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Examining the Feasibility of Using Naturalistic Driving Study Data for Validating Speed Prediction Models

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Abstract

Numerous curve speed models have been developed for purposes such as predicting driver behavior, evaluating roadway design consistency, and setting curve advisory speeds. With any model development efforts, questions can be raised about the transferability of the model between geographic regions. It is desirable to develop speed prediction models that can be used to predict vehicle speeds across different regions, as these models can then form the basis for consistent roadway analysis and evaluation methods. However, speed model validation and especially calibration are expensive tasks because of the need to collect field data. The main objective of this paper is to present a validation of speed prediction models for horizontal curves using the Naturalistic Driving Study (NDS) database. For this purpose, four two-lane rural highway sections from the State of Indiana were selected where each section includes multiple horizontal curves. Roadway design characteristics were used to predict the speed at the midpoint of each curve based on models that were previously calibrated using Texas data. Actual vehicle speeds at each curve were then computed and compared with the predicted speed using the Texas models. The results of the analysis suggest that the predicted speed from the Texas model provides an unbiased estimate of observed curve midpoint speeds in Indiana, and can provide good estimates of speeds at the beginning and ending of each curve with minor adjustment. The successful use of the NDS database for model validation shows that this database can facilitate similar efforts in additional states.

Keywords: speed prediction; horizontal curve; rural two-lane highway; NDS; GPS speed.

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1. Introduction

Numerous speed prediction models have been developed and documented in the research literature. Models have been developed to estimate vehicle speeds on various roadway elements, including tangents and curves, on different types of highway facilities. Speed prediction models are used for applications including estimating roadway performance, evaluating the consistency of successive design elements along a continuous highway section, and setting curve advisory speeds. Though the literature contains many such models, new models are often calibrated when predictions are desired in a region where studies have not been conducted, as there is concern about the transferability of models between geographic regions.

In the process of evaluating and establishing a method for setting advisory speeds for rural horizontal curves, Bonneson and Pratt (2009) developed a speed prediction model using data collected at 41 rural curve sites in the State of Texas. The application of this speed prediction model has been tested in the States of Texas and Tennessee (Miles and Pratt, 2012), and the comparison with trends in Tennessee was found to be favorable.

One objective of the study described in this paper is to conduct additional testing of the models' predictions on curves in the State of Indiana. This effort will reveal 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 geometric and traffic control variables needed to apply the models. The Second Strategic Highway Research Program (SHRP2) conducted the largest and most comprehensive naturalistic driving study (NDS) in Florida, Indiana, North Carolina, New York, Pennsylvania, and Washington. These data include vehicle speeds that can be used to validate the speed prediction models in those states and check if calibration is needed. Another objective is to demonstrate the feasibility of using the SHRP2 database to validate models, such that resources needed for validating models in additional states can be reduced.

This paper is organized in four sections. The first section provides a literature review covering curve speed behavior. The second section presents a descriptive analysis of the data used to validate the curve speed prediction models. The results of an empirical analysis of speed data and model predictions are provided in the third section. The concluding section provides a summary and suggestions for future research.

2. Literature review

Various curve speed prediction models have been calibrated and documented in the literature. Models have been developed for designing horizontal curves, evaluating design consistency, and to establish curve advisory speeds (Bonneson and Pratt, 2012). A sampling of these models is summarized in Table 1 and described in this section.

Table 1 Operating Speed Prediction Models

Reference	Model	Notes
Bonneson and Pratt (2012)	$V_{85} = \sqrt{\dfrac{15R_p(b_0 + b_1V_t + b_2V_t^2 + b_3I_{tk} + e/100)}{1 + 0.00322b_2R_p}} \le V_t$ $R_p = R + \dfrac{3}{1 - \cos\frac{\Delta}{2}}$	V_{85} = 85th-% MC speed; b_0 = 0.196; b_1 = -0.00106; b_2 = 0.000073; b_3 = -0.0150; R = radius; Rp = path radius; Δ = deflection angle; V_t = tangent speed.
Pratt et al. (2015)	$V_{85} = \sqrt{\dfrac{15R_p(b_0 + b_1V_t + b_2V_t^2 + e/100)}{1 + 0.00322b_2R_p}} \le V_t$ $R_p = R + \dfrac{3}{1 - \cos\frac{\Delta}{2}}$	V_{85} = 85th-% MC speed; b_0 = 0.2202; b_1 = -0.00142; b_2 = 0.000041; R = radius; Rp = path radius; Δ = deflection angle; G_{MC} = grade at MC; G_{PT} = grade at PT; V_t = tangent speed; $\Delta V_{PC\text{-}MC}$ = PC-MC differential;

	$\Delta V_{PC-MC} = -54.886 + 58.768\sqrt{\frac{V_t}{V_{85}}} - 0.521\frac{5730}{R}$ $\Delta V_{MC-PT} = -12.399 + 15.197\sqrt{\frac{V_t}{V_{85}}} - 0.803\left(\frac{G_{MC} + G_{PT}}{2}\right)$	$\Delta V_{MC\text{-}PT}$ = MC-PT differential.
Lamm et al. (1990)	$V_{85} = 58.656 - 1.135DC$	DC = degree of curve
Kannellaidis et al. (1990)	$V_{85} = 32.2 + \frac{2226.9}{R} - \frac{533.6}{\sqrt{R}} + 0.839V_t$	
Islam and Seneviratne (1994)	$V_{85,PC} = 95.41 - 1.48DC - 0.012DC^2$ $V_{85,MC} = 103.03 - 2.41DC - 0.029DC^2$ $V_{85,PT} = 96.11 - 1.07DC$	PC = point of curvature; MC = midpoint of curve; PT = point of tangency.
Krammes et al. (1995)	$V_{85} = 103.66 - 1.95DC$ $V_{85} = 102.45 - 1.57DC + 0.0037L - 0.10I$ $V_{85} = 41.62 - 1.29DC + 0.0049L - 0.10I + 0.95V_t$	
Fitzpatrick and Collins (2000)	$V_{85} = a - \frac{b}{R}$	a and b are coefficients that vary based on different conditions.

Bonneson and Pratt (2009) hypothesized that drivers modify their speed and hence their side friction demand based on a desire for both safe and efficient travel, and proposed a curve speed model by combining the point-mass model or "simplified curve formula" from AASHTO's A Policy on Geometric Design of Highways and Streets (Green Book) (AASHTO, 2011) with the relationship between side friction demand and vehicular speed. To calibrate the model coefficients, Bonneson and Pratt assembled data at 41 curve sites in Texas. Geometric and traffic control data of each site were collected. Speeds of over 6600 passenger cars and 1700 trucks were observed across the sites, and the speed data collection continued through both daytime and nighttime conditions. The coefficients were then calibrated using a nonlinear regression procedure. Bonneson and Pratt further validated the prediction model using speed data observed in a previous project (Bonneson, 2000). It was found that the proposed model could accurately predict curve speeds with minimal bias (within 0.3 mph).

Miles and Pratt (2012) later evaluated the model developed by Bonneson and Pratt (2009) using data collected in the State of Tennessee. Site characteristics (i.e., radius, superelevation, posted speed limit, etc.) of 19 curves on two-lane rural highways were collected, and vehicular speeds were observed at two points on each curve. The predicted 85th-percentile curve speeds were estimated by the model and compared with the observed speeds. It was found that 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. The curve model was developed using Texas data and was found to be transferable to Tennessee.

In a later study, Pratt et al. (2015) calibrated a model similar to the one developed by Bonneson and Pratt (2009) 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. These models are shown in the third row of Table 1. For the speed differential models, Pratt et al. used functional forms that were previously documented by Misaghi and Hassan (2005).

One of the earliest operating speed prediction model was developed by Lamm et al. (1990), who collected data to describe vehicle speeds, vehicle type, and geometry on 24 curved roadway sections on two-lane rural highways in

New York State. They used multiple linear stepwise regression to evaluate the quantitative effects of curve factors on operating speeds. The analysis revealed that degree of curve (DC) was the best available single-variable predictor of operating speeds. Lamm et al. (1990) evaluated other variables that may influence operating speed, but the other variables did not show much significance.

Kannelaidis et al. (1990) 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. Their results suggested that operating speed is strongly correlated with the curve radius.

Islam and Seneviratne (1994) 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, the MC, and the PT.

Krammes et al. (1995) conducted one of the most comprehensive studies on operational speed on rural two-lane highways. They 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). 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.

To evaluate highway design consistency, Fitzpatrick and Collins (2000) and Fitzpatrick et al. (1999) developed speed prediction models for two-lane rural highways. Several equations were developed to predict horizontal curve operating speeds for different alignments. Design consistency has been shown to be related to roadway safety (1999).

3. Descriptive data analysis

3.1. Data needs

The authors proposed to validate Texas-calibrated models obtained from Bonneson and Pratt (2012) and Pratt et al. (2015) in this study because these models are sensitive to both radius and approach tangent speed, and hence are likely to be transferrable to more geographic regions. To validate the Texas-calibrated models, the following data are required to describe curve sites:

- Curve radius.
- Superelevation rate.
- Deflection angle.
- Roadway grade at curve MC and PT.
- Vehicle speeds at the approach tangent, PC, MC, and PT.

These variables are available in the SHRP2 RID, along with additional variables that are useful to characterize and categorize the sites. These additional data include regulatory speed limit, curve length, and an inventory of signs and delineation devices.

3.2. SHRP2 data

To carry out the empirical analysis, the authors explored the SHRP2 database. The SHRP2 program consists of the NDS data (SHRP2 NDS, 2016) and the companion RID (SHRP 2 RID, 2016). The NDS data were collected from more than 3500 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 regions in the database were located in Indiana and Pennsylvania and covered about 10 counties in each state. Collected data included vehicle speed, acceleration, and braking; vehicle controls, when available; lane position; forward radar; and video views forward, to the rear, and on the driver's face and hands. The RID contains detailed roadway data collected on 12,538 centerline miles of highways in the study States. NDS trip data can be linked to RID roadway data using unique identifier code values (labeled as LinkID) for each roadway segment or latitude and longitude coordinates.

3.3. Roadway design characteristics

The RID provides the roadway location, curvature, grade, lane widths, and intersection characteristics as well as time of day and environmental data such as weather. RID mobile data were collected from the roads frequently driven by NDS participants.

The roadway design characteristics of the selected highway sections were obtained from the alignment shape file available from the RID. Descriptive statistics of the RID variables for all roadway segments are presented in Table 2.

Table 2 Descriptive Statistics of Roadway Geometry Design Elements

Roadway Segment	Number of Curves		Statistics	Radius (ft)	Superelevation rate (%)	Curve Length (ft)	Speed Limit (mph)
US-50W	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	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	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	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

3.4. NDS trip data

The authors requested the following trip information data from the indicated highway sections:

- Trip ID.
- Location coordinates (latitude/longitude).
- Link ID.
- Network speed (measured with the vehicle's speedometer).
- GPS speed (measured with a GPS receiver).
- Longitudinal acceleration.
- Lateral acceleration.

The authors analyzed NDS trip data from four rural highway sections in Indiana, as shown in Figure 1. The data query included 273 trips (traversals). The GPS speed for each traversal had been recorded at millisecond intervals, and the duration of the trips vary from 12 to 30 minutes. The number of the traversals per road section is reported in Table 3.

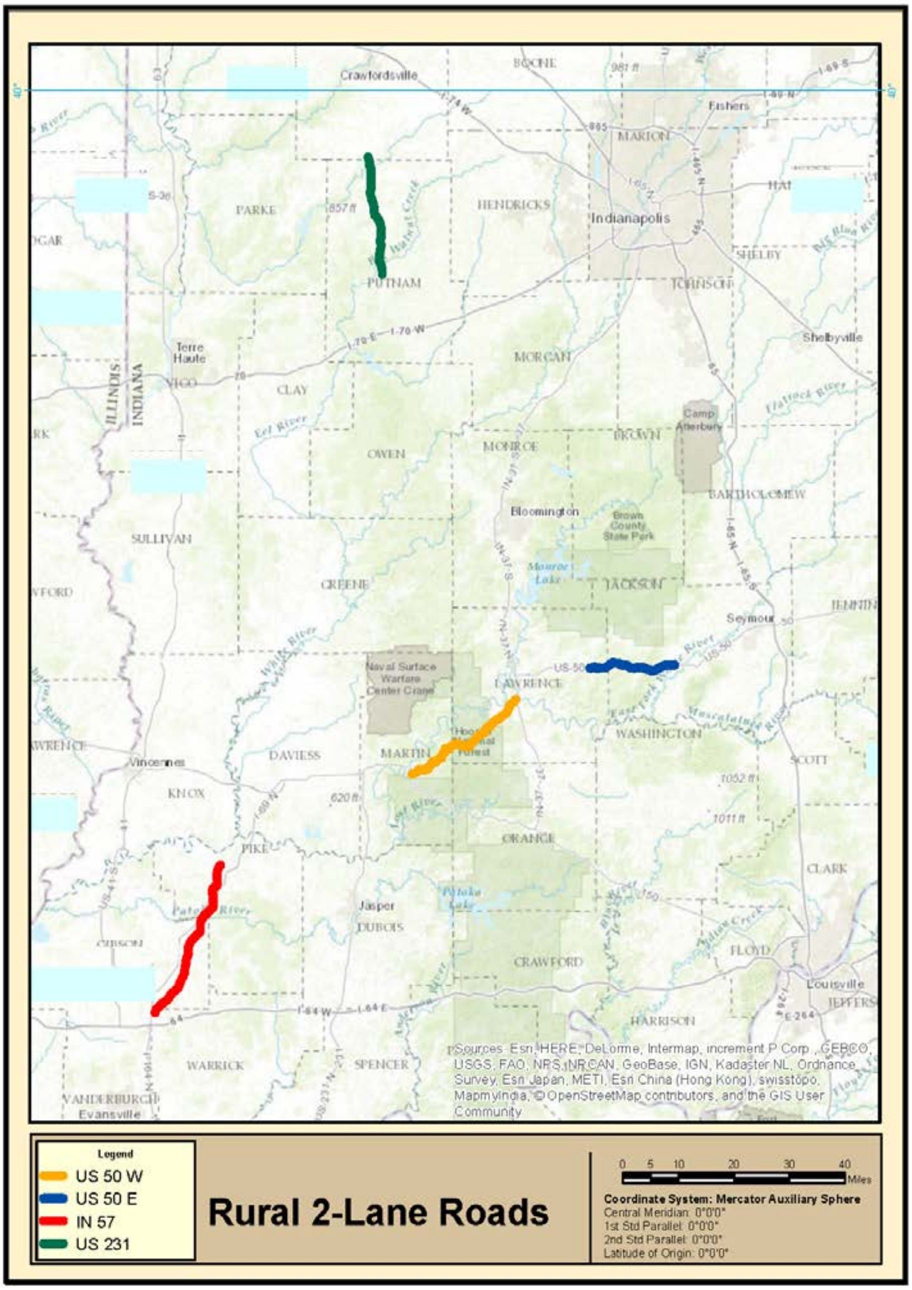


Figure 1 Selected roadway sections in Indiana.

To match and link the NDS trip data to RID data, unique Link ID values were used. However, the NDS data is a point data which reports the GPS and network speed at every point while RID is a linear (polyline) data which shows 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 centre were selected from the NDS trip files of the road segment under study.

Table 3 Number of Available Traversals per Highway Section

Highway Section	Road Side	Number of Trips	Number of Curves
US-50W	Left	26	50
	Right	37	50
US-50E	Left	49	20
	Right	51	21
IN-57	Left	6	29
	Right	32	30
US-231	Left	36	26
	Right	36	26
	Total:	273	252

To merge the GPS speed and curve geometry data, the authors used the latitude and longitude coordinates from both datasets. However, since the coordinates did not exactly match across the two databases (as shown in Figure 2), the authors allowed for a tolerance of 0.0002 degrees in both coordinates, which equates to a distance tolerance of about 90 feet. 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.

4. Model evaluation results

The speed predictions obtained from the curve speed models developed by Bonneson and Pratt (2009) 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 (SAS).

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.

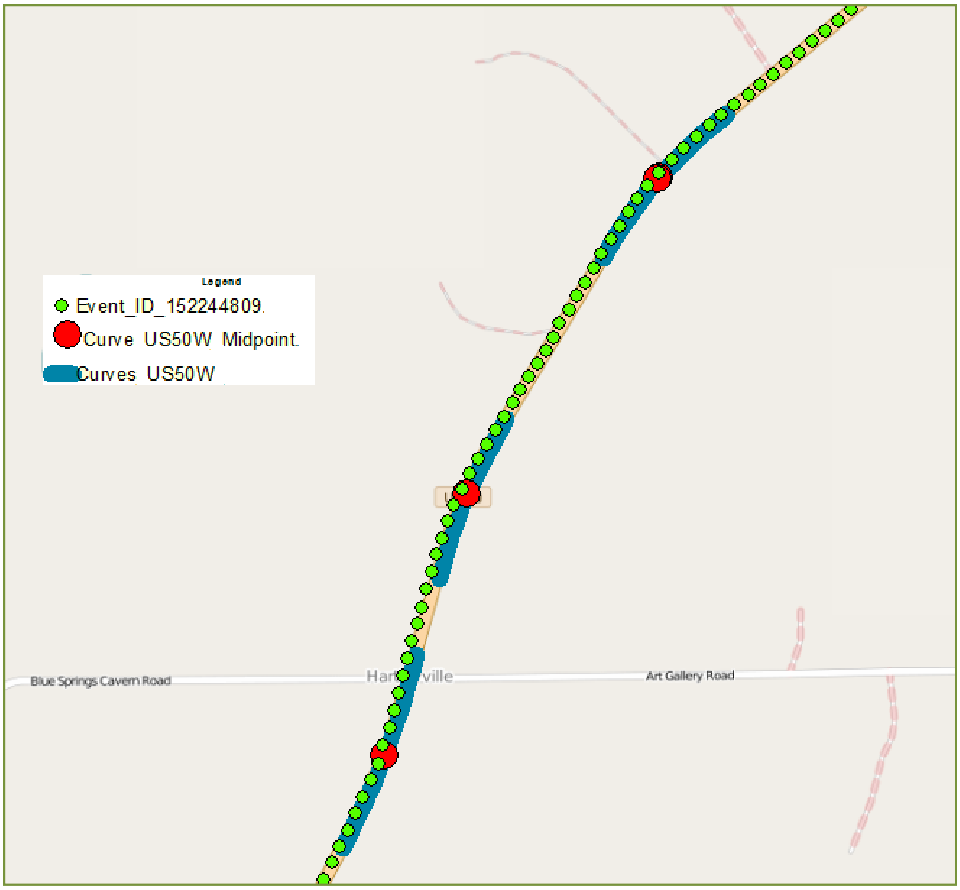
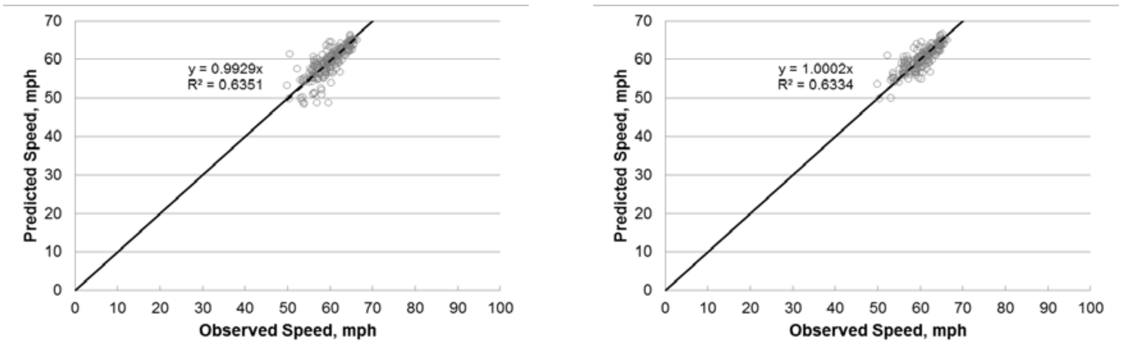


Figure 2 Matching NDS and RID data for one trip.

Once the deflection angles and corrected superelevation rates were computed for each curve, the models developed by Bonneson and Pratt (2009) and Pratt et al. (2015) 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. The observed and predicted MC speeds are compared in Figure 3. 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 3a, and a total of 185 curves are included in the comparison shown in Figure 3b. 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.



a. Predicted by Bonneson and Pratt (2009)

b. Predicted by Pratt et al. (2015)

Figure 3 Comparison of observed and predicted 85th-percentile MC speeds.

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

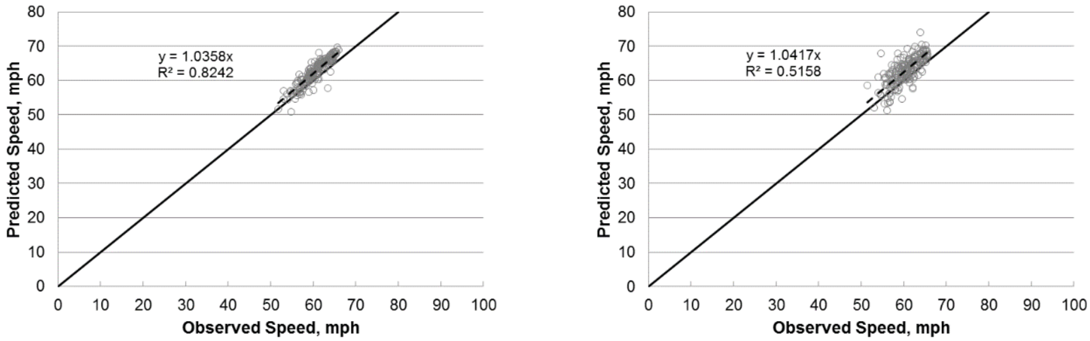
The trend lines in Figure 3 are fitted with a forced zero intercept value. Linear regression estimates were obtained with and without a nonzero intercept. The results of these estimates are provided in Table 4. The overall fit of the linear estimate, as described by the coefficient of determination (R^2) 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 ($p = 0.062$).

Table 4 Linear Estimate Parameter Results for MC Speed Models

Linear Estimate Parameter	Bonneson and Pratt (2009), Intercept = 0	Pratt et al. (2015), Intercept = 0	Bonneson and Pratt (2009), Intercept $\neq$ 0	Pratt et al. (2015), Intercept $\neq$ 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

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.

Comparisons of observed and predicted PC and PT speeds are shown in Figure 4a and Figure 4b, respectively. The linear estimate parameters are provided in Table 5. Both models are found to produce a slight overestimate of their respective speeds of about four 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 4 Comparison of observed and predicted 85th-percentile PC and PT speeds.

Table 5 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.

5. Conclusions and future research

5.1. Summary

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, etc.). 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.

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 SHRP2 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 (2009) and by Pratt et al. (2015) 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. (2015) 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.

5.2. Future Research

The availability of the NDS and RID databases allows for more sophisticated speed models to be developed for curves as well as 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 like 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 documents like the Highway Safety Manual to determine if enhanced speed prediction methodologies could improve the performance of safety prediction models or even network screening procedures.

The availability of driver data in the NDS database allows for the inclusion of additional variables in speed analysis efforts. For example, if given participants traversed a given highway section often enough, it may be possible to explore the change in speed choice as the driver becomes more familiar with the highway. Information about citations and enforcement activity could also be included in an enhanced analysis of vehicle speeds.

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