Applying the Highway Safety Manual to Two-Lane Road Curves

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This paper evaluates the Highway Safety Manual (HSM) crash prediction model using data on two-lane rural horizontal curves in North Carolina. An analysis of the local conditions calibration factor for the HSM predictive model in North Carolina found that a large number of sites (approximately 300) are required to meet HSM recommendations. The results showed that annual average daily traffic, curve radius, and curve length were the most important factors in determining crash prediction accuracy, but that average or default values may be used for other parameters with less risk to accuracy.

INTRODUCTION

Horizontal curves are relatively risky portions of the highway system in the United States and elsewhere. Collisions on two-lane curves have been found to be more than twice as likely to result in a fatality as all two-lane roadway segments (Hummer et al. 2010). Fortunately, curves are also places where highway agencies have many options and opportunities for making safety improvements. Agencies can add signs, markings, beacons, guardrails, and/or superelevation (cross-slope of the roadway), or can widen, straighten, and flatten sideslopes, just to name some common and proven examples of potential improvements. This paper focuses on the analysis of two-lane rural horizontal curves.

Typically, the analysis of a horizontal curve or a set of curves for safety purposes by a highway agency is based on field visits and the judgments of experienced personnel. Many agencies seem to rely on a drive-through by an engineer or a technician and a small set of countermeasures that seem to have proven themselves through the years. Analytical tools have existed for a number of years, such as the 1991 FHWA curve crash prediction model (Zegeer et al. 1991). That study developed a model to predict the number of curve crashes based on such geometric factors as degree of curve (amount of curvature of an arc), length of curve, roadway width, roadside hazard rating, superelevation on the curve, and presence or absence of spiral transitions to the curve (i.e., a smooth transition from the straight tangent to the curve) as well as traffic volume (ADT). While this model predicted curve crashes well for these mostly geometric variables, it did not incorporate the effects of traffic control devices such as signs, markings, flashing lights, rumble strips, lighting, and other variables. Also, the model that was developed by Zegeer et al. (1991) was based exclusively on data from a single state (Washington), even though it is recognized that there are state-to-state differences in crash reporting thresholds, climate, terrain, driver characteristics, and other factors that can affect crash frequencies and rates for a given set of roadway conditions.

Therefore, there has been a need for a model or tool to allow agencies to predict the crash potential of horizontal curves within a state or jurisdiction based on a wide variety of geometric, traffic, and other site-specific features, and for that model to be validated for the state where it is to be applied. There have also been barriers to widespread implementation of past curve crash models and tools due to the large number of competing highway safety objectives, real or perceived difficulties in collecting the necessary data, and possibly the need to calibrate the model for local conditions, among other reasons.

The publication of the Highway Safety Manual (HSM) offers a chance to overcome this impasse and get a crash model in use in the field (AASHTO 2010). The HSM contains a crash prediction model for horizontal curves and estimates of crash modification factors (CMFs) for popular curve countermeasures. A CMF is defined as the expected change in crashes that results from a given safety treatment. For example, if a countermeasure is expected to reduce crashes by 20%, the CMF is expressed as 1.00 - 0.20 = 0.80. The model and CMFs have been approved by a committee of leading safety researchers and practitioners, and this provides credibility to the tools it provides. The HSM also contains detailed instructions for applying the model and CMFs to the usual steps in a safety program, including evaluating installed countermeasures. Despite the promise of the HSM and the fact that draft versions circulated widely for several years before publication, it is yet to be widely applied in curve safety studies. Perceived or real difficulties in calibrating the HSM models and collecting needed data may be contributing to this slower-than-expected adoption process.

The objectives of this paper are to provide highway agencies with practical advice on how to use the new HSM to analyze horizontal curves to supplement the usual methods that identify curves with abnormally high crash experience. This paper answers the following questions: Can agencies use the new HSM to identify and analyze horizontal curves in need of safety improvements? If so, how should an agency calibrate the HSM curve crash prediction model to fit local conditions? If an HSM analysis is possible, how much effort should the agency expect to make? Is an HSM analysis possible without a field visit? If so, what accuracy can be expected? What steps should agencies take to make the HSM analysis more efficient so that they can utilize the results and apply them to improve curves in a more cost-effective manner? Satisfying these objectives should shorten the learning curve for agencies in using the HSM curve crash prediction procedure and reduce the risk agencies and professionals assume in using this new tool.

LITERATURE REVIEW

Due to the recent release of the HSM, only a few studies have been completed on calibrating its crash prediction models. This literature review consists of relevant studies that have evaluated the HSM application for two-lane and rural roads, the variance in crash modeling, and the calibration of HSM models. Sun et al. (2006) evaluated the applicability of the HSM safety prediction model to states from which crash data were not used in the original model development. The prediction model evaluated in this study was that for two-lane rural roads in the draft HSM. Data from state routes in Louisiana were used. Due to data limitations, the authors did not follow the recommended HSM procedure for calibrating the predictive model. However, the research team was able to create a database with important highway variables, including average daily traffic (ADT), segment length, lane width, shoulder width and type, and driveway density. Since the average predicted values were smaller than the observed values, a calibration parameter was calculated as a function of ADT. The results of this analysis were presented for two sets of road sections: the first consisted of 26 randomly selected sections, and the second, 16 sections ranked in the top 30 in the state for crash frequencies over three years. The analysis indicated that the HSM model successfully predicted crash frequencies, but the level of effort required to obtain the data necessary to calibrate the model was a challenge.

Martinelli et al. (2009) calibrated the HSM crash prediction model for the Italian Provence of Arezzo using 1,300 kilometers of rural two-lane highways. A comparison of observed crashes and results from four models with different calibration procedures showed they strongly overestimated crashes. Additionally, it was found that the models overestimated crashes at low crash locations and underestimated crashes at high crash locations. The authors concluded that calibration of the model is absolutely necessary to avoid over prediction in the base model. They also note that a primary issue with calibration exists because the high segmentation of the HSM procedures leads to low or zero crash segments, which are not predicted accurately by the HSM.

The accuracy of models using baseline data is also of interest for this paper. A recent study by Lord et al. (2010) compared crash prediction models for rural four-lane highways in Texas. Two full models with several covariates and the product of baseline models and accident modification factors (AMFs) were compared using predicted mean values and variances. The results of this analysis showed that the full models have much smaller variances than the product of baseline models and AMFs. This finding led the authors to conclude that when a study's objective includes variance as part of the decision-making process, a full model should be used.

Further details on which elements are critical to the outcome of a crash prediction model are also of interest in determining which elements will have the least effect if they remain as default settings. A study by Nowakowska (2010) developed logistic models for crash severity based on road characteristics of rural highways in Poland. This study found that shoulder presence and type, area type, sidewalk presence, and interactions had a statistically significant influence on crash severity. Easa et al. (2009) evaluated crash prediction models for three-dimensional alignments of rural two-lane highways in Washington State. They found that the most significant predictors of crashes were degree of curvature, roadway width, access density, grades, section length, and average annual daily traffic (AADT).

Xie et al. (2011) applied the HSM procedures to roadway segments in Oregon for the purpose of calibrating the model for local conditions. They included randomly selected roadway segments and found a two-lane roadway calibration factor of 0.74 across 75 sites with 394 reported collisions and 533 HSM predicted collisions. The authors presented a methodology for sites that did not meet the recommended 100 collisions per year among 30 to 50 locations. To overcome the under-represented collision locations, the authors applied sample size estimation procedures based on average Oregon crash history for that type of site to modify the expected total yearly collisions. Another study also examined the calibration of the HSM as well as the development of new models (Banihashemi 2011) and found that a calibrated HSM model performs as well as the newly developed models, and it is the preferred safety model. Banihashemi (2011) also predicted a total of 150 collisions per year for the sites employed in the calibration process.

METHODOLOGY

Data Collection

The collection of different data needed for calibrating one HSM model is described below for each of the selected curve sample sites in North Carolina. The selected samples of curves were all on two-lane rural roads. The researchers asked NCDOT to select 50 curve sites, with no more than five of the curves on any given roadway for the calibration effort. Field investigation forms developed by the researchers were distributed to NCDOT personnel who were assigned the task of collecting the necessary data on 21 variables for each curve. The procedure for measuring curve radius and the superelevation of the curve is described in Findley and Foyle (2009). In this validation effort, each selected curve must be isolated from other curves by tangent segments on both ends. Then relevant variables were collected for each curve along with similar data for the adjoining tangent sections on both ends of the curve. Table 1 lists the 21 variables on which data were collected for this study and provides a brief description of the data collection process for some variables.

HSM Predictive Method Calibration

The HSM predictive method is used to estimate crash frequency, severity, and types of crashes on a highway with known characteristics. To improve the accuracy of the model, the HSM predictive methods were developed such that they can be calibrated and adjusted based on local conditions.

Table 1: Field Data Collection Elements

Feature		Value
1.	Posted Speed Limit (mph):	
2.	Lane Width (feet): *(Measure from center of the lane-line of the roadway to center of edgeline, round to the nearest foot)*	
3.	Inside Shoulder Width (feet): *(Measure from center of edgeline to edge of shoulder, round to the nearest foot)*	
4.	Inside Shoulder Type: *(Paved, Gravel, Turf, or Composite)*	
5.	Outside Shoulder Width (feet): *(Measure from center of edgeline to edge of shoulder, round to the nearest foot)*	
6.	Outside Shoulder Type: *(Paved, Gravel, Turf, or Composite)*	
7.	Length of Section (feet): *(Measure from beginning of the curve to the end of the curve along the edgeline, in feet, measure tangents from end of curve to within 100' of the nearest intersection or next curve)*	
8.	Radius of Horizontal Curve (feet): *(Determine the radius using the attached Field Investigation Procedure and completed Field Investigation Form below)*	
9.	Roadside Hazard Rating (1-7): *(See the attached photos for examples)*	
10.	Inside Lane Superelevation (%): *(Determine the superelevation using the attached Field Investigation Procedure and completed Field Investigation Form below)*	
11.	Outside Lane Superelevation (%): *(Determine superelevation using the attached Field Investigation Procedure and completed Field Investigation Form below)*	
12.	Grade (%): *(Determine the grade using the digital level to find the steepest grade)*	
13.	Number of Driveways: *(Record the total number of driveways along the length of the roadway from beginning to end of segment on both sides)*	
14.	Presence of Raised Pavement Markers (Yes/No):	
15.	Presence of Passing Lanes* (Yes/No):	
16.	Presence of Roadway Lighting* (Yes/No):	
17.	Presence of Centerline Rumble Strips* (Yes/No):	
18.	Presence of Two-Way Left-Turn Lanes* (Yes/No):	
19.	Presence of Shoulder Rumble Strips (Yes/No):	
20.	Presence of Skid Treatments (overlay) (Yes/No):	
21.	Presence of Skid Treatments (groove pavement) (Yes/No):	

Examples of local conditions that may differ from the given predictive model include climate, geographic conditions, driver characteristics, and crash reporting thresholds.

The HSM predictive method for rural two-lane, two-way highways was applied in this evaluation to North Carolina highways. Other roadway types are available for analysis within the HSM through similar, but different methods which are specific to the characteristics that influence safety on those roadways. This application followed the steps provided in the HSM to estimate the expected average crash frequency of curve segments. The HSM predictive model contains 18 steps starting with defining the segment and period of study to evaluating the results. The focus of this paper is on Step Nine, which selects and applies safety performance functions (SPF); Step Ten, which applies CMFs to the segments; and Step 11, which involves applying a local calibration factor. These steps are applied after the roadway segments have been identified and the data collection, including crash history and geometric conditions, is complete. Each step must be completed separately for all identified segments to develop a SPF, CMF, and a calibration factor, which are then used to predict crashes for each segment.

Step Nine: Select and Apply SPF

This step develops the SPF for each selected roadway segment. The SPFs are used to determine predicted crash frequency with HSM base conditions. The SPF is adjusted to local conditions using the calibration factor in Step 11. For each segment, the SPF is found using the following equation in the HSM:

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

Where:

N_{spfrs} = predicted total crash frequency for roadway segment base conditions (spfrs refers to the SPF for the roadway segment)

AADT = average annual daily traffic volume (vehicles per day)

L = length of roadway segment (miles) or length of curve

The HCM also provides default distributions for crash severity and collision type which are based on data for Washington State. These distributions may also be updated using local data for improved accuracy.

Step Ten: Apply the Appropriate CMFs to SPF to Account for the Difference in Base and Site-Specific Conditions

After an SPF is found for base conditions in each segment, it is multiplied by the appropriate CMFs to adjust the estimated crash frequency to site specific conditions. For example, if the road segment does not have a shoulder, the SPF estimate is adjusted by a CMF of 1.50 to show an increase in predicted crashes.[1] The HSM identifies 12 appropriate CMFs for horizontal curves. The most common CMFs used to adjust for local conditions on the curves are: lane width, shoulder width and type, length, radius, and presence or absence of spiral transition, superelevation, grade, and driveway density.

The Federal Highway Administration (FHWA) has established a CMF Clearinghouse for CMFs.[2] These CMFs are multiplicative factors used to estimate the change in the number of crashes after a given countermeasure is implemented under specific conditions. Included in this Clearinghouse are the horizontal CMFs that have been developed. Of the 2,546 CMFs from 150 studies that are included in the Clearinghouse (as of March 2011), 221 CMFs and 18 studies relate to horizontal curves. However, due to the base conditions in this HSM analysis, only the CMFs presented in Section 10.7 of the HSM can be used with the SPFs developed in the previous step. The development process for CMFs are presented in Part D of the HSM, but the focus of improvements is toward future editions of the HSM, not for inclusion of additional CMFs by the user.

Step Eleven: Apply a Calibration Factor to the Result of Step 10

Once the estimated crash frequency for each segment is found and adjusted for site-specific conditions, it is multiplied by an appropriate calibration factor developed for local conditions. The calibration factor is used to adjust the results of the HSM predictive model to local conditions and it is calculated as the ratio of total observed crash frequency to total expected average crash frequency during the same period. For example, for one group of curves in this analysis, the reported collisions per year is 8.8 and the predicted number of collisions from the HSM procedure is 6.6, resulting in a calibration factor of 8.8/6.6 or 1.33. In this analysis, several calibration factors were developed, including an overall factor for all segments, a non-random selection curve segment factor, and a random selection curve segment factor. The results of this analysis are presented in the next section.

ANALYSIS

Calibration Factor Analysis

The calibration factor is a critical component of the HSM procedure to adjust the standardized factors presented in the manual to account for local conditions (e.g., crash reporting thresholds, climate and geographic features, and driver factors for a given state). This paper focuses on calculating a calibration factor for two-lane rural road segments, including curved segments, tangent segments, and composite segments (including all curves and tangents). The HSM recommends that the calibration factors should be calculated every two or three years for those who wish to implement the procedures in the manual regularly. Additionally, the manual specifies a desirable minimum sample size of 30 to 50 sites that experience a total of at least 100 collisions per year. This analysis included 51 sites that experienced 85 collisions per year on average, over a five-year period (Table 2). However, these 51 sites include 26 curve segments that have abnormally high collision histories or have previously been identified as hazardous locations. The other 25 sites were selected randomly by NCDOT personnel by arbitrarily choosing a curve site while on other assignments.

Table 2: HSM Calibration Factors Calculated

Sample Type (Sample Size)	Roadway Type	Calibration Factor	Reported Collisions (Collisions per Year)	Predicted Collisions (Collisions per Year)
All Segments (51)	Curve	2.82*	35.4	12.5
	Tangent	1.12	49.4	44.0
	Composite	1.50*	84.8	56.5
Random Selection (25)	Curve	1.33	8.8	6.6
	Tangent	1.00	20.4	20.4
	Composite	1.08	29.2	27.0
Non-random Selection (26)	Curve	4.5*	26.6	5.9
	Tangent	1.23	29.0	23.6
	Composite	1.88*	55.6	29.5

*Denotes a statistical difference from a calibration factor of 1.00 at the 95% confidence level.

HSM calibration factors were calculated by first applying the HSM method to calculate the predicted number of crashes using site characteristic data like lane width, shoulder width, and roadside design. Once these predicted crashes were found, the calibration factor was calculated as the ratio of observed to predicted crashes. For example, in this analysis, the observed number of curve crashes for all 51 segments was 35.4 and the predicted 12.5, resulting in a calibration factor of 2.83. The calibration methodology implied by the HSM involves using extended roadway sections consisting of numerous tangent and curve sites. However, to examine the differences between tangents and curves, this analysis considered curve and tangent sections individually (and combined as "composite" sections). The HSM does not specify how calibration segments should be selected or if high crash location data should be used for this purpose. But Table 2 shows that the inclusion of high crash locations significantly impacts the calibration factor. When considering curved roadway segments, the calibration factor varies from 2.83 when including all 51 sites to 1.33 when counting only those sites that were randomly selected, and to 4.5 when incorporating only high crash sites. To meet HSM recommendations for collisions, additional sites would be needed in each sample type. For instance, if a user decided to develop a two-lane curve calibration factor based on randomly selected curves to meet the criterion of 100 total crashes, almost 300 sites would be needed in the analysis. Collecting the detailed data needed to calibrate the HSM for 300 curve sites would require an appropriate amount of additional labor.

A paired t-test was conducted to examine the importance or need for the calibration factors in Table 2. The test compared the reported and predicted collisions among each type of sample. The comparison found a difference in reported and predicted collisions in four of the nine samples and roadway types, indicating that only four of the calibration factors differed significantly from a calibration factor of one. Besides this finding, annual variations could exist when calculating calibration factors. Table 3 shows five years of calibration factors from the same data in Table 2. The calibration factor chosen in Table 3 for each year used only one year of data, so the samples of collisions were small. This table can provide users with an estimate of how much variation could exist when calculating annual calibration factors.

Table 3: Annual Calibration Factors (All Segments, Random Segments, and Non-Random Segments)

Sample Type (Sample Size)	Roadway Type	2004 Calibration Factor	2005 Calibration Factor	2006 Calibration Factor	2007 Calibration Factor	2008 Calibration Factor	Standard Deviation
All Segments (51)	Curve	2.63	2.07	3.19	3.75	2.47	0.65
	Tangent	1.04	1.14	1.11	1.32	1.00	0.12
	Composite	1.40	1.34	1.57	1.86	1.33	0.22
Random Selection (25)	Curve	1.36	1.51	1.97	1.06	0.76	0.46
	Tangent	0.88	0.98	0.78	1.13	1.22	0.18
	Composite	1.00	1.11	1.07	1.11	1.11	0.05
Non-random Selection (26)	Curve	4.05	2.70	4.56	6.75	4.39	1.46
	Tangent	1.19	1.27	1.40	1.48	0.80	0.26
	Composite	1.76	1.56	2.03	2.54	1.52	0.42

At each site, the field investigation to collect all necessary elements for HSM analysis took approximately 30 minutes to complete (not including driving time). Thus, the requirement of 300 sites to develop a calibration factor for curve sites could be expected to require at least one person-month of labor, plus drive time between sites. However, most of these elements do not change much or at all over time. So the data collected intensively for the first HSM calibration or application can likely be used for many years. The effort required to collect collision data varies in the way the data are stored and how efficiently they can be retrieved. And that effort may be substantial in some agencies. For example, field data collection efforts could vary considerably by agency, depending on the desired precision of crash prediction and available data sources within the agency. However, field data collection might not be necessary for some agencies or could require similar time commitments as noted in this study. Appendix A to Part C of the HSM defines data needs for each element as required or desirable, and provides suggested assumptions for defaults, average values, and actual data. Implementing the concepts for data collection presented in the HSM, along with utilizing available computer-based techniques (inventories, GIS data, and design plans), can significantly reduce or eliminate the need for field data collection, thereby reducing labor requirements substantially for the calibration effort.

Sensitivity Analysis

The sensitivity analysis focused on the effect of changing various HSM inputs on the number of predicted collisions. The objective of this analysis was to understand the most critical HSM inputs that might lend themselves more readily to default values, thus saving data collection effort. Several HSM inputs were not included in this sensitivity analysis because little or no variation existed among the curves in our sample. These included spiral transition, passing lanes, roadway lighting, centerline rumble strips, two-way left-turn lanes, and automated speed enforcement. Table 4 shows descriptive statistics about the data.

Table 4: Input Values for HSM (Minimum, Maximum, and Average)

HSM Input Factor	Minimum Value	Maximum Value	Mean Value
AADT	240	21,000	3,885
Lane Width (feet)	9	12	10.4
Inside Shoulder Width (feet)	3	12	7.4
Outside Shoulder Width (feet)	3	12	8.0
Length of Horizontal Curve (feet)	200	1,550	579
Radius of Horizontal Curve (feet)	202	6,011	1,360
Super elevation (feet/feet)	0.010	0.102	0.056
Grade (%)	0.0	5.1	1.3
Driveway Density (driveways/mile)	0.0	54.6	9.6
Roadside Hazard Rating (1-7)	3.0	6.0	3.8

Utilizing the field data resulted in a predicted collision rate of 12.5 collisions per year for the set of 51 curves. Table 5 shows the HSM outputs from the sensitivity analysis. The table emphasizes the importance of collecting and using individualized data for AADT, curve radius, and curve length of the segment. The AADT had a range of 62.6 predicted collisions per year between using the minimum value and using the maximum value. There was also a 0.9 collisions per year (or 7%) difference between the predicted collisions using the averages of the inputs and actual field values. Radius had a range of 18.9 predicted collisions per year between using the minimum and maximum values. There was also a 0.8 collisions per year (or 7%) difference between the predicted collisions using the average input and actual field values. Length had a range of 19.5 predicted collisions per year between using the minimum value and maximum values, and there was a 0.5 collisions per year (or 4%) difference between predicted collisions using the averages of the inputs and actual field values.

Table 5: Output Values from HSM (Predicted Collisions Per Year)

HSM Input	HSM Predicted Collisions per Year for Set of 51 Curves				
	Using Minimum Value from Table 1	Using Maximum Value from Table 1	Difference Between Using Maximum Value and Minimum Value	Using Mean Value from Table 1	Difference Between Using Mean Value and Actual Field Measured Values
AADT	0.8	63.4	62.6	13.4	0.9
Lane Width	14.7	11.5	3.2	13.4	0.9
Inside Shoulder Width	13.4	12.3	1.1	12.5	0.0
Outside Shoulder Width	13.4	12.3	1.1	12.2	0.3
Length of Curve	6.6	26.1	19.5	12.1	0.5
Radius of Curve	28.4	9.5	18.9	11.7	0.8
Superelevation	14.1	11.7	2.4	12.5	0.0
Grade	12.3	13.5	1.3	12.6	0.1
Driveway Density	11.5	21.5	10.0	12.4	0.1
Roadside Hazard Rating	11.9	14.6	2.6	12.6	0.0

The number of predicted crashes on curves for various traffic and geometric conditions using the HSM base model (not the calibrated North Carolina model) is in Table 6. Specifically, the variables that had the most effect on the number of crashes on curves (as measured by the difference between the minimum and maximum values) are AADT, curve radius, and length of curve. In Table 6, the predicted crashes on curves for five-year periods are based on the crash-prediction model for AADT's of 500, 1,000, 2,000, 5,000, 10,000, and 20,000. This table has a range of curve radius from 250 feet to 5,000 feet, and a range of curve lengths from 250 to 1,500 feet. For example, for a curve on a road with an AADT of 1,000, a 500-foot radius, and length of 750 feet, the expected number of curve crashes per five years would be approximately 0.54 (i.e., one curve crash every 10 years), as shown in Table 6. The calculations in Table 6 assume average NC conditions for the other variables included in the prediction model for crashes on curves. Specifically, it assumes a lane width of 10.4 feet, inside shoulder width of 7.4 feet, outside shoulder width of eight feet, superelevation of 0.056, grade of 1.3 %, 9.6 driveways per mile, average roadside hazard rating of four (on a seven-point scale), speed limit of 55 mph, no transition spiral, no passing lane, no roadway lighting, no centerline rumble strips, no two-way left-turn lane, and no automated speed enforcement.

Calibration Factor Validation

Calibration is a critical task to adjust a broad model for local analysis. In the case of the HSM, the calibration provides a multiplicative factor to adjust the predicted model to account for differences that are not determined by physical roadway elements, such as driver population, reporting threshold, and others. However, the calculation of a calibration factor in a research setting is incomplete without validating the model with the predetermined calibration factor. Therefore, an additional set of curve geometric and collision data was acquired to validate the previously calculated calibration factor.

Table 6: Predicted Collisions (over 5 years) for Two-Lane Road Horizontal Curves

Radius (Degree of Curvature)	Predicted Collisions for 500 vehicles/day						Predicted Collisions for 1,000 vehicles/day					
	Length (feet)						Length (feet)					
	250	500	750	1,000	1,250	1,500	250	500	750	1,000	1,250	1,500
250 feet (22.9°)	**	0.30	0.35	**	**	**	**	0.66	0.76	**	**	**
500 feet (11.5°)	0.15	0.20	0.25	**	**	**	0.33	0.43	0.54	**	**	**
1000 feet (5.7°)	0.10	0.15	0.20	0.24	0.29	0.34	0.22	0.32	0.42	0.53	0.63	0.73
2000 feet (2.9°)	0.07	0.12	0.17	0.22	0.26	0.31	0.16	0.26	0.37	0.47	0.57	0.68
3000 feet (1.9°)	0.07	0.11	0.16	0.21	0.26	0.30	0.14	0.24	0.35	0.45	0.55	0.66
4000 feet (1.4°)	0.06	0.11	0.16	0.20	0.25	0.30	0.13	0.23	0.34	0.44	0.54	0.65
5000 feet (1.1°)	**	0.11	0.15	0.20	0.25	0.30	**	0.23	0.33	0.44	0.54	0.64

Radius (Degree of Curvature)	Predicted Collisions for 2,000 vehicles/day						Predicted Collisions for 5,000 vehicles/day					
	Length (feet)						Length (feet)					
	250	500	750	1,000	1,250	1,500	250	500	750	1,000	1,250	1,500
250 feet (22.9°)	**	1.52	1.76	**	**	**	**	3.80	4.40	**	**	**
500 feet (11.5°)	0.76	1.00	1.24	**	**	**	1.90	2.50	3.10	**	**	**
1000 feet (5.7°)	0.50	0.74	0.98	1.22	1.46	1.69	1.25	1.85	2.44	3.04	3.64	4.24
2000 feet (2.9°)	0.37	0.61	0.85	1.09	1.32	1.56	0.92	1.52	2.12	2.71	3.31	3.91
3000 feet (1.9°)	0.33	0.56	0.80	1.04	1.28	1.52	0.81	1.41	2.01	2.61	3.20	3.80
4000 feet (1.4°)	0.30	0.54	0.78	1.02	1.26	1.50	0.76	1.36	1.95	2.55	3.15	3.75
5000 feet (1.1°)	**	0.53	0.77	1.01	1.25	1.49	**	1.32	1.92	2.52	3.12	3.71

Radius (Degree of Curvature)	Predicted Collisions for 10,000 vehicles/day						Predicted Collisions for 20,000 vehicles/day					
	Length (feet)						Length (feet)					
	250	500	750	1,000	1,250	1,500	250	500	750	1,000	1,250	1,500
250 feet (22.9°)	**	7.61	8.80	**	**	**	**	15.22	17.61	**	**	**
500 feet (11.5°)	3.80	5.00	6.19	**	**	**	7.61	10.00	12.39	**	**	**
1000 feet (5.7°)	2.50	3.69	4.89	6.08	7.28	8.47	5.00	7.39	9.78	12.16	14.55	16.94
2000 feet (2.9°)	1.85	3.04	4.24	5.43	6.62	7.82	3.69	6.08	8.47	10.86	13.25	15.64
3000 feet (1.9°)	1.63	2.82	4.02	5.21	6.41	7.60	3.26	5.65	8.04	10.42	12.81	15.20
4000 feet (1.4°)	1.52	2.71	3.91	5.10	6.30	7.49	3.04	5.43	7.82	10.21	12.59	14.98
5000 feet (1.1°)	**	2.65	3.84	5.04	6.23	7.43	**	5.30	7.69	10.08	12.46	14.85

Notes: Assumed values are mean values for lane width (10.5 feet), inside shoulder width (composite - six feet), outside shoulder width (composite - eight feet), superelevation (0.056 ft/ft), grade (1.3%), driveway density (9.6 driveways/mile), roadside hazard rating (4),speed limit (55 mph), no spiral transition, no passing lanes, no roadway lighting, no centerline rumb le strips, no two -way left-turn lanes, and no automated speed enforcement.

** = Data does not support generation of collisions for this combination of radius and length

This validation effort included two two-lane roads—NC42 and NC96—which are predominantly rural and run through central and eastern North Carolina. Horizontal curve data collection for this effort used GIS techniques (Rasdorf et al. 2012). The analysis included all the curved sections of each route except where a higher order route (i.e., a US route) ran concurrently with the NC route. The entire route of NC42 is 223 miles long; the analysis sections included 168 miles of this route and 246 curves. The entire route of NC96 is 107 miles long; the analysis sections included 95 miles of it and 174 curves. None of the calibration sites was included in the validation data set.

The HSM analysis of the curves predicted 114 collisions per year, while the curves experience 174 reported collisions per year, giving a calibration factor of 1.5267. Applying the suggested calibration factor of 1.33 from Table 2 to the HSM prediction gives 152 collisions per year. This is approximately 10% less than the reported collisions. Comparatively, the original prediction is approximately 35% less than the reported collisions. A paired t-test of the collision rates for each curve and for each of the three data sets (reported collisions, HSM prediction, and calibrated HSM prediction) shows that pairing reported collisions and calibrated HSM predicted collisions did not result in a statistically significant difference between them (95% confidence at p = 0.05). Comparatively, the other two pairings were statistically different. Differences in the data collection methods and randomness of collisions could contribute to the difference between reported collisions and the calibrated HSM prediction. Similar differences between predicted and actual crashes on horizontal curves could also be due to randomness of collisions. Furthermore, since the difference between the actual and HSM predicted curve crashes was not statistically significant, it might be reasonable to assume a calibration factor of one.

CONCLUSIONS

The publication of the Highway Safety Manual (HSM) offers agencies an analytical tool to evaluate the safety of a horizontal curve or set of curves efficiently and proactively. The HSM provides a crash prediction model for horizontal curves that can be applied to identify the highest priority locations for safety treatments as well as common and effective countermeasures. The calibration of the HSM predictive method was evaluated and tested on horizontal two-lane rural roads in North Carolina in this paper. Based on the analysis, it is found that approximately 300 curve sites are needed to meet HSM recommendations for the number of collisions in the calibration data set. This large number of sites is partly due to the finding that the selection of random segments provides a more accurate outcome (in terms of matching the HSM prediction model) than the crash results from a high-crash location group as identified by a transportation agency.

One challenge with requiring a large number of sites to develop an accurate model based on local conditions is the manpower needed for data collection. For each of these sites, field investigations took approximately 30 minutes to complete (not including driving time) for the collection of necessary elements for HSM analysis. However, most of the elements on which data were collected do not change much or at all over time. So, some data collection may not be needed during each calibration. Also, considerably less manpower may be required by some agencies that have curve inventories and/or in-house data sources for some of the needed curve features. To further lessen the data collection burden, an analysis of differences in predicted collisions based on field data collection and average or default values was performed. It was found that for AADT, curve radius, and curve length of the segment, individualized data are necessary for accuracy, but that the other data inputs may be assumed with less penalty for the accuracy of overall predicted crash value. It is possible for each of these three elements, which are the most sensitive to individual curve data, to be collected from existing agency GIS data or roadway inventory databases if available. These findings can allow agencies to more efficiently apply and utilize HSM procedures for the cost-effective improvement of curves, in some cases without a field visit.

To properly calibrate the predictive models to HSM standards, the research team found that at least for North Carolina conditions, approximately 300 segments are required to meet the HSM recommendations for collisions. This number of sites may vary for other local and state situations. Additionally, while it will require many sites, randomly selected road segments are recommended for this process because they have a low calibration factor. AADT, curve radius, and curve length are the most important data in terms of the prediction of curve crashes in the HSM model. Fortunately, as demonstrated elsewhere (Rasdorf et al. 2012), many of these important variables can be collected without a field visit, thus saving time and resources. A calibration factor or 1.33 was found to be appropriate to apply the HSM prediction method for it to match North Carolina crash values.

However, a calibration factor of one could be justified since the differences between the actual and HSM predicted number of curve crashes are not statistically significant.

Although some of the analyses performed for specific two-lane rural roads in this paper are not applicable to all road types or jurisdictions, several key findings can be applied by traffic engineers and researchers conducting similar analyses. First, engineers should consider the impact of site-specific or average data on their analysis. If some variables are not highly sensitive to small changes in value or if the variable of interest is fairly consistent among the type of roadways under analysis, an average value might be sufficient to minimize data collection costs. Secondly, annual or ongoing costs should be considered. Although the initial resource needs for the type of analyses presented in this paper is considerable, the costs to update the data in future years will be considerably less. Thirdly, site selection is a critical component of this process and randomly selected locations are preferred over high crash locations. Finally, with available data through internet-based sources and centralized databases, along with average values for non-sensitive elements, it is possible to achieve reasonable estimates of collisions on a roadway without a field visit.

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Endnotes

1. See Table 10-9 of the HSM.

2. See www.cmfclearinghouse.org.

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