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Calibration of the Highway Safety Manual and the SafetyAnalyst Methodologies for Ontario Highways

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CALIBRATION OF THE HIGHWAY SAFETY MANUAL AND THE SAFETYANALYST METHODOLOGIES FOR ONTARIO HIGHWAYS

by

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ABSTRACT

SafetyAnalyst and the Highway Safety Manual (HSM) are two tools that are expected to revolutionize highway safety analyses. A key issue that allows SafetyAnalyst and HSM to become the new standards in road safety engineering is the calibration of their safety performance functions (SPFs) across time and jurisdictions. In this study, the methodologies of SafetyAnalyst and HSM are calibrated for Ontario to evaluate the effective transferability of their SPFs to local topographical conditions. A SafetyAnalyst calibration has been completed for Ontario highways and freeways, intersections, and ramps for six years (1998 to 2003) of traffic and accident counts. A data set which consists of 78 kilometres of rural two-lane two-way highways and 71 three- and four-legged stop controlled intersections located in the eastern and central regions of the Ministry of Transportation of Ontario (MTO) with six years (2002 to 2007) of traffic volume and collision counts has been used to evaluate the HSM SPFs to Ontario data. Several goodness-of-fit (GOF) measures are computed to assess the transferability and suitability of the crash models for applicability in Ontario. The study suggests that while most of the SafetyAnalyst SPFs for highways and ramps are not adaptable to Ontario data, the recalibrated SafetyAnalyst SPFs for intersections and also the recalibrated HSM Part C predictive models for two-lane rural highways and intersections provide satisfactory results in comparison to the crash models developed specifically for Ontario. Finally, this research highlights the substantial need for future improvements in data quality for more reliable safety performance estimations and evaluations.

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Ali Sabbaghi

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LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
AMF	Accident Modification Factor
APM	Accident Prediction Model
CG	Comparison Group Study
CI	Confidence Interval
CURE	Cumulative Residuals
EB	Empirical Bayes
FI	Fatal and Injury (Collisions)
FHWA	Federal Highway Administration
GEE	Generalized Estimating Equation
GLM	Generalized Linear Modeling
GOF	Goodness-Of-Fit Statistics
HSM	Highway Safety Manual
IHSDM	Interactive Highway Safety Design Model
k	Dispersion Parameter, a parameter describing the relationship between mean and variance.
LHRS	Linear Highway Referencing System
MTO	Ministry of Transportation, Ontario
MPB	Mean Prediction Bias
MAD	Mean Absolute Deviation
MSE	Mean squared Error

MSPE	Mean Squared Prediction Error
n	Number of years of collision used for the study
NB	Negative Binomial Regression
NCHRP	National Cooperative Highway Research Program
OPF	Ontario-specific safety Performance Function
PDO	Property Damage Only (collisions)
VPI	Vertical Point of Intersections
RHR	Roadside Hazard Rating
RTM	Regression-To-Mean
SAS	Statistical Analysis Software
SPF	Safety Performance Function
TWLT	Two Way Left Turn

1 INTRODUCTION

According to Transport Canada (2006), almost 22 million people drive an average of 16,000 km per year on Canadian roads. Moreover, an average of 8 deaths, 600 injuries, and 1,600 crashes take place every day on Canadian roads which cost $27,000,000 to society. This alone testifies the significance of transportation safety. Hence, the Council of Ministers of Transportation and Highway Safety in 1996 introduced Canada's inaugural national road safety vision "to have the safest roads in the world". In October 2000, a longer term plan, Road Safety Vision 2010, received approval to carry forward the work of Canada's inaugural national road safety plan. Its national target was a reduction of 30% in the average number of fatalities and serious injuries during the period of 2008-2010 over comparable 1996-2001 figures. Achievement of this national target is supposed to reduce Canada's road fatality total to fewer than 2,100 by 2010.

1.1 BACKGROUND

The key weakness of highway safety management is the lack of a proper method to reliably estimate the safety performance of an entity. As Ezra Hauer (1992) indicated, it is of interest to estimate the safety performance of an entity or its “unsafety” to discover whether it should be treated, the effects of intervention on its “unsafety”, and if its “unsafety” depends on specific traits. A proper method not only estimates the past or the present safety performance of an entity, but should also be reliable enough to estimate the future safety performance of a projected design or a current entity due to intervention. An entity here is described as an individual site (a homogeneous roadway segment or an intersection), facility, or the entire road network, and “the unsafety of an entity means the expected (long-term average of) total number of accidents by type and severity per unit of time in a certain period for that entity” (Hauer,E 1992).

The traditional approaches, used alone, have critical weaknesses in estimating the current or the future safety performance of a network, facility, or individual site. These methods have been using average crash frequencies, statistical models based on regression analyses, before-after studies, and engineering judgments to predict the safety performance of a site (Harwood et al. 2000). A quick description of these traditional methods will be provided below, and then a new method, the “safety performance function (SPF)” approach which contains elements of each of these traditional methods, will be described.

1.1.1 Estimates from Accident Counts

To measure the safety improvement of an entity due to a treatment, safety itself must be first clarified. One might equate safety with the number of accident sequences in that particular entity in a period of time. However, accident counts cannot be used to measure safety due to regression-to- the -mean (RTM) bias.

RTM is the fluctuation of crash frequencies at a particular site over the long term in which an unusually high collision count is likely to subsequently decrease even if no safety treatment was implemented. In estimating safety by using accident counts, a selection bias would occur as sites with randomly high before collisions may be chosen for treatment even though their safety performances are reasonable. Moreover, RTM would indicate changes in the safety performance for one entity from time to time even though no safety treatment had been employed.

Table 1.1 presented by Persaud and Lyon (2007), illustrates the existence of the RTM phenomena which uses data for 1,669 California rural 4-legged stop controlled intersections. In this data set, the average accident counts for the period 1994-1996 is 0.81 accidents/year and 0.83 accidents/year for the period 1997-1999. In spite of the fact that there have been no significant alterations to these intersections during both periods, a trend in accident count changes is evident from comparing the data in columns 3 and 5 in Table 1-1.This trend shows that most sites with a larger than average number of accidents per year during 1994-1996 experienced a reduction in the number of accidents in the next period and vice versa. An increase in the number of accidents is apparent for sites with a lower than average number of accidents.

Column 1: sites with (*x*) accidents in 1994–1996	Column 2: accidents/site in 1994–1996 (*x*)	Column 3: accidents/site per year in 1994–1996	Column 4: accidents/site per year in 1997–1999	Column 5: observed percent change
584	0	0	0.21	Increase
348	1	0.33	0.40	21.2
203	2	0.67	0.72	7.4
144	3	1.00	0.93	-7.0
103	4	1.33	1.17	-12.0
63	5	1.67	1.48	-11.4
56	6	2.00	1.60	-20.0
31	7	2.33	1.99	-14.6
28	8	2.67	2.12	-20.6
31	9	3.00	3.13	4.3
21	10	3.33	2.62	-21.3
11	11	3.67	3.03	-17.4
46	>=12	5.30	4.99	-5.9

Table 1-1 Data from 1,669 California rural stop controlled intersections to illustrate regression to the mean

These changes in accident counts can only be explained by the RTM phenomena since no safety treatment had taken place at these intersections during the study period.

1.1.2 Estimates from Statistical Models

Statistical models have been used in safety analyses for many years now. To develop such models, a high-quality data set which contains accident history and road characteristics (e.g., traffic volume, geometric characteristics, and traffic control features) is obtained, an appropriate model form is selected, and then the model parameters are estimated by using Poisson or negative binomial (NB) regression. Despite improvements in the accuracy of statistical models in estimating the expected total number of accidents of an entity, there remain a few issues as follows(Harwood et al. 2000):

- incapability to adequately isolate the effects of individual geometric or traffic control features,
- “assuming statistical correlations between roadway characteristics and accidents that do not necessarily represent cause-and-effect relationships”(Harwood et al. 2000),
- incapability to separate the individual effect of correlated independent variables, and
- the coefficient of a variable in the model may actually represent the effect of a missing variable from the model if they are strongly correlated.

As a result, even though statistical methods can be useful in the overall safety prediction of an entity, the estimated regression parameters might not be a reliable indicator of the safety effects of individual roadway features.

1.1.3 Estimates from before-and-after studies

Before-after evaluations are conducted by almost 97% of jurisdictions surveyed across the North America (NCHRP Synthesis295, 2001). They are used to assess the efficiency of an implemented countermeasure for an entity. However, the accuracy of a simple before-after comparison of accident counts is questionable due to the following reasons:

- the treatment may affect the comparison group itself due to spillover and migration,
- other treatments may affect treatment and comparison sites, and
- previous counts of accidents may have been randomly high or randomly low-RTM bias.

Persaud and Lyon (2007) demonstrated the effect of RTM for a simple Comparison Group (CG) study in which the before-after safety performance of two groups of sites (i.e., one group with the same implemented safety treatment and the other group with no safety treatment) were compared. The same data set for 1,669 California rural stop controlled intersections was used. The ratio of accident count average of all intersections for both periods (0.83/0.81) was used as the comparison ratio and applied to the number of accidents/ site per year (column 3) during 1994-1996 and shown in column 6 (Table 1-2).

Ezra Hauer (1997) developed a new approach (i.e., the Empirical Bayes (EB) approach) to overcome the selection bias caused by the RTM phenomena from before-after evaluations. This approach makes the before-after study a more reliable method to estimate the effects of safety improvements. The efficiency of this method in practice for estimating the safety effect of roundabout conversion in the United States has been demonstrated by Persaud et al. (2001). Persaud and Lyon (2007) also demonstrated the validity of the EB approach by analyzing accident counts from 1,669 California rural 4-legged stop control intersections. The estimated EB values are shown in column 7 of Table 1-2.

sites with (x) accidents in 1994–1996	Column 3: accidents/site per year in 1994–1996	Column 4: accidents/site per year in 1997–1999	Column 5: observed percent change	Estimate of accidents/site per year in 1997–1999		Percent difference	
				Column 6: CG	Column 7: EB	Column 8: CG	Column 9: EB
584	0.00	0.21	Increase	0.00	0.20	Increase	5.0
348	0.33	0.40	21.2	0.34	0.42	17.6	-4.8
203	0.67	0.72	7.4	0.69	0.67	4.3	7.4
144	1.00	0.93	-7.0	1.03	0.92	-9.7	1.1
103	1.33	1.17	-12.0	1.37	1.20	-14.6	-2.5
63	1.67	1.48	-11.4	1.72	1.43	-14.0	3.5
56	2.00	1.60	-20.0	2.06	1.75	-22.3	-8.6
31	2.33	1.99	-14.6	2.40	2.00	-17.1	-0.5
28	2.67	2.12	-20.6	2.75	2.37	-22.9	-10.5
31	3.00	3.13	4.3	3.09	2.64	1.3	18.6
210	3.33	2.62	-21.3	3.43	3.01	-23.6	-13.2
11	3.67	3.03	-17.4	3.78	3.33	-19.8	-9.0
46	5.30	4.99	-5.9	5.46	4.73	-8.6	5.5

Table 1-2 The effect of RTM on the CG method and the validity of the EB approach (Persaud and Lyon, 2007)

In the case of the CG study, a comparison of the results in columns 3 and 5 with columns 6 and 8 indicates that the RTM effect is still substantial due to a small comparison ratio in this case.

Column 7 shows the EB estimates of after period accident frequencies of each entity if no treatment had been applied which should be comparable to the actual 1997-1999 accident counts. Columns 8 and 9 contain the comparison results between the CG and EB estimates (columns 6 and 7) with the actual accidents per year during the after period (column 4). The comparison verifies that:

- the EB method is more accurate than the CG method in predicting the safety performance of an entity as its estimates are closer to the actual 1997-1999 counts,
- the CG method, like the naive method, tends to overestimate counts for sites with a larger than average crash history, and
- the EB method is unbiased (sometimes overestimates and sometimes underestimates counts).

1.1.4 Estimates from Expert Judgment

Expert judgment gained and developed through years of research and engineering experience can be useful in comparative judgments. Experts are able to make reliable interpretations and evaluations based on the results of historical accident data, statistical models, or before-and-after study estimations.

1.1.5 Safety Performance Function Approach (Empirical Bayes Method)

Accident prediction models (APMs) known as safety performance functions (SPFs) relate the annual accident frequency of an entity to its characteristics, such as its average annual daily traffic (AADT). The SPF method contains elements of each of the above conventional methods and has overcome their weaknesses in estimating the safety performance of an entity by using the EB approach. The EB approach eliminates RTM bias that occurs whenever accident history plays a role in selecting an entity for treatment. The EB method combines two clues about the safety of an entity (Hauer et al. 2002):

- accident counts of an entity before the implementation of a treatment (K) weighted by $[1- \alpha(j)]$, and
- accident experience expected at a reference population of similar entities [$E\{\tau(j)\}$ *and* VAR$\{\tau(j)\}$], determined by the SPF weighted by $\alpha(j)$.

Estimate of the expected accidents for an entity ($\kappa(j)$) = Weight X Accidents expected on similar entities + (1- Weight) X Count of accidents on this entity:

$$\kappa(j) = \alpha\,(j)\; E\,\{\tau\,(j)\} + [1- \alpha\,(j)]\; K\,(j)$$

$$VAR\,\{\kappa(j)\} = [1- \alpha\,(j)]\,\{\kappa(j)\}$$

where $0 \leq Weight \leq 1$ and is:

$$\alpha\,(j) = [1+VAR\,\{\tau\,(j)\}/E\,\{\tau\,(j)\}]^{-1}$$

Using the EB method in measuring safety increases the precision of safety evaluation by pulling the accident counts towards the mean, and corrects for RTM bias by taking into account, the safety performance of the “similar sites” which is produced by an SPF.

An SPF is the relationship between expected accident counts per unit of time at an entity and its characteristics such as its AADT, lane width, etc. SPFs are calibrated by statistical regression analyses from collision data. It used to be assumed that these data come from a Poisson distribution. However, researchers have revealed that the differences between the accident counts and model predictions are larger than what is consistent with the Poisson assumption. Therefore, the NB distribution is used to represent the distribution of accident counts. SPFs are applied in network screening to diagnose sites with potential safety improvements, to estimate the benefits of a potential treatment by using accident modification factors (AMFs), and to evaluate the safety effects of an implemented countermeasure.

The overdispersion parameter is one of the important characteristics of NB distribution. A positive value of an overdispersion parameter is a way to account for additional variation in the model caused by variables not included. It is of interest to estimate the overdispersion parameter of each NB regression model since the accident counts themselves are dispersed in nature. As discussed by Ezra Hauer (2001), it is undesirable to assume the same overdispersion parameter *k* for all entities. Alternatively, the overdispersion parameter is estimated as a factor of road section length (i.e., per-unit- length [1/km] or [1/mi]). The application of the overdispersion parameter in calculating the variance of NB distribution and the weight $\alpha\ (j)$ in the EB method is as follows:

$$\mathrm{VAR}\{\tau(j)\} = E\{\tau(j)\} + kE\{\tau(j)\}^2$$

$$\alpha\ (j) = \frac{1}{1 + kE\{\tau(j)\}}$$

It is evident that:

- a smaller *k* will lead to a more reliable accident model estimate, and
- a better EB estimate will be attained by a smaller *k*

1.2 PURPOSE OF THE HSM AND SAFETY ANALYST

The need for factual information and tools in the consideration of safety effects during planning, design, construction, operations, and maintenance phases of an entity has raised the necessity for a safety manual to assist transportation professionals. Hence, extensive research has been done by highway agencies across North America in the past decade, which has culminated in the preparation of two tools that are expected to revolutionize highway safety analysis. The first tool, SafetyAnalyst, developed by the US Federal Highway Administration (FHWA), is a set of software procedures for all aspects of safety management which includes network screening, diagnosis, development and evaluation of potential treatments and the evaluation of implemented treatments. SafetyAnalyst has been directly spawned by the Science of Highway Safety initiative and has benefited from significant involvement by the research team that worked on the Ministry of Transportation of Ontario (MTO) project, including Ryerson University.

The second tool, the Highway Safety Manual (HSM), documents state-of-the-art analytical and other tools for the same safety management process that is the focus of SafetyAnalyst. The HSM also contains predictive methodologies to assess the safety of a design and the safety implications of design choices. The HSM preparation involved more than seven National Cooperative Highway Research Program (NCHRP) projects for the amount of 2.8 million dollars since 2001. “The Highway Safety Manual will likely become a new standard in road safety engineering, as the Highway Capacity Manual is the standard for traffic engineering” (Martinelli et al. 2009). The purpose of the HSM is to formalize the safety evaluation process to provide factual information which will measure the safety implications of decisions made in planning, design, operations, and maintenance.

The HSM will provide important information and methodologies for practitioners in conducting highway safety analyses, including:

- predicting the expected collision frequency for new and existing locations,
- evaluating the safety impacts of alternate design scenarios,
- applying a cost-benefit analysis for contemplated countermeasures by applying collision modification factors,
- screening the road network for locations with potential for safety improvements,
- diagnosing specific safety problems by conducting site-specific investigations,
- selecting countermeasures,
- prioritizing safety improvement projects, and
- evaluating safety improvements.

1.3 SCOPE OF THE RESEARCH PROJECT

Many jurisdictions have recognized the importance of gearing up for the application of these tools as soon as they are released and have undertaken research to facilitate the application. This project aims to ensure the maximum use of these two safety tools for application in Ontario. The project comprises several interrelated tasks to collect and analyze data in order to assess and adopt the methodologies in the SafetyAnalyst and the HSM for Ontario.

- The SafetyAnalyst SPFs have been calibrated for adaptation to local conditions of Ontario highways.
- The HSM baseline model is calibrated and evaluated for two-lane two-way rural roads.
- The HSM Accident Modification Factors (AMFs) are calibrated and evaluated for two-lane two-way rural roads.
- Jurisdiction-specific SPFs have been developed for Ontario rural two-lane intersections for use in HSM predictive chapters.

Various goodness-of-fit (GOF) measurements are undertaken to assess the suitability of transferring the SafetyAnalyst and HSM SPFs to Ontario conditions. In addition, the reliability of the jurisdiction-specific model is examined by several GOF statistics. In calibrating the jurisdiction-specific model, SAS software is employed. The accident prediction model calibration is performed by using the generalized linear regression procedure.

1.4 THESIS STRUCTURE

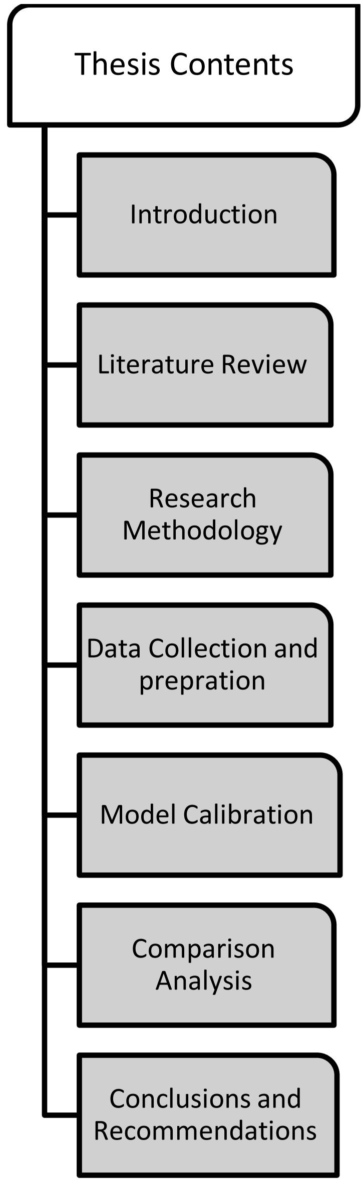

Figure 1-1 Thesis Contents

2 LITERATURE REVIEW

A detailed literature review was undertaken to identify materials related to the research topic. The following sources were identified valuable to the research:

Persaud, Lord, and Palmisano (2002) demonstrated the difficulty of calibrating SPFs and their transferability for urban intersections. SPFs have different important uses in transportation safety which make their proper calibration an essential task. However, despite their significance, there are a relatively small number available because of the complexity of their calibration. This complexity is due to three primary reasons, which is the need for high-quality traffic, collision, and geometric data, several years of collision data to assemble a large enough sample size, and finally, there is the complexity of the actual calibration process itself.

To calibrate the Accident Prediction Models (APMs) of Toronto intersections, a six year data set (1990 to 1995) was used. Toronto models (injury models and all models that combine collision severities) were developed for both four-legged and three-legged signalized and un-signalized intersections.

The first step of calibration is recognizing a suitable functional form. To do so, an exploratory analysis was conducted on the data set based on using the" integrate- differentiate (ID)" method proposed by Hauer and Bamfo(1997). As a result, three forms of equations (Equations 1 to 3) were declared based on the two selected forms - power and gamma functions.

1. F_1= power, F_2= Gamma: $E(K) = \alpha F_1^{\beta_1} F_2^{\beta_2} e^{(\beta_3 F_2)}$
2. F_1= Gamma, F_2= Power: $E(K) = \alpha F_1^{\beta_1} F_2^{\beta_2} e^{(\beta_4 F_1)}$
3. F_1= Power, F_2= Power: $E(K) = \alpha F_1^{\beta_1} F_2^{\beta_2}$

where

E (K): the expected annual number of accidents for the period 1990 to 1995;

F_1, F_2: entering AADT of the major and minor roads, averaged over the period 1990 to 1995; and

α, β_1, β_2, β_3, β_4: coefficients to be estimated.

These models were then estimated with Genstat 5 which takes the NB distribution characteristics into account. This makes it possible to estimate the overdispersion parameter γ and to measure and compare the GOF ($R_\alpha^2 = 1 - (\frac{\gamma_{min}}{\gamma})$) of the above models. In addition, the built-in Generalized

Estimating Equation (GEE) procedure of Genstat was employed to account for the temporal correlation in the data due to the trend in accident counts since several years of data were used to calibrate the models.

Finally, the values of γ and R_{α}^{2}, the t-statistics assessment, and the cumulative residuals (CURE) plots Hauer and Bamfo (1997) were used to confirm the suitability of the selected form. The results indicated that these models are rather reasonable. The general shapes of these accident prediction plots are quite similar to those published models for Vancouver and California; the estimated values for γ and R_{α}^{2} are relatively high; the AADT exponents are positive and less than one, and eventually the CURE plots show a reasonable fit of the models over the entire range of the major and minor road AADTs.

To test the transferability of APMs, Toronto intersection data were used as the sample for the "new" jurisdiction. Then, recently calibrated models for Vancouver and California Intersections were selected as the base models and became recalibrated based on Toronto intersection collision history. As proposed by Harwood et al.(2000), the calibration factor (C) is equal to the ratio of the total number of observed accidents for the sample and the sum of the predicted accidents from the original base model. Next, this calibration factor is multiplied by the original base model to generate the new model for the new jurisdiction.

$$C = \Sigma \text{ (observed crashes for all sites)} / \Sigma \text{ (predicted crashes for all sites)}$$

The results of the model transferability procedure tests confirmed that the recalibrated Vancouver model for three-legged un-signalized intersections and the recalibrated California model for four-legged un-signalized intersections can be efficiently used for Toronto applications. The research also pointed out that the quality of the base model (e.g., with a large overdispersion parameter γ) plus the similarity of the base model form and AADT exponents to those directly calibrated for the sample jurisdiction (i.e., Toronto) would guarantee the success of the transferability of the APMs for urban intersections.

Sawalha and Sayed (2006) discussed methods for recalibrating NB performance functions before transferring them for use in different jurisdictions. The lack of a complete data set and the difficulty of calibrating new collision models, have put the transferability of APMs in time and space under the spotlight of researchers and highway agencies. In this research, the accident model transferability of Vancouver's urban arterial segments to the city of Richmond in British Columbia is investigated. According to Sawalha and Sayed, there are two options in transferring an APM. The more direct and easier alternative is the adoption of the model with no changes in the form and parameters of the original model. However, the more reliable method is to adopt the original model by first calibrating the constant of the model which accounts for differential conditions between two jurisdictions. Despite the differences, the recalibration of the shape parameter (i.e., overdispersion parameter) of the transferred model is extremely essential for both alternatives. The paper proposes two transferability methods in conjunction with each transfer alternatives. Choosing the easy transfer alternative leads to a so called moment method which involves only the recalibration of the shape parameter of the transferred model. The second method would be choosing the more desirable transfer alternative. In this method, both the shape parameter and the model constant are recalibrated. The model constant can be recalibrated according to the Interactive Highway Safety Design Model (IHSDM) procedure or the maximum likelihood procedure. The shape parameter can also be recalibrated based on the moment procedure or the maximum likelihood procedure.

The IHSDM recalibration factor is calculated as:

$$\mathrm{F} = \frac{\sum Observed\ accidents}{\sum Estimated\ accidents}$$

The moment procedure for recalibrating the NB shape parameter is as follows:

$$k = \frac{\frac{1}{N}\sum_{i=1}^{N}(\mu_i)^2}{\frac{1}{N}\sum_{i=1}^{N}[(y_i - \mu_i)^2 - \mu_i]}$$

where y_i is the observed accident count in section i; μ_i is the mean accident frequency at location i; and N is the number of observations in the new data set for the same period of time.

Last but not least, the recalibration procedure presented in this paper is the maximum likelihood procedure that recalibrates both parameters of the transferred model by using the software GLIM4. The results of all mentioned transferability methods then become compared based on their z-score, the score used in previous research to test the transferability of accident models.

$$Z = \frac{\chi_P^2 - E(\chi_P^2)}{\sigma(\chi_P^2)}$$

$$E(\chi_P^2) = N; \quad \sigma(\chi_P^2) = \sqrt{2N\left(1 + {}^{3}/_{k}\right) + \sum_{i=1}^{N}\frac{1}{\mu_i(1 + {}^{\mu_i}/_{k})}}$$

$$\chi_P^2 = \frac{(y_i - \mu_i)^2}{\mu_i(1 + {\mu_i}/_{k})}$$

where $E(\chi_P^2)$ is the expected value of the Pearson's chi-square statistic and $\sigma(\chi_P^2)$ is the standard deviation of the Pearson's χ^2 statistic.

The z score is an index of the variation of the χ^2 from the mean of the Pearson's chi-square. Small values of z which score close to zero support the model. The z-score comparison indicates more reliability for the maximum likelihood method in comparison with other recalibration procedures since it results in the lowest z-score.

Lord et al. (2009) discussed the reliability of HSM predictive models by comparing their application and the application of full models or models with several covariates. The HSM predictive chapter uses baseline models that are structured based on data which meet specific nominal designs or operational conditions to estimate the accident predictions of base conditions. These baseline models are normally one covariate models that use traffic flow as their covariates (e.g., $\mu = \beta_0\ F_1^{\beta_1}\ F_2^{\beta_2}$). To predict the total expected average crash frequency for each entity, the values of the baseline models need to be multiplied by AMFs in order to count for geometric design and operational characteristics changes. The HSM predictive methodology formulated below is based on the important assumption that these AMFs are not strongly correlated which is not always the case in practice.

$$\mu_{fianl} = \mu_{baseline} \times AMF_1 \times \ldots \times AMF_n$$

where

μ_{fianl} = final predicted number of accidents per unit of time

$\mu_{baseline}$= predicted average crash frequency determined for base conditions via the SPF developed for that entity

AMF_i = accident modification factors specific to the entity and specific geometric design and traffic control features i

This study examines the predicted values of full and baseline models combined with AMFs, and associated inferences which use the data of rural four-lane highways in Texas originally collected for NCHRP 17-29. "Two different values for AMFs i.e., one based on a base condition set of AMFs for lane width, shoulder width and curve density and the second with different values of shoulder width and curve density on each segment, were extracted from that work. Then, the two modeling approaches were compared as a function of the predicted values; the 95% predicted confidence intervals (CIs) and different hypothetical variances used for characterizing the uncertainty associated with each AMF"(Lord et al. 2009). The results of the comparison analysis confirmed the superior of the full models predictions to the baseline models and AMFs. It has been observed that the baseline models and AMF predictions hold a much larger variance and hence wider 95% predicted CI.

Nevertheless, baseline models are often preferred by practitioners over full models as they can be recalibrated and used from one jurisdiction to another, especially when there are not enough variables available in the data set.

Vogt and Bared (1998) developed APMs for rural two-lane highways with minor road stop-controlled intersections in the states of Minnesota and Washington. The main variables used in segment modeling included AADT, horizontal and vertical curvatures, lane and shoulder width, roadside design, driveway density, and exclusive left turn and right turn lanes. The intersection variables were AADTs for minor and major intersection approaches, total number of injuries and all severity intersection related accidents, horizontal curvature, vertical grade rate, posted speed on the minor road, roadside hazard rating and number of driveways within ±76.2 m of the intersection on the main road, channelization, and intersection skew angle.

The models are of the form of NB and extended NB which take local conditions into account more precisely than ordinary NB models. The GOF measures examined for this research were t-statistics, accident reduction factors, R-squared, and z scores. The purpose of modeling is to find the best choice of explanatory variables and their coefficients in a model form of:

$$\hat{y} = (exp a_0)(exp x_1)^{a_1}(exp x_2)^{a_2} \dots (exp x_n)^{a_n}$$

where ŷ is the predicted mean, $x_1, x_2, \dots, x_n$ are the explanatory variables, and $a_0, a_1, a_2, \dots, a_n$ are the intercept and the desired parameter estimates.

The analyses support the states combined segment model and the Minnesota intersection model. The model coefficients and accident reduction factors are reasonably estimated. The models forms are consistent with each other and other models. Although the segment model is strongly correlated to most of the roadway variables, the intersection model primarily depends on AADT.

Sayed and Rodriguez (1999) estimated the safety performance of urban un-signalized intersections in British Columbia by developing site-specific APMs. Three years of traffic volume data and intersection related collision history (i.e., collisions which occurred within 30 m of the intersection) for 186 three-legged and 233 four-legged urban un-signalized (stop-controlled) intersections in the Greater Vancouver Regional District and Vancouver Island were used to calibrate jurisdiction-specific models.

In developing new models, the generalized linear modeling (GLM) method was utilized. The GLM approach usually assumes a Poisson or NB error structure (a non-normal error structure). This is advantageous for GLIM in properly describing collision characteristics, such as randomness, discrete counts, and usually periodic events with positive values.

The model form of power function is chosen for this study with traffic flow as its only primary covariate. The effects of other geometric design and traffic control feature variables have been introduced to the model by a multiplier as shown below:

$$E(\Lambda) = a_0 V_1^{a_1} V_2^{a_2} \times e^{\sum b_j x_j}$$

where

$E(\Lambda)$ = expected accident frequency

V_1 = major road annual average daily traffic (AADT)(veh/day)

V_2 = minor road AADT (veh/day)

x_j = a representative of any additional explanatory variable

a_0, a_1, a_2, b_j =model parameters

First, the Poisson error structure has been derived to estimate the model parameters. The Poisson distribution overdispersion parameter σ_d is determined and further analysis with the NB error structure is recommended where σ_d is greater than 1.00. Satisfactory GOF is obtained for developed models by measuring Pearson'sχ_P^2, CURE plot, Pearson residuals (PR) plot, and t ratio (the ratio of the variable constant to its standard error, e.g., a ratio of 1.96 for 95% confidence interval) statistics. Then, in order to provide more precise, site-specific safety predictions, the EB approach was employed to each site accident prediction.

Finally, the developed models are used to identify accident-hazard locations, rank identified accident hazard locations, develop critical accident frequency curves, and evaluate before-and –after safety performance of the locations of interest. These applications demonstrate the significance of APMs in reliably measuring the safety performance of urban stop-controlled intersections.

Following lessons were learned from the literature review:

- Difficulty of SPFs calibration and transferability from one jurisdiction to another
- Recalibration methods for negative binomial structured SPFs before being transferred in time and space
- Reliability of one covariate SPFs used in HSM Part C predictive chapters in comparison with multi-covariate SPFs
- Procedure of finding the best choice of explanatory variables and their coefficients in a NB multi-covariate model form for rural two-lane highways with minor road stop-controlled intersections
- Developing site-specific SPFs using GLM approach for urban un-signalized intersections
- Various goodness-of-fit measurements to examine the reliability of the developed or transferred crash model

3 RESEARCH METHODOLOGY

APMs are used to conduct many highway safety studies and are significantly important to highway agencies. Nevertheless, not all agencies are able to develop their own specific models due to the lack of sufficient accident statistics. This will hike the interest in transferring the SPFs of one jurisdiction to another in order to estimate the safety performance of the new jurisdiction.

In developing Ontario applications of the methodologies, the default models in SafetyAnalyst and the HSM would be first considered for recalibration to local conditions to ensure the accuracy and reliability of the predictions. New four-legged stop-controlled intersection models are estimated for comparison with HSM and SafetyAnalyst models calibrated to Ontario data. The models are calibrated to Ontario data by using the calibration procedure to be documented in the HSM.

3.1 CALIBRATION OF PREDICTIVE MODELS TO ONTARIO DATA

Before transferring any AMFs, they need to be recalibrated for application in each jurisdiction. Recalibration is important because the general level of safety may considerably differ from one jurisdiction to another due to geographical diversities such as climate, driver populations, animal populations, accident reporting thresholds, and accident investigation practices.

For each facility type that is used in the SafetyAnalyst interim tools and HSM predictive chapters, a calibration factor is derived. This calibration factor (multiplier) is calculated as the ratio of the sum of collision counts for the calibration data to the sum of the predictions from the model for all sites during the same time period (Harwood et al. 2000). A calibration factor equal to 1.00 indicates an equal number of observed and predicted accident frequencies. When more accidents are predicted by an APM than what had been observed, the calibration factor will be smaller than 1.00, whereas a calibration factor greater than 1.00 verifies an underestimation of crash predictions by an APM.

$$\mathrm{Cr\ (or\ Ci)\ )} = \frac{\sum Observed\ accidents}{\sum Estimated\ accidents} \qquad \text{Equation 3-1}$$

where

Cr = calibration factor for road segments

Ci = calibration factor for intersections

As presented in the HSM, the calibration procedure is shown in Figure 3-1.

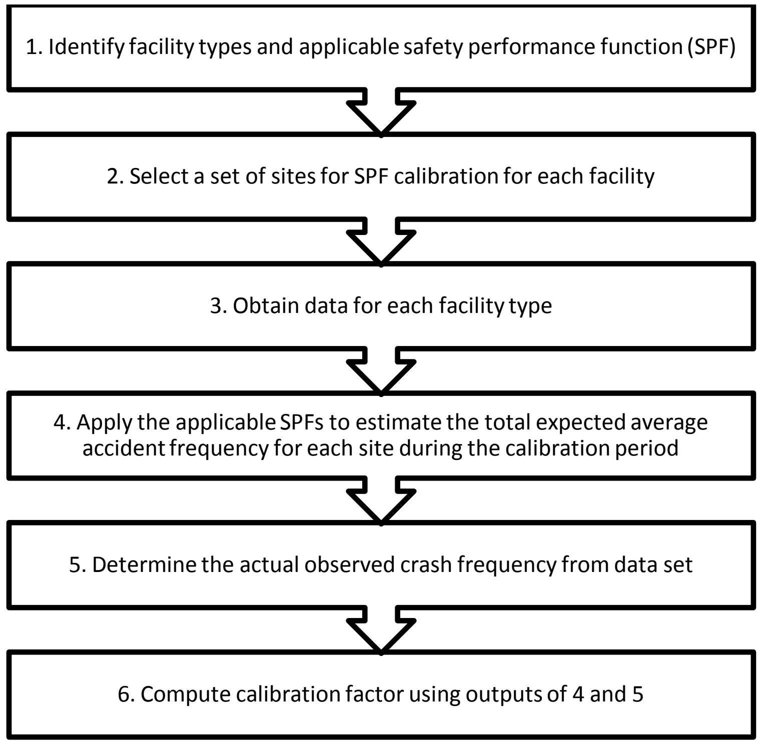

Figure 3-1 Flow diagram of calibration process

The calibration procedure is separately applied for each facility type and each region of the MTO jurisdiction due to the variety in topography and climate in each region. According to the HSM Part C predictive chapter the minimum number of sites for calibration in the data set is 30 to 50 with an overall of 100 plus accidents per year. However, a larger data set means that the calibration results will be more useful. If a suitable data set is not available, which is the case for rural two-lane intersections in this project, the calibration data must be assembled. According to HSM predictive chapters, the data set should include a minimum of one year of total observed accident frequency plus all site characteristic data required to apply the applicable APM. More details about data assembly will be discussed in the next chapter.

The site required data set is then used to apply the applicable safety performance function to each site to predict total crash frequency. An SPF is a regression equation developed based on data from similar sites for specific site types and “base conditions”. For example, the prediction algorithm in HSM has the following form for predicting the number of accidents ($N_{predicted}$) at a site:

$$N_{predicted} = N_{spf\ x} \times (AMF_{1x} \times AMF_{2x} \times \ldots \times AMF_{yx}) \times C_x \qquad \text{Equation 3-2}$$

where

$N_{predicted}$ = predicted average crash frequency for a specific year for site type *x*

$N_{spf\,x}$ = predicted average crash frequency determined for base conditions of the SPF developed for site type *x*

AMF_{yx} = Accident modification factors specific to SPF for site type *x*

C_x = calibration factor to adjust SPF for local conditions for site type *x*

Table 3-1 Indicates all applicable SPFs used in this project:

Facility Type	Road Segments	Equation No.
MTO	$Collisions\ (Km/Year) = \alpha \times AADT^{\beta}$	Equation 3-3
SafetyAnalyst	$Acc = e^{\alpha} \times AADT^{\beta} \times L$	Equation 3-4
HSM Part C	$N_{spf\ rs} = AADT \times L \times 365 \times 10^{-6} \times e^{\alpha}$	Equation 3-5
	Intersections	
MTO	$E(K) = e^{\alpha} \times (\frac{AADT_{min}}{1000})^{\beta_1} \times (\frac{AADT_{maj}}{1000})^{\beta_2} \times e^{(\beta_3 \times (\frac{AADT_{min}}{1000}) + \beta_4 \times (\frac{AADT_{min}}{1000})^2)}$	Equation 3-6
SafetyAnalyst	$Acc = e^{\alpha} \times {AADT_{maj}}^{\beta_1} \times {AADT_{min}}^{\beta_2}$	Equation 3-7
HSM Part C	$N_{spf\ 4ST} = \exp\left[(\alpha + \beta_1 \times \ln(AADT_{maj}) + \beta_2 \times \ln(AADT_{min})\right]$	Equation 3-8
	Ramps	
MTO	$Collsions\ per\ Year = \alpha \times AADT^{\beta_1} \times e^{\beta_2 \times (Length)}$	Equation 3-9
SafetyAnalyst	$Acc = e^{\alpha} \times AADT^{\beta}$	Equation 3-10
HSM	n/a	n/a

Table 3-1 the applicable safety performance functions for various facility types employed in this project

where

Acc = predicted accident frequency per mile per year for road segments, and accidents per year for intersections and ramps

AADT = average annual daily traffic (veh/day)

$AADT_{maj}$ and $AADT_{min}$ = average annual daily traffic on the major and minor road (veh/day)

L = segment length (mile)

$\alpha, \beta_1, \beta_2, \beta_3, \beta_4$ = calibration parameter estimates

The MTO operational performance models (MTO equivalent of "SPFs") for highways and ramps were obtained from reports developed by Ryerson University (2008) and (Persaud et al. 2006) and those for intersections were obtained from the iTrans final report for the Ontario Ministry of Transportation (iTRANS Consulting Inc., 2005). The SafetyAnalyst APMs were extracted from a report developed by the Midwest Research Institute (2004) for Federal Highway Administration (FHWA). Finally, the HSM SPFs were obtained from the HSM draft of Chapter C: Predictive Methods.

Then, to account for the difference between the base conditions and Ontario site conditions, AMFs are multiplied to the base condition SPF. AMF is an index of the amount of changes in accident predictions due to a change in design characteristics or traffic control features. Equation 3-11 shows the calculation of an AMF from a site with the base condition to site condition 'b'.

$$AMF = \frac{estimated\ average\ crash\ frequency\ with\ condition\ 'b'}{estimated\ average\ crash\ frequency\ with\ \text{base}\ condition} \quad \text{Equation 3-11}$$

A value of AMF equal to 1.00 will be assigned to a site under base conditions. An AMF value less than 1.00 indicates that the base condition modification leads to a reduction in expected accident frequency. Moreover, an AMF value greater than 1.00 indicates that the intervention increases the estimated crash frequency in comparison to the base condition. Table 3-2 shows the HSM AMFs used for each facility type in this research and their reference equations and exhibits from the HSM draft of Part C: Predictive Models.

Facility type	AMF	AMF Description	AMF Base Condition	AMF Equations and Exhibits from HSM Part C
Rural Two-Lane Two-Way Roadway Segments	AMF_{1r}	Lane Width	12 feet	Exhibit10-14, 10-15; Equation10-11
	AMF_{2r}	Shoulder Width and Type	6 feet, Paved	Exhibit 10-16, 10-17, 10-18; Equation 10-12
	AMF_{3r}	Horizontal Curves: length, Radius, and Presence or Absence of Spiral Transitions	None	Equation 10-13
	AMF_{4r}	Horizontal Curves: Superelevation	None	Equation 10-14, 10-15, 10-16
	AMF_{5r}	Grades	0%	Exhibit 10-19
	AMF_{6r}	Driveway Density	5 driveways per mile	Equation 10-17
	AMF_{7r}	Centreline Rumble Strips	None	See HSM Part C
	AMF_{8r}	Passing Lanes	None	See HSM Part C
	AMF_{9r}	Two-Way Left-Turn Lanes	None	Equation 10-18, 10-19
	AMF_{10r}	Roadside Design	3	Equation 10-20
	AMF_{11r}	Lighting	None	Exhibit 10-20; Equation 10-21
	AMF_{12r}	Automated Speed Enforcement	None	See HSM Part C
Three- and four-leg STOP control intersections	AMF_{1i}	Intersection skew Angle	0˚	Equation 10-22, 10-23
	AMF_{2i}	Intersection Left-Turn Lanes	None on approaches without stop control	Exhibit 10-21
	AMF_{3i}	Intersection Right-Turn Lanes	None on approaches without stop control	Exhibit 10-22
	AMF_{4i}	Lighting	None	Exhibit 10-23; Equation 10-24

Table 3-2 Summary of Accident Modification Factors (AMFs) for rural tow-lane two-way roads

3.2 DEVELOPMENT OF JURISDICTION-SPECIFIC SPFs

Developing jurisdiction-specific SPFs using local data is likely to improve the reliability of the HSM predictive method. As pointed out in the HSM, jurisdiction-specific SPFs must meet the following conditions in order to be acceptable for use in the HSM predictive chapter:

- in data assembly, crashes are assigned to roadway segments and intersections as defined in the HSM predictive chapter,
- a statistical technique such as NB regression which accounts for the overdispersion parameter should be used to develop jurisdiction-specific SPFs so that SPF estimates could be refined using the collision history in an EB procedure,
- the same base conditions presented in HSM should be correspondingly used by the jurisdiction-specific SPF,
- the jurisdiction-specific SPF should take into account the effects of AADT for road segments and $AADT_{major}$ and $AADT_{minor}$ for intersections, and
- jurisdiction- specific SPFs for roadway segments must directly consider the segment length in predicting the average crash frequency of that segment.

In this practice, jurisdiction-specific models are developed by using data set with all applicable base-condition variables, but with different values from the base-condition variables. These variables are included in the initial model. Then, the initial model is adjusted to the base conditions by replacing the corresponding values to the base conditions into the model.

In general, four steps must be taken in developing any new safety performance function. These four steps are choosing appropriate explanatory variables, appropriate model form, proper error structure, and proper model GOF statistics.

As presented by Sawalha and Sayed (2003), the chosen model form must meet two criteria: first, no negative value in predicting the number of accidents; and second, prediction of zero accident for zero value of the exposure variable such as AADT in the case of intersections. To meet these two criteria and overcome the limitations of traditional linear regression models, SPFs are developed by using GLIM. The most common SPF is represented as a product of highway exposure variables (i.e., AADT for intersections) raised to various powers and multiplied by an exponential that introduces other highway variables into the model including a constant or intercept term. For example, the following model form of power function:

$$E(\Lambda) = a_0 V_1^{a_1} V_2^{a_2} \times e^{\sum b_j x_j}$$

This type of SPF can be linearized by the logarithmic function as shown below.

$$\ln\,[E(\Lambda)] = \ln\,(a_0) + a_1 \ln\,(V_1) + a_2 \ln\,(V_2) + \sum b_j x_j$$

To account for the dispersion of accident counts, the NB error structure was chosen to develop jurisdiction-specific safety performance models. The model structure of an NB distribution is as follows with an expected value of $E(Y) = \mu$ and a variance equal to $Var(Y) = \mu + \frac{\mu^2}{k}$:

$$P(Y = y) = \frac{\Gamma(k + y)}{\Gamma(k) y!} (\frac{k}{k + \mu})^k (\frac{\mu}{k + \mu})^y$$

where Y is the random variable which represents the crash frequency at a given jurisdiction in the study time period and y is a certain realization of Y, k is the shape parameter of the gamma distribution or the “inverse dispersion parameter”.

To estimate the model parameters and also count for GLM approach characteristics, the GENMOD procedure from the SAS software package was used. The software uses the maximum likelihood process in estimating the parameter vector β in order to apply the GLM approach to data. The same procedure (maximum likelihood) is used to estimate the dispersion parameter of each variable.

The selection of the explanatory variables was based on the statistical significance of their model parameters estimated by the SAS program. A candidate model was first developed which included candidate independent variables of entire intersections presented at FHWA-RD-99-207 (Harwood et al. 2000) if the required data were available. Then, the developed candidate model was re-evaluated excluding variables that were not statistically significant with an 85% confidence interval (i.e., Chi Sq < Pr = 0.15). Finally, model suitability assessments were conducted only for models that contained statistically significant variables with a 0.15 or less confidence level.

Two types of model validity control were assessed (Oh et al. 2003): internal validity control and external validity control. Internal validation is an evaluation of the logical defensibility of the calibrated model. This tool assesses the theoretical suitability of the proposed model with respect to past safety research, key features of the accident prediction phenomenon, and basic knowledge of physical mechanics and dynamics involved with crashes.

External validation, however, assesses the transferability of the model to future time periods and/or at different jurisdictions by the mean of several GOF measurements. GOF statistics which are used to assess external model validation will be described in the next subsection.

3.3 GOODNESS-OF-FIT (GOF) STATISTICS

To examine how well a statistical model fits the data set, GOF measurements are tested. GOF measurements summarize the difference between the observed and predicted values from related SPFs. The GOF measures employed in this project are described in this section.

3.3.1 Cumulative Residuals (CURE) Method

The CURE method is based on the assumption that when consecutive accident residuals are cumulated, an informative order appears. In this method, CURE (the difference between the observed and estimated crash frequencies) is individually plotted in ascending order for each variable. This visual order could be used to assess whether the chosen model form fits the data with respect to each explanatory variable. The CURE plot would oscillate around zero and end near zero if the chosen functional form fits the data all along the entire range of values.

The CURE method could also be used to examine whether a new variable is needed to be represented by the equation model. If the cumulative residual graph oscillates around zero, ends close to zero, and lies down within the range of ±2 σ*, it is not necessary to introduce the new explanatory variable into the model equation. In computing ±2 σ*, the cumulative squared residuals are arranged in increasing order of the candidate variable and then the σ*(n) is estimated from the following equation:

$$\sigma *^2 = \sigma^2(n)(1 - \frac{\sigma^2(n)}{\sigma^2(N)})$$

where

N = total number of observations in the data set

n = an observation between one and N

3.3.2 Mean Absolute Deviation (MAD)

The mean absolute deviation (MAD) is the sum of the absolute value of the recalibrated crash predictions minus the number of observed crashes divided by the number of observations. The MAD measures the average magnitude of the prediction variability. Smaller values are more favoured than larger values.

$$MAD = \frac{\sum_{i=1}^{n}\left|\hat{Y}_i - Y_i\right|}{n}$$ Equation 3-12

where $\hat{Y}_i$ is the predicted (fitted) number of accidents by SPF for section *i*, Y_i is the observed number of accidents for section *i*, and n is the total number of sample size.

3.3.3 Mean Prediction Bias (MPB)

The MPB is the sum of predicted accident frequencies minus observed accident frequencies in the validation data set, divided by the number of validation data points. MPB provides a measure of the magnitude and direction of the average model bias as compared to validation data. A smaller average prediction bias means that the model is better at predicting observed data. The MPB can be positive or negative, and is given by:

$$MPB = \frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)}{n}$$ Equation 3-13

where n is the validation data sample size, $\hat{Y}$ is the fitted value, and Y_i is the observation value. A positive value of MPB indicates an overestimation of the observed data by the model and vice versa. The value of MPB will be zero for models that are already recalibrated by the calibration factor presented by Harwoodet al. (2000).

3.3.4 Mean Squared Prediction Error (MSPE) and Mean Squared Error (MSE)

MSPE is the sum of the squared differences between observed and predicted crash frequencies, divided by the sample size. MSPE is typically used to assess errors associated with a validation or external data set. MSE is the sum of the squared differences between observed and predicted crash frequencies, divided by the sample size minus the number of model parameters. MSE is typically a measure of model error associated with the calibration or estimation data, and so degrees of freedom are lost (p) as a result of producing Ŷi, the fitted value.

$$MSE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n_1 - p}$$ Equation 3-14

$$MSPE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n_2}$$ Equation 3-15

where n1 is the estimation data sample size and n2 is the validation data sample size.

A comparison of MSPE and MSE reveals potential over fitting or under fitting of the models to the estimation data. An MSPE that is higher than MSE may indicate that the models may have been over fit to the estimation data, and that some of the observed relationships may have been spurious instead of real. This finding could also indicate that important variables were omitted from the model or the model was misspecified. Finally, data inconsistencies could cause a relatively high value of MSPE. Values of

MSPE and MSE that are similar in magnitude indicate that validation data fit the model similar to the estimation data and that deterministic and stochastic components are stable across the comparison being made. Typically, this is the desired result.

3.3.5 *Pearson χ2* Statistics

The Pearson χ2 Statistics is used to examine the GOF of GLM models and defined as:

$$Pearson\ \chi 2 = \sum_{i=1}^{n} \frac{[y_i - E(y_i)]^2}{Var(y_i)}$$ Equation 3-16

where y_i is the accident count observed in section i, n is the total number of sections, and $E(y_i)$ and $Var(y_i)$ are the expected average accident frequency and its variance for section i , respectively.

3.3.6 The Pearson Product Moment Correlation Coefficients

The Pearson product moment correlation coefficient is used to examine the linear association between observed and predicted accident frequencies and defined as:

$$r_{12} = \frac{\sum(Y_{i1} - \overline{Y}_1)(Y_{i2} - \overline{Y}_2)}{\left[\sum(Y_{i1} - \overline{Y}_1)^2 \sum(Y_{i2} - \overline{Y}_2)^2\right]^{1/2}}$$ Equation 3-17

where $\overline{Y}$ is the mean of Y_i observations on section i. A perfect prediction of accident data by a model leads to a straight-line plot between the observed and the predicted values with a correlation coefficient value of 1.00. Hence, a closer value of r to 1.00 means a more reliable prediction derived by the developed model.

3.3.7 R_α-Squared

$R^2_\propto$ is a dispersion parameter-based R^2. $R^2_\propto$ yields a value between 0.0 and 1.0 and the higher that value is, the better model fits the data. The R^2 equation is shown below:

$$R^2_\propto = 1 - \left(\frac{k_0}{k} \times \frac{n-1}{n-p-1}\right)$$ Equation 3-18

where according to Miaou et al. 1996, k is the actual shape parameter for the calibrated model, , k_0 is theshape parameter assuming that all sites have an identical accident prediction estimate that is equal to the mean over all sites (i.e., shape parameter for an accident model with no covariates), p is the number of variables in the calibrated model, and n is the total number of sites.

4 DATA COLLECTION AND PREPRATION

4.1 DATA CHARACHTERISTICS FOR SAFETYANALYST CALIBRATION

The required databases were made available by the MTO. The data set used in recalibration of the SafetyAnalyst SPFs and MTO SPFs included three master files with traffic volume, collision counts, traffic control features, and geometric characteristics for Ontario highways and freeways, intersections, and ramps. Data were available in Excel files for five regions, i.e., central, eastern, northeast, northwest, and southwest; and for the period 2000 to 2005. Counts were provided for fatal and injury (FI) and property damaged only (PDO) accidents for every single year of the calibration period.

The highway data set was classified into eight groups and organized for each 100 meter homogeneous segment identified by the Linear Highway Referencing System (LHRS) number and offset. Road segment geometric design data included the number of lanes, lane width, shoulder width and type, surface width and type, highway functional class, road environment, terrain, median width, median shoulder width and other variables. Table 4-1 provides a summary of the data characteristics for 8 groups of 100 m homogeneous road segments.

Group	No. Of Segments	Variables	Min.	Max.	Mean	Frequency	Variance
1. Complex Freeways	70	FI	0	25	4.09	286	20.21
		PDO	0	71	10.37	726	154.75
		Total collisions	0	83	14.46	1012	267.98
		AADT	179250	368700	275815		
2. Simple Freeways 4 lanes	7385	FI	0	15	0.42	3065	0.74
		PDO	0	72	1.21	8985	3.96
		Total collisions	0	87	1.63	12050	8.89
		AADT	5575	94550	23691		
3. Simple Freeways > 4 lanes	1686	FI	0	27	1.04	1721	3.57
		PDO	0	83	3.80	6274	42.77
		Total collisions	0	102	4.84	7995	64.95
		AADT	18517	354383	86216.54		
4. King's Rural < 4 lanes	65535	FI	0	8	0.12	8108	0.14
		PDO	0	13	0.43	28003	0.65
		Total collisions	0	16	0.55	36111	0.90
		AADT	530	31550	4147.45		
5. King's Rural > 4 lanes	922	FI	0	7	0.38	350	0.54
		PDO	0	32	1.26	1166	4.99
		Total collisions	0	39	1.64	1516	7.07
		AADT	5058	49433	19603.45		
6. King's Urban <4 lanes	534	FI	0	5	0.30	160	0.37
		PDO	0	14	0.66	351	1.61
		Total collisions	0	18	0.96	511	2.53
		AADT	5917	19817	9495.49		
7. King's Urban > 4 lanes	209	FI	0	5	0.39	82	0.62
		PDO	0	20	1.34	281	5.98
		Total collisions	0	24	1.74	363	8.46
		AADT	9225	41283	19004.27		
8. Secondary All	48884	FI	0	3	0.02	955	0.02
		PDO	0	8	0.09	4402	0.12
		Total collisions	0	11	0.11	5357	0.15
		AADT	27	7717	461.36		

Table 4-1 Summary of segment groupings and collision and traffic volume information

The intersection database obtained from the MTO included a list of 238 central region intersections with highway numbers, crossing street names and LHRS number and offset. The information contained in the data set included the number of legs (three or four), lane configurations, major road and minor road AADTs from 1998 to 2004, traffic control device (signalized or un-signalized), road functional classification (arterial, collector, etc.), road environment (urban, semi-urban, and rural), etc.

For the database provided by the MTO for Ontario ramps, a total of 1545 ramps from the central, southwest, and northeast regions was deemed sufficient (i.e., contained traffic flow and collision counts) for calibration. Ramp geometric data included interchange configuration, number of lanes on mainline, ramp length, number of lanes on ramp, and ramp configuration. Each interchange location was labelled by its LHRS number and offset. Based on the interchange configurations presented in an MTO report (Persaud et al. 2006), the following classifications were made to the data set:

- Flared ramps: categories 1,10,11,4,40/41,5,50/51,52,32,7 in MTO classification
- Loop ramps: categories 2,20/21,3,30/31,6,60/61 in MTO classification
- Freeway to freeway ramps: category 8 in MTO classification

Table 4-2 to Table 4-4 present some statistics for FI and PDO accidents for different classes of Ontario ramps.

Ramp Type	Collision type	Sites	Total Collisions	Mean	Median	Min. Value	Max. Value	Variance
Flared on-ramps	Total FI	400	318	0.80	0	0	13	2.07
	Total PDO	400	1455	3.64	2	0	58	36.95
Flared off-ramps	Total FI	544	681	1.25	1	0	20	5.30
	Total PDO	544	2801	5.15	3	0	65	59.34

Table 4-2 Summary statistics of collisions on flared ramps

Ramp Type	Collision type	Sites	Total Collisions	Mean	Median	Min. Value	Max. Value	Variance
Loop on-ramps	Total FI	319	185	0.58	0	0	5	0.94
	Total PDO	319	857	2.69	2	0	25	13.33
Loop-off ramps	Total FI	138	134	0.97	0	0	10	3.36
	Total PDO	138	518	3.75	2	0	46	39.71

Table 4-3 Summary statistics of collisions on loop ramps

Ramp Type	Collision type	Sites	Total Collisions	Mean	Median	Min. Value	Max. Value	Variance
Freeway-to-Freeway All ramps	Total FI	120	394	3.28	1	0	33	29.68
	Total PDO	120	1657	13.96	7	0	106	391.57

Table 4-4 Summary statistics of collisions on freeway to freeway ramps

Table 4-5 summarizes the traffic flow characteristics for three classes of Ontario ramps.

Ramp type	No of ramps	Mean AADT	Min. AADT	Max. AADT
Flared	944	5886	14	45008
Loop	457	4591	18	33545
Freeway to freeway	120	11990	320	43693

Table 4-5 Summary of ramp volume data

4.2 DATA CHARACTERISTICS FOR HSM CALIBRATION

The Ontario data for two lane two way road segments was received in an IHSDM format file from the Ministry of Transportation and included data for Highways 17 and 148 in the eastern region. This file is the most comprehensive and useful form of data available at the time of the research even though there are missing data for some of the variables, some of the years for AADT, and the presence of centreline rumble strip, lighting, and automated speed enforcement are also missing. Default values of Ontario highway design standards and some low tech means, such as Google maps, and local knowledge were used to fill in the missing data. Also, required AADT and intersection turn lane data were extracted from the subsequently acquired information from MTO for Highway 17.

The IHSDM file was then exported to an Excel file format and stratified to homogeneous segments as prescribed by the HSM. According to the HSM, a new homogeneous segment starts at any of the following:

- the centre of each intersection,
- beginning or end of a horizontal curve with or without a spiral transition,
- Vertical Point of Intersections (VPIs). for any type of vertical curves,
- beginning or end of a centre two-way left-turn lane (TWLT), passing lane, and a short four-lane section, and
- at locations where at least one of the highway characteristics, such as its AADT, lane width, shoulder width or type, etc., changes.

The stratification starts from the horizontal alignment by separating the tangents from the horizontal curves, then proceeds to the vertical curves by splitting all VPIs. More new homogeneous segments are created after any changes in AADT volume, lane width, shoulder width and type, start of a passing lane or a two-way left-turn lane, roadside design rating, and driveway density. Although there is no actual minimum segment length to apply to the predictive models, the homogeneous roadway segment length was specified to be not less than 100 meters in order to minimize the calculations.

This stratification produced a total number of 483 segments with a total length of 78 km. Table 4-6 shows the summary statistics for all of these homogeneous segments.

Variables	Min.	Max.	Mean (SD)	Total	% Zero
Segment length (Km)	0.0012	0.83	0.16	77.92	
AADT (Vehicles/day)	2406.00	10681.00	3332.00	1,609,360.00	
Lane Width (m)	3.35	4.00	3.68		
Shoulder Width (Right + Left – both sides combined) (m)	3.52	6.00	4.95		
Number of Curves	0.00	1.00	1.00	55.00	65%
Roadside Hazard Rating= RHR= 1 RHR=3 RHR=4 RHR=5 RHR=6				22.00 (5%) 136.00 (28%) 244.00 (51%) 73.00 (15%) 8.00 (2%)	
Driveway Density (dwys per km)	1.30	25.00	4.69		
Curve Density (Curves/Km)	1.01	65.32	4.79	832.88	
Grade Factor (%)	0.00	7.06	2.36		2%
All Severity Crashes	0.00	8.00	1.11	534.00	54%
Fatal and Injury Crashes	0.00	3.00	1.23	141.00	76%

Table 4-6 Descriptive statistics for two-lane two-way road segments used in HSM calibration

The HSM baseline model estimates the expected average crash frequency based on all severity collisions. Then, the other crash severity levels and types are determined by multiplying the proportional values for severity levels and collision types for that area of study. Table 4-7 provides the local proportions for crash severity levels and collision types on Highways 17 and 148.

Percentage of total roadway segment crashes				
Crash Severity Level	Hwy 17 (sectoion1)	Hwy 17 (sectoion 2)	Hwy 148 (sectoion 1)	Hwy 148 (sectoion 2)
Fatal and Injury (FI)	25 %	29 %	26 %	37 %
Property Damaged Only (PDO)	75 %	71 %	74 %	63 %
Crash type for all severity collisions				
Ran off road	27.84%	29.57%	28.1%	17.03%
Head-on collision	1.9%	1.89%	1.9%	1.86%
Sideswipe opposite direction	2.41%	2.4%	2.4%	2.23%
Sideswipe same direction	2.63%	2.65%	2.6%	3.83%
Sum	34.55%	34.78%	35%	24.95%

Table 4-7 Local distribution of accidents for collision types and severity levels on Highways 17 and 148

In order to develop jurisdiction-specific models for intersections on rural two-lane two-way highways in Ontario, the geometric design, traffic control, traffic volume, and collision data were gathered from three different sources. For Ontario Central Region (CR) intersections, the traffic flow and collision data were extracted from iTrans master file (iTRANS Consulting Inc., 2005) and the required geometric data were obtained via Google maps. The traffic flow included six years of data for the intersections AADTs for the major and minor approaches from 1998 to 2003. The collision data included six years of intersection related collisions for PDO and FI crash severity levels. For the Eastern Region (ER) intersections, most of required data were provided by MTO and the rest obtained via Google maps.

In general, after elimination of the outliers (i.e., intersections with the AADT values larger than the AADTs ranges clarified in the HSM for the intersections major and minor road legs), two sample sizes of 19 four-legged stop-controlled intersections and 52 three-legged stop-controlled intersections were organized to develop new models. The candidate independent variables considered in developing SPFs for four-legged stop controlled intersections were:

- average daily traffic volume on the major roads,
- average daily traffic volume on the minor roads,
- intersection skew angle,
- presence of a Right Turn (RT) lane on a major road (i.e., 0.0 for no RT and 1.0 for one or more RTs),
- presence of a Left Turn (LT) lane on a major road (i.e., 0.0 for no LT and 1.0 for one or more LTs), and
- Number of Driveways (ND) on a major road within 76 m (250 ft) of the intersection.

Table 4-8 shows the summary statistics of the candidate variables for four-legged stop controlled intersections on rural two-lane roadways.

Variables	Min.	Median	Mean (SD)	Max.	Total	% Zero
Major AADT (veh/day)	2955.00	7930.00	7959.50	13836.00	15123.00	
Minor AADT (veh/day)	94.00	1304.67	1707.29	4384.00	32438.00	
Skew (absolute degree)	0.00	10.00	12.11	60.00		
ND	0.00	0.00	0.95	4.00		
LT	0.00	1.00	0.58	1.00		42%
RT	0.00	1.00	0.79	1.00		21%
All Severity Crashes	0.00		7.00	21.00	140.00	5%
Fatal and Injury Crashes	0.00		2.00	6.00	41.00	42%

Table 4-8 Descriptive statistics for 19 four-legged stop controlled intersections in CR Ontario

The candidate independent variables considered in developing SPFs for three-legged stop controlled intersections were:

- average daily traffic volume on the major roads,
- average daily traffic volume on the minor roads,
- intersection skew angle
- Presence of a RT lane on a major road (i.e., 0.0 for no RT and 1.0 for one or more RTs),
- presence of a LT lane on a major road (i.e., 0.0 for no LT and 1.0 for one or more LTs),
- ND on a major road within 76 m (250 ft) of the intersection, and
- Roadside Hazard Rating (RHR) along a major road within 76 m (250 ft) of the intersection (i.e., an average value of 4.0 was assigned to central region intersections with missing RHR actual data).

Table 4-9 shows the summary statistics of the candidate variables for three-legged stop controlled intersections on rural two-lane roadways.

Variables	Min.	Median	Mean (SD)	Max.	Total	% Zero
Major AADT (veh/day)	2406.00	4442.00	6227.70	1632.001	32384.001	
Minor AADT (veh/day)	25.00	296.00	818.03	3406.00	42537.00	
Skew (absolute degree)	9.19	0.00	2.63	35.00		
RHR	3.00	4.00	3.94	4.00		
ND	0.00	1.00	1.06	5.00		
LT	0.00	0.00	0.35	1.00		65%
RT	0.00	0.00	0.42	1.00		58%
All Severity Crashes	0.00		3.00	24.00	150.00	56%
Fatal and Injury Crashes	0.00		1.00	7.00	45.00	65%

Table 4-9 Descriptive statistics for 52 three-legged stop controlled intersections in ER and CR

5 MODEL CALIBRATION RESULTS

5.1 RECALIBRATION OF SAFETYANALYST SPFs TO MTO DATA

In this task, the performance of the SafetyAnalyst interim tools, SPFs, is compared with those of the Ontario OPFs. To do so, the databases and models for Ontario highways, intersections, and ramps were organized and then matched with the relevant SafetyAnalyst categories.

MTO OPF models predict the average crash frequency base on PDO and FI collision severities. Hence, the total accident prediction values for all collision severity types will be the summation of both the prediction values for PDO and FI.

Next, both the MTO and SafetyAnalyst models were used to predict the expected long term average crash frequency for each MTO region and facility type. Crash predictions were done for total and FI crashes for the same number of years. This process is done through Excel for all sites in all regions and highway groups.

As presented by Hardwood et al. (2000), calibration factors are then obtained by dividing the total number of observed accidents from MTO data sets by the sum of the estimated accidents.

$$\text{Cr (or Ci))} = \frac{\sum Observed\ accidents}{\sum Estimated\ accidents}$$

The recalibration procedure is done for the whole province and for each MTO individual region wherever the OPF models are available. The SPF recommendations for Ontario road segments and that used in the SafetyAnalyst interim tools are the following:

- MTO OPF (Ryerson University, 2008):

$$Collsions\ (Km/Year) = \alpha \times AADT^{\beta}$$

- SafetyAnalyst SPF (Midwest Research Institute, 2004):

$$Acc = e^{\alpha} \times AADT^{\beta} \times SL$$

where

Acc = predicted accident frequency per mile per year for road segments, and accidents per year for intersections and ramps,

AADT = average annual daily traffic (veh/day), SL =segment length (mile), and

α, β = calibration parameter estimates.

The following table (Table 5-1) illustrates the calibration parameter estimates for each model category and the calculated calibration factors for Ontario freeways.

Group	Region	Model	ln(alpha)	beta	Initial overdispersion	Calibration Factor
Group 1	CR	PDO	-6.99	0.79	1.46	
		FI	-11.06	1.04	1.07	1.01
		Total				1.01
Group 2	CR	PDO	-6.61	0.75	0.38	
		FI	-8.31	0.81	0.21	0.92
		Total				0.86
	ER	PDO	-6.65	0.75	0.37	
		FI	-8.43	0.81	0.21	0.99
		Total				0.95
	SW	PDO	-6.64	0.75	0.37	
		FI	-8.53	0.81	0.21	0.90
		Total				0.74
SafetyAnalyst	Rural Fwy (4 lane)	PDO				
		FI	-8.82	0.89	0.16	0.37
		Total	-6.82	0.81	0.17	0.45
	Urban Fwy (4 lane)	PDO				
		FI	-8.82	1.02	1.15	0.10
		Total	-7.85	1.00	0.99	0.18
Group 3	CR	PDO	-6.94	0.77	0.41	
		FI	-10.33	0.96	0.38	0.97
		Total				0.96
	SW	PDO	-10.52	0.96	0.38	
		FI	-7.05	0.77	0.41	1.06
		Total				1.00
Safetyanalyst	Rural Fwy (6+ lane)	PDO				
		FI	-10.25	1.03	0.09	0.24
		Total	-8.28	0.94	0.09	0.42
	Urban Fwy (6 lane)	PDO				
		FI	-7.60	0.85	0.54	0.13
		Total	-5.96	0.78	0.48	0.27
	Urban Fwy (8+ lane)	PDO				
		FI	-19.16	1.85	0.52	0.09
		Total	-16.24	1.67	0.45	0.17

Table 5-1 MTO OPFs and SafetyAnalyst SPFs parameter estimates and their calibration factors for Ontario's Freeways

Table 5-2 illustrates the calibration parameter estimates for each model category and the calculated calibration factors for Ontario king's highways.

Group	Region	Model	ln(alpha)	beta	Initial overdispersion	Calibration Factor
Group4	CR	PDO	-5.47	0.62	0.15	
		FI	-7.12	0.68	0.14	0.99
		Total				0.99
	ER	PDO	-5.40	0.62	0.15	
		FI	-7.34	0.68	0.14	1.01
		Total				0.99
	SW	PDO	-5.63	0.62	0.15	
		FI	-7.38	0.68	0.14	1.04
		Total				1.05
	NE	PDO	-5.50	0.62	0.15	
		FI	-7.07	0.68	0.14	0.98
		Total				0.97
	NW	PDO	-5.21	0.62	0.15	
		FI	-7.18	0.68	0.14	0.99
		Total				0.96
SafetyAnalyst	Rural (2lane)	PDO				
		FI	-4.86	0.53	0.67	0.22
		Total	-3.63	0.53	0.50	0.28
Group 5	CR	PDO	-11.24	1.21	0.27	
		FI	-11.06	1.07	0.08	1.02
		Total				0.99
	SW	PDO	-11.58	1.21	0.27	
		FI	-11.28	1.07	0.08	0.99
		Total				1.01
SafetyAnalyst	Rural Multilane undivided	PDO				
		FI	-4.20	0.50	0.53	0.18
		Total	-3.17	0.49	0.53	0.27
	Rural Multilane divided	PDO				
		FI	-7.46	0.72	0.09	0.54
		Total	-5.05	0.66	0.32	0.39
Group 6	CR	PDO	-14.136	1.56	0.22	
		FI	-14.03	1.45	0.12	0.993981
		Total				0.898906
SafetyAnalyst	Urban arterial (2lane)	PDO				
		FI	-8.84	0.89	4.54	0.62
		Total	-7.16	0.84	4.40	0.58
Group7	CR	PDO	-13.41	1.43	0.44	
		FI	-16.27	1.61	0.35	0.86
		Total				0.96
SafetyAnalyst	Urban Multilane undivided	PDO				
		FI	-12.07	1.39	0.81	0.04
		Total	-10.24	1.29	0.85	0.09
	Urban Multilane divided	PDO				
		FI	-14.87	1.52	5.81	0.43
		Total	-11.85	1.34	5.91	0.56

Table 5-2 MTO OPFs and SafetyAnalyst SPFs parameter estimates and their calibration factors for Ontario's King's Highways

The calibration parameter estimates for each model category and the calculated calibration factors for Ontario secondary highways are presented in Table 5-3.

Group	Region	Model	ln(alpha)	beta	Initial overdispersion	Calibration Factor
Group 8	NE	PDO	-7.19	0.84	0.42	
		FI	-8.64	0.85	0.22	1.00
		Total				1.03
	NW	PDO	-6.67	0.84	0.42	
		FI	-8.46	0.85	0.22	1.01
		Total				0.93
SafetyAnalyst	Rural (2lane)	PDO				
		FI	-4.86	0.53	0.67	0.11
		Total	-3.63	0.53	0.50	0.19

Table 5-3 MTO OPFs and SafetyAnalyst SPF parameter estimates and their calibration factors for all Ontario secondary highways

Small values for calibration factors (i.e., less than 1) indicate that the SafetyAnalyst models, in most cases, strongly overestimate the number of accidents which occur on Ontario highways (e.g., the calibration factor for rural two-lane secondary highways- group 8- is very small and close to zero). This could be due to differences in climate, driver behaviour, accident reporting practices, etc. between Ontario and the jurisdiction that the SafetyAnalyst models are based on. Figure 5-1 illustrates how the original SafetyAnalyst model for Ontario urban multilane King's Highways, group 7, overestimates the crashes on segments with low number of observed accidents of all severities and underestimates the crashes for segments with a higher number of accidents of all severities.

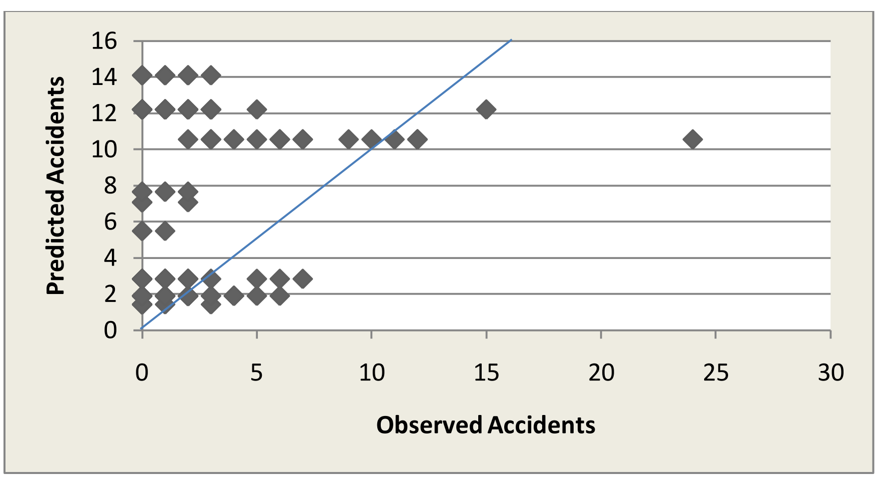

Figure 5-1 Observed vs. predicted all severities accidents for un-calibrated SafetyAnalyst SPF on Ontario multilane King's highways, group 7

To adapt the SafetyAnalyst models for Ontario intersections, data were organized based on the MTO model category. The FI accidents and accidents for all types of severities (Total) were predicted by both models. Then, the same procedure was done in EXCEL to recalibrate the MTO and SafetyAnalyst models. The prediction models and the recalibration results (Table 5-4 and Table 5-5) are illustrated below:

- MTO OPF (iTRANS Consulting Inc., 2005):

  $$^{1}E(K) = e^{\alpha} \times (\frac{AADT_{min}}{1000})^{\beta_1} \times (\frac{AADT_{maj}}{1000})^{\beta_2} \times e^{(\beta_3 \times (\frac{AADT_{min}}{1000}) + \beta_4 \times (\frac{AADT_{min}}{1000})^2)}$$

- SafetyAnalyst SPF (Midwest Research Institute, 2004):

$$Acc = e^{\alpha} \times AADT_{maj}{}^{\beta_1} \times AADT_{min}{}^{\beta_2}$$

where

Acc = predicted accident frequency per mile per year for road segments, and accidents per year for intersections and ramp,

$AADT_{maj}$= average annual daily traffic on the major road (veh/day),

$AADT_{min}$= average annual daily traffic on the minor road (veh/day), and

α, β_1, β_2, β_3, $\beta 4$ =model parameter estimates.

[1] *For un-signalized four-legged arterial intersections use:* $E(K) = e^{\alpha} \times (AADT_{min}/1000)^{\beta_1} \times (AADT_{maj}/1000)^{\beta_2} \times e^{(\beta_3 \times (AADTmaj/1000) + \beta_4 \times (AADTmaj/1000)^2)}$

Model Type	Description	Accident Severity Level	Intercept	β2 Logaadt	β1 Minor Logaadt	β3	β4	Initial Dispersion Prameter	Calibration Factor
MTO	3-leg Arterial Rural and Collector	PDO	-0.55	-0.22	0.25	0.65	-0.07	1.44	
		FI	0.16	-1.15	-0.81	1.18	-0.08	1.55	1.15
		Total							1.08
SafetyAnalyst	3-leg Rural	PDO							
		FI	-7.83	0.75	0.14			0.50	0.32
		Total	-6.57	0.66	0.20			0.33	0.45
	3-leg Urban	PDO							
		FI	-10.22	0.91	0.21			0.27	n/a
		Total	-12.37	1.22	0.27			0.47	n/a
MTO	4-leg Freeway and Arterial	PDO	-2.24	0.62	1.29	-0.10	-0.00	2.73	
		FI	-2.53	0.58	0.25	0.20	-0.01	3.17	1.08
		Total							1.13
SafetyAnalyst	4-leg Rural	PDO							
		FI	-7.83	0.75	0.14			0.50	0.62
		Total	-6.57	0.66	0.20			0.33	0.87
	4-leg Urban	PDO							
		FI	-5.11	0.49	0.16			0.30	n/a
		Total	-3.47	0.42	0.14			0.32	n/a
MTO	4-leg collector Urban	PDO	-2.47	0.46	-1.03	0.99	-0.05	3.34	
		FI	-3.20	0.70	0.02	0.47	-0.03	2.58	1.07
		Total							1.223
SafetyAnalys t	4-leg Urban	PDO							
		FI	-5.11	0.49	0.16			0.30	0.33
		Total	-3.47	0.42	0.14			0.32	0.53
MTO	4-leg Collector Rural & Semi-Urban	PDO	0.07	0.07	0.58	-0.17	0.01	2.64	
		FI	-0.70	0.10	0.29	-0.09	0.01	2.61	1.07
		Total							1.22
SafetyAnalys t	4-leg Rural	PDO							
		FI	-7.83	0.75	0.14			0.50	0.33
		Total	-6.57	0.66	0.20			0.33	0.53

Table 5-4 APM parameter estimates and calibration factors for Ontario's signalized intersections

In general, the SafetyAnalyst models overestimate the total number of accidents on Ontario's signalized intersections as the values of calibration factors in all cases are less than one. Moreover, the

SafetyAnalyst SPFs tend to overestimate the total number of accidents in the signalized intersections with a relatively small number of observed accidents and vice versa. For instance, Figure 5-2 illustrates this crash overestimation and underestimation for four-legged signalized intersections on Ontario arterials and freeways.

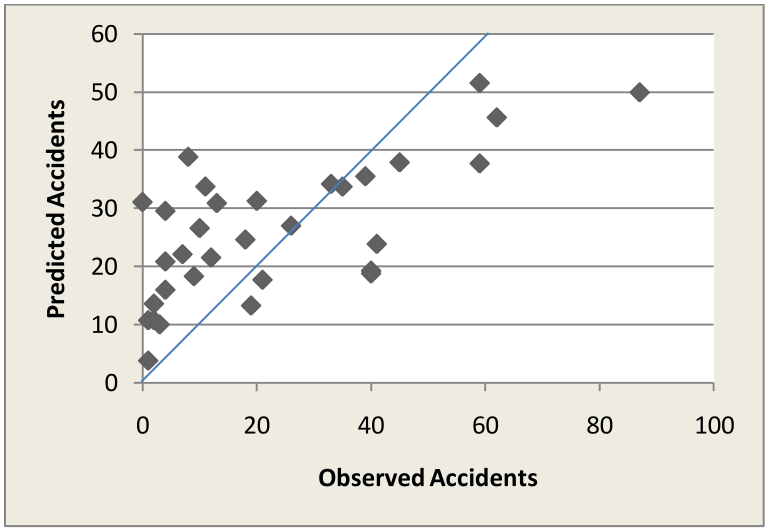

Figure 5-2 Observed vs. predicted all severities accidents for un-calibrated SafetyAnalyst SPF at four-legged signalized intersections

Table 5-5 demonstrates the model parameters and their calibration factors for three- and four-legged un-signalized intersections based on MTO OPFs and SafetyAnalyst SPFs:

Model Type	Description	Accident Severity Level	Intercept	β2 Logaadt	β1 Minor Logaadt	β3	β4	Initial Dispersion Prameter	Calibration Factor
MTO	3-leg Arterial & Collector	PDO	-2.30	0.45	-0.06	1.12	-0.20	2.21	
		FI	-2.97	0.34	-0.21	1.26	-0.19	1.79	0.96
		Total							1.09
SafetyAnalyst	3-leg Rural	PDO							
		FI	-9.35	0.71	0.21			1.23	1.30
		Total	-8.78	0.71	0.24			1.07	1.93
	3-leg Urban	PDO							
		FI	-8.45	0.49	0.39			1.23	0.90
		Total	-5.35	0.34	0.28			1.28	1.56
MTO	4-leg Collector	PDO	-1.62	0.36	0.23	0.74	-0.18	3.12	
		FI	-1.19	0.29	1.32	-0.36	-0.01	1.96	0.93
		Total							1.06
SafetyAnalyst	4-leg Rural	PDO							
		FI	-9.36	0.66	0.40			0.00	0.83
		Total	-8.96	0.65	0.47			0.70	1.14
	4-leg Urban	PDO							
		FI	-4.35	0.29	0.19			0.99	0.40
		Total	-3.12	0.27	0.16			0.86	0.52
MTO	4-leg Arterial	PDO	0.46	-2.20	0.67	0.49	-0.01	3.44	
		FI	-0.14	-1.96	0.63	0.45	-0.01	3.75	0.77
		Total							0.82
SafetyAnalyst	4-leg Rural	PDO							
		FI	-9.36	0.66	0.40			0.00	0.72
		Total	-8.96	0.65	0.47			0.70	0.89
	4-leg Urban	PDO							
		FI	-4.35	0.29	0.19			0.99	n/a
		Total	-3.12	0.27	0.16			0.86	n/a

Table 5-5 AMF parameter estimates and calibration factors for Ontario's un-signalized intersections

The calibration factors are close to one and to those for MTO models. This shows the compatibility of the SafetyAnalyst models with MTO models in accident predictions of un-signalized intersections. However, it is observed that the SafetyAnalyst SPFs for un-signalized intersections overestimates the total number of crashes for intersections with small number of accidents and underestimates the accidents for intersections with large number of accidents. This is shown in Figure 5-3 for the SafetyAnalyst accident predictions for four-legged un-signalized collector intersections.

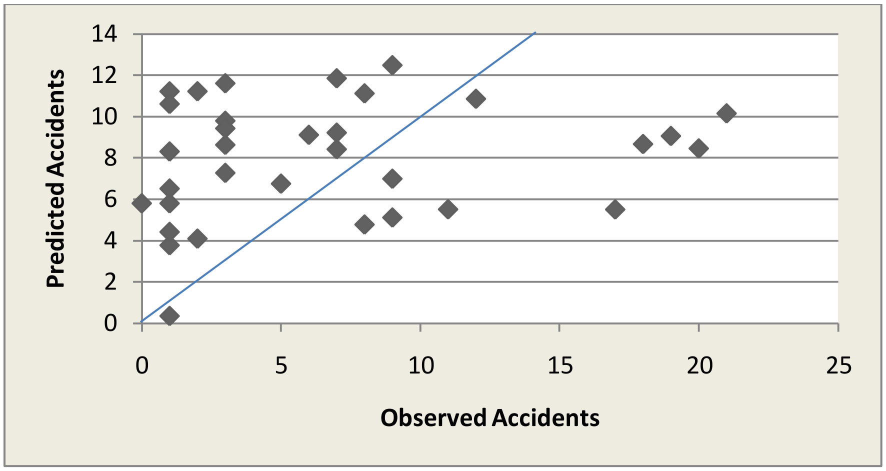

Figure 5-3 Observed vs. predicted all severities accidents for un-calibrated SafetyAnalyst SPF at four-legged un-signalized intersections

SPFs of Ontario and SafetyAnalyst for ramps are used to predict the average crash frequency of the Ontario's ramps. Then, the total number of observed crashes for each ramp category is divided by this predicted value to calculate the calibration factor for the facility type for both FI and all collision severity types. Table 5-6 illustrates the models parameter estimates and the calibration results for Ontario flared ramps.

- MTO OPF (B Persaud C. L., 2006):

$$Collisions\ per\ Year = \alpha \times AADT^{\beta_1} \times e^{\beta_2 \times (Length)}$$

- SafetyAnalyst SPF (Midwest Research Institute, 2004) :

$$Acc = e^{\alpha} \times AADT^{\beta}$$

Model Type	Description	Accident Severity Level	INTERCEPT	β_1(Logaadt)	β_2	Initial Dispersion Parameter	Calibration Factor
MTO	Flared On-Ramps	PDO	-7.41	0.75	0.95	0.83	
		FI	-8.90	0.80	0.34	0.66	0.83
		Total					0.87
SafetyAnalyst	Rural Diamond On-Ramp	PDO					
		FI	-8.12	0.86		0.98	0.25
		Total	-2.16	0.19		1.86	1.16
	Urban Diamond On-Ramp	PDO					
		FI	-8.00	0.86		0.69	0.22
		Total	-8.20	1.03		1.21	0.33
MTO	Flared Off-Ramps	PDO	-8.04	0.89	0.20	0.38	
		FI	-9.15	0.851	0.36	0.61	0.90
		Total					0.91
SafetyAnalyst	Rural Diamond Off-Ramp	PDO					
		FI	-4.54	0.47		2.66	2.18
		Total	-3.07	0.46		1.34	2.80
	Urban Diamond Off-Ramp	PDO					
		FI	-3.86	0.47		1.94	1.10
		Total	-3.52	0.54		1.15	2.17

Table 5-6 APMs parameter estimates and calibration factors for Ontario flared ramps

The models parameter estimates and the calibration results for Ontario loop ramps and also freeway-to-freeway ramps are presented in Table 5-7.

Model Type	Description	Accident Severity Level	INTERCEPT	β_1 (Logaadt)	β_2	Initial Dispersion Parameter	Calibration Factor
MTO	Loop ON-Ramps	PDO	-6.04	0.56	1.36	0.46	
		FI	-8.44	0.67	1.22	0.29	0.94
		Total					0.96
SafetyAnalyst	Rural Parclo loop On-Ramp	PDO					
		FI	-1.30	0.24		1.02	0.04
		Total	-5.59	0.82		0.97	0.14
	Rural Free-flow loop On- Ramp	PDO					
		FI	-1.30	0.24		1.02	0.04
		Total	-1.17	0.35		2.32	0.09
	Urban Parclo loop On- Ramp	PDO					
		FI	-1.34	0.24		1.20	0.05
		Total	-5.59	0.82		0.97	0.14
	Urban Free-flow loop On- Ramp)	PDO					
		FI	-1.34	0.24		1.18	0.05
		Total	-0.55	0.29		2.42	0.08
MTO	Loop OFF-Ramps	PDO	-8.11	0.85	0.97	0.68	
		FI	-8.37	0.70	1.47	1.25	0.96
		Total					0.96
SafetyAnalyst	Rural Parclo loop Off-Ramp	PDO					
		FI	-4.29	0.59		0.94	0.08
		Total	-1.15	0.26		0.12	0.26
	Rural Free-flow loop Off- Ramp)	PDO					
		FI	-4.29	0.59		0.94	0.08
		Total	-5.10	0.78		1.69	0.16
	Urban Parclo loop Off- Ramp	PDO					
		FI	-3.68	0.53		0.67	0.11
		Total	-1.15	0.26		0.12	0.49
	Urban Free-flow loop Off- Ramp	PDO					
		FI	-3.68	0.53		0.67	0.07
		Total	-4.60	0.73		1.32	0.15
MTO	Freeway to Freeway Ramps	PDO	-7.87	0.87	0.55	0.75	
		FI	-8.34	0.77	0.44	0.91	1.04
		Total					0.10

Table 5-7 APMs parameter estimates and calibration factors for Ontario loop and freeway-to-freeway ramps

Generally, the prediction models of the SafetyAnalyst for ramps strongly overestimate the number of crashes on loop ramps, whereas, SafetyAnalyst predicts collisions quite randomly on flared ramps-underestimates for some and overestimates for others. Specifically, SafetyAnalyst models overestimates accidents for ramps with small number of observed accidents and underestimates accidents for ramps with large number of observed accidents as illustrated in Figure 5-4 and Figure 5-5.

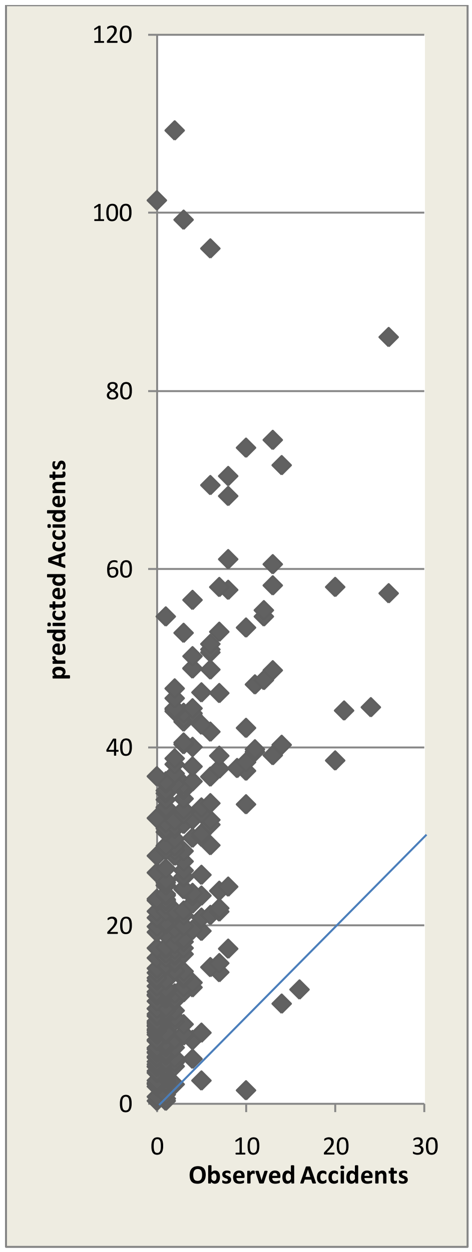

Figure 5-4 Observed vs. predicted all severities accidents for un-calibrated SafetyAnalyst SPF on rural parclo loop on-ramps

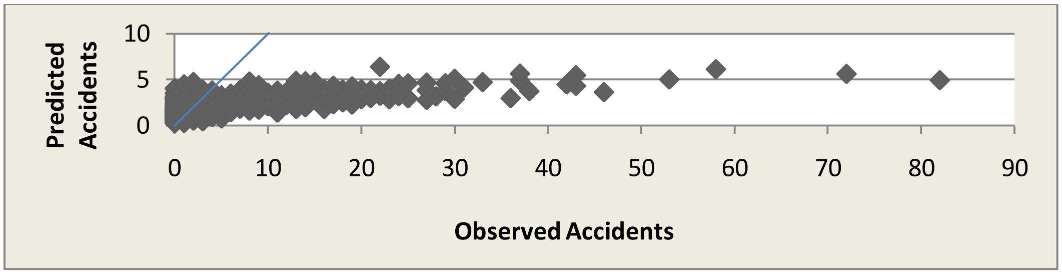

Figure 5-5 Observed vs. predicted all severities accidents for un-calibrated SafetyAnalyst SPF on rural diamond off-ramps

As mentioned earlier, the SafetyAnalyst SPF crash predictions are random for flared off-ramps. For instance, the SafetyAnalyst SPF tends to strongly underestimate the number of accidents for rural diamond off-ramps as illustrated in Figure 5-5.

To ensure that the recalibration process has been done properly, two checks should be considered. The first check is that the predictions should be done for the same number of years for both MTO and SafetyAnalyst models. The second check is that the sum of residuals after recalibration should always be zero or close to zero due to rounding.

5.2 RECALIBRATION OF HSM SPFs

The recalibration procedure includes estimating the predicted average crash frequency for two highways (Highways 17 and 148) under the northern east jurisdiction of the MTO. The SPF for rural two-lane roads in HSM is used to predict the average crash frequency for these rural two-lane two-way highways. A total number of 483 homogeneous segments with the total length of 77.9 km were selected for calibration. All available data (i.e., segment's length, AADT, number of observed collisions, lane width, shoulder width and type, etc.) were extracted from IHSDM software to an Excel file and the HSM base condition default values were assumed for the missing ones (e.g., no centre line rumble strip, no lighting, and no automated speed enforcement).

Then, relative AMFs for each segment were determined according to the HSM predictive chapter as described in Section 3.1 of this thesis. To predict total crash frequency for each site, the HSM SPF for rural two-lane two-way roads was applied without using the EB method and employing any calibration factors. The calibration factor in this step is assumed to be 1.00.

$$N_{predicted\ \ rs} = N_{spf\ \ rs} \times (AMF_{1r} \times AMF_{2r} \times \ldots \times AMF_{12r}) \times 1.0$$ Equation 5-1

$$N_{spf\ rs} = AADT \times L \times 365 \times 10^{-6} \times e^{(-0.312)}$$ Equation 5-2

$$K = \frac{0.236}{L}$$

Equation 5-3

The prediction results demonstrate an overestimation of collision predictions by the HSM baseline model in comparison with MTO data for small number of accidents and an underestimation of number of accidents for larger amount of observed accidents.

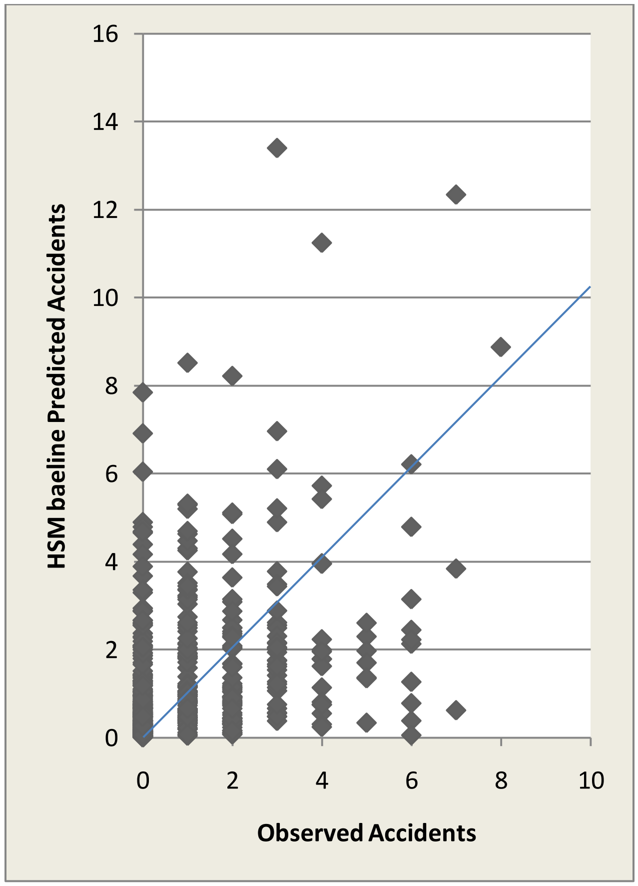

Figure 5-6 Observed vs. predicted all severities accidents for un-calibrated HSM Part C predictive model on two-lane two-way roadways

Then, the calibration factor proposed in the HSM predictive chapter (Equation 3-1) is applied as the ratio of the sum of the observed crashes for all sites to the total number of predicted crashes by the base model for all sites during the same period of study.

The models used to predict the total average crash frequency during the eight year study period (2000 to 2007) in this practice are as follows:

- MTO OPF for rural King's Highways, Group 4 NE region (Ryerson University, 2008):

$$Total\ PDO\ Collisions = N \times L \times (-5.5048) \times AADT^{(0.6208)}$$

$$Total\ FI\ Collisions = N \times L \times (-7.0729) \times AADT^{(0.6825)}$$

$$Total\ All\ Severity\ Collisions = PDO\ collisions + FI\ collisions$$

- HSM SPF base model for rural two-lane roadway segments:

$$N_{spf\ rs} = N \times AADT \times L \times 365 \times 10^{-6} \times e^{(-0.312)}$$

where

AADT = average annual daily traffic for roadway segment,

L = segment length, and

N = number of years of the calibration.

The table below illustrates an example of various steps of calibration for two-lane two-way highways and the estimated calibration factor for HSM SPF models.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crash Severity Level	$N_{spf\ rs}$	Overdispersion Parameter, K	Crash Severity Distribution	$N_{spf\ rs}$ by Severity distribution	Combined AMFs	Calibration Factor, C_r	Predicted average crash frequency, $N_{predicted\ rs}$
	Equation 5-2	Equation 5-3	Table 4-7	(2) Total*(4)	Table 5-9		(5)*(6)*(7)
Total	0.31	2.44	1.00	0.31	1.1	0.79	0.27
Fatal and Inury (FI)	----	----	0.29	0.09	1.1	0.74	0.07

Table 5-8 Worksheet for roadway segment crashes for rural two-lane two-way roadways

The analysis shows that the calibration factors for adjusting HSM SPF to local conditions of the highways of interest are 0.79 for all severity accidents and 0.74 for FI accidents. These values are less than one and indicate an overestimation of crash predictions by the HSM SPF for associated highways. On the other hand, the calculated calibration factor values for MTO models are very close to one (i.e., 1.095 for FI and 1.06 for all severity crashes) which indicates a more reliable crash prediction by the initial MTO model.

5.3 RECALIBRATION OF HSM AMFs

In order to recalibrate HSM AMFs, first, the AMFs are determined as described in Table 3-2 for two-lane two-way road segments. After obtaining the value for each AMF, a combined AMF is assigned as the multiplied value of all of the AMFs. Then, the HSM baseline model becomes recalibrated to account for the site specific geometric design and traffic control feature effects. Next, a value of 1.00 will be assigned to each AMF one at a time and the model recalibration process will be redone based on the value of 1 for the AMF under consideration for all sites. The new recalibration factor is applied to estimate the new predicted average crash frequency. Table 5-9 illustrates the AMF recalibration procedure.

(1)	Lane Width	AMF1r	Table 3-2	1.00
(2)	Shoulder Width and Type	Original AMF_{2r}		0.95
(2i)		Substitute AMF_{2r}		1.00
(3)	Horizontal Curve	AMF_{3r}	Table 3-2	1.00
(4)	Superelevation	AMF_{4r}		1.00
(5)	Grades	AMF_{5r}		1.00
(6)	Driveway Density	AMF $_{6r}$		1.00
(7)	Centerline Rumble Strips	AMF_{7r}		1.00
(8)	Passing Lanes	AMF_{8r}		1.00
(9)	TWLT Lane	AMF_{9r}		1.00
(10)	Roadside Design	AMF_{10r}		1.14
(11)	Lighting	AMF_{11r}		1.00
(12)	Automated Speed Enforcement	AMF_{12r}		1.00
(13)	Combined AMF	AMF_{COMB}	(1)*(2i)*(3)*…*(12)	1.14

Table 5-9 AMFs described in HSM for rural two-lane two-way roadways

Finally, for each different value of the AMF under consideration, the number of sites, sum of observed crashes, sum of predicted crashes, and ratio of the two (i.e., sum of observed crashes/ sum of predicted crashes) is documented. Then, each of these ratios is divided by the baseline ratio (the ratio of the sum of observed to sum of predicted for the AMF=1.0). For instance, the value of the ratio compared to baseline for total accidents for the lane width equal to 3.5 meter is calculated as: 0.27/ 1.17= 0.23. The above procedure will be separately done for all AMFs. This will make it clear which AMFs are performing badly in our data.

Table 5-10demonstrates the recalibration results for all of the AMFs.

AMF Description	Original AMF	Observed Accidents		Predicted Accidents		Ratio		Ratio Compared to Baseline	
		Total	FI	Total	FI	Total	FI	Total	FI
AMF_{1r} Lane Width	1.00	495.00	125.00	424.84	105.69	1.17	1.18		
	1.01	23.00	9.00	84.89	29.40	0.27	0.31	0.23	0.26
	1.02	16.00	7.00	24.27	5.91	0.66	1.19	0.57	1.00
AMF_{2r} Shoulder Width and type	1.00	1.00	0.00	3.47	0.81	0.29	0.00		
	0.99	9.00	2.00	5.05	1.18	1.78	1.69	6.18	n/a
	0.98	2.00	0.00	11.76	2.75	0.17	0.00	0.59	n/a
	0.97	33.00	12.00	95.15	31.83	0.35	0.38	1.20	n/a
	0.96	399.00	105.00	368.38	92.04	1.08	1.14	3.76	n/a
	0.95	90.00	22.00	50.19	12.39	1.79	1.78	6.22	
AMF_{3r} Horizontal Curve	1.00	348.00	95.00	353.42	95.02	0.98	1.00		
	1<AMF<=2	178.00	44.00	167.94	42.37	1.06	1.04	1.08	1.04
	2<AMF	8.00	2.00	12.65	3.61	0.63	0.55	0.64	0.55
AMF_{4r} Superelevation	1.00	484.00	126.00	445.18	117.98	1.09	1.07		
	1.10	41.00	13.00	77.35	20.34	0.53	0.64	0.49	0.60
	1.20	9.00	2.00	11.48	2.68	0.78	0.75	0.72	0.70
AMF_{5r} Grade Factor	1.00	343.00	86.00	398.86	107.48	0.86	0.80		
	1.10	136.00	36.00	105.11	26.43	1.29	1.36	1.50	1.70
	1.16	55.00	19.00	30.03	7.09	1.83	2.68	2.13	3.35
AMF_{6r} Driveway Density	1.00	403.00	103.00	346.96	85.01	1.16	1.21		
	1.10	38.00	13.00	50.63	13.23	0.75	0.98	0.65	0.81
	1.20	32.00	6.00	45.41	12.51	0.70	0.48	0.61	0.40
	1.30	32.00	8.00	18.24	5.03	1.75	1.59	1.51	1.31
	1.40	29.00	11.00	72.77	25.23	0.40	0.44	0.34	0.36
AMF_{8r} Passing Lanes	1	379.00	101.00	413.55	110.85	0.92	0.91		
	0.75	138.00	33.00	110.27	27.50	1.25	1.20	1.37	1.32
	0.65	17.00	7.00	10.18	2.65	1.67	2.64	1.82	2.90
AMF_{10r} Roadside Design	1	187.00	54.00	210.78	62.55	0.89	0.86		
	1.1	325.00	82.00	312.52	75.97	1.04	1.08	1.17	1.25
	1.2	22.00	5.00	10.70	2.47	2.06	2.02	2.32	2.34

Table 5-10 HSM AMFs evaluation results for rural two-lane two-way roadways

To interpret this table, ratios that have been compared with the baseline ratios (i.e., values for the last two columns) will be examined. As the value of AMF changes due to a change in roadway geometric characteristics or traffic control features, the amount of this ratio changes as well for both FI and all severity accidents. If this change in the amount of ratio follows the logic behind the change in AMF and the alteration magnitude seems reasonable, then the AMF performs well in the data.

5.4 JURISDICTION-SPECIFIC SPF CALIBRATION RESULT

In developing the full model for three- and four-legged stop controlled intersections on two-lane rural roads, the approaches presented by Harwood et al. (2000), and Vogt and Bared (1998) were attempted. The NB structure form was considered in the development of the models. The best available candidate base conditions were incorporated into the model as additional independent variables with the purpose of using the variable coefficients to determine AMFs. A good choice of independent variables is choosing variables that are strongly related to the dependent variable and are not correlated to other variables. To do so, the Pearson moment correlation matrix for four-legged stop controlled intersections is estimated and presented in Table 5-11. Small coefficients of correlations indicate that a weak relationship exists between each pair of study. As well, the negative signs show downhill (inverse) relationships between these pairs.

Variables	LT	majaadt	minaadt	ND	RT	SKEW	totalacc
LT	1.00	-0.045	0.413	0.05	-0.18	-0.24	0.083
majaadt		1.00	-0.327	-0.12	0.254	-0.05995	-0.0387
minaadt			1.00	0.177	0.005	0.2588	0.38827
ND				1.00	-0.55	-0.222	0.06205
RT					1.00	0.245	0.153
SKEW						1.00	0.486
totalacc							1.00

Table 5-11 Pearson moment correlation matrix for four-legged stop controlled in two-lane highways

where

LT = the presence of an LT on major approaches, 0.0 for no LT and 1.0 for one and more LTs,

majaadt= the average annual daily traffic on the intersection's major approaches (veh/day),

minaadt= the average annual daily traffic on the intersection's minor approaches (veh/day),

ND = number of driveways within 250 feet of the intersection,

RT = presence of an RT on major approaches, 0.0 for no RT and 1.0 for one and more RTs,

SKEW = the absolute skew angle of the intersection in degrees, and

totalacc= total observed crashes for all severity types for all sites.

Except for the major AADT which has an inverse relationship with the total accidents, the rest of the variables are positively correlated with the total accidents. A candidate model for four-legged stop controlled intersections developed using the GLM procedure is:

$$N_{4ST} = \exp\left[-8.52 + 0.39\ln(AADT_{maj}) + 0.66\ln(AADT_{min}) + 0.017SKEW + 0.06RT + 0.48\,LT + 0.013\,ND\right]$$

Equation 5-4

Equation 5-4 indicates the full model for four-legged stop controlled intersections with all the independent variables. Table 5-12 summarizes the model parameters and GOF statistics for the Equation 5-4.

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-8.5153	5.7988	-19.8807	2.8500	2.16	0.1420
LOGMAJ	1	0.3915	0.5358	-0.6588	1.4417	0.53	0.4651
LOGMIN	1	0.6631	0.3110	0.0535	1.2727	4.55	0.0330
SKEW	1	0.0174	0.0144	-0.0109	0.0457	1.45	0.2281
RT	1	0.0610	0.5538	-1.0243	1.1464	0.01	0.9122
LT	1	0.0476	0.4626	-0.8590	0.9543	0.01	0.9180
ND	1	0.0131	0.1909	-0.3610	0.3873	0.00	0.9451
Dispersion	1	0.4524	0.2134	0.0342	0.8707		

Table 5-12 Model parameter estimates and goodness-of-fit measures for candidate SPF for four-legged stop controlled intersections

Except for minor AADTs, other variables have a P value greater than 0.15 and could not be considered in the model as documented by Harwood et al. (2000) (i.e., they are not statistically significant with a confidence interval of 85%).

The only AADT variable model attempted to check the effect and GOF of exposure on the model. The estimated model equation plus the model parameters and GOF are illustrated in Equation 5-5 and Table 5-13.

$$N_{4ST\ finall} = e^{-10.79} \times (AADT_{maj})^{0.56} \times (AADT_{min})^{0.82}$$ Equation 5-5

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-10.7940	5.6121	-21.79	0.2055	3.70	0.0544
LOGMAJ	1	0.5620	0.5109	-0.439	1.5633	1.21	0.2713
LOGMIN	1	0.8153	0.2700	0.286	1.345	9.12	0.0025
Dispersion	1	0.5304	0.2293	0.081	0.9799		

Table 5-13 Model parameter estimates and goodness-of-fit measures for final SPF for four-legged stop controlled intersections

The P-value for the major AADT is greater than 0.15 and this variable is not statistically significant in the range of 85% confidence level. As a result, no model could be developed for four-legged stop controlled intersections that could satisfy the development of jurisdiction-specific models requirements i.e., taking into account the exposure (traffic volume) of the intersection.

Next, the data for three-legged stop controlled intersections in the central and eastern regions of MTO were used to develop the relative full model. The independent variables considered for this model were exposure, LT, RT, ND, roadside design, and the skew of the intersection. The Pearson correlation matrix for the candidate variables is summarized in Table 5-14.

Variable	LT	majaadt	minaadt	ND	RHR	RT	SKEW	totalacc
LT	1.00	0.39	0.56	0.24	0.00	0.22	-0.17	0.24
majaadt		1.00	0.66	0.12	0.23	-0.11	0.08	0.63
minaadt			1.00	0.15	0.19	-0.01	0.16	0.45
ND				1.00	-0.12	-0.04	0.17	0.21
RHR					1.00	-0.31	0.21	0.12
RT						1.00	-0.01	0.02
SKEW							1.00	0.21
Totalacc								1.00

Table 5-14 Pearson correlation matrix for three-legged stop controlled intersections on two-lane roadways

The correlation matrix indicates that all the candidate independent variables are positively correlated to the total accidents. Among all variables, the skew and Number of Driveways exhibit a larger positive correlation with the total number of accidents for all severity levels. The strong interrelationship between two or more independent variables in the Pearson moment correlation matrix indicates that the presence of one variable in the model equation may disguise the effect of another input variable.

Despite this concern, all the variables were tried in the development of the candidate model as presented below:

$$N_{3ST} = \exp\left[-17.13 + 1.9\ln\left(AADT_{maj}\right) + 0.17\ln(AADT_{min}) - 0.003SKEW - 0.49\ RHR + 0.085RT - 0.04LT + 0.256ND\right]$$ Equation 5-6

Table 5-15 presents the model parameter for each independent variable and their GOF.

Parameter	DF	Estimate	Standard Error	Wald 95% confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-17.1266	6.0677	-29.0191	-5.2341	7.97	0.0048
LOGMAJ	1	1.9043	0.7470	0.4402	3.3684	6.50	0.0108
LOGMIN	1	0.1698	0.2804	-0.3797	0.7194	0.37	0.5447
SKEW	1	-0.0027	0.0406	-0.0823	0.0769	0.00	0.9469
RHR	1	-0.4902	1.2191	-2.8796	1.8992	0.16	0.6876
RT	1	0.0846	0.5067	-0.9085	1.0777	0.03	0.8674
LT	1	-0.0396	0.6720	-1.3567	1.2776	0.00	0.9531
ND	1	0.2556	0.2171	-0.1699	0.6811	1.39	0.2391
Dispersion	1	1.4622	0.6046	0.2773	2.6472		

Table 5-15 Model parameter estimates and goodness-of-fit measures for candidate SPF for three-legged stop controlled intersections

Except for exposure, none of the candidate variables are statistically significant with a significance level of 0.15. Hence, the candidate model was re-evaluated based on only AADT as its primary variable. The re-evaluated model and the model coefficients are presented in Equation 5-7 and Table 5-16.

$$N_{3ST\ finall} = e^{-18.01} \times (AADT_{maj})^{1.82} \times (AADT_{min})^{0.175}$$ Equation 5-7

Parameter	DF	Estimate	Standard Error	Wald 95% confidence Limits		Wald Chi-Square	Pr > ChiSq
Intercept	1	-18.0068	5.0307	-27.8669	-8.14667	12.81	0.0003
LOGMAJ	1	1.8147	0.7002	0.442	3.187	6.72	0.0095
LOGMIN	1	0.1750	0.2324	-.2805	0.6306	0.57	0.4514
Dispersion	1	1.3575	0.5372	0.3045	2.4104		

Table 5-16 Model parameter estimates and goodness-of-fit measures for final SPF for three-legged stop controlled intersections

Even though the coefficient parameter for Equation 5-7 seems reasonable, the minor AADT is still not statistically significant with a P-value= 0.45- greater than 0.15.

The HSM baseline models for the discussed types of intersections are:

- four-legged stop controlled intersections:

$$N_{spf\ 4ST} = \exp\left[-8.56 + 0.60 \times \ln\left(AADT_{maj}\right) + 0.61 \times \ln\left(AADT_{min}\right)\right]$$ **Equation 5-8**

- three-legged stop controlled intersections:

$$N_{spf\ 3ST} = \exp\left[-9.86 + 0.79 \times \ln\left(AADT_{maj}\right) + 0.49 \times \ln\left(AADT_{min}\right)\right]$$ **Equation 5-9**

6 COMPARISION ANALYSIS

Several goodness-of-prediction measures are used to assess the suitability of each HSM and SafetyAnalyst model calibrated to Ontario data and the reliability of the jurisdiction-specific model. These include:

- plots of the CURE (observed minus predicted crash frequencies) graphed versus each variable in the model,
- MAD (absolute value of sum of observed minus predicted crash frequencies divided by sample size),
- Pearson's χ^2 statistics, and
- R_α-Squared.

As mentioned earlier, the CURE plot is an indicator of how well the model fits the data. A model fits the data well if the CURE oscillates around zero and lies between the two standard deviation limits $(\pm 2STD)$.These plots are calculated and drawn in Excel for all models with respect to their individual covariates.

The MAD measures the average magnitude of the prediction variability. A smaller MAD means less inconsistency in prediction.

The maximum absolute deviation from the CURE plot is the maximum value away from 0.0 the CURE plot goes, taking the absolute value. A lower maximum value means that the predictions are more compact.

The SAS 9.2 program (SAS Institute Inc., 2002) is used to estimate the overdispersion parameter for the recalibrated SafetyAnalyst and MTO models. The program finds the most likely value of *d* and *d* is equal to *1/dispersion*. Moreover, it is *dispersion* that is put into the comparison table.

6.1 TRANSFERABILITY OF SAFETYANALYST SPFs

Table 6-1shows the values for GOF statistics in addition to the total number of FI and all severity crashes and the relevant SPFs used to predict the crashes for the selected set of sites on Ontario freeways.

OPF Category	Model Applied	Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
Complex Fwy, Grou1	OPF Rur/Urb All Lanes	286	1012	0.58	2.09	1.08	1.33	31.65	117.95
Simple Fwy, Group 2	OPF Rur/Urb 4ln	3065	12050	0.58	1.68	1.369	1.54	112.90	419
	SafetyAnalyst Rur; Fwy 4 ln	3065	12050	0.58	1.68	1.36	1.54	110.50	408.90
	SafetyAnalyst Urb; Fwy 4 ln	3065	12050	0.60	1.73	1.75	1.72	435.20	1592.60
Simple Fwy, Group 3	OPF Rur/Urb >4 ln	1721	7995	1.10	4.54	1.37	1.47	98.72	360.94
	SafetyAnalyst Rur; Fwy >=6ln	1721	7995	1.12	4.63	1.37	1.49	94.71	449.22
	SafetyAnalyst Urb; Fwy >=6ln	1721	7995	1.11	4.62	1.37	1.47	79.34	322.07

Table 6-1 Goodness-of-fit comparison table for Ontario freeways

GOF results for SafetyAnalyst models and MTO models applied to Ontario highways are presented in Table 6-2.

OPF Category	Model Applied	Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
King's Highways, Group 4	OPF Rur, <4 ln	8108	36111	0.21	0.67	0.65	0.76	122.36	427.19
	SafetyAnalyst Rur; 2 ln	8108	36111	0.22	0.67	0.68	0.77	321.17	1049.83
King's Highways, Group 5	OPF Rur, >=4 ln	350	1516	0.50	3.94	0.55	2.04	13.58	2522.01
	SafetyAnalyst Rur;Multilane	350	1516	0.52	3.93	0.61	2.17	33.84	2533.05
King's Highways, Group 6	OPF Urb, <4 ln	160	511	0.43	0.97	0.41	0.77	13.59	33.60
	SafetyAnalyst Urb; 2 ln arterial	160	511	0.44	0.96	0.41	0.90	15.82	63.33
King's Highways, Group 7	OPF Urb, >=4 ln	82	363	0.46	1.47	0.30	0.87	6.65	28.98
	SafetyAnalyst Urb;Multilane	82	363	0.47	1.47	0.30	0.86	5.61	33.51
Secondary Highways, Group 8	OPF Rur/Urb All Lanes	955	5357	0.04	0.19	0.63	1.38	22.63	285.93
	SafetyAnalyst Rur; 2 ln	955	5357	0.04	0.19	1.90	1.56	113.52	783.73

Table 6-2 Goodness-of-fit comparison table for Ontario highways

In assessing the GOF measurements of the models, their values of MAD, recalibrated overdispersion, and MAD from the CURE plot being compared, models with the smallest value of GOF tests perform better in predicting the long term average crash frequency. Also, the recalibrated SafetyAnalyst models with similar GOF test values to those for MTO models are suitable to be transferred for use in Ontario.

Even though the examination of the recalibrated SafetyAnalyst SPF cure plots indicated that the CURE plots of all segment groups do not fit the Ontario data very well, the CURE plots for groups two, three, and seven lie within the range of the two standard deviations in most of the data range and partially fit the Ontario data. The SafetyAnalyst models fit in Ontario data (CURE plots), the similarities of the SafetyAnalyst SPFs CURE plots with the MTO SPFs CURE plots, and finally, the similarities of the SafetyAnalyst power functions with the MTO models for these three groups are illustrated in Figure 6-1, Figure 6-2, and Figure 6-3.

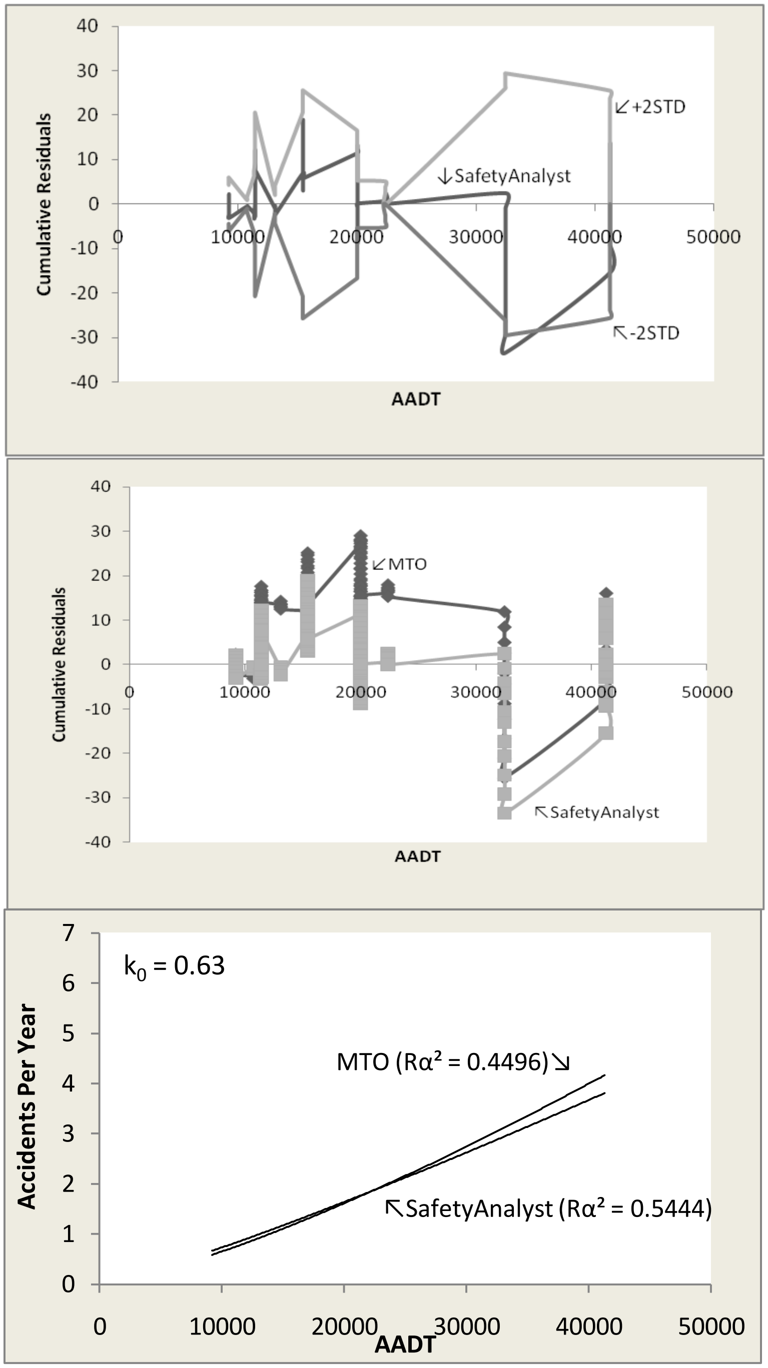

Figure 6-1 Recalibrated APMs and CURE for all severities accidents on Ontario urban multilane King's Highways, group 7

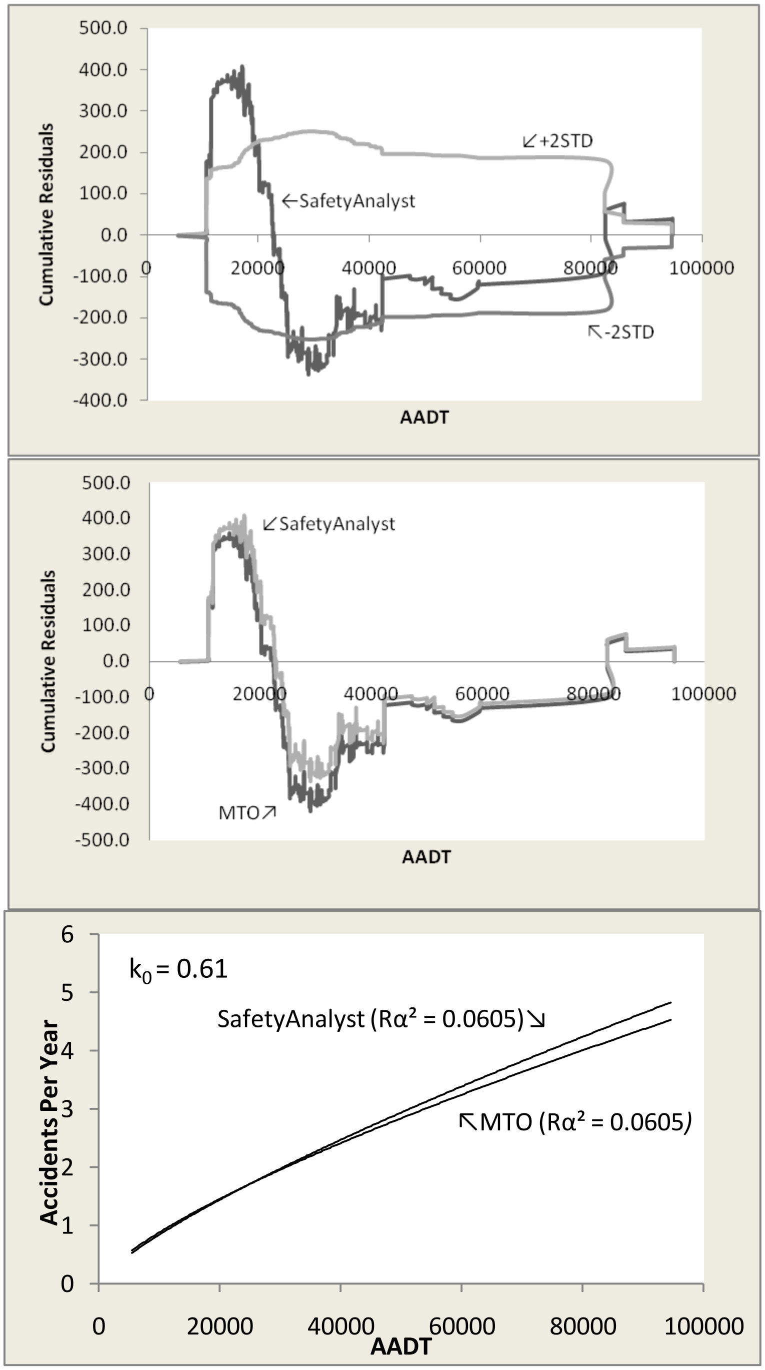

Figure 6-2 Recalibrated APMs and CURE for all severities accidents on Ontario rural freeways, groups 2

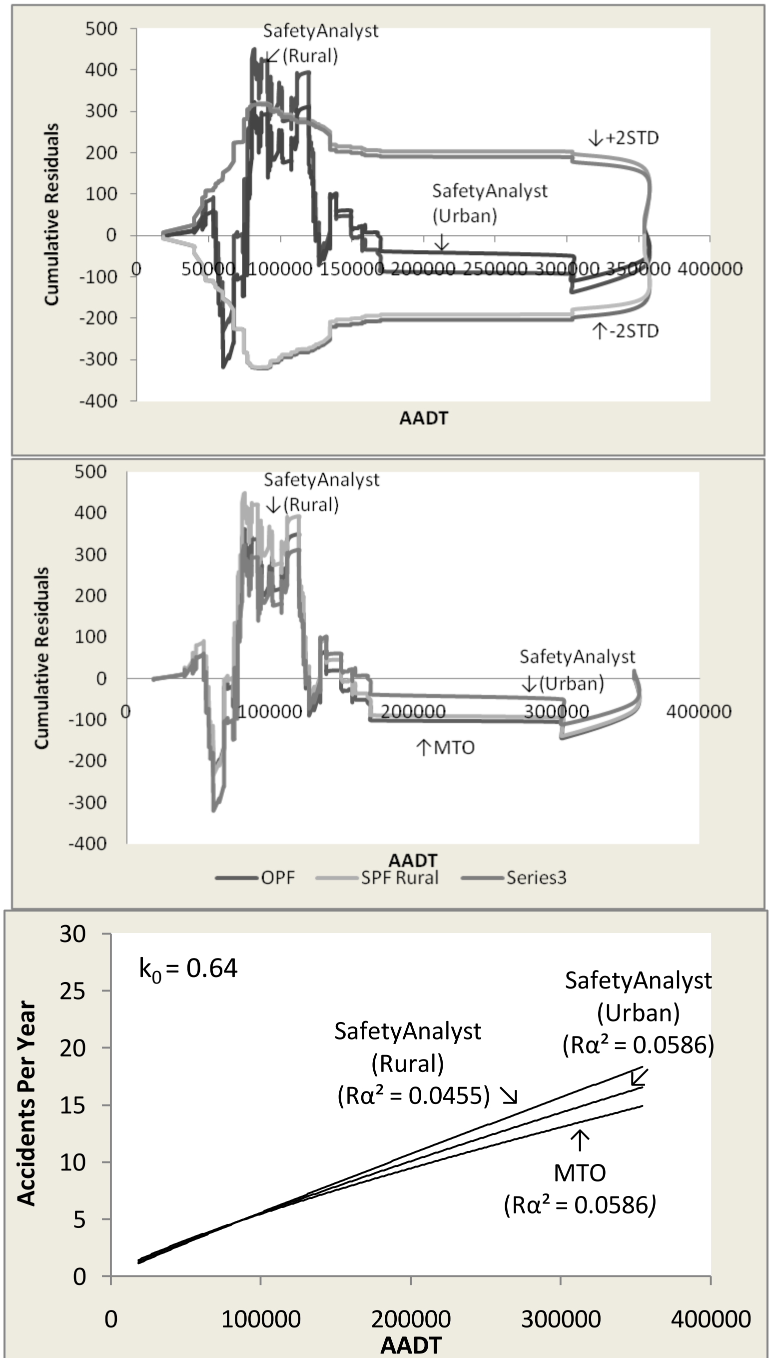

Figure 6-3 Recalibrated APMs and CURE for all severities accidents on Ontario freeways, groups 3

These figures prove the reliability of the GOF statistics in which the value of all GOF tests for both SafetyAnalyst and MTO models are very close to groups [2]two, three, and seven. Groups four, five, six,

[2] For group two, the SafetyAnalyst model for only rural freeways matches the MTO OPF and not the model for urban freeways.

and eight fail the CURE plot test since the cumulative residuals of models do not lie between the two standard deviations and also their APMs do not match.

GOF statistics results for Ontario signalized intersections are illustrated below in Table 6-3.

OPF Category	Model Applied	Total Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
3-legged	MTO OPF	60	222	2.05	6.76	0.78	0.98	8.30	14.90
	SafetyAnalyst	60	222	2.75	8.66	1.82	1.49	14.50	50.50
4-legged Arterial & Freeway	MTO OPF	223	735	2.98	10.09	0.26	0.42	14.40	66.40
	SafetyAnalyst	223	735	3.99	13.49	0.56	0.67	14.60	79.40
4-legged Collector Rural & Semi-urban	MTO OPF	193	706	2.54	7.28	0.54	0.38	21.50	57.70
	SafetyAnalyst	193	706	3.07	9.58	0.74	0.52	32.60	66.30
4-legged Collector Urban	MTO OPF	94	329	3.06	11.11	0.39	0.30	12.90	72.00
	SafetyAnalyst	94	329	2.63	9.71	0.45	0.49	5.80	42.40

Table 6-3 Goodness-of-fit comparison table for Ontario signalized intersections

Table 6-4 demonstrates the GOF statistics comparison between MTO SPFs and SafetyAnalyst SPFs for Ontario un-signalized intersections.

OPF Category	Model Applied	Total Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
3-legged	MTO OPF	114	398	1.55	4.16	0.78	0.58	11.30	23.90
	SafetyAnalyst	114	398	1.51	4.25	0.70	0.62	14.60	35.60
4-legged Arterial	MTO OPF	44	120	1.49	4.05	0.02	0.32	5.80	18.90
	SafetyAnalyst	44	120	1.62	4.17	0.13	0.36	3.90	14.20
4-legged Collector	MTO OPF	79	242	1.54	4.51	0.45	0.63	7.40	21.30
	SafetyAnalyst	79	242	1.69	4.94	0.55	0.69	12.60	27.40

Table 6-4Goodness-of-fit comparison table for Ontario un-signalized intersections

Following figures demonstrates the CURE and APMs for all Ontario signalized and un-signalized intersection types analyzed in this research. In the first figure, both types of CURE plots- one based on the minor road entering AADT and another based on the major road entering AADT- are presented. For other types of intersections the CURE for minor road entering AADT is not presented in this report although it was analyzed.

As demonstrated by the power function graph for the major road entering AADT and major and minor road entering AADT CURE plots for four-legged signalized collector urban intersections(Figure 6-4), the SafetyAnalyst model is not only similar in shape to the CURE from the MTO model, but also tends to be more consistent and compressed than that for MTO. However, the SafetyAnalyst model for this type of intersections tend to predict more accidents than the MTO model when the minor road AADT is low and less accidents than the MTO model when the minor road AADT is high.

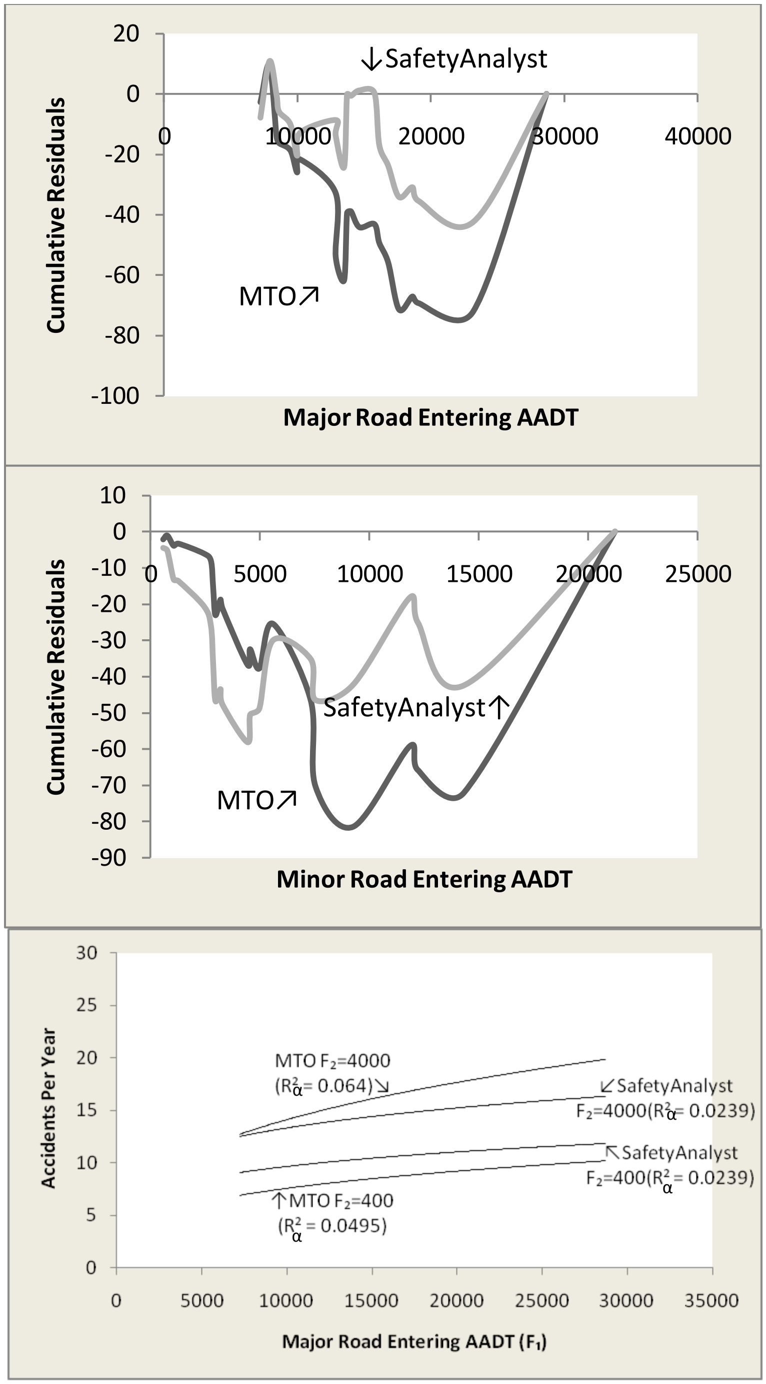

Figure 6-4 Recalibrated APMs and CURE for Ontario signalized four-legged collector urban intersections for selected minor road entering AADT and all severities accidents

The visual tests of model transferability for un-signalized three-legged intersections are shown in **Error! Reference source not found.**. It is observed that the recalibrated SafetyAnalyst model for this type of intersections perform very well for high volumes of minor road entering AADTs; But, it tends to predict more accidents than the MTO model when the minor road AADT is low. Also, The SafetyAnalyst model CURE plot for signalized three-legged intersections is very similar to the MTO model CURE plot.

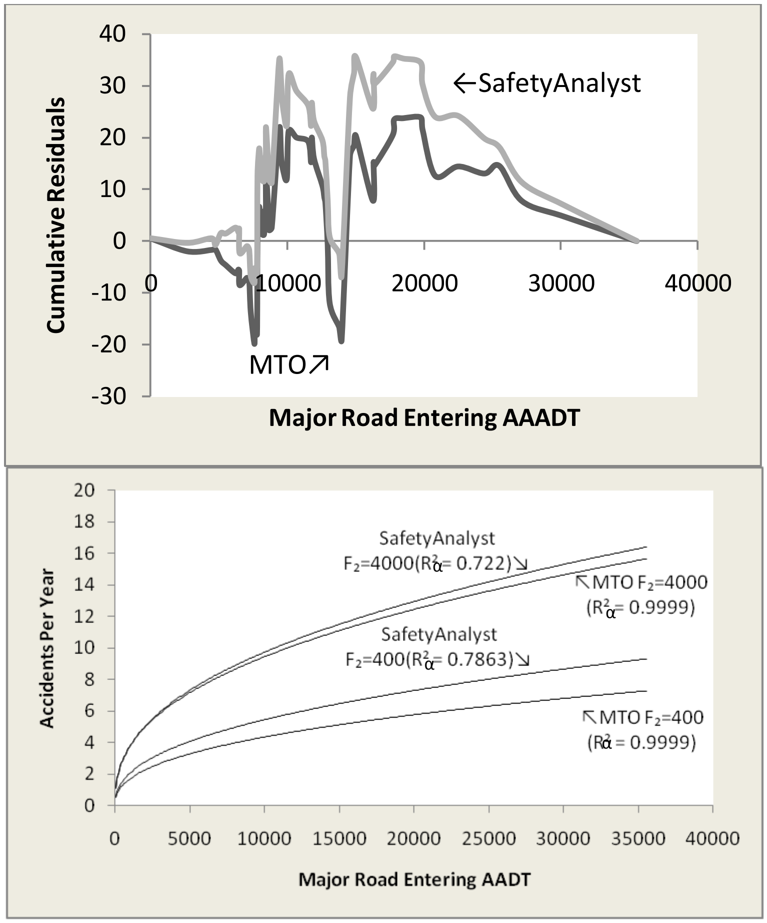

Figure 6-5 Recalibrated APMs and CURE for Ontario un-signalized three-legged intersections for selected minor road entering AADT and all severities accidents

The following figures illustrate the CURE and the recalibrated APMs for SafetyAnalyst SPFs and MTO SPFs for the rest of the intersection types. It is observed that the recalibrated SafetyAnalyst CURE graphs are either similar or very close to the MTO CURE graphs. However, the recalibrated SafetyAnalyst APMs overestimate or underestimate the accidents in compare with the MTO APMs for different minor roads entering traffic volumes.

Figure 6-6, Figure 6-7, and Figure 6-8 indicate that the SafetyAnalyst model for these types of intersections tend to predict more accidents than the MTO model for any minor road entering traffic volume. However, The SafetyAnalyst CURE for these types of intersections suites the Ontario data as good as the MTO CURE and both models result in similar GOF values.

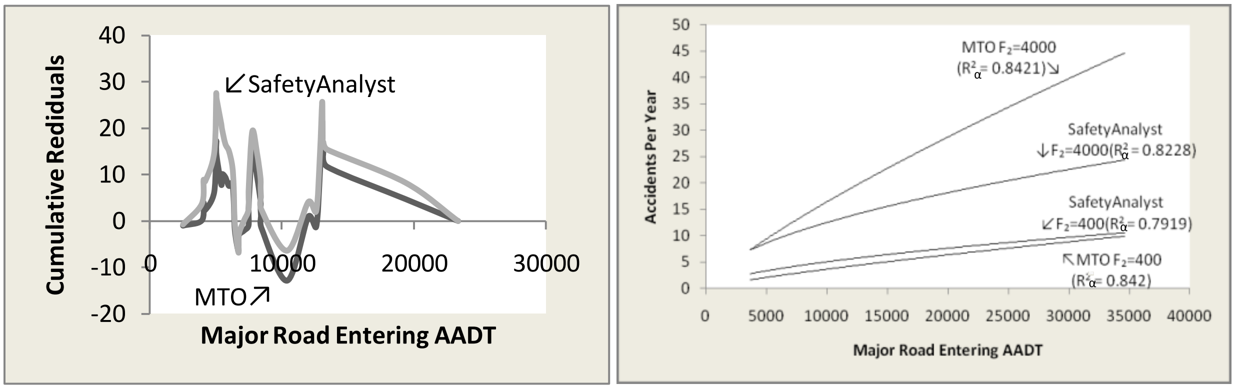

Figure 6-6 Recalibrated APMs and CURE for Ontario un-signalized four-legged collector intersections for selected minor road entering AADT and all severities accidents

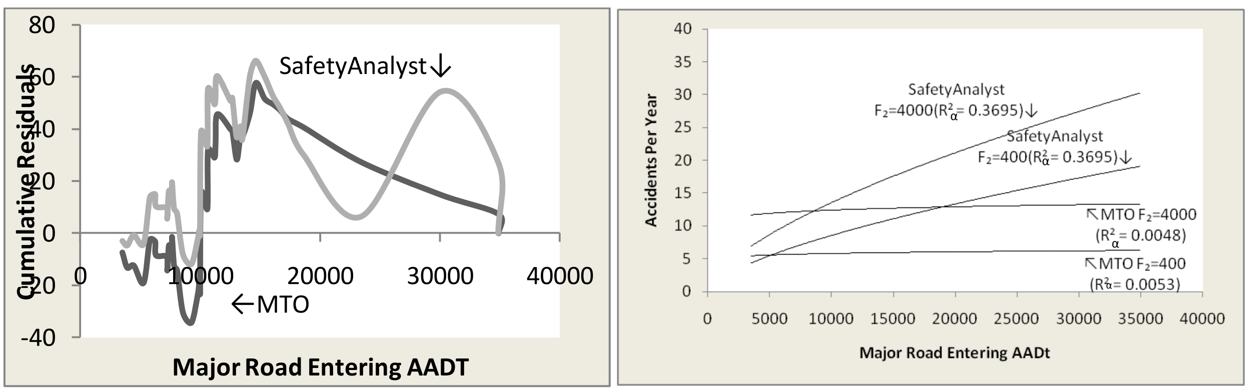

Figure 6-7 Recalibrated APMs and CURE for Ontario signalized four-legged collector rural and semi-urban intersections for selected minor road entering AADT and all severities accidents

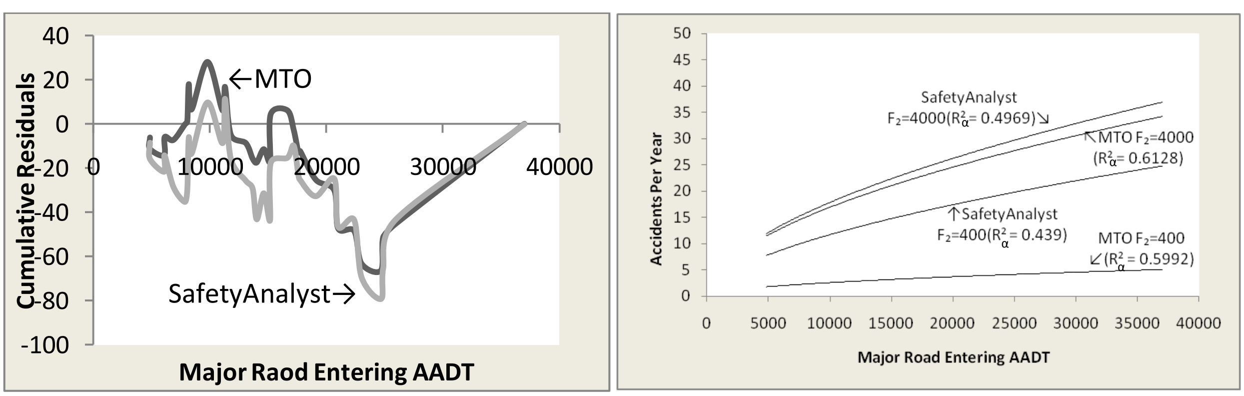

Figure 6-8 Recalibrated APMs and CURE for Ontario signalized four-legged Arterial and freeway (all severities) for selected minor road entering AADT and all severities accidents

By examining the CURE plots for major and minor entering AADTs, it becomes clear that most of the SafetyAnalyst models for intersections fit Ontario data very well. The shapes of their CURE plots are also very similar to those of MTO OPFs. In addition, the large value of R^2, the small value for MAD and maximum deviation from CURE plots and their similarities with those values from MTO models prove the suitability of transferring the SafetyAnalyst intersection models to Ontario data.

In general, the recalibrated SafetyAnalyst SPFs perform better in predicting the average accident frequencies of intersections and are preferred over the Ontario SPFs.

Table 6-6 demonstrates the GOF measurements for flared ramps.

OPF Category	Model Applied	Total Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
Flared On-ramps	MTO OPF	318	1773	0.79	3.65	0.79	0.85	23.30	128.10
	SafetyAnalyst Diamond Rural	318	1773	0.79	3.97	0.80	1.33	27.00	470.80
	SafetyAnalyst Diamond Urban	318	1773	0.79	3.43	0.80	0.93	27	174.10
Flared Off-ramps	MTO OPF	681	3482	1.13	4.02	0.83	0.65	45.50	172.10
	SafetyAnalyst Diamond Rural	681	3482	1.24	4.79	1.12	0.96	121.40	697.10
	SafetyAnalyst Diamond Urban	681	3482	1.24	4.59	1.12	0.87	121.40	594.40

Table 6-5 Goodness-of-fit comparison table for Ontario flared ramps

The GOF statistics for loop ramps and freeway-to-freeway ramps are demonstrated in Table 6-6.

OPF 0Categor y	Model Applied	Total Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
Loop On-ramps	MTO OPF	185	1042	0.60	2.07	0.34	0.41	16.90	106.30
	SafetyAnalyst Parclo Rural	185	1042	0.68	2.21	066	0.52	47.10	59.40
	SafetyAnalyst Parclo Urban	185	1042	0.68	2.21	0.67	0.40	47.10	59.40
	SafetyAnalyst FreeFlow rural	185	1042	0.68	2.39	0.87	0.62	47.10	213.00
	SafetyAnalyst FreeFlow Urban	185	1042	0.68	2.44	0.87	0.66	47.10	232.80
Loop Off-ramps	MTO OPF	134	652	0.95	3.18	1.16	0.68	7.30	30.60
	SafetyAnalyst Parclo Rural	134	652	1.05	4.25	1.43	1.28	12.10	184.40
	SafetyAnalyst Parclo Urban	134	652	1.04	3.81	2.63	1.41	37.10	119.90
	SafetyAnalyst FreeFlow Rural	134	652	1.05	3.42	1.43	0.78	12.10	36.50
	SafetyAnalyst FreeFlow Urban	134	652	1.06	3.44	1.47	0.79	15.50	48.30
Freeway-to-Freeway	MTO OPF	394	2069	2.66	11.41	0.91	0.68	47.20	106.40

Table 6-6 Goodness-of-fit comparison table for Ontario loop and freeway-to-freeway ramps

Even though most of the SafetyAnalyst SPFs reasonably fit the Ontario data- their CURE oscillates around zero and lays in the two ranges of the STD- the SafetyAnalyst models tend to mostly overestimate the predictions and underestimate otherwise. The large gap between the MAD values and maximum absolute deviation values from the CURE plots between the two models appear to support this assumption.

However, three SafetyAnalyst models (i.e., diamond urban SPF from flared-on OPF category, free flow rural and urban SPF from loop-off category, and rural parclo SPF from loop-on OPF category) perform very well relative to MTO OPFs. The power function, and the CURE shapes and estimates are very close and similar to those from MTO OPFs.

Figure 6-9 Recalibrated APMs and CURE for Ontario loop on-ramps (all severities)

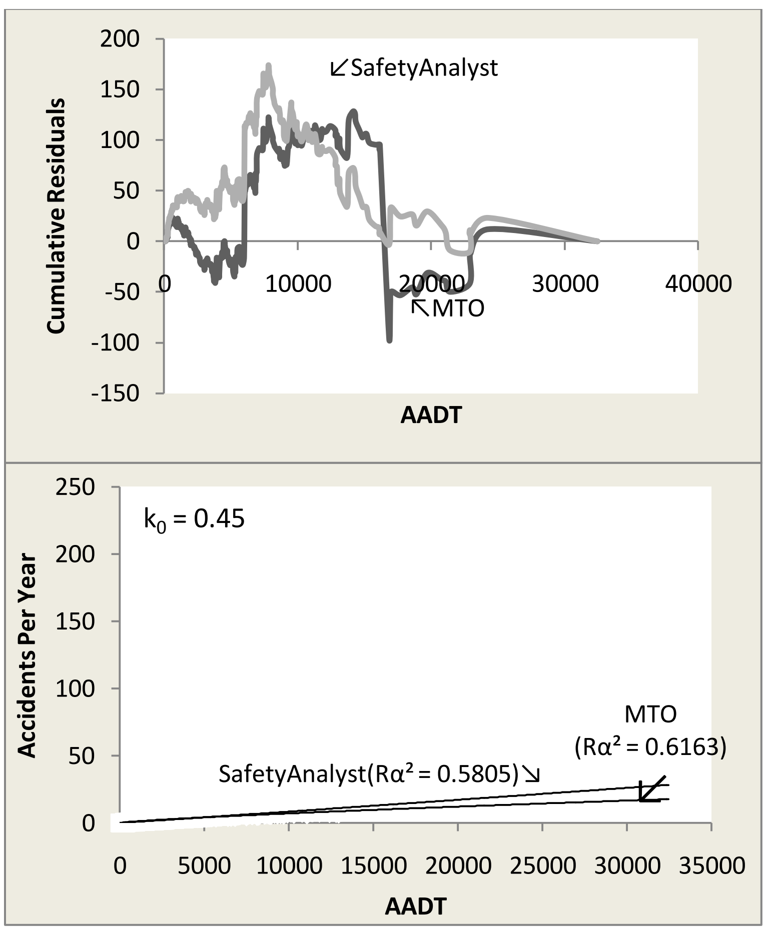

Figure 6-10 Recalibrated APMs and CURE for all severities accidents on Ontario flared on-ramps

The similarities of the APMs shapes and CURE plots for flared on-ramps are shown in Figure 6-10. The figure and GOF measures confirm the suitability of the SafetyAnalyst SPF adaption for Ontario methodologies for this type of ramps. The same conclusion might as well be taken for the Ontario loop off-ramps as illustrated below in Figure 6-11.

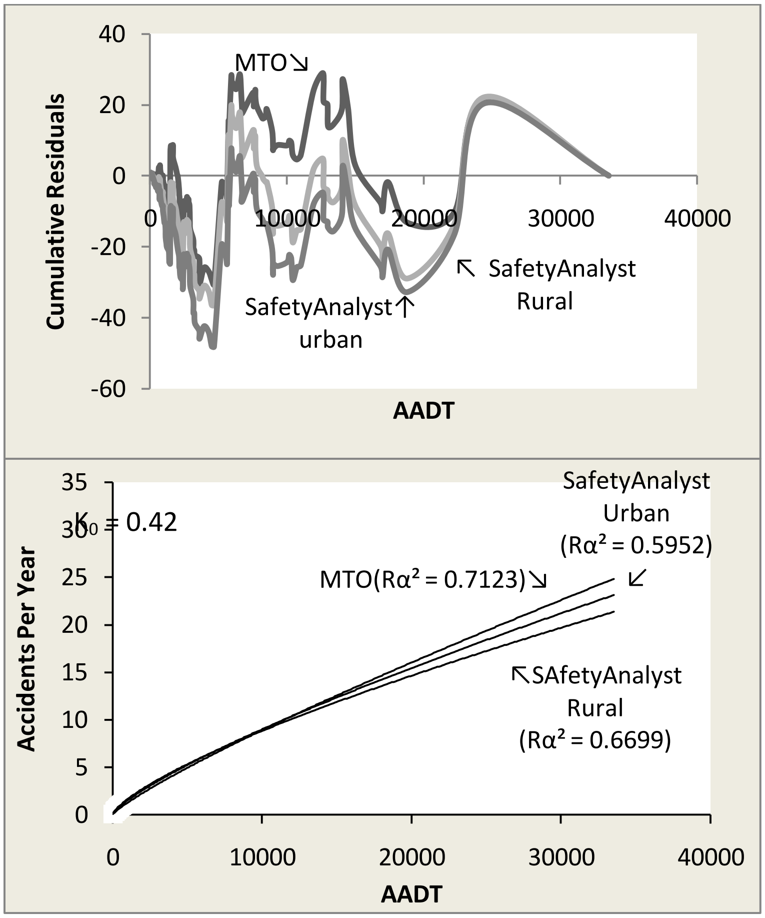

Figure 6-11 Recalibrated APMs and CURE for all severities accidents on Ontario loop off-ramps

The GOF statistics also confirm the assumption that these three models can be appropriately adapted to Ontario data. The MAD from the CURE plots, and recalibrated overdispersion parameter values of these SafetyAnalyst SPFs are low and comparable with those from MTO OPFs.

6.2 HSM SPFs EVALUATION

The visual test of transferring the HSM base model to Ontario data (Figure 6-12) indicates that the HSM SPF tends to overestimate the crash predictions on Ontario two-lane two-way road segments. This could be due to two issues: first, the differences in driver behaviours, traffic patterns and road design standards, law enforcement, and so on; secondly, the considerable number of sites with “zero accident” (Table 4-6) for which an estimate is driven by the HSM model.

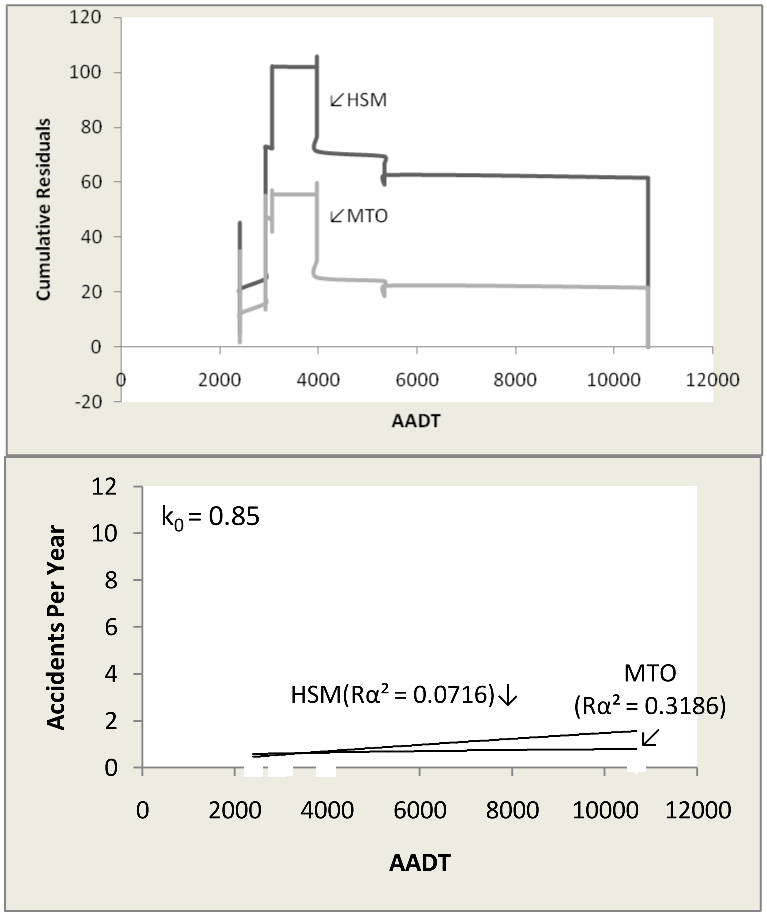

Figure 6-12 Recalibrated APMs and CURE for two-lane two-way road segments

GOF measures concluded that the recalibrated HSM SPF overestimates the overall prediction of accidents on Ontario two-lane two-way highways. However, the model is adaptable to Ontario jurisdiction due to the similarities of their GOF statistics and CURE plots.

The measured GOF statistics are presented in Table 6-7.

OPF Category	Model Applied	Total Observed FI Crashes	Total Observed Crashes	MAD for FI	MAD for Total	Re-calibrated Over dispersion Parameter for FI	Re-calibrated Over dispersion Parameter for Total	Maximum Absolute Deviation from CURE Plot for FI	Maximum Absolute Deviation from CURE Plot for Total
Two-Lane Two-Way Roadway	MTO OPF	141	534	0.36	1.02	0.01	0.80	19.17	59.82
	HSM SPF	141	534	0.38	1.09	0.42	1.09	30.78	105.94

Table 6-7 Goodness-of-fit comparison table for Ontario two-lane two-way road segments

6.3 HSM AMFs EVALUATION

A comparison of the ratios of the sum of observed accidents to the sum of predicted accidents to the baseline ratios from Table 5-10 verify that some AMFs do not fit the data. These AMFs are AMFs for lane width, shoulder width and type, superelevation, driveway density, and AMF for passing lane. For lane width, the total and FI ratios disagree with the AMF that decreased lane width leads to more accidents. For shoulder type and width, the total ratios disagree with the AMF for decreasing order in accidents. For horizontal curve, the middle range for total and FI agrees with the AMF (i.e., an increase in AMF leads to more accidents). However, the upper range disagrees with AMF. For superelevation, the total and FI ratios disagree with the increasing order of AMF. For grade factor, AMF_{5r}, for total and FI, the ratios agree with AMF that increased grade leads to more accidents, although the magnitudes seem off. For driveway density, two middle range of AMF disagree, but the upper range agrees with the AMFs. For passing lanes, total and FI ratios disagree with AMF for all ranges. For roadside design, the total and FI ratios agree with the increasing order of AMF in that an increase in roadside hazard rating leads to more accidents. However, the magnitude for the upper range seems off.

Also, note that results are based on relatively few crashes and the effect of AMFs with missing data i.e., lighting, centreline rumble strip, and automated speed enforcements need further investigations.

6.4 JURISDICTION-SPECIFIC SPFs EVALUATION

As mentioned earlier, two types of model validations were tested: the fit of the jurisdiction-developed models to data. The first test, internal validity, examined the logical defensibility of the models in comparison with past research. The second test, external validity, determined the transferability of the model across time and space with the means of some GOF measurements.

By examining the estimated model parameters of the developed models in the previous chapter, several shortcomings were observed with respect to the logical defensibility of the accident models as follows:

1. there are omitted known variables, such as vertical and horizontal curvatures, intersection approaching speed, lighting, etc.,

2. there are omitted unknown variables which might have a significant impact on the accident predictions across regions, and

3. variables are poorly measured. These variables include intersection skew angles and ND within 250 feet of the intersection for which guesstimated values were assigned from Google maps. The variable RHR could also be considered as poorly measured since a value of 4.0 was assumed for road side hazard rating of the central region three-legged intersections.

To test the external validity of the developed models for four- and three-legged stop controlled intersections, several GOF measures were derived. These GOF statistics describes how good the developed models fit the Ontario data and are presented in Table 6-8.

Intersection Type	Four-Legged Stop Controlled		Three-Legged Stop controlled	
Model Type	Jurisdiction-specific SPF (Equation 5-5)	HSM SPF (Equation 5-8)	Jurisdiction-specific SPF (Equation 5-7)	HSM SPF (Equation 5-9)
Number of observations	19	19	52	52
Degree of Freedom(DF)	16	16	49	49
MAD (Equation 3-12)	4.783	4.67507	2.037	2.079
MPB (Equation 3-13)	0.521	-5.6E-16	0.2435	-7.5E-16
MSPE (Equation 3-15)	38.036	31.544	15.466	15.349
MSE (Equation 3-14)	45.168	37.459	16.413	16.288
r (Equation 3-17)	0.388	0.459	0.613	0.59
Pearson Chi-Square χ^2/DF (Equation 3-16)	1.54	1.28	3.38	3.36

Table 6-8 Validation statistics for jurisdiction-specific and HSM models for three- and four-legged Stop Controlled intersections

The GOF measures from Table 6-8 suggested that the recalibrated HSM SPFs and related AMFs performs relatively better than the jurisdiction-specific model in predicting the total number of crashes for three- and four-legged stop controlled intersections on two-lane highways. Both models possessed the same value for MAD for both types of intersections. However, the MPB values for recalibrated HSM SPFs were much smaller than the MPB values for the jurisdiction-specific model. The positive MPB values for the jurisdiction-specific models verified that these models tend to overestimate the accident predictions on both types of intersections. And, the MPB values of almost 0.0 for the recalibrated HSM models confirmed the suitability of these SPFs to use for Ontario methodologies for three- and four-legged stop controlled intersections on two-lane rural highways. The comparison of MSPE and MSE revealed potential under-fitting of the models to the estimation data. Small values of correlation coefficients indicated unreliable predictions by both models.

7 CONCLUSIONS AND RECOMMENDATIONS

In this research, Ontario data were used to calibrate HSM and SafetyAnalyst methodologies for Ontario highways. The HSM calibration procedure was applied to OPFs, SafetyAnalyst SPFs, and HSM SPFs for several facility types and road networks. Then, several GOF measurements were undertaken to examine the fit of SafetyAnalyst and HSM SPFs to Ontario data and assess the transferability of those models to Ontario local conditions.

In the final task, jurisdiction-specific SPFs were developed for three- and four-legged stop controlled intersections for Ontario two-lane rural roadways. Jurisdiction-specific models were developed based on the HSM procedure and then were compared with the recalibrated HSM baseline model and its AMFs for selected facility types. Several GOF statistics were also determined to assess the suitability of the developed models. The following paragraphs summarize the results of this study.

1. The calibration of SafetyAnalyst SPFs for adaptation to local conditions of Ontario highways

It was observed that in general, SafetyAnalyst SPFs tend to overestimate the accident predictions for Ontario highways and ramps. Among all recalibrated SafetyAnalyst models for Ontario highways, only models for groups 2, 3, and 7 fitted the Ontario data and were transferable to Ontario topographical conditions. Among the recalibrated SafetyAnalyst SPFs for Ontario ramps, only accident prediction models for urban diamond on-ramps, free flow off-ramps, and parclo on-ramps were adaptable to Ontario local conditions.

On the other hand, recalibrated SafetyAnalyst models performed well in predicting the total number of accidents on Ontario intersections. These SPFs were adaptable to Ontario conditions and are preferred over Ontario SPFs in SafetyAnalyst software.

To assess the adaptability of all SafetyAnalyst SPFs, their cumulative residual plots, MAD values, maximum absolute deviation values from CURE plots, overdispersion parameters of the recalibrated models, and values of the R_α-square of their model functions were estimated and compared with the values of Ontario SPFs.

2. The calibration and evaluation of the HSM baseline model and AMFs for two-lane two-way rural roads

The HSM SPF calibration to Ontario jurisdictional conditions indicated an overestimation of accidents by the HSM Part C predictive model in comparison to the relevant MTO OPF for two-lane two-way highways. Despite this overestimation, the HSM predictive model provided reasonable results and could be adapted for Ontario methodologies due to acceptable GOF measurements.

3. The evaluation of HSM AMFs for two-lane two-way rural roadways

For the HSM baseline model, an investigation of the effect of HSM AMFs on accident predictions for rural two-lane two-way highways indicated that not all AMFs perform well in the model and some of them do not fit the data. The AMFs that need to be recalibrated for Ontario methodologies are AMF_{1r} for lane width, AMF_{2r} for shoulder width and type, AMF_{4r} for superelevation, AMF_{6r} for driveway density, and AMF_{8r} for passing lanes.

4. Developing jurisdiction-specific SPFs for Ontario rural two-lane three- and four-legged stop controlled intersections for use in HSM predictive chapters

In developing jurisdiction-specific SPFs for three- and four-legged intersections on two-lane highways, it was observed that no model with statistically significant coefficient parameters could be developed with the available data. Hence, SPFs with major and minor AADTs as their only variables were developed and compared with the recalibrated HSM predictive models in predicting the total number of crashes. The comparison revealed that the calibration of HSM Part C SPFs provides satisfactory results. However, jurisdiction-specific SPFs may have produced more reliable estimations if more sufficient and comprehensive data sets existed.

It is recommended that the recalibration procedure be applied in each jurisdiction at least every two to three years. Moreover, the most recent calibration factor is recommended for use in all assessments of future proposed projects.

As discussed by Sawalha and Sayed (2006) other recalibration approaches could also be attempted since there is no scientific evidence that the calibration procedure presented by Harwood et al. (2000) and shown in Equation 3-1 accounts for the safety variations between different regions. A maximum likelihood procedure for recalibrating both the overdispersion parameter and constant of a transferred SPF is shown by Sawalha and Sayed (2006) to be superior to the recalibration method presented by Harwood et al. (2000).

Future improvements in data quality are required for the SafetyAnalyst methodology calibration (i.e., more up to date data of traffic flow and accident counts) and HSM SPF calibration (i.e., more comprehensive data of geometric design characteristics and traffic control features of more randomized sites). Small sample size, poor quality data, non-random site selections, and large number of independent variables were significant obstacles in estimating more precise safety performance functions.

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