Effects of Geometry and Pavement Friction on Horizontal Curve Crash Frequency

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ABSTRACT

Horizontal curves tend to be associated with a disproportionate number of severe crashes. Many treatments have been proposed to reduce traffic crashes and fatalities occurring on horizontal curves. The application of high-friction surface treatments is one among many treatments that agencies have been considering. However, relatively less research has been conducted on the safety implications of pavement friction improvements caused by these treatments. Before-after case studies have been conducted on the effectiveness of high-friction surface treatments, but pavement variables like skid number (coefficient of friction multiplied by 100) have not yet been incorporated into safety prediction methodologies. The objective of this study is to develop a crash modification factor (CMF) for skid number for all crashes, wet-weather crashes, run-off-the-road crashes and wet-weather run-off-the-road crashes. A horizontal curve database from a southern state in the United States was used to accomplish the study objective. The skid number variable was found to be statistically significant, in addition to traditional variables such as traffic volume, curve radius, and cross-sectional widths. The CMF developed in this study can be applied to evaluate the safety performance of a curve of interest and estimate the potential safety benefit of installing a high-friction surface treatment.

Keywords: Horizontal Curves, Friction, Skid Number, Safety Performance Function, Crash Modification Factors

EFFECTS OF GEOMETRY AND PAVEMENT FRICTION ON HORIZONTAL CURVE CRASH FREQUENCY

1. INTRODUCTION

Horizontal curves are a necessary part of any highway system, yet they can present significant safety concerns. In general, curves represent only a small fraction of most state highway systems, but a disproportional number of serious crashes occur at these locations (Bogenreif et al. 2012). Research shows that curves are associated with more crashes as their radius decreases or speeds on the roadway increase. These safety concerns arise from:

- The increased driver workload associated with the negotiation of a curve.
- The possibility of failing to detect a curve or judge its sharpness.
- The existence of inadequate side friction supply to keep vehicles on the curve.

Many options to improve curve safety exist, including signs and pavement markings to alert drivers of the presence and sharpness of a curve, surface treatments to increase pavement friction, and geometric improvements like straightening the curve or increasing its superelevation rate. These treatments can decrease side friction demand (by lowering vehicle speeds or providing more generous curve design) or increase side friction supply (by improving the tire-pavement interface). In general, the objective of curve safety treatments is to improve the curve's margin of safety, which is defined as the side friction demand subtracted from the side friction supply.

Much research has been conducted on the safety implications of geometric and traffic characteristics of curves. Variables describing curve geometry and speed have been incorporated into safety prediction methodologies. A few studies characterized when, where, and how horizontal-curve collisions occur on two-lane roads (e.g. Hummer et al. 2010). However, relatively less research has been conducted on the safety implications of pavement friction. Before-after case studies have been conducted on the effectiveness of high-friction surface treatments, but pavement variables like skid number have not yet been incorporated into safety prediction methodologies. Research on this issue would yield improvements to the understanding of friction treatment effectiveness, and better assist decision-makers in the selection of curve safety treatments. The objective of this study is to develop a crash modification factor (CMF) for the skid number for all crashes, wet-weather crashes, run-off-the-road crashes and wet-weather run-off-the-road crashes. The CMF can be applied to evaluate the safety performance of a curve of interest and estimate the potential safety benefit of installing a high-friction surface treatment.

2. BACKGROUND

This part of the paper addresses horizontal curve safety trends, focusing on design and operational issues and safety treatments that are commonly used. Geometric attributes such as curve radius and superelevation rate affect curve safety, and so do operational issues such as driver steering fluctuation, acceleration, and braking. The interaction between these factors results in different margins of safety existing along different portions of the curve.

This part of the paper consists of three sections. The first section explores curve crash trends and identifies causes for curve crashes. The second section summarizes the concepts of side friction demand and supply. The third section presents findings from case-study evaluations that have been conducted on high-friction surface treatments. Some general background information is provided below to help support this paper; the full literature review can be found in the research report (Pratt et al. 2014).

2.1. Crash Trends

This subsection covers topics related to horizontal curve crashes, roadway departure crashes and wet-weather crashes.

2.1.1. Horizontal Curve Crashes

Statistics have consistently shown that the crash rate on horizontal curves is significantly greater than that on tangent roadway segments of similar characteristic. In an exploration of curve safety trends, Zegeer et al. (1991) found that a 1000-ft-radius curve is likely to have 50 percent more crashes than a tangent segment of equivalent length, and a 500-ft-radius curve is likely to have 200 percent more crashes than a tangent segment. This trend may be caused by drivers failing to detect the presence of a curve or attempting to negotiate the curve at unsafe speeds.

Fitzpatrick et al. (2000) analyzed curve safety trends by categorizing curves in terms of speed reduction. They defined speed reduction as the difference between 85th percentile vehicle speeds on the approach tangent and at the curve midpoint. They found that a curve requiring a 5-mph speed reduction is likely to have 90 percent more crashes than a tangent segment, and a curve requiring a 10-mph speed reduction is likely to have 250 percent more crashes. They calibrated the following CMF to estimate a relationship between curve crash frequency and the 85^{th}-percentile curve and tangent speeds:

$$CMF_{sr} = e^{0.126\left(v_{t,85} - v_{c,85}\right)} \tag{1}$$

where:

CMF_{sr} = crash modification factor for curve speed reduction;
$v_{t,85}$ = 85^{th} percentile approach tangent speed, mph; and
$v_{c,85}$ = 85^{th} percentile curve speed, mph.

The trend in Equation 1 shows that curve crash frequency increases exponentially as the required speed reduction increases. For the purpose of estimating the speed reductions chosen by drivers through curves, Bonneson et al. (2007) developed a model to predict the 85th percentile vehicle speed at the midpoint of a curve. The model was calibrated using a data set of 6,677 passenger cars and 1741 trucks at 41 curve sites in Texas. It is described as follows:

$$v_{c,85} = \sqrt{\frac{15.0R_p(0.1962 - 0.00106v_{t,85} + 0.000073{v_{t,85}}^2 - 0.0150I_{tk} + e/100)}{1 + 0.00109R_p}} \le v_{t,85} \tag{2}$$

where:

R_p = vehicle path radius, ft; and

I_{tk} = indicator variable for trucks (=1.0 if model is used to predict truck speed, 0.0 otherwise).

This curve speed model reflects drivers' choice of curve speed as influenced by:

- Their perception of lateral acceleration (which is influenced by speed and curve geometry).
- Comfort limits.
- Desire to maintain speed and minimize travel time (which is more prevalent on higher-speed roadways).

Bonneson and Pratt (2009) calibrated a safety prediction model to estimate the effects of geometry and traffic operations on safety. The model was calibrated for rural highways using Texas data. It includes a CMF to account for the expected increase in crash frequency due to the presence of a horizontal curve. The following equation describes the horizontal curve CMF:

$$CMF_{cr} = 1.0 + 0.97(0.147V)^4 \frac{(1.47V)^2}{32.2R^2}\left(\frac{L_c}{L}\right) \tag{3}$$

where:

CMF_{cr} = crash modification factor for horizontal curve radius;

V = posted speed limit, mph;

R = curve radius, ft;

L_c = horizontal curve length (including spiral transitions), mi; and

L = segment length, mi.

The CMF is illustrated in FIGURE 1 for a range of curve radii and three posted speed limit values. Two trends are evident. First, crash frequency increases significantly when a curve of any radius is present, but especially if the curve radius is less than about 2,000 ft. Second, a curve of a given radius will be associated with a larger increase in crashes if vehicle speeds are higher. For example, a curve with a radius of 2,865 ft (i.e., degree of curve = 2.0) would be associated with a crash frequency increase of about 6 percent (CMF_{cr} = 1.06) on a 50-mph roadway and about 44 percent (CMF_{cr} = 1.44) on a 70-mph roadway.

Torbic et al. (2004) analyzed the distribution of curve-related fatal crashes that were reported in the nationwide Fatality Analysis and Reporting System (FARS) in 2002. They found that 76 percent of fatal crashes on curves were single-vehicle crashes, which were primarily run-off-the-road crashes, and another 12 percent of the crashes were head-on or sideswipe-opposite direction crashes. Both of these collision types involve lane departure. A head-on or sideswipe-opposite direction crash results if a vehicle crosses into the opposing lane while an opposing vehicle is present. The occurrence of lane departure indicates that the driver either misjudged the curvature or was unable to maintain the curved trajectory.

2.1.2. Roadway Departure Crashes

Lord et al. (2011) analyzed roadway departure crash trends in Texas using crash data from 2003 through 2008. Their analysis included all roadway departure crashes—on tangents as well as on curves. They calibrated the following model that predicts annual roadway departure crash frequency per mile. The model applies to crashes of all severities and all regions in Texas.

$$\mu = e^{-6.894} \times F^{0.8035} \times e^{\left(-0.084\,LW - 0.058\,SW - 0.048\,ST2 - 0.285\,ST4 + 0.1118\,C\,Dens - 0.019\,D\,Dens\right)} \tag{4}$$

where:

μ = estimated annual number of crashes per mile.
F = traffic volume, vehicles per day.
LW = lane width, ft.
SW = shoulder width, ft.
$ST2$ = indicator variable for surface shoulder type presence.
$ST4$ = indicator variable for combination-surface/stabilized shoulder type presence.
$CDens$ = curve density, curves per mile.
$DDens$ = driveway density, driveways per mile.

This model suggests that roadway departure crash frequency per mile will increase exponentially with an increase in curve density. The magnitude of the exponent is 0.1118 multiplied by the curve density, which is measured in curves per mile.

Lord et al. (2011) calibrated a second model to predict the annual roadway departure crash frequency per mile on curves. This model suggests that crash frequency per mile increases exponentially with an increase in degree of curve (or a decrease in radius). This model is described as follows:

$$\mu = e^{-6.448} \times F^{0.7657} \times e^{\left(-0.076\,LW - 0.062\,SW + 0.075\,CD\right)} \tag{5}$$

where:

μ = estimated annual number of crashes per mile.
F = traffic volume, vehicles per day.
LW = lane width, ft.
SW = shoulder width, ft.
CD = degree of curve.

Lord et al. (2011) also conducted an exploratory analysis of single-vehicle roadway departure fatal-and-injury crash rates for horizontal curves. They were further able to determine that there is a positive correlation between speed limit and curve density, such that the expected increase in roadway departure crash rate due to curve density is more noteworthy on roadways with higher speed limits.

Finally, Lord et al. (2011) examined the effects of weather and light condition on the severity distribution of roadway departure crashes. They found that a lower percentage of crashes were property-damage-only during clear or cloudy weather than during other weather conditions. For example, 48 percent of roadway departure crashes were property-damage-only during clear or cloudy weather, compared with 63 percent during rain. They opined that this trend may be caused by drivers reducing speed during inclement weather. Their examination of light condition suggested that the percentage of fatal crashes is slightly lower during daylight (2 percent of crashes) than other light conditions (3–5 percent).

2.1.3. Wet-Weather Crashes

A before-after examination of wet-weather crashes and pavement friction on several rural highway types was conducted by Blackburn et al. (1978). They derived the relationship between skid number and wet-pavement crash rate that is illustrated in FIGURE 2. As expected, wet-weather crash rates are highly influenced by pavement friction.

If the trends in FIGURE 2 for multilane uncontrolled-access and controlled-access highways are averaged, the following observations can be derived:

- On two-lane highways, the crash rate for a skid number of 25 is about 1.30 times the crash rate for a skid number of 40, while the crash rate for a skid number of 50 is about 0.80 times the crash rate for a skid number of 40.
- On multilane highways, the crash rate for a skid number of 25 is about 1.56 times the crash rate for a skid number of 40, while the crash rate for a skid number of 50 is about 0.63 times the crash rate for a skid number of 40.

The proportions stated in the preceding observations can be interpreted as CMF values for a base skid number of 40.

More recently, Long et al. (2014) analyzed the relationship between wet-weather crashes and pavement skid resistance in a research project that ran concurrent to the one conducted by Pratt et al. (2014). Their results are shown in the form of a crash rate ratio in FIGURE 3. They defined crash rate ratio as the cumulative percentage of crashes at or below a specific skid number (SK) threshold divided by the cumulative percentage of lane-miles at or below a specific skid number threshold. This quantity is roughly analogous to a CMF that could be obtained from a safety prediction model that includes only skid number as an input variable.

Long et al. (2014) suggested the use of the following skid number thresholds for the purpose of managing pavement friction and minimizing wet-weather crashes:

- $SK < 17$: Consider short-term treatment to improve skid resistance.
- $17 < SK \leq 29$: Conduct detailed project-level testing to assess need for improvement.
- $29 < SK \leq 73$: Exercise vigilance in pavement monitoring.
- $SK > 73$: Increased skid resistance will likely have little effect in reducing crashes.

2.2. Side Friction Demand and Supply

The American Association of State Highway and Transportation Officials' (AAHTO) *A Policy on Geometric Design of Highways and Streets* (*Green Book*) states that the design of horizontal curves should be based on a proper relationship between speed, curvature, superelevation rate, and side friction demand (AASHTO 2004). The *Green Book* offers the following equation to describe the relationship between these variables:

$$f_D = \frac{v^2}{gR} - \frac{e}{100} \quad (6)$$

where:

f_D = side friction demand (lateral acceleration divided by g).
v = vehicle speed, ft/s.
g = gravitational constant (= 32.2 ft/s^2).
R = curve radius, ft.
e = superelevation rate, percent.

This equation is referred to as the "point-mass model" or the "simplified curve formula." It shows that the side friction demand f_D of a vehicle traveling at speed v increases as curve radius R or superelevation rate e decrease. For design purposes, the *Green Book* recommends side friction factors that represent driver comfort limits. These factors are used to determine an appropriate curve radius and superelevation rate for the roadway's design speed.

The design side friction factors in the Green Book are lower than the side friction supply f_S provided in the worst-case combination of worn tires and wet pavement. In other words, vehicles traveling at a speed not exceeding the design speed should be able to traverse the curve safely.

In the design process, curve design safety can be assessed in terms of "margin of safety," which is defined as the difference between side friction demand and side friction supply at a given vehicle speed. If the side friction demand exceeds the side friction supply available to the vehicle, a sliding failure will occur. As Equation 6 shows, vehicle speed and curve geometry affect side friction demand. Tire-pavement interface properties such as tire tread condition, pavement texture, and presence of water or solid contaminants on the pavement surface all affect side friction supply.

Various methods can be used to measure surface friction at horizontal curve sites where side friction supply is believed to be inadequate. The side friction supply can then be subtracted from the side friction demand to obtain the curve's margin of safety. An inadequate margin of safety can indicate the need to increase side friction supply through the provision of a surface treatment, and also indicate the amount of side friction supply increase that would be needed. It would then be necessary to identify a surface treatment that could provide the needed increase in side friction supply.

2.3. Field Assessment of Surface Treatment Effectiveness

Case-study evaluations of various types of high-friction surface treatment have been reported in the literature. Some of these case studies were conducted at curve sites, where side friction is of concern, while others were conducted at tangent sites where increased pavement friction is needed because of frequent stopping, such as at toll plazas. The studies generally report positive results in terms of reduced crashes or improvements in safety surrogate measures like shoulder encroachments. However, benefit-cost analysis does not always show that the treatments were cost-justified.

Micro-surfacing is an advanced form of slurry seal that uses a combination of emulsified asphalt, water, fine aggregate, mineral filler, and polymer additives. The New York Department of Transportation has successfully used this form of surface treatment in its Skid Accident Reduction Program (SKARP) (Bray 2003). Between 1990 and 2000, Bray (2003) reported a 34 percent reduction in annual roadway fatalities in New York. Bray attributes this reduction to the state's pavement preservation program (which features the application of thin non-carbonate overlays or micro-surfacing treatments on high-crash frequency, low friction pavements) combined with the state's SKARP and Safety Appurtenance Program.

A surface treatment called Typegrip® was installed on a loop entrance ramp in Florida, and before-after analyses were conducted on crashes and safety surrogate measures (Reddy et al. 2008). The Typegrip® treatment consists of an epoxy resin topped with calcined bauxite. A small reduction in crashes was observed following the installation of the treatment, but it was not found to be statistically significant. Speeds were found to decrease by an average of 3.72 mi/h in dry conditions and 2.62 mi/h in wet conditions, and the proportion of vehicles encroaching on the shoulder in wet conditions decreased substantially.

Surface treatments consisting of calcined bauxite were evaluated at five sites in New Zealand (Iskander and Stevens 2005). Two of the sites were highway entrance ramps, two were exit ramps, and one was a traffic circle at an interchange. Crash counts were conducted before and after the treatments were installed. Though the findings are limited due to a paucity of time included in the "after" periods, the authors suggested that the exit ramp sites experienced notable reductions in crashes, which were frequent in the "before" period due to loss of control while cornering.

De Leon Izeppi et al. (2010) conducted a benefit-cost analysis of several types of surface treatments. They reported crash counts for a steel-slag-based treatment called Italgrip® that was installed at four sites in Wisconsin. TABLE 1 provides the crash counts. Along with these crash counts, the authors considered the installation costs of the surface treatments. They reported benefit-cost ratios of 0.47, 3.41, 8.45, and 2.23, respectively, for the four sites.

Case studies like these have shown varying degrees of benefit in reducing crashes by applying high-friction surface treatments. However, safety prediction methodologies have not yet incorporated pavement friction to the extent that they have incorporated curve geometry.

3. METHODOLOGY

The section describes the safety performance functions (SPFs) that are used to describe the relationship between crash frequency and traffic, geometric, and pavement variables for horizontal curves in a southern state. The development of cross-sectional safety prediction models offer the advantage of quantifying the effects of a range of variables even if some of the variables are correlated, and yielding insight that is more applicable to a range of sites. In general, a robust safety prediction methodology would require the use of a cross-sectional study approach. Furthermore, as documented in a very recent study, cross-sectional studies based on regression models can provide reliable CMFs (Wu, L. et al. 2014).

Cross-sectional data each have an independent variable value averaged for each site over a particular period of time. In contrast, with panel data, each observation contains dependent and independent variable values for each year and thus the independent variables are repeated if they have not changed over time. The cross-sectional data approach has the following advantages:

- It provides a more robust predictive model than panel data when the year-to-year variability in the independent variables is largely random.
- Using cross-sectional data for model calibration will minimize the problems associated with over-representation of segments or intersections with zero crashes.

3.1. Model Formulation

The probabilistic structure used for developing the SPFs was the following: the number of crashes at the i^{th} segment, Y_i, when conditional on its mean μ_i, is assumed to be Poisson distributed and independent over all segments as (Miaou and Lord 2003):

$$Y_i \mid \mu_i \sim Po(\mu_i) \tag{7}$$

where:

i = 1, 2, …, I.

The mean of the Poisson distribution is structured as:

$$\mu_i = f(X;\beta)e^{e_i} \tag{8}$$

where:

$f(.)$ = function of the covariates (X).
β = vector of unknown coefficients.
e_i = model error independent of the covariates.

It is usually assumed that e^{e_i} is independent and Gamma distributed with a mean equal to 1 and a variance $1/\phi$ for all i (with $\phi > 0$). With this characteristic, it can be shown that Y_i, conditional on $f(.)$ and ϕ, is distributed as a negative binomial (or Poisson-gamma) random variable with a mean $f(.)$ and a variance $f(.)(1+f(.)/\phi)$ respectively. The term ϕ is usually defined as the "inverse dispersion parameter" for the negative binomial distribution.

Although the dispersion parameter ($\alpha = 1/\phi$) or its inverse (ϕ) is now often modeled as a function of the covariates in the data (Hauer 2001; Geedipally et al. 2009), the models were estimated using a fixed dispersion parameter to simplify the model development.

For this work, the functional form is as follows:

$$\mu_i = L \times y \times e^{\beta_0} \times F^{\beta_1} \times CMF_R \times CMF_{LW} \times CMF_{SW} \times CMF_{SK} \tag{9}$$

with:

$$CMF_R = 1 + \beta_2 (0.147V)^4 \frac{(1.47V)^2}{32.2R^2} \tag{10}$$

$$CMF_{LW} = e^{\beta_3 (LW-12)} \tag{11}$$

$$CMF_{SW} = e^{\beta_4 (SW-8)} \tag{12}$$

$$CMF_{SK} = e^{\beta_5 (SK-40)} \tag{13}$$

where:

μ_i = estimated annual number of crashes per mile, i = 2U (two-lane undivided), 4U (four-lane undivided), or 4D (four-lane divided).
L = segment length, mi.
y = number of years of crash data, years.
F = traffic volume, vehicles per day.
CMF_R = curve radius crash modification factor.
CMF_{LW} = lane width crash modification factor.
CMF_{SW} = shoulder width crash modification factor.
CMF_{SN} = skid number crash modification factor.
V = posted speed limit, miles per hour.
R = curve radius, ft.
LW = lane width, ft.
SW = shoulder width, ft.
SK = skid number.
β_i = coefficients to be estimated.

The coefficients of the regression models were estimated using the Statistical Analysis Software (SAS) program (SAS 2009). The log-likelihood and Akaike Information Criterion (AIC) statistics were used to assess the model goodness-of-fit. Only variables that had a large influence on the predicted values were included in the models.

3.2. Database Development

The database assembled for developing the cross-sectional models consisted of a set of similar horizontal curves. The horizontal curve information was extracted from the roadlog database maintained by the state's Department of Transportation (DOT). The roadlog database contains traffic volumes and geometrics for all curves on all highways in the state. Each curve is given a unique curve identifier number, and the beginning and end milepoints of each curve are located through a given reference marker and curve length from that marker. Only normal curves (i.e., curves that deflect at a constant rate) that are ≥ 0.1 miles in length were considered in this analysis.

Pavement data were obtained from a pavement inventory database maintained by the state. Specifically, the following quantities were extracted:

- Skid number.
- Condition score.
- Distress score.
- Ride score.
- International roughness index (IRI).

These quantities provide insight into friction supply and general pavement condition. The curves of interest were located in the pavement inventory database using reference markers and displacements. Reference markers are small signs placed on the road so that the data records are physically located in the field by relationship to posted reference markers. Displacement is the distance in miles from a posted reference marker on the signed highway to a data attribute or feature.

Researchers retrieved crash data for the years 2007–2011 from state's crash database. The crash data are collected and submitted by the state law enforcement officers to the state DOT. The DOT is responsible for maintaining a statewide, automated database for reportable motor vehicle traffic crashes. These data consisted of information describing date and location of the crash, severity, and weather conditions. Since it is widely recognized that property damage only (PDO) crash counts vary widely on a regional basis due to significant variation in reporting threshold, only those crashes that are associated with injury or fatality were considered in this study. The following four crash severity levels were used:

- Fatal (K) (A crash that results in one or more deaths within thirty days of the motor vehicle traffic crash).
- Incapacitating injury (A) (Any injury which prevents the injured person from walking, driving or normally continuing the activities he was capable of performing before the injury occurred).
- Non-incapacitating injury (B) (Any injury which is evident to observers at the scene of the crash).
- Minor injury (C) (Any injury reported or claimed which is not a fatal, incapacitating or non- incapacitating injury).

Three separate databases were built, for curves on the following roadway types:

- Two-lane rural highways.
- Four-lane undivided rural highways.
- Four-lane divided rural highways.

TABLE 2 presents the summary statistics of the variables used for SPF development. The lower and upper quartiles of skid number were computed as 34 and 55 for two-lane rural highways, 26 and 49 for four-lane undivided rural highways, and 26 and 43 for four-lane divided rural highways. The crash data were separated into four categories:

- All crashes.
- All wet-weather-related crashes (Crashes that occur in adverse weather (i.e., rain, sleet, snow, fog, severe crosswinds, or blowing snow/sand/debris) or on slick pavement (i.e., wet pavement, snowy/slushy pavement, or icy pavement)).
- Run-of-the-road (ROR) crashes (A ROR crash occurs when a vehicle in transit leaves the road and collides with a tree, a pole, other natural or artificial objects, or overturns on non -traversable terrain.).
- ROR wet-weather-related crashes.

Geometric design features, traffic control features, and traffic characteristics were included as independent variables.

4. MODELING RESULTS

TABLE 3 summarizes the parameter estimates associated with the calibrated SPFs for horizontal curves by highway type. It should be noted that the base conditions for the SPFs are no horizontal curvature, 12-foot lanes, 8-foot shoulders, and a skid number of 40. If a segment satisfies these base conditions, then all of its computed CMF values will be 1.0. The predictive models were developed separately for the four categories described above. A backward stepwise regression method was adopted to select the final list of variables. A 5% significance level is used to test the significance of a variable. For a few variables that are marginally or insignificant at 5-percent level, it was decided that the variable was important to the model and its trend was found to be intuitive and, where available, consistent with previous research findings. The variables that are significant for all type of crashes were also significant for ROR crashes. An examination of the coefficient values and their implication on the corresponding SPF predictions are documented further below. In general, the sign and magnitude of the regression coefficients in TABLE 3 are logical and consistent with previous research findings. The list of variables presented in TABLE 3 reflects the findings from several preliminary regression analyses where different combinations of variables were examined. The list that is presented in TABLE 3 represents the variables that are significant in the model, while also having coefficient values that are logical and constructs that are theoretically defensible and properly bounded. Although superelevation is an important variable in estimating crash frequency, it was not included in this analysis because the state database does not include information related to this variable.

The annual crash frequency for horizontal curves on two-lane highways is obtained by combining Equation 9 with the coefficients in TABLE 3. The effects of traffic volume and the site characteristics described by the preceding CMFs are discussed in the following paragraphs. The CMFs developed in this study are compared with the CMFs in the *Roadway Safety Design Workbook* (Bonneson and Pratt 2009) because the data used in the *Workbook* are similar to the data used in this study.

4.1. Traffic Volume

FIGURE 4 shows the relationship between the traffic demand variable and crash frequency. The estimated values are for a one-mile section of a horizontal curve with a 2,500-ft radius. All other variables are fixed at the base values. The positive value of the associated coefficient (in TABLE 3) indicates that as the volume increases, all type of crashes increases, almost in a linear fashion. The length of the trend lines in FIGURE 4 reflects the range of ADT in the data. The trends in FIGURE 4 indicate that wet-weather crashes represent about 15 percent of all crashes.

4.2. Curve Radius

FIGURE 5 illustrates the CMF for curve radius. This figure shows that the CMF becomes lower as the radius increase, which previous studies have supported. For instance, the CMF that Bonneson and Pratt (2009) developed is applicable to both two-lane and four-lane horizontal curves, and shows a similar relationship. The slight difference in estimated CMF values for smaller-radius curves on two-lane highways (see FIGURE 5a) may be attributable to the inclusion of skid number as a variable in the proposed model but not the Bonneson and Pratt (2009) model. Skid number is likely to have a more notable effect on crash frequency on sharper curves, especially if only one lane is available and drivers are limited in their ability to “cut” the curve.

4.3. Lane Width

FIGURE 6 illustrates the CMF for lane width. The lane width used in this CMF is an average for all through lanes on the segment. The nominal condition reflects a 12-ft lane width. The lane width variable is not statistically significant for four-lane divided highways. The CMF is shown in FIGURE 6 using a dotted trend line, whereas the other lines are extracted from the work of Bonneson and Pratt (2009). This figure shows that the number of crashes goes down as the lane width increases. For two-lane highways, the relationship found in this study is close to the low-volume CMF documented in Bonneson and Pratt (2009). Note that for the Bonneson and Pratt (2009) model, “low-volume” is defined as < 400 veh/day and “high-volume” is defined as > 2000 veh/day, while the average volume at the two-lane highway curve sites for the proposed model is 1443 veh/day (see TABLE 2). For four-lane highways, the relationship found in this analysis is close to the CMF documented in Bonneson and Pratt (2009).

4.4. Shoulder Width

FIGURE 7a illustrates the CMF for outside shoulder width for horizontal curves on two-lane highways. FIGURE 7b illustrates the CMF for inside shoulder width for horizontal curves on four-lane divided highways. The shoulder width represents an average for both directions of travel. As before, the results are compared to the work of Bonneson and Pratt (2009). Interestingly, for two-lane highways, although the number of crashes goes down as the shoulder width increases, Bonneson and Pratt (2009) found that the number of crashes is not as sensitive to a modification in shoulder width for the low-volume roads, since the curve is relatively flat.

For four-lane divided highways, the relationship found in this analysis is close to the CMF documented in Bonneson and Pratt (2009).

4.5. Skid Number

The CMF for skid number is shown in FIGURE 8. The skid number describes the overall skid resistance of the road section (e.g., representative of values obtained from skid tests in the vicinity of the curve, not just in the curve itself, based on the assumption that the same type of pavement is used on the curve as in the general road section). Skid number is based on locked-wheel skid trailer measurements at 50 miles/hour with a smooth tire and wet pavement, and is defined as coefficient of friction multiplied by 100. It is a unitless number that varies from 01 (least skid resistance) to 99 (most skid resistance). A value greater than 70 is rarely found and the nominal condition was set at 40. The negative value of the associated coefficient (in TABLE 3) indicates that as the skid number increases, the crash frequency decreases. The skid number variable has a more pronounced effect in influencing wet-weather crashes for all highway types.

TABLE 4 provides a comparison of the skid number CMF values plotted in FIGURE 8 with those derived from FIGURE 2. As shown, the values are similar. This comparison is limited by the range of skid number values reported by Blackburn et al. (1978) and reflects an assumption that the average characteristics of the multilane highways in the dataset used by Blackburn et al. are similar to the four-lane highways in the calibration dataset for Equation 13.

FIGURE 9 shows a comparison of the wet-weather crash CMF for two-lane highways from FIGURE 8a (solid line) and an adjusted version of the plot from FIGURE 3 (broken line). The adjustment to FIGURE 3 was obtained by dividing the crash rate ratio values for each given skid number by the crash rate ratio value for a skid number of 40. In other words, the base skid number value was recalibrated as 40 so the two models would have the same base condition. This adjustment facilitates comparison. As shown, the two models yield similar predictions for skid number values between 20 and 100. The deviation at skid number values less than 20 is likely due to differences in modeling approaches. The model developed by Pratt et al. (2014) was a full model, including variables for curve radius, lane width, and shoulder width in addition to skid number, and was specific to curves. Conversely, Long et al. (2014) developed their model using data for tangents as well as curves, and their model in its raw form does not directly produce a CMF. Regardless, the results are similar for a notable range of skid number values.

5. CONCLUSIONS

This study presented the results of the statistical analyses conducted on crashes that occurred on horizontal curve segments from 2007 to 2011. The primary objective of this analysis was to develop SPFs to describe the relationship between crash frequency and traffic, geometric, and pavement variables for horizontal curves in a southern state in the United States. Curve radius, lane width, and shoulder width have been identified as key geometric variables. The skid number, which describes the skid resistance of a pavement, was found to significantly influence all crashes, particularly wet-weather-related crashes.

The analysis results suggest that the curve radius has a significant effect on all crashes and ROR crashes but had little influence on wet-weather crashes on two-lane horizontal curves. However, the curve radius has a significant influence on all crashes on four-lane horizontal curves. Wider lane and shoulder widths on horizontal curves have a notable positive impact on safety. The skid number, which describes the skid resistance of a pavement, showed that pavement friction influence crashes. Importantly, friction conditions highly influence wet-weather crashes.

Inclusion of pavement friction as an input variable has been shown to improve methodologies to predict safety performance, particularly for wet-weather crashes on horizontal curves. The CMF values for the skid number developed in this study can help the analyst in understanding the potential safety benefits if one wishes to change the surface friction on the horizontal curves by either resurfacing or installing a new high-friction surface treatment. Additional research on the safety effect of pavement friction would also likely be beneficial for roadway facilities that are susceptible to wet-weather crashes. These facilities may include horizontal curves on highway mainlines as well as turning roadways, and locations that tend to experience significant amounts of acceleration and deceleration, such as high-speed intersection approaches and toll plazas. Further research needs to be conducted by including superelevation and other properties of the horizontal curve.

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TABLE 1. Before-After Crash Counts at Four Surface Treatment Sites.

Site Number	Before Period (3 years)				After Period (3 years)			
	Incidents	Vehicles Involved	Injuries	Fatalities	Incidents	Vehicles Involved	Injuries	Fatalities
1	5	7	2	0	0	0	0	0
2	11	30	6	0	1	4	0	0
3	3	16	3	0	0	0	0	0
4	9	10	3	0	1	3	2	0

TABLE 2. Summary Statistics for Horizontal Curve SPF Development.

Variable	Two-Lane			Four-Lane Undivided			Four-Lane Divided		
	Range	Mean (SD)*	Total	Range	Mean (SD)*	Total	Range	Mean (SD)*	Total
Curve Length (Miles)	0.1–0.99	0.19 (0.09)	4051	0.1–0.86	0.21 (0.1)	154	0.1–0.99	0.29 (0.16)	381
ADT (Vehicles/day)	14–40,200	1443 (1990)	--	412–34,400	9045 (6558)	--	972–70368	15633 (11333)	--
Average Lane Width (ft)	8–16	10.96 (1.1)	--	10–16	12.5 (1.5)	--	10–15	12.0 (0.4)	--
Average Inside Shoulder Width (ft)	--	--	--	--	--	--	0–14	4.63 (1.69)	--
Average Outside Shoulder Width (ft)	0–17	3.7 (2.9)	--	0–12	4.4 (3.7)	--	0–16	9.63 (1.94)	--
Radius (ft)	355–28662	2705 (2032)	--	520–28250	3886 (2580)	--	755–40866	5740 (3437)	--
Maximum Speed (Miles/hour)	30–75	60.0 (7.1)	--	35–75	60.0 (9.6)	--	45–80	68.3 (7.1)	--
All Crashes	0–13	0.69 (1.26)	3772	0–34	0.67 (1.66)	486	0–31	1.35 (2.24)	1807
All Wet-Weather Crashes	0–4	0.12 (0.45)	495	0–3	0.09 (0.35)	65	0–20	0.31 (0.95)	411
ROR Crashes	0–10	0.59 (1.14)	2956	0–12	0.37 (0.85)	270	0–14	0.85 (1.38)	1128
ROR Wet-Weather Crashes	0–4	0.10 (0.42)	430	0–3	0.06 (0.30)	46	0–8	0.21 (0.65)	286

*SD: standard deviation

TABLE 3. Parameter Estimation for Horizontal Curves by Highway Type.

Highway Type	Variable	All Crashes		Wet Weather Crashes		Run-off-the-Road Crashes		Wet Weather Run-off-the-Road Crashes	
		Estimate	**Std. err.**	**Estimate**	**Std. err.**	**Estimate**	**Std. err.**	**Estimate**	**Std. err.**
2U	Intercept	−8.0034	0.194	−9.9089	0.507	−8.186	0.219	−9.8329	0.539
	LN (ADT)	0.8225	0.021	0.8462	0.057	0.8018	0.024	0.8152	0.061
	Curve Radius	0.5796	0.036	--	--	0.8129	0.093	--	--
	Lane Width	−0.0642	0.020	−0.0903	0.053	−0.0625	0.023	−0.0962	0.056
	Shoulder Width	−0.0421	0.007	--	--	−0.0473	0.008	--	--
	Average Skid Number	−0.0032	0.001	−0.0189	0.003	−0.0047	0.001	−0.0233	0.004
	Dispersion	1.4036	0.126	0.2577	0.046	1.0761	0.101	0.2467	0.048
	AIC	18497		4103		15927		3683	
4U	Intercept	−6.6487	0.905	−12.582	2.439	−6.5047	1.132	−12.4655	3.112
	LN(ADT)	0.6588	0.091	1.0221	0.236	0.5596	0.112	0.9597	0.297
	Curve Radius	1.0077	0.379	3.2688	2.334	2.3278	0.828	5.3898	5.679
	Lane Width	−0.0406	0.0396	--	--	−0.0676	0.051		
	Average Skid Number	−0.0077	0.005	−0.0331	0.013	−0.0049	0.006	−0.0254	0.016
	Dispersion	1.2430	0.203	0.6559	0.359	1.0298	0.242	0.2797	0.139
	AIC	1494		393		1091		316	
4D	Intercept	−9.3399	0.562	−9.4156	1.097	−8.4124	0.643	−7.602	1.218
	LN(ADT)	0.9437	0.054	0.7758	0.105	0.7985	0.061	0.5601	0.118
	Curve Radius	0.8213	0.260	0.8351	0.492	1.0199	0.319	0.7480	0.523
	Lane Width	--	--	--	--	−0.1436	0.091	−0.2726	0.217
	Inside Shoulder Width	−0.0373	0.019	–0.0296	0.042	−0.0228	0.022	−0.0491	0.048
	Average Skid Number	−0.0071	0.003	−0.0319	0.006	−0.0065	0.003	−0.0298	0.007
	Dispersion	2.0358	0.221	0.5759	0.092	2.0004	0.297	0.4833	0.093
	AIC	3749		1669		3036		1367	

TABLE 4. Comparison of CMF Values

Highway Type	Source	Figure/Equation	CMF Value by Skid Number	
			25	50
Two-lane	Blackburn et al. (1978)	FIGURE 2 (two-lane)	1.30	0.80
	Proposed	Equation 13 (two-lane)	1.33	0.83
Multilane	Blackburn et al. (1978)	FIGURE 2 (multilane)	1.56	0.63
	Proposed	Equation 13 (undivided)	1.64	0.72
	Proposed	Equation 13 (divided)	1.61	0.73

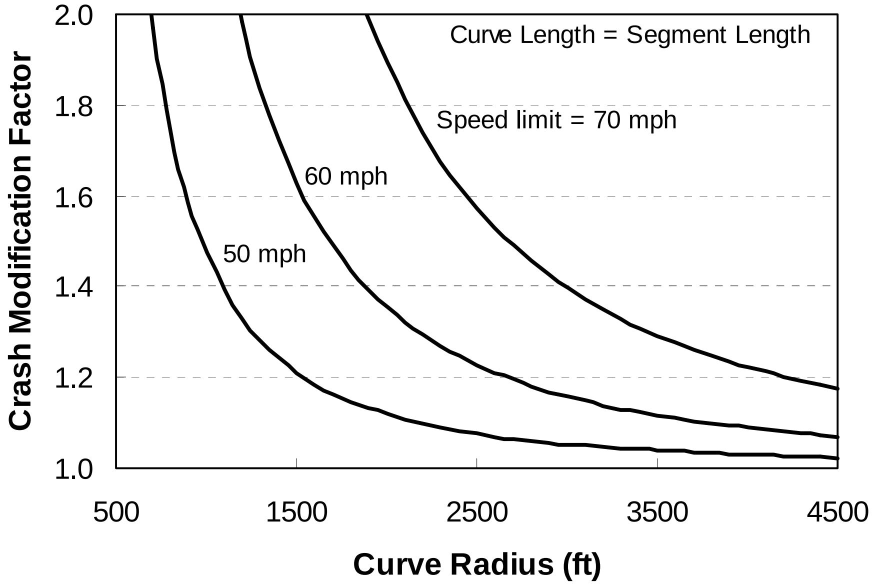


FIGURE 1. Curve Radius Crash Modification Factor (Bonneson and Pratt, 2009).

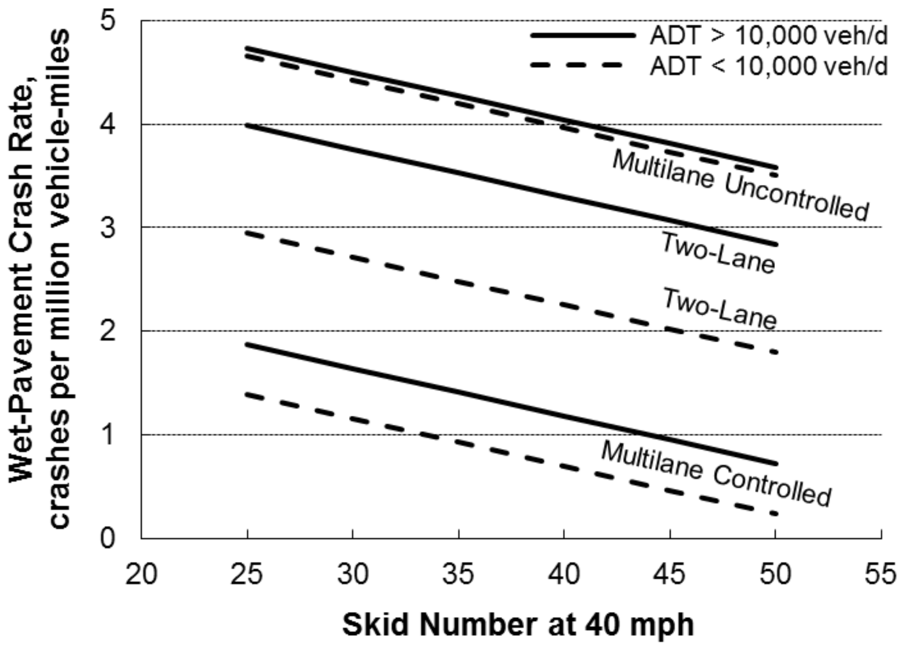


FIGURE 2. Relationship between Pavement Friction and Wet-Weather Crash Rate (Blackburn et al. 1978).

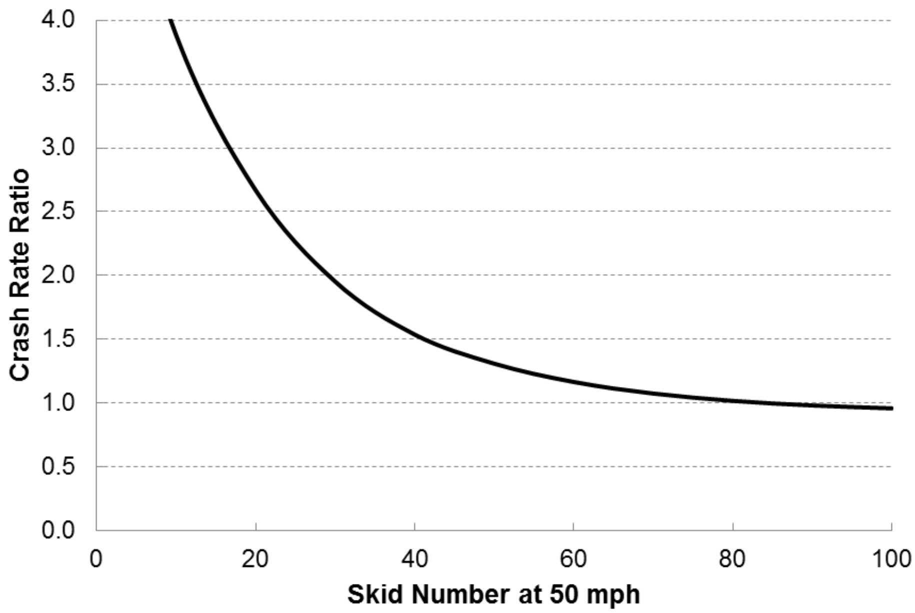
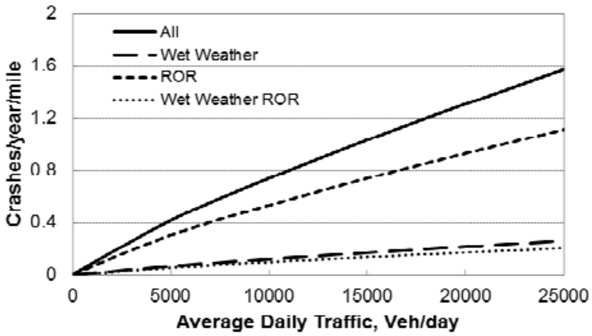
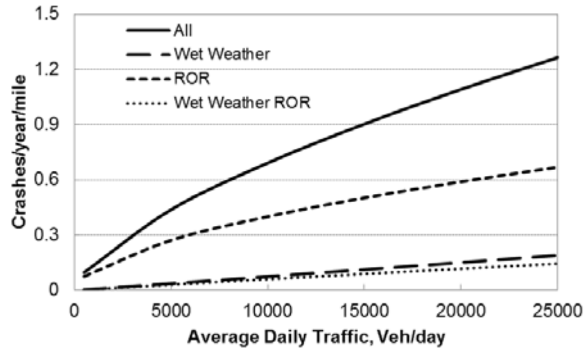


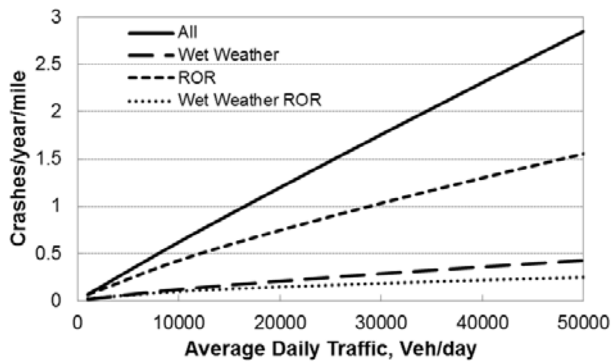
FIGURE 3. Relationship between Skid Number and Wet-Weather Crash Frequency (Long et al. 2014, Wu, H. et al. 2014).



a) Two-lane Highways

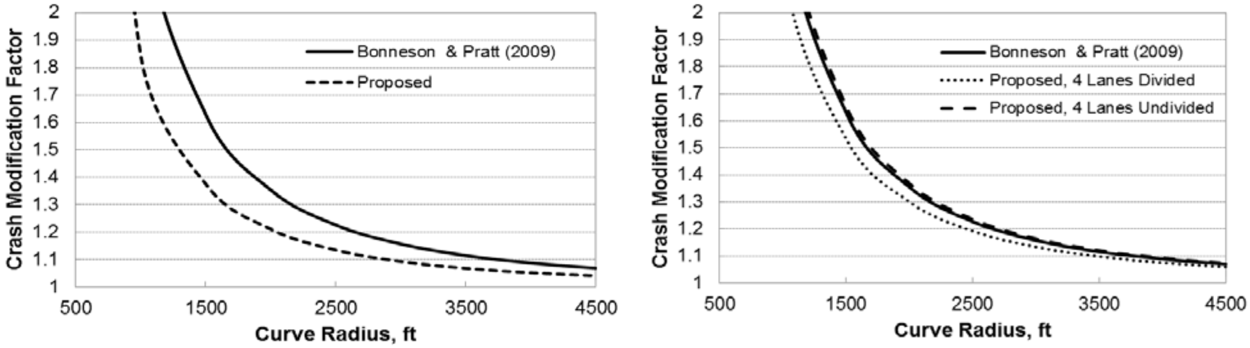


b) Four-lane Undivided Highways



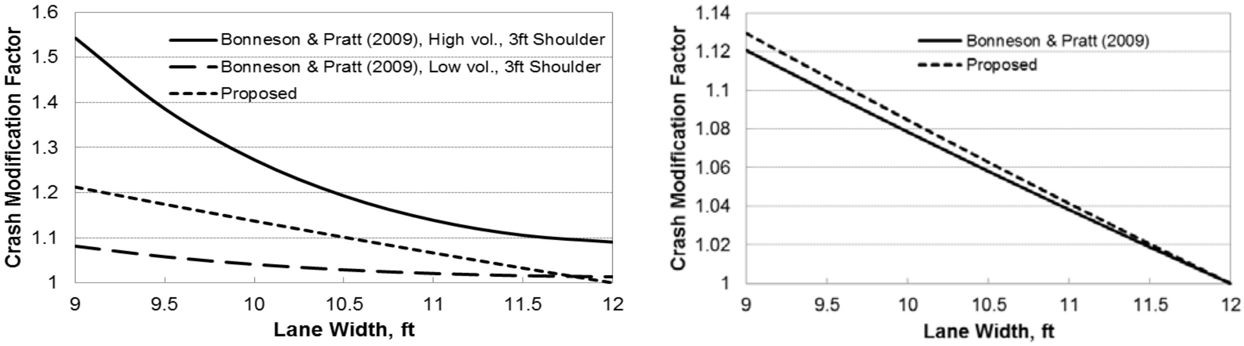
c) Four-lane Divided Highways

FIGURE 4. Number of Crashes with Change in the Average Daily Traffic.



a) Two-lane Highways b) Four-lane Highways

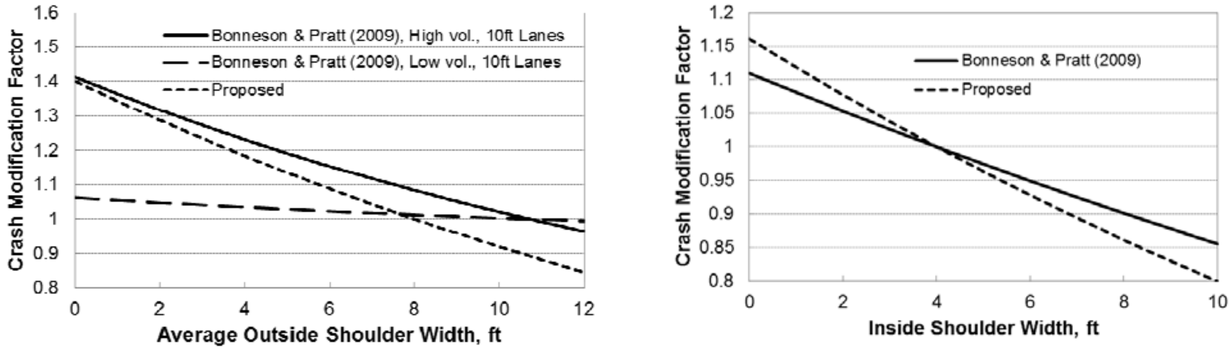
FIGURE 5. Curve Radius CMF.



a) Two-lane Highways

b) Four-lane Undivided Highways

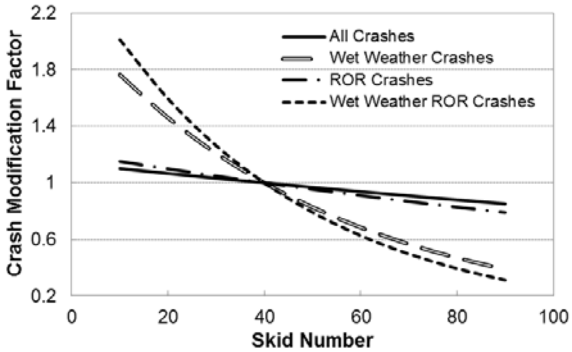
FIGURE 6. Lane Width CMF.



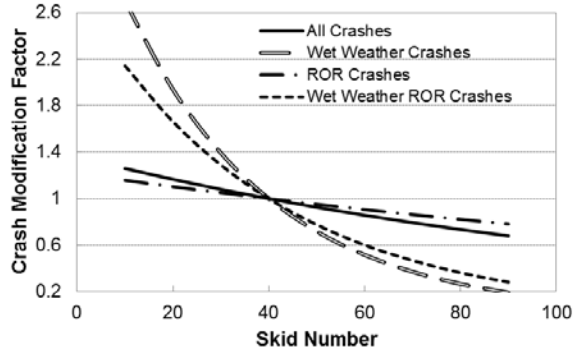
a) Two-lane Highways

b) Four-lane Divided Highways

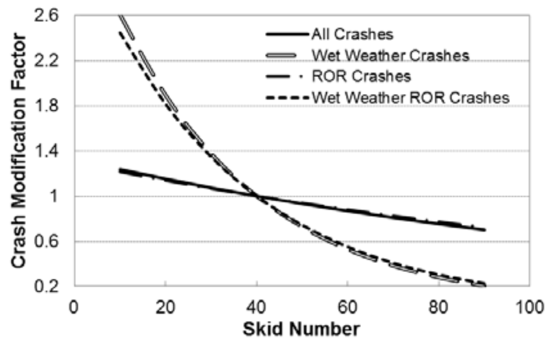
FIGURE 7. Shoulder Width CMF.



a) Two-lane Highways



b) Four-lane Undivided Highways



c) Four-lane Divided Highways

FIGURE 8. Skid Number CMF.

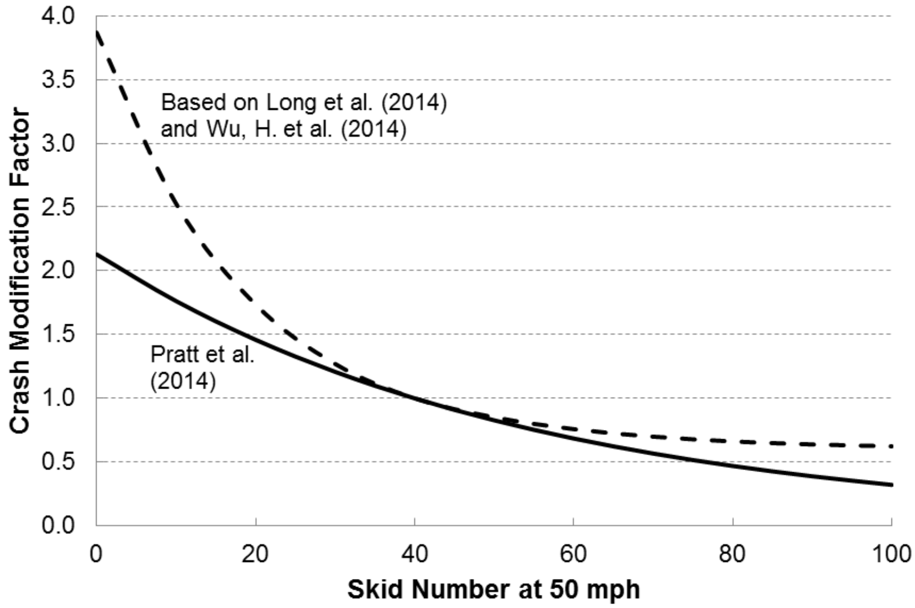


FIGURE 9. Comparison of Skid Number CMFs
(Pratt et al. 2014, Long et al. 2014 and Wu, H. et al. 2014).