Calibration of the Highway Safety Manual (HSM) Safety Performance Functions (SPFs) and Development of Independent Models for Utah

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Abstract: This paper documents the calibration of the Highway Safety Manual (HSM) safety performance function (SPF) for rural two-lane two-way roadway segments in Utah and the development of new SPFs using both negative binomial regression and hierarchical Bayesian modeling. Crash data from 2005-2007 on 157 selected study segments in Utah provided a 3-year frequency of observed crashes for use in obtaining a calibration factor for the HSM SPF and developing new SPFs. The calibration factor for the HSM SPF for rural two-lane two-way roads in Utah is 1.16, indicating that the HSM model underpredicts crashes in Utah.

The HSM recommends that agencies develop jurisdiction-specific SPFs when possible. Negative binomial and hierarchical Bayes modeling were used to develop new models that estimate the expected number of crashes occurring on rural two-lane two-way highway segments. Average annual daily traffic (AADT), segment length, speed limit, and the percentage of AADT comprised of combo-unit trucks were found to be significant in the new models developed. AADT and segment length are already used in the HSM SPF; this research found that the latter two may have a measurable effect on crash frequencies.

The hierarchical Bayes technique can determine the likelihoods of observed crash frequencies occurring on road segments. A comparison of these likelihoods is proposed as a means to rank segments and identify safety 'hot spots.' From the 157 segments analyzed in this study, five are identified as 'hot spots.'

INTRODUCTION

The Highway Safety Manual (HSM), published in 2010 by the American Association of State Highway and Transportation Officials (AASHTO), contains safety performance functions (SPFs) that predict the safety of a roadway in terms of the number of crashes. SPFs incorporate known information about a roadway entity into an equation that gives predicted crash frequency (AASHTO 2010).

SPFs that accurately predict crashes are valuable to state and local transportation agencies because of the ability this provides to DOT personnel to detect areas of concern with respect to safety. The base SPFs in the HSM have been developed through extensive research across the United States; however, it is known that there are many factors that affect safety, some of which are specific to local geographic areas. As a result, AASHTO recommends that the HSM SPFs be calibrated to local conditions (AASHTO 2010). In response to this recommendation, the Utah Department of Transportation (UDOT) desired to calibrate HSM SPFs for rural two-lane two-way roadways in the state. In addition, new SPFs were also developed to identify local variables that affect safety (Saito et al. 2011).

The purpose of this paper is to summarize the findings of developing the HSM calibration factor and developing new jurisdiction-specific models for two-lane two-way roadways in Utah. The results of this research have been published previously, or are currently being published, in the literature (Brimley et al. 2012, Saito et al. 2011). As a result, the purpose of this paper is to briefly summarize the research, while providing the reader with the references necessary to obtain full analysis results in the areas of: 1) background, 2) results, and 3) conclusions.

BACKGROUND

Highway Safety Manual Predictive Method

SPFs, contained in Chapters 10-12 (Part C) of the HSM are developed utilizing known information about a roadway (e.g., geometry and average annual daily traffic (AADT)) to predict the number of crashes expected on a roadway entity for one year. The SPFs in the HSM were developed from studies that covered a large area of the United States. These SPFs are recommended to be calibrated to better predict crashes in a specific location. Equation 1 is the SPF for rural two-lane two-way road segments that meet the base conditions outlined in the HSM (AASHTO 2010).

$$N_{spf} = AADT \times L \times 365 \times 10^{-6} \times e^{-0.312} \quad (1)$$

where:

N_{spf} = predicted number of annual crashes,
$AADT$ = average annual daily traffic, and
L = segment length (mi).

SPFs can be modified using Crash Modification Factors (CMFs) when the characteristics of the site deviate from those of the base conditions. SPFs are multiplied by the various CMFs to adjust the base predicted crash frequency to meet the actual conditions as illustrated in Equation 2 (AASHTO 2010). A CMF greater than 1 indicates an increase in predicted crashes, while a CMF less than 1 indicates a reduction in predicted crashes.

$$N = N_{spf} \times CMF_1 \times CMF_2 \times ... \times CMF_i \quad (2)$$

where:

N = predicted number of crashes considering all conditions, and
CMF_i = crash modification factor.

Calibrating the HSM SPFs and Developing Jurisdiction-Specific SPFs

SPFs can be better utilized to predict crashes when they are calibrated to local conditions. Calibration is performed by applying a multiplicative factor to an SPF so that its aggregate crash prediction within a specific jurisdiction is equal to the aggregate number of observed crashes according to the relationship outlined in Equation 3 (AASHTO 2010).

$$N_{local} = C \times N \quad (3)$$

where:

N_{local} = total predicted crashes in a local jurisdiction, and
C = calibration factor.

The HSM recommends a total of 30-50 sites be utilized to determine a calibration factor for an entire jurisdiction (AASHTO 2010).

When enough data are available, the HSM provides a methodology wherein users can create jurisdiction-specific SPFs. These SPFs are recommended to be developed using negative binomial regression techniques that account for the dispersion present in crash data and that estimate an overdispersion parameter (AASHTO 2010, Brimley et al. 2012). Data requirements for the development of jurisdiction-specific SPFs are outlined in the HSM (AASHTO 2010).

RESULTS

HSM Model Calibration

A total of 157 segments were evaluated for the model calibration and to develop jurisdiction-specific models. Data were collected utilizing UDOT traffic records (UDOT 2011b, UDOT 2011c), Roadview Explorer (UDOT 2011a), and Google Earth (2010) to obtain the necessary data for calibration. The data collected included AADT, segment length, lane width, shoulder width, shoulder type, driveway density, passing lanes, horizontal curvature, vertical curvature, grade, lighting, roadside hazard ratings, centerline rumble strips, two-way left-turn lanes, automated speed enforcement, number of driveways, shoulder rumble strips, centerline striping (passing ability), speed limit, percent single-unit trucks, and percent combo-unit trucks. The segments were dispersed throughout the state as illustrated in Figure 1 (Saito et al. 2011).

There were 426 reported crashes on the 157 segments from the time period analyzed, 2005-2007. The HSM predicts 368 crashes during this same time period, indicating a calibration factor of 1.16. Equation 4 provides the Utah-calibrated HSM SPF, while Equation 5 provides a simplified version of this relationship (Brimley et al. 2012, Saito et al. 2011).

$$N_{local} = 1.16 \times AADT \times L \times 365 \times 10^{-6} \times e^{-0.312} \tag{4}$$

$$N_{local} = AADT \times L \times 3.09 \times 10^{-4} \tag{5}$$

Jurisdiction-Specific Negative Binomial Models

Four negative binomial models were developed using two different model types at two levels of confidence according to the negative binomial model form outlined in Equation 6. A rearrangement of Equation 6 can be utilized to directly predict the number of crashes for a given year, as illustrated in Equation 7 (Brimley et al. 2012, Saito et al. 2011).

$$\ln(N) = \beta_0 + \sum_{i=1}^{p} \beta_i x_i \tag{6}$$

where:

β_0 = intercept,
β_i = coefficient for variable x_i,
x_i = independent variable, and
p = number of independent variables.

$$N = e^{\beta_0 + \sum_{i=1}^{p} \beta_i x_i} = \exp[\beta_0 + \sum_{i=1}^{p} \beta_i x_i] \tag{7}$$

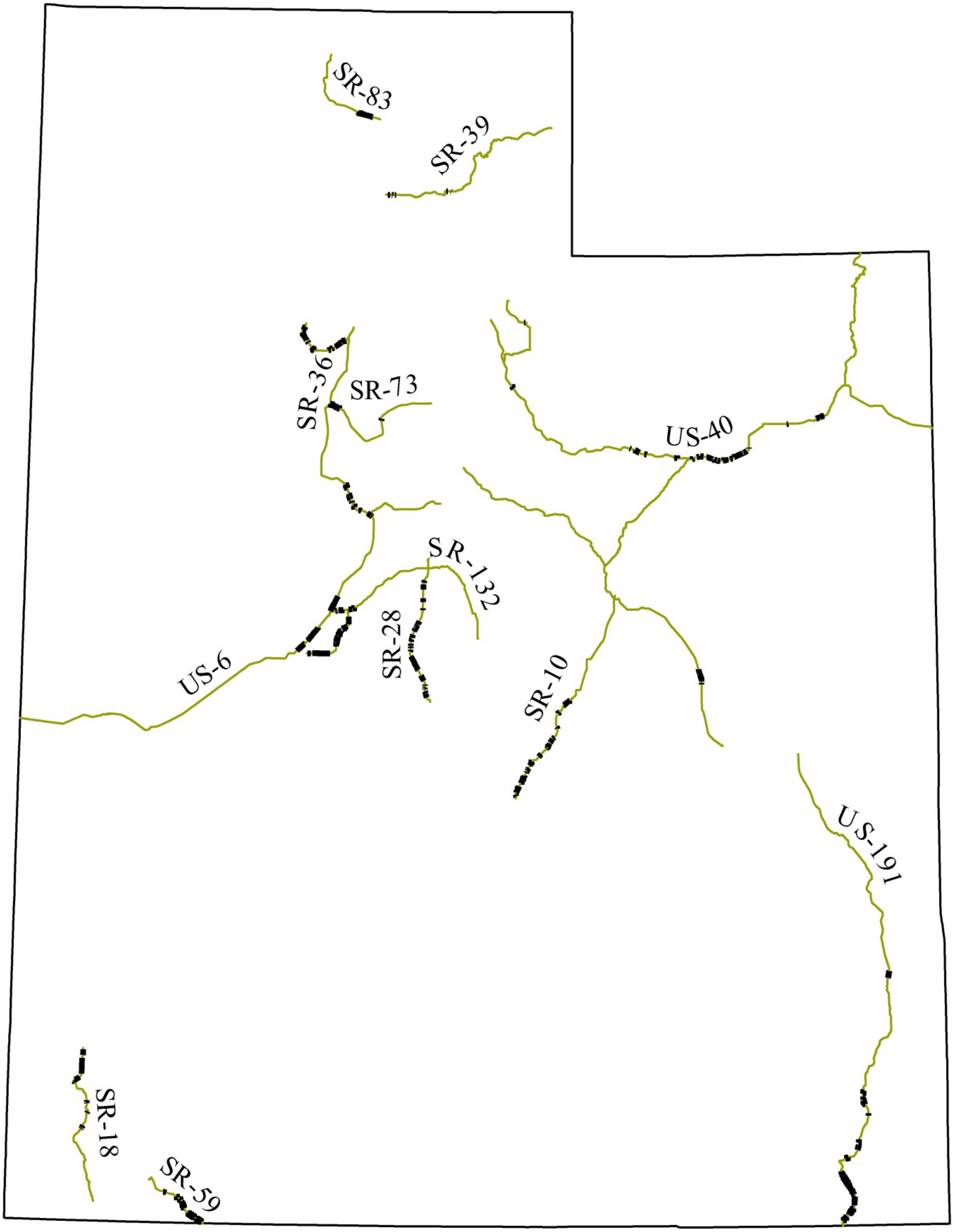

Figure 1. Study segments (Saito et al. 2011).

The first two negative binomial models (conventional negative binomial SPFs) incorporated the original data (one at 75 percent and one at 95 percent levels of confidence), while the remaining two models used a natural log transformation of AADT to normalize the data, again at 75 percent and 95 percent levels of confidence. The SPFs were developed using the statistical software SAS (SAS Institute Inc. 2011) using a backward stepwise technique. Details on the development of the model can be found in the literature (Brimley et al. 2012, Saito et al. 2011).

The results of the models are provided in Equation 8 for the conventional negative binomial SPF at a 75 percent level of confidence (overdispersion parameter = 1.20), in Equation 9 for the conventional negative binomial SPF at a 95 percent level of confidence (overdispersion parameter = 1.24), in Equation 10 for the log transformation of AADT SPF at a 75 percent level of confidence (overdispersion parameter = 1.14), and in Equation 11 for the log transformation of AADT SPF at a 95 percent level of confidence (overdispersion parameter = 1.19). Details on the model development can be found in the literature (Brimley et al. 2012, Saito et al. 2011).

$$N = \exp[-7.49 + (0.0002)(AADT) + (0.429)(L) + (0.0286)(DD) - (1.60)(\textit{No Passing}) - (0.128)(\textit{1-Direction Passing}) - (0.268)(\textit{No SRS}) - (0.0219)(CT) + (0.104)(\textit{Speed})] \quad (8)$$

where:

DD	=	driveway density (driveways/mi),
No Passing	=	1 if passing is prohibited, 0 if permitted for one or both directions,
1-Direction Passing	=	1 if passing is permitted for one direction, 0 if otherwise,
No SRS	=	lack of shoulder rumble strip (1 if not present, 0 if present),
CT	=	percent combo-unit trucks (%), and
Speed	=	speed limit (mph).

$$N = \exp[-7.17 + (0.0003)(\mathrm{AADT}) + (0.423)(\mathrm{L}) - (1.51)(\mathrm{No\ Passing}) - (0.0812)(\textit{1-Direction Passing}) - (0.0219)(CT) + (0.0938)(\textit{Speed})] \quad (9)$$

$$N = AADT^{0.753} \times \exp[-12.1 + (0.442)(L) - (0.0498)(SW) - (1.22)(\textit{No Passing}) - (0.116)(\textit{1-Direction Passing}) + (0.0277)(DD) - (0.346)(\textit{No SRS}) - (0.0257)(CT) + (0.101)(\textit{Speed})] \quad (10)$$

where:

SW = shoulder width (ft).

$$N = AADT^{0.840} \times \exp[-12.1 + (0.450)(L) - (0.0271)(CT) + (0.0824)(\textit{Speed})] \quad (11)$$

The results of the analysis provide interesting results, not the least of which is the relationship between crashes and rumble strip or combo-unit trucks. Although not tested, it is hypothesized that crashes may be higher in areas with shoulder rumble strips because areas with rumble strips are oftentimes areas with initially higher crash rates, or shoulder rumble strips may cause more crashes due to overcorrecting. The reduction in crashes in areas with combo-unit trucks may be related to the fact that combo-unit trucks are driven by professional drivers who are generally more cautious and as the percentage of combo-unit trucks increases, the percentage of less experienced drivers on the roadway decreases. It is possible that there are other unknown confounding effects on these crashes (Brimley et al. 2012).

Several methodologies are available to help aid in selecting a preferred model for use by UDOT. The method used in this analysis is that of Bayesian information criteria (BIC). The equation used to calculate BIC is provided in Equation 12, where the model with the smallest BIC value is the preferred model (Ramsey and Schafer 2002).

$$BIC = n \times \ln(RSS) + p \times \ln(n) \quad (12)$$

where:

BIC	=	Bayesian information criterion,
n	=	number of observations,
RSS	=	sum of squared residuals, and
p	=	number of independent variables.

BIC increases with higher squared residuals (*RSS*) and the number of independent variables (*p*). The calibrated HSM SPF had the highest value of BIC (1095.6) as a result of the less accurate predictions for individual segments and the greater number of variables using the CMFs. The conventional models had BIC values of 607.4 and 601.5 for the confidence levels of 75 percent (Equation 8) and 95 percent (Equation 9), respectively. The BIC values for the log transformation of AADT models were the lowest at 596.7 at 75 percent confidence (Equation 10) and 583.7 at 95 percent confidence (Equation 11) (Brimley et al. 2012, Saito et al. 2011).

It should be noted that there are more variables that could be considered and more data that could be included in the model, but were not included, due to data limitations at the time of the study.

CONCLUSIONS

The purpose of this study was to calibrate the HSM SPF for rural two-lane two-way roads to represent conditions in Utah and to develop jurisdiction-specific SPFs that may be used in place of the HSM SPF. The Utah-specific SPFs were developed from the same dataset used to calibrate the HSM SPF with some additional variables that were evaluated to determine their potential correlation with crash frequencies (Brimley et al. 2012).

The results are summarized as follows (Brimley et al. 2012):

- The calibration factor of the HSM SPF for rural two-lane two-way roads in Utah was found to be 1.16. More crashes occur on rural two-lane two-way roads in Utah than the HSM SPF predicts.
- The jurisdiction-specific models developed as part of the research show that the relationships between crashes and roadway characteristics in Utah may be different from those presented in the HSM.
- The jurisdiction-specific models include some variables that have not been examined extensively in the literature and deserve further investigation within Utah and other jurisdictions (e.g., the new SPFs predict fewer crashes when passing maneuvers are restricted or combo-unit traffic increases). It must be emphasized, however, that the SPFs

only show correlation. There may be confounding effects among variables that can only be found with additional study.

An examination of the general consistencies (or inconsistencies) found among the variables of the discussed models can help transportation agencies make informed decisions that affect the safety of the roadways within their respective jurisdictions. Ongoing safety-related research is critical to maintain safe roads as the components of the roadway system and its users change. Effective safety improvements can be made with a better understanding of the relationships between the factors discussed in this research, or others not yet considered, and roadway safety (Brimley et al. 2012).

ACKNOWLEDGEMENTS

The authors would like to thank UDOT and Brigham Young University (BYU) for providing the funding and facilities to complete this research. Special thanks to Robert Hull, W. Scott Jones, Tim Taylor, and David Stevens for the role played as members of the technical advisory committee. Special thanks to Andrew Olsen for his assistance in the statistical modeling discussed in the paper. The contents of this paper reflect the views of the authors, who are responsible for the facts and accuracy of the information presented herein, and are not necessarily representative of the sponsoring agency.

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