found that some vagueness with respect to the precise database and procedure used for the development of these two safety criteria exists. The safety classes for the operating speed consistency measures were established based on two sets of linear regression models, one relating curvature change rate (CCR) to collision rates, and the other relating CCR to the consistency measures. The regression models were mainly based on a US database of 261 curved sections located in a limited area in the State of New York. The breakpoint values of safety were first determined in terms of CCR , and then incorporated into the models relating CCR to the design consistency measures. It is not clear why a more direct approach was not taken, i.e. relating the speed based

measures to collision rates to directly identify their values that correspond to breakpoints in safety.

Two concerns were raised upon this review of the criteria development process. Firstly, the collision rates rather than collision frequencies were modeled to allow the consideration of section length and traffic volume. This approach leads exposure, which is a chief variable in explaining the variability of collisions, to be used indirectly in calculating the model parameters. Furthermore, the use of collision rates has been greatly criticized since it is based on the false assumption that a linear relationship exists between traffic volume and collision rate (Pasupathy et al., 2000). Secondly, the development of collision models based on linear regression has several associated flaws as emphasized by numerous researchers including Jovanis and Chang (1986). Presently, the mainstream statistical approaches used for the modelling of count data such as collisions are Poisson and negative binomial regression.

Although the average collision rates for these classes correspond to significant increases in collision rates, the validity of these classes as showing the breakpoints in safety requires further justification. Lamm et al. (1988) stated that caution should be exercised in extrapolating these models for use in different locations due to the limited geographical area from which data was collected for model development. Thus, these criteria may not be applicable to different national situations, and it is recommended that their applicability to different areas be verified.

An additional concern regarding the use of Safety Criteria I and II is that they promote a rigid approach to highway design. For example, a curve experiencing a speed reduction of 10.1 km/h, and a curve with a speed reduction of 20 km/h are both considered

to fall within the “Fair” safety level. In this study, continuous functions relating each of the consistency measures to safety were developed as an alternative approach for consistency evaluation. These models allow a clearer assessment of the safety impact of varying the consistency of design elements, and the tradeoffs between improving design consistency and the additional cost associated. Thus, this system provides a more flexible approach, which is in accordance with the “design domain” concept, since it allows the designer to identify what is acceptable in terms of safety, without providing rigid categories for “Good”, “Fair” or “Poor” designs.

2.1.4 Operating Speed Prediction on Curves

The prediction of operating speed is a crucial stage in conducting operating speed based consistency evaluations. Compared to alternative consistency measures, a relatively high share of research has been dedicated to the area of operating speed prediction. Traditionally, researchers have focused on developing operating speed prediction models for horizontal curves of two lane highways due to the overrepresentation of collisions on these roadway segments. Models for vertical curves and combined horizontal and vertical curves have also been developed, in addition to attempts to predict operating speed on tangent sections. Although the operating speed selected by drivers on horizontal curves can depend on many factors, the key geometric variable that studies have repeatedly found to affect operating speed and collision experience is the radius of horizontal curve or degree of curvature. Thus, most operating speed prediction models are based on either of these variables.

Operating speed prediction models are generally limited to highway sections with the following characteristics: (1) intersections are not present; (2) no physical features

adjacent to or in the course of the highway that may cause abnormal hazard such as narrow bridges; (3) shoulders are paved and the sections are delineated; (4) lane width does not change; and (5) grades are less than 5% (Gibreel et al., 1999). This is considered a significant limitation in current models, since design elements such as changes in lane width and grades have a significant impact on design consistency. It is noteworthy that the operating speed prediction models developed in previous studies are applicable to both dry and wet roadway surfaces, since studies have shown that the existence of a wet roadway surface does not influence driver speed. Many drivers do not realize that the wetter the roadway surface, the less the friction available between the pavement and the vehicle tires. This may lead drivers to adopt inappropriate vehicle speeds that enhance their collision risk (Lamm et al., 1999).

Another note regarding operating speed prediction models is that they mainly focus on the prediction of operating speed for passenger cars only. Al-Masaeid et al. (1995) developed operating speed reduction models in Jordan based on a total of 93 horizontal curves for different vehicle classes. Models for operating speed reduction were developed for passenger cars, trucks, light trucks and all vehicle classes combined. Based on this analysis, it was found that the speed reduction for all vehicle types was highly comparable to the speed reduction for each vehicle type separately, with passenger cars representing the lowest values in speed reduction. Thus, it can be concluded that developing operating speed models for only passenger cars does not represent a significant limitation, particularly since they provide the most conservative results. However, further studies are required to validate the applicability of this conclusion to Canadian road conditions.

Numerous operating speed prediction models have been developed worldwide. The most significant and extensive operating speed prediction models developed in North America are those developed by Fitzpatrick et al. (2000c) for the IHSDM. These models were derived from speed data collected at 176 two-lane rural highway sites in six states. Several equations were developed to predict the impact of both the horizontal and vertical alignments on operating speed, in addition to equations for the prediction of acceleration and deceleration rates on tangents. These speed prediction models are based on horizontal curve radius and vertical curvature, and are replicated in Table 2.2.

Like many other operating speed prediction models, the predicted speeds resulting from Table 2.2 represent the speeds measured at the curve mid-point. It is assumed that speed is constant throughout the horizontal or vertical curve and that acceleration and deceleration occurs on tangents only. The error in operating speed resulting from these simplifications was believed to be insignificant (Krammes et al., 1995). This appears to be a common assumption in speed prediction models. However, several researchers have suggested that there is a significant variation in speed within a curve (e.g. Islam and Seneviratne, 1994). Thus, using the midpoint of the curve for data collection and model estimation may compromise the accuracy of consistency ratings provided by the resulting operating speed prediction models.

Table 2.2: Operating Speed Prediction Models (Fitzpatrick et al., 2000c).

EQ. No.	Alignment Condition	Equation	No. of Obs.	R ²	MSE
1	Horizontal Curve of Grade: -9% ≤ G < -4%	$V_{85} = 102.10 \times \frac{3077.14}{R}$	21	0.58	51.95
2	Horizontal Curve of Grade: -4% ≤ G < 0%	$V_{85} = 105.98 \times \frac{3709.90}{R}$	25	0.76	28.46
3	Horizontal Curve of Grade: 0% ≤ G < 4%	$V_{85} = 104.88 \times \frac{3574.51}{R}$	25	0.76	24.34
4	Horizontal Curve of Grade: 4% ≤ G < 9%	$V_{85} = 96.61 \times \frac{2752.19}{R}$	23	0.53	52.54
5	Horizontal Curve Combined with Sag Vertical Curve	$V_{85} = 105.32 \times \frac{3438.19}{R}$	25	0.92	10.47
6	Horizontal Curve Combined with Non-Limited Sight Distance Crest Vertical Curve	Use lowest of the speeds predicted from EQ. No. 1 or 2 (for downgrade) and EQ. No. 3 or 4 (for upgrade)	13	N/a	N/a
7	Horizontal Curve Combined with Limited Sight Distance Crest Vertical Curve	$V_{85} = 103.24 \times \frac{3576.51}{R}$	22	0.74	20.06
8	Sag Vertical Curve on Horizontal Tangent	$V_{85} = \text{assumed desired speed}$	7	N/a	N/a
9	Vertical Crest Curve with Non-Limited Sight Distance Crest on Horizontal Tangent	$V_{85} = \text{assumed desired speed}$	6	N/a	N/a
10	Vertical Crest Curve with Limited Sight Distance Crest on Horizontal Tangent	$V_{85} = 105.08 \times \frac{149.69}{K}$	9	0.60	31.10

In Canada, guidelines for operating speed consistency evaluation were presented in the 1999 Geometric Design Guide published by the Transportation Association of Canada. These guidelines were obtained directly from the operating speed profile model developed in the United States by Krammes et al. (1995), which is described as follows:

$$V_{85} = 102.45 + 0.0037L - \frac{(8995 + 5.37L)}{R} \quad (2.1)$$

Where: V_{85} = 85th percentile speed (km/h);

L = length of curve (m); and

R = radius of curvature (m).

However, there are two models for predicting operating speed on horizontal curves that have been developed in Canada: Morall and Talarico (1994), and Gibreel et al. (2001). The model by Gibreel et al. takes into account the effect of combined horizontal and vertical alignments, while that by Morall and Talarico considers the horizontal alignment only. These models are expected to be more suitable for Canadian road conditions than U.S. models. This is because a considerable spread exists in the values of operating speeds adopted by drivers in different countries, even on roads with very similar characteristics (Cafiso, 2000).

Morall and Talarico (1994) collected speed data for nine horizontal curve sites on rural two-lane highways in Alberta using a radar speedometer. Linear, multiplicative, exponential and reciprocal regression models were investigated and the following model was found to provide the best fit to the data:

$$V_{85} = \text{Exp}(4.561 - 0.00586DC); \quad R^2 = 0.631 \quad (2.2)$$

Where: DC = degree of curve (degrees/100m).

Although this model has a reasonable coefficient of determination (R^2), the small sample size necessitates further research to provide a more reliable model for Canadian operating speed prediction. An additional disadvantage of this model is that it does not take the effect of spiral curves on operating speed into account and cannot be used for compound curves. German operating speed models are based on the curvature change rate (CCR) defined as the absolute sum of angular changes per unit length of highway section. The advantage of using this measure over radius or degree of curve is that CCR can be applied to compound curves and curves with spirals. Lamm et al. (1999) modified the model developed by Morall and Talarico (1994) using CCR as follows:

$$V_{85} = \text{Exp}(4.561 - 0.000527CCR) \quad (2.3)$$

Another drawback related to the model developed by Morall and Talarico (1994) is that it was developed for simple horizontal curves of two lane rural highways only. When applied to combined horizontal and vertical curves, it was found that the predicted speed values were significantly different from speeds observed in the field (Gibreel et al., 2001). Thus, Gibreel et al. (2001) developed two sets of 3D models for the operating speed prediction of sag and crest curves. The geometric design and operating speed data needed for this study was collected from 38 sites on Highway 61 and Highway 102 in Ontario. The operating speed of free-flowing vehicles was collected using a speed radar-gun device at five different points along the curve to account for speed variability within a curve. In total, ten equations for sag and crest combinations were developed. The multiple linear regression method was applied for model estimation. The models for sag and crest combination curves both resulted in high coefficients of determination ranging from 0.79 to 0.98. The model verification process showed that the maximum difference

between the observed and predicted speeds on combined curves did not exceed 2.5%, while other 2D models provided results with 5-17 times this value. Thus, the 3D-model exhibited results that are far more accurate when dealing with combined horizontal and vertical curves than previous 2D models.

More recently, Misaghi (2003) conducted a study for developing operating speed (V_{85}), and operating speed differential ($\Delta_{85}V$) prediction models based on 20 of the 70 curve sites in this study. The $\Delta_{85}V$ corresponds to the 85th percentile speed reduction, which is computed as the 85th percentile of the speed reduction experienced by each driver from approach tangent to curve. Data collection was conducted with the use of automatic Traffic Counters/Classifiers for the collection of speed data, a rain gauge for the recording of rain data at the site during speed data collection, and a ball bank indicator for the collection of superelevation data. Counters were installed at the middle of the curve, and both the approach and departure tangents for a 24-hour period. Only data for daytime and dry roadway surface conditions were included in the model database. In addition, a radar gun was used to calibrate counter readings, and was found to provide very similar results. The geometric variables investigated for model development consisted of all variables included in the last five decades of research in operating speed model development.

Considering the operating speed prediction model, it was found that operating speed has no statistically significant relationship to any of the variables considered. It was unexpected that even curve radius would have a statistically insignificant relationship to safety. Particularly since almost all speed prediction models in the past are based on radius, degree of curve, or curvature change rate. Thus, it was concluded by Misaghi

(2003) that a relationship between geometric and traffic curve features to operating speed does not exist. It was stated that since over 90% of previous studies were based on radar guns, the presence of speed operators may have caused drivers to reduce their selected speeds, and thus compromise the accuracy of previous model results. For the purpose of this study, the model database developed by Misaghi was adapted by removing four of the curve sites to allow the development of an acceptable model, shown in Equation 2.4.

$$V_{85} = 91.943 + (0.01 \times R); R^2 = 0.505 \quad (2.4)$$

On the other hand, speed differential ($\Delta_{85}V$) was found to have a strong correlation to tangent speed (V_{Tang}), deflection angle (def_ang), shoulder width (SW), curve direction ($curve_dir$), longitudinal grade (G), and the presence of a driveway (drv_flag). This speed differential model is illustrated in Equation 2.5. However, this model was further simplified for application in this study to include only the two most significant variables: operating speed on tangents and the deflection angle as shown in Equation 2.6.

$$\Delta_{85}V = -184.707 + (20.123 \times V_{Tang}^{0.5}) + (5.717 \times def_ang) - (4.336 \times SW) - (5.665 \times curve_dir) + (0.889 \times G) + (3.192 \times drv_flag); R^2 = 0.854 \quad (2.5)$$

$$\Delta_{85}V = -167.96 + (17.35 \times V_{Tang}^{0.5}) + (0.0893 \times def_ang); R^2 = 0.700 \quad (2.6)$$

Among the operating speed prediction models presented, those shown in Equations 2.4 and 2.6 were selected for application in this study. These models were preferred since they are based on the same geographic location of the curves in this study database, and are thus expected to provide more accurate operating speed predictions.

Another approach for operating speed prediction on curves is based on sight distance. Lee et al. (2000) developed a model for operating speed prediction based on the

effect of minimum sight distance on driver speeds. One of the main differences between this and previous models is the hypothesis that drivers within a curve travel at a constant speed when the available sight distance does not change. However, if at a certain point within the curve the sight distance were increased, drivers would accelerate inside the curve and reach their desired speed at a point outside of the curve. This model also provides equations for determining the length of the deceleration and acceleration sections. One of the advantages of using this model is that it can be easily applied to evaluate combined horizontal and vertical alignments.

2.1.5 Operating Speed Prediction on Tangents

The prediction of operating speed on independent tangents is also essential for conducting an operating speed consistency evaluation. However, it is far more complex than the prediction of operating speed on curves. This is due to the fact that the speed on tangents is dependent on a large range of road characteristics including length of tangent section, radius of horizontal curve prior to and after the section, cross-sectional elements, vertical alignment, general terrain, and available sight distance (Polus et al., 2000). Because of the complexity of this task, and the large database needed to model the speeds on tangents, the few research projects that attempted to model speeds on tangents received limited success and very low R^2 values.

For example, Polus et al. (2000) conducted a study using data collected from 162 sites and presented a preliminary model for the estimation of operating speed on tangent sections. This model was based on a geometric measure dependant on the tangent length and the previous and following curve radii. Four prediction models were developed for four groups of data with similar characteristics: Group 1: small radii and short tangent

length; Group 2: small radii and intermediate tangent length; Group 3: intermediate radii and intermediate tangent length; and Group 4: any radius and long tangent length. The models for Groups 1 and 2 met some success with R^2 values of 0.553 and 0.684 respectively, while the models for Groups 3 and 4 received little success and are still in the preliminary stage.

Since there is no satisfactory model that can be included in the operating speed evaluation of two-lane rural highways so far, estimates based on field observations of vehicle speeds on tangents under free-flow conditions are used. Based on research conducted for the IHSDM, the average operating speeds on long tangents were found to range between 93 km/h and 104 km/h. The use of a speed equal to 100 km/h was suggested as an estimate when a representative speed on independent tangents is requested (Fitzpatrick et al., 2000c). Alternatively, the operating speed on tangents can be estimated as 95.7 km/h by simply setting DC and CCR to zero in Equation 1 and Equation 2 respectively. The field measurement of operating speed at 20 of the 70 curve sites under study resulted in the recommendation of an 85th percentile speed of 103.0 km/h on all independent, and 96.0 km/h on all non-independent tangents (Misaghi, 2003).

2.1.6 Operating Speed Profile

A speed profile is a graphical display that facilitates the identification of locations with operating speed inconsistencies. Several European countries use speed-profile models to identify where critical speed changes occur along a roadway alignment. Different speed profile models have been developed by Leish and Leish (1977); Lamm et al. (1988); Krammes et al. (1995); and Fitzpatrick et al. (2000c). However, the basic

principles behind these different speed profile models remain the same. A speed profile is generally constructed by carrying out the following procedure:

1. Select the desired speed on independent roadway tangents,
2. Predict the operating speed of the curves (speed is assumed constant throughout the curve in most models), and
3. Adjust the speeds for acceleration and deceleration entering and departing the curve.

The speed profile model applies the operating speed on curves and tangents, and the acceleration and deceleration rates in combination with the basic equations of motion to estimate the operating speed at each point along the horizontal alignment (Krammes et al., 1995). The acceleration to and deceleration from the tangent speed are usually performed on the tangents or spiral curves if available. In the case of compound curves, the change in speed is assumed to take place on the flatter curve. Previously, the rate of acceleration and deceleration on tangents was assumed to occur at 0.85 m/s^2 . However, a recent study by Fitzpatrick et al. (2000c) suggested that this assumption is not valid except for curve radii less than 250 m, and developed new models for calculating acceleration and deceleration rates based on curve radius.

Faghri (2000) developed a new knowledge-based expert system, combined with Geographic Information Systems to evaluate horizontal alignment design consistency on U.S. highways. By evaluating the degree of curve for each roadway element, this program can construct a speed profile and evaluate the operating speed consistency of horizontal alignments. The driver workload, an alternative method for consistency evaluation, is also considered when the operating speed evaluation is on the border of two consistency ratings.

2.2 VEHICLE STABILITY

When a vehicle negotiates a curve, it experiences a centrifugal force that directs it outwards of the curve's circular path. The centrifugal force acting on vehicles is balanced by the lateral friction between the tires and the surface, and a component of vehicle weight caused by superelevation. If vehicles travelling on a curve demand a side friction that is in excess of what is provided, this may lead to skidding, vehicle rollover or head-on collisions. The inability of drivers to navigate this curve without loss of vehicle control violates their expectancy and can consequently be labelled as a design inconsistency. For a curve to ensure a safe level of vehicle stability and design consistency, it should supply enough side friction demand to balance centrifugal forces. Indeed, many researchers have stressed that providing sufficient side friction supply is to be regarded as an essential safety issue. Lamm et al. (1999) developed a design consistency measure for the evaluation of vehicle stability based on a margin of safety of the difference between side friction supply and side friction demand on a curve, referred to as Safety Criterion III.

The side friction factor is one of the most basic controls related to highway curve design, and is often used to design critical curve elements such as the minimum radius. Values of design side friction factors are considered to represent upper limits of driver comfort. It is assumed that drivers will reduce their vehicle speed when they reach a state of discomfort before causing the vehicle to slide laterally due to lack of side friction. However, these side friction values are based on research conducted in the 1930's and 1940's, and surprisingly little research has been conducted in this area since then. Thus, many researchers have rightly argued that the side friction factors used in current

guidelines are no longer applicable to today's drivers, vehicles and roads, and have emphasized the need for further research in this area (e.g. Fitzpatrick, 1994). In this section, a review of the basic driving dynamic formula currently used in design guidelines is first presented, followed by the recommended consistency measure based on vehicle stability. Finally, a subjective approach for overall consistency evaluation based on Safety Criteria I, II and III is presented.

2.2.1 The Point Mass Formula

The basic driving dynamic formula used for curve design is commonly known as the point mass formula. This formula provides a basic relationship between design speed, curve radius, superelevation, and the coefficient of side friction, which is dependant on speed. The point mass formula is expressed as follows (*A policy*, 2001):

$$f_r + e = \frac{V_D^2}{127R} \quad (2.7)$$

Where: f_r = coefficient of side friction;

e = superelevation rate (m/m); and

V_D = design speed (km/h).

The point mass formula has been subjected to considerable criticism from several researchers. Glennon and Weaver (1972) raised several main concerns related to this model. Firstly, the point mass formula does not consider the 3-dimensional (3D) nature of highways. The results of previous research suggest that 2-dimensional (2D) analysis may tend to overestimate or underestimate results, while 3D analysis has proved to be more reliable. Secondly, the variation in the distribution of friction between different tires is not considered, since the vehicle is represented by a point mass rather than a body. It is

noted that new models that consider the friction variation between different tires and the interaction between longitudinal and side friction have been developed, including the bicycle model (Kontaratos et al., 1994). Thirdly, it is assumed that the vehicle moves with a constant speed and follows a path with a radius equal to the curve radius. Studies have shown that vehicle speeds tend to vary on curves rather than travelling with constant speed, and experience their critical path manoeuvres near the start and end of the curve rather than following a constant radius.

Another concern raised regarding this model is that some studies have shown that faster drivers frequently accept side friction below comfort levels to maintain speed, thus increasing their collision risk. This violates the basic assumption behind design side friction factors, which is that drivers will reduce vehicle speed at upper limits of driver comfort. Bonneson (2001) developed a side friction prediction model based on the hypothesis that drivers will modify their side friction demand to achieve a combination of safe and efficient travel. This model reflects the desire of drivers to decrease side friction demand with increased speed, likely due to driver sensitivity to side friction supply, and also reflects the willingness of drivers to tolerate slightly higher side friction demand to minimize the amount of speed reduction required on sharp curves. Bonneson's model was mainly based on the approach speed and operating speed reduction of a curve. Used with the allowed speed reduction, this model can provide the maximum allowable side friction for the design of critical design control elements.

Nonetheless, the application of the point mass formula is much simpler than the different models developed to overcome its shortcomings. Thus, the point mass formula is still the most widely applied method for the design of curves in highway geometric

design guidelines. In this study, the point mass formula was applied to reduce the complexity of the safety-based consistency models developed. The vehicle stability and design speed consistency measures both relied on the point mass formula for the estimation of the side friction demand and limiting speed on the horizontal curves.

2.2.2 Consistency of Vehicle Stability

A major drawback of current North American curve design procedures is that they do not indicate a margin of safety for the difference between side friction supply and side friction demand on a curve. To overcome this lacking, Lamm et al. (1999) suggested a criterion for vehicle stability based on the above margin of safety as a measure for consistency evaluation, (Safety Criterion III). This measure is determined by calculating the difference between friction supply and friction demand on a curve. If friction demand exceeds supply, this may prohibit safe vehicle operation and would imply inconsistency and vehicle instability. It should also be noted that this measure is similar to Criterion I in the sense that it provides an evaluation of individual design elements, namely single curved sections. One of the advantages of this model is that it is not limited to two-lane rural highways, and is thus applicable to multi-lane rural and suburban roads.

Side friction is directly related to the tangential friction factor as shown in Equation 2.8 below. To develop a model for side friction supply, Lamm et al. (1999) developed a relationship between maximum permissible tangential friction and design speed based on the highway geometric design guidelines in Germany, France, Sweden, Switzerland, and the United States. This formula is shown in Equation 2.9. Accordingly, different side friction models based on topography conditions, and different utilization ratios reasonable for the highway category examined were developed. The formula

applicable for most highways investigated in this study is shown in Equation 2.10, developed for flat topography, and a maximum superelevation rate of 8%.

$$f_{Rperm} = N \times 0.925 \times f_{Tperm} \quad (2.8)$$

$$f_{Tperm} = 0.59 - 4.85 \times 10^{-3} \times V_D + 1.51 \times 10^{-5} \times V_D^2 \quad (2.9)$$

$$f_r = 0.25 - (2.02 \times 10^{-3} \times V_D) + (0.63 \times 10^{-5}) \times V_D^2 \quad (2.10)$$

Where: f_{Rperm} = maximum side friction factor;

f_{Tperm} = maximum tangent friction factor;

N = utilization ratio; and

f_r = side friction supply.

Furthermore, one of the highways investigated in this study was characterized as having mountainous terrain. Thus, the formulas for tangential and side friction developed for hilly and mountainous topography were also applied, with a maximum superelevation rate of 7%, as shown in Equations 2.11 and 2.12. It should be noted that the value of the design speed (V_D) in Equations 2.10 and 2.12 is to be taken as the design speed for the highway section, therefore leading to a constant side friction supply along the highway.

$$f_{Tperm} = 0.27 - 2.19 \times 10^{-3} \times V_D + 0.58 \times 10^{-5} \times V_D^2 \quad (2.11)$$

$$f_r = 0.22 - (1.79 \times 10^{-3} \times V_D) + (0.58 \times 10^{-5}) \times V_D^2 \quad (2.12)$$

On the other hand, side friction demand is based on the predicted operating speed of drivers. It is calculated using the point mass formula by simply inserting the operating speed in place of the design speed as shown in Equation 2.13. Despite its many drawbacks, this formula was used in this study due to its simplicity. An additional advantage of using this model for estimating side friction demand is that it is based on the

actual curve radius and superelevation rate, with the only estimated value in the calculation being operating speed.

$$f_{rd} = \frac{V_{85}^2}{127R} - e \quad (2.13)$$

Based on the collision research and the underlying assumptions of the operating speed based safety criteria presented in Section 2.1.3, Safety Criterion III was suggested for consistency evaluation based on vehicle stability as shown in Table 2.3. It is noted that the same concerns regarding the use of Safety Criteria I and II apply to Safety Criterion III as well.

Table 2.3: Vehicle Stability Consistency Criterion (Lamm et al., 1999).

Evaluation	Safety Criterion III
Good	$\Delta f_r = f_r - f_{rd} \geq +0.01$
Fair	$+0.01 > \Delta f_r \geq -0.04$
Poor	$\Delta f_r < -0.04$

2.2.3 Overall Module Suggested by Lamm et al. (1999)

In addition to the three Safety Criteria presented above, Lamm et al. (1999) suggested a subjective technique for overall consistency evaluation. This overall safety module is based on the assumption that the consistency measures have equal importance with respect to their impact on safety as follows:

- Good design: 3 good; 2 good and 1 fair; or 2 good and 1 poor.
- Fair design: 3 fair; 2 fair and 1 good; or 2 fair and 1 poor.
- Poor design: 3 poor; 2 poor and 1 good; or 2 poor and 1 fair.

This module is considered useful; however, the assumption that each consistency measure has an equal impact on the consistency level of a design is not necessarily accurate. Safety research has suggested that Safety Criterion II has the strongest relationship to safety, followed by Safety Criterion III, and Safety Criterion I respectively (Lamm et al., 1999). Thus, the assumption made by Lamm et al. (1999) is not suitable for an accurate overall consistency evaluation. An objective approach for ranking the importance of consistency measures that is based on the relationships of each measure to safety would provide a superior approach for overall consistency evaluation. Another considerable drawback in this model is that it does not consider the potential of other consistency measures that have been found to have a noteworthy impact on safety, namely alignment indices and driver workload.

2.3 ALIGNMENT INDICES

Alignment indices are quantitative measures of the general character of a roadway segment's alignment. Geometric inconsistencies occur when the general character of the alignment changes in different sections. Sudden changes in the alignment, such as a succession of flat curves followed by a sharp curve, violate driver expectancy and can lead to unsafe speed changes and/or driving manoeuvres, and a higher collision risk. Alignment indices provide a simple method to measure consistency by directly quantifying certain design characteristics in the roadway geometry that are likely to impact driver behaviour. Alignment indices are derived from the dimensions of horizontal and/or vertical design features over an entire section of roadway, and thus provide a simple method for quantitative evaluation of consecutive elements on a roadway section. Proposed indicators of design inconsistency are: large

increases/decreases in the values of alignment indices for successive segments, a high rate of change in the alignment indices over some length of the roadway, and large differences between the individual feature and the average value of the alignment index (Fitzpatrick et al., 2000a).

Only limited work on alignment indices has been conducted in North America. However, they have been applied for many years in Germany for consistency evaluation, and in England as a basis for operating speed prediction (Fitzpatrick et al., 2000a). Researchers have suggested numerous alignment indices for consistency evaluation. For example, Polus and Dagan (1987) proposed design consistency measures based upon: the proportion of a roadway section that is curved, the ratio of the minimum and maximum radii of a roadway section, the ratio of the average radius of curves on a roadway section to the minimum section of the roadway design speed, and a spectral analysis of the extent to which the alignment exhibits a cyclical pattern. Their initial analyses indicated that these indices are potentially useful measures of consistency.

The potential of alignment indices as measures for consistency evaluation was also studied for possible application to the IHSDM's design consistency module. Based on extensive research of alignment indices used in other countries or proposed indices, Fitzpatrick et al. (2000c) documented a list of promising alignment indices for evaluation of horizontal, vertical and combined alignments. These indices were initially studied to determine their applicability in predicting operating speeds on tangents. However, this postulation was later dismissed after they were all found to be statistically insignificant with respect to the prediction of operating speeds on tangents.

Regarding their applicability to consistency evaluation, Fitzpatrick et al. (2000c) found the relationships of select alignment indices to safety to provide more encouraging results. The alignment indices recommended as potential measures of design consistency on a road section were:

1. Average radius of curvature;
2. Maximum radius of curvature to minimum radius of curvature;
3. Average tangent length;
4. Average rate of vertical curvature;
5. Ratio of individual curve radius to average radius; and
6. Ratio of individual tangent length to average tangent length.

The first four indices are measures of the whole highway segment, while the last two measures are ratios of individual elements to the highway segment. Regression models between each alignment index and collision frequency were developed. Based on this analysis, the following four alignment indices were found to have statistically significant relationships to safety: average radius of curvature, ratio of maximum radius of curvature to minimum radius of curvature, curve radius to average radius, and average rate of vertical curvature. Thus, these four measures were considered the most promising alignment indices for consistency evaluation. On the other hand, the regression models for average tangent length, and ratio of individual tangent length to average tangent length were unsatisfactory, and were not recommended for use as measures of consistency.

The main advantage of alignment indices is that they are extremely easy for designers to use, understand and explain. Another advantage of alignment indices is that

they can provide a mechanism for quantitatively comparing successive geometric elements from a system wide perspective (Anderson et al., 1999). Of the consistency measures presented, only alignment indices are capable of providing this sort of system wide evaluation, which is a basic concept in design consistency. In addition to use in an overall consistency model, it is recommended that alignment indices be used separately since they can provide the designer with a conceptual advantage in understanding the general character of the roadway. However, caution should be exercised since these measures can be deceiving in cases of extremities in the geometric design.

2.3.1 Average Radius of Curvature

The Average Radius (AR) expresses the sharpness of curves representative of a given section of the roadway. It is determined by dividing the sum of curve radii on a highway section by the number of curves on that section as shown in Equation 2.15. Many studies have found that curve radius is the primary predictor of operating speed and safety on horizontal curves, thus the average radius of curves can be used as a general indicator to the operating speeds on a specific roadway segment. A large average radius is an indication of high speeds on that road segment, and vice versa.

$$AR = \sum \frac{R_i}{n} \quad (2.14)$$

2.3.2 Ratio of Maximum Radius to Minimum Radius

The ratio of the maximum and minimum curve radii (RR) is a measure of the range of curve radii on a highway alignment, and represents the consistency of the design based on the similarity of curves used. As the value of RR approaches 1.0, the design consistency is expected to improve. However, one of the problems associated with the

use of this ratio is that it only reflects the similarity of curves, and does not indicate whether it is due to a series of similar flat curves or similar sharp curves. An additional disadvantage of this measure is that it does not demonstrate the number of curves or the length of highway evaluated. RR is calculated as follows:

$$RR = \frac{R_{\max}}{R_{\min}} \quad (2.15)$$

2.3.3 Curve Radius to Average Radius

An extension of AR is the Curve Radius to Average Radius (CRR), which is a ratio comparing individual horizontal curves to all horizontal curves in the roadway section under study. CRR is calculated as follows:

$$CRR_i = \frac{R_i}{AR} \quad (2.16)$$

The hypothesis behind this index is that if the curve radius is considerably different from the average radius of the curve section, a violation to driver expectancy will occur. The principles of design consistency propose that not only is the radius of a curve important to safety, but also the curve features relative to the roadway environment in which it is located. Statistical studies have shown that differences in collision rates between curves of the same radius exist mainly due to the characteristics of the upstream horizontal alignment. One of the advantages of applying CRR is that in addition to identifying design inconsistencies due to sharper than average curves, it also identifies inconsistencies due to flatter than average curves. This is particularly valuable, since other measures of design consistency generally identify violation of driver expectancy due to sharp curves only. Thus, this alignment index was selected for further collision analysis in this study.

A major shortcoming in current alignment indices is the lack of an explicit criterion for rating consistency level. Currently, engineering judgement can be used to determine whether an alignment index value is considered to lead to safe or unsafe driving conditions. With respect to the ratio of curve radius to average radius (*CRR*), as the value approaches 1.0, a reduced collision frequency is expected. A curve with a *CRR* value of 0.5 will be considered by many to have a relatively higher potential for collisions. However, the cut-off points between “Good”, “Fair” and “Poor” safety ratings are not as clear. For example, some might disagree whether a curve with a *CRR* of 0.6 is considered “Fair” or “Poor”. Thus, additional research relating *CRR* to safety is needed to help establish an objective safety criterion for consistency evaluation based on this measure. It should also be noted that since this measure only provides relative information, there is no indication to the general sharpness of curves within an alignment. For example, a *CRR* near 1.0 could be based on a series of curves with $R = 1000$ m, or a series of curves with $R = 200$ m.

An additional shortcoming is that the variation of *CRR* along a highway, which is also an indicator of alignment inconsistency, is not directly addressed. However, the variation of radius can be visualized by plotting the radius to average radius as a function of location. However, the exact degree of variation considered an indicator to inconsistency is not yet clear.

2.3.4 Average Rate of Vertical Curvature

The average rate of vertical curvature (*AVC*) provides an indication to the amount of change in the vertical alignment of a roadway. The hypothesis is that the amount of hilliness may have an effect on speeds and collisions. *AVC* is determined as follows:

$$AVC = \frac{L_i / |A_i|}{n} \quad (2.17)$$

Where: AVC = average rate of vertical curvature (m/ % grade);

L_i = length of i^{th} vertical curve on the roadway section (m);

$|A_i|$ = absolute value of the algebraic difference in grade of the i^{th} curve (%); and

n = number of curves within a section.

2.4 DRIVER WORKLOAD

The mental workload experienced by drivers is one of the most important concepts to be considered in the design and safety evaluation of roadway systems. Mental workload can be generally defined as the expenditure of mental capacity required when performing a task or a combination of tasks. Messer (1980) defined driver workload as the time rate at which drivers must perform a given amount of driving tasks. As the complexity of highway geometric features increases, the time rate required to perform a given driving task is expected to increase also, consequently reflecting higher driver workload. How the driving task is performed is influenced by driver mental characteristics including expectancy, attention level, and mental workload capacity (Heger, 1995). Traffic reactions such as variation in operating speed are the result of these driver characteristics (Krammes et al., 1995). On the other hand, the estimation of driver workload is an attempt to determine the direct impact of the roadway environment on the driver, which leads it to be a more appealing method for consistency evaluation.

When guiding a vehicle along a path, drivers allocate mental capacity to the guiding task based on their estimates of the mental workload conditions ahead. The greater the mental workload estimate, the greater the attention or capacity allocated to the

task. A consistent roadway design allows accurate prediction of the correct path using little mental capacity, and thus allows more capacity to be dedicated to obstacle avoidance and navigation (Fitzpatrick et al., 2000b).

Most rural highways require relatively low workload demands; therefore, drivers tend to have relatively low attention levels on them. In response, most drivers will attempt to increase their workload by increasing their vehicle speed. A design inconsistency in the alignment imposes higher driving workloads than normally required, and therefore more than drivers expect. Drivers who fail to identify the disparity between their expectation and the actual workload level may make speed or path errors, consequently increasing their collision risk (Krammes et al., 1995). On the other hand, consistently designed highways facilitate accurate recognition of driver workload demand, and thus improve safety. Research has shown that the consideration of driver workload can enhance the accuracy of design consistency evaluation (Wooldridge, 1994).

Locations with high driver workload values tend to have higher collision frequency since the required workload may exceed driver mental capacity and result in dangerous reactions to roadway situations. On the other hand, highway sections requiring extremely low driver workload may also lead to higher collision risk due to driver boredom and less concentration on the road. The relationship between human mental workload and performance can thus be described based on the Yerkes-Dodson Law (Heger, 1995). At low workload levels, human performance is also low because pre-processed and appropriately arranged information is missed due to inattention. As the workload increases, the level of human performance increases until a maximum level is reached. The area around this maximum performance is the optimal workload for the

given task. Beyond the optimal level, additional mental workload demands cause a dramatic decrease in performance because there is too much information to process.

Since human error tends to increase with decreasing performance, it can be concluded that designers should have two major concerns about driver workload. Firstly, to ensure that geometric features provide workload levels that are low enough to avoid overloading drivers. Secondly, to provide workload levels high enough to prevent driver inattention (Heger, 1995). Figure 2.1 shows the general shape of the hypothesized relationship between workload and error. Models relating safety to driver workload should express this relationship.

Although driver workload is a compelling measure of consistency since it provides a direct measure for the impact of road geometry on driver behaviour, the use of driver workload as a measure of consistency has been much more limited than operating speed. This is due to the difficulty in measuring driver workload by analytical models. However, there have been several different approaches applied for modelling workload. The following four basic approaches for measuring driver workload were identified by Fitzpatrick et al. (2000a):

1. Primary task measures: as the task becomes more difficult, the performance deteriorates.
2. Secondary task measures: while performing a primary task, the driver also performs a secondary task, such as mental arithmetic. The more difficult the primary task, the poorer the performance of the secondary task.
3. Physiological measures: as the primary task increases in difficulty, physiological arousal increases.

4. Subjective measures: as the primary task increases in difficulty, so does the driver's estimate of his/her own workload.

In the United States, driver workload estimation has been the subject of two major studies: Messer (1980) and Wooldridge et al. (1999; 2000). Messer (1980) developed a model based on a subjective rating scale, while Wooldridge et al. (1999; 2000) developed a quantitative model based on visual demand. In Germany, Heger (1995) developed a model for driver workload estimation using a different approach that was based on psycho-physiological driver reactions. Unfortunately, no similar research efforts have been conducted in Canada. It is strongly recommended that driver workload models based on Canadian road conditions be developed, since models that reflect local conditions will provide far better results in terms of accuracy.

Figure 2.1: Relationship of Driver Workload and Collision Rate (Wooldridge, 1994).

2.4.1 Subjective Ratings

Messer (1980) used a subjective rating scale (from 0 to 6) to estimate an average workload value (R_f) for different roadway features. The roadway features that were rated are: bridges, divided highway transitions, lane drops, intersections, railroad grade crossings, shoulder width changes, alignment, lane width reductions, and the presence of cross road overpasses. The ratings were based on the collective experience of a group of road experts, and were subsequently modified with respect to their locations based on the type and severity of the design element. This model also considered the following additional variables (on the same scale): driver familiarity factor, sight distance factor, similarity to previous elements, workload of previous segments, and the percentage of drivers perceived to be familiar with the roadway. The regression model developed to estimate the expected driver workload experienced on geometric features is described as:

$$WL_n = UESR_f + CW_L \quad (2.17)$$

Where: WL_n = workload;

U = driver familiarity factor;

E = feature expectancy factor;

S = sight distance factor;

R_f = basic workload potential rating;

C = carryout factor; and

WL_l = workload of the previous feature.

One of the main advantages of the model developed by Messer (1980) is that it provides an explicit criterion for evaluating design consistency. This has not yet been addressed in other models. Based on this model, a feature with a driver workload value

less than or equal to one is considered to meet the requirements of a consistent design, while a feature with a driver workload value exceeding six is considered to be a safety problem. Another advantage of using this model is that it takes into consideration the similarity of the design feature to previous elements as well as the workload values of previous elements. This is important because driver expectancy is partly shaped by this short-range experience. The main drawback of this model is that it relies on a subjective measure, which is difficult to validate and may compromise the reliability of results.

2.4.2 Psycho-physiological Reactions

Heger (1995) developed a model that estimated driver workload based on Psycho-physiological reactions such as cardiac, electro-dermal, and electromyographic responses under existing road and traffic conditions. The data analyzed in this study included geometric measures, operating speed, subjective ratings, and physiological measures. A total of twelve individuals were selected for the study, and were required to navigate on twelve road sections with different levels of difficulty. In-car measurements using an instrumented car enabled the collection of detailed data regarding driver behaviour. A stepwise evaluation of multiple response systems was used to provide an overall standardized Driver Mental Workload Index. This index is then adjusted by weight functions to account for the influence of the different psychological parameters. This model can be used for measuring driver workload in order to evaluate design consistency.

The method developed by Heger (1995) has the advantage of allowing the measurement of workload under real field conditions on an existing traffic environment, as well as the capability to evaluate multiple driver responses. Some of the main results of this study are as follows. It was confirmed that inconsistent locations such as sharp

curves with high speeds resulted in high workload levels. With respect to vehicle stability, driver workload levels were found to correspond to side friction demand on the curves. Another noteworthy result of this study was related to the location of collision experience. The study showed that most psychological parameters reach their maximum after the driver has passed the inconsistent design feature. Regarding inconsistently designed curves, this study showed that a relatively high percentage of collisions occurred on the subsequent tangent. One of the drawbacks of this measure is that it seems to be exceedingly complex when compared to other workload models.

2.4.3 Visual Demand

In 1984, German researchers developed the visual occlusion method for modelling driver behaviour (Heger, 1995). This concept was used by Krammes et al. (1995) to develop a regression model for driver workload based on visual demand, which was later enhanced by Wooldridge et al. (1999; 2000). Visual demand refers to the amount of visual information needed by a driver to maintain an acceptable path on the roadway. A consistent roadway conforms to driver expectancy allowing the use of little visual capacity, i.e. lower driver workload, thus permitting greater attention to obstacle avoidance and navigation (Wooldridge et al., 2000).

Research efforts using test track studies (24 subjects), on-road studies (six subjects), and simulator studies (24 subjects) were conducted using visual occlusion to develop regression models for driver workload. In this method, the driver is given control over the presence or absence of visual information required for the driving task. When not receiving information, the driver relies on the information previously received to make predictions concerning the future performance requirements. One of the drawbacks

of this approach to estimating driver workload is that it is predominantly conducted in a protected environment for drivers due to safety reasons, thus it does not fully reflect actual traffic conditions.

Visual demand is measured as the ratio of the glimpse length divided by the time elapsed from the last glimpse until the time of the present request. This measure provides a percentage of time that a driver is observing the roadway at any point along the roadway (Fitzpatrick et al., 2000a). Twenty-four subject drivers were selected and tested on both a Campus Test Facility, and a driving simulator, which displayed a wide variety of large-scale driving scenarios. These studies included six different test curves that were each repeated six times by drivers. The on-road study was conducted mainly for validating test track results, and included only six driver's traversing five curves, with only four repetitions per curve per driver. It is noted that several safety precautions were taken to avoid the safety risk associated with testing periodically blinded drivers on public roads. In addition, the computation of the visual demand for a horizontal curve was conducted over a short fixed-length of the roadway after the start of the curve to eliminate confusion related to curve length. Similar to design speed consistency and vehicle stability, this method evaluates consistency for individual curve segments only.

Two different models were developed, one representing driver's familiar to the road and the other representing drivers unfamiliar with the road. The reason for this separation is that drivers familiar with a roadway require significantly less visual information processing capacity. These two models related visual demand to the inverse of the horizontal curve, since driver workload increases as curve radius becomes sharper, and it was found that driver workload varied linearly with the inverse of curve radius.

The models developed for evaluating design consistency based on the visual demand of familiar and unfamiliar drivers averaged over the curve length are (Wooldridge et al., 1999):

$$VD_{LU} = 0.173 + \frac{43.0}{R} \quad (2.18)$$

$$VD_{LF} = 0.198 + \frac{29.2}{R} \quad (2.19)$$

Where: VD_{LU} = visual demand of unfamiliar drivers; and
 VD_{LF} = visual demand of familiar drivers.

A recent study subjected several highway alignments to this model in an exercise of consistency evaluation, and it was found that this model should be limited to curves with a maximum radius of 552 m (Hassan et al., 2001). This is because after exceeding a radius of 552 m, the visual demand of familiar drivers becomes higher than unfamiliar drivers, which is clearly counter-intuitive. The range of curve radii that were included in the development of the visual demand models was approximately between 150 m and 350 m. Thus, the estimates derived from this model are only reliable within these ranges of curve radius. In an attempt to overcome the contradiction between the familiar and unfamiliar visual demand models, only one of the visual demand models was included in this analysis. The model predicting visual demand of unfamiliar drivers was selected since it represents a more critical driving condition.

An additional limitation is that the visual demand models do not represent the hypothesized relationship between safety and visual demand. Namely, at lower levels of visual demand, collisions are expected to decrease until the optimum visual demand is reached, and then collisions are expected to increase. Furthermore, visual demand models

are similar to alignment indices in that they lack an explicit evaluation criterion. The impact of workload on driver behaviour makes it increasingly complex to develop a safety criterion. A future safety criterion for visual demand should reflect this relationship to collisions. Although Wooldridge et al. (1999; 2000) recommended the use of visual demand as a measure of consistency, no research relating visual demand to safety was found. Despite these drawbacks, this model was preferred over alternative driver workload models for inclusion in the overall model for consistency evaluation. However, further research to develop better driving workload models, especially on Canadian roads, is strongly recommended.

2.5 RELATIONSHIPS OF CONSISTENCY MEASURES TO SAFETY

This section presents the results of previous North American research that has attempted to quantify the relationships between design consistency measures and safety. Anderson et al. (1999) conducted a regression analysis based on 5,287 horizontal curves on two-lane rural highways in six US states. This study investigated the relationship of operating speed reduction, and the *AR*, *RR*, *CRR* and *AVC* alignment indices to safety based on Poisson regression. These consistency measures were found to have statistically significant relationships to safety at the 95% confidence level.

The collision models developed based on speed reduction and *CRR* are shown in Equations 2.20 and 2.21, with estimated R^2 values of 19.5% and 19.6% respectively. Although these models only explained a small proportion of the variability in collisions, this is very common in collision models due to the complex nature of collision occurrence.

$$Y = \exp(-7.1977)AADT^{0.9224}L^{0.8419}\exp(0.0662\Delta V_{85}) \quad (2.20)$$

$$Y = \exp(-5.932)AADT^{0.8265}L^{0.7727}\exp(-0.3873\Delta V_{85}) \quad (2.21)$$

Where: Y = number of collisions that occurred on the curve during a 3-year period

Fitzpatrick et al. (2000c) conducted a sensitivity analysis based on this same database and stated that collision frequency varied with speed reduction in a manner that was realistic and meaningful in engineering terms. Furthermore, it was shown that CRR has the strongest sensitivity to safety compared to the remaining consistency measures. However, CRR was not as sensitive to collision frequency as speed reduction, which led to the conclusion that a design consistency methodology based on speed reduction would provide better results than a review of horizontal curve radii alone (Fitzpatrick et al., 2000c). Thus, alignment indices were considered as a complement to operating speed reduction rather than an alternative to it. Accordingly, operating speed reduction is considered the primary measure of consistency in the IHSDM's design consistency module.

Anderson and Krammes (2000) conducted a statistical analysis to investigate the relationship between mean operating speed reduction and mean collision rate (Acc_Rate). This study indicated that mean operating speed reduction has a statistically significant relationship to mean collision rate, confirming the value of applying this measure in consistency evaluation. This model was also presented in the 1999 TAC guide, and represents an approximately linear relationship between speed reduction and collision rate. This relationship is illustrated in Equation 2.22, which also shows that this model has an uncommonly high R^2 value. This is attributed to the grouping of curve sites into speed reduction intervals instead of modelling the speed reduction of individual curve sites.

$$Acc_Rate = 0.54 + 0.27(mean\Delta V_{85}); R^2 = 0.93 \quad (2.22)$$

Ng and Sayed (2003) conducted a study to quantify the safety benefits of each of the consistency measures presented in this study based on 319 horizontal curves located in the province of British Columbia, Canada. Two sets of models were developed. The first set of models considered the relationships of the individual consistency measures to safety. The second set of models contained as many consistency measures as are statistically significant, with the purpose of serving as an overall tool for investigating the impact of consistency on safety. Six models relating each of $(V_{85} - V_D)$, ΔV_{85} , VD_{LU} , VD_{LF} , Δf_r , and CRR to safety were developed, and are replicated in Table 2.4. This study found that each of these consistency measures has a statistically significant relationship to safety in the direction expected. Furthermore, two models for overall consistency evaluation were developed by Ng and Sayed (2003), and are provided in Table 2.5. The first model includes $(V_{85} - V_D)$, ΔV_{85} , and Δf_r , and is applicable to horizontal curves only, while the second model includes ΔV_{85} and Δf_r , and is applicable to both horizontal curves and tangent sections.

Although the main objectives of this thesis are also to quantify the safety benefits of consistency measures, and provide a tool for overall consistency evaluation based on safety, this thesis investigated several modelling aspects not addressed by Ng and Sayed (2003). Firstly, the operating speed prediction models selected for this study were based on the operating speed background of the curves under study, rather than the use of operating speed models based on other geographic locations. Secondly, in addition to the more traditional measure of speed reduction (ΔV_{85}), a model describing the relationship of the 85th percentile of speed reduction ($\Delta_{85}V$) to safety was developed. Thirdly, the

collision data was processed into nine alternative collision sets based on collision type and severity, and these were examined to identify the set most appropriate for model development. Fourthly, the differentials of visual demand and *CRR* between two successive curves were modelled to overcome the bias of these measures towards flatter curves, and to examine the impact of short-term driver experience on safety. Finally, a model reflecting the “U” shaped relationship between driver workload and safety was developed. In summary, several additional aspects have been considered in this thesis, leading to the investigation of over 300 models before the final safety based consistency models could be recommended.

Table 2.4: Models Relating Consistency and Safety (Ng & Sayed, 2003).

#	Model Form	t-ratio	κ	Pearson χ^2 (χ^2 test) SD
DIFFERENCE BETWEEN OPERATING AND DESIGN SPEED ($V_{85} - V_d$)				
1	$Acc/5\text{ yrs} = \exp(-3.380) \times L^{0.8920} \times V^{0.5913} \times \exp[0.009091 \times (V_{85} - V_d)]$	a_0 -1.904 a_1 6.511 a_2 2.784 a_3 1.985	1.539	293.24 (357.39) 341.26
SPEED REDUCTION (ΔV_{85})				
2	$Acc/5\text{ yrs} = \exp(-3.796) \times L^{0.8874} \times V^{0.5847} \times \exp(0.04828 \times \Delta V_{85})$	a_0 -2.072 a_1 6.482 a_2 2.742 a_3 2.043	1.533	289.19 (357.39) 341.26
DIFFERENCE BETWEEN SIDE FRICTION DEMANDED AND ASSUMED (Δf_p)				
3	$Acc/5\text{ yrs} = \exp(-3.303) \times L^{0.8733} \times V^{0.5680} \times \exp(-2.194 \times \Delta f_p)$	a_0 -1.851 a_1 6.412 a_2 2.672 a_3 -1.986	1.521	294.01 (357.39) 341.27
RATIO OF THE RADIUS OF INDIVIDUAL SECTION TO THE AVERAGE RADIUS OF THE ALIGNMENT (CRR)				
4	$Acc/5\text{ yrs} = \exp(-3.159) \times L^{0.8898} \times V^{0.5906} \times \exp(-0.3606 \times CRR)$	a_0 -1.791 a_1 6.514 a_2 2.785 a_3 -2.016	1.541	294.06 (357.39) 341.27
VISUAL DEMAND OF UNFAMILIAR DRIVERS (VD_{LU})				
5	$Acc/5\text{ yrs} = \exp(-4.297) \times L^{0.8866} \times V^{0.5831} \times \exp(3.076 \times VD_{LU})$	a_0 -2.231 a_1 6.476 a_2 2.735 a_3 2.040	1.531	295.34 (357.39) 341.23
VISUAL DEMAND OF FAMILIAR DRIVERS (VD_{LF})				
6	$Acc/5\text{ yrs} = \exp(-4.679) \times L^{0.8873} \times V^{0.5811} \times \exp(4.566 \times VD_{LF})$	a_0 -2.323 a_1 6.481 a_2 2.740 a_3 2.027	1.533	295.58 (357.39) 341.26

Table 2.5: Models for Evaluating Overall Consistency (Ng & Sayed, 2003).

#	Model Form		t-ratio	κ	Pearson χ^2 (χ^2 test) SD
7a	$Acc/5\text{ yrs} = \exp(-3.369) \times L^{0.8858} \times V^{0.5841}$ $\times \exp[0.0049 \times (V_{85} - V_d) + 0.0253 \Delta V_{85} - 1.177 \Delta f_R]$	a_0	-1.894	1.734	248.66
		a_1	6.480		(355.26)
		a_2	2.749		339.26
		a_3	2.085		
		a_4	2.022		
		a_5	-1.932*		
7b	$Acc/5\text{ yrs} = \exp(-2.338) \times L^{1.092} \times V^{0.4629}$ $\times \exp[IC \times (0.022 \times \Delta V_{85} - 1.189 \Delta f_R)]$	a_0	-2.25	2.511	828.68
		a_1	22.46		(889.81)
		a_2	3.81		841.06
		a_3	2.06		
		a_4	-1.64*		
		where IC = dummy variable (0 for tangents and 1 for horizontal curves)			

CHAPTER THREE

3.0 DATA COLLECTION

This chapter provides a detailed description of the database developed in this study for model development. In Section 3.1, the population of highways from which curve samples were selected is introduced, in addition to the sources from which data were obtained and an outline of the main data variables collected. Section 3.2 presents the sample selection criteria and the final sample of curves selected. Subsequently, Sections 3.3 to 3.5 discuss the collection of alignment, traffic volume, and collision data.

3.1 OVERVIEW OF DATA COLLECTED

Seven two-lane rural highway segments located in the Eastern Ontario region were chosen for analysis. The selection of these highways, which are predominantly located near the Ottawa area, was mainly based on limitations in data availability. However, it was ensured that the selected highways encompass a variety of highway classifications, design speed, terrain, traffic volume, and collision history, in hope that this sample would cover most of the two-lane rural highway conditions found in Ontario. The data requirements in this study were divided into three main categories: (1) geometric alignment data; (2) traffic volume data; and (3) collision history. The required data were provided by two principal sources:

- The Planning and Design Office, and the Traffic Office of the Eastern Region of the Ontario Ministry of Transportation (MTO); and
- The Stormont Dundas and Glengarry (SDG) County Roads Department.

Initially, data for eight different two-lane rural highway segments were obtained from the MTO and SDG combined. The highway numbers, their classifications, segment lengths and number of horizontal curves available are summarized in Table 3.1 below. A combined length of 201.8 km of two-lane rural highways, with 91 horizontal curves was initially available for analysis. However, King's Highway 34, in addition to a sizeable section of King's Highway 17 were eliminated, as the horizontal curves on these highway segments did not satisfy the selection criteria of this study. Thus, the final number of highways investigated in this study was reduced to seven highways with varying characteristics.

Table 3.1: Summary of Selected Highways.

Highway Number	Highway Classification	Design Classification	Segment length (km)	Total number of horizontal curves
43	Secondary Highway (Former King's Hwy)	Unavailable	17.2	7
41	King's Highway	RC80	26.5	16
34	King's Highway	RC100	9.2	2
31	Secondary Highway (Former King's Hwy)	Not provided	33.5	12
17	King's Highway	RAU100	54.5	13
15	King's Highway	RAU100	16.0	12
12	County Road	Not Provided	31.4	18
7	King's Highway	Not Provided	13.5	11

The MTO provided data for the King's Highways, while the SDG provided data for the Secondary Highways and the County Road. Both sources supplied as-built construction plans that were used to extract the required horizontal alignment data. The traffic volume data were obtained from both the MTO's Traffic Volume Information System for all King's and Secondary Highways, and the SDG's Municipal Road Appraisal Sheets for County Road 12. Similarly, the collision data were obtained from a combination of the MTO's Accident Database for King's Highways, which were supplemented by the Highway Keypoints for Accident Location Identification; and the SDG's collision police reports for all Secondary Highways and County Road 12. In addition, the data provided by the MTO and SDG were supplemented by site visits and field measurements. A summary of the main data variables that were collected from these databases is provided in Table 3.2.

Table 3.2: Summary of Data Collected.

Category	Variables Collected
Alignment Data	<ul style="list-style-type: none"> • Radius • Length of curve • Length of spiral (if present) • Length of associated tangents • Superelevation
Traffic Volume Data	<ul style="list-style-type: none"> • Average Annual Daily Traffic (AADT) • Traffic growth factors if applicable • Location
Collision Data	<ul style="list-style-type: none"> • Collision type and severity • Date, time, and location • Initiating event and perceived cause of collision • Driver condition • Number, direction and type of vehicles involved • Weather, light and road surface conditions

3.2 SITE SELECTION

A final sample of 70 curves was selected from the population of 91 curves located in the seven highway segments under study. The curve selection criteria were based on a review of the scope of the different consistency measures considered in this study, and an examination of the scopes of common collision models found in literature. Based on this review, the following constraints were imposed for the selection of curve sites:

1. Rural area: not near town or built up area.
2. Relatively low traffic volume: $AADT \leq 10,000$ veh/day.
3. Marked and paved roadways with constant lane width.
4. No recent roadway improvements.
5. No stop control or signalized intersections within 0.8 km of curve.
6. No features that may create abnormal hazard (e.g. narrow bridge).
7. Curve radius < 1200 m, and total curve length > 100 m.

These criteria generally attempt to eliminate features that may inhibit an accurate analysis, and are mostly based on an understanding of the impact of different roadway features on safety. However, it was not possible to represent the limited scope of the visual demand model, which is unsuitable for curves above 552 m in radius, since this would overly restrict site selection and prevent the development of a reasonable size database. Furthermore, highway segment lengths were limited to minimum and maximum values of 6.4 km and 34 km as recommended by Fitzpatrick et al. (2000c). This is mainly suited for the alignment index *CRR*, since roadway segments shorter than 6.4 km may not have enough geometric features to be representative of the alignment, while segments longer than 34 km may be too varied for representation by a single value.

Fortunately, the highway segment lengths selected in this study were already within these limits. Otherwise, any segments less than 6.4 km would be dropped, while those greater than 34 km would be divided.

The highway plans were first reviewed to identify the full list of all horizontal curves available in each highway segment, which are summarized in Table 3.1. These curves were then closely inspected to establish potential sites based on the site selection criteria above. This process resulted in 75 potential curves for database development. However, some of the latest highway plan revisions available were dated as far back as 1971. The plans for the King's Highways and Secondary Highway 43 were mostly new, while the remaining highway plans were relatively old. Regarding the older plans, it was expected that there would be a considerable number of changes in these areas. A major concern was the likelihood of many of these rural areas turning into small towns with time. Thus, the sample selection was not finalized before a windshield survey was conducted to review the actual road conditions and nearby land features, particularly new construction, intersections, and the posted speed limit. The curve locations were determined by using the highway plans to calculate their distances from adjacent intersections. Ultimately, several curve segments were eliminated as a result of these site visits due to the presence of buildings and signalized intersections that were not reflected in the plans.

Upon conducting the site visits and reviewing the traffic volumes on the highway segments, the curve sites that did not comply with the study criteria were eliminated. As a result, a sample of 70 curves and their associated tangent sections was selected for model development. It should be noted that the number of cases recommended for building a

regression model generally depends on the number of potential predictor variables available. A general rule of thumb is 6 to 10 cases for each predictor variable investigated (Neter et al., 1996). Thus, the 70 cases available in this study sufficiently accommodate the number of cases required for model building. Finally, it is also noteworthy that during the collection of geometric, traffic volume and collision data for these curves, double and sometimes triple checks were conducted to ensure the reliability and accuracy of the database developed, particularly while merging the different data categories. The final model database for the 70 selected sites is provided in Tables A.1 to A.7 in Appendix A.

3.3 GEOMETRIC ALIGNMENT

The geometric alignment data were extracted from a combination of plan-profile sheets and computerized alignment drawings of as-built construction plans, and entered into a spreadsheet. The data obtained from the plans included: the stations at the beginning of the curve, point of intersection, and the end of the curve; the radius of curvature; length of curve; and the length of spiral if present. In addition, the approach and departure tangent lengths associated with each curve were calculated to identify independent and non-independent tangents for speed reduction calculations. The summary statistics for the main geometric variables are illustrated in Table 3.3.

Table 3.3: Summary Statistics for Main Variables Used in Model Database.

Data element	Minimum	Maximum	Mean	Standard Deviation
Curve Radius (m)	317.52	1166.50	664.16	235.30
Curve Length (m)	113.49	1062.85	366.35	227.99
AADT (veh/day)	1,420	10,670	5,162.43	2,899.95

The MTO also provided the highway design criteria for Highways 41, 17, and 15, which included design speed, stopping sight distance, maximum grades, minimum radius, pavement width, shoulder width, and posted speed. However, this data was not provided for the section of Highway 7 under study. The main design criterion that was required in this study was the design speed of the highway alignments. Although the design speed of County Road 12 was provided by the SDG, the design speeds were not available for the remaining Highways 31 and 43. Based on an examination of similar highways, it was suggested that the particular category of Highways 31 and 43 commonly have speed limits that are equivalent to their design speeds. In return, the design speeds of these highways were estimated to equal their posted speed limits, which are both 80 km/h. Highways 12 and 41 also have 80 km/h speed limits and design speeds. On the other hand, Highway 17 has a speed limit of 90 km/h and a design speed of 100 km/h, while Highway 15 has a speed limit of 80 km/h and a design speed of 100 km/h. The posted speed limit of Highway 7 is 90 km/h, and since the design speed was not provided, it was assumed to be 100 km/h, similar to Highways 15 and 17.

The main deficiency in the geometric data provided was the lack of superelevation data, which is necessary for the estimation of side friction demand in the vehicle stability measure. The superelevation was also needed for the estimation of the limiting speeds of individual curves. Thus, the data provided was supplemented by field measurements of superelevation at all selected curve sites using a digital ball-banking indicator. Measurements were taken at three points along each direction, and these values were then averaged for each curve. These multiple measurements were taken due to the fact that although superelevation is constant in theory, in reality it tends to vary along

curves. This is mainly due to the road construction process and additional settlement following construction. Finally, it is noted that the topography of the highways investigated in this study was mostly flat, while the topography of King's Highway 41 was mountainous. It is noted that the models for the estimation of side friction supply were selected according to the highway topography.

3.4 TRAFFIC VOLUME

The traffic volume data for the King's Highways were obtained from the MTO's Traffic Volume Information System (TVIS) History Listing, which included data up to and including the year 2000. These traffic data are mostly based on short-term count stations placed at strategic positions on the provincial highway network every three years, in addition to a relatively small number of highway sections that are monitored on a permanent basis. Following are definitions of some of the main variables in the TVIS database that are relevant to this study:

- LHRs: Linear Highway Reference System number.
- O/S: Offset from start of the LHRs section to the traffic volume section.
- Location: Section description.
- DIST: MTO Engineering District (e.g. Ottawa = 9).
- TYPE: Highway Type (Kings Highway/Freeway; Kings Highway/Non-Freeway; Secondary Highway; and Tertiary Highway).
- LEN: Length of highway traffic volume section (km).
- HWY: Provincial highway number.
- YR: year for which traffic data applies.

- AADT: Average Annual Daily Traffic, defined as the average 24 hour, two-way traffic from the period January 1 to December 31.

The LHRS is a database that provides a common referencing system for the location of traffic volume and collision data. The LHRS references mostly coincide with the location of intersections or other major features along a highway. The Highway Keypoints for Accident Location Identification in Highway Sequence was used as the source of LHRS data, a sample sheet of which is shown in Figure 3.1. In this study, the stations at the start and end of each curve, as well as the station of the nearest intersection available in the LHRS database were used to calculate the exact location of each curve in terms of the LHRS reference and a range of offsets. These LHRS and offset ranges were calculated as accurately as possible, and were used to merge the different databases to identify the traffic volume and collision frequency experienced at each curve.

The traffic volume data for Secondary Highways 43 and 31, which were previously King's highway, were also obtained from the TVIS database, however only traffic volumes up to 1992 were available. On the other hand, the traffic volumes for County Road 12 were obtained from its Municipal Road Appraisal Sheet, which provided data up to the year 1991. These databases also provided growth factors for these highways, which were used for predicting the traffic volumes for the years in the selected study period.

Ministry of Transportation Ontario		HIGHWAY KEYPOINTS FOR ACCIDENT LOCATION IDENTIFICATION IN HIGHWAY SEQUENCE		EFFECTIVE DATE: 02/07/01	
EFFECTIVE DATE : 02/07/01		PAGE: 3			
MTO REGION : EASTERN		HIGHWAY NO: 7			
KPT NO	OFFSET	DESCRIPTION	HWY DIR	OPP DIST	CHG RD PLG STATUS
14050	04.3	INNISVILLE ROAD SOUTH	W	10	A
	05.7	DRUMMOND TWP RD 10B (S)	W	10	A
	06.2	PAULS RD(N)	W	10	A
	07.2	DRUMMOND TWP RD 9A	W	10	A
	08.0	GARDINER ROAD	W	10	A
	08.6	MISSISSIPPI WEST SHORE DR(S)	W	10	A
	08.6	DRUMMOND TWP RD(N) - MILLER ROAD	W	10	A
	10.3	DRUMMOND TWP RD C 7	W	10	A
14070	00.0	DRUMMOND TWP RD C 7	W	10	A
	02.9	DRUMMOND SCHOOL RD	W	10	A
	03.7	DRUMMOND TWP RD C 5	W	10	A
	04.1	LEACHS RD	W	10	A
	06.2	DRUMMOND TWP RD C 4 - RICHMOND'S ROAD	W	10	A
	06.2	DRUMMOND TWP RD C 4	W	10	A
	06.6	DRUMMOND TWP RD L 7	W	10	A
	07.2	EWART RD (N)	W	10	A
	07.8	DRUMMOND TWP RD L 6	W	10	A
	08.8	DRUMMOND TWP RD L 3 - DUFFERIN RD	W	10	A
	09.1	MORRIS RD(N)	W	10	A
	09.9	DRUMMOND ST(S)	W	10	A
	10.2	HWY 43-WILSON ST(S)	W	10	A
14080	00.0	HWY 43-WILSON ST(S)	W	10	A
	00.0	OTTAWA-KINGSTON MTO DIST BDY	W	10	A
	00.6	LANARK CTY RD 511 PERTH W LTS	W	10	A
14084	00.0	LANARK CTY RD 511 PERTH W LTS	W	10	A
	00.8	BLACKBURN CK CULV	W	10	A
	04.0	GLEN TAY RD(S) HARPER RD (N)	W	10	A
	09.2	GAMBLES RD	W	10	A
	09.9	BATHURST TWP RD C 5	W	10	A
	10.3	E JCT ANGLICAN CHURCH RD(N)	W	10	A
14090	00.0	E JCT ANGLICAN CHURCH RD(N)	W	10	A
	00.4	CHRISTIE LAKE RD	W	10	A
	03.0	W JCT ANGLICAN CHURCH RD(N)	W	10	A
	06.5	KIRKHAM RD(N)	W	10	A
	07.5	STRONG RD	W	10	A
	09.9	CAMERON SIDE ROAD	W	10	A
	11.3	BEAVER DAM CK CULV	W	10	A
	12.0	CTY RD 36-BOB'S LAKE RD(S)ELPHIN RD(N) K	W	10	A
14100	00.0	CTY RD 36-BOB'S LAKE RD(S)ELPHIN RD(N) K	W	10	A
	00.9	ARMSTRONG RD	W	10	A
	01.4	FALL R BR	W	10	A
	04.9	LANARK-FRONTENAC CTY BDY	W	10	A
Rd Status Na: Municipal Roads (Non Assumed)			A: Provincial Highways (Assumed)		

Figure 3.1: Sample of Highway Keypoints for Accident Location Identification.

3.5 COLLISION HISTORY

The common time period of available collision data for the seven highways in this study was from 1997 to 1999. This results in a three-year study period, which is within the time generally recommended in collision analysis studies (Harwood et al., 2000a). The collision data for Highways 7, 15, 17 and 41 were obtained from the MTO's computer based Accident Record database. This database contains summarized traffic collision data for all collisions on the provincial highway system, with locations based on LHRS references and offsets. The collision data for Highways 43, 31 and 12 were obtained directly from the original police reports, and later entered into a spreadsheet. Although the data provided in the police reports were not as readily coded as the Accident Record database, it was sufficient for the purposes of this study. Some of the main variables provided by the collision databases are described below:

- Date and time of collision.
- LHRS reference and offset (accurate to 100m).
- Road location (e.g. at Intersection, Non-intersection, Driveway, and Overpass).
- Road Alignment (either Straight Level, Curve Level, Straight Hill or Curve Hill)
- Light condition in which collision took place (e.g. Day, Dark, Dusk and Dawn).
- Surface condition in which collision took place (e.g. Dry, Wet, Ice and Snow).
- Initiating event and cause of crash as perceived by officer.
- Driver condition (Normal, Drinking, Impaired, Inattentive, Fatigue or Unknown driver condition).
- Number of vehicles involved in crash, and their direction of travel.
- Vehicle types involved in crash.

- Crash type, as one of 7 main collision types defined by the MTO (Angle, Approach, Sideswipe, Rear-End, Single-Vehicle, Turning or Other).
- Crash Severity
 - Fatal: a vehicle collision resulting in the death of at least one person within 30 days of the collision.
 - Injury: a vehicle collision resulting in the bodily injury of at least one person, and not resulting in death.
 - Property damage only (PDO): a vehicle collision in which no person suffers a bodily injury, but in which there is reportable damage to public or private property including the vehicle or its load.

The collisions located on the curve segments of Highways 7, 15, 17 and 41 were identified using the same LHRS information calculated for traffic volumes. One of the main problems faced in this process was that a number of the collisions that were attributed to tangent sections in their description occurred on curves based on the LHRS offsets calculated and vice versa. It is possible that some of these incorrect collision locations were due to inaccuracies in assigning LHRS offsets to collisions by accident coders. To help overcome this limitation in data quality, the location of collisions was based on both the LHRS references, and the description of the collision location provided in the Accident Record database (curve or tangent section). On the other hand, the collisions located in the curve segments of Highways 12, 31 and 43 were determined based on calculations of their distances to the nearest intersections in each direction, and a search of collisions referenced to these intersections in the police reports. In general, these highways experienced far less collisions than the King's Highways in this study.

When dealing with collision data, several inherent factors may limit data accuracy. One of the main problems that may be encountered in collision analysis studies is the under-reporting due to changes in the collision-reporting threshold. While, fatal and injury collisions are always reported, property damage only collisions are only reportable when the property damage exceeds a certain monetary value, which is prescribed by regulation. However, the collision-reporting threshold is not always fixed during the study period; for example, the threshold in Ontario increased from \$700 to \$1000 in January 1, 1997. To deal with this change in collision reporting threshold, one could either ignore PDO collisions, or assume that reporting thresholds remained constant during the study period. Fortunately, this problem was avoided in this study since the study period starts with the implementation of the new collision-reporting threshold.

Finally, it should be noted that all collisions within approximately 100 m of the curves were included in the model database. This is because many collisions, particularly run off the road, occur shortly after leaving the deficient horizontal curve rather than within it. Figure 3.2 shows that the 70 curves in the study database experienced a total of 44 collisions from 1997 to 1999, with three-year collision frequencies ranging from zero to five at each curve. As shown in Figure 3.3, the frequency distribution of these collisions shows that approximately 87% of the horizontal curves experienced none or one collision during the study period.

Figure 3.2: Collision Frequencies at Curves for all Collisions.

Figure 3.3: Collision Frequency Distribution at Curves for all Collisions.

CHAPTER FOUR

4.0 MODELLING TECHNIQUE

This chapter provides a background of the collision model building techniques applied in this study. Firstly, section 4.1 presents an introduction to the uses of collision models in highway safety analysis. Following, Section 4.2 provides a review of the regression techniques applied in this study, namely Poisson and negative binomial regression. Sections 4.3 to 4.7 consider further aspects of model development, specifically the model functional form, modelling approach, selection of predictor variables, and goodness-of-fit measures.

4.1 BACKGROUND

In modern highway safety research, the application of regression analysis plays a vital role in understanding the impact of roadway features on safety. Regression models developed for highway safety studies can be divided into two main uses, collision causation models and collision prediction models (Persaud, 2001). Causation models attempt to estimate the safety impact of changing different roadway elements, while prediction models attempt to estimate the expected collision experience at a certain location. Since the goal of this study is to quantify the importance of different consistency measures to safety rather than to predict collisions at any particular site, the developed models fall under the category of causation models.

A regression analysis will result in the parameters and strengths of the relationships between alternative consistency measures and safety, in addition to the proportion of safety that is not explained by these measures. Although regression models have proved to be accurate tools in the prediction of collision experience, their ability to

isolate the safety impacts of individual design elements has met less success. Collisions are complex events that can rarely be attributed to any single roadway element, thus it is very difficult to estimate the impact of roadway design features on safety. Furthermore, Harwood et al. (2000a) explained that the direct interpretation of coefficients as showing the impact of changing the associated variable is not always valid since:

- (1) Statistical correlations in a regression model do not necessarily represent cause-and-effect-relationships, and may be the result of a casual relation.
- (2) Correlations among variables may be present in a model, leading to difficulty in separating their individual impacts.
- (3) A variable may be strongly correlated to another variable that is not included in the model, leading the associated coefficient to represent the impact of an unavailable variable rather than its own.

Thus, it is recommended that great care be exercised in the application and interpretation of the parameters in collision models. It should also be noted that inherent limitations in data accuracy, particularly collision data, lead to an added uncertainty in the reliability of model parameters. Examples of collision data limitations that may have comprised the study results include underreporting of property damage only (PDO) collisions and incorrect collision locations due to both data entry errors. Nonetheless, the application of statistical techniques in the analysis of highway collisions has been common practice for several decades, and has led to the identification of several roadway features that have important impacts on safety. To this effect, Pasupathy et al. (2000) stated "Past research has given us information in a number of areas that has proved vital for the construction of safer roads in an economical way".

4.2 PROBABILITY DISTRIBUTIONS AND REGRESSION ANALYSIS

In order to identify the most suitable regression technique for the data under study, a review of numerous collision models developed in previous research was first conducted. Traditionally, collisions were modelled using multiple linear regression analysis. More recently, researchers including Jovanis and Chang (1986) have emphasized the flaws associated with using linear regression to model collision data. A major concern was that linear regression models follow a continuous probability distribution (the normal distribution), and thus are not considered appropriate for the modelling of discrete data such as collisions. Another concern was that the symmetrical shape of the normal distribution conflicts with the distribution of collisions, which tends to be positively skewed. This skewed shape is due to the fact that collisions are rare, non-negative events, and with a high proportion of highway segments experiencing zero collisions. Collision data also tend to violate the assumption of equal variance at different levels of the predictor variables. Moreover, it is possible that a linear regression model will predict a negative value, which is meaningless in terms of collisions (Pasupathy et al., 2000).

The mainstream statistical approach used for modelling count data such as collisions is Poisson regression (Lawless, 1987). The positively skewed Poisson distribution has become very widely accepted in modelling collisions since it is particularly suited for modelling rare, discrete, and non-negative events. A number of studies have assessed the usefulness of both Poisson and linear regression models in predicting collisions at roadway segments, and have concluded that Poisson regression provided superior results when modelling collision data (e.g. Miaou et al., 1992).

However, a well-known drawback of the Poisson distribution is that collision data often displays extra variation or over-dispersion over the Poisson mean.

In response, several researchers have turned to an extension of Poisson regression termed negative binomial regression. The negative binomial distribution is considered an extension of the Poisson distribution, since it is similar to it in every aspect except for the assumption that the mean is equal to the variance. The negative binomial distribution adds an extra term to the variance that accommodates over-dispersion, and is therefore more appropriate for modelling collision data with extra variation. At this point, it should also be noted that to apply either the Poisson or negative binomial distributions, the only assumptions needed are that the events must occur randomly and independently of one another.

Despite the recurrent recommendation of these regression techniques in previous literature, one should avoid the blind application of any specific model type without further justification based on the data at hand. To verify the suitability of Poisson and negative binomial regression for the database of this present study, the frequency distributions of total collisions in the three-year study period, already shown in Figure 3.4, were first examined. The right skewed shape of this frequency distribution combined with the large number of sites with zero or one collision indicate that the data is well represented by the Poisson and negative binomial distributions. Based on both the recommendations of previous research and the actual distribution of the data at hand, the Poisson and negative binomial regression techniques were selected for modelling.

4.2.1 Poisson Regression

The Poisson probability distribution is a discrete distribution that provides an accurate approximation to binomial probabilities when the number of observations (n) is large; and the average number of successes (μ) is small, preferably with $\mu < 7$. Based on the Poisson distribution, the probability of observing y collisions at a particular site during a specified time period is expressed by:

$$P(y) = \frac{\mu^y \exp(-\mu)}{y!} \quad (4.1)$$

Observing Equation 4.1 reveals that the Poisson distribution is based on only one parameter, namely the mean. In the Poisson distribution, the model mean and variance are assumed equal, as shown in Equation 4.2. Thus, if collisions follow the Poisson distribution, and the mean collision frequency for a curve with radius $R = 200$ m is higher than the mean collision frequency for a curve with $R = 400$ m, the variances of the two curves will also differ. This is unlike the normal distribution, where the variance is assumed to remain constant for all levels of the predictor variables.

$$E(Y) = \mu ; \text{Var}(Y) = \mu \quad (4.2)$$

The regression coefficients for Poisson regression models are estimated by the maximization of the log-likelihood function $L(\beta)$, which is determined as follows:

$$\log L(\beta) = \sum [y_i \log(\mu_i) - \mu_i - \log(y_i!)] \quad (4.3)$$

Maximum log-likelihood estimates can be obtained using the generalized linear model procedure PROC GENMOD in the SAS statistical software package. SAS is the most widely used statistical software package by highway safety analysts in North America; used by approximately 36% of the jurisdictions surveyed by Persaud (2001).

SAS applies the maximum log-likelihood procedure to provide estimates for the regression model coefficients (β), standard errors, and p -values, in addition to the scaled deviance and Pearson chi-square statistics for both the Poisson and negative binomial models.

4.2.2 Negative Binomial Regression

As previously mentioned, the main drawback of the Poisson distribution is the likely over-dispersion of the collision data. Over-dispersion occurs when the variance of an independent variable exceeds its mean, causing the mean to follow the Gamma distribution. This over-dispersion represents the variance of other variables that are not included in the model (Vogt et al., 1999). Studies examining the impact of over-dispersion on inferences made under a Poisson model found that although over-dispersion does not influence the value of model coefficients, it causes the t -statistics used for tests of significance to be unreliable (Agresti, 1990). As a result, numerous approaches for dealing with over-dispersion have been developed, including weighted least squares and quasiliikelihood (McCullagh & Nelder, 1989). However, Lawless (1987) stated that perhaps the most familiar and convenient method for accommodating over-dispersion is the negative binomial distribution. Negative binomial models have been applied in several highway safety research projects (e.g. Harwood et al., 2000a) and are considered very appropriate for the modelling of over-dispersed collision data.

In the negative binomial distribution, adding a quadratic term ($K\mu^2$) to the variance accommodates over-dispersion. This term is the extra component of variation arising from mixing the Poisson distribution with the gamma distribution in such a way that leads to the negative binomial distribution. When K equals zero, the negative

binomial distribution reduces to the Poisson distribution. The mean and variance of the negative binomial distribution are expressed as follows:

$$E(Y) = \mu ; \text{Var}(Y) = \mu + K\mu^2 \quad (4.4)$$

Where: K = the over-dispersion parameter.

One of the main advantages of the negative binomial distribution compared to alternative approaches for accommodating over-dispersion is that it allows the use of standard maximum-likelihood methods (Lawless, 1987). The regression model parameters for the negative binomial distribution are estimated by the maximization of the log-likelihood function $L(\beta, K)$, which is also provided by SAS software. In addition, the negative binomial distribution easily allows the improvement of model predictions by including previous collision data from a particular site through the Empirical Bayesian method. This is not possible for Poisson regression models. A further discussion of this can be found in Hauer, Terry and Griffith (1994), Pendleton (1996), Hauer and Persaud (1996) and Hauer (1997), as referenced by Vogt et al. (1999). On the other hand, the main benefit of Poisson regression over negative binomial regression is simplicity, due to the presence of only one variable in the model, namely the mean (Ng & Sayed, 2003). Nevertheless, this characteristic can also be a major weakness since collision data tend to be over-dispersed, and in this case, the negative binomial distribution is closer to reality.

4.2.3 Selection of Regression Technique

It is important to understand that neither the Poisson nor negative binomial approach is always best. The selection of either regression technique should always be based on an analysis of the data under study. Determining whether the Poisson or negative binomial technique is more appropriate can be achieved by examining several

statistics, the most common of which is based on the Pearson chi-square statistic (χ^2). This statistic is an approximately chi-squared random variable with degrees of freedom equal to the number of observations (n) minus the number of parameters (p) for a valid Poisson model. If the value of the χ^2 statistic is greatly in excess of $n - p$, this suggests over-dispersion, in other words, when the χ^2 statistic divided by the degrees of freedom is considerably larger than one over-dispersion is indicated. This value is referred to here as the dispersion parameter (k). It should be noted that cases where the dispersion parameter is less than one, referred to as under-dispersion, have also been reported in collision models, but are far less likely to occur. When the dispersion is close to one, Poisson and negative binomial models will provide approximately identical results, and the use of Poisson regression is preferable. Generally, values of k between 0.8 and 1.2 are acceptable. The χ^2 statistic and its associated dispersion parameter (k) are calculated as:

$$\chi^2 = \sum_{i=1}^n \frac{(y_i - \hat{y}_i)^2}{\hat{y}_i} \quad (4.5)$$

$$k = \frac{\chi^2}{n - p} \quad (4.6)$$

Where: χ^2 = Pearson chi-squared value of model;

n = number of observations; and

p = number of coefficients considered in model.

A similar test can be conducted based on the model scaled deviance (D^m), which is also an approximately χ^2 random variable with degrees of freedom equal to $n - p$. The scaled deviance, expressed in Equation 4.7, represents twice the difference between the log-likelihood achievable by a model that fits the data exactly, and that achieved by the

model under consideration. This measure is generally used to represent the discrepancy of model fit, with the maximum log-likelihood achievable used as a baseline value.

$$D^m = 2(L^f - L^m) \quad (4.7)$$

Where: L^f = the log-likelihood achieved if the model gave a perfect fit; and
 L^m = the log-likelihood of the model under study.

As with the previous measure, over-dispersion is also indicated when the value of k in Equation 4.8 is greatly in excess of one.

$$k = \frac{D^m}{n - p} \quad (4.8)$$

Both the χ^2 and scaled deviance measures are provided as SAS goodness of fit output. Poisson regression is initially applied to the data and the above statistics are examined for over-dispersion. If the values vary greatly from one, the data are then modelled using negative binomial regression to see if there is any improvement in the model. These statistics are also used as a means of assessing the model's goodness of fit, as will be shown in Section 4.5.

4.3 MODEL FORM

After the identification of an appropriate regression technique, suitable model forms are now investigated. Neter et al. (1996) stated that some of the most common functions used in Poisson regression models are:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots \beta_n X_n \quad (4.9a)$$

$$Y = \exp(\beta_0) \exp(\beta_1 X_1) \exp(\beta_2 X_2) \dots \exp(\beta_n X_n) \quad (4.9b)$$

$$Y = \log \beta_0 + \log \beta_1 X_1 + \dots + \beta_n X_n \quad (4.9c)$$

Where: Y = expected mean collision frequency;

$\beta_0, \beta_1, \beta_2, \dots, \beta_n$ = model parameters; and

$X_1, \dots, X_n$ = model predictor variables.

The general form typically found in collision models is the multiplicative model form shown in Equation 4.9b. This multiplicative form ensures zero values of collision frequency at zero values of the exposure variable. It also ensures that the mean value of collisions remains positive, since an additive model may result in negative values for certain parameter combinations. These are among the most important requirements that should be satisfied by a collision model's functional form (Swalha & Sayed, 2001).

The chief variable that explains the occurrence of collisions on roadway segments is the amount of exposure to traffic that is experienced. There are two main approaches for considering exposure. The first approach is based on modelling collision rate, leading exposure to be an indirect input in calculating the model parameters. The collision rate is determined by dividing collision frequency by traffic volume, and is measured in units of collisions/million vehicle-km. It should be noted that although the Poisson and negative binomial distributions are best suited for count data, they could also be applicable to rates. However, collision rates are based on the false assumption that there is a linear relationship between traffic volume and safety. Alternatively, the second approach models collision frequency, leading exposure to be a direct input in estimating model parameters (Pasupathy et al., 2000). In addition, using exposure as a predictor variable in the model can allow the true relationship between safety and traffic volume to be expressed more accurately, without necessarily assuming a linear relationship. Although the use of collision rates was more common in the past, the approach of modelling

collision frequency rather than collision rate has recently been accepted and applied by more and more researchers. Therefore, the use of collision frequency rather than collision rate has been selected in this study.

Furthermore, there are two main methods for expressing exposure in collision models. The first approach includes traffic volume and section length separately, with each variable having a separate coefficient. This approach predicts the collision frequency for the number of years of collision data included in the database (Anderson et al., 1999), which in this study is a three-year collision frequency. The second approach combines traffic volume and curve length into a single exposure term as expressed in Equation (4.10).

$$Expo = (NumberOfYears)(AADT)(365)(L)(10^{-6}) \quad (4.10)$$

Where: *Expo* = single exposure term (million vehicle-km);

AADT = average annual daily traffic volume (veh/day); and

L = curve length (m).

Another important decision regarding model form is identifying the exact method of incorporating exposure in the regression model. Numerous studies have investigated the relationship between traffic volume and collision rate, dating back to over half a century ago. Based on these studies, it has become well recognized that traffic volume has a distinct “U” shaped relationship to safety, with higher collision rates observed at the higher and lower values of traffic volume. Since assuming a linear relationship between traffic volume and collision rate may not be valid, the model form may be modified to represent a more realistic relationship between traffic volume and safety. Considering the

“U” shaped relationship of exposure and safety was commonly achieved in previous collision models by revising the model form shown in Equation 4.9b to include exposure in a power form, as shown in Equations 4.11 and 4.12. It should be noted that the natural logarithms of traffic volume and curve length, and the single exposure term are commonly taken to linearize these models. On the other hand, successful collision models based on the untransformed values of exposure have also been developed in previous studies. As with the selection of a suitable regression technique, the blind application of any one approach should be avoided. Thus, the selection of a model form in this study was based on the best fit for the data at hand.

$$Y = \exp(\beta_0) AADT^{\beta_1} L^{\beta_2} \exp(\beta_3 X_3) \exp(\beta_4 X_4) \dots \exp(\beta_n X_n) \quad (4.11)$$

$$Y = \exp(\beta_0) EXPO^{\beta_1} \exp(\beta_2 X_2) \exp(\beta_3 X_3) \dots \exp(\beta_n X_n) \quad (4.12)$$

The use of the single exposure term has also been applied as a scale factor in previous studies. This approach means that the exposure variable coefficient is forced to one so that the parameters of the remaining variables can be interpreted as their pure collision risk, rather than their combined impact with exposure (Fridstrom et al., 1995). Furthermore, this approach allows the collision model to estimate annual collision frequency despite the use of multiple years of collision data (Harwood et al., 2000a). However, Fridstrom et. al. (1995, p.7) criticized this approach stating that “This formulation, however, would be tantamount to assuming strict proportionality between exposure and accidents, something that appears unreasonably restrictive”.

Anderson et al. (1999) examined the two approaches for incorporating exposure expressed in Equations 4.11 and 4.12, and found that including the natural logarithms of

traffic volume and curve length as separate terms improved the model's goodness of fit. Fitzpatrick et al. (2000c), and Swalha and Sayed (2001) have also preferred this approach for incorporating exposure. Furthermore, Vogt et al. (1998) and Harwood et al. (2000a) developed successful collision models based on the use of the single exposure term as a scale factor. On the other hand, Pasupathy et al. (2001) modelled the natural logarithm of the single exposure term without taking it as a scale factor. The above are only a few examples of previous studies that have applied the presented approaches for incorporating exposure.

4.4 SELECTION OF COLLISIONS FOR MODEL DATABASE

Different collision types have been applied in previous collision models, thus it was decided to investigate three groups that represent some of the main approaches found in the literature. The first approach (Group A) involves the modelling of all collision types that have occurred within the specified distance from each curve section (100 m). Thus, even those collisions that cannot be directly attributed to the consistency measures, such as collisions due to intersections, impaired driving, animals, etc, are considered. This approach requires the least processing of collision data. However, it may be considered inaccurate since it attempts to relate consistency measures for horizontal curves to collisions that are not related to the roadway geometric alignment, and intersection related collisions. The second approach (Group B) limits collisions to all non-intersection related collisions. This was found to be a relatively common approach. However, not all non-intersection related collisions could be directly attributed to the roadway segment geometry. This leads us to the third group of collisions investigated in this study.

The third approach (Group C) only includes collision types that are generally related to design deficiencies in curve sections. These collisions are single vehicle run-off the road collisions, multiple vehicle collisions in opposing directions, and multiple vehicle collisions in the same direction (Zegeer et al., 1990). In this approach, collisions involving any of the following conditions are excluded from analysis: driver asleep; animal in the roadway; parked, turning or passing vehicle; mechanical defect; and bicycle, motorcycle or truck. The main limitation of this approach is that not all curve related collisions are of the type classified above (Harwood et al., 2000a). Thus, this approach for selecting collisions may be overly restrictive, and could result in the elimination of collisions that are in fact related to the roadway design.

Furthermore, each of the above groups was separated into 3 classes of collisions: (1) Class I: sum of total collisions (PDO+IN+FA); (2) Class II: equivalent property damage only (EPDO); and (3) Class III: sum of injury and fatal collisions only (IN+FA). The first class of collisions in this study is simply the sum of different collision severities experienced at each site. However, one of the disadvantages of this approach is that it considers fatal, injury and PDO collisions to carry equal importance. The technique attempted in this study to overcome this drawback is the estimation of the equivalent property damage only (EPDO), which is based on collision severity numbers that assign more weight to fatality and injury collisions than PDO collisions. The most common weights used are 12 to a fatal collision, 6 to an injury collision, and 1 to a PDO collision (Zuehlke, 2002). These values are then summed to obtain the EPDO number. Finally, the use of injury and fatal collisions only was considered to help eliminate inaccuracies due to the common underreporting of PDO collisions.

Three groups, each divided into three classes resulted in the nine different collision sets investigated in this study. Ultimately, the best set of collisions used would be the one that correlates best to the consistency measures and exposure. The collision data on each curve identified during data collection were processed to determine the three-year collision frequency based on each of the above groups and classes. This resulted in the collision database used in model development, which is detailed in Tables A.8 to A.10 of Appendix A, and is summarized in Table 4.1.

Table 4.1: Summary Collision Experience by Class and Group.

GROUP	PDO	INJ	FA	PD+INJ+FA	EPDO	INJ+FA
A	32	10	2	44	116	12
B	27	9	2	38	105	11
C	22	9	1	32	88	10

4.5 SELECTION OF PREDICTOR VARIABLES

After the preliminary screening of alternative consistency measures in the literature review, the following six main variables were selected for potential inclusion in the final model: reduction of 85th percentile speed; 85th percentile of speed reduction; difference between operating speed and design speed; differential of side friction supply and demand; visual demand of unfamiliar drivers; and ratio of curve radius to average radius. Exposure, which is represented in terms of traffic volume and curve length, is basic to each model developed. It is very likely that several of these consistency measures are highly correlated to each other. Although the presence of correlated variables in a regression model does not prevent achieving an acceptable model fit, it renders the direct

interpretation of coefficients as showing the impacts of their associated variable invalid. Furthermore, multi-collinearity can greatly increase sampling variation of coefficients, diminish the models descriptive abilities, increase the problem of round off errors, and may worsen the models predictive ability. In this case, it might be desirable to drop some of the correlated variables in the regression model, with caution not to drop important predictor variables.

After identifying the initial functional form for the overall consistency model in the previous section, the best subset of potential predictor variables can now be identified. This is perhaps one of the most complex tasks in the process of regression analysis. This is due to the fact that the uses of regression models vary, and no one subset of potential predictor variables is likely to always be best. For example, since collision causation models attempt to estimate the safety impact of changing different factors, there is emphasis on the precise estimation of the regression coefficients. On the other hand, collision prediction models attempt to estimate the expected collision experience as a function of the strongest predictor variables, thus there is an emphasis on prediction errors. An additional concern while selecting predictor variables is to be careful not to eliminate key variables that could reduce the predictive power of the model, while avoiding over-fitting the regression model, which may lead to higher variances. In general, reducing the number of predictor variables is preferred, since the smaller the number of variables in a regression model, the easier it is to use and understand.

Often, investigators will screen out predictor variables by fitting a model with all the variables and simply dropping those with small absolute values for the t -statistic (Neter et al., 1996). This can lead to the dropping of important inter-correlated

explanatory variables. In this study, variable selection was based on complete enumeration, which is possible since the number of predictor variables in this study is relatively small (less than 12). Complete enumeration fits all possible subsets of predictor variables and identifies a few “good” variables according to a specified criterion. In this study, the criteria for variable selection were significance at the 95% confidence level, and the verification of the parameter signs based on engineering judgment.

The SAS software package yields estimates of the p -values, which are used to test the null hypothesis that the slope of the relationship is zero. If the p -value of a regression coefficient is sufficiently small, this indicates that the corresponding variable is statistically significant. The null hypothesis is based on the assumption that the estimated regression coefficient for each covariate must be statistically significant in order to be relevant. It is worthwhile to note that many prominent statisticians have questioned the use of such statistical tests of significance. Hauer (2002) stated that the use of statistical tests of significance might strip data of its useful meaning and lead to conclusions that are contradictory to a direct and common sense interpretation of the data. It was also stated that it is likely that variables may be statistically insignificant not due to a lack of a safety relationship, but due to limitations in data accuracy.

4.6 TESTING MODEL GOODNESS OF FIT

It is always important to thoroughly check model goodness of fit, or in other words, the discrepancy between the original data values and the fitted values generated from the model. Several goodness of fit measures are available to verify that the model provides an acceptable level of quality. While a small discrepancy would be acceptable, a large discrepancy between the original data values would be unacceptable. Furthermore,

the coefficient of each variable should be statistically significant to verify that variables do have explanatory power. Finally, engineering judgment should be able to confirm the validity and practicality of the sign and rough magnitude of each estimated coefficient.

McCullagh and Nelder (1989) recommended the testing of model goodness of fit based on the scaled deviance and Pearson χ^2 statistics, which were previously described in Section 4.4.3. The main measure recommended for testing goodness of fit is the scaled deviance, previously described in Equation 4.7, which represents model discrepancy as twice the difference between the maximum log-likelihood achievable and that achieved by the model developed. The Pearson χ^2 statistic, shown in Equation 4.5, is another important measure for goodness of fit. However, McCullagh and Nelder (1989) consider it more of a measure of residual variation than goodness of fit measure.

As previously mentioned, the scaled deviance and χ^2 statistics are approximately chi-squared random variables with degrees of freedom equal to $n - p$. This property is used to construct goodness of fit tests by identifying the maximum allowable values of the scaled deviance and χ^2 statistics. Generally, lower values of these measures indicate better model goodness of fit. The decision rule for testing goodness of fit based on scaled deviance, which also applies to the χ^2 statistic, is shown in Equation 4.13. Concluding H_a implies that the model goodness of fit is acceptable, while H_o implies an unacceptable model quality and goodness of fit.

$$\text{If } D^m(X_0, X_1, \dots, X_{p-1}) \leq \chi^2(1 - \alpha; n - p), \text{ conclude } H_a \quad (4.13)$$

$$\text{If } D^m(X_0, X_1, \dots, X_{p-1}) > \chi^2(1 - \alpha; n - p), \text{ conclude } H_o$$

The analysis of residuals is an additional technique for assessing model goodness of fit, particularly the deviance residual (Neter et al., 1996). The deviance residual for case i is defined as the signed square root contribution of the i^{th} case to the sum for model deviance. Thus, summing the squared root deviance residuals would result in the model deviance. Constructing an index plot of the deviance residuals is considered helpful in identifying outlying residuals; however, it does not provide any guidance for determining whether they should be treated as outliers.

The use of the traditional coefficient of determination (R^2), which is the most common goodness of fit measure, has been avoided in this study since it is not considered appropriate for Poisson or negative binomial regression models. In fact, the suitability of R^2 as a goodness of fit measure has been widely debated by researchers due to several problems associated with its application. Miaou et al. (1995) demonstrated the many drawbacks associated with the use of R^2 for assessing the goodness of fit of collision prediction models.

Miaou (1996) recommended a fairly simple goodness of fit measure for negative binomial models based on the model over-dispersion parameter (K), and the maximum over-dispersion parameter (K_{max}), as shown in Equation 4.14. The maximum over-dispersion parameter is estimated in the model with only a constant term and no predictor variables, and thus represents all of the systematic variation that exists in the model. It is noted that this measure is different from the traditional measure of multiple correlation.

$$R_K^2 = 1 - \frac{K}{K_{max}} \quad (4.14)$$

CHAPTER FIVE

5.0 RELATING CONSISTENCY TO SAFETY

This chapter presents the main results of the regression analyses conducted to examine the relationships of the alternative consistency measures to safety. Firstly, Section 5.1 presents an overview of the modelling process, and the alternative factors considered in model development. The modelling results are organized into five main categories. In Section 5.2, the results of the Poisson and negative binomial regression models are examined and compared, and the most appropriate regression technique is identified. In Section 5.3, the models based on the alternative collision sets are reviewed, and the collision set providing the best fit is recommended. In Section 5.4, the alternative exposure terms are investigated, and the most suitable approach for incorporating exposure is determined. In Section 5.5, the regression models relating each of the individual consistency measures to collision frequency are presented and discussed. Finally, Section 5.6 outlines the results of the variable selection procedure conducted towards the development of an overall safety-based consistency model.

5.1 REVIEW OF MODELLING ATTEMPTS

In this study, numerous models relating each of the consistency measures to safety have been generated based on: (1) both Poisson and negative binomial regression; (2) each of the nine alternative collision sets considered for investigation; and (3) three approaches for incorporating exposure. In addition, fifteen variants of the original six consistency measures described in Chapter 2 were investigated. Thus, in order to reduce the complexity of model development, and the presentation of modelling results, the modelling process was organized as follows:

1. Keeping the exposure term constant, models for each of the nine sets of collisions were generated for the fifteen consistency measures based on both Poisson and negative binomial regression. This resulted in the development of 270 regression models. However, in terms of selecting the best set of collisions, the conclusions based on the Poisson and negative binomial regression models were similar. Furthermore, since only three of the nine collision sets provided acceptable results, the selection of either Poisson or negative binomial regression was based on these three collision sets only. This greatly reduced the number of models in this study requiring thorough investigation.
2. Based on the results of the previous step, the best regression technique and set of collisions were identified. Thus, these factors were kept constant while the application of the alternative exposure methods were examined. This simplification was conducted to reduce the number of models required to identify the most appropriate exposure term, which were only 45 regression models, among which fifteen were developed in the previous step.

This process resulted in the development and investigation of 300 models relating each of the individual consistency measures to safety. However, only the models based on the selected regression technique, collision set, and exposure terms are documented in this chapter. A summary of the alternative factors considered in modelling is presented in Table 5.1. In addition, eleven additional models including all possible subsets of the consistency measures were generated. This process was conducted towards the development of an overall safety-based consistency model. The results of this analysis are further detailed in Section.5.5.

Table 5.1: Summaries of Modelling Considerations.

Parameter	Number of Cases	Description
Collision Group	3	A: All collisions B: Non-intersection related collisions only C: Run-off the road collisions only
Collision Class	3	I: Sum of all collisions (PDO+INJ+FA) II: Sum of injury and fatal collisions (INJ+FA) III: Weighted sum of all collisions (EPDO)
Traffic Exposure	3	(1) Natural logarithms of length and volume separately (2) Natural logarithm of single exposure term (3) Untransformed single exposure term
Regression Technique	2	(1) Poisson (2) Negative binomial
Consistency Measures:		
Design speed Consistency	3	(1) $ V_{85}-V_D $ (alignment) (2) $(V_{85}-V_D)^*$ (alignment) (3) $ V_{85}-V_L $ (curve) (4) $(V_{85}-V_L)$ (curve) *Identical to $ V_{85}-V_D $ (alignment)
Operating Speed Consistency	4	(1) ΔV_{85} (critical direction) (2) ΔV_{85} (average of two directions) (3) $\Delta_{85}V$ (critical direction) (4) $\Delta_{85}V$ (average of two directions)
Vehicle Stability	1	(1) Δf_r
Alignment Index	3	(1) CRR (exponential) (2) $ \Delta CRR $ (critical) (3) (ΔCRR) (critical)
Visual Demand	4	(1) VD_{LU} (exponential) (2) VD_{LU} (power) (3) $ \Delta VD_{LU} $ (critical) (4) (ΔVD_{LU}) (critical)
Total Models Attempted	= (9 collision sets x 2 regression techniques x 15 measures) + (2 additional exposure terms x 15 measures) = 300 models	

5.2 SELECTION OF REGRESSION TECHNIQUE

In order to decide whether the Poisson or negative binomial regression technique is more suitable for this study, the fifteen measures described in the second half of Table 5.1 were first generated based on the Poisson distribution, and their dispersion parameters were examined. The negative binomial regression technique was then implemented to determine whether it could accommodate the problem of over-dispersion. As previously mentioned, over-dispersion is a common problem in collision models, which represents the impact of omitted variables that are outside the study scope. The level of model dispersion was assessed based on the values of the scaled deviance and χ^2 statistics divided by the model degrees of freedom, which are referred to here as the dispersion parameters. These values were provided in the SAS output as part of the criteria for assessing model goodness of fit. In general, values that deviate greatly from 1.0 indicate an unacceptable level of model dispersion and goodness of fit.

The values of the dispersion parameters varied greatly depending on the class of collisions used in model development (i.e. PDO+IN+FA, IN+FA, or EPDO). For each of Group A, B and C collisions, only models based on the sum of collisions (PDO+IN+FA) were found to provide acceptable results. Furthermore, Group B collisions provided superior results in terms of model goodness of fit. These results are discussed in greater detail in the following section. However, in this section, the Poisson and negative binomial regression models are compared based on the sum of Group B collisions, since these models were found to provide the best results. In the Poisson regression models, the dispersion parameters based on the scaled deviance ranged from approximately 0.83 to 1.06, and were thus acceptable. On the other hand, the χ^2 dispersion parameters ranged

from approximately 1.20 to 1.60; with the model based on $\Delta_{85}V$ experiencing the highest over-dispersion and that based on *CRR* the lowest. Thus, considering the Poisson assumption of equal mean and variance, the Poisson regression models developed in this study were found to experience an unacceptably high level of over-dispersion, and were thus considered unsatisfactory.

The application of negative binomial regression was found to considerably improve the over-dispersion of all models, particularly that based on $\Delta_{85}V$, where the χ^2 over-dispersion parameter dropped from approximately 1.60 to 1.20. Based on the sum of collisions for Group B, all models were found to be generally within the acceptable range of 0.8 to 1.2 for over-dispersion. Thus, the negative binomial regression technique was selected for final model development, and only the results of these models are presented in this thesis. As mentioned earlier, the main advantage of using negative binomial regression over Poisson regression is that it allows for future model improvements based on the application of the Empirical Bayesian approach, which is strongly recommended for future research.

5.3 SELECTION OF COLLISION SET

Regression models based on each of the nine sets of collisions discussed in Section 4.4 were generated to identify the set of collisions that correlated best to the consistency measures. As previously described, the collision data was divided into three main groups based on the cause of collision: Group A included all collision types; Group B included all non-intersection related collisions; while Group C excluded collisions related to: driver asleep; animal in the roadway; parked, turning or passing vehicle; mechanical defect; and bicycle, motorcycle or truck. In addition, each group was divided

into three classes based on collision severity: the total sum of collisions (PDO+INJ+FA), the sum of injury and fatal collisions (INJ+FA), and the weighted collisions in terms of equivalent property damage only (EPDO).

Firstly, the regression models resulting from the different classes of collisions in each group are discussed. The class of collisions that correlated best to the consistency measures was consistently found to be the sum of collisions (PDO+INJ+FA). The modelling of INJ+FA collisions led all of the consistency measures to be statistically insignificant at the 95% confidence level for all three groups of collisions. In addition, these models experienced a high degree of under-dispersion. Although under-dispersion of collision data is not very common, this was expected due to the large number of curve sites with zero injury or fatal collisions. Considering EPDO collisions, the consistency measures were also found to be statistically insignificant, in addition to extremely high over-dispersion parameters of up to 5.0. These high values of over-dispersion are likely for EPDO collisions due to the high variation of collision frequencies resulting from the weights ascribed to injury and fatal collisions. Thus, the regression models based on the INJ+FA and EPDO classes of collisions were found to be unacceptable, and their results are not further discussed.

The models based on the sum of collisions for Groups A, B and C are now considered. Firstly, for all three groups of collisions, $|V_{85} - V_D|$ was found to be statistically insignificant. Considering Group A collisions, the remaining consistency measures were statistically significant. However, the over-dispersion and model goodness of fit measures for the collision model based on *CRR* were found to be unacceptable. Group B collisions also provided statistically significant relationships for the consistency

measures, except for the untransformed value of visual demand, which did not consider the “U” shaped relationship between safety and driver workload. Otherwise, Group B collisions were found to provide generally lower scaled deviances, and lower p -values compared to Group A collisions. Finally, Group C collisions also resulted in statistically significant results. However, the 85th percentile of speed reduction ($\Delta_{85}V$) was found to experience an unacceptable level of under-dispersion based on the model χ^2 statistic. Furthermore, the use of Group C collisions resulted in under-dispersion, and somewhat higher p -values compared to Group A.

In summary, the sum of collisions for Groups A, B and C generally provided statistically significant models. However, when comparing the results of these collision groups, the sum of Group B collisions were found to provide superior values in terms of statistical significance and model goodness of fit, followed by Group A, and then Group C collisions. Thus, the final regression models recommended in this thesis were based on the sum of Group B collisions. Nonetheless, the application of the models based on Group A and C collisions are also considered acceptable, and may be applied, if preferred by the designer. These models are presented in Tables B.1 and B.2 in Appendix B.

5.4 SELECTION OF EXPOSURE VARIABLE

Three main techniques for incorporating exposure in the collision models were examined. The first approach includes traffic volume and curve length separately, while the second approach combines traffic volume and curve length into a single exposure term (Equation 4.10). Taking the natural logarithm of these variables was recommended in previous research, and was thus investigated in this study. The third approach considered the untransformed value of the exposure term.

Modelling the sum of three-year collisions in Group B as a function of the natural logarithms of both curve length (L) and three-year traffic volume ($AADT$) based on negative binomial regression, resulted in the following model:

$$Y = \exp(-9.5721) \times AADT^{0.5743} \times L^{0.6088} \quad (5.1)$$

The results of this model are detailed in Table 5.2. Curve length was found to be statistically significant at the 95% confidence level, with an estimated p -value of 0.0049, while traffic volume was not significant at this level, with a p -value of 0.0767. The dispersion parameters of this model based on the scaled deviance and χ^2 parameters respectively are 0.8857 and 1.2210. Although 1.2210 is slightly outside the maximum acceptable value of 1.2, it was still considered acceptable in this study. The model R_k^2 coefficient of determination is relatively low, at 0.4817. Although this model may not provide satisfactory predictive capability, the directions of the relationships between traffic volume and curve length to safety are as expected.

Table 5.2: Models for Traffic Exposure Only (Group B, Sum of Collisions).

Variable	Estimate	p -value	Scaled Deviance, χ^2 , (Test) Values	Scaled Deviance, χ^2 Dispersion, (R_k^2)
$Y = \exp(b_0) AADT^{b_1} L^{b_2}$				
b_0	-9.5721	0.0049	59.3409, 81.8103	0.8857, 1.2210
b_1	0.5743	0.0767	(86.6501)	($R_k^2 = 0.4817$)
b_2	0.6088	0.0280		
$Y = \exp(b_0) Expo^{b_1}$				
b_0	-0.8725	0.0001	59.4156, 81.9333	0.8738, 1.2049
b_1	0.5939	0.0033	(87.9430)	($R_k^2 = 0.4844$)
$Y = \exp(b_0 + b_1(Expo))$				
b_0	-1.2896	<0.0001	57.9005, 72.8763	0.8515, 1.0717
b_1	0.2859	0.0042	(87.9430)	($R_k^2 = 0.4088$)

Alternatively, modelling the natural logarithm of the single exposure term (million vehicle-km for three-year period) resulted in the following regression model:

$$Y = \exp(-0.8725) \times Expo^{0.5939} \quad (5.2)$$

As shown in Table 5.2, the *Expo* variable was statistically significant at the 95% level, with a *p*-value of 0.0033, which indicates that it has a strong relationship to safety. The dispersion parameters of this model based on scaled deviance and χ^2 respectively are 0.8738 and 1.2049, which expresses an acceptable deviation of variance from the mean, and a slight improvement over the previous model. The model R_k^2 is also slightly higher than the previous model, but remains relatively low at 0.4844.

In order to decide which technique is most appropriate in this study, each approach for incorporating exposure was modelled with the alternative consistency measures based on negative binomial regression, and the sum of Group B collisions. It was found that when combined with the individual consistency measures, the use of the natural logarithm of the single exposure term provided better results. Following, the use of the untransformed value of the single exposure term was examined, and is presented in Equation 5.3.

$$Y = \exp(-1.2896 + 0.2859Expo) \quad (5.3)$$

The untransformed exposure variable was statistically significant at the 95% level, with a slightly higher *p*-value of 0.0042, in addition to a slightly lower R_k^2 value of 0.4088. Although these values are faintly less favourable than that resulting from the natural logarithm of exposure, the dispersion parameters of this model based on scaled deviance and χ^2 dropped from 0.8738 and 1.2049; to 0.8515 and 1.0717 respectively. This also reflects an improvement in model goodness of fit. The collision models based

on this exposure term and the alternative consistency measures revealed even better results in terms of model over-dispersion and goodness of fit. For example, considering the collision model based on *CRR*, the use of the natural logarithm of exposure and the natural logarithms of traffic volume and curve length separately resulted in χ^2 dispersion parameters of 1.2708 and 1.3024, and R_k^2 values of 0.9891 and 0.9921, respectively. On the other hand, the use of the untransformed value of exposure resulted in the improvement of the critical dispersion parameter to 1.0543, although R_k^2 was slightly lower at 0.9836. Thus, a model form that incorporates the exponential rather than the power of the exposure term was selected for application in this study.

5.5 INDIVIDUAL CONSISTENCY MEASURES AND SAFETY

Since each of the main design consistency measures evaluates a slightly different aspect of the highway design, and are based on differing assumptions, they are expected to have varying relationships to safety. Thus, the relationships of the individual consistency measures to safety have been quantified based on regression analysis, and these results will later be used to rank these measures in order of their importance to safety. As previously mentioned, the purpose of these regression models is not to predict collisions, but rather to provide a better understanding of the relative impact of each consistency measure on safety.

5.5.1 Analysis of Design Speed Consistency

Traditionally, this measure is based on the absolute difference between the predicted operating speed on curves and the design speed of the alignment, $|V_{85} - V_D|$. The operating speed on curves (V_{85}) was estimated using an operating speed prediction model adapted from Misaghi (2003), which was shown in Equation 2.4. The curve design

speed was taken as the design speed of the whole alignment, as recommended by Lamm et al. (1999). In calculating this measure, V_{85} was found to be greater than V_D for all of the curves in the study database. Many of the curves experienced relatively high values for $|V_{85} - V_D|$, resulting from predicted operating speeds that greatly exceeded the design speeds of the highway alignments. As previously described in Sections 2.1.1 and 2.1.3, desired speeds that greatly exceed the design speed of the alignment are indicators of a poor highway safety level.

To examine the relationship of this measure to safety, the three-year collision frequency was modelled as a function of the three-year exposure term, and the $|V_{85} - V_D|$ experienced on curve segments. These results are presented in Table 5.3, which shows that only a statistically insignificant regression model resulted, with this measure corresponding to a p -value of 0.5586. Furthermore, these models provided a counter-intuitive direction for this variable's relationship to safety, which suggests that increasing the difference between operating speed and design speed would cause a decrease in collision frequency. Thus, based on this study, the traditional $|V_{85} - V_D|$ consistency measure does not have a statistically significant relationship to safety, and is thus excluded from further analysis in this study.

Nonetheless, as discussed in the previous chapter, it has been argued that tests of statistical significance may lead to the dismissal of variables that may have an important impact on safety, and inhibit a more direct interpretation of the data. Thus, it is concluded that although this measure does not provide an acceptable regression model based on this study database, it is stressed that this measure may still have an impact on safety, and it is not recommended that it be disregarded totally in highway consistency evaluation.

Table 5.3: Models for Design Speed Consistency (Group B, Sum of Collisions).

Variable	Estimate	p-value	Scaled Deviance, χ^2 , (Test) Values	Scaled Deviance, χ^2 Dispersion, (R_k^2)
$Y = \exp(b_0 + b_1(V_{85} - V_D) + b_2(Expo))$				
b_0	-1.0538	0.0371	58.0535, 73.8105	0.8665, 1.1016
b_1	-0.0166	0.5586	(86.6501)	($R_k^2 = 0.4295\%$)
b_2	0.2549	0.0217		
$Y = \exp(b_0 + b_1(V_{85} - V_L) + b_2(Expo))$				
b_0	-0.7871	0.0031	66.6414, 77.4449	0.9946, 1.1559
b_1	-0.0715	0.0004	(86.6501)	($R_k^2 = 0.9734\%$)
b_2	0.4228	<0.0001		
$Y = \exp(b_0 + b_1(V_{85} - V_L) + b_2(Expo))$				
b_0	-0.9709	0.0002	66.6446, 78.3297	0.9947, 1.1691
b_1	0.0571	0.0014	(86.6501)	($R_k^2 = 0.9403\%$)
b_2	0.4047	<0.0001		

As an additional attempt to relate this measure to safety, it was calculated based on the approximate design speeds at individual curve segments, referred to here as the limiting speed, V_L . The limiting speeds were estimated based on the point mass formula, where the superelevation values were obtained from field measurements, while the side friction values (f_r) were assumed to be dependent on the design speed. The limiting speeds were calculated based on an iterative procedure for determining f_r . Counter to the previous approach, this resulted in values that were generally higher than the predicted operating speed.

As shown in Table 5.3, the use of limiting speeds at individual curves rather than the design speed of the whole alignment was found to result in a statistically significant relationship to safety for design speed consistency. However, an illogical direction for this variable resulted, and this model was also rendered unacceptable. However, it was found that when relating collision frequency to $(V_{85} - V_L)$, without taking the absolute value of this measure, the resulting model provided statistically significant results, with

an acceptable model fit and a logical direction for this relationship. It should be noted that the modelling of $(V_{85} - V_D)$ based on the design speed of the alignment was also considered. However, since all values of V_{85} were greater than V_D , the values of this measure are identical to $|V_{85} - V_D|$. The collision model based on $(V_{85} - V_D)$ is detailed in Table 5.3, and is expressed as follows:

$$Y = \exp(-0.9709 + 0.0571(V_{85} - V_L) + 0.4047(Expo)) \quad (5.4)$$

The positive sign of the $(V_{85} - V_L)$ variable parameter expresses the expected direction of this relationship. Namely, larger differences between operating and design speeds are associated with higher collision frequency. Both variables were found to be statistically significant at the 95% confidence level, with $(V_{85} - V_L)$ and exposure having p -values of 0.0014 and <0.0001 respectively. Thus, there is strong evidence that this measure has an important impact on the safety level on horizontal curves. As expected, the exposure term, with an associated χ^2 value of 22.79, was found to explain most of the variability in collision frequency, while the $(V_{85} - V_D)$ variable, with an associated χ^2 value of 10.24, explained far less of the collision variation than exposure.

Furthermore, the model dispersion parameters based on the scaled deviance and χ^2 statistics respectively are 0.9947 and 1.1691, which indicates an acceptable level of dispersion. The model scaled deviance and χ^2 values also indicate an acceptable model goodness of fit, as these statistics are both below their maximum allowable value of 86.6501. This maximum value was obtained from the standard table of percentiles of the χ^2 distribution, based on $\chi^2(0.95; 67)$. This value is represented in Table 5.3 as the “Test” value, and was applied for assessing the goodness of fit of all models developed based on the individual consistency measures. Furthermore, this model experienced a high R_k^2

value of 0.94%, which indicates that a large proportion of the systematic variability available is explained by this model.

It is noted that many curves experienced relatively high negative values based on this measure, which may seem to indicate a favourable level of highway safety. However, based on the original design consistency measure $|V_{85} - V_D|$, it is hypothesized that design speeds that are much greater than the desired speeds of drivers may encourage the adoption of high operating speeds, and are thus considered to lead to a poor level of safety and consistency. Thus, not taking the absolute value of this measure defies its purpose and its underlying hypothesis as a consistency measure. Particularly, it is expected that the application of such a consistency measure be biased towards flatter curves, thus providing similar results as the AASHTO guideline, and encouraging designers to adopt the flattest curve radii possible.

Furthermore, the use of the limiting speed for individual curves rather than the design speed of the whole alignment leads this measure to be highly correlated to vehicle stability, which is also based on the point mass formula. In turn, this measure is considered to provide results that are physically equivalent to the vehicle stability measure. Thus, although statistically significant, this method of measuring the design speed consistency was not considered in overall consistency model development, or sensitivity analysis, since it lacks its basis as a consistency measure.

5.5.2 Analysis of Operating Speed Consistency

Two techniques for estimating the speed reduction on curves have been presented in this thesis. The more traditional approach is based on the difference between the 85th percentile speeds on a curve and its preceding tangent, or on two successive curves (ΔV_{85}

$= |V_{85i} - V_{85i-1}|$). However, a previous study has shown that ΔV_{85} tends to underestimate the actual speed reduction experienced by drivers, since it is based on independent speed distributions at each location. An alternative approach is based on the 85th percentile of the speed reductions from tangent to curve, or from two successive curves for each driver ($\Delta_{85}V$). The relationship of each approach to safety has been examined in order to select the most suitable speed reduction model for consistency evaluation.

As previously mentioned, the models used for the prediction of 85th percentile operating speeds (V_{85}) and 85th percentile of speed reductions ($\Delta_{85}V$) are both based on the study conducted by Misaghi (2003). These models were provided in Equations 2.4 and 2.6 respectively. Furthermore, Misaghi recommended that the operating speeds on independent and non-independent tangents be estimated as approximately 103.0 km/h, and 96.0 km/h respectively. The use of these models provides an important advantage for the collision models based on operating speed consistency, since the operating speed prediction models are based on the operating speed background of the curves under study, rather than the use of operating speed models based on other geographic locations.

Comparing the predicted speed reductions on the curves based on each approach, $\Delta_{85}V$ was found to result in values approximately 3.0 times higher than ΔV_{85} . This is highly consistent with the results of previous research by McFadden and Elefteriadou (2000). Thus, the use of $\Delta_{85}V$ would result in far less favourable safety ratings compared to ΔV_{85} for the curve segments under study.

Several curves in the model database experienced differing speed reductions in each direction, namely due to the presence of an independent tangent in one direction and a non-independent tangent preceded by a curve in the other. In these cases, two methods

a non-independent tangent preceded by a curve in the other. In these cases, two methods were considered for estimating the representative speed reduction on the curve. The first technique was based on the critical value of speed reduction, while the second technique was based on the average speed reduction experienced in both directions. For curves with differing speed reductions in each direction, the values for speed reduction based on the two techniques were found to be fairly close to each other. In addition, since most curves had independent tangents on both sides, leading the average speed reduction to be identical to the critical speed reduction, the two approaches were found to provide highly comparable model results (Table 5.4). However, taking the critical value of speed reduction provided slightly better p -values and model goodness of fit for both ΔV_{85} and $\Delta_{85}V$. Thus, the use of the critical speed reduction was selected in this study, and the collision models developed based on the critical speed reductions are now further discussed.

Firstly, the modelling results of the reduction in 85th percentile speeds (ΔV_{85}) considering the critical direction of speed reduction are exhibited in Equation 5.5.

$$Y = \exp(-2.9874 + 0.2829(\Delta V_{85}) + 0.4275(Expo)) \quad (5.5)$$

Both the ΔV_{85} and exposure variables were found to be statistically significant at the 95% confidence level, with p -values of 0.0010 and <0.0001 respectively. The relationship between ΔV_{85} and safety was positively correlated as expected, since as the speed reduction on a curve increases, collision frequency is also expected to increase. Based on an examination of the χ^2 values of each variable, the exposure term was also found to explain more of the variability of collisions than speed reduction.

Table 5.4: Models for Operating Speed Consistency (Group B, Sum of Collisions).

Variable	Estimate	<i>p</i> -value	Scaled Deviance, χ^2 , (Test) Values	Scaled Deviance, χ^2 Dispersion, (R_k^2)
$Y = \exp(b_0 + b_1(\Delta V_{85\text{critical}}) + b_2(\text{Expo}))$				
b_0	-2.9874	<0.0001	67.1407, 81.2878	1.0021, 1.2133
b_1	0.2829	0.0010	(86.6501)	($R_k^2 = 0.9607$)
b_2	0.4275	<0.0001		
$Y = \exp(b_0 + b_1(\Delta V_{85\text{average}}) + b_2(\text{Expo}))$				
b_0	-2.3313	<0.0001	68.0968, 85.8509	1.0164, 1.2814
b_1	0.2406	0.0030	(86.6501)	($R_k^2 = 0.9448$)
b_2	0.3816	<0.0001		
$Y = \exp(b_0 + b_1(\Delta_{85}V_{\text{critical}}) + b_2(\text{Expo}))$				
b_0	-3.3287	0.0008	59.7649, 80.8651	0.8920, 1.2069
b_1	0.1885	0.0257	(86.6501)	($R_k^2 = 0.6502$)
b_2	0.2035	0.0282		
$Y = \exp(b_0 + b_1(\Delta_{85}V_{\text{average}}) + b_2(\text{Expo}))$				
b_0	-2.5200	0.0018	59.9044, 80.3672	0.8941, 1.1195
b_1	0.1277	0.0863	(86.6501)	($R_k^2 = 0.6037$)
b_2	0.2032	0.0402		

The model dispersion parameters as based on the scaled deviance and χ^2 statistics are 1.0021 and 1.2133 respectively. Although the χ^2 dispersion parameter of this model is just outside the acceptable value of 1.2, it is still considered an acceptable level of over-dispersion. The model scaled deviance and χ^2 values also indicate an acceptable model goodness of fit, as these statistics are both below the acceptable upper limit. Furthermore, this model experiences a high R_k^2 value, which indicates that this model explains a large proportion of the variation in observations. Overall, the model scaled deviance, χ^2 , and R_k^2 values indicate an acceptable level of over-dispersion and model goodness of fit.

The collision model based on the 85th percentile of speed reduction ($\Delta_{85}V$) is now presented in Equation 5.6, and is detailed in Table 5.4.

$$Y = \exp(-3.3287 + 0.1885(\Delta_{85}V) + 0.2035(\text{Expo})) \quad (5.6)$$

Both the $\Delta_{85}V$ and exposure variables were also found to be statistically significant at the 95% confidence level, with p -values of 0.0257 and 0.0282 respectively. In addition, the relationship of this speed reduction variable to safety was in the direction expected. The model dispersion as based on the scaled deviance and χ^2 statistics are 0.8920 and 1.2069 respectively, and are considered to be within the acceptable range. However, comparing this model's goodness of fit measures to the model based on ΔV_{85} provided contradicting results. Based the scaled deviances and χ^2 values, it is concluded that the results of the collision model based on $\Delta_{85}V$ provide a lower discrepancy from the actual collision frequency. However, ΔV_{85} experienced a notably higher value of R_k^2 , and a lower p -value. The relationships between these two measures and safety will be further examined in the following chapter based on a sensitivity analysis.

5.5.3 Analysis of Vehicle Stability

Vehicle stability is determined based on the difference between side friction supply and side friction demand experienced on horizontal curves ($\Delta f_r = f_r - f_{rd}$). The side friction supply values for the highway alignments were determined based on Equation 2.10 for Highways 43, 31, 17, 15, 7 and 12 (characterized as flat topography), and Equation 2.12 for Highway 41 (characterized as mountainous topography). The side friction demand was based on the point mass formula, with the use of the predicted operating speed in place of the design speed, as previously described in Equation 2.13. The majority of curves under study experienced positive values of Δf_r , which would indicate a good level of vehicle stability, and hence safety, on these curves. Curves that experienced side friction demands in excess of their side friction supply may indicate a possible safety problem.

The relationship between vehicle stability and safety was quantified through a regression model relating three-year collision frequency to vehicle stability and three-year traffic exposure as follows:

$$Y = \exp(-0.8660 - 16.1188(\Delta f_r) + 0.3526(Expo)) \quad (R_k^2 = 0.8957) \quad (5.7)$$

This model verifies the expected direction of the relationship between vehicle stability and safety. As the side friction demand exceeds the side friction supply on a curve, the collision frequency is expected to increase. Both the vehicle stability and exposure variables in this model were statistically significant at the 95% confidence level, with p -values of 0.0014 and <0.0001 respectively. This implies that vehicle stability has an important impact on safety. The model dispersion parameters based on the scaled deviance and χ^2 statistics are 0.9626 and 1.1367 respectively. The actual scaled deviance and χ^2 values associated with this model are 64.4910 and 76.1580 respectively, which are both below the maximum allowable value 86.6501. These statistics indicate an acceptable level of over-dispersion and model goodness of fit. The model R_k^2 was also relatively high; however, it was lower than the model based on ΔV_{85} .

5.5.4 Analysis of Alignment Index *CRR*

The Curve Radius to Average Radius (*CRR*) measure expresses the ratio comparing individual curves to all curves in the roadway section. A design inconsistency is indicated when *CRR* is significantly greater or less than 1.0. Three-year collision frequency as a function of *CRR* and traffic exposure is expressed as follows:

$$Y = \exp(1.6425 - 3.3682(CRR) + 0.3318(Expo)) \quad (5.8)$$

The direction of *CRR* was found to be logical, since a curve radius that is much sharper than the average curve radius of the alignment violates driver expectancy, and

increases the collision risk on that curve. The *CRR* and exposure variables were both statistically significant with *p*-values less than 0.0001, which indicates that *CRR* has a strong relationship to safety. Although the exposure term ($\chi^2 = 22.15$) continues to explain most of the collision variability, the gap between the variability of collisions explained by exposure and *CRR* ($\chi^2 = 19.16$) is noticeably smaller compared to the other consistency measures. This suggests that *CRR* explains a higher percentage of the variation of collision frequency. Table 5.5 summarizes the model estimates, dispersion parameters, and goodness of fit measures based on the scaled deviance, χ^2 and R_k^2 statistics. These values indicated an acceptable level of over-dispersion, and an acceptable model goodness of fit. Furthermore, it is noteworthy that this model experienced the lowest model scaled deviance, and highest R_k^2 values in this study.

Table 5.5: Models for *CRR* (Group B, Sum of Collisions).

Variable	Estimate	<i>p</i> -value	Scaled Deviance, χ^2 , (Test) Values	Scaled Deviance, χ^2 Dispersion, (R_k^2)
$Y = \exp(b_0 + b_1(CRR) + b_2(Expo))$				
b_0	1.6425	0.0081	57.1032, 70.6395	0.8523, 1.0543
b_1	-3.3682	<0.0001	(86.6501)	($R_k^2 = 0.9836$)
b_2	0.3318	<0.0001		
$Y = \exp(b_0 + b_1(\Delta CRR) + b_2(Expo))$				
b_0	-1.2803	0.0050	57.8899, 72.8707	0.864, 1.0876
b_1	-0.0203	0.9773	(86.6501)	($R_k^2 = 0.4084$)
b_2	0.2852	0.0055		
$Y = \exp(b_0 + b_1(\Delta CRR) + b_2(Expo))$				
b_0	-1.4205	<0.0001	58.7032, 70.5025	0.8762, 1.0523
b_1	0.8606	0.0519	(86.6501)	($R_k^2 = 0.5881$)
b_2	0.3035	0.0014		

One of the advantages of using *CRR* as a consistency measure is that it is not biased towards flat curves. However, the collision models developed in this study do not

represent this property. In response, a model fitting the absolute value of ΔCRR , which represents the differential of CRR between two consecutive curves was developed, since it was hypothesized that $|\Delta CRR|$ would provide an un-biased alternative to CRR . This measure also attempts to represent the impact of short-term driver experience in explaining the variation of collision experience. It is noted that the values of ΔCRR in the critical direction of vehicle travel were selected rather than the average of both directions. This was based on previous knowledge gained from modelling collision frequency and operating speed reduction in Section 5.5.2.

Modelling $|\Delta CRR|$ resulted in a highly statistically insignificant model, with an associated p -value of 0.9773. A model based on the non-absolute value of ΔCRR was then attempted. Although this model resulted in a statistically significant relationship, the direction of this relationship was found to be counter-intuitive, leading it to be unacceptable. The results of these two models are detailed in Table 5.5.

5.5.5 Analysis of Visual Demand

Models predicting the visual demand of familiar and unfamiliar drivers have been provided in previous studies; however, the visual demand for unfamiliar drivers only was applied in this study since this is the more critical case for visual demand requirements. Based on this study, the relationship of this measure to safety is described as:

$$Y = \exp(-6.1863 + 18.7713(VD_{LU}) + 0.3680(Expo)) \quad (5.9)$$

The direction of this model reflects that the higher the visual demand on a curve, the higher the collision frequency expected on that curve, which is in agreement with engineering judgement. However, this model was not considered acceptable since visual demand provided a statistically insignificant relationship to safety at the 95% confidence

level, with an associated p -value of 0.0984, as shown in Table 5.6. Thus, it is recommended that additional research be conducted to improve the model for estimating driver visual demand. Specifically, a model database including a larger scope of design variables should be developed, as previously noted in Chapter 2.

To improve this model, the inclusion of visual demand in a power format was attempted to better express its hypothesized “U” shaped relationship to safety. This was achieved by modelling the natural logarithm of visual demand, and the following statistically significant model resulted:

$$Y = \exp(5.3212 + 0.3740(Expo)) \times VD_{LU}^{4.9046} \quad (5.10)$$

Table 5.6: Models for Visual Demand (Group B, Sum of Collisions).

Variable	Estimate	p -value	Scaled Deviance, χ^2 , (Test) Values	Scaled Deviance, χ^2 Dispersion, (R_k^2)
$Y = \exp(b_0 + b_1(VD_{LU}) + b_2(Expo))$				
b_0	-6.1863	0.0297	61.0783, 74.6402	0.9116, 1.1140
b_1	18.7713	0.0984		($R_k^2 = 0.7599$)
b_2	0.368	0.0004		
$Y = \exp(b_0 + b_1(\ln(VD_{LU})) + b_2(Expo))$				
b_0	5.3212	0.0207	62.2858, 75.7663	0.9296, 1.1308
b_1	4.9046	0.0048		($R_k^2 = 0.8034$)
b_2	0.374	<0.0001		
$Y = \exp(b_0 + b_1(\Delta VD_{LU}) + b_2(Expo))$				
b_0	-1.3855	0.0011	58.1241, 72.2987	0.8675, 1.0791
b_1	3.3309	0.7305		($R_k^2 = 0.4233$)
b_2	0.2919	0.0037		
$Y = \exp(b_0 + b_1(\Delta VD_{LU}) + b_2(Expo))$				
b_0	-1.3215	<0.0001	59.4273, 74.1881	0.887, 1.1073
b_1	-11.2248	0.0648		($R_k^2 = 0.6016$)
b_2	0.2852	0.0023		

The direction of the relationship between $\ln(VD_{LU})$ and safety was also found to be logical. Furthermore, both variables in this model were statistically significant, with

VD_{LU} and exposure having p -values of 0.0048 and <0.0001 respectively. Thus, representing the “U” shaped relationship of visual demand and safety provides far better model results, and is recommended for all collision models relating driver workload measures to safety. As shown in Table 5.6, the model dispersion parameters as based on the scaled deviance and χ^2 statistics are both well within the acceptable range for dispersion. These values also indicate an acceptable model goodness of fit.

As with CRR , the differential of visual demand between two consecutive curves (ΔVD_{LU}) was considered. As illustrated in Table 5.6, this measure provided results similar to those obtained for ΔCRR . The model fitting the absolute value of ΔVD_{LU} resulted in highly insignificant results with an associated p -value of 0.7305, while the non-absolute value of ΔVD_{LU} resulted in a statistically insignificant relationship at the 95% confidence level, in addition to a counter-intuitive direction for this relationship.

5.6 VARIABLE SELECTION FOR OVERALL CONSISTENCY MODEL

After establishing the relationships of each consistency measure to safety, the development of an overall safety-based consistency model through regression analysis was attempted. The availability of an overall model that reflects the varying relationships of alternative consistency measures to safety was considered a promising approach for assessing the tradeoffs between results provided by different consistency measures. To achieve this, the development of a collision model containing as many consistency measures as are statistically significant was attempted.

As previously mentioned, the variable selection process was based on complete enumeration, where all possible subsets of predictor variables are fit. The criterion for retaining a variable in the overall model was statistical significance at the 5% confidence

level, in addition to the ability of engineering judgment to confirm the validity of the sign and rough magnitude of each estimated coefficient. It is noted that the exposure term is basic to all models and was thus retained regardless of statistical significance. In the previous chapter, several variants of the consistency measures were examined. The final set of variables recommended and selected as potential variables in an overall consistency model were: ΔV_{85} , $\Delta_{85}V$, Δf_r , CRR , and $\ln(VD_{LU})$.

Although the separate consistency measures evaluate different aspects of the highway design, it should be noted that multi-collinearity was a particular concern in the development of an overall consistency measure, since each of the consistency measures is a function of curve radius (R). Although multi-collinearity does not violate the model assumptions, it causes several problems in the regression estimates. In order to investigate the presence of multi-collinearity among variables, a correlation matrix was developed and is shown in Table 5.7. Highly correlated variables are those with correlation values of 0.7 or higher (Persaud et al., 2001). Although the correlation matrix displays a high degree of correlation among the predictor variables, models with all possible subsets were still generated and examined in this study. It should be noted that the overall model was fit with $\Delta_{85}V$ rather than ΔV_{85} since this measure provided less correlation to the other variables and a higher correlation to safety, as shown in Table 5.7. Furthermore, the scope of ΔV_{85} is limited to curves with predicted speed differentials less than 10 km/h as discussed in the following chapter.

Based on these four measures, 11 models describing all possible subsets of these variables in an overall model were generated, and are shown in Table 5.8. For the sake of simplicity, only the model with the full number of variables followed by the results of

four regression models with select subsets of consistency measures are presented. These models summarize the variable selection procedure conducted towards the development of an overall consistency model, and were particularly selected for illustrative purposes.

Table 5.7: Pearson's Correlation Coefficients Matrix.

Variable	3-year collision frequency	$\Delta_{85}V$	ΔV_{85}	Δf_r	$\ln(VD_{LU})$	CCR
3-year collision frequency	1.0000	0.3670	0.1035	-0.1891	0.1341	-0.3487
$\Delta_{85}V$	0.3670	1.0000	0.3349	-0.3615	0.4108	-0.3850
ΔV_{85}	0.1035	0.3349	1.0000	-0.9147	0.9630	-0.7728
Δf_r	-0.1891	-0.3615	-0.9147	1.0000	-0.9609	0.7904
$\ln(VD_{LU})$	0.1341	0.4108	0.9630	-0.9609	1.0000	-0.7964
CCR	-0.3487	-0.3850	-0.7728	0.7904	-0.7964	1.0000

Table 5.8: All Possible Subsets of Combined Consistency Measures.

Model	Subset of Variables
1	$\Delta_{85}V, \Delta f_r, Expo$
2	$\Delta_{85}V, \ln(VD_{LU}), Expo$
3	$\Delta_{85}V, CCR, Expo$
4	$\Delta f_r, \ln(VD_{LU}), Expo$
5	$\Delta f_r, CCR, Expo$
6	$\ln(VD_{LU}), CCR, Expo$
7	$\Delta_{85}V, \Delta f_r, \ln(VD_{LU}), Expo$
8	$\Delta_{85}V, \Delta f_r, CCR, Expo$
9	$\Delta_{85}V, \ln(VD_{LU}), CCR, Expo$
10	$\Delta f_r, \ln(VD_{LU}), CCR, Expo$
11	$\Delta_{85}V, \Delta f_r, \ln(VD_{LU}), CCR, Expo$

5.6.1 Model 1: Including All Consistency Measures

The model generated with the full set of consistency measures is shown in Table 5.9. This table indicates that the model goodness of fit is acceptable based on both the scaled deviance and χ^2 statistics. Furthermore, the model scaled deviance and χ^2 over-dispersion parameters are 0.7663 and 0.9501 respectively, which indicates some under-dispersion in terms of the scaled deviance. This may be an indication that this regression model is over-fit, or in other words, contains unnecessary predictor variables.

Examining the p -values associated with each variable in this model, it is found that the consistency measures provide statistically significant results, although the exposure term is rendered statistically insignificant. However, further examination of the estimated model parameters reveals that the direction of the relationship between visual demand and safety is counter-intuitive, since collisions are not expected to increase with decreasing visual demand. Counter-intuitive variable signs are a common indication of collinearity between predictor variables. Thus, the subsequent model to be presented will exclude this consistency measure. It is also noted that although vehicle stability is technically insignificant at the 95% confidence level, the p -value indicated a confidence level only slightly below 90%, and was thus retained.

Table 5.9: Variable Selection for Overall Model (I).

Variable	Parameter	p -value	Scaled deviance, χ^2 , (Test) Values	Scaled deviance, χ^2 Dispersion, (R_k^2)
Intercept	-25.7132	0.0504	49.0451, 60.8100 (79.3600)	0.7663, 0.9501 (0.9956)
$Expo$	0.0643	0.6477		
Δ_{85V}	0.2264	0.0890		
Δf_r	-36.5897	0.1131		
CRR	-5.4818	0.0002		
$\ln(VD_{LU})$	-20.5268	0.0329		

5.6.2 Model 2: Excluding Visual Demand

The results of the model excluding visual demand are summarized in Table 5.10. Based on the p -values, both $(\Delta_{85}V)$ and (Δf_r) become statistically insignificant, in addition to (Δf_r) having a counter-intuitive variable sign. Based on this model, only the exposure term and CRR should remain. However, the next model presented will exclude the vehicle stability term only, retaining both $(\Delta_{85}V)$ and (Δf_r) .

Table 5.10: Variable Selection for Overall Model (II).

Variable	Parameter	p -value	Scaled deviance, χ^2 , (Test) Values	Scaled deviance, χ^2 Dispersion, (R_k^2)
<i>Intercept</i>	1.8328	0.2498	56.4713, 71.7341 (80.6425)	0.7648, 0.9547 (0.9926)
<i>Expo</i>	0.2934	0.0011		
$\Delta_{85}V$	0.0320	0.7294		
Δf_r	8.3715	0.3426		
<i>CRR</i>	-4.2317	0.0016		

5.6.3 Model 3: Excluding Vehicle Stability

The results of the model excluding vehicle stability are presented in Table 5.11. Based on the p -values, only $(\Delta_{85}V)$ becomes statistically insignificant, in addition to visual demand having a counter-intuitive variable sign. Based on this model also, only the exposure term and CRR remain acceptable. The next model presented excludes the vehicle stability and visual demand terms, leaving $(\Delta_{85}V)$ and CRR only.

Table 5.11: Variable Selection for Overall Model (III).

Variable	Parameter	<i>p</i> -value	Scaled deviance, χ^2 , (Test) Values	Scaled deviance, χ^2 Dispersion, (R_k^2)
Intercept	-7.5221	0.1126	53.4213, 69.7042 (80.6425)	0.8232, 1.0712 (0.9958)
<i>Expo</i>	0.1812	0.1059		
$\Delta_{85}V$	0.1203	0.2487		
$\text{Ln}(VD_{LU})$	-7.2144	0.0410		
<i>CRR</i>	-5.5216	0.0002		

5.6.4 Model 4: Excluding Visual Demand and Vehicle Stability

The results of the model including $\Delta_{85}V$ and *CRR* only are shown in Table 5.12. This particular combination was selected for illustration in this chapter since these two variables provided the least correlation to each other (Table 5.7). Based on the associated *p*-values of each variable, $\Delta_{85}V$ becomes highly statistically insignificant, leaving only *CRR* and exposure as the only acceptable variables.

Table 5.12: Variable Selection for Overall Model (IV).

Variable	Parameter	<i>p</i> -value	Scaled deviance, χ^2 , (Test) Values	Scaled deviance, χ^2 Dispersion, (R_k^2)
Intercept	1.6000	0.3129	57.4144, 71.0289 (80.6425)	0.8732, 1.1113 (0.9919)
<i>Expo</i>	0.3304	<0.0001		
$\Delta_{85}V$	0.0033	0.9728		
<i>CRR</i>	-3.3576	0.0004		

5.6.5 Model 5: Including *CRR* Only

It is clear that all previous models show that the *CRR* was the only consistency measure that consistently provided statistically significant results, with a direction that is in agreement with engineering judgement. After removing the $\Delta_{85}V$ variable, *CRR* remains as the only consistency measure in an overall consistency model. The automatic

stepwise procedure for variable selection provided in SAS was employed for the purpose of confirmation, and also resulted in a model containing the *CRR* and exposure variables only. This model was presented in Equation (5.8).

In summary, it can be concluded that due to the high correlation among the available design consistency variables, the development of a regression model containing more than one consistency measure is not possible. It was found that any combination of consistency measures provided counter intuitive variable signs, and statistically insignificant results. An alternative approach to regression analysis that may overcome the problem of multi-collinearity is artificial neural networks. This approach has recently been gaining greater application, however, it is considered a black box and does not allow for engineering judgement. An additional disadvantage is that this approach requires a large database compared to regression analysis.

Thus, a sensitivity analysis was conducted to further examine the impacts of each measure on safety, and provide a ranking system in order of their importance to safety. This would allow an alternative approach for overall consistency evaluation based on the use of each measure separately, and the knowledge of the importance of each to safety. Thus, the safety predictions provided by each measure would be examined in light of the ranking system developed, as will be further discussed in the following chapter.

CHAPTER SIX

6.0 SENSITIVITY ANALYSIS

Sensitivity analyses are generally conducted to determine which variables are most sensitive with respect to affecting a change on the dependent variable. In this chapter, the estimated impacts of the consistency measures on safety were quantified based on a sensitivity analysis in order to determine which measure produces the greatest change in safety when manipulated. This sensitivity analysis also facilitated a clearer illustration of the modelling results, and further verified that safety performance varies with consistency in a manner that is generally realistic, and practical in terms of the safety evaluation of two-lane rural highways. Sections 6.1 to 6.4 illustrate the results of the sensitivity analysis conducted for each of the consistency measures recommended in the previous chapter, namely ΔV_{85} and $\Delta_{85}V$, Δf_r , CRR , and $\ln(VD_{LU})$ respectively. It is noted that all of the sensitivity analyses were based on the ranges of annual exposure present in the databases used in model development.

6.1 ANALYSIS OF OPERATING SPEED CONSISTENCY

The sensitivity of both ΔV_{85} and $\Delta_{85}V$ to safety were investigated in order to identify which measure has the strongest impact on safety. The results of the sensitivity analysis for the collision model based on ΔV_{85} (Equation 5.6) are first presented. Table 6.1 and Figure 6.1 both illustrate the predicted variation of collision frequency with ΔV_{85} at different levels of annual exposure.

Table 6.1: Sensitivity of Safety to ΔV_{85} .

ΔV_{85} (km/h)	Annual Traffic Exposure (million vehicle-km)					
	0.5	1.0	1.5	2.0	2.5	3.0
0	0.062	0.07	0.09	0.11	0.14	0.18
5	0.25	0.31	0.39	0.48	0.60	0.74
10	1.05	1.30	1.62	2.00	2.48	3.07
15	4.34	5.38	6.66	8.25	10.22	12.66
20	17.89	22.15	27.43	33.97	42.07	52.09

Figure 6.1: Sensitivity of Safety to ΔV_{85} .

The percent rate of change of collision frequency with the alternative consistency measures was calculated based on Equation 6.1.

$$\% \text{ Change in Collision Frequency} = \frac{\Delta Y}{Y} \quad (6.1)$$

For further illustration, the calculations involved in determining the rate of change of collision frequency with changes in ΔV_{85} are detailed in Equation 6.2.

$$Y = (-2.9874 + 0.2829\Delta V_{85} + 0.4275Expo) \quad (6.2a)$$

$$\Delta Y = [(-2.9874 + 0.2829(\Delta V_{85} + 1) + 0.4275 \text{Expo})] - [(-2.9874 + 0.2829\Delta V_{85} + 0.4275 \text{Expo})] \quad (6.2b)$$

$$\% \text{ Change in Collision Frequency} = \frac{\Delta Y}{Y} = 100 * [(\exp(0.2829) - 1)] \quad (6.2c)$$

According to Equation 6.2c, ΔV_{85} was found to increase by 32.70% with a unit increase of 1 km/h in speed reduction. Among all of the consistency measures investigated, this measure represents the highest sensitivity to safety. However, observing Table 6.1 and Figure 6.1, it was found that after exceeding a speed reduction of 10 km/h, a very rapid increase in the predicted collision frequency occurs, which provides results greatly higher than what would be reasonably expected. For example, at an exposure of 1.5 million vehicle-km, increasing the speed reduction from 10 km/h to 15 km/h would cause a predicted increase in collision frequency from approximately 2 collisions to 7 collisions. Furthermore, increasing the speed reduction from 15 km/h to 20 km/h would cause collision frequency to increase from 7 collisions to an unreasonably high 27 collisions. This is attributed to the fact that the curves used in model development did not experience ΔV_{85} values in excess of 10 km/h, which limits the scope of the model in Equation 5.6.

Thus, it is recommended that a database including a larger range of ΔV_{85} values be developed to improve this model and increase its applicability. Nonetheless, the collision model based on ΔV_{85} is the most promising measure for consistency evaluation in terms of sensitivity to safety. However, the model developed in this study is not recommended for use with curves that are predicted to experience speed reductions in excess of 10 km/h. The results of the sensitivity analysis based on $\Delta_{85}V$ (Equation 5.7) are now illustrated in Table 6.2 and Figure 6.2.

Table 6.2: Sensitivity of Safety to $\Delta_{85}V$.

$\Delta_{85}V$ (km/h)	Annual Traffic Exposure (million vehicle-km)					
	0.5	1.0	1.5	2.0	2.5	3.0
0	0.04	0.04	0.04	0.05	0.06	0.06
5	0.10	0.11	0.12	0.13	0.15	0.16
10	0.26	0.28	0.32	0.35	0.39	0.43
15	0.67	0.74	0.82	0.91	1.00	1.11
20	1.72	1.90	2.11	2.33	2.58	2.86

Figure 6.2: Sensitivity of Safety to $\Delta_{85}V$.

Applying Equation 6.1, it was found that increasing $\Delta_{85}V$ by 1 km/h caused the predicted collision frequency to increase by 20.74%. Unlike ΔV_{85} , Table 6.2 and Figure 6.2 show that $\Delta_{85}V$ experiences very limited sensitivity to safety at speed reduction values less than 10 km/h. Although this value exhibits significantly less sensitivity to safety than ΔV_{85} speed reduction, observing Figure 6.2 shows that this model increases more gradually with collision frequency, and is thus considered to vary more realistically with

collision frequency after exceeding 10 km/h. It was also observed that based on this model, safety exhibits far less variation with exposure, which implies that this measure has a relatively more dominant impact on predicted collision frequency.

6.2 ANALYSIS OF VEHICLE STABILITY

The results of the sensitivity analysis examining the magnitude of the relationship between vehicle stability and collision frequency (Equation 5.8) at different levels of traffic exposure are presented in Table 6.3 and Figure 6.3.

Table 6.3: Sensitivity of Safety to Δf_r .

Δf_r	Annual Traffic Exposure (million vehicle-km)					
	0.5	1.0	1.5	2.0	2.5	3.0
-0.05	1.03	1.05	1.08	1.11	1.16	1.22
-0.04	0.87	0.89	0.92	0.95	0.99	1.04
-0.03	0.74	0.76	0.78	0.81	0.84	0.88
-0.02	0.63	0.64	0.66	0.68	0.71	0.75
-0.01	0.54	0.55	0.56	0.58	0.61	0.64
0.00	0.46	0.47	0.48	0.49	0.52	0.54
0.01	0.39	0.40	0.41	0.42	0.44	0.46
0.02	0.33	0.34	0.35	0.36	0.37	0.39
0.03	0.28	0.29	0.29	0.30	0.32	0.33
0.04	0.24	0.24	0.25	0.26	0.27	0.28
0.05	0.20	0.21	0.21	0.22	0.23	0.24

Figure 6.3: Sensitivity of Safety to Δf_r .

The predicted collision frequency was found to decrease by 19.69% with a unit increase in vehicle stability of 0.0136. This unit value was selected based on a correlation analysis, and represents the change in vehicle stability corresponding to an increase of 1 km/h in speed reduction. Similar unit values were obtained for the remaining consistency measures to allow comparison of the sensitivity analysis results. The rate of change of vehicle stability was found to be only slightly less sensitive to safety than $\Delta_{85}V$, thus these two measures have the lowest ranking sensitivity to safety. Furthermore, observing Table 6.3 and Figure 6.3 shows that safety does not vary greatly with vehicle stability, and is effectively invariable at different levels of exposure.

6.3 ANALYSIS OF ALIGNMENT INDEX *CRR*

The sensitivity of safety based on *CRR* (Equation 5.9) at different levels of traffic exposure is illustrated in Table 6.4 and Figure 6.4.

Table 6.4: Sensitivity of Safety to *CRR*.

<i>CRR</i>	Annual Traffic Exposure (million vehicle-km)					
	0.5	1.0	1.5	2.0	2.5	3.0
0.50	1.13	1.33	1.57	1.86	2.19	2.59
0.60	0.80	0.95	1.12	1.33	1.57	1.85
0.70	0.57	0.68	0.80	0.94	1.12	1.32
0.80	0.41	0.48	0.57	0.67	0.80	0.94
0.90	0.29	0.34	0.41	0.48	0.57	0.67
1.00	0.21	0.24	0.29	0.34	0.40	0.48
1.10	0.15	0.17	0.20	0.24	0.29	0.34
1.20	0.10	0.12	0.14	0.17	0.20	0.24
1.30	0.07	0.09	0.10	0.12	0.14	0.17
1.40	0.05	0.06	0.07	0.08	0.10	0.12
1.50	0.03	0.04	0.05	0.06	0.07	0.08

Figure 6.4: Sensitivity of Safety to *CRR*.

The predicted collision frequency was found to decrease by 28.50% with a unit increase of 0.0996 in *CRR*, providing the second highest sensitivity to safety following ΔV_{85} . Thus, *CRR* is considered one of the most promising measures for safety based consistency evaluation. Observing Table 6.4 and Figure 6.4 shows that the collision

frequency varies with *CRR* in a manner that is realistic and practical in terms of highway safety evaluation. It is noted that a breakpoint in the relationship between *CRR* and safety was observed in Figure 6.4 at approximately 0.75. This value is suggested to be a reasonable threshold value for establishing guidelines for safety based consistency evaluation based on *CRR*, which were not previously available. However, it is recommended that in addition to the application of Equation 5.9, the actual values of *CRR* be investigated separately to identify potential inconsistencies due to curves that are greatly flatter than average.

6.4 ANALYSIS OF VISUAL DEMAND

The results of the sensitivity analysis based on VD_{LU} (Equation 5.9) are shown in Table 6.5 and Figure 6.5.

Table 6.5: Sensitivity of Safety to $\ln(VD_{LU})$.

$\ln(VD_{LU})$	Annual Traffic Exposure (million vehicle-km)					
	0.5	1.0	1.5	2.0	2.5	3.0
0.20	0.09	0.11	0.13	0.16	0.19	0.23
0.22	0.14	0.17	0.21	0.25	0.31	0.37
0.24	0.22	0.27	0.32	0.39	0.47	0.57
0.26	0.33	0.40	0.48	0.58	0.70	0.84
0.28	0.47	0.57	0.69	0.84	1.01	1.22
0.30	0.67	0.81	0.97	1.17	1.42	1.71
0.32	0.92	1.11	1.34	1.61	1.94	2.35
0.34	1.24	1.49	1.80	2.17	2.62	3.16
0.36	1.64	1.98	2.39	2.88	3.47	4.18
0.38	2.14	2.58	3.11	3.75	4.52	5.46
0.40	2.75	3.32	4.00	4.83	5.82	7.02

Figure 6.5: Sensitivity of Safety to $\ln(VD_{LU})$.

The predicted collision frequency was found to increase by an average of 22.58% with a unit increase of 0.0110 in visual demand. Based on this value, visual demand has the third highest sensitivity to safety. Table 6.5 and Figure 6.5 also show that collision frequency varies realistically with VD_{LU} . It is noted that based on this study, these results are only achievable by taking the natural logarithm visual demand, as previously discussed in Section 5.5.

CHAPTER SEVEN

7.0 CONCLUSIONS AND RECOMMENDATIONS

The concept of design consistency is one of several tools used by highway designers to improve roadway safety. The most promising consistency measures identified in previous research fall into four main categories, namely: operating speed, vehicle stability, alignment indices, and driver workload. Most research related to design consistency has been dedicated to the development of models that can estimate these consistency measures, while little research has considered their relationships to safety. The main objective of this thesis is to quantify the relationships between the individual consistency measures to actual collision experience through regression analysis, and provide a ranking system in terms of their importance to safety. A subsequent objective is to provide an overall safety-based model for highway consistency evaluation. It is noted that the scope of this study is limited to the horizontal curves of two-lane rural highways due to their overrepresentation of collision occurrence.

Seven two-lane rural highway segments located in the Eastern Ontario region were chosen for analysis. The required geometric, traffic volume and collision data were provided by the MTO and SDG, and were supplemented by site visits and field measurements. Based on the site selection criteria, a sample of 70 curves was selected for model development. The application of both Poisson and negative binomial regression techniques were investigated, and the use of negative binomial regression was selected.

The main conclusion of this study is that statistically significant collision models based on operating speed consistency, vehicle stability, the ratio of curve radius to average radius, and visual demand were developed for safety-based consistency

evaluation. These models are expected to serve as a useful tool for helping designers maximize highway safety. Considering the development of an overall safety-based consistency model, it was found that any combination of consistency measures in a regression model provided counter-intuitive variable signs, and statistically insignificant results due to the high multi-collinearity existing among the predictor variables.

However, the development of an overall consistency model may still be possible with future enhancements of the consistency measures. Furthermore, the application of neural networks is suggested for future research to overcome multi-collinearity.

Numerous factors were considered in the model development process; in addition, several variants of the original consistency measures identified in previous research were modelled to investigate additional possibilities for estimating consistency. This led to the investigation of over 300 models before the final safety based consistency models were recommended. The main conclusions and recommendations resulting from the regression analyses are summarized as follows:

- The developed models verified that the main design consistency measures have an important impact on safety, excluding the design speed consistency measure $|V_{85} - V_D|$. Nonetheless, it is stressed that this measure may still have an impact on safety, and it is not recommended that it be disregarded totally in design consistency evaluation.
- An important advantage of the collision models developed based on operating speed is that the operating speed prediction models selected were based on the operating speed background of the curves under study, rather than the use of operating speed models based on other geographic locations.

- Both ΔV_{85} and $\Delta_{85}V$ resulted in statistically significant models. Although the different goodness of fit measures provided contradicting results, $\Delta_{85}V$ experienced a lower scaled deviance, and is thus considered to have higher goodness of fit.
- Although the modelling of *CRR* and safety resulted in a statistically significant model, it is recommended that the original *CRR* measure be used separately in order to provide the designer with a conceptualization of the general character of the roadway.
- Representing the “U” shaped relationship between visual demand and safety provided far better model results, and is recommended for all collision models relating driver workload measures to safety.
- The differentials of visual demand and *CRR* between two successive curves were modelled to overcome the bias of these measures towards flatter curves, and to examine the impact of short-term driver experience on safety. However, it was found that the differentials of both measures do not provide statistically significant relationships to safety.
- All models recommended in this study experienced acceptable levels of goodness of fit and over-dispersion. Furthermore, the R_k^2 values of these models were relatively high, ranging from approximately 65% to 98%. This indicates that these models explain a large proportion of the systematic variability in collision frequency. These results are very promising, especially considering the complicated nature of collision occurrence.

- The main advantage of this approach compared to the overall module recommended by Lamm et al. (1999) is that it provides a more flexible tool for highway designers. The continuous functions relating each of the consistency measures to safety can be used to evaluate the safety impact of varying the consistency of design elements.
- The implementation of model validation was not possible due to the lack of sufficient observations. Thus, additional data collection is greatly recommended in order to allow model validation. The use of curve sites from different areas could be used in order to allow cross validation, which is a good opportunity to see how the model will perform in different areas.
- Since the development of an overall consistency model based on regression analysis was not possible due to multi-collinearity, the application of neural networks, which may overcome this problem, is recommended for future research.
- As an alternative, sensitivity analyses were conducted, and these results were examined and compared in order to rank the consistency measures in terms of the strength of their relationship to safety. Based on this analysis, the consistency measures were ranked as follows:
 1. ΔV_{85}
 2. *CRR*
 3. Visual Demand
 4. $\Delta_{85}V$
 5. Vehicle Stability

- ΔV_{85} , which is also the most common approach for consistency evaluation, was found to provide the highest sensitivity to safety. However, the model developed in this study was not considered applicable for speed reductions in excess of 10 km/h due to limitations in model scope, and should thus be applied with care. For highway segments with curves predicted to have speed reductions greater than 10 km/h, the use of $\Delta_{85}V$ is recommended.
- It is noted that the aim of the ranking system is only to provide designers with the knowledge of the relative importance of consistency measures to safety, leaving model selection open to designer preference. For example, if a certain area is dominated with run off the road collisions, the designer may prefer to rely on the model based on vehicle stability for conducting a safety evaluation.
- It also noted that this ranking system would evolve with future enhancements to the individual consistency measures, and further improvements cannot be made prior to additional research in this area.
- Based on the literature review, several weaknesses in the consistency measures were identified, specifically driver workload models based on Canadian road conditions. Thus, future improvements in consistency estimation are greatly recommended in order to improve safety based consistency evaluation.

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APPENDIX A:
MODEL DATABASE

Table A.1: Alignment and Traffic Volume Data for Highway 41.

Curve#	Station# (PI)	LHRS (Offset)	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average Traffic Volume
1	126+90.93	29640 (8.884) - (9.165)	388.00	159.79	60.96	0.066	1,550
2	136+93.09	29640 (9.216) - (9.449)	582.12	110.91	60.96	0.038	1,550
3	205+35.50	29650 (1.151) - (1.673)	873.19	430.66	45.72	0.050	1,550
4	256+68.03	29650 (2.831) - (3.131)	873.19	208.79	45.72	0.058	1,550
5	336+30.65	29650 (5.139) - (5.680)	806.00	541.13	45.72	0.040	1,550
6	356+86.57	29650 (5.954) - (6.117)	582.12	71.12	45.72	0.046	1,550
7	382+00.02	29650 (6.705) - (6.867)	436.59	100.14	45.72	0.056	1,550
8	397+06.63	29650 (7.110) - (7.406)	436.59	204.66	45.72	0.058	1,550
9	11+915.302	29690 (1.680) - (2.117)	388.08	314.23	60.96	0.053	1,420
10	15+238.372	29690 (4.994) - (5.474)	873.19	358.18	60.96	0.039	1,420
11	16+570.919	29690 (6.407) - (6.724)	388.08	194.96	60.96	0.052	1,420
12	17+031.136	29690 (6.855) - (7.204)	1164.25	226.91	60.96	0.035	1,420
13	18+188.717	29690 (8.098) - (8.277)	388.08	87.99	60.96	0.037	1,420
14	20+886.703	29700 (1.637) - (1.812)	436.59	53.02	60.96	0.055	3,470
15	26+043.167	29700 (6.256) - (7.215)	537.35	836.90	60.96	0.052	3,470
16	27+621.685	29700 (7.725) - (8.849)	635.05	1001.89	60.96	0.051	3,470
		Average Radius	611.00				

Table A.2: Alignment and Traffic Volume Data for Highway 17.

Curve#	Station# (PI)	LHRS (Offset)	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average traffic volume
17	27+042.694	20682 (1.647) - (2.620)	1166.50	821.42	76.20	0.044	10,670
18	20+347.506	20682 (8.467) - (9.164)	993.00	544.07	76.20	0.048	10,670
19	22+700.738	20701 (0.765) - (1.073)	1000.00	170.91	76.20	0.047	7,950
20	19+396.383	20703 (1.478) - (2.191)	876.00	561.34	76.20	0.048	7,950
21	15+700.826	20703 (5.334) - (5.699)	880.00	212.62	76.20	0.052	7,950
22	13+200.664	20708 (0.580) - (1.279)	1164.00	546.95	76.20	0.051	6,450
23	11+683.094	20708 (1.996) - (2.923)	1160.00	775.28	76.20	0.046	6,450
24	10+312.542	20708 (3.563) - (4.065)	866.00	349.72	76.20	0.059	6,450
		Average Radius	1011.00				

Table A.3: Alignment and Traffic Volume Data for Highway 15.

Curve#	Station# (PI)	LHRS (Offset)	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average traffic volume
25	11+011.695	20110 (1.737) - (2.024)	582.13	165.71	60.96	0.060	5,970
26	16+364.029	20110 (7.132) - (7.338)	873.19	83.34	60.96	0.0377	5,970
27	20+705.088	20110 (11.547) - (11.605)	873.19	58.10	60.96	0.042	5,970
28	11+050.986	20110 (12.761) - (13.164)	873.19	281.40	60.96	0.050	5,970
29	17+324.484	20120 (3.703) - (4.190)	600.00	365.70	60.96	0.051	5,170
30	17+882.942	20120 (4.335) - (4.685)	600.00	227.09	60.96	0.047	5,170
31	19+619.382	20120 (6.074) - (6.420)	900.00	234.31	56.00	0.042	7,600
32	20+565.516	20120 (6.952) - (7.429)	900.00	365.02	56.00	0.044	7,600
33	21+383.625	20120 (7.848) - (8.171)	600.00	205.20	59.00	0.051	7,600
34	22+501.418	20120 (8.991) - (9.268)	600.00	155.95	60.96	0.052	7,600
		Average Radius	657.00				

Table A.4: Alignment and Traffic Volume Data for Highway 7.

Curve#	Station# (PI)	LHRS (Offset)	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average traffic volume
35	12+782.386	14040 (0.529) - (1.371)	873.19	726.24	57.98	0.040	7,230
36	10+484.786	14040 (2.920) - (3.537)	873.19	501.10	60.96	0.049	7,230
37	16+501.665	14050 (0.519) - (1.104)	873.19	462.57	60.96	0.045	10,010
38	15+805.846	14050 (1.274) - (1.736)	698.55	340.60	60.96	0.045	10,010
39	15+003.084	14050 (2.054) - (2.631)	410.91	455.37	60.96	0.054	10,010
40	14+304.340	14050 (2.882) - (3.120)	873.19	116.46	60.96	0.047	10,010
41	13+963.290	14050 (3.248) - (3.436)	582.13	66.450	60.96	0.042	10,010
42	13+063.321	14050 (4.143) - (4.341)	582.13	75.45	60.96	0.052	10,010
43	11+687.846	14050 (5.459) - (5.780)	582.13	199.22	60.96	0.060	10,010
44	10+114.883	14050 (7.077) - (7.305)	436.59	105.67	60.96	0.049	10,010
		Average Radius	680.00				

Table A.5: Alignment and Traffic Volume Data for Highway 43.

Curve#	Station# (PI)	Reference	Offset	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average traffic volume
45	115+82.16	Boundary Rd	100 – 704 E	873.19	604.65	60.96	0.049	5,690
46	220+46.43	Kerrs Ridge Rd	702W & 336E	388.00	203.99	60.96	0.041	5,690
47	237+45.38	Reid Mills Rd	0 – 240 E	388.00	240.00	60.96	0.055	5,690
48	254+49.29	Shaw/ Church Rd	340 – 560 N	582.12	101.60	60.96	0.053	5,690
49	262+51.60	Shaw/ Church Rd	140 – 360 S	582.12	110.91	60.96	0.036	5,690
50	297+20.01	Mountain Rd	1120 – 1485 W	436.59	259.08	53.34	0.046	5,690
51	313+91.55	Mountain Rd	1018 – 1387 E	436.59	263.65	53.34	0.063	5,690
			Average Radius	526.00				

Table A.6: Alignment and Traffic Volume Data for Highway 31.

Curve#	Station# (PI)	Reference	Offset	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average traffic volume
52	516+50.57	Hess Rd	267 - 467S	873.20	77.60	60.96	0.044	4,820
53	537+48.61	Hess Rd	172 - 371N	873.20	76.60	60.96	0.053	4,820
54	583+91.94	Barkley Rd	553 - 1400N	873.20	464.20	60.96	0.043	4,820
55	621+53.91	Barkley Rd	1695 - 2290N	873.20	474.00	60.96	0.044	4,820
56	121+04.34	Boundary Rd	498 - 782N	436.60	162.40	60.96	0.067	4,820
57	12+572.902	Hollister Rd	85S & 206N	580.00	170.00	60.96	0.049	4,820
58	16+551.184	County Rd 38	93 - 592N	583.00	377.328	60.96	0.057	4,200
59	17+978.435	County Rd 38	1235 - 2140N	583.00	783.64	60.96	0.047	4,200
60	26+621.125	Ormond Rd	250S & 230N	349.00	472.38	60.96	0.060	5,500
61	27+731.038	Harmony Rd	398S & 251N	388.08	527.00	60.96	0.064	5,580
			Average Radius	680.00				

Table A.7: Alignment and Traffic Volume Data for Highway 12.

Curve#	Station# (PI)	Reference	Offset	Radius (m)	Length (m)	Spiral (m)	Superelevation (radian)	Average traffic volume
62	110+87.82	CTY Rd 14	373S & 210N	367.65	579.98	0.00	0.065	2,170
63	232+09.23	CON Rd 1-2	0 - 163S	388.08	124.86	0.00	0.060	2,170
64	239+82.24	CON Rd 1-2	0 - 200N	388.08	128.07	0.00	0.049	2,170
65	38+51.72	CON Rd 3-4	95S & 260N	698.55	352.96	0.00	0.043	2,170
66	79+33.66	CON Rd 4-5	0 - 233S	436.59	233.04	0.00	0.042	2,170
67	239+30.10	CON Rd 6-7	0 - 175S	698.55	121.92	0.00	0.032	2,170
68	246+37.77	CON Rd 6-7	0 - 160N	698.55	113.49	0.00	0.043	2,170
69	286+90.81	CON Rd 7-8	280N & 165S	317.52	443.34	0.00	0.055	2,170
70	305+58.89	Yelle Rd	88 - 533 S	317.52	445.47	0.00	0.069	2,170
			Average Radius	470.00				

Table A.8: "Group A" Collisions by Severity.

Curve#	Group A					
	PDO	INJ	FATAL	INF+FA	EPDO	PD+IN+FA
1	0	1	0	1	6	1
2	2	0	0	0	2	2
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	1	0	1	6	1
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	2	0	0	0	2	2
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	1	0	0	0	1	1
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	1	0	0	0	1	1
16	1	0	0	0	1	1
17	0	1	0	1	6	1
18	0	0	1	1	12	1
19	1	0	0	0	1	1
20	2	0	1	1	14	3
21	0	1	0	1	6	1
22	0	0	0	0	0	0
23	0	1	0	1	6	1
24	1	0	0	0	1	1
25	0	0	0	0	0	0
26	0	0	0	0	0	0
27	0	0	0	0	0	0
28	0	0	0	0	0	0
29	0	0	0	0	0	0
30	0	1	0	1	6	1
31	0	0	0	0	0	0
32	0	0	0	0	0	0
33	0	0	0	0	0	0
34	0	0	0	0	0	0
35	3	0	0	0	3	3
36	0	0	0	0	0	0
37	1	0	0	0	1	1
38	1	0	0	0	1	1
39	4	1	0	1	10	5

Table A.8 continued: "Group A" Collisions by Severity.

40	1	0	0	0	1	1
41	0	0	0	0	0	0
42	1	0	0	0	1	1
43	0	0	0	0	0	0
44	3	0	0	0	3	3
45	0	0	0	0	0	0
46	0	0	0	0	0	0
47	0	0	0	0	0	0
48	0	0	0	0	0	0
49	0	0	0	0	0	0
50	0	0	0	0	0	0
51	0	0	0	0	0	0
52	0	0	0	0	0	0
53	0	0	0	0	0	0
54	0	0	0	0	0	0
55	0	0	0	0	0	0
56	0	0	0	0	0	0
57	2	0	0	0	2	2
58	0	0	0	0	0	0
59	0	0	0	0	0	0
60	1	1	0	1	7	2
61	2	1	0	1	8	3
62	0	0	0	0	0	0
63	0	0	0	0	0	0
64	1	0	0	0	1	1
65	0	0	0	0	0	0
66	0	1	0	1	6	1
67	0	0	0	0	0	0
68	0	0	0	0	0	0
69	0	0	0	0	0	0
70	1	0	0	0	1	1

Note: "Group A" includes all collisions.

Table A.9: "Group B" Collisions by Severity.

Curve#	Group B					
	PDO	INJ	FATAL	INF+FA	EPDO	PD+IN+FA
1	0	1	0	1	6	1
2	2	0	0	0	2	2
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	1	0	1	6	1
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	2	0	0	0	2	2
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	1	0	0	0	1	1
16	1	0	0	0	1	1
17	0	1	0	1	6	1
18	0	0	1	1	12	1
19	1	0	0	0	1	1
20	2	0	1	1	14	3
21	0	1	0	1	6	1
22	0	0	0	0	0	0
23	0	1	0	1	6	1
24	1	0	0	0	1	1
25	0	0	0	0	0	0
26	0	0	0	0	0	0
27	0	0	0	0	0	0
28	0	0	0	0	0	0
29	0	0	0	0	0	0
30	0	1	0	1	6	1
31	0	0	0	0	0	0
32	0	0	0	0	0	0
33	0	0	0	0	0	0
34	0	0	0	0	0	0
35	1	0	0	0	1	1
36	0	0	0	0	0	0
37	1	0	0	0	1	1
38	1	0	0	0	1	1
39	4	1	0	1	10	5

Table A.9 continued: "Group B" Collisions by Severity.

40	1	0	0	0	1	1
41	0	0	0	0	0	0
42	0	0	0	0	0	0
43	0	0	0	0	0	0
44	3	0	0	0	3	3
45	0	0	0	0	0	0
46	0	0	0	0	0	0
47	0	0	0	0	0	0
48	0	0	0	0	0	0
49	0	0	0	0	0	0
50	0	0	0	0	0	0
51	0	0	0	0	0	0
52	0	0	0	0	0	0
53	0	0	0	0	0	0
54	0	0	0	0	0	0
55	0	0	0	0	0	0
56	0	0	0	0	0	0
57	2	0	0	0	2	2
58	0	0	0	0	0	0
59	0	0	0	0	0	0
60	1	1	0	1	7	2
61	2	1	0	1	8	3
62	0	0	0	0	0	0
63	0	0	0	0	0	0
64	0	0	0	0	0	0
65	0	0	0	0	0	0
66	0	0	0	0	0	0
67	0	0	0	0	0	0
68	0	0	0	0	0	0
69	0	0	0	0	0	0
70	1	0	0	0	1	1

Note: "Group B" includes all non-intersection related collisions only.

Table A.10: "Group C" Collisions by Severity.

Curve#	Group C					
	PDO	INJ	FATAL	INJ+FA	EPDO	PD+IN+FA
1	0	1	0	1	6	1
2	2	0	0	0	2	2
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	1	0	1	6	1
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	2	0	0	0	2	2
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	0	0	0
16	1	0	0	0	1	1
17	0	1	0	1	6	1
18	0	0	0	0	0	0
19	1	0	0	0	1	1
20	2	0	1	1	14	3
21	0	1	0	1	6	1
22	0	0	0	0	0	0
23	0	1	0	1	6	1
24	1	0	0	0	1	1
25	0	0	0	0	0	0
26	0	0	0	0	0	0
27	0	0	0	0	0	0
28	0	0	0	0	0	0
29	0	0	0	0	0	0
30	0	1	0	1	6	1
31	0	0	0	0	0	0
32	0	0	0	0	0	0
33	0	0	0	0	0	0
34	0	0	0	0	0	0
35	1	0	0	0	1	1
36	0	0	0	0	0	0
37	0	0	0	0	0	0
38	0	0	0	0	0	0
39	4	1	0	1	10	5

Table A.10 continued: "Group C" Collisions by Severity.

40	0	0	0	0	0	0
41	0	0	0	0	0	0
42	0	0	0	0	0	0
43	0	0	0	0	0	0
44	3	0	0	0	3	3
45	0	0	0	0	0	0
46	0	0	0	0	0	0
47	0	0	0	0	0	0
48	0	0	0	0	0	0
49	0	0	0	0	0	0
50	0	0	0	0	0	0
51	0	0	0	0	0	0
52	0	0	0	0	0	0
53	0	0	0	0	0	0
54	0	0	0	0	0	0
55	0	0	0	0	0	0
56	0	0	0	0	0	0
57	1	0	0	0	1	1
58	0	0	0	0	0	0
59	0	0	0	0	0	0
60	1	1	0	1	7	2
61	2	1	0	1	8	3
62	0	0	0	0	0	0
63	0	0	0	0	0	0
64	0	0	0	0	0	0
65	0	0	0	0	0	0
66	0	0	0	0	0	0
67	0	0	0	0	0	0
68	0	0	0	0	0	0
69	0	0	0	0	0	0
70	1	0	0	0	1	1

Note: "Group C" includes all collisions excluding driver asleep, impaired driving, animal, mechanical problem, or intersection related collisions.

APPENDIX B:
MODELS BASED ON GROUP “A” AND “C” COLLISIONS

Table B.1: Models Based on Group “A” Collisions.

Variable	Estimate	<i>p</i> -value	Scaled Deviance, χ^2 Values	Scaled Deviance, χ^2 Dispersion Parameters
Intercept	-0.7726	0.0346	79.3754, 86.6638	1.1847, 1.2935
$ V_{85}-V_D $	-0.0173	0.4276		
<i>Expo</i>	0.2061	0.003		
Intercept	-0.6148	0.0115	70.5427, 73.5208	1.0529, 1.0973
$ V_{85}-V_L $	-0.063	0.0007		
<i>Expo</i>	0.3834	<0.0001		
Intercept	-0.7669	0.001	71.7568, 74.9415	1.071, 1.1185
$(V_{85}-V_L)$	0.0516	0.0014		
<i>Expo</i>	0.3677	<0.0001		
Intercept	-2.4616	<0.0001	72.8382, 79.6699	1.0871, 1.1891
ΔV_{85} (critical)	0.2362	0.0025		
<i>Expo</i>	0.3774	<0.0001		
Intercept	-1.9389	<0.0001	74.0391, 85.18	1.1051, 1.2713
ΔV_{85} (average)	0.2049	0.0056		
<i>Expo</i>	0.3412	<0.0001		
Intercept	-2.6682	0.0034	65.4045, 72.9502	0.9762, 1.0888
$\Delta_{85}V$ (critical)	0.1499	0.0566		
<i>Expo</i>	0.1906	0.0215		
Intercept	-1.8427	0.0136	65.3873, 71.5877	0.9759, 1.0685
$\Delta_{85}V$ (average)	0.0831	0.2504		
<i>Expo</i>	0.1999	0.0305		
Intercept	-0.6593	0.0053	70.5291, 73.4634	1.0527, 1.0965
Δf_r	-15.0113	0.0008		
<i>Expo</i>	0.3206	<0.0001		
Intercept	1.0458	0.0645	67.8014, 86.5238	1.012, 1.2914
<i>CRR</i>	-2.3213	0.0004		
<i>Expo</i>	0.2819	<0.0001		

Table B.1 continued: Models Based on Group "A" Collisions.

Intercept	-1.1092	0.007	63.5575, 68.2549	0.9486, 1.0187
$ \Delta CRR $	0.1157	0.8511		
<i>Expo</i>	0.258	0.0047		
Intercept	-1.1246	<0.0001	77.4303, 81.614	1.1557, 1.2181
(ΔCRR)	0.7459	0.0317		
<i>Expo</i>	0.2547	<0.0001		
Intercept	-5.4923	0.0006	74.004, 77.6119	1.1045, 1.1584
VD_{LU}	17.1197	0.0034		
<i>Expo</i>	0.3237	<0.0001		
Intercept	4.6648	0.0252	68.1585, 71.754	1.0173, 1.071
$\ln(VD_{LU})$	4.239	0.007		
<i>Expo</i>	0.3343	<0.0001		
Intercept	-1.0731	0.0017	75.2928, 81.1781	1.1238, 1.2116
$ \Delta VD_{LU} $	1.1716	0.8828		
<i>Expo</i>	0.25	0.0003		
Intercept	-1.0855	<0.0001	68.2154, 73.7585	1.0181, 1.1009
(ΔVD_{LU})	-10.6058	0.0382		
<i>Expo</i>	0.2549	0.0003		

Table B.2: Models Based on Group “C” Collisions.

Variable	Estimate	p-value	Scaled Deviance, χ^2 Values	Scaled Deviance, χ^2 Dispersion Parameters
Intercept	-1.2481	0.0446	49.575, 66.2711	0.7399, 0.9891
$ V_{85}-V_D $	-0.0128	0.7139		
<i>Expo</i>	0.2528	0.0688		
Intercept	-0.9448	0.0098	55.4324, 69.536	0.8273, 1.0379
$ V_{85}-V_L $	-0.0763	0.0143		
<i>Expo</i>	0.4286	0.0002		
Intercept	-1.1271	0.0009	54.3277, 69.1636	0.8109, 1.0323
$(V_{85}-V_L)$	0.0627	0.0082		
<i>Expo</i>	0.4116	0.0004		
Intercept	-3.1769	0.0001	54.6888, 71.7852	0.8163, 1.0714
ΔV_{85} (critical)	0.288	0.0136		
<i>Expo</i>	0.4168	0.0006		
Intercept	-2.6054	<0.0001	61.917, 86.5634	0.9241, 1.292
ΔV_{85} (average)	0.2652	0.005		
<i>Expo</i>	0.3784	0.0002		
Intercept	-3.9408	0.0015	51.1434, 76.1689	0.7633, 1.1368
$\Delta_{85}V$ (critical)	0.2329	0.031		
<i>Expo</i>	0.1626	0.1691		
Intercept	-1.8427	0.0005	130.7746, 143.1755	0.9546, 1.0451
$\Delta_{85}V$ (average)	0.0831	0.1041		
<i>Expo</i>	0.1999	0.0022		
Intercept	-0.9475	0.0005	69.0406, 88.2253	1.0305, 1.3168
Δf_r	-20.549	<0.0001		
<i>Expo</i>	0.3645	<0.0001		
Intercept	2.1643	0.0015	55.2907, 82.01	0.8252, 1.224
<i>CRR</i>	-4.2885	<0.0001		
<i>Expo</i>	0.3483	<0.0001		

Table B.2 continued: Models Based on Group "C" Collisions.

Intercept	-1.4253	0.0081	49.5493, 66.4048	0.7395, 0.9911
$ \Delta CRR $	-0.0139	0.9869		
<i>Expo</i>	0.2762	0.0298		
Intercept	-1.6869	<0.0001	49.7342, 61.8114	0.7423, 0.9226
(ΔCRR)	1.2907	0.0226		
<i>Expo</i>	0.308	0.008		
Intercept	-7.2523	0.0014	53.6004, 72.2688	0.8, 1.0786
VD_{LU}	22.189	0.008		
<i>Expo</i>	0.3714	0.001		
Intercept	6.2283	0.0292	53.8638, 72.367	0.8039, 1.0801
$\ln(VD_{LU})$	5.7085	0.0081		
<i>Expo</i>	0.3779	0.0009		
Intercept	-1.5037	0.0027	49.6515, 65.3213	0.7411, 0.9749
$ \Delta VD_{LU} $	2.5651	0.8262		
<i>Expo</i>	0.2806	0.0248		
Intercept	-1.5295	<0.0001	51.2138, 74.8455	0.7644, 1.1171
(ΔVD_{LU})	-16.5231	0.0241		
<i>Expo</i>	0.2774	0.0128		