EVALUATING CURVE SPEED BEHAVIOR USING SHRP 2 DATA

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by

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16. Abstract

Horizontal curves are associated with a disproportionate number of severe crashes. Factors that mostly influence horizontal curve safety are speed limit compliance, geometric features of the curve, sight distance, and traffic volume. In recent years, several attempts have been made to explore horizontal curve safety using the Second Strategic Highway Research Program (SHRP 2) data, but none focused on operating speeds on curves. The SHRP 2 data include vehicle speeds that can be used to validate the speed prediction models developed in other states and check if the calibration is needed. The first objective of this study was to use the SHRP 2 database to assess the transferability of the speed prediction models developed in Texas to the state of Indiana. The second objective is to identify any relationship between speeds and the frequency that the given driver traverses the curve or road of interest. The third objective is to simultaneously assess curve severity and crash rates at horizontal curves using operating characteristics and safety data, respectively. The study results revealed that the speed differential models developed in Texas can be extended to multiple states with the application of a multiplicative adjustment factor. It was also found that the 85^{th}-percentile speeds of familiar drivers are greater than that of unfamiliar drivers at the curve midpoint and the prediction models worked better for unfamiliar drivers than familiar drivers. Finally, the results show that, for the curves belonging to more severe categories, side friction differential is positively associated with the crash rate.

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LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
DC	Degree of curve
EPDO	Equivalent property damage only
HSM	Highway Safety Manual
IHSDM	Interactive Highway Safety Design Model
kph	Kilometers per hour
MC	Midpoint of the curve
mph	Miles per hour
NDS	Naturalistic Driving Study
OSWC	Observed speed with constant accepted side friction demand limits
OSWV	Observed speed with varying accepted side friction demand limits
PC	Point of curve
PDO	Property damage only
PSWC	Predicted operating speed with constant accepted side friction demand limits
PSWV	Predicted operating speed with varying accepted side friction demand limits
PT	Point of tangent
RID	Roadway Information Database
SHRP 2	Second Strategic Highway Research Program
SPF	Safety performance function
SVROR	Single vehicle run-off-road

CHAPTER 1. INTRODUCTION

Horizontal curves are associated with a disproportionate number of severe crashes. Due to the predominance of horizontal curves on typical rural roads, a higher percentage of fatal curve-related crashes occur on rural roads, particularly on two-lane rural roadways. Fatality rates on rural roads are typically more than twice the rate on urban roads because of a number of infrastructure and non-infrastructure related issues. Factors that mostly influence horizontal curve safety are speed limit compliance, geometric features of the curve, sight distance, and traffic volume.

In the process of evaluating and establishing advisory speeds for rural horizontal curves, Bonneson and Pratt (*1*) developed speed prediction models using data collected at 41 rural curve sites in the state of Texas. The application of speed prediction models and the method for setting curve advisory speeds have been tested in the states of Texas and Tennessee (*2*).

In a later study, Pratt et al. (*3*) calibrated a model similar to the one developed by Bonneson and Pratt (*1*) for predicting operating speeds the midpoint of horizontal curves, and also calibrated models to obtain speed differentials as vehicles traversed from the point of curvature (PC) to the midpoint of the curve (MC) and then the point of tangency (PT), such that a complete speed profile could be estimated through the curve.

The Second Strategic Highway Research Program (SHRP 2) conducted the largest and most comprehensive naturalistic driving study (NDS) in Florida, Indiana, North Carolina, New York, Pennsylvania, and Washington. Hallmark et al. (*4*) evaluated the driving behavior on rural 2-lane curves using the SHRP 2 data. At the time their research was conducted, information on crash or near-crash was not available, so the authors considered the likelihood of crossing the right or left lane line (encroachments) and speeding as dependent variables.

Research was not conducted so far to see if the SHRP 2 data can be used to calibrate or validate the speed prediction models. The SHRP 2 data include vehicle speeds that can be used to validate the speed prediction models and check if the calibration is needed. This will reveal the differences in driver behavior and speed limit compliance among various states. The Roadway Information Database (RID) contains detailed roadway data in and around the study sites and can be used to obtain other needed variables in the models.

The first objective of this study was to use the SHRP 2 database to assess the transferability of the speed prediction models developed by Bonneson and Pratt (*1*) and Pratt et al. (*3*) to the state of Indiana. The second objective is to identify any relationship between speeds and the frequency that the given driver traverses the curve or road of interest. Mainly, the aim is to identify the difference in speeds along the curve of a familiar driver when compared with an unfamiliar driver. The third objective is to simultaneously assess curve severity and crash rates at horizontal curves using operating characteristics and safety data, respectively.

The rest of this document is organized as follows. In chapter 2, literature review is provided. Chapter 3 presents the descriptive data analysis. Chapter 4 provides the results of the speed prediction analyses. Chapter 5 presents the curve severity analysis results. The document ends with conclusions and future research.

CHAPTER 2. LITERATURE REVIEW

Horizontal curves are essential elements of highway systems. However, curves have been consistently identified as a safety concern by roadway agencies. Each year, about 25 percent of fatal crashes occur at horizontal curves, causing approximately 10,000 fatalities, as shown in Figure 1 (*5*-*7*). However, the total mileage of curve segments accounts for a relatively low percentage. For example, the total length of curve segments accounts for about 10 percent of the highway system in a region of southern Minnesota, but the crashes occurred on these curves account for more than 30 percent of the total crashes. Crashes are over-represented on horizontal curves, and the average crash rate for curves is much higher than that of tangents (*8*).

Crash analysis has shown that single vehicle run-off-road (SVROR) and head-on crashes are the most prevalent collision types among the fatal crashes occurring on horizontal curves (*6*). SVROR and head-on crashes account for 76 and 11 percent, respectively.

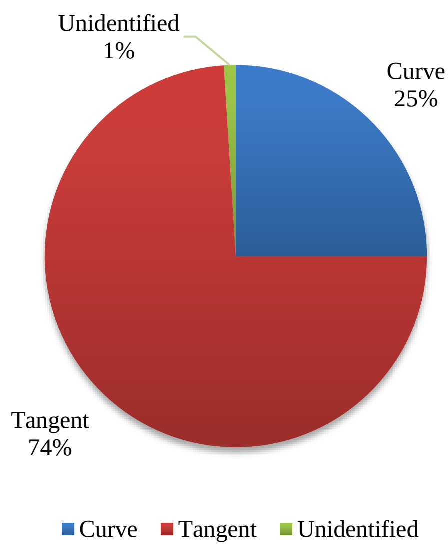


Figure 1. Percentage of Fatalities by Roadway Alignment.

(Source: Torbic et al. (*6*))

Usually, drivers have to decelerate when entering a horizontal curve from a straight section. The drivers adjust their speeds on curves based on various factors, such as curve radius, superelevation, side friction, sight distance, vehicle type, driving desire, etc. Typically, sharper curves (i.e., smaller radii) require slower speeds to negotiate. The American Association of State Highway and Transportation Officials *A Policy on Geometric Design of Highways and Streets* (commonly known as *Green Book*) (*9*) provides an equation to describe the kinematics of vehicle motion on a horizontal curve, as shown in Equation 1**Error! Reference source not found.**:

$$V_c = \sqrt{gR(f_D + e/100)} \tag{1}$$

Where,

V_c = curve speed, ft/s.

f_D = side friction demand factor (or lateral acceleration).

e = superelevation rate, percent.

g = gravitational acceleration.

R = radius of curve, ft.

Given a specific curve, if the vehicular speed is not consistent with the curve speed, the vehicle is very likely to run off the road. This happens more frequently when the operating speed on the adjacent tangents is significantly greater than the curve speed. Besides, vehicles' trajectories are not exactly the same as the curves' alignments. Drivers trend to drive toward the center of the pavements (*10*). These might be the reasons for over-represented run-off-the-road and head-on crashes on horizontal curves. Acknowledging the importance of speeds on curve safety, studies on the operating speeds of horizontal curves have been extensively conducted in the past couple of decades.

SPEED AND CURVE CRASHES

Speeding and driving too fast for conditions have been considered the most prevalent factors contributing to traffic crashes on horizontal curves. Liu and Chen (*11*) analyzed speeding-related crashes in six states. Researchers found that the relative proportion of crashes that occurred on curved sections of the road was much higher in speeding-related crashes. About 40 percent of speeding-related fatalities occurred on a curve, which is nearly twice the proportion of non-speeding related fatalities (about 20 percent) that occurred on a curve. At least 50 percent of curve crashes were a result of speeding or driving too fast for conditions. In comparison, only about one-third of total crashes were speeding-related (*12*).

Speed reduction on horizontal curves from preceding tangents is another reason for curve crashes. Studies have shown that the larger the speed reduction required from the preceding tangent to the subsequent curve, the higher the crash rate on the curve. In other words, the higher the required speed reduction, the more likely it is that some drivers will not reduce their speed as much as required (*10*). The Interactive Highway Safety Design Model (IHSDM) provides the relative crash rates on curves that require speed reductions compared to curves that do not require speed reductions, as shown in Figure 2 (*13*). As the required speed reduction increases, the crash rate becomes greater. When the speed reduction is 10 kilometers per hour (kph), the crash rate is about three times higher than that of no speed reduction. In the IHSDM consistency design model, 10 and 20 kph are used as the threshold for categorizing the curves. If the speed reduction is less than 10 kph, the design is typically considered as good; fair if it is between 10 and 20 kph; and poor if greater than 20 kph.

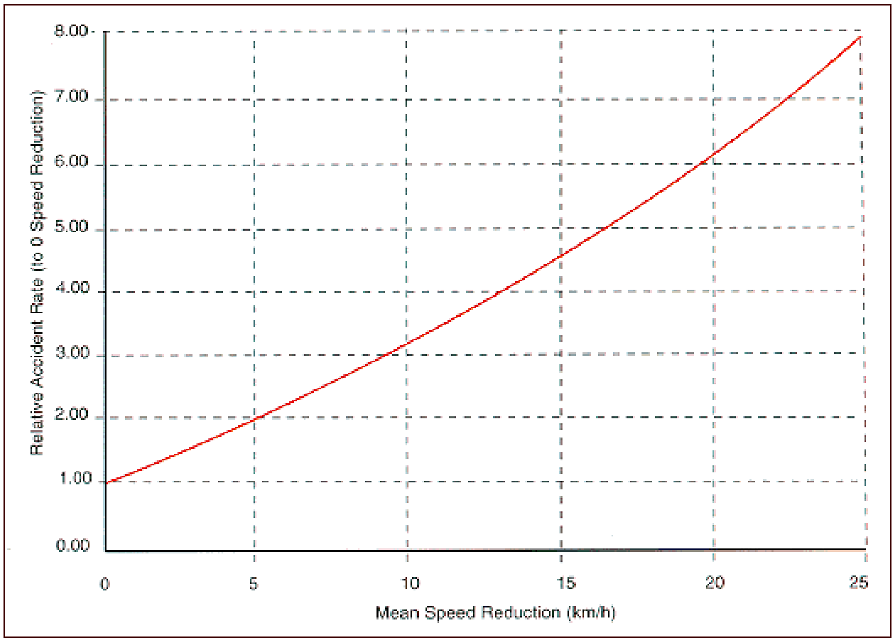


Figure 2. Relative Crash Rate vs Speed reduction on Horizontal Curves.

(Source: *Krammes (13)*)

de Oña et al. (*14)* studied the relationship between speed reduction and crashes for horizontal curves on Spanish two-lane rural roads. Although the model coefficients estimated in Spain were not exactly the same as that provided in IHSDM, the results were similar, that is higher speed reduction is associated with greater crash rates.

Anderson et al. (*15*) developed crash prediction models for horizontal curves. In the model, speed reduction was included as an independent variable. The modeling result, as shown in Equation 2**Error! Reference source not found.**, indicates that the speed reduction is positively related with expected crashes on horizontal curves. As the speed reduction increases by one unite (i.e., kph), the expected crash number increases by about 7 percent.

$$Y = e^{-7.1977} AADT^{0.9224} CL^{0.8419} e^{0.0662SR} \quad (2)$$

Where,

Y = expected number of crashes occurred on the horizontal curve during a 3-year period.
$AADT$ = average annual daily traffic (vpd).
CL = horizontal curve length (km).
SR = speed reduction on horizontal curve from adjacent tangent or curve (kph).

Similar results were reported by Ng and Sayed (*16*) while analyzing horizontal curves on two-lane rural highways in Canada. With 1 kph reduction in speed on curves, the expected crashes increase by 5 percent.

Pratt et al. (*17*) developed an analysis framework to assess the need for surface treatments at horizontal curves. In the study, researchers developed safety performance function (SPF) for curves. Based on the SPF, the estimated number of crashes on a horizontal curve is directly related with the radius. The smaller the radius is, the more expected number of total crashes. Equation 3 **Error! Reference source not found.**shows the CMF for curve radius:

$$CMF = 1 + 0.5796(0.147V)^4 \frac{(1.47V)^2}{32.2R^2} \tag{3}$$

Where,

CMF = crash modification factor for a curve radius.
V = posted speed limit (miles per hour [mph]).
R = curve radius (ft).

Recently, Geedipally and Pratt (*18*) developed models to predict vehicle travel paths along horizontal curves with speed differential (i.e., 85th-percentile curve speed – posted advisory speed) as one of the influential variables. They found that as speed difference increases, the likelihood of cutting, swinging, and drifting travel path types increases, which are considered to be undesirable. These paths represent situations where drivers may have misjudged the severity of the curve.

As can be seen in the previous studies, operating speeds on both a curve and its preceding tangent play an important role in curve safety. In considering speeds and other characteristics of curves, researchers have proposed the concept of curve severity to describe the safety level of a curve (*19*). Bonneson et al. (*20*) reviewed relevant literature and concluded that there are three viable measures of curve severity: speed differential, energy differential, and friction differential.

Pratt and Bonneson (*21*) pointed out that defining curve severity based on speed differential (i.e., difference between speeds at a curve and its adjacent tangent) may result in improper assessments, since drivers are more reluctant to reduce their speeds on roadways with higher speed limits and thus they accept speeds associated with higher crash risk. Researchers further developed curve severity measures based on side friction demand differential and kinetic energy differential, which are proportional to each other. They recommended side friction differential for road agencies as a measure of curve severity. Thus, this study will use the side friction differential to measure curve severity, and compare the severity of curves with crash rates.

CURVE OPERATING SPEED PREDICTION MODELS

Design speed is one of the most important measures that designers use to determine various geometric features of a highway, such as curve radius, superelevation rate, sight distance, etc. However, operating speed (often referred to as the 85th-percentile speeds) is usually inconsistent with the design speed (*22*, *23*). As mentioned in the previous section, researchers proposed using speed consistency to examine the road safety level. For doing that, researchers often developed statistical models to predict the operating speed. Operating speed prediction models were then extensively used for examining the highway design consistency.

One of the earliest operating speed prediction model was developed by Lamm et al. (*24*). Researchers collected data (e.g., speeds, geometric, vehicle type) on 24 curved roadway sections on two-lane rural highways in New York State. Multiple linear stepwise regression technique was used for the evaluation of the quantitative effects of curve factors on operating speeds. The analyses revealed that degree of curve (DC) was the best available single-variable predictor of operating speeds. Equation 4 shows the model:

$$V_{85} = 58.656 - 1.135DC \tag{4}$$

Where,

V_{85} = estimated operating speed on horizontal curves (mph).
DC = degree of curve.

Lamm et al. (*24*) used other variables that influence the operating speed, but they did not show much significance. Equation 5**Error! Reference source not found.** shows the full model:

$$V_{85} = 34.700 - 1.005DC + 2.081LW + 0.174SW + 0.004AADT \tag{5}$$

Where,

LW = lane width (ft).
SW = shoulder width (ft).
$AADT$ = average annual daily traffic (vpd).

Kannellaidis et al. (*25*) conducted another study on driver's speed behavior on horizontal curves. The relationship between operating speed on curves and various geometric design parameters was investigated. The results suggested that the operating speed is strongly related to the curve radius. Equation 6**Error! Reference source not found.** shows the relationship between operating speed and curve radius:

$$V_{85} = 32.2 + \frac{2226.9}{R} - \frac{533.6}{\sqrt{R}} + 0.839V_t \tag{6}$$

Where,

V_{85} = estimated operating speed on horizontal curves (kph).
R = curve radius (m).
V_t = adjacent tangent operating speed (kph).

Islam and Seneviratne (*26*) also pointed out that the radius of curve is the most significant parameter in predicting operating speeds on horizontal curves. In addition, the operating speed values on different curve points differed significantly. Three prediction models were developed for the speeds at the PC, MC, and PT. The models are shown in Equations 7**Error! Reference source not found.** to 9**Error! Reference source not found.**, respectively:

$$V_{85,PC} = 95.41 - 1.48DC - 0.012DC^2 \tag{7}$$

$$V_{85,MC} = 103.03 - 2.41DC - 0.029DC^2 \tag{8}$$

$$V_{85,PT} = 96.11 - 1.07DC \tag{9}$$

Where,

$V_{85,PC}$, $V_{85,MC}$, and $V_{85,PT}$ = estimated operating speeds at PC, MC, and PT, respectively (kph).
DC = degree of curve.

Krammes et al. (*27*) conducted one of the most comprehensive studies on operational speed on rural two-lane highways. Researchers collected speed and geometric data for 138 horizontal curves on rural two-lane highways in five states (i.e., New York, Pennsylvania, Washington, Oregon, and Texas). The operating speeds were observed at three locations: the midpoint of the horizontal curve, the approach tangent, and the departure tangent. Three models including different independent variables were developed for predicting horizontal curve operating speeds, as shown in Equations **Error! Reference source not found.** 10 to 12**Error! Reference source not found.**:

$$V_{85} = 103.66 - 1.95DC \tag{10}$$

$$V_{85} = 102.45 - 1.57DC + 0.0037L - 0.10I \tag{11}$$

$$V_{85} = 41.62 - 1.29DC + 0.0049L - 0.10I + 0.95V_t \tag{12}$$

Where,

V_{85} = estimated operating speed on horizontal curves (i.e., midpoint of the horizontal curve) (kph).
DC = degree of curve.
L = length of curve (m).
I = deflection angle (degree).
V_t = measured operating speed on approach tangent (kph).

To evaluate the highway design consistency, Fitzpatrick and Collins (*28*) and Fitzpatrick et al. (*29*) developed speed prediction models for two-lane rural highways. Several equations were developed to predict horizontal curve operating speeds for different alignments. Equation 13**Error! Reference source not found.** shows a general equation developed by Fitzpatrick et al. (*29*):

$$V_{85} = a - \frac{b}{R} \tag{13}$$

Where,

V_{85} = estimated operating speed on horizontal curves (kph).
R = curve radius (m).

In the above equation, *a* and *b* are two coefficients, and they vary based on different conditions. For example, when the horizontal curve is on a grade between −9 percent and −4 percent, a and b equal to 102.10, and 3077.13, respectively. For complete speed prediction equations, please refer to Fitzpatrick et al. (*29*). The models were then incorporated into the

IHSDM to predict highway operating speeds and evaluate design consistency. This model is probably the most widely used for predicting operating speeds on two-lane rural highways.

Bonneson and Pratt (*1*) hypothesized that drivers modify their side friction demand based on a desire for both safe and efficient travel, and proposed a curve speed model by combining the side friction demand equation with the relationship between the demand and vehicular speed. Equation 14 shows the general model form:

$$V_{85} = \left(\frac{15R(b_0 - b_1V_t + b_2V_t^2 + e/100}{1 + 32.2Rb_2}\right)^{0.5} \leq V_t \tag{14}$$

Where,

V_{85} = estimated operating speed on horizontal curves (mph).
R = curve radius (ft).
V_t = tangent speed (mph).
e = superelevation rate, percent.
b_0, b_1, b_2 = coefficients to be calibrated.

The model form may vary more or less depending on the pre-assumed relationship between speed reduction and friction. To calibrate the parameters, researchers assembled data at about 40 curve sites in Texas. The geometric and traffic control data of each site were collected. Speeds of over 6,600 passenger cars on both directions were observed at each site during a 24-h period, which includes daytime and nighttime conditions. The coefficients were then calibrated using nonlinear regression procedure. Researchers further validated the prediction model using the speed data observed in a previous project (*30*). Researchers found that the proposed model could accurately predict curve speeds. The bias was within 0.3 mph.

Miles and Pratt (*2*) later evaluated the model developed by Bonneson and Pratt (*1*) using data collected in another state (i.e., Tennessee). Characteristics (i.e., radius, superelevation, posted speed limit) of 19 curves on two-lane rural highways were collected, and vehicular speeds were observed at two points of each curve. The predicted 85^{th}-percentile curve speeds were estimated by the model and compared with the observed speeds. In all cases, the two were not statistically different from each other, indicating the model was able to accurately predict the operating speeds on horizontal curves.

In the aforementioned study (*17*), researchers calibrated Bonneson and Pratt (*1*)'s base model for predicting operating speeds at horizontal curves. Equation 15 shows the model:

$$V_{85} = \left(\frac{15R(0.2202 - 0.00142V_t + 0.000041V_t^2 + e/100}{1 + 0.000061R}\right)^{0.5} \leq V_t \tag{15}$$

Although speed prediction models were initially developed for designing horizontal curves and evaluating design consistency, they have also been used to establish curve advisory speeds (*20*).

In addition to the operational speed prediction models documented above, several other studies have also developed models to predict the operating speeds, but most of them are not widely used. Thus, they are not documented in this study. Some researchers have reviewed the operating speed prediction models and found that these models are generally similar (*29, 31, 32*). McLean (*33*) reviewed the speed prediction models and concluded that they can be classified into two classes: models of Class 1 based only on curve radii; and models of Class 2 based on both curve radii and approach speed. Bonneson (*30*) pointed out the regression fitting results of Class 2 models were better than that of Class 1, since approach speed in Class 2 models provided additional information about speed environment of the horizontal curve. The research further compared a couple of speed prediction models. Results indicated these models were generally in very good agreement. Table 15 and Table 16 in the Appendix summarize the most common speed predicting models and the list of variables used in the speed prediction models developed in Texas, respectively.

CHAPTER 3. DATA DESCRIPTION AND INTEGRATION

DATA DESCRIPTION

To carry out the empirical analysis, researchers explored the SHRP 2 data. The SHRP 2 program consists of a NDS data and a companion, RID. The NDS data were collected from more than 3,500 volunteer passenger-vehicle drivers aged 16 to 98 during a three-year period, with most drivers participating for one to two years (2010–2012). The study was conducted at sites in six states: Indiana, New York, North Carolina, Washington, Pennsylvania, and Florida. The two predominantly rural sites were in Indiana and Pennsylvania and covered about 10 counties each. The other four urban or mixed sites covered one to three counties each. The total study area encompassed more than 21,000 square miles. Specifically, NDS collection sites were in Bloomington, IN; Buffalo, NY; Durham, NC; Seattle, WA; State College, PA; and Tampa, FL. RID roadway geometric design and historical crash data encompasses the six NDS sites. This study analyzed the RID and NDS data from four rural roadway sections in Indiana (Figure 3):

- US-50W (21.7 miles).
- US-50E (43.0 miles).
- US-231 (17.6 miles).
- I-57 (24.5 miles).

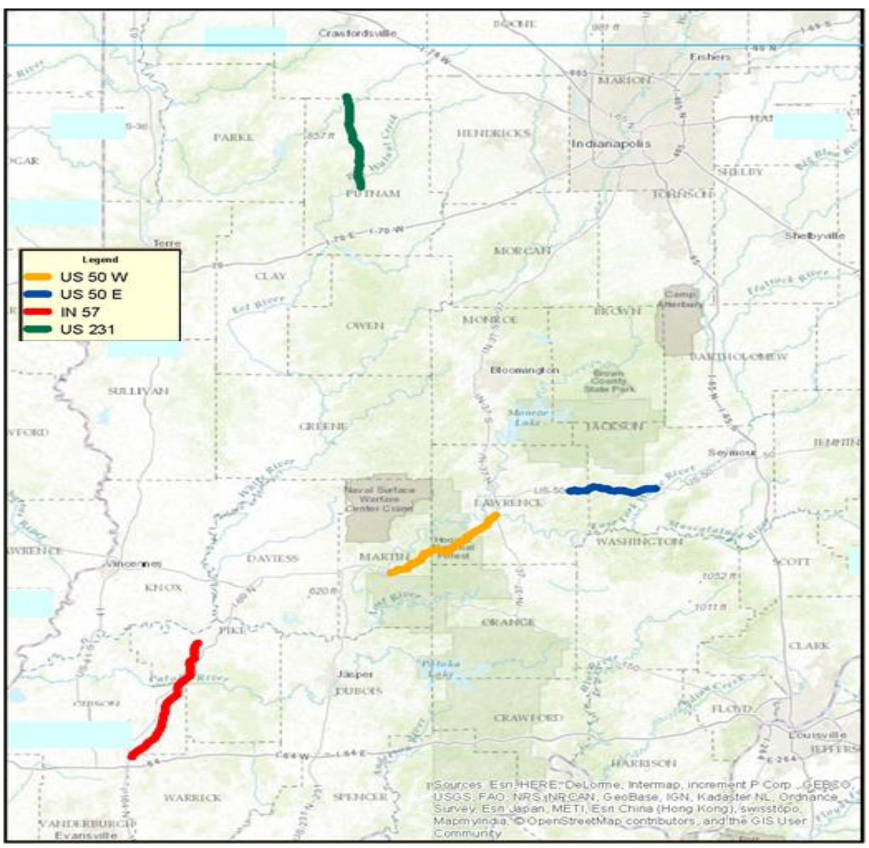


Figure 3. Location of Study Sites.

DATA INTEGRATION

A total of 252 curves were identified (considering both directions of travel) on the four selected roadway sections. To conduct the data analysis, this study integrated the RID and NDS data in three steps as described below.

Integrating RID Roadway Design Layers

First, several RID layers indicating the alignment, lane, shoulder and grade data were integrated using the ArcGIS tools and R-CRAN open source software. To integrate the RID layers, both directions of travel were treated separately. The missing data for some of the segments were obtained using Google Earth.

The linear segmentation had been applied for each RID layer based on the characteristics of the design element. For example, the segments in alignment layer are based on the length of the curve and tangent. However, they cannot be matched with the segments in the lane layer since the lane segments are shorter. To match the alignment layer and the lane layer, researchers identified the lane segments falling within the alignment segment and computed the weighted average of lane widths. For example, in Figure 4, there are two segments in the alignment layer but they are divided into three segments in the lane layer. The lane width for segment I was calculated as a weight average of A and B based on their length. The same approach was applied to segment II.

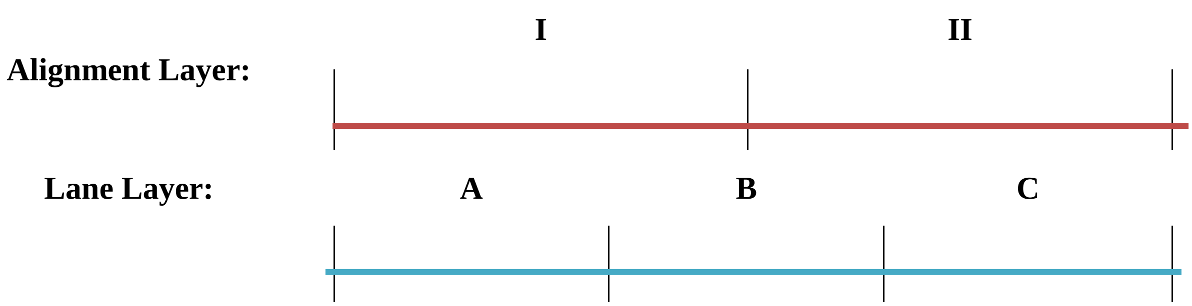


Figure 4. Linear Segmentation of RID Layers.

Table 1 shows the descriptive statistics of all the design elements obtained from the integrated RID layers.

Table 1. Descriptive Statistics of Curves.

Roadway Section	Number of Curves		Statistics	Radius (ft)	Super-elevation Rate (%)	Curve Length (ft)	Speed Limit (mph)
US-50W (Route 490)	Left	50	Min	602	0.50	397.0	50
			Max	6,156	7.60	2,858.0	55
	Right	50	Mean	1,883.6	4.34	975.24	52.1
			S.D.	1,240.1	1.93	388.59	2.49
US-50E (Route 493)	Left	20	Min	602	0.50	397.0	50
			Max	6,156	7.60	2,858.0	55
	Right	21	Mean	1,953.4	4.17	1,001.62	52.2
			S.D.	1,267.4	1.95	397.18	2.51
IN-57 (Route 619)	Left	29	Min	821	-0.50	732.0	55
			Max	6,146	9.80	2,123.0	55
	Right	30	Mean	2,108.3	4.80	1,083.20	55.0
			S.D.	1,300.0	2.69	313.17	0.0
US-231 (Route 1753)	Left	26	Min	821	-1.40	732.0	55
			Max	11,541	9.80	2,126.0	55
	Right	26	Mean	2,663.9	4.33	1,149.95	55.0
			S.D.	2,383.3	2.98	393.47	0.0

Integrating RID and NDS

In the second stage of data integration process, this study identified the NDS trips (traversals) along the four segments in both direction of travel and integrated the data with the resulting RID file from the previous step. Table 2 shows number of trips on each highway.

Table 2. Number of Trips per Curve.

Roadway Section	Road Side	Number of Trips	Number of Curves
US-50W	Left	26	45
	Right	37	45
US-50E	Left	49	24
	Right	51	24
IN-57	Left	6	21
	Right	32	21
US-231	Left	36	36
	Right	36	36
Total		273	252

To match and link the NDS trip data to RID data, unique Link ID values were used. However, the NDS data are point data that report the GPS and network speed at every point while RID are linear (polyline) data, which show the roadway characteristics of a selected segment or curve, which can be few feet long. Moreover, to conduct the speed prediction analysis, the driver’s speed at the curve center is required. Therefore, the RID and NDS data were merged as point data, where each observation shows the roadway geometry of the curve midpoint and the driver speed at that point. For this purpose, the authors initially classified both NDS and RID data into left and right sides of the road based on the direction of travel of increasing roadway mileposts. The GPS speed data at the curve center were selected from the NDS trip files of the road segment under study.

To merge the GPS speed and curve geometry data, the authors used the latitude and longitude coordinates from both data sets. However, since the coordinates did not exactly match across the two databases (as shown in Figure 5), the authors allowed for a tolerance of 0.0002 degrees in both coordinates, which equates to a distance tolerance of about 90 ft. The authors used computed headings to ensure that vehicle speed observations were properly assigned to the appropriate direction of travel (e.g., eastbound vehicle speeds are assigned to the eastbound side of the roadway). If more than one speed observation was obtained for the same vehicle at the same point of interest, the observations were averaged, and if the resulting coefficient of variation (i.e., standard deviation divided by mean) was greater than 0.1 for the readings, the vehicle's readings were deleted from the database, as a large variation would likely indicate either erroneous data or erratic behavior on the part of the driver. As a result of these merging and quality-control procedures, a total of 211 curves remained that had speed data available at the approach tangent and the MC; 185 curves remained that had speed data available at the approach tangent, the PC, the MC, and the PT.

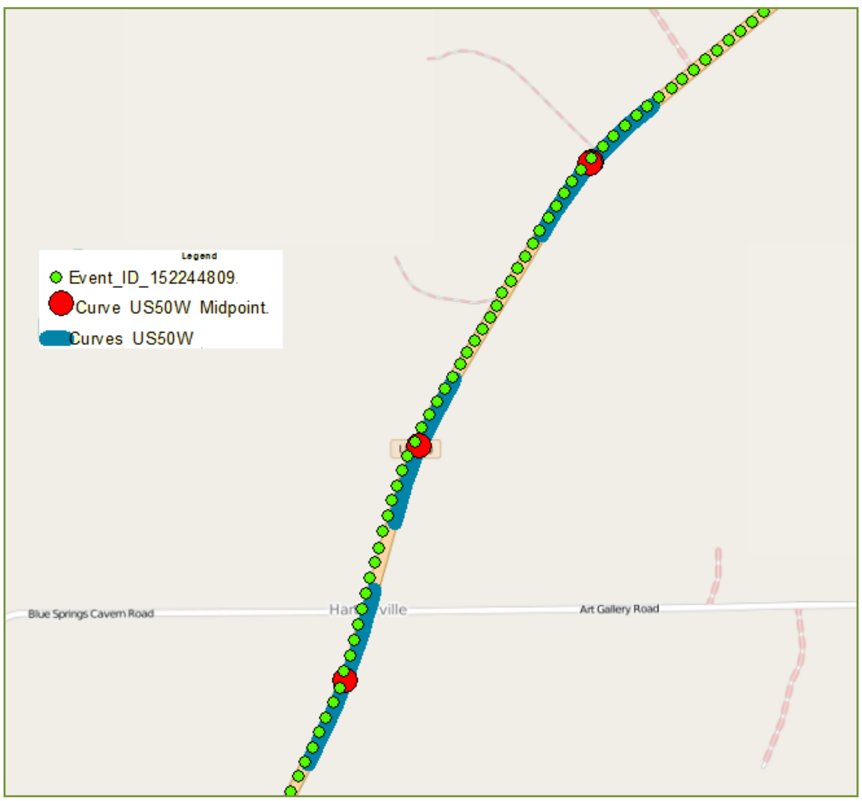


Figure 5. Matching NDS and RID Data for One Trip.

After integrating the RID and NDS data, operating speeds for curves and preceding tangents, as well as the deflection angle, were calculated using the speeds observed in NDS traversals. Table 3 shows a summary statistics of these variables.

Table 3. Summary Statistics of NDS Trips.

Variable	Min	Max	Mean	S.D.
Posted Speed Limit (mph)	50	55	53.8	2.1
Operating Curve Speed (mph)	49.9	66.2	59.9	3.4
Operating Tangent Speed (mph)	13.0	67.4	59.1	6.3

Integrating RID and Crash Data

In addition to the roadway geometry data, the RID database contains 8-years of historical crash data and AADT data (2006–2013). RID crash data were obtained from Indiana State Department of Transportation. The RID crash database incorporates the crash details and other contributing factors such as weather, roadway conditions, and driver characteristics. Figure 6 shows crash severity heat map for one of the rural highway segments, US-50W. Overall, the crashes have mostly occurred on the curves; the curves with smaller radii seem to be associated with more crashes. Table 4 illustrates the summary statistics of the crash data together with the AADT.

Table 4. Summary Statistics of Crashes on Horizontal Curves.

Variable	Min	Max	Mean	S.D.
AADT	1,744	8,841	4091.2	1361.1
Fatal Crashes (8 Yrs)	0	1	0.1	0.3
Injury Crashes (8 Yrs)	0	7	0.6	1.2
Total Crashes (8 Yrs)	0	16	1.9	3.1

Researchers also identified the curves with and without intersections to better understand the crash distribution on these locations. As shown in Table 5, the curves with the intersections were found to be associated with considerably higher number of crashes compared to the curves without intersections.

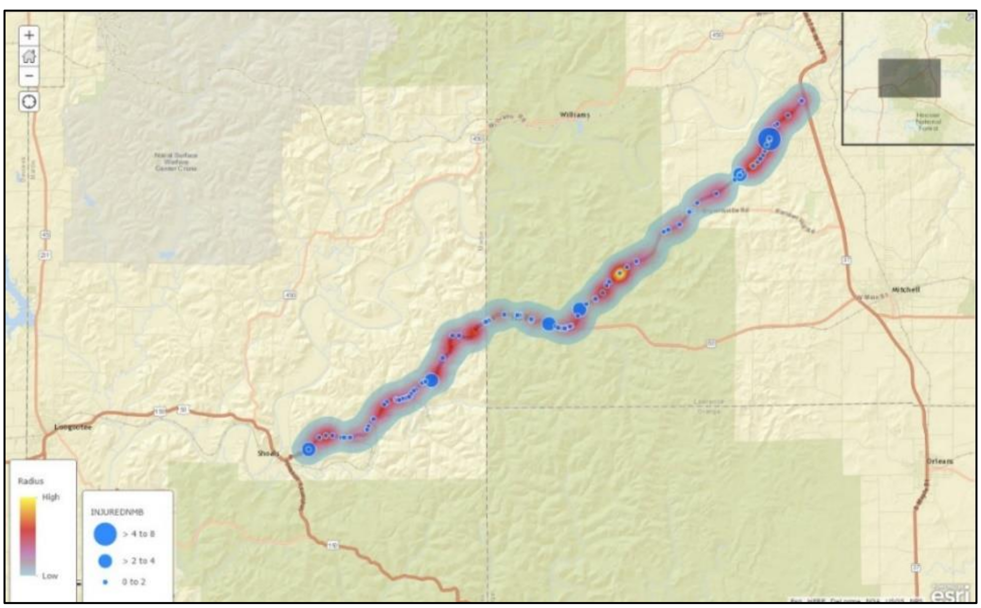


Figure 6. Crash Frequency vs. Curve Radius.

Table 5. Crash Distribution by the Curve Type.

Curve Type	Statistic	Fatal	Injury	Property Damage Only	Total Crashes
Curves with intersections	Min	0	0	0	0
	Max	1	7	22	25
	Mean	0.13	1.29	4.47	5.89
	S.D.	0.34	1.54	4.71	5.74
Curves without intersections	Min	0	0	0	0
	Max	1	7	14	21
	Mean	0.04	0.48	1.39	1.90
	S.D.	0.19	1.04	2.34	3.16

CHAPTER 4. ANALYSIS OF SPEED PROFILES

SPEED PREDICTION ANALYSIS

Methodology

The speed predictions obtained from the curve speed models developed by Bonneson and Pratt (*1*) and Pratt et al. (*3*) were compared to the GPS-measured speeds obtained from the NDS data. GPS-measured speeds were extracted from the NDS data at or close to the midpoint of each curve, as well as near the midpoint of the approach tangent and near the curve PC and PT, using Statistical Analysis Software.

For the RID data, several calculations had to be performed before a predicted speed could be computed for each curve. Specifically, the NDS speed was converted from kph to mph, deflection angle was computed from the curve length and radius variables, and the sign conventions for the superelevation rates were corrected to match with those used in the application of the curve speed models. The superelevation rate term in the models is defined as positive if the superelevation is helping, or sloped toward the center of the curve, such that it serves to decrease side friction demand. In the RID, superelevation rate was defined as positive if sloping toward the right side of the road, regardless of actual curve direction, such that a helping superelevation would be defined as negative if it is located on a curve on the left side of the road.

Once the deflection angles and corrected superelevation rates were computed for each curve, the models developed by Bonneson and Pratt (*1*) and Pratt et al. (*3*) were used to compute a predicted 85th-percentile speed for each curve. Then, the 85th-percentiles of observed speeds for each curve MC were computed. These two models are described by Equations **Error! Reference source not found.** and **Error! Reference source not found.**, respectively.

In a similar manner, researchers compared the observed 85th-percentile speeds at each curve PC and PT with the predicted values obtained from the models developed by Pratt et al. (*3*). These models are used in tandem with Equation 15**Error! Reference source not found.** and are described as follows:

$$\Delta_{85}v_{PC-MC} = -54.886 + 58.768\sqrt{\frac{v_{t,85}}{v_{c,85}}} - 0.521\frac{5730}{R} \tag{16}$$

$$\Delta_{85}v_{MC-PT} = -12.399 + 15.197\sqrt{\frac{v_{t,85}}{v_{c,85}}} - 0.803\left(\frac{G_{MC} + G_{PT}}{2}\right) \tag{17}$$

Where,
$\Delta_{85}v_{PC\text{-}MC}$ = MC speed subtracted from PC speed, mph.
$\Delta_{85}v_{MC\text{-}PT}$ = PT speed subtracted from MC speed, mph.
$v_{t,85}$ = 85th-percentile tangent speed, mph.
$v_{c,85}$ = 85th-percentile curve MC speed, mph.
R = curve radius, ft.
G_{MC} = roadway grade at curve MC, %.
G_{PT} = roadway grade at curve PT, %.

Curves were included in the comparison if the following criteria were satisfied:

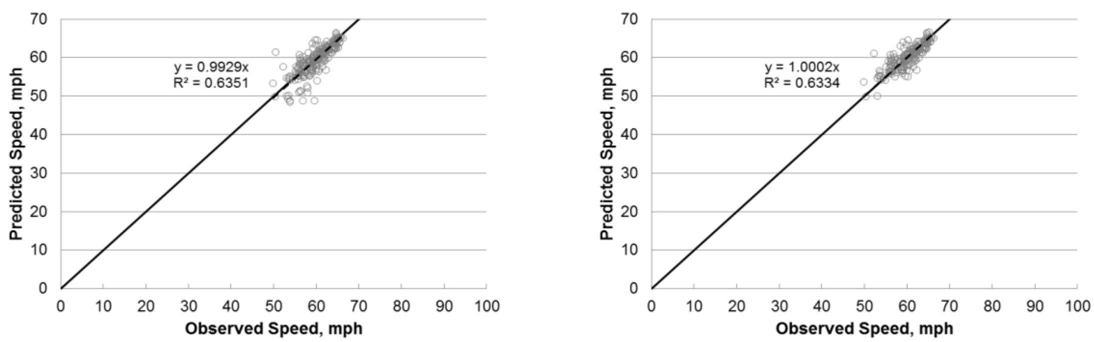
- At least 10 observations of vehicle speed were obtained at the key points (e.g., curve PC, MC, and PT, and midpoint of the approach tangent).
- The coefficients of variation of speed observations at the key points were less than 0.5.

These criteria ensured that the observed speed data were stable and not biased due to the presence of outliers. Predicted speeds were computed using the observed tangent speeds rather than predicted tangent speeds.

Researchers compared the predicted and observed speeds using linear regression and by conducting paired *t*-tests. The results of the comparisons are provided in the next section.

Results and Discussion

Figure 7 compares the observed and predicted MC speeds. As shown, the models provide an estimate of 85th-percentile curve speed without bias. A total of 211 curves are included in the comparison shown in Figure 7a, and a total of 185 curves are included in the comparison shown in Figure 7b.



a. Predicted by Bonneson and Pratt (*1*) **b. Predicted by Pratt et al. (*3*)**

Figure 7. Comparison of Observed and Predicted 85th-Percentile MC Speeds.

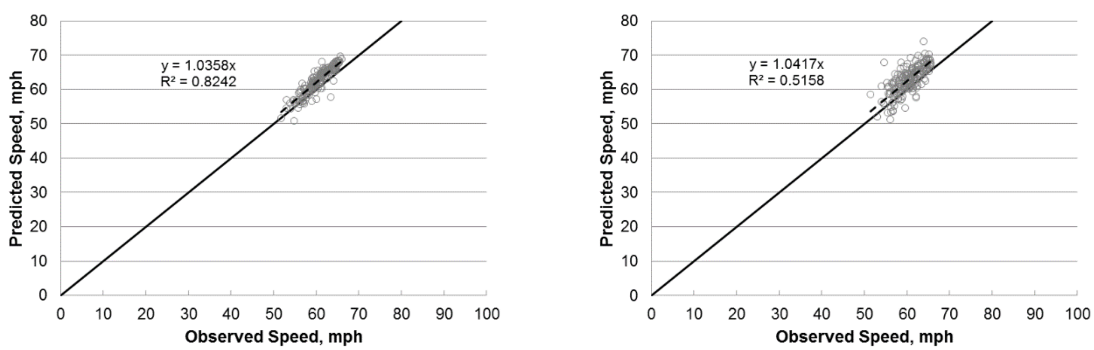
The trend lines in Figure 7 are fitted with a forced zero intercept value. Linear regression estimates were obtained with and without an intercept. Table 6 provides the results of these estimates. The overall fit of the linear estimate, as described by the coefficient of determination (R^2) value, is slightly better when the intercept is allowed to vary from zero (0.641 versus 0.635). However, the estimated intercept value of 5.279 for the Bonneson and Pratt model was found to be statistically insignificant at a 95-percent confidence level (p = 0.062).

In addition to this analysis, paired *t*-tests were performed to compare the predicted and observed 85th-percentile MC speeds. These tests yielded *t*-statistics of 0.012 and 0.695 for the two models, with p-values of 0.99 and 0.49, indicating no statistically significant difference between observed and predicted values.

Table 6. Linear Estimate Parameter Results for MC Speed Models.

Linear Estimate Parameter	Bonneson and Pratt *(1)*, Intercept = 0	Pratt et al. *(3)*, Intercept = 0	Bonneson and Pratt *(1)*, Intercept ≠ 0	Pratt et al. *(3)*, Intercept ≠ 0
Slope Value	0.993	1.000	0.905	0.777
Slope *t*-statistic	371	432	19.3	20.20
Slope *p*-value	< 0.001	< 0.001	< 0.001	< 0.001
Intercept Value	0	0	5.279	13.458
Intercept *t*-statistic	Not applicable	Not applicable	1.878	5.801
Intercept *p*-value	Not applicable	Not applicable	0.062	< 0.001
R^2	0.635	0.633	0.641	0.691

Comparisons of observed and predicted PC and PT speeds are shown in Figure 8a and Figure 8b, respectively. Table 7 provides the linear estimate parameters. Both models are found to produce a slight overestimate of their respective speeds of about 4 percent. The overestimate suggests that Texas drivers are likely to choose higher speeds at the curve PC and PT compared to drivers in Indiana. This difference may be attributed to the higher regulatory speed limits on many rural two-lane highways in Texas. The Indiana sites had no regulatory speed limits greater than 55 mph, while the Texas sites had regulatory speed limits in the range of 55–70 mph. Hence, to extend the Texas-calibrated curve PC and PT speed models to Indiana sites, a recalibration with a multiplicative adjustment factor would be advised. The functional forms of the models appear to be transferable because the bias appears not to vary across the range of speeds at the various sites.



a. PC **b. PT**

Figure 8. Comparison of Observed and Predicted 85th-Percentile PC and PT Speeds.

Table 7. Linear Estimate Parameter Results for PC and PT Speed Models.

Linear Estimate Parameter	PC	PT
Slope Value	1.036	1.042
Slope *t*-statistic	544	307
Slope *p*-value	< 0.001	< 0.001
R^2	0.824	0.512

In addition to this analysis, paired *t*-tests were performed to compare the predicted and observed 85th-percentile PC and PT speeds. These tests yielded *t*-statistics of less than 0.001 with *p*-values of greater than 0.99, indicating no statistically significant difference between observed and predicted values.

The following limitation must be acknowledged: The curve speed models provide estimates of free-flowing passenger car speeds, and free-flowing is defined as not constrained by slower-moving vehicles within a headway of 7 seconds leading or trailing. Headways were not provided in the NDS data query, so it is possible that some of the vehicle speeds were not truly free-flow speeds and are biased low.

DRIVER FAMILIARITY ANALYSIS

Methodology

Researchers further conducted the speed differential analysis between familiar and unfamiliar drivers. The main objectives was to identify any potential relationship between speeds and the frequency that the given driver traverses the curve or road of interest, and identify the difference in speeds along the curve of a familiar driver when compared to an unfamiliar driver. In this study, a familiar driver is defined as the driver who traverses the same roadway section at least four times (e.g., two round trips).

As used in the previous section, paired *t*- test is commonly preferred to compare the means of two populations (i.e., operating speed in this study). Paired *t*-test assumes that the data are normally distributed. Preliminary test indicated that the observed speeds corresponding to familiar and unfamiliar drivers separately at horizontal curves are not always normally distributed. As a result, paired *t*-test, if used to compare the speed between familiar and unfamiliar drivers, might produce biased results. So, this analysis used a nonparametric test approach, Wilcoxon signed rank test.

In recent years, Wilcoxon signed rank test has been used in transportation studies, (*4, 34-37*), and it has shown to be superior over traditional test approaches. The Wilcoxon signed rank test is mainly based on the ranking of the difference between pairs of sample. The Wilcoxon statistic W is calculated as follows (*38*):

1. Compute the difference between the two paired values.
2. List the set of the absolute differences.
3. Omit any zero values of the difference. Thus the sample size may be reduced, which is called actual sample size.
4. Assign ranks to each pair such that at the smallest absolute difference values get the rank one. If two or more are equal, assign each of them the mean of the ranks they would have been assigned individually had ties in the data not occurred.
5. Reassign the symbol + or − to each of the ranks, depending on whether the difference was originally positive or negative.
6. Compute the Wilcoxon test statistic, W-statistic, as the sum of the positive ranks.

The null and alternative hypotheses for the Wilcoxon signed rank test (one-tail) are:

H_0: $D \leq 0$ (the difference between the two samples is equal or less than 0).
H_1: $D > 0$ (the difference between the two samples is greater than 0).

If the null hypothesis is true, the test statistics W is expected to be close to its mean value ($\frac{n' \times (n'+1)}{4}$, where n' is the actual sample size). If the null hypothesis is false, the value of the test statistic W is expected to be close to zero or $\frac{n' \times (n'+1)}{2}$.

Table 8 shows the critical values of Wilcoxon statistics for $n' \leq 20$.

Table 8. Lower and Upper Critical Values of Wilcoxon Signed Ranks Test (95 Percent Level).

Sample Size	Lower	Upper	Sample Size	Lower	Upper
5	0	15	13	21	70
6	2	19	14	25	80
7	3	25	15	30	90
8	5	31	16	35	101
9	8	37	17	41	112
10	10	45	18	47	124
11	13	53	19	53	137
12	17	61	20	60	150

For a one-tail test in the lower tail, reject the null hypothesis if the computed W test statistic is less than or equal to the lower critical value.

For samples of n>20, the test statistic W is approximately normally distributed with mean equals:

$$\mu = \frac{n' \times (n'+1)}{4} \tag{18}$$

The standard deviation equals:

$$\sigma = \sqrt{\frac{n' \times (n'+1) \times (2n'+1)}{24}} \tag{19}$$

The large sample Wilcoxon statistics can be approximated as:

$$Z_{STAT} = (W - \frac{n' \times (n'+1)}{4}) / \sqrt{\frac{n' \times (n'+1) \times (2n'+1)}{24}} \tag{20}$$

Where,

Z_{STAT} = large sample Wilcoxon statistics.
W = the W statistic for large sample (sample size greater than 20).
n' = actual sample size.

Then, the standard normal distribution can used to determine the acceptance and rejection regions.

For illustration purpose, assume that the speeds of familiar and unfamiliar drivers at 10 curves were observed, as shown in the second and third columns of Table 9, respectively.

Following the steps introduced earlier, the differences, absolute differences, and rankings are calculated, as shown in the remaining columns of Table 9. There are five out of 10 pairs that have a positive sign (numbers with underline), and the W statistics is calculated as 19.

Table 9. Example Showing Wilcoxon Test.

No.	V_f (mph)	V_{un} (mph)	Diff.	Sign	Absolute Diff	Ranking
1	55.5	60.5	-5.0	-	5.0	10
2	55.5	60.4	-4.9	-	4.9	9
3	53.1	56.1	-3.0	-	3.0	8
4	52.7	53.0	-0.3	-	0.3	2
5	53.0	52.6	0.4	+	0.4	3
6	56.4	55.7	0.7	+	0.7	4
7	56.7	55.8	1.0	+	1.0	6
8	56.5	55.7	0.8	+	0.8	5
9	56.5	56.3	0.2	+	0.2	1
10	55.4	56.6	-1.2	-	1.2	7
Mean	55.1	56.3				W = 19

Notes: V_f = speed of familiar drivers; V_{un}=speed of unfamiliar drivers.

The null hypothesis is that there is no difference between speeds of familiar and unfamiliar drivers. Since the sample size is 10, and the upper and lower critical values are 10 and 45, respectively, at a 95 percent confidence level (from Table 8). The W statistic is calculated as 19, which is between the two critical values. The null hypothesis cannot be rejected. Thus, there is no evidence that the speeds between familiar and unfamiliar drivers are different for the given example data.

Results and Discussion

Researchers compared the 85th-percentile speeds between familiar and unfamiliar drivers at MC using the Wilcoxon signed ranking test introduced in the previous section. Similar to that in speed prediction analysis, two criteria were used to ensure that the observed speed data of familiar and unfamiliar drivers were stable and not biased due to the presence of outliers:

- At least 10 observations of vehicle speed for both familiar and unfamiliar drivers were obtained.
- The coefficients of variation of speed observations were less than 0.5.

For MC, 109 data samples were analyzed finally. Table 10 shows the summary statistics of the speeds, and Figure 9 illustrates the scatter plots. Of the 109 data sample, speeds of familiar drivers are higher than that of unfamiliar drivers at 71 curves. At other 39 curves, speeds of unfamiliar drivers are higher.

Table 10. Summary Statistics of Speed of Familiar and Unfamiliar Drivers at MC.

Statistics	Familiar	Unfamiliar
Sample Size	109	109
Mean (mph)	59.3	58.6
SD (mph)	2.57	3.11

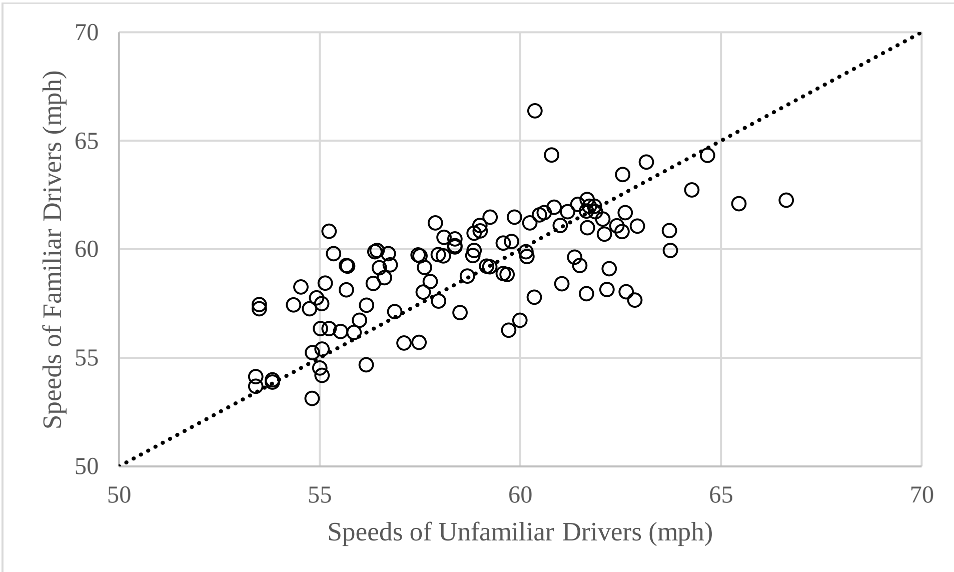


Figure 9. Speed Scatter Plots for Familiar and Unfamiliar Drivers.

The W statistic was calculated as 2,179, and the actual sample size was found to be 71. The p-value was 0.0134. Since it is less than 0.05, we have to reject the null hypothesis that the two data samples are the same. Thus, the 85th-percentile speeds of familiar drivers are significantly greater than that of unfamiliar drivers at MC. In other words, familiar drivers tend to drive faster than unfamiliar drivers when traveling through horizontal curves.

The tests were further conducted between the predicted speeds and observed speeds of familiar drivers, and between the predicted speeds and observed speeds of unfamiliar drivers (Note that the predicted speeds refer to the speeds predicted using Equation **Error! Reference source not found.** for all drivers). Table 11 and Table 12 illustrate the summary of the speed data and Wilcoxon test results. As can be seen, the p-value for the former test is small, indicating there is difference between the predicted speeds and speeds of familiar drivers. However, the p-value for the latter test is 0.11, indicating there is no significant difference between the predicted speeds and speeds of unfamiliar drivers. To conclude, the prediction model worked better for unfamiliar drivers than familiar drivers.

Table 11. Predicted Speeds versus Observed Speeds at MC—Familiar Drivers.

Statistics	Predicted	Observed
Sample Size	97	97
Mean (mph)	56.5	59.3
SD (mph)	8.51	2.57
Actual Sample Size	72	
W Statistic	3,788	
p-value	3.832e-07	

Table 12. Predicted Speeds versus Observed Speeds at MC—Unfamiliar Drivers.

Statistics	Predicted	Observed
Sample Size	97	97
Mean (mph)	56.5	58.6
SD (mph)	8.51	3.11
Actual Sample Size	52	
W Statistic	2,817	
p-value	0.11	

CHAPTER 5. CURVE SEVERITY ANALYSIS

METHODOLOGY

This section documents the analysis on curve severity and is divided into two parts. In the first part, the concept of curve severity is reviewed. In the second part, the approach used in this document to compare curve severity and crash rate is discussed.

Curve Severity and Side Friction Differential

The concept of curve severity was initially proposed for examining design consistency of horizontal curves and for determining the type and use of traffic control devices (e.g., warning sign, advisory speed plaque, delineation) at curves. As discussed above, currently there are mainly three types of measures to quantify curve severity: speed differential, energy differential, and friction differential. Side friction differential and energy differential have been shown to be more appropriate than speed differential (*21*), so side friction differential is used in this study. Thus, this section is mainly focused on characteristics of curve severity as defined by side friction differential.

When a vehicle is traveling on a horizontal curve, a lateral force must be provided to keep the vehicle on the curve (*21*). A certain amount of side friction is required to provide this force. The relationship between side friction demand, speed, and curve geometry is provided in the *Green Book*, and can be derived using Equation **Error! Reference source not found.Error! Reference source not found.**, which is a transformed version of Equation 1**Error! Reference source not found.**:

$$f_D = \frac{V_c^2}{gR} - \frac{e}{100} \tag{21}$$

Where,

V_c = curve speed, ft/s.

f_D = side friction demand factor (or lateral acceleration).

e = superelevation rate, percent.

g = gravitational acceleration.

R = radius of curve, ft.

The side friction differential is defined as the difference between the side friction demand and accepted side friction, as shown in Equation 22**Error! Reference source not found.**:

$$\Delta f = max(f_D\text{-}f_{Accept}, 0) \tag{22}$$

Where,

f_{Accept} = the accepted upper limit of comfortable side friction demand.

As Bonneson et al. (*20*) suggested, the accepted side friction demand limit can be specified either as a constant, usually 0.19, or as a function of speed, as shown in Equation 23**Error! Reference source not found.**:

$$f_{Accept} = b_0 - b_1 \times V_t \tag{23}$$

Where,

V_t = tangent speed, mph.
b_0 and b_1 = two calibration coefficients.

This study considered both constant and varying accepted side friction demand limits. For the latter one, the estimates reported by Bonneson et al. (*20*) are adopted (i.e., b_0 = 0.1962, and b_1 = 0.00106 [Equation 47 in (*20*)]).

Note that the procedure for calculating side friction differential (i.e., Equations **Error! Reference source not found.** to **Error! Reference source not found.**) can be based on either *observed speeds* or *predicted speeds*. In this study, the curve prediction model developed by Bonneson and Pratt (*1*) is applied to calculate the predicted speeds. In the model, Bonneson and Pratt (*1*) hypothesize that the drivers modify their side friction demand based on a desire for both safe and efficient travel, and proposed a curve speed model by combining the side friction demand equation with the relationship between the demand and vehicular speed. Equation 14**Error! Reference source not found.** shows the functional form of this model. The coefficients b_0, b_1, and b_2 in that equation are equal to 0.196, 0.00106, and 0.000034, respectively.

By substituting Equations **Error! Reference source not found.** and **Error! Reference source not found.** into Equation **Error! Reference source not found.**, Bonneson et al. (*20*) obtained the side friction differential with predicted speeds as shown in Equation **Error! Reference source not found.** (*20*).

$$\Delta f = max(0.000073 \times (V_t^2 - V_c^2), 0) \tag{24}$$

Four methods can be used for calculating the side friction differential:

- Observed speed with constant accepted side friction demand limits (OSWC).
- Observed speed with varying accepted side friction demand limits (OSWV).
- Predicted operating speed with constant accepted side friction demand limits (PSWC).
- Predicted operating speed with varying accepted side friction demand limits (PSWV).

Once the side friction differential for a horizontal curve is calculated, it can be used as a measure to assess curve severity. Curve severity is divided into five categories ranging from A to E, where each category refers to a different curve severity level from the least severe outcome (i.e., A) to the most severe one (i.e., E). The side friction differential is compared to the predefined threshold values to assign the curves a severity level. These thresholds are 0, 0.03, 0.08, 0.13, and 0.16 for A, B, C, D, and E, respectively (*20*). For example, if the side friction differential of a curve is calculated to be equal to 0.04, the curve is assigned a B severity level.

Table 13 shows the curve severity level and recommended traffic control device treatments proposed by Bonneson et al. (*20*).

Table 13. Curve Severity and Recommended Traffic Control Device Treatments.

Curve Severity	Typical Traffic Control Device Treatments	Threshold Friction Differential
A	Curve or turn sign and raised pavement markers	0.00
B	Curve warning sign with advisory speed plaque	0.03
C	Redundant curve warning sign and advisory speed plaque and delineators	0.08
D	Redundant curve warning sign, advisory speed plaque, and chevrons (or large arrow sign)	0.13
E	Special treatments*	0.16

Note: * for details of special treatments, refer to Table 5-2 of (*20*).

Comparison between Curve Severity and Crash Rate

To compare curve severity with crash rate, this study used a cross-sectional analysis approach, which has been described in details by Wu et al. (*39*). The process is briefly described below.

Step 1: Divide Curves into Bins

Divide horizontal curves into a number of bins according to the side friction differential. Calculate the average side friction differential of curves in each bin. Note that a logical way to divide the curves is based on curve severity level. However, this is not necessary for a given curve data set (sample size, distribution of side friction differential, and crash counts of the dataset need to be considered while dividing curves).

Step 2: Calculate Crash Rate for Each Bin

For each bin, calculate the crash rate. In this study, three types of crash rates were calculated: fatal and injury crash rate, total crash rate, and equivalent property damage only (EPDO) crash rate. Total crash rate is the total number of crashes divided by the total exposure (i.e., vehicle mileage traveling). For the EPDO crash rate, all crash severities are converted into property damage only (PDO) based on the specified weights. For more details on the EPDO, the reader is referred to the *Highway Safety Manual* (HSM) (*40*). The weights are usually based on crash costs (*41*). In this study, a fatal crash is estimated as equal to 39 PDO crashes, and an injury crash is equal to five PDO crashes.

Step 3: Compare Curve Severity and Crash Rate

Generate scatter plots of crash rates against average side friction differential to identify any pattern between the two. If there is an obvious pattern, it indicates that curve severity is associated with crash rates and/or crash severity on horizontal curves. Otherwise, curve severity may not be directly related to crash rates or enough safety treatments have already been implemented at the severe curves to make them safer.

RESULTS

Data Analysis Results

Using the four methods introduced in the earlier section, the side friction differential of each curve was evaluated. The curves were divided into four or five bins, and three types of crash rates were calculated for each bin: fatal and injury, total, and EPDO crash rates. Table 14 shows the results.

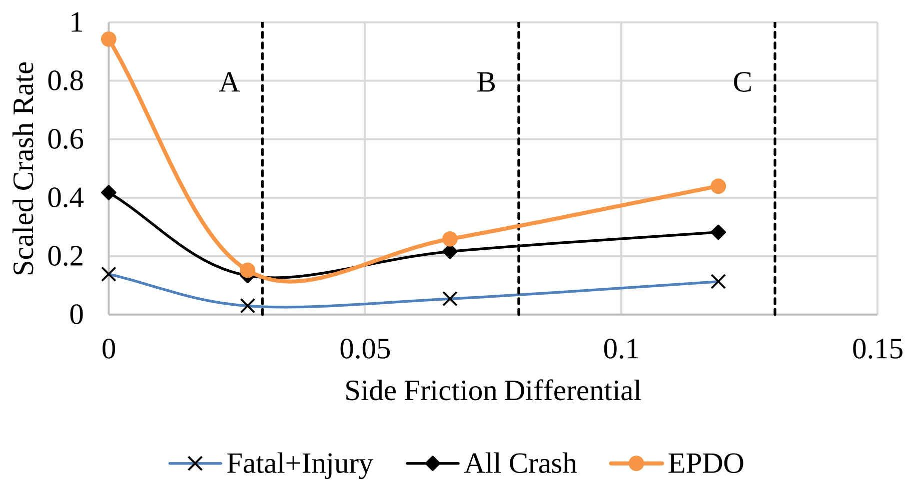
A large number of the curves have zero side friction differential, regardless of the method used. Specifically, curves with zero side friction differential account for 81.0 percent, 63.9 percent, 77.8 percent, and 73.4 percent of total in the four curve severity assessment methods, respectively. They all fall into curve severity level A, indicating that most of the curves are relatively flat. However, the range of the side friction differential varies between the four methods. The maximum value with OSWV is 0.190 (Curve Severity Level E, the most severe category), whereas that with PSWV is only 0.075 (Curve Severity Level B).

Table 14. Crash Rates and Curve Severity.

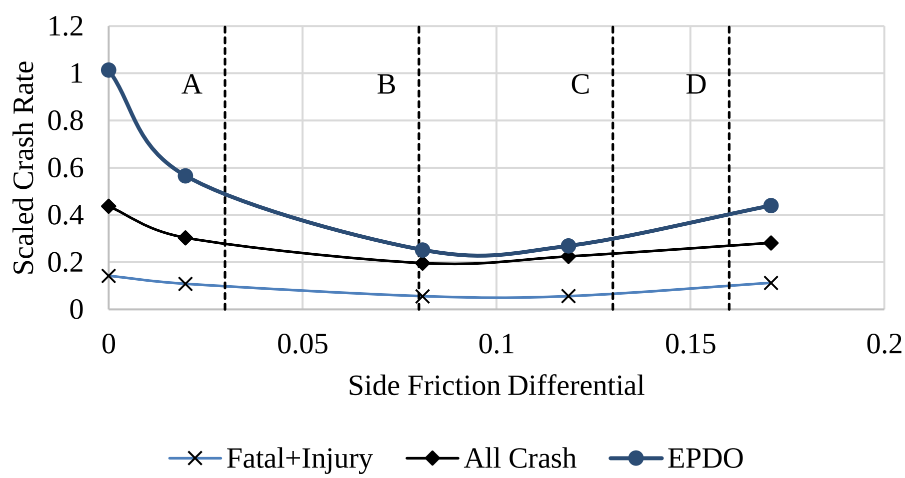
Method	Bin	No. of Curves (Percentage)	Min. Δf	Max. Δf	Ave. Δf	F+I Crash Rate	All Crash Rate	EPDO Rate
OSWC	1	204 (81.0%)	0.000	0.000	0.000	0.154	0.418	0.942
	2	23 (9.1%)	0.002	0.048	0.027	0.030	0.133	0.151
	3	13 (5.2%)	0.051	0.090	0.067	0.054	0.216	0.259
	4	12 (4.8%)	0.101	0.141	0.119	0.113	0.282	0.440
OSWV	1	161 (63.9%)	0.000	0.000	0.000	0.161	0.437	1.014
	2	43 (17.1%)	0.000	0.049	0.020	0.114	0.304	0.566
	3	23 (9.1%)	0.056	0.100	0.081	0.056	0.196	0.252
	4	13 (5.2%)	0.102	0.141	0.119	0.056	0.224	0.269
	5	12 (4.8%)	0.156	0.190	0.171	0.113	0.282	0.440
PSWC	1	196 (77.8%)	0.000	0.000	0.000	0.155	0.424	0.957
	2	19 (7.5%)	0.001	0.038	0.025	0.065	0.081	0.205
	3	32 (12.7%)	0.042	0.079	0.061	0.052	0.198	0.243
	4	5 (2%)	0.087	0.099	0.092	0.171	0.685	0.822
PSWV	1	185 (73.4%)	0.000	0.000	0.000	0.153	0.418	0.964
	2	44 (17.5%)	0.000	0.033	0.019	0.110	0.295	0.441
	3	19 (7.5%)	0.038	0.064	0.054	0.033	0.098	0.138
	4	4 (1.6%)	0.069	0.075	0.072	0.259	1.036	1.243

Notes: Δf = side friction differential; F+I crash rate = fatal and injury crash rate; EPDO = equivalent property damage only crash; OSWC = observed speed with constant accepted side friction demand limits; OSWV = observed speed with varying accepted side friction demand limits; PSWC = predicted operational speed with constant accepted side friction demand limits; PSWV = predicted operational speed with varying accepted side friction demand limits; crash rates are on vehicle mileage travel basis and have been scaled for illustration purpose.

To compare curve severity and crash occurrence, the crash rates are plotted against side friction differential, as shown in Figure **10**. For all the four curve severity assessing methods, the relationship between crash rate and side friction differential shows a U shape. The crash rate is relatively high when the side friction differential is zero, then it starts to decrease as the side friction differential increases. After a certain point, the crash rate starts to increase again. Especially for the assessment methods using the predicted speeds (i.e., PSWC and PSWV), the crash rates increase substantially when the curve severity falls beyond category A, as shown in Figure **10**(c) and (d). This implies that severe curve severity level might be associated with higher crash rates. From this perspective, the curve severity assessment methods with predicted operating speeds show better compliance with crash rates.

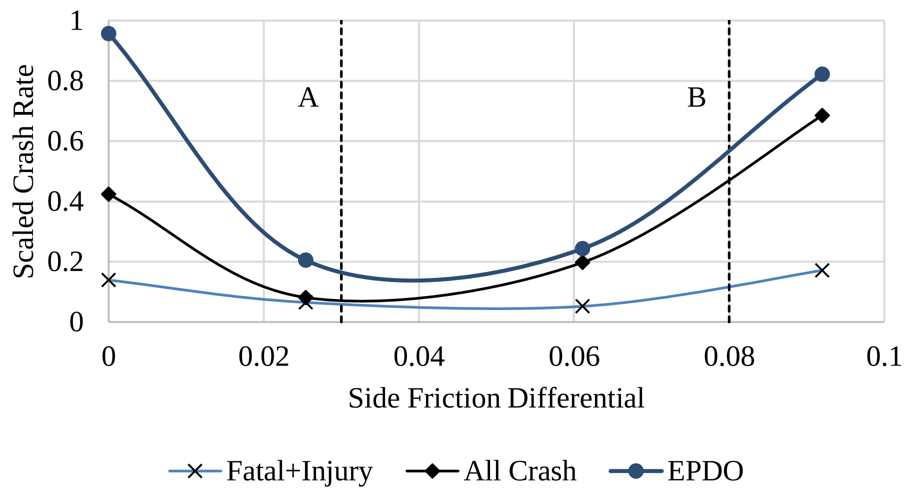


(a) Observed Speed with Constant Accepted Side Friction Demand Limits

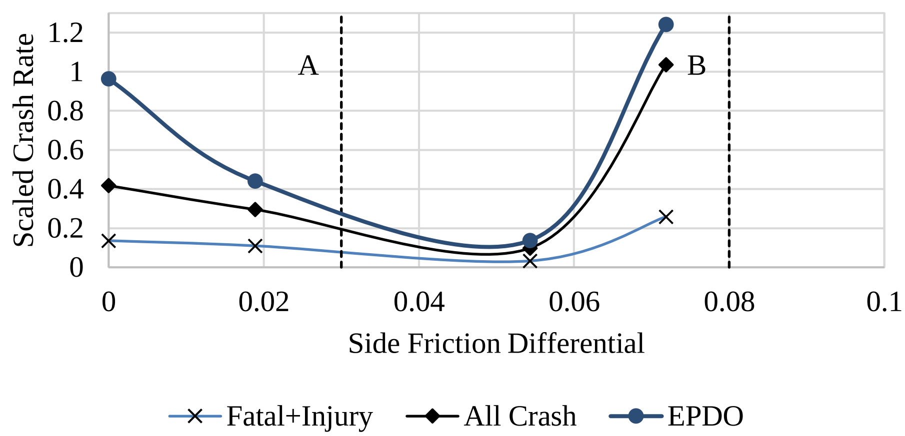


(b) Observed Speed with Varying Accepted Side Friction Demand Limits

Figure 10**. Crash Rate and Curve Severity Using Four Methods.**



(c) Predicted Operational Speed with Constant Accepted Side Friction Demand Limits



(d) Predicted Operational Speed with Varying Accepted Side Friction Demand Limits

Figure 10. Crash Rate and Curve Severity Using Four Methods. Continued.

In all the four plots, curves with zero side friction differential have relatively high crash rates. It is possible that there are additional confounding factors. For example, these curves may be relatively flat and the speeds may be higher than other curves, and experience more crashes. It is also possible that when the curves are flat, drivers may not realize the presence of a curve and run off the road as a result.

Discussion

This study used four curve severity assessment methods to explore the crash rates on rural two-lane highways in Indiana. Three crash types (fatal and injury crash rate, all crash rate, and EPDO crash rate) were used for comparison. SHRP 2 curve data were requested and 252 horizontal curves on rural two lane highways were identified. The geometric characteristics (i.e., radius, deflection angle, superelevation) of the curves and the historical crash data were obtained from the RID roadway data while the operating speeds on the curves and preceding tangents were obtained from the NDS data.

The results of the computational analysis indicate that the side friction differential and curve severity differ significantly when calculated using different methods and inputs (i.e., observed vs. predicted speeds, constant vs. varying accepted side friction demand limits). For the low-severity curves, crash rates are not necessarily increasing as the side friction demand increases. However, when the curve severity is beyond category A (i.e., low curve severity level), the crash rates goes up with the increase in side friction differential. This indicates that, for the curves belonging to more severe categories, side friction differential will be positively associated with crash rate. This study also found that the curve severity assessment methods using predicted speeds provide more reasonable conclusions compared to the ones using observed speeds.

Nevertheless, there are a few limitations in this analysis. First, the comparison between curve severity and crash rates was conducted based on cross-sectional data. It may suffer from the common problems observed in cross-sectional analyses, such as the confounding bias (also known as omitted variable bias) (*42*). Secondly, the sample size used in the study is relatively small. Based on the method used, about 64 to 81 percent of 252 curves included in the study belong to curve severity category A. Small sample sizes are known to cause inconsistent results.

CHAPTER 6. CONCLUSIONS AND FUTURE RESEARCH

This chapter summarizes the findings of this study and presents topics for future research using the SHRP 2 database.

CONCLUSIONS

A considerable amount of effort has been expended to develop and revise horizontal curve operating speed prediction models in the past decades. Various models have been established to predict operating speeds, and some of them have been shown to be able to predict speeds on horizontal curves accurately. Although the speed prediction models differ in terms of model functional form and dependent variable selection, they were nearly all derived from regression models as a function of curve geometric characteristics (e.g., curve radius, length, superelevation). Curve radius and approach tangent speed play the most significant role in predicting curve speeds; the former variable has been included in more models than the latter. All the models include curve radius or degree of curve (which is inversely proportional to the radius). In recent years, several attempts have been made to explore horizontal curve safety using NDS data, but none focused on operating speeds on curves.

The first objective of this study aimed to further assess the common speed prediction models with detailed information extracted from the NDS database. In this study, a speed prediction model was tested using SHRP 2 data. Key curve characteristics, including radius, superelevation rate, deflection angle, and regulatory speed limit, were extracted from the RID files, and curve midpoint speeds were extracted from NDS trip files for drivers traversing along rural highway sections in Indiana. The curve speed models developed by Bonneson and Pratt (*1*) and Pratt et al. (*3*) were found to predict curve midpoint speeds at the Indiana sites without bias, suggesting that the models are transferable to multiple states. The analysis revealed that the speed differential models developed by Pratt et al. (*3*) for the purpose of estimating speed profiles through an entire curve can be extended to multiple states with the application of a multiplicative adjustment factor. In addition, the analysis results also show that SHRP 2 data can be used instead of collecting new speed data, saving a lot of resources. The speed prediction models developed using Texas data can be used for setting advisory speed limits in other states.

The availability of driver data in the NDS database allowed for the inclusion of additional variables in speed analysis efforts. The database provided information about the number of times participants traversed a given highway section, which helped in exploring the change in speed choice as the driver becomes more familiar with the highway. Researchers compared the 85^{th}-percentile speeds between familiar and unfamiliar drivers at the curve midpoint using the Wilcoxon signed ranking test. The results suggested that the 85^{th}-percentile speeds of familiar drivers are statistically significantly greater than that of unfamiliar drivers at the curve midpoint. The tests were further conducted between the predicted speeds and observed speeds of familiar drivers, and between the predicted speeds and observed speeds of unfamiliar drivers. The results indicated that there is a significant difference between the predicted speeds and speeds of familiar drivers, and no significant difference between the predicted speeds and speeds of unfamiliar drivers. It was concluded that the prediction model worked better for unfamiliar drivers than familiar drivers.

Many efforts have been conducted to improve curve safety and efficiency; however, in many previous studies the curve safety and operational characteristics were analyzed separately.

With the development of the SHRP 2 program and related technologies, data and emerging approaches are available for an analyst to incorporate curve operational characteristics into safety. This study used four curve severity assessment methods to explore the crash rates on rural two-lane highways in Indiana. The results of the computational analysis indicate that the side friction differential and curve severity differ significantly when calculated using different methods and inputs (i.e., observed vs. predicted speeds, constant vs. varying accepted side friction demand limits). For the low-severity curves, crash rates are not necessarily increasing as the side friction demand increases. However, when the curve severity is beyond category A (i.e., low curve severity level), the crash rate goes up with the increase in side friction differential. This indicates that, for the curves belonging to more severe categories, side friction differential will be positively associated with crash rate. This study also found that the curve severity assessment methods using predicted speeds provide more reasonable conclusions compared to the ones using observed speeds.

FUTURE RESEARCH

Safety Performance Functions

Researchers have put together a comprehensive horizontal curve database by integrating the NDS and RID data. This database can be used for several purposes. One of the potential purposes involves the development of SPFs by accounting for the speed element. Traffic crashes and their severity are significantly influenced by speeding behavior. However, the existing SPFs for rural two–lane facilities do not include speed elements. Researchers suggest developing new SPFs for rural two-lane facilities that would account for speed measures (e.g., mean speed, speed variance, 85^{th}-percentile speed, and predicted speed).

Speed Prediction Models

Not all variables impact speed in the same way. The NDS database will allow exploration of the important variables in more detail. Research is needed on prioritizing the variables that influence speed. The integrated databases allow for more sophisticated speed models to be developed for curves and tangents, with a larger sample (e.g., multiple states) than what is typically obtainable when data must be collected anew. New models could include geometric design factors such as lane and shoulder width, grade, and tangent length in addition to curve variables such as radius, superelevation rate, and deflection angle. The availability of continuous speed profiles allows for exploration of the influence of preceding roadway elements' characteristics on speeds at following elements. For example, the relationship between speed on a curve of interest and the preceding three tangents and curves could be analyzed. The findings of these analyses should be compared with relevant portions of resources such as the IHSDM and the HSM to determine if enhanced speed prediction methodologies could improve the performance of safety prediction models or even network screening procedures. Information about citations and enforcement activity could also be included in an enhanced analysis of vehicle speeds.

In the future, comparisons between curve severity and crash rates need to be conducted with methods that overcome the common problems observed in cross-sectional analyses. It is also recommended to include more curves belonging to higher severity categories to validate the results of the curve and crash severity analysis.

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APPENDIX

Table 15. Operating Speed Prediction Models.

Study	Model	Unit	Note
Lamm et al. (*24*)	$V_{85} = 58.656 - 1.135DC$	US Customary	
Kannellaidis et al. (*25*)	$V_{85} = 32.2 + \frac{2226.9}{R} - \frac{533.6}{\sqrt{R}} + 0.839V_t$	Metric	
Islam and Seneviratne (*26*)	$V_{85,PC} = 95.41 - 1.48DC - 0.012DC^2$ $V_{85,MC} = 103.03 - 2.41DC - 0.029DC^2$ $V_{85,PT} = 96.11 - 1.07DC$	Metric	Point of curve; middle of curve; and point of tangent
Krammes et al. (*27*)	$V_{85} = 103.66 - 1.95DC$ $V_{85} = 102.45 - 1.57DC + 0.0037L - 0.10I$ $V_{85} = 41.62 - 1.29DC + 0.0049L - 0.10I + 0.95V_t$	Metric	
Fitzpatrick and Collins (*28*)	$V_{85} = a - \frac{b}{R}$	Metric	a and b are two coefficients, and they vary based on different conditions.
Bonneson and Pratt (*1*)	$V_{85} = (\frac{15R(b_0 - b_1V_t + b_2V_t^2 + b_3I_{tk} + e/100}{1 + 0.00136R})^{0.5} \le V_t$	US Customary	b_0=0.196; b_1=0.00106; b_2=0.000073; b_3=-0.0108; V_t=tangent speed.
Pratt et al. (*17*)	$V_{85} = (\frac{15R(b_0 - b_1V_t + b_2V_t^2 + e/100}{1 + 0.000061R})^{0.5} \le V_t$	US Customary	b_0=0.2202; b_1=0.00142; b_2=0.000041; V_t=tangent speed.

Note: if an equation uses metric system, the units for speed and radius are kph and meter, respectively. If US customary, they are mph and feet, respectively. Typically, V_{85} is the predicted operating speed on horizontal curves. R is radius for the curve. V_t is operating speed on adjacent tangent(s). DC is the degree of curve, DC = 1,748/R if R is measured in meter or DC = 5,730/R if R is measured in feet.

Table 16. List of Variables included in the Speed Prediction Models.

Bonneson et al. (*20*)			
Equation	**Eq. 27**	**Eq. 28 and Eq. 29**	**Eq. 30 and Eq. 31**
Prediction Variable	$V_{t,85,pc}$ = 85th-percentile tangent speed	V_c = curve speed (mph)	$V_{c,85}$ = 85th-percentile curve speed (mph) $V_{c,a}$ = average curve speed (mph)
Independent Variables	V_{sl}= Regulatory speed limit (mile)	V_t = tangent speed (mph)	$V_{t,85}$ = 85th-percentile tangent speed (mph)
	R=Radius of curve (ft)	R_p = travel path radius (ft.)[1]	$V_{t,a}$ = average tangent speed (mph)
		b_3 = calibration coefficient for trucks;	R_p = travel path radius (ft)[1]
		I_{tk} = indicator variable for trucks (= 1.0 if model is used to predict truck speed; 0.0 otherwise)	I_{tk} = indicator variable for trucks (= 1.0 if model is used to predict truck speed; 0.0 otherwise)
		b_4 = calibration coefficient for other factors (e.g., Chevron presence)	e = superelevation rate (percent)
		I_x = indicator variable (= 1.0 if factor is present; 0.0 otherwise)	
		e = superelevation rate (percent)	
		I_c = curve deflection angle (degrees)	

Pratt et al. (*17*)				
Equation	**Eq. 71**	**Eq. 73 & Eq. 74**	**Eq. 76**	**Eq. 78**
Prediction Variable	$V_{t,85}$ = 85th-percentile tangent speed	$V_{c,85}$ = curve speed (mph)	$\Delta_{85}V_{PC\text{-}MC}$= Speed differential (PC to MC) (mph)	$\Delta_{85}V_{MC\text{-}PT}$= Speed differential (MC to PT) (mph)
Independent Variables	V_{sl}= Regulatory speed limit (mile)	$V_{t,85}$ = 85th -percentile tangent speed (mph)	$V_{c,85}$ = curve speed (mph)	$V_{c,85}$ = curve speed (mph)
	R=Radius of curve (ft.)	R_p = travel path radius (ft)[1]	$V_{t,85}$ = 85th-percentile tangent speed (mph)	$V_{t,85}$ = 85th-percentile tangent speed (mph)
		Δ=Curve deflection angle (degrees)	R=Radius of curve (ft.)	G_{MC}=Grade at MC (percent)
		e = superelevation (percent)		G_{PT}=Grade at PT (percent)

[1] Equation 73 estimates this variable as a function of Δ.
[1] Equation 29 estimates this variable as a function of R and I_c.