DAYTIME AND NIGHTTIME PASSENGER CAR OPERATING SPEED MODELS FOR TWO-LANE RURAL HIGHWAYS

A Thesis in
Civil Engineering

by
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ABSTRACT

Operating speed models need to be developed to understand how traffic control and geometric features affect driver’s speed selection. Once operating speed models are developed, they can be incorporated into the geometric design process to ensure that roadways are designed to maintain consistency and anticipated operating speeds coincide with the design speed. While it is well known that driving at night poses a significant risk, it is not well understood how drivers behave at night. There is a significant body of research on passenger car operating speeds, which focuses on daytime and ideal conditions, but very little research has focused on nighttime operating speeds. To discover some of the potential differences between operating speeds during the daytime and nighttime, three-stage least squares (3SLS) regression was used to estimate both the speed magnitude (mean speed) and speed dispersion (speed deviation) during the daytime and nighttime.

The models for estimating mean speed and speed deviation were then compared to each other to determine if there were differences, and the result of a transferability test shows that the two models are different. The comparison of the coefficients in the models and the transferability test show that there are differences between how drivers select their operating speeds during the daytime and nighttime, and these differences should be considered during the geometric design process. At higher approach speeds, there may be less of a concern about design consistency and more of a concern about vehicles exceeding the design speed during the nighttime since the models show that drivers maintain a speed closer to their approach speed through the curve more so during the night than day. Possible ways to lower operating speeds during the nighttime and have them more closely match operating speeds during the daytime are to reduce approach speeds since drivers maintain a more constant speed entering a curve during the nighttime than daytime.
or increase the delineation of the curve so drivers can judge the geometric layout of the curve better. This research can also be expanded upon to explore other potential differences between operating speeds during the day and night. Based on the additional analysis that is done and the coefficients of additional variables, it may be found that there are other variables that have a significant difference on operating speeds during the daytime and nighttime, and these differences should be considered in geometric design policy and processes.
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Chapter 1

Introduction

Operating speed models need to be developed to gain an understanding of how geometric features affect drivers’ speed selection. Once it is known how drivers choose their speed, roadways can be designed to maintain consistency by matching geometric features with drivers’ expectations. The operating speed is the speed drivers select based on their perception of the roadway, while the design speed is a measure that engineer’s use to select the roadway features for a highway. These can be vastly different from one another, which is why research needs to be completed to determine which variables affect drivers’ choice of operating speed.

Currently, the American Association of State Highway and Transportation Officials’ (AASHTO) *A Policy on Geometric Design of Highways and Streets*, commonly referred to as the “Green Book,” provides guidance for the design elements of new construction and major reconstruction of highways and streets. The design speed concept is intended to produce alignments that meet driver expectations and maintain design consistency among successive roadway features. However, this concept implies that all drivers will travel at or below the design speed, which is not always the case. As a result, it is important to develop operating speed models to determine the range of speeds expected on roadways as a function of the roadway features present along the alignment.

A significant body of research exists for passenger car operating speeds on rural two-lane highways, but most of the research is focused on daytime speeds and does not consider how the nighttime driving environment affects driver speed choice. If it is known how geometric design and traffic control variables affect nighttime travel speeds, then these variables can be incorporated into the design of roadways to maintain design consistency and improve the safety
of travel at night. Very limited research has been done in the area of operating speed model estimation for nighttime driving, but this limited research has shown there are possible differences between operating speeds during nighttime and daylight conditions (Guzman, 1996).

The National Highway Traffic Safety Administration (NHTSA) reported that 49 percent of passenger vehicle occupant fatalities occur at night, while only 25 percent of travel occurs during the night (Varghese and Shankar, 2007). It was also reported that the fatality rate is approximately three times higher at night than during the day. While these data suggest that travel during nighttime is more dangerous than travel during the day, there is very limited research concerning driver behavior at night. Transportation Research Circular: Number E-C151 (2011) recommends that future speed modeling work be designed to allow for nighttime operating speed models to be developed.

1.1 Purpose of Thesis

This thesis seeks to determine differences among roadway features, traffic control devices, and operating speeds during nighttime and daylight conditions through the development of both daytime and nighttime operating speed models. Ordinary least squares (OLS) linear regression has been the most common method to model operating speeds, but recent research has shown more advanced models are able to produce more efficient and unbiased estimates, along with being able to model the entire speed distribution. These more advanced models [e.g., three-stage least squares (3SLS) regression and seemingly unrelated regression (SUR)] were utilized to estimate the mean speed and standard deviation since it was determined they provided an advantage over OLS linear regression. The individual coefficients for each variable in the models were compared to each other. A comparison was also made between the two models to determine if the models, as a whole, were different. Based on the differences between the operating speed
models for daytime and nighttime conditions, recommendations were provided on how the results can be incorporated into geometric design policy and practice.

1.2 Organization of Thesis

This thesis contains six subsequent chapters. Chapter 2 is a comprehensive literature review that describes the published operating speed literature, including the benefits and shortcomings of past work in relation to the present study. Chapter 3 discusses the process that was used to collect and reduce the data for analysis. Chapter 4 outlines the econometric modeling methods that were used in this thesis to estimate daytime and nighttime mean operating speeds and speed dispersion. This chapter also discusses a transferability test, which was used to determine if the daytime and nighttime models differed. Chapter 5 shows the three models that were estimated: the model with all of the observations, the model with only daytime observations, and the model with only nighttime observations. Chapter 6 focuses on the comparison between the daytime and nighttime models. Chapter 7 provides conclusions for this thesis, discusses how the results of this thesis can be incorporated into geometric design policy and processes, and possible areas for future research related to daytime and nighttime operating speed models.
Chapter 2

Literature Review

2.1 AASHTO Horizontal Alignment Design Policy

The AASHTO Green Book contains guidance regarding the design of horizontal alignments in the United States. The design speed concept, which is defined as: “a selected speed used to determine the various geometric design features of the roadway” (AASHTO, 2011), explicitly relates to horizontal curve radius-superelevation design. AASHTO recommends that the selected design speed “be a logical one with respect to the anticipated operating speed, topography, the adjacent land use, and the functional classification of highway. In selection of design speed, every effort should be made to attain a desired combination of safety, mobility, and efficiency within the constraints of environmental quality, economics, aesthetics, and social or political impacts” (AASHTO, 2011). Additionally, the design speed should be related to all pertinent features to obtain a balanced design and fit the travel desires and habits of nearly all drivers expected to use a facility. Even if these guidelines are followed, there are many instances when design consistency may not be maintained in the geometric design process. The Green Book provides minimum or limiting values for horizontal curve design criteria and recommends “above-minimum design values should be used, where practical” (AASHTO, 2011). The intended consequence of using above-minimum (or below-limiting) design values is that it affords drivers greater comfort to travel at higher speeds, and thereby leads to an “inferred” design speed greater than the designated design speed (Donnell et al., 2009).
2.2 Design Consistency Evaluation Criteria

In 1977 Leisch and Leisch developed an alternative to the design speed concept that was intended to provide a more consistent speed along an alignment (Leisch & Leisch, 1977). The authors observed drivers continually speeding up and slowing down, especially in the lower range of design speeds (55 mph or less). The speed differential between passenger cars and trucks was also noted as a barrier to achieving design consistency. As a result, the authors recommended an updated design speed approach. The updated design speed approach introduced a 10-mph (15-km/hr) rule, which was defined as follows:

- A reduction in design speed along an alignment should be avoided, but if required, the reduction should not exceed 10 mph (15 km/hr)
- Within a given design speed, potential passenger car speeds along the highway normally should not vary by more than 10 mph (15 km/hr)
- Potential truck speeds generally should be not more than 10 mph (15 km/hr) below passenger car speeds at any time on common lanes.
- To ensure these three rules are not violated along an alignment and to maintain design consistency, operating speed profiles were recommended.

Lamm and Choueiri also developed a method to evaluate design consistency along an alignment and identify locations where speed transition problems exist for motorists (Lamm and Choueiri, 1987). Using 261 road sections of two-lane rural state routes in New York, the authors developed a rating system to evaluate successive horizontal elements. The horizontal alignment is evaluated based on the change in degree of curvature ($\Delta DC$) and/or the change in the 85th percentile speed ($\Delta V_{85}$) between successive elements. The ratings the authors developed for a horizontal alignment fit the following three categories:
• Good design: \( \Delta DC \leq 5^\circ \) or \( \Delta V_{85} \leq 6 \text{ mph} \) (10 km/hr)
• Fair design: \( 5^\circ < \Delta DC \leq 10^\circ \) or \( 6 \text{ mph} < \Delta V_{85} \leq 12 \text{ mph} \) (20 km/hr)
• Poor design: \( \Delta DC > 10^\circ \) or \( \Delta V_{85} > 12 \text{ mph} \) (20 km/hr)

### 2.3 Daytime Speed Prediction Models

A significant body of research exists related to operating speed models for two-lane rural highways. Much of this work is focused on free-flow passenger car operating speeds during the daytime with no adverse weather conditions. This section of the proposal synthesizes the daytime operating speed prediction modeling literature.

Lamm et al. (1987, 1988, and 1990) were among the first to estimate statistical models for passenger car operating speeds predicting the 85th percentile speed on horizontal curves on two-lane rural highways in New York. There were 261 road sections included in the study, each with varying degrees of curvature (DC). The sites had the following characteristics:

- No influence from intersections
- No physical features adjacent to or on the roadway that may influence speeds
- Delineated with a paved shoulder
- No changes in pavement or shoulder width, grades between -5 and 5 percent
- An average annual daily traffic (AADT) between 400 and 5,000 vehicles/day.

Predictor (independent) variables considered in the linear regression model were: degree of curvature, lane width, shoulder width, length of curve, average annual daily traffic, superelevation, available sight distance, vertical grade, and posted speed limit. The degree of curvature, lane width, shoulder width, and average annual daily traffic were all found to be statistically significant at the 95 percent confidence level. Sight distance, length of curve, and gradient were not included in the model because they were not significantly different than zero at the 95 percent confidence level. The posted speed limit was not included in the regression equation since it was highly correlated with the degree of curvature. For this same reason, the
superelevation was also left out of the regression model. Using Ordinary Least Squares (OLS) linear regression with a stepwise specification procedure, the following model was developed:

\[ V_{85} = 34.7000 - 1.00(DC) + 2.081(LW) + 0.174(SW) + 0.0004(AADT) \]

\[ R^2 = 0.842 \]

where,

- \( V_{85} \) = estimate of operating speed expressed by the 85th percentile speed (mph)
- DC = degree of curvature (range 0° to 27°)
- LW = lane width (feet)
- SW = shoulder width (feet)
- AADT = average annual daily traffic (vehicles per day).

The model is significant at the 95 percent confidence level with a coefficient of determination \((R^2)\) of 0.842. However, the authors determined that the lane width, shoulder width, and average annual daily traffic did not significantly enhance the predictive power of the model, explaining only approximately 5.5 percent of the variation in operating speeds.

Since it was determined that the predictive power of the model did not improve much with the addition of lane width, shoulder width, and average annual daily traffic independent variables, Lamm et al. (1988) estimated additional models using the same data from New York. These models predicted the 85th percentile speed by separating the data by lane width and then using OLS linear regression. Two models were predicted for each lane width, one using degree of curvature as a predictor variable and the other using only the posted speed limit as a predictor variable. Table 1 shows the models that were estimated.
Table 1 Models estimating V85 separated by lane width (Lamm et al. 1988).

<table>
<thead>
<tr>
<th>Lane Width (ft)</th>
<th>V85</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>58.656 - 1.135 DC</td>
<td>0.787</td>
</tr>
<tr>
<td></td>
<td>25.314 + 0.554 RS</td>
<td>0.719</td>
</tr>
<tr>
<td>10</td>
<td>55.646 - 1.019 DC</td>
<td>0.753</td>
</tr>
<tr>
<td></td>
<td>27.173 + 0.459 RS</td>
<td>0.556</td>
</tr>
<tr>
<td>11</td>
<td>58.310 - 1.052 DC</td>
<td>0.746</td>
</tr>
<tr>
<td></td>
<td>29.190 + 0.479 RS</td>
<td>0.744</td>
</tr>
<tr>
<td>12</td>
<td>59.746 - 0.998 DC</td>
<td>0.824</td>
</tr>
<tr>
<td></td>
<td>26.544 + 0.562 RS</td>
<td>0.835</td>
</tr>
</tbody>
</table>

where,

\[ \text{DC} = \text{degree of curvature (range } 0^\circ \text{ to } 27^\circ) \]
\[ \text{RS} = \text{posted speed limit of the curve (mph)} \]

Morrall and Talarico (1994) estimated a model to predict the 85th percentile operating speed of passenger cars on horizontal curves. The model was estimated using speed data collected on nine curves on rural two-lane highways in Alberta, Canada. Only the degree of curvature was used as a predictor variable in the model, since each site was on flat terrain with above-minimum sight distance. The lane and shoulder widths, and design speed were the same for all the curves so these were not used in the model. The model estimated was:

\[ V_{85} = e^{[4.561 - 0.00586(\text{DC})]} \quad R^2 = 0.631 \]

where,

\( V_{85} \) = 85th percentile speed (km/hr)
\( \text{DC} \) = degree of curve (degrees per 100m)
\( R^2 \) = coefficient of determination.
Islam and Seneviratne (1994) also developed models to predict the operating speed of vehicles on horizontal curves. Speed data were collected at eight sights on Highway 89 in the Logan Canyon section of Utah. Highway 89 is a two-lane rural highway, and the degree of curvature for all sites ranged between 4 and 28 degrees. Also, the vertical grade at the sites was less than five percent. Speeds were collected for 125 vehicles at the point of curvature (PC), midpoint of the curve (MC), and within 5 meters before the point of tangency (PT), for all eight curves. Three different models were estimated, one to estimate the 85th percentile speed at each of the three data collection points. The models estimated were:

\[
V_{85_{PC}} = 95.41 - 1.48(D) - 0.12(D)^2 \quad R^2 = 0.99
\]

\[
V_{85_{MC}} = 103.03 - 2.41(D) - 0.029(D)^2 \quad R^2 = 0.98
\]

\[
V_{85_{PT}} = 96.11 -1.07(D) \quad R^2 = 0.90
\]

where,

- \( V_{85_{PC}} \) = expected 85th percentile speed at PC (km/hr)
- \( V_{85_{MC}} \) = expected 85th percentile speed at MC (km/hr)
- \( V_{85_{PT}} \) = expected 85th percentile speed at PT (km/hr)
- \( D \) = degree of curvature (degrees per 30m).

The authors’ also determined that there was a significant difference between the operating speeds at the point of curvature (PC), the midpoint of the curve (MC), and the point of tangency (PT). The difference in predicted operating speeds between these three points increased as the degree of curvature increased. It was determined that, when the degree of curvature is greater than nine degrees, the operating speeds at the three points of the curve are all greater than the AASHTO recommended design speed. To evaluate design consistency it was recommended that the difference between the speed at the PT and design speed be used. The design speed was selected based on the assumption that the speed on a curve is uniform and the operating speed at the PT is always higher than at the MC.
Krammes et al. (1995) estimated models to predict the 85\textsuperscript{th} percentile speed for passenger cars on horizontal curves. Data were collected on rural two-lane highways in three different regions of the country. The east region consisted of New York and Pennsylvania, the west region consisted of Washington and Oregon, and the South region included Texas. Speeds were collected on both the horizontal curve and approach tangent. The 85\textsuperscript{th} percentile operating speeds on long tangents (minimum length of 244 m or 800 feet) are shown in Table 2, and these speeds are assumed to be the desired speed of drivers.

Table 2 Mean 85\textsuperscript{th} percentile speeds (km/hr) on approach (Krammes et al., 1995).

<table>
<thead>
<tr>
<th>Region</th>
<th>Terrain</th>
<th>Level</th>
<th>Rolling</th>
<th>All Terrain</th>
</tr>
</thead>
<tbody>
<tr>
<td>South</td>
<td>Level</td>
<td>102.4*</td>
<td>99.2</td>
<td>99.8</td>
</tr>
<tr>
<td>East and West</td>
<td>Level</td>
<td>97.9</td>
<td>95.5*</td>
<td>96.0</td>
</tr>
<tr>
<td>All Regions</td>
<td>Level</td>
<td>99.8</td>
<td>96.6</td>
<td>97.9</td>
</tr>
</tbody>
</table>

* Difference is significant at α=0.05

The desired speed was used as a predictor variable in one of the estimated models. The OLS linear regression models were:

\[
V_{85} = 103.66 - 1.95DC \quad R^2 = 0.80
\]

\[
V_{85} = 102.45 - 1.57DC + 0.0037L - 0.10I \quad R^2 = 0.82
\]

\[
V_{85} = 41.62 - 1.29DC + 0.0049L - 0.12I + 0.95V_t \quad R^2 = 0.90
\]

where,

\( V_{85} = \) estimated 85\textsuperscript{th} percentile speed on horizontal curves (km/hr)

\( DC = \) degree of curvature (degrees per 30m)

\( L = \) length of curve (m)

\( I = \) deflection angle (degrees)

\( V_t = 85\textsuperscript{th} \) percentile speed on approach (km/hr).
Ottesen (1993) also estimated a model to predict the 85\textsuperscript{th}-percentile speed at the curve midpoint. Data from the Krammes et al. (1995) study were used, but a different model was estimated. The data consisted of 138 horizontal curves and 78 approach tangents on rural two-lane highways. Free-flow speeds were collected at the curve midpoint and on the tangent prior to the curve where vehicles were traveling at their desired speed. Unlike the model estimated by Krammes et al., only the radius was used as a predictor variable. The model estimated was:

\[
V_{85} = 103.64 - \frac{3400.73}{R}
\]

\[R^2 = 0.80\]

where,

\[V_{85} = 85\textsuperscript{th}-\text{percentile speed at curve midpoing (km/h)}\]
\[R = \text{radius of curvature (m)}\]

Voigt (1996) expanded upon the work that Ottesen completed to estimate the 85\textsuperscript{th}-percentile speed at the midpoint of horizontal curves. Voigt used the same data set as Krammes et al. (1995) and Ottesen (1993). The model developed by Ottesen was verified, and it was also determined that superelevation was statistically significant in predicting operating speeds at the curve midpoint. The model developed using OLS linear regression was:

\[
V_{85} = 101.98 - 2.08D + 40.33e
\]

\[R^2 = 0.81\]

where,

\[V_{85} = 85\textsuperscript{th}-\text{percentile speed at curve midpoing (km/h)}\]
\[D = \text{degree of curvature (º)}\]
\[e = \text{superelevation rate (m/m)}\]

Another model was developed, which included the length and degree of curvature:

\[
V_{85} = 99.61 - 1.69D + 0.014L - 0.13\Delta + 71.82e
\]

\[R^2 = 0.84\]
where,

\[ V_{85} = 85^{th}\text{-percentile speed at curve midpoint (km/h)} \]
\[ D = \text{degree of curvature (°)} \]
\[ L = \text{length of curve (m)} \]
\[ \Delta = \text{deflection angle (°)} \]
\[ e = \text{superelevation rate (m/m)} \].

Fitzpatrick et al. (2000) expanded on the research by Krammes et al. (1995) by enhancing the operating speed models that were previously estimated. Speed data were collected at 176 two-lane rural highway sites and used to estimate speed models for horizontal curves, vertical curves, and the combination of these two. Ten alignment conditions were identified, and models were estimated for seven of them. Table 3 shows the speed prediction equations resulting from this effort.
Table 3 Speed prediction equations for passenger vehicles (Fitpatrick et al., 2000).

<table>
<thead>
<tr>
<th>AC EQ#</th>
<th>Alignment Condition</th>
<th>Equation</th>
<th>No. of Sites</th>
<th>R²</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Horizontal Curve on Grade: -9% ≤ g ≤ -4%</td>
<td>( V_{85} = 102.10 - \frac{3077.13}{R} )</td>
<td>21</td>
<td>0.58</td>
<td>51.95</td>
</tr>
<tr>
<td>2</td>
<td>Horizontal Curve on Grade: -4% ≤ g ≤ 0%</td>
<td>( V_{85} = 105.98 - \frac{3709.90}{R} )</td>
<td>25</td>
<td>0.76</td>
<td>28.46</td>
</tr>
<tr>
<td>3</td>
<td>Horizontal Curve on Grade: 0% ≤ g ≤ 4%</td>
<td>( V_{85} = 104.82 - \frac{3574.51}{R} )</td>
<td>25</td>
<td>0.76</td>
<td>24.34</td>
</tr>
<tr>
<td>4</td>
<td>Horizontal Curve on Grade: 4% ≤ g ≤ 9%</td>
<td>( V_{85} = 96.61 - \frac{2752.19}{R} )</td>
<td>23</td>
<td>0.53</td>
<td>52.54</td>
</tr>
<tr>
<td>5</td>
<td>Horizontal Curve Combined with Sag Vertical Curve</td>
<td>( V_{85} = 105.32 - \frac{3438.19}{R} )</td>
<td>25</td>
<td>0.92</td>
<td>10.47</td>
</tr>
<tr>
<td>6</td>
<td>Horizontal Curve Combined with Nonlimited Sight Distance Crest Vertical Curve</td>
<td>See Note 1</td>
<td>13</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>7</td>
<td>Horizontal Curve Combined with Limited Sight Distance Crest Vertical Curve</td>
<td>( V_{85} = 103.24 - \frac{3576.51}{R} )</td>
<td>22</td>
<td>0.74</td>
<td>20.06</td>
</tr>
<tr>
<td>8</td>
<td>Sag Vertical Curve on Horizontal Tangent</td>
<td>( V_{85} = \text{assume desired speed} )</td>
<td>7</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>9</td>
<td>Vertical Crest Curve with Nonlimited Sight Distance on Horizontal Tangent</td>
<td>( V_{85} = \text{assume desired speed} )</td>
<td>6</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>10</td>
<td>Vertical Crest Vertical Curve with Limited Sight Distance on Horizontal Tangent</td>
<td>( V_{85} = 105.08 - \frac{149.69}{K} )</td>
<td>9</td>
<td>0.60</td>
<td>31.10</td>
</tr>
</tbody>
</table>

Notes:
AC EQ# = Alignment Condition Equation Number
\( V_{85} \) = Expected 85\(^{th} \) percentile speed of passenger cars at curve midpoint (km/h)
R = Radius of Horizontal Curve (m)
K = Rate of Vertical Curvature
G = Grade (%)
1. Use lowest speed of the speeds predicted by equations 1 or 2 (for the downgrade) and equations 3 or 4 (for the upgrade).
2. Check the speeds predicted from equations 1 or 2 (for the downgrade) and equations 3 or 4 (for the upgrade) and use the lowest speed. This will ensure that the speed predicted along the combined curve will not be greater than if just the horizontal curve was present (i.e., that the inclusion of a limited sight distance crest vertical curve result in a higher speed).

It was determined that the inverse radius (1/R) was the suitable functional form of the predictor variable to estimate operating speeds of passenger cars, which is shown in Equations 1-5 and 7 in Table 3. When a sag or limited sight distance crest vertical curve is in combination with a horizontal curve, the radius of the horizontal curve was the best predictor of speed (Equation 5).
When a non-limited sight distance crest vertical curve is in combination with a horizontal curve, the operating speed is the lower of the speed predicted by the equation for horizontal curves on grades or the assumed desired speed (Equation 6). For sag vertical curves on horizontal tangents, the desired speed was also assumed (Equation 8). No acceptable regression equation could be estimated for road segments with crest vertical curves that had above-minimum stopping sight distance available to the driver, so the desired speed was assumed in this case (Equation 9). For vertical curves with limited sight distance on horizontal tangents (Equation 10), operating speeds were estimated using the inverse of the rate of vertical curvature (1/K) as the independent variable. It was also found that operating speeds on horizontal curves are similar to speeds on tangent sections when the radius of the curve exceeds 800 m (2635 ft). For this condition, the vertical grade affects the vehicle operating speed, while the radius of the curve is negligible. Also, operating speeds drop sharply when the radius of the horizontal curve is less than 250m (820 ft). Fitzpatrick et al. also compared operating speeds between horizontal curves with spiral transitions and ones without spiral transitions and determined there is no significant difference in speeds.

Gibreel et al. (2001) estimated operating speed models for two-lane rural highways that accounted for the three-dimensional features of highways. To improve upon existing work, the authors’ estimated models for a horizontal curve combined with a sag vertical curve and a horizontal curve combined with a crest vertical curve. Data were collected on Highway 61 and Highway 102 in Ontario with data collected at five points for each site. The five points were: the approach tangent (AT), departure tangent (DT), beginning of curve (BC), middle of curve (MC), and the end of curve (EC). Only free-flow vehicles were considered in the analysis to avoid the effects of ambient traffic on operating speeds. The authors concluded that there is a significant difference between speed predictions from three-dimensional models and models that do not use
vertical curve information as predictor variables. They recommended that 3-D models be used in the design of horizontal curves and for design consistency evaluations since there was a difference between the two models. The estimated models are shown in Table 4.

### Table 4 3-D speed models (Gibreel et al., 2001).

<table>
<thead>
<tr>
<th>Location</th>
<th>Model</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sag Curves</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AT</td>
<td>$V85 = 91.81 + 0.010 R + 0.468(\sqrt{L_V}) - 0.006 G_1^2 - 0.878 \ln(A) - 0.826 \ln(L_0)$</td>
<td>0.98</td>
</tr>
<tr>
<td>BC</td>
<td>$V85 = 47.96 + 7.216 \ln(R) + 1.534 \ln(L_V) - 0.258 G_1 - 0.653 A + 0.02 e^E - 0.008 L_0$</td>
<td>0.98</td>
</tr>
<tr>
<td>MC</td>
<td>$V85 = 76.42 + 0.023 R + 0.00023 K^2 - 0.008 e^A + 0.026 e^E - 0.00012 L_0^2$</td>
<td>0.94</td>
</tr>
<tr>
<td>EC</td>
<td>$V85 = 82.78 + 0.011 R + 2.068 \ln(K) - 0.361 G_2 + 0.036 e^E - 0.00011 L_0^2$</td>
<td>0.95</td>
</tr>
<tr>
<td>DT</td>
<td>$V85 = 109.45 - 1.257 G_2 - 1.586 \ln(L_0)$</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>Crest Curves</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AT</td>
<td>$V85 = 82.29 + 0.003 R - 0.05 DFC + 3.441 \ln(L_V) - 0.533 G_1 + 0.017 e^E - 0.000097 L_0^2$</td>
<td>0.94</td>
</tr>
<tr>
<td>BC</td>
<td>$V85 = 33.69 + 0.002 R + 10.418 \ln(L_V) - 0.544 G_1 + [8.699/ \ln(1+A)] + 0.032 e^E - 0.011 L_0$</td>
<td>0.97</td>
</tr>
<tr>
<td>MC</td>
<td>$V85 = 26.44 + 0.251(\sqrt{R}) + 10.381 \ln(L_V) - 0.423 G_1 + [6.462/ \ln(1+A)] + 0.051 e^E - 0.028 L_0$</td>
<td>0.98</td>
</tr>
<tr>
<td>EC</td>
<td>$V85 = 74.97 + 0.292 (\sqrt{R}) + 3.105 \ln(K) - 0.85 G_2 + 0.026 e^E - 0.00017 L_0^2$</td>
<td>0.90</td>
</tr>
<tr>
<td>DT</td>
<td>$V85 = 105.32 - 0.418 G_2 - 0.123 (\sqrt{L_V})$</td>
<td>0.83</td>
</tr>
</tbody>
</table>

where:
- AT = approach tangent,
- DT = departure tangent,
- BC = beginning of curve,
- MC = middle of curve,
- EC = end of curve,
- $R$ = radius of curvature (m),
- $L_V$ = length of vertical curve (m),
- $L_0$ = distance between horizontal and vertical points of intersection (m),
- $G_1, G_2$ = first and second grade in direction of travel, respectively (%),
- $A$ = algebraic difference in grades (%),
- $e, E$ = superelevation rate (%),
- $K$ = length of vertical curve for 1% change in grade (m), and
- $DFC$ = deflection angle of curve (degrees).
Figueroa, Medina, and Tarko (2005) developed an operating speed model that was not limited to only the 85th-percentile speed so that the entire speed distribution could be modeled. Most of the operating speed models previously described considered only a single point of the speed distribution (e.g., 85th-percentile), and therefore, speed dispersion was not explicitly considered in those operating speed models. Free-flow speeds were collected at 158 rural two-lane highway locations. There was an average of 360 speed observations collected at each site with a minimum of 100 for each site. The speed measurements were taken at various points before, within, and after the horizontal curve. Also, all of the sites had a speed limit of either 50 or 55 mph. Ordinary least squares (OLS) regression was applied to panel data (PD) so the model developed was an OLS-PD model with the following general functional form:

\[ V_{ip} = \sum_{j} a_{ij} \cdot X_{ij} + \sum_{k} b_{ik} \cdot (Z_{p} \cdot X_{ik}) + \varepsilon \]

where,

- \( V_{ip} \) = the \( p \)th percentile speed at site \( i \)
- \( X_{ij}, X_{ik} \) = parameters affecting both the mean speed and standard deviation, respectively
- \( Z_{p} \) = standard normal value for the \( p \)th percentile (assumes normal distribution of speeds)
- \( a_{ij}, b_{ik} \) = coefficients representing relations between \( X_{ip}, X_{ik} \) and \( V_{ip} \)
- \( \varepsilon \) = random disturbance.

The advantages of this model over most previous models were that it can predict any percentile speed instead of a single percentile speed (e.g. V85), and the association between design features and the mean speed and speed variance were considered separately. The resulting models are shown in Table 5. The coefficient of determination (\( R^2 \)) was 0.9322.
Table 5 OLS-PD percentile speed model for horizontal curves (Figueroa, Medina, & Tarko, 2005).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Value</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean Speed Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>47.6639</td>
<td>0.7038</td>
<td>67.73</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Sight distance, SD</td>
<td>3.4400 x 10^{-3}</td>
<td>3.8581 x 10^{-4}</td>
<td>8.91</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Residential development indicator, RES</td>
<td>-2.6388</td>
<td>0.3777</td>
<td>-6.99</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Degree of curvature, DC</td>
<td>-2.5409</td>
<td>0.0722</td>
<td>-35.17</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Superelevation rate, SE</td>
<td>7.9535</td>
<td>0.2564</td>
<td>31.02</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Superelevation rate squared, SE²</td>
<td>-0.6239</td>
<td>0.0192</td>
<td>-32.57</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td><strong>Speed Dispersion Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant, Z₀</td>
<td>4.1576</td>
<td>0.4049</td>
<td>10.27</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Degree of curvature, Z₀=DC</td>
<td>0.2358</td>
<td>0.067</td>
<td>3.52</td>
<td>0.0005</td>
</tr>
<tr>
<td>Superelevation rate, Z₀=SE</td>
<td>-0.1987</td>
<td>0.0679</td>
<td>-2.92</td>
<td>0.0038</td>
</tr>
</tbody>
</table>

Misaghi and Hassan (2005) developed models to estimate operating speeds at the midpoint of horizontal curves and also the speed differential from the tangent to curve midpoint. Data were collected at 20 sites on four different two-lane rural highways in Ontario on different highway classes. Data were collected on the approach tangent, curve midpoint, and departure tangent. Data were collected for 24 hours, but nighttime data, wet-pavement, and nonfree-flow vehicles were not included in the database used for modelling. Two models were estimated to predict the 85th-percentile speed, and only the radius or square of the radius were found to be statistically significant in the models using OLS linear regression. The two models estimated were:

\[
V_{85MC} = 91.85 + 9.81 \times 10^{-3} R \quad R^2 = 0.464
\]

\[
V_{85MC} = 94.30 + 8.67 \times 10^{-2} R^2 \quad R^2 = 0.524
\]

where,

\[
V_{85MC} = 85^{th}\text{-percentile speed at the curve midpoint (km/h)}
\]

\[
R = \text{radius of curve (m)}.
\]
The $85^{th}$-percentile speed differential from the tangent to curve midpoint was also predicted. The speed differential was calculated for each vehicle, and then the $85^{th}$ percentile of the speed differentials, which was referred to as $\Delta$(Delta)V85, was calculated, too. The $\Delta$V85 is different than the speed differential that results from subtracting the operating speeds on two successive elements ($\Delta$V85 = $V_{85i} - V_{85i-1}$), which underestimates the real values of speed differential, as shown in a study and by McFadden and Elefteriadou (2000). The two models developed by Misaghi and Hassan (2005) were:

$$\Delta V85 = -83.63 + 0.93V_T + e^{8.93 + 3507.10/R}$$  \hspace{1cm} R^2 = 0.640
$$\Delta V85 = -198.74 + 21.42(\sqrt{V_T} + 0.11DFC - 4.55SW - 5.36(curve\_dir) + 1.30G + 4.22(drv\_flag))$$  \hspace{1cm} R^2 = 0.889

where,

$\Delta V85 =$ $85^{th}$-percentile speed differential  
$V_T =$ speed on approach tangent (km/h)  
DFC = deflection angle of circular curve (°)  
G = average longitudinal grade from approach tangent to midpoint of curve  
SW = shoulder width (m)  
curve\_dir = curve direction flag (left = 1 & right = 0)  
drv\_flag = driveway flag (intersection on curve = 1 & no intersection = 0).

Operating speeds of passenger cars have been analyzed and modeled ever since Leisch and Leisch proposed an alternative to the design speed concept. Most of the models estimate the $85^{th}$-percentile speed at the curve midpoint by OLS linear regression. These models have used the following variables to predict operating speeds: radius of curve, superelevation, deflection angle, degree of curvature, length of curve, rate of vertical curvature (K), grade, lane width, shoulder width, AADT, speed on tangent, curve direction, and if there was an intersection within the curve. Many of these variables are recurring in different speed models (e.g. radius, degree of curvature, etc.), which suggest that research is converging on these as acceptable predictors of driver speed.
choice. Recent models have been developed that are not limited to one specific speed (e.g. V85) but can represent the entire distribution. Some of these models assume a normal distribution of speeds and do not explicitly model the distribution of speeds (standard deviation). Additional research can be done to model the entire distribution of speeds and analyze the endogenous relationship between mean speed and speed deviation. Also, most of the previous research focuses at operating speeds at a specific point (e.g. curve midpoint), but with LiDAR and GPS data collection methods now readily available, a speed profile can be estimated for vehicle approaching and traveling through the entire horizontal curve.

2.4 Nighttime Speed Prediction Models

There is little published research comparing the differences between operating speeds during the daytime and nighttime. Guzman (1996) compared day and night speeds selected by drivers on horizontal curves along two-lane rural highways. Speed measurements were taken on the approach and midpoint, in both directions, on nine horizontal curves. The vehicles were tracked through the curve, and only free flow, two-axle unopposed vehicles were included in the analysis. The speed difference between the approach and midpoint was calculated for each vehicle.

Twenty of the 48 t-tests comparing daytime and nighttime mean speeds indicated a statistically significant difference between the mean operating speeds during daytime and nighttime travel. Nine of the 20 significant differences were at the midpoint of the curve. There was no specific geometric feature of the roadway that was associated with differing speeds between the daytime and nighttime periods.

Guzman did not recommend a variable accounting for daytime versus nighttime conditions when modeling operating-speeds to evaluate design consistency of a horizontal alignment. This recommendation was based on the following:
- The difference in nighttime and daytime midpoint speeds ranged from −2.9 mph to 3.8 mph for sites where there was a statistically significant difference between the two speed data collection periods. A negative value indicates that nighttime speeds were higher than daytime speeds. The mean significant difference was 2.5 mph.

- The difference in speed reduction between nighttime and daytime speeds ranged from -1.7 mph to -0.7 mph for sites where there was a statistically significant difference between daytime and nighttime speeds. The speed reduction was greater at nighttime for all of the sites where there was a statistically significant difference between daytime and nighttime speeds. The mean significant difference was 1.1 mph.

- The magnitude of the differences between daytime and nighttime speeds was small for all degrees of curvature, therefore, the author concluded that this did not necessitate a variable indicating daytime versus nighttime periods in operating speed profile models.

Quaium (2010) also considered the possible difference between vehicle speeds during the daytime and nighttime on rural horizontal curves. The author developed a linear mixed model to estimate vehicle speeds at the curve midpoint of two-lane rural horizontal curves in the outside lane. Data were collected on 18 rural two-lane horizontal curves near Nashville, Tennessee. Vehicle speeds were recorded at four points for each site: approximately 1000 feet upstream of the curve warning sign, at the advance curve warning sign or the location one would be if a sign of this type was used, the PC, and the MC. Data were collected for at least 48 hours at each site. The predictor variables used in the models were: radius, superelevation, deflection angle, posted speed limit, and pavement edgeline retroreflectivity. The model predicts nighttime vehicle speeds decrease as retroreflectivity increases. The resulting mixed model was:
\[ \text{Speed (MC)} = 22.376 + 0.614\sqrt{\text{Radius}} + 1.837\sqrt{\text{MC Superelevation}} \]

- 0.065(Deflection Angle) + 0.105(Posted Speed Limit)
- 0.003 (Retroreflectivity * Day/Night Code)

where,

- Speed(MC) = Speed at curve midpoint (mph)
- Radius = Curve radius (feet)
- MC Superelevation = Superelevation at the curve midpoint (percentage)
- Retroreflectivity = Retroreflectivity of edgeline (mcd/m²/lx)
- Day/Night Code = 0 for day vehicle and 1 for night vehicle.

The horizontal curves were grouped using eight different methods to determine if there was a difference between speeds during the daytime and nighttime. Analysis of variance (ANOVA) was used to determine if there was a difference in speeds between the daytime and nighttime periods. The results of the research indicated that the daytime and nighttime operating speeds were essentially the same and the difference was statistically and practically insignificant.

These previous studies do not provide conclusive results about whether there is a difference between operating speeds during the daytime and nighttime. Guzman completed a basic analysis by performing t-tests between daytime and nighttime speeds. The author discovered there were statistically significant differences between the speeds during the daytime and nighttime at many curves. Guzman also stated there was not a trend in curve geometry between the tangent-curve sections, however, no models were estimated that would be able to determine if there was a significant difference in the effects of geometric elements on operating speeds between the daytime and nighttime. The results were not very conclusive with nighttime speeds increasing at some sites while decreasing at other sites. The author found a maximum difference in speeds between the two ambient light conditions of 3.8 mph, which could be a practical difference. Quaium improved on the work done by Guzman and estimated a model that predicted speeds at
the curve midpoint by using daytime/nighttime as a predictor variable in the model. An analysis of variance was also performed, and it was determined that operating speeds between the daytime and nighttime operating speeds were essentially the same. These two approaches offer differing conclusions, and there is no consensus as to whether operating speeds differ significantly between the daytime and nighttime. None of the previous work estimated separate models for daytime and nighttime speeds or modeled the entire speed distribution. This work can be continued by estimating models to predict the mean speeds of passenger cars during the daytime and nighttime and modeling the distribution of speeds. This allows for a comparison between daytime and nighttime operating speeds, which will provide more conclusive results as to whether operating speeds differ significantly and practically between the day and night, which can then be integrated into geometric design practices.

2.5 Modeling Approaches

There have been many different modeling methods used to estimate operating speeds of vehicles on horizontal curves. Most of the previously estimated models were estimated using OLS linear regression, which provides the advantage of being robust and simple to estimate. However, OLS linear regression does not account for repeated measurements at a site, can estimate only specific point speeds (e.g. mean, V85, etc.), and if any of the five assumptions of OLS linear regression are violated then the predictions are no longer efficient and the results may be biased, possibly leading to incorrect conclusions drawn from the models. Typically, the 85th-percentile speed is modeled, which does not account for the entire distribution of speeds and information about extreme speeds is lost (Himes et al., 2011). Many models also only account for roadway geometric elements at the curve, while ignoring the surrounding environment and entire roadway alignment that may have an effect on operating speeds (e.g. surrounding land use, intersections and curves, previous upstream curve, etc.).
Recently, more sophisticated statistical approaches have been used to estimate operating speeds. Poe and Mason (2000) used a mixed model to estimate operating speeds that was able to account for influences of both random and fixed effects. This allows for the correlation between successive data collection locations (i.e., “tracking” vehicles through a site) to be considered by specifying the driver as a “random” effect in the model. Tarris et al. (1996) used a panel model that was able to account for repeated measurements (time sequence) among drivers at a data collection site. Figueroa, Medina, and Tarko (2005) applied the OLS estimator to panel data, which resulted in an OLS-PD model. A panel model was able to account for the fact that there were multiple speed observations for each driver (vehicle). Park et al. (2010) used multilevel models to estimate speed differentials between different highway segments. Such a modeling approach considers the correlation resulting from multiple speed observations (time sequence), nested within a site. Cruzado and Donnell (2011) also modeled operating speeds in transition zones (places where the speed limit changes from high to low) using a three-level multilevel model to capture site-level speed variance that a panel model could not. Recently, Himes and Donnell, (2010); Himes et al., (2011); Porter and Mason, (2008); Shankar and Mannering, (1998); and Ulfarsson et al., (2005), have used systems methods to model the entire speed distribution by modeling the mean speed and speed deviation simultaneously. By modeling these simultaneously the possible endogeniety and contemporaneous correlation between the two disturbance terms of the mean speed and speed deviation are accounted for. Specific uses of systems models are discussed in more detail below.

Porter et al. (2007) modeled speeds and speed deviation in work zones using a seemingly unrelated regression (SUR) model. Data were collected at 17 construction work zones -- 11 lane closures and six median crossovers. Data were collected between two and 19 locations for each site, with one location being upstream of the work zone and temporary traffic control devices.
For each location, approximately 200 free-flow speeds were collected, with 18,739 free-flow observations and 136 locations in the final data set. The speed limit ranged from 55 to 70 mph for all sites prior to the work-zone. The models to estimate the 85th-percentile speed and standard deviation were estimated using the following general functional form:

\[ V_{85i} = \alpha + \beta X_i + \varepsilon_i \]
\[ \sigma_i = \tau + \eta V_i + \nu_i \]

where,

- \( V_{85} \) = 85th-percentile speed of passenger cars at location \( i \)
- \( X_i \) = vector of exogenous variables influencing 85th-percentile speeds
- \( \sigma_i \) = standard deviation of passenger car speed at location \( i \)
- \( V_i \) = vector of exogenous variables influencing \( \sigma_i \)
- \( \alpha, \beta, \tau, \eta \) = vectors of coefficients to be estimated
- \( \varepsilon_i, \nu_i \) = disturbance terms.

Similar factors may affect the disturbances for both the 85th-percentile speed and standard deviation, which results in contemporaneous correlation between the two disturbance terms. SUR estimation is a full-information method and uses a generalized least squares (GLS) estimator. OLS assumes the correlation between the two error terms is zero, but SUR models offer greater efficiency over OLS when \( \text{cov}(\varepsilon_i, \nu_i) \neq 0 \) and \( X_i \neq V_i \) (explanatory variables are different in the two equations). If either of these is not true then OLS and GLS are the same, and the two equations can be estimated separately using OLS regression. GLS also increases in efficiency with increasing correlation between the error terms and diminishing correlation between the exogenous variable matrices. It was recommended to consider SUR estimation when two or more operational measures are being modeled, and the error terms may be correlated.

Himes et al. (2013) analyzed the effects on speed prediction models when the posted speed limit is incorporated into the model as a predictor variable. Prior to this there was question as to
whether or not it should be included, since it is might be correlated with roadway features. Others argue that the speed limit should be included since there is a high level of statistical correlation between the speed limit and operating speeds. The focus of the research was to evaluate omitted variable bias, multicollinearity, and endogeneity that is associated with including the posted speed limit as a predictor variable in operating speed models. The data used were collected at 79 sites across nine different roadway segments of two-lane rural and urban highways in Pennsylvania and Virginia. Omitted variable bias was evaluated by estimating two models, one with the posted speed limit and one without the posted speed limit. The results show the posted speed limit should be included since the influence of the other variables is overestimated when the posted speed limit is not included. Also, an instrumented variable (IV) was used to determine if correlation exists between the speed limit (predictor variable) and error term. The difference in parameter estimates between the estimate with OLS and IV were small. The gains by using IV were very small, which indicates that including the posted speed limit as an instrumented variable is not necessary. The authors concluded the following from the research:

1. The speed limit should be included in operating speed models.
2. The speed distribution should be estimated in addition to speed magnitude and not only a single speed, which can be done with three-stage least squares (3SLS) regression.
3. The speed limit should be considered as an exogenous variable, and an instrumented variable for the posted speed is not necessary.
4. Disaggregated data should be used whenever possible to minimize the amount of data lost from data aggregation.
5. The effects of data collection at more than one location should be considered in future operating speed modeling research that considers a system modeling approach.
In summary, operating speed models have been estimated since Leisch and Leisch (1977) proposed evaluating the design consistency along an alignment by the speed difference between consecutive elements of a continuous alignment. As the previous discussion shows, ordinary least squares (OLS) linear regression has been the main method to model operating speeds. The disadvantage of OLS is it has several assumptions that, if violated, will result in biased, inefficient, or inconsistent model parameters, possibly producing incorrect speed estimates or predictions. These models also do not predict the entire speed distribution and only can be used for specific point speeds (e.g. mean speed and V85). However, there are many other types of models that can be used to estimate operating speed models that may provide benefits when an assumption of the OLS estimator is violated. These various models include: panel models, multilevel models, and systems models (3SLS and SUR). Recent research has demonstrated that modeling the entire speed distribution is important to gain an understanding of how driver speed choice is affected by horizontal curves and other site-specific features. Systems models are able to model the entire distribution, while also accounting for possible endogeneity that may exist between the mean speed and speed deviation, or contemporaneous correlation between the two disturbance terms. These advanced statistical methods are becoming more commonly used than OLS linear regression in estimating operating speed models.
Chapter 3

Field Data Collection and Preparation

3.1 Locations

The data used for this thesis were collected under the “Informational Report on Methods to Achieve Safe Speeds on Rural and Suburban Roadways” project funded by the Federal Highway Administration (FHWA). The objective of this project was to document known speed and safety relationships between roadway and traffic calming features approaching and within horizontal curves on rural and suburban highways, and to evaluate speed or safety relationships for novel treatments that have not been rigorously evaluated on these same roadway types. This thesis focused only on the speed data collected as part of the FHWA effort.

Operating speed data were collected before and after the treatments were applied so only the before period data were used for estimating the models. This ensured that any effects the treatments had on vehicle operating speeds are not captured in the statistical models. Data were collected at 27 sites -- eight in Massachusetts, eight in Alabama, seven in West Virginia, and four in Arizona. The sites had vastly different land use characteristics ranging from residential to rural wooded or desert parcels. The roadway geometry also varied among the sites.

3.2 Equipment Used and Data Collection Procedures

The speed data were collected using Nu-metrics Hi-Star pavement sensors, which were placed on the pavement and use magnetic imaging technology to record a vehicle’s speed, headway, length, pavement temperature, pavement condition (dry or wet), and the time stamp when a vehicle passes over the sensor. The sensors were placed in the center of the travel lane and a black rubber cover was placed over them to protect the sensor and reduce the conspicuity of the recording
device to drivers, thereby minimizing the effect on driver speed choice. The sensors have a relatively small profile with a thickness of only 0.625 inches, a length of 6.5 inches, and a width of 5.5 inches. The sensors were programmed using the Nu-Metrics Highway Data Management (HDM) software. The sensors were operational at a time that allowed for both daytime and nighttime periods to be collected.

At the West Virginia sites, the sensors were placed as follows: (1) approximately 300 feet prior to the beginning of the horizontal curve, (2) at the point of curvature (PC), (3) at the midpoint of the horizontal curve, and (4) at the midpoint of the horizontal curve in the opposite travel lane, which was used to determine the presence of a vehicle in the opposite travel lane. Using the time stamp and headway of each vehicle, the vehicles were “tracked” as they traveled through the curve so there was an individual speed profile for every vehicle. Any vehicle that could not be tracked at all three sensors was deleted from the data set. The vehicle’s speed and time stamp when it crossed the sensor placed in the opposite travel lane were used to determine the time period when a vehicle was in the opposing lane. An indicator variable representing if an opposing vehicle was present or not was added to the data set since the presence of an opposing vehicle may affect a driver’s speed choice. Only unopposed vehicle speeds were included in the database used to estimate the models in this thesis. Figure 1 shows the data collection set-up used in West Virginia.
The sensors were installed differently at the Massachusetts, Arizona, and Alabama sites when compared to the West Virginia sites. The sensors were placed at the following locations in Alabama, Arizona, and Massachusetts: (1) 0.2 to 0.8 miles before the approach tangent of the curve, (2) along the curve approach tangent (216-800 feet before the PC), (3) at beginning of the horizontal curve (PC), (4) at the midpoint of the horizontal curve, (5) at the midpoint of the horizontal curve in the opposite travel lane, and (6) between the curve approach and PC in the opposite lane. Vehicles were tracked the same way as at the West Virginia sites. Again, any vehicle that could not be tracked at all four sensors was deleted from the data set. The control point was not used in the speed models, since this data collection point did not exist at the West Virginia sites. The vehicle’s speed and time stamp when it crossed the sensor placed in the opposite travel lane at the midpoint were used to determine the time period when a vehicle was in the opposing lane. The second sensor in the opposite lane was not used to determine when vehicles were present in the opposing travel lane. Figure 2 shows the data collection set-up used in Alabama, Arizona, and Massachusetts.
The data from Massachusetts, Arizona, and Alabama had to be further reduced because many observations were prone to errors resulting from the magnetic fields of the sensors in opposite travel lanes overlapping at the data collection sites. Figure 3 shows a typical speed profile through a curve as reported by Figueroa, Medina, and Tarko (2005). The last data collection point in the proposed study was at the curve midpoint, whereas Figure 3 suggests that vehicle operating speeds should be lower at this location when compared to locations before or approaching the curve.

Figure 2 Location of sensors at the Massachusetts, Arizona, and Alabama sites.
In previous research by Hu and Donnell (2010), it was determined that the maximum deceleration rates entering a horizontal curve are $4.4 \text{ ft/s}^2$ on two-lane rural highways. It was assumed the approach point speed was correct in the current data set (no interference for magnetic fields in opposite travel lane), so the acceleration rate from the approach to PC and from the approach to the curve midpoint were calculated. If the acceleration rate was less than $-4.5 \text{ ft/s}^2$ or greater than $1.0 \text{ ft/s}^2$ for either point for any observation, then the PC, midpoint, or both observations were removed from the data set for that observation. An acceleration rate of $1.0 \text{ ft/s}^2$ was considered in the proposed study to account for vehicles that may moderately increase speeds from the approach tangent through the midpoint of the horizontal curve (e.g., mis-judging curve radius, etc.). Approximately 11.5% of the data were eliminated from using these criteria.

3.3 Site Information Collected

Geometric features, land use, signage, and pavement marking information were collected for each site. The information was either obtained in the field while collecting the speed data, or by using Google Earth. The data collected included the following:
• Posted speed limit
• Advisory speed
• Presence of advisory speed plaques before curve
• Radius of curvature
• Length of curve
• Curve direction
• Chevrons
• Adjacent land use(s)
• Horizontal sight line obstructions
• Lane width
• Shoulder width
• Shoulder surface type
• Pavement markings (worn, missing, or in “good shape”)
• Grade (flat, downgrade, or upgrade)
• Access points within curve
• Access points within 300 feet of PC
• Distance between PC of analysis curve and the PT of the closest upstream curve

Many of these measurements were used as predictor variables in the speed models. A summary of the variables that were considered in the analysis is shown in Table 6.
Table 6 Summary statistic of site characteristics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Proportion of Sites</th>
<th>Mean (ft)</th>
<th>Minimum (ft)</th>
<th>Maximum (ft)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25 mph Speed Limit</td>
<td>0.074</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>30 mph Speed Limit</td>
<td>0.074</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>35 mph Speed Limit</td>
<td>0.259</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>40 mph Speed Limit</td>
<td>0.111</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>45 mph Speed Limit</td>
<td>0.074</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>55 mph Speed Limit</td>
<td>0.407</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Advisory Speed Sign</td>
<td>0.481</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Prior Warning Sign</td>
<td>0.667</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Curve Warning Sign</td>
<td>0.222</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Turn Warning Sign</td>
<td>0.037</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Winding Road Sign</td>
<td>0.222</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Reverse Curve Sign</td>
<td>0.074</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Reverse Turn Sign</td>
<td>0.074</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Directional Arrow Sign</td>
<td>0.185</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Chevrons</td>
<td>0.296</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Right Curve</td>
<td>0.704</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Left Curve</td>
<td>0.296</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Residential</td>
<td>0.370</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Wooded</td>
<td>0.444</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Agricultural</td>
<td>0.037</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Downgrade</td>
<td>0.407</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Upgrade</td>
<td>0.148</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Flat</td>
<td>0.444</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Edgeline Faded/Missing</td>
<td>0.259</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Paved Shoulder</td>
<td>0.593</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Gravel Shoulder</td>
<td>0.370</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Soil/Grass Shoulder</td>
<td>0.222</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Vegetation/Cut Slope on Inside of Curve</td>
<td>0.370</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Lane Width</td>
<td>-</td>
<td>11.31</td>
<td>9.00</td>
<td>13.00</td>
</tr>
<tr>
<td>Paved Shoulder Width</td>
<td>-</td>
<td>1.32</td>
<td>0.00</td>
<td>4.50</td>
</tr>
<tr>
<td>Delta(^1)</td>
<td>-</td>
<td>63.30</td>
<td>17.38</td>
<td>150.06</td>
</tr>
<tr>
<td>Radius</td>
<td>-</td>
<td>701.05</td>
<td>209.97</td>
<td>1213.64</td>
</tr>
<tr>
<td>Length</td>
<td>-</td>
<td>623.13</td>
<td>186.21</td>
<td>1213.64</td>
</tr>
<tr>
<td>Access Points in Curve(^2)</td>
<td>-</td>
<td>1.19</td>
<td>0.00</td>
<td>9.00</td>
</tr>
<tr>
<td>Access Points 300ft Before Curve(^2)</td>
<td>-</td>
<td>0.74</td>
<td>0.00</td>
<td>4.00</td>
</tr>
<tr>
<td>Distance from Previous Curve</td>
<td>-</td>
<td>1059.59</td>
<td>149.00</td>
<td>6384.00</td>
</tr>
</tbody>
</table>

Notes:
\(^1\)Units for delta are degrees
\(^2\)Units for access points are the number per site
The data used in developing the models was disaggregated as much possible, as recommended by Himes et al. (2013). This reduced the amount of data that was lost from aggregating the data. Data were aggregated into bins of 30 speed observations, and a mean and standard deviation were calculated for each bin. A few of the bins had less than 30 speed observations, but they all had more than 24 observations. Summary tables of the data used in the analysis can be seen in Tables 7 and 8. The data presented in these tables has already been aggregated into bins of 30 speed observations.

Table 7 Summary statistics of mean speeds.

<table>
<thead>
<tr>
<th>Location</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Approach</td>
<td>44.04</td>
<td>5.83</td>
<td>33.70</td>
<td>59.77</td>
<td>280</td>
</tr>
<tr>
<td>Day Approach</td>
<td>44.70</td>
<td>6.08</td>
<td>33.87</td>
<td>59.77</td>
<td>164</td>
</tr>
<tr>
<td>Night Approach</td>
<td>43.10</td>
<td>5.34</td>
<td>33.70</td>
<td>57.04</td>
<td>116</td>
</tr>
<tr>
<td>All PC</td>
<td>43.10</td>
<td>7.36</td>
<td>31.60</td>
<td>66.00</td>
<td>280</td>
</tr>
<tr>
<td>Day PC</td>
<td>43.64</td>
<td>7.49</td>
<td>32.57</td>
<td>66.00</td>
<td>164</td>
</tr>
<tr>
<td>Night PC</td>
<td>42.34</td>
<td>7.13</td>
<td>31.60</td>
<td>64.30</td>
<td>116</td>
</tr>
<tr>
<td>All Midcurve</td>
<td>41.11</td>
<td>6.33</td>
<td>27.33</td>
<td>59.33</td>
<td>280</td>
</tr>
<tr>
<td>Day Midcurve</td>
<td>41.10</td>
<td>6.65</td>
<td>27.33</td>
<td>57.33</td>
<td>164</td>
</tr>
<tr>
<td>Night Midcurve</td>
<td>41.11</td>
<td>5.87</td>
<td>28.53</td>
<td>59.33</td>
<td>116</td>
</tr>
</tbody>
</table>

Table 8 Summary statistics of standard deviations.

<table>
<thead>
<tr>
<th>Location</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Approach</td>
<td>6.15</td>
<td>1.76</td>
<td>2.76</td>
<td>12.34</td>
<td>280</td>
</tr>
<tr>
<td>Day Approach</td>
<td>6.26</td>
<td>1.80</td>
<td>3.14</td>
<td>12.34</td>
<td>164</td>
</tr>
<tr>
<td>Night Approach</td>
<td>5.99</td>
<td>1.69</td>
<td>2.76</td>
<td>10.60</td>
<td>116</td>
</tr>
<tr>
<td>All PC</td>
<td>6.47</td>
<td>2.29</td>
<td>2.32</td>
<td>14.83</td>
<td>280</td>
</tr>
<tr>
<td>Day PC</td>
<td>6.38</td>
<td>2.25</td>
<td>2.32</td>
<td>14.32</td>
<td>164</td>
</tr>
<tr>
<td>Night PC</td>
<td>6.60</td>
<td>2.34</td>
<td>3.06</td>
<td>14.83</td>
<td>116</td>
</tr>
<tr>
<td>All Midcurve</td>
<td>7.66</td>
<td>2.36</td>
<td>2.98</td>
<td>16.45</td>
<td>280</td>
</tr>
<tr>
<td>Day Midcurve</td>
<td>7.43</td>
<td>2.51</td>
<td>2.98</td>
<td>16.45</td>
<td>164</td>
</tr>
<tr>
<td>Night Midcurve</td>
<td>8.00</td>
<td>2.09</td>
<td>3.53</td>
<td>14.67</td>
<td>116</td>
</tr>
</tbody>
</table>
Chapter 4

Statistical Analysis

4.1 Ordinary Least Squares (OLS) Models

As shown in the literature review, OLS linear regression has been the main estimation method used to model vehicle operating speeds. The five assumptions of the OLS linear regression model are (Kennedy, 2003):

1. The dependent variable can be modeled linearly based on the independent variables,
2. The expected error (disturbance) term is zero, \( E(\varepsilon) = 0 \),
3. The errors (disturbances) have the same variance (homoscedasticity) and are not correlated with each other, \( \text{var}(\varepsilon) = \sigma^2 \),
4. The errors for different observations are not correlated (no serial correlation), \( \text{cov}(\varepsilon_i, \varepsilon_j) = 0 \), and
5. The independent variables are not random and are fixed in repeated samples, \( \text{cov}(x, \varepsilon) = 0 \).

If any of these assumptions are violated, then the OLS estimator is either biased or inefficient. This research first considered single-equation OLS linear regression models of mean speed and speed deviation. However, it was assumed that these equations would have biased parameter estimates resulting from endogeneity and contemporaneous correlation across the disturbance terms. These assumptions were confirmed by using OLS regression to estimate the mean speed and speed deviation. The standard deviation was included as a predictor variable in the curve midpoint speed model, and the curve midpoint speed was included in the standard deviation model. Each of these variables was statistically significant in predicting the other. As such, systems modeling methods were estimated in this research.
4.2 Three-Stage Least Squares (3SLS) Models

Previous research has shown that it is important to model both the speed magnitude and speed dispersion (speed deviation), which can be accomplished by using three-stage least squares (3SLS) regression or seemingly unrelated regression (SUR) (Himes and Donnell, 2010; Himes et al., 2011; Porter and Mason, 2008; Shankar and Mannering, 1998; Ulfarsson et al., 2005). A three-stage least squares model was estimated in this research since it is able to account for shared unobserved effects between the speed magnitude and speed deviation. A 3SLS model handles endogeneity \( \text{cov}(d, us) \neq 0, \text{and} \text{cov}(s, ud) \neq 0 \) using instruments for \( s \) and \( d \). These instruments are variables that are correlated with the endogenous variables but are not correlated with the disturbances. Also, 3SLS is a full information estimator that accounts for error covariance \( \text{cov}(us, ud) \neq 0 \), which may be a result of shared unobserved variables between the two measures. There is likely contemporaneous correlation between the two disturbance terms since there are similar factors that affect both disturbance terms. For this, a 3SLS model was estimated instead of a 2SLS model that estimates the equations separately, compared to a system in a 3SLS model, which is able to account for this contemporaneous correlation.

The systems of equations to model the speed and speed deviation are:

\[
\begin{align*}
  s &= \alpha_s + X_s\beta_s + d\theta_s + u_s \\
  d &= \alpha_d + X_d\beta_d + s\theta_d + u_d
\end{align*}
\]

where,

\[
\begin{align*}
  s &= \text{mean speed} \\
  d &= \text{speed deviation} \\
  \alpha &= \text{constant for mean speed and speed deviation, respectively} \\
  X &= \text{vector of exogenous variables for mean speed and speed deviation, respectively} \\
  \beta &= \text{vector of estimable regression parameters for exogenous variables} \\
  u &= \text{random disturbance term for mean speed and speed deviation, respectively} \\
  \theta &= \text{estimable regression parameters for endogenous variables for mean and speed deviation.}
\end{align*}
\]
Kennedy (2003) outlines the steps to estimate a 3SLS as:

1. Use 2SLS to estimate the models of the mean speed and standard deviation equations,
2. Use these 2SLS estimates to estimate the equations’ disturbances and use them to estimate the contemporaneous variances-covariance matrix of the structural equations’ disturbance terms, and
3. Re-estimate the structural equations using generalized least-squares (GLS) approach in order to estimate the model coefficients using the estimated contemporaneous variance-covariance matrix for the disturbances.

However, if the disturbances of the two equations were found to be uncorrelated, the error variance-covariance matrix is diagonal ($\text{cov}(u_s, u_d) = 0$), and after doing a 3SLS, a 3SLS provides no advantage over 2SLS.

4.3 Comparison of Daytime and Nighttime Models

A transferability test was performed to determine if there is a difference between the model estimated for nighttime speeds and the model estimated for daytime speeds. Washington et al. (2003) state that a transferability test can be used to determine if the estimated parameters are the same between two models. A likelihood ratio test was used to perform the test, and has the following form:

$$X^2 = -2[\text{LL}(\beta_A) - \text{LL}(\beta_D) - \text{LL}(\beta_N)]$$

where,

- $\text{LL}(\beta_A) = \text{log likelihood at convergence of model using both day and night observations}$
- $\text{LL}(\beta_D) = \text{log likelihood at convergence of model using day observations}$
- $\text{LL}(\beta_N) = \text{log likelihood at convergence of model using night observations}$. 
The same variables were used in all of the models (e.g. all observations, day, and night). The $X^2$ statistic is $\chi^2$ distributed with degrees of freedom equal to the summation of the number of estimated parameters in the day and night models minus the number of estimated parameters in the model of both day and night. This results in the probability that the models have different estimated parameters. If $\chi^2$ is significant at the 95 percent confidence level, it can be concluded that the operating speed models for daytime and nighttime are significantly different.
Chapter 5

3SLS Model Results

5.1 Development of Models

The models shown in this thesis were estimated as a systems model using 3SLS. OLS models were estimated first, and the results of those showed there was an endogenous relationship between the curve midpoint speed and the midcurve standard deviation (i.e. midcurve speed was significant in the midcurve standard deviation model and midcurve standard deviation was significant in the midcurve speed model). The OLS curve midpoint speed model is shown in Table 18 and the OLS curve standard deviation model is shown in Table 19, which can be found in the appendix. This endogenous relationship caused OLS regression to be biased and no longer an efficient estimator. Since this was the case, 3SLS was used to estimate the curve midpoint speed and curve midpoint standard deviation since 3SLS is better equipped to handle endogenous relationships and produce efficient and unbiased estimates. The midcurve standard deviation was highly statistically significant in predicting curve midpoint speeds in the OLS model, but it was only marginally statistically significant in the 3SLS model. The coefficient for the midcurve standard deviation was also higher in the OLS model, and the standard error was lower, which shows the OLS model overestimated the coefficient of the midcurve standard deviation. This shows that the OLS estimator was not efficient in the curve midpoint speed model.

An iterative process was used to determine the best independent variables to include in the model. The variables in these models were chosen based on their significance, the coefficients of variables, and the overall affect on the predictive power of the model (i.e. RMSE). The model was estimated by adding additional variables to the model and analyzing the impacts of the additional variable. If a variable was insignificant, had a small coefficient that has no practical
significance, or the RMSE increased, that variable was removed from the model and the model was re-estimated. This iterative process, of adding and removing variables was repeated until the model did not improve when more variables were added. Most of the variables in this thesis were statistically significant, with a p-value less than 0.05. However, variables with p-values less than 0.25 were also considered in the model since they most likely have some level of predictive power and this reduced the likelihood that there was omitted variables bias. The determination of how well the model fit the data was based on the coefficient of determination (Adj. R²), with a value closer to one being more desirable. Once the models were estimated, the residuals were plotted against the different variables to determine if there were any patterns in the residuals. The results of these plots showed there were no obvious patterns, so it was concluded there was not heteroskedasticity in the models.

5.1 Best Model- All Observations

Tables 9 and 11 below show the best-fit model for estimating the curve midpoint speed for all of the data, both daytime and nighttime observations. The models shown in Table 9 and Table 11 were estimated as a systems model using 3SLS.
Table 9 All Observations- midcurve speed.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>z-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve standard deviation (mph)</td>
<td>0.320</td>
<td>0.228</td>
<td>1.41</td>
<td>0.16</td>
</tr>
<tr>
<td>Inverse radius (ft)</td>
<td>-2417.543</td>
<td>184.145</td>
<td>-13.13</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Number of access points 300 ft before PC</td>
<td>-1.463</td>
<td>0.268</td>
<td>-5.45</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>-0.238</td>
<td>0.028</td>
<td>-8.45</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Distance from previous curve (100's of ft)</td>
<td>0.069</td>
<td>0.026</td>
<td>2.72</td>
<td>0.007</td>
</tr>
<tr>
<td>Approach speed (mph)</td>
<td>0.498</td>
<td>0.053</td>
<td>9.38</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-2.455</td>
<td>0.549</td>
<td>-4.47</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if true; 0 otherwise)</td>
<td>-2.720</td>
<td>0.624</td>
<td>-4.36</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-2.130</td>
<td>0.731</td>
<td>-2.91</td>
<td>0.004</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>-0.921</td>
<td>0.416</td>
<td>-2.22</td>
<td>0.027</td>
</tr>
<tr>
<td>Chevrons indicator (1 if present; 0 otherwise)</td>
<td>1.713</td>
<td>0.467</td>
<td>3.67</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Speed limit of 40/45/55 mph (1 if present; 0 otherwise)</td>
<td>2.186</td>
<td>0.486</td>
<td>4.50</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>24.869</td>
<td>3.196</td>
<td>7.78</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Number of observations = 280

R² = 0.8822

Adjusted R² = 0.8769

Root MSE = 2.1676
The baseline values for the binary variables used in the midcurve speed model are shown below in Table 10.

**Table 10** Baseline values of midcurve speed binary variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Baseline Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lane width of 9 or 10 ft</td>
<td>Lane widths greater than ten feet</td>
</tr>
<tr>
<td>Data collected in upgrade direction</td>
<td>Flat or downgrades</td>
</tr>
<tr>
<td>Left-hand curve indicator</td>
<td>Right-hand curve</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft</td>
<td>Paved shoulder widths greater than two feet</td>
</tr>
<tr>
<td>Chevrons indicator</td>
<td>No chevrons present</td>
</tr>
<tr>
<td>Speed limit of 40/45/55 mph</td>
<td>Speed limits less than 40 mph (i.e. 25, 30, 35 mph)</td>
</tr>
</tbody>
</table>

As the model in Table 9 shows, the coefficient was negative for the following variables: inverse radius, number of access points 300 feet before the PC, difference between the posted speed limit and advisory speed, a 9- or 10- foot travel lane width indicator, upgrade indicator, left-hand curve indicator, and an indicator for a paved shoulder width of two feet or less. The only negative coefficient that may not be intuitive is the variable indicating a left-hand curve. The coefficient for this binary variable was negative most likely because vehicles do not cross the centerline as they travel through a left-hand curve; whereas with a right-hand curve, vehicles are able to drive on the shoulder and increase the radius of the curve, so they are able to travel at a higher speed.

As the model in Table 9 shows, the coefficient was positive for the following variables: curve midpoint standard deviation, distance from previous curve, approach speed, chevrons indicator, and a posted speed limit of 40, 45, or 55 mph indicator. It was expected that all of these variables would have a positive coefficient. The coefficient for chevrons may be positive because drivers may feel more comfortable traversing a curve that has added guidance. A goodness-of-fit of 87.7% indicates that the data fit the model well.
The midcurve standard deviation was statistically significant in the OLS model for estimating the curve midpoint speed, but it was not significant in the 3SLS model. This shows that the OLS estimator was inefficient and that the 3SLS is better able to handle the endogenous relationship between the curve midpoint speed and standard deviation.

### Table 11 All Observations- midcurve standard deviation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>z-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve mean speed (mph)</td>
<td>0.219</td>
<td>0.022</td>
<td>9.97</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>0.150</td>
<td>0.030</td>
<td>5.08</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Speed limit of 55 mph (1 if present; 0 otherwise)</td>
<td>-4.644</td>
<td>0.583</td>
<td>-7.96</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-1.190</td>
<td>0.305</td>
<td>-3.90</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-1.185</td>
<td>0.294</td>
<td>-4.04</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dirt or grass shoulder indicator (1 if present; 0 otherwise)</td>
<td>-1.007</td>
<td>0.275</td>
<td>-3.66</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Prior warning sign (1 if true; 0 otherwise)</td>
<td>-0.674</td>
<td>0.280</td>
<td>-2.41</td>
<td>0.016</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if present; 0 otherwise)</td>
<td>-0.724</td>
<td>0.321</td>
<td>-2.25</td>
<td>0.024</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>0.827</td>
<td>0.263</td>
<td>3.14</td>
<td>0.002</td>
</tr>
<tr>
<td>Vegetation/cutslope indicator (1 if present; 0 otherwise)</td>
<td>1.382</td>
<td>0.303</td>
<td>4.57</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>-0.646</td>
<td>1.038</td>
<td>-0.62</td>
<td>0.534</td>
</tr>
</tbody>
</table>

Number of observations = 280

R² = 0.5116

Adjusted R² = 0.4934

Root MSE = 1.6452
The baseline values for the binary variables used in the midcurve standard deviation model are shown below in Table 12.

**Table 12** Baseline values of midcurve standard deviation binary variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Baseline Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed limit of 55 mph</td>
<td>Speed limits less than 55 mph (i.e. 25, 30, 35, 40, 45 mph)</td>
</tr>
<tr>
<td>Left-hand curve indicator</td>
<td>Right-hand curve</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft</td>
<td>Lane widths greater than ten feet</td>
</tr>
<tr>
<td>Dirt or grass shoulder indicator</td>
<td>Paved shoulder or no dirt or grass shoulder present</td>
</tr>
<tr>
<td>Prior warning sign</td>
<td>No previous warning sign before the curve</td>
</tr>
<tr>
<td>Data collected in upgrade direction</td>
<td>Flat or downgrades</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft</td>
<td>Paved shoulder widths greater than two feet</td>
</tr>
<tr>
<td>Vegetation/cutslope indicator</td>
<td>No vegetation or cutslope on the inside of the curve that restricted sight distance</td>
</tr>
</tbody>
</table>

As the model in Table 11 shows, the coefficient was negative for the following variables: speed limit 55 mph indicator, left-hand curve indicator, a 9- or 10- foot travel lane width indicator, dirt or grass shoulder indicator, a warning sign prior to the curve (e.g. curve advisory, turn advisory, winding road, etc.) indicator, and a vertical grade indicator. It was expected that all of these variables would have a negative coefficient.

As the model in Table 11 shows, the coefficient was positive for the following variables: curve midpoint mean speed, the difference between the posted speed limit and advisory speed, and if there was vegetation or a cutslope restricting horizontal sight distance. It was expected that all of these variables would have positive coefficients. A goodness-of-fit of 49.3% indicates that the data fit the model reasonably well. A lower adjusted coefficient of determination than in the curve midpoint speed model was expected since it is typically harder to explain the variance in drivers’ speed selection. This is a result of more variability in the speed dispersion data when compared to the mean speed data.
5.2 Discussion of Independent Variables

*Midcurve Speed Variables*

The midcurve standard deviation variable indicates that speeds were 0.320 mph higher for every mile per hour increase in the midcurve standard deviation, holding all other variables constant. It was expected that operating speeds would be higher as the standard deviation increased, and this supports previous research that has shown estimated speeds are higher as the standard deviation increases (Porter and Wood, 2013; Himes et al., 2013). The midcurve standard deviation was only marginally significant at predicting curve midpoint speeds. As previously mentioned, this shows the OLS model was inefficient and overestimating the influence of the midcurve standard deviation on midcurve operating speeds.

The inverse radius variable indicates that speeds were lower by $1/2417.543$ mph for every one-foot increase in the radius of the horizontal curve, holding all other variables constant. The models used the inverse radius rather than the radius because of the inverse relationship that was visible from plotting operating speeds versus radius. This means that as the radius of the horizontal curve decreased, lower operating speeds resulted. It was expected that operating speeds would be higher as the radius of the curve increased since less side friction is demanded. This supports previous research that has shown operating speeds are higher as the radius increases and there is an inverse relationship (Fitpatrick et al., 2000; Otteson, 1993) between radius of curve and midcurve operating speed.

The number of access points 300 ft before the PC indicates that speeds were lower by 1.463 mph for each access point that was within 300 ft of the PC, holding all other variables constant. It was expected that operating speeds would be lower as the number of access points before the PC increased since drivers probably sense the increased “side friction” and drivers most likely
decrease their speed choice incase something were to enter the roadway from one of the access points. This supports previous research that has shown operating speeds are lower as the number of access points before the curve increases (Himes et al., 2013).

The difference between the posted advisory speed and advisory speed variable indicates that speeds were 0.238 mph lower for every mile per hour increase in the difference between the posted speed limit and advisory speed, holding all other variables constant. It was expected that operating speeds would be lower as the difference between the posted speed limit and advisory speed increased since the larger difference signals to drivers that they need to slow down more as they enter the curve. This supports previous research that has shown operating speeds are lower as the difference between the posted speed limit and advisory speed increases (Bonneson, 2007).

The distance from the previous curve variable indicates that speeds were 0.069 mph higher for every 100-foot increase in the distance from the PT of the previous curve to the PC of the curve of interest, holding all other variables constant. It was expected that operating speeds would be higher as the distance from the previous curve increased since there is more distance for drivers to accelerate. No previous research was found that shows a relationship between the distance from the previous curve and operating speeds.

The approach speed variable indicates that speeds were 0.498 mph higher for every mile per hour increase in the approach speed, holding all other variables constant. This is a lag variable and it was expected that operating speeds would be higher as a vehicle’s approach speed was higher since a vehicle travelling at a higher speed on the approach is more likely to have a higher speed through the curve. A lag variable is one where a predicted variable is based on a past value; in this model a driver’s prior speed choice on the approach is associated with his speed choice at the
curve midpoint. This supports previous research that has shown operating speeds are higher as the approach speed before the horizontal curve increases (Kerman et al., 1982).

The lane width of nine or ten feet indicator variable indicates that speeds were 2.455 mph lower at sites with lane widths of nine or ten feet compared to sites with lane widths greater than ten feet, holding all other variables constant. It was expected that operating speeds would be lower for narrower lane widths since drivers probably feel more constrained from the narrower lane width and drive more cautiously by selecting a lower speed. This supports previous research that has shown operating speeds are lower as the lane width decreases (Lamm et al., 1987, 1988, and 1990).

The data collected in the upgrade direction indicator variable indicates that speeds were 2.720 mph lower for vehicles travelling on a horizontal curve that was located on an upgrade compared to vehicles travelling on level ground or a downgrade, holding all other variables constant. It was expected that operating speeds would be lower for vehicles travelling on an upgrade since additional work is required to maintain a higher speed on an upgrade, and there may also be vehicle performance characteristics that limit drivers from achieving a higher speed. This supports previous research that has shown operating speeds are lower on steeper grades (Fitpatrick et al., 2000).

The left-hand curve indicator variable indicates that speeds were 2.130 mph lower for vehicles traversing a left-hand curve compared to vehicles traversing a right-hand curve, holding all other variables constant. As previously discussed, it was expected that operating speeds would be lower for vehicles traversing a left-hand curve since most vehicles do not cross the centerline as they travel through a left-hand curve; whereas, for a right-hand curve, vehicles are able to drive on the shoulder and increase the radius of the curve, so they are able to travel at a higher speed.
This supports previous research that has shown operating speeds are lower on left-hand curves (Himes et al., 2013).

The paved shoulder width of two feet or less indicator variable indicates that speeds were 0.912 mph lower at sites with a paved shoulder width of two feet or less to sites with a wider shoulder width, holding all other variables constant. It was expected that operating speeds would be lower at sites with narrower paved shoulder widths since drivers probably feel more constrained and drive more cautiously since there is less room to recover, should the vehicle depart the roadway. This supports previous research that has shown operating speeds increase as the paved shoulder width increases (Lamm et al., 1987, 1988, and 1990; Misaghi and Hassan, 2005).

The chevrons indicator variable indicates that speeds were 1.713 mph higher for vehicles traversing a curve with chevrons located on the outside of the curve compared to vehicles traversing a curve without chevrons, holding all other variables constant. Speeds may have been higher at sites with chevrons present as a result of drivers being provided with additional positive guidance near the curve, enabling drivers to better recognize the curve and thus travel at a higher speed through the curve. Previous research has shown that operating speeds are lower with the presence chevrons, but the speed decreases were minimal (Vest and Stamatiadis, 2005; Charlton, 2007; Ré et al., 2010).

The speed limit of 40, 45, or 55 mph indicator variable indicates that speeds were 2.186 mph higher at sites with a speed limit of 40, 45, or 55 mph compared to sites with a lower speed limit, holding all other variables constant. The mean curve midpoint speeds were similar for sites with a speed limit of 40, 45, or 55 mph, so they were grouped into one indicator variable. Speeds at sites with speed limits of 55 mph were similar to speeds at sites with speed limit of 40 and 45 mph because there were curve advisory speeds at all of these sites, which were accounted for in
the continuous variable for the difference between the posted speed limit and curve advisory speed. It was expected that operating speeds would be higher for sites with a higher posted speed limit since drivers use the speed limit to guide their speed selection, so they most likely select a higher operating speed when the speed limit is higher. This supports previous research that has shown operating speeds are higher as the posted speed limit increases (Jessen et al., 2001; Himes et al., 2013).

**Midcurve Standard Deviation Variables**

The midcurve mean speed variable indicates that standard deviations were 0.219 mph higher for every mile per hour increase in the midcurve mean speed, holding all other variables constant. It was expected that standard deviations would be higher as the midcurve mean speed increased since the side friction design values are more conservative for higher design speeds, so drivers can select a wider range of speeds and still be able to traverse the curve. This supports previous research that has shown the standard deviation is higher as the midcurve mean speed increases (Shanker and Mannering, 1998).

The difference between the posted speed limit and advisory speeds indicates that standard deviations were 0.150 mph higher for every mile per hour increase in the difference between the posted speed limit and advisory speed, holding all other variables constant. It was expected that standard deviations would be higher as the difference between the posted speed limit and advisory speed increased since some drivers will follow the advisory speed and slow down, while others will ignore the advisory speed and maintain a higher speed. No previous research was found about the relationship between the difference between the posted speed limit and advisory speed, and the standard deviation of operating speeds.
The speed limit of 55 mph indicator variable indicates that standard deviations were 4.644 mph lower at sites with posted speed limits of 55 mph compared to sites with a lower speed limit, holding all other variables constant. It was expected that standard deviations would be lower at sites with a posted speed limit of 55 mph since more drivers likely select a speed around the speed limit, and because there is likely a limit on the risk that drivers are willing to take when traveling at high speeds. Also, all of the sites with a posted speed limit of 55 used in this thesis also had an advisory speed, which discourages drivers from travelling at higher speeds, perhaps achieving greater speed uniformity. Previous research has shown that the standard deviation is higher as the speed limit increases, but most of this research has used sites with higher speed limits (e.g. 50, 55, 60, 65, or 70 mph) and has not included sites with lower posted speed limits, such as in this thesis (Porter and Wood, 2013; Himes et al., 2013).

The left-hand indicator variable indicates that standard deviations were 1.190 mph lower at left-hand curves compared to right-hand curves, holding all other variables constant. It was expected that the standard deviation would be lower at left-hand curves since most drivers do not cross the centerline; whereas with a right-hand curve some drivers may cross the edgeline so they are able to travel at a higher speed, while others may stay in the lane. This supports previous research that has shown the standard deviation of operating speeds decreases on left-hand curves (Himes et al., 2013).

The lane width of nine or ten feet indicator variable indicates that standard deviations were 1.185 mph lower at sites with lane widths of nine or ten feet compared to sites with lane widths greater than ten feet, holding all other variables constant. It was expected that the standard deviation would be lower for narrower lane widths since drivers feel more constrained and drivers who may select higher speeds at sites with wider lane widths will probably select a lower speed, which
lowers the standard deviation. Previous research has shown that the standard deviation of operating speeds increases with narrower lane widths (Porter et al., 2007).

The dirt or grass shoulder indicator variable indicates that standard deviations were 1.007 mph lower at sites with a dirt or grass shoulder compared to sites with no dirt or grass shoulder, holding all other variables constant. It was expected that the standard deviation would be lower for sites with a dirt or grass shoulder since drivers feel more constrained and recognize the less forgiving roadside, and drivers that may select higher speeds at sites with paved shoulders will probably select a lower speed that is more uniform to others, which lowers the standard deviation. Previous research has shown that the standard deviation of operating speeds is higher as the unpaved shoulder width increases (Himes et al., 2013).

The prior warning sign indicator variable indicates that standard deviations were 0.674 mph lower at sites with a warning sign prior to the curve compared to sites without a warning sign, holding all other variables constant. It was expected that standard deviations would be lower at sites with a prior warning sign since drivers who typically select a higher speed will probably acknowledge the sign and slow down and thus reduce speed variability; whereas, the drivers already travelling at a lower speed may ignore the sign since they are already travelling slow enough for the curve. No previous research was found concerning the relationship between the presence of a warning sign and the standard deviation.

The data collected in the upgrade direction indicator variable indicates that standard deviations were 0.724 mph lower at sites with a horizontal curve that was located on an upgrade compared to sites where the curve was on level ground or a downgrade, holding all other variables constant. It was expected that standard deviations would be lower at sites located on an upgrade since more work is required to maintain higher speeds, while less work is required to maintain a lower speed.
on upgrade. This supports previous research that has shown the standard deviation of operating speeds to decrease as the grade increases (Himes et al., 2013).

The paved shoulder width of two feet or less indicator variable indicates that standard deviations were 0.827 mph higher at sites with paved shoulder widths of two feet or less compared to sites with wider paved shoulders, holding all other variables constant. It was expected that the standard deviation would be higher at sites with a paved shoulder width of two feet or less since some drivers probably feel more constrained and recognize the less forgiving roadside, so they select a lower speed; whereas other drivers may ignore the less forgiving roadside and travel at the same speed they would have if the paved shoulder width was wider, so the standard deviation is higher. No previous research was found that shows a relationship between the paved shoulder width and standard deviation of operating speeds, but previous work has shown that standard deviations are higher as the total paved width increases (Porter et al., 2007).

The vegetation or cutslope indicator variable indicates that standard deviations were 1.382 mph higher at sites with vegetation or a cutslope on the inside of the curve that restricts sight distance compared to sites without restricted sight distance from vegetation or a cut slope, holding all other variables constant. It was expected that the standard deviation would be higher at sites with restricted sight distance from vegetation or cutslope since some drivers probably recognize their sight distance is limited, so they select a lower speed to compensate for it; whereas other drivers may ignore the limited sight distance and travel at the same speed they would have if their sight distance was not limited, so the standard deviation is higher. No previous research was found that shows a relationship between vegetation or a cutslope restricting sight distance and the standard deviation.
### 5.2 Best Model - Day Observations

The models shown in Tables 13 and 14 have the same independent variables as the models shown in Tables 9 and 11, but only day observations were used in these models. These models were also estimated as a systems model using 3SLS.

**Table 13** Day Observations - midcurve speed.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>Z-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve standard deviation (mph)</td>
<td>0.064</td>
<td>0.228</td>
<td>0.28</td>
<td>0.778</td>
</tr>
<tr>
<td>Inverse radius (ft)</td>
<td>-2576.440</td>
<td>243.009</td>
<td>-10.60</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Number of access points 300 ft before PC</td>
<td>-1.674</td>
<td>0.353</td>
<td>-4.74</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>-0.238</td>
<td>0.037</td>
<td>-6.47</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Distance from previous curve (100's of ft)</td>
<td>0.080</td>
<td>0.029</td>
<td>2.77</td>
<td>0.006</td>
</tr>
<tr>
<td>Approach speed (mph)</td>
<td>0.435</td>
<td>0.071</td>
<td>6.10</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-2.258</td>
<td>0.688</td>
<td>-3.28</td>
<td>0.001</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if true; 0 otherwise)</td>
<td>-2.681</td>
<td>0.837</td>
<td>-3.20</td>
<td>0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-2.148</td>
<td>0.926</td>
<td>-2.32</td>
<td>0.020</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>-1.398</td>
<td>0.528</td>
<td>-2.65</td>
<td>0.008</td>
</tr>
<tr>
<td>Chevrons indicator (1 if present; 0 otherwise)</td>
<td>1.281</td>
<td>0.601</td>
<td>2.13</td>
<td>0.033</td>
</tr>
<tr>
<td>Speed limit of 40/45/55 mph (1 if present; 0 otherwise)</td>
<td>1.941</td>
<td>0.641</td>
<td>3.03</td>
<td>0.002</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>30.349</td>
<td>4.078</td>
<td>7.44</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Number of observations = 164

R² = 0.8796

Adjusted R² = 0.8700

Root MSE = 2.3001
As the model in Table 13 shows, the signs remained the same for all of the independent variables in the model for predicting curve midpoint speeds. The adjusted coefficient of determination was 0.8700.

Table 14 Day Observations- midcurve standard deviation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>z-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve mean speed (mph)</td>
<td>0.221</td>
<td>0.031</td>
<td>7.03</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>0.143</td>
<td>0.041</td>
<td>3.47</td>
<td>0.001</td>
</tr>
<tr>
<td>Speed limit of 55 mph (1 if present; 0 otherwise)</td>
<td>-4.683</td>
<td>0.795</td>
<td>-5.89</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-1.533</td>
<td>0.414</td>
<td>-3.7</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-0.870</td>
<td>0.393</td>
<td>-2.21</td>
<td>0.027</td>
</tr>
<tr>
<td>Dirt or grass shoulder indicator (1 if present; 0 otherwise)</td>
<td>-1.288</td>
<td>0.393</td>
<td>-3.27</td>
<td>0.001</td>
</tr>
<tr>
<td>Prior warning sign (1 if true; 0 otherwise)</td>
<td>-1.052</td>
<td>0.394</td>
<td>-2.67</td>
<td>0.008</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if present; 0 otherwise)</td>
<td>-0.604</td>
<td>0.448</td>
<td>-1.35</td>
<td>0.177</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>0.832</td>
<td>0.352</td>
<td>2.37</td>
<td>0.018</td>
</tr>
<tr>
<td>Vegetation/cutslope indicator (1 if present; 0 otherwise)</td>
<td>1.930</td>
<td>0.411</td>
<td>4.70</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>-0.629</td>
<td>1.508</td>
<td>-0.42</td>
<td>0.676</td>
</tr>
</tbody>
</table>

Number of observations = 280

$R^2 = 0.5268$

Adjusted $R^2 = 0.4959$

Root MSE = 1.7198

As the model in Table 14 shows, the signs remained the same for all of the independent variables in the model for predicting curve midpoint standard deviations. The adjusted coefficient of determination was 0.4945.
5.3 Best Model- Night Observations

The models shown in Tables 15 and 16 have the same independent variables as the models shown in Tables 9 and 11, but only night observations were used in these models. These models were also estimated as a systems model using 3SLS.

Table 15 Night observations- midcurve speed.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>Z-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve standard deviation (mph)</td>
<td>0.137</td>
<td>0.463</td>
<td>0.3</td>
<td>0.768</td>
</tr>
<tr>
<td>Inverse radius (ft)</td>
<td>-2047.265</td>
<td>331.137</td>
<td>-6.18</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Number of access points 300 ft before PC</td>
<td>-1.477</td>
<td>0.344</td>
<td>-4.29</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>-0.282</td>
<td>0.046</td>
<td>-6.16</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Distance from previous curve (100's of ft)</td>
<td>0.077</td>
<td>0.048</td>
<td>1.59</td>
<td>0.111</td>
</tr>
<tr>
<td>Approach speed (mph)</td>
<td>0.608</td>
<td>0.093</td>
<td>6.52</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-3.649</td>
<td>1.020</td>
<td>-3.58</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if true; 0 otherwise)</td>
<td>-3.294</td>
<td>0.957</td>
<td>-3.44</td>
<td>0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-2.816</td>
<td>1.045</td>
<td>-2.69</td>
<td>0.007</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>0.039</td>
<td>0.693</td>
<td>0.06</td>
<td>0.956</td>
</tr>
<tr>
<td>Chevrons indicator (1 if present; 0 otherwise)</td>
<td>2.225</td>
<td>0.799</td>
<td>2.78</td>
<td>0.005</td>
</tr>
<tr>
<td>Speed limit of 40/45/55 mph (1 if present; 0 otherwise)</td>
<td>2.506</td>
<td>0.801</td>
<td>3.13</td>
<td>0.002</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>20.925</td>
<td>4.559</td>
<td>4.59</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Number of observations = 116

R² = 0.8809

Adjusted R² = 0.8670

Root MSE = 2.0167
As the model in Table 15 shows, the signs remained the same for all of the independent variables in the model for predicting curve midpoint speeds, except the sign for a paved shoulder width of 2 feet or less became positive. The adjusted coefficient of determination was 0.8670.

**Table 16** Night observations- midcurve standard deviation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>Z-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve mean speed (mph)</td>
<td>0.207</td>
<td>0.028</td>
<td>7.41</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>0.205</td>
<td>0.039</td>
<td>5.22</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Speed limit of 55 mph (1 if present; 0 otherwise)</td>
<td>-5.299</td>
<td>0.810</td>
<td>-6.54</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-0.974</td>
<td>0.420</td>
<td>-2.32</td>
<td>0.020</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-1.770</td>
<td>0.411</td>
<td>-4.31</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dirt or grass shoulder indicator (1 if present; 0 otherwise)</td>
<td>-0.759</td>
<td>0.348</td>
<td>-2.18</td>
<td>0.029</td>
</tr>
<tr>
<td>Prior warning sign (1 if true; 0 otherwise)</td>
<td>-0.384</td>
<td>0.363</td>
<td>-1.06</td>
<td>0.290</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if present; 0 otherwise)</td>
<td>-0.845</td>
<td>0.416</td>
<td>-2.03</td>
<td>0.042</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>0.722</td>
<td>0.369</td>
<td>1.96</td>
<td>0.050</td>
</tr>
<tr>
<td>Vegetation/cutslope indicator (1 if present; 0 otherwise)</td>
<td>0.414</td>
<td>0.416</td>
<td>0.99</td>
<td>0.320</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>0.023</td>
<td>1.276</td>
<td>0.02</td>
<td>0.985</td>
</tr>
</tbody>
</table>

Number of observations = 280
R² = 0.5604
Adjusted R² = 0.5185
Root MSE = 1.3829

As the model in Table 16 shows, the signs remained the same for all of the independent variables in the model for predicting curve midpoint standard deviations. The adjusted coefficient of determination was 0.5185.
Chapter 6

Comparison of Daytime and Nighttime Models

6.1 Comparison of Midcurve Speed Model

Table 17 shows a comparison between the model for estimating curve midpoint speeds that was estimated using daytime observations and the model that was estimated using nighttime observations. The table shows the differences in the coefficients, which were calculated by subtracting the coefficients in the nighttime model from the coefficients in the daytime model. The ratios of the coefficients are also shown in the table, which were calculated using the following equation:

\[
\text{Ratio of coefficients} = \frac{\text{Daytime coefficient}}{\text{Nighttime coefficient}}
\]

A value of 1.0 means the coefficients in the two models are the same, while a value exceeding 1.0 means the coefficient in the daytime model has a larger magnitude than the coefficient in the nighttime model, and a value less than 1.0 means the coefficient in the nighttime model has a larger magnitude than the coefficient in the daytime model.

All of the independent variables were significant in both models, except the variable indicating a paved shoulder width of two feet or less was significant in the daytime model, but it was insignificant in the nighttime model.
Table 17 Comparison of daytime and nighttime midcurve speed model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Day Observations</th>
<th>Night Observations</th>
<th>Difference in Coefficients</th>
<th>Ratio of Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve Speed (mph)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variable Midcurve standard deviation (mph)</td>
<td>0.064</td>
<td>0.137</td>
<td>-0.073</td>
<td>0.47</td>
</tr>
<tr>
<td>Inverse radius (ft)</td>
<td>-2576.440</td>
<td>-2047.265</td>
<td>-529.175</td>
<td>1.26</td>
</tr>
<tr>
<td>Number of access points 300 ft before PC</td>
<td>-1.674</td>
<td>-1.477</td>
<td>-0.198</td>
<td>1.13</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>-0.238</td>
<td>-0.282</td>
<td>0.044</td>
<td>0.84</td>
</tr>
<tr>
<td>Distance from previous curve (100's of ft)</td>
<td>0.080</td>
<td>0.077</td>
<td>0.004</td>
<td>1.05</td>
</tr>
<tr>
<td>Approach speed (mph)</td>
<td>0.435</td>
<td>0.608</td>
<td>-0.173</td>
<td>0.72</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-2.258</td>
<td>-3.649</td>
<td>1.391</td>
<td>0.62</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if true; 0 otherwise)</td>
<td>-2.681</td>
<td>-3.294</td>
<td>0.613</td>
<td>0.81</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-2.148</td>
<td>-2.816</td>
<td>0.668</td>
<td>0.76</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>-1.398</td>
<td>0.039</td>
<td>-1.436</td>
<td>-36.31</td>
</tr>
<tr>
<td>Chevrons indicator (1 if present; 0 otherwise)</td>
<td>1.281</td>
<td>2.225</td>
<td>-0.944</td>
<td>0.58</td>
</tr>
<tr>
<td>Speed limit of 40/45/55 mph (1 if present; 0 otherwise)</td>
<td>1.941</td>
<td>2.506</td>
<td>-0.565</td>
<td>0.77</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>30.349</td>
<td>20.925</td>
<td>9.425</td>
<td>1.45</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.8700</td>
<td>0.8670</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Comparison of Independent Variables Coefficients

Figures 4 through 9 show graphical representations of the coefficients of the daytime and nighttime curve midpoint speed models. For the indicator variables, the point estimate from the model, along with the 95 percent confidence intervals, is plotted against the speed metric. For the continuous variables, the range of the independent variable is plotted along the horizontal axis while the estimated operating speed from the model is plotted along the vertical axis.

Figure 4 shows the coefficients for a lane width of nine or ten feet indicator, data collected in the upgrade direction indicator, left-hand curve indicator, a paved shoulder width of two feet or less indicator, chevrons indicator, and a posted speed limit of 40, 45, or 55 mph indicator.

As Table 17 shows, the difference between the coefficients for the lane width of nine or ten feet indicator variable is 1.391 mph. Speeds were 1.391 mph lower during the nighttime than daytime at sites with lane widths of nine or ten feet, holding all other variables constant. It was expected that the speeds would be lower during the daytime since drivers are probably better able to judge the lane width during the daytime and slow down. However, the models show speeds were lower during the nighttime, which may be the result of drivers having a harder time judging the lane width and driving more cautiously as a result. The retroreflective properties of the center- and edge-lines may also make it easier for drivers to detect the narrow lane widths. However, as Figure 4 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 17 shows, the difference between the coefficients for the data collected in the upgrade direction indicator variable is 0.613 mph. Speeds were 0.613 mph lower during the nighttime than daytime at horizontal curves located on an upgrade, holding all other variables constant. One possible explanation for the difference is during the nighttime drivers may be more cautious
since eventually they will traverse a crest curve and it is harder to see the roadway during the nighttime from the angle of the headlights, so they may select a lower speed to compensate. However, as Figure 4 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 17 shows, the difference between the coefficients for a left-hand curve indicator variable is 0.668 mph. Speeds were 0.668 mph lower during the nighttime than daytime on left-hand curves, holding all other variables constant. One possible explanation for the difference is headlights are stationary on most vehicles and are not able to move their aim point to match the angle of the tires, so sight distance is limited more during the nighttime since the opposing lane is not illuminated like it would on a right-hand curve and drivers probably select a lower speed to compensate for the limited sight distance around the curve. However, as Figure 4 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 17 shows, the difference between the coefficients for a paved shoulder width of two feet or less indicator variable is -1.436 mph. Speeds were 1.436 mph lower during the daytime than nighttime at sites with paved shoulder widths of two feet or less, holding all other variables constant. A paved shoulder width of two feet or less was not significant at predicting curve midpoint speeds during the nighttime. One possible explanation for the difference is it is harder to judge the paved shoulder width during the nighttime since headlights are aimed at the roadway, so drivers may not reduce their speeds during the nighttime as a result of the narrower shoulder. However, as Figure 4 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 17 shows, the difference between the coefficients for the chevrons indicator variable is -0.944 mph. Speeds were 0.944 mph higher during the nighttime than daytime at sites with
chevrons present, holding all other variables constant. One possible explanation for the difference is drivers probably rely on traffic control devices more during the nighttime since they have retro-reflective properties that allow them to be seen at night; whereas drivers can see the layout of the curve more easily during the daytime and probably rely less on signing. However, as Figure 4 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 17 shows, the difference between the coefficients for the speed limit of 40, 45, or 55 mph is -0.565 mph. Speeds were 0.565 mph higher during the nighttime than daytime at sites with a posted speed limit of 40, 45, or 55 mph, holding all other variables constant. As previously mentioned, one possible explanation is drivers may rely on traffic control devices during the nighttime since they have retro-reflective properties and it is harder to see and judge the curve during the night. However, as Figure 4 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.
Figure 4 Midcurve speed 95 percent confidence intervals.
As Table 17 shows, the difference between the coefficients for the inverse radius of the curve is 
-1/529.175 mph for every one-foot increase in the radius of the curve. Speeds increased more 
during the daytime than nighttime, but with a decreasing rate of 1/529.175 mph for every one-
foot increase in the radius of the curve, holding all other variables constant. One possible 
explanation for this is drivers may change their operating speeds based on the radius of the curve 
more during the daytime than nighttime since it is easier to judge the radius during the daytime. 
Figure 5 shows a graphical representation of the three models estimated by varying the radius of 
the curve. The mean values for all of the independent variables, except the radius were calculated 
and then multiplied by their respective coefficient, and then the models were plotted by varying 
the radius. The models show that nighttime speeds are predicted to be higher on curves with 
tighter radii, but at a radius close to 460 feet, daytime speeds are predicted to be higher. The 
figure shows that depending the radius of the curve, nighttime speeds may be higher or lower 
than daytime speeds. However, the differences between the speeds predictions are small and the 
maximum difference between the speed predictions is approximately 1.5 mph, which occurs at a 
radius of 200 feet.
As Table 17 shows, the difference between the coefficients for the difference from the previous curve is 0.004 mph for every 100-foot increase from the PT of the previous curve to the PC of the curve of interest. Speeds were 0.004 mph higher during the daytime than nighttime for every 100-foot increase in the distance from the previous curve, holding all other variables constant. Figure 6 shows a graphical representation of the three models estimated by varying the distance from the previous curve. The mean values for all of the independent variables, except the distance from the previous curve were calculated and then multiplied by their respective coefficient, and then the models were plotted by varying the distance from the previous curve.

**Figure 5** Midcurve speed estimates by varying the radius.
The models show that the coefficients are essentially the same and the speed predictions are almost identical during the daytime and nighttime.

![Graph showing midcurve speed estimates by varying the distance from the previous curve.](image)

**Figure 6** Midcurve speed estimates by varying the distance from the previous curve.

As Table 17 shows, the difference between the coefficients for the number of access points 300 feet before the PC is -0.198 mph for each additional access point. Speeds were 0.198 mph lower during the daytime than nighttime for each additional access point, holding all other variables constant. One possible explanation for this is drivers are able to see the access points during the day, but they might not be able to see them as clearly during the nighttime, so they maintain a higher speed. Figure 7 shows a graphical representation of the three models by varying the
number of access points 300 feet before the PC. The mean values for all of the independent variables, except the number of access points were calculated and then multiplied by their respective coefficient, and then the models were plotted by varying the number of access points. The model shows that nighttime and daytime speeds are predicted to be the same when there are zero access points 300 feet before the PC, but the difference between daytime and nighttime speed predictions increases as the number of access points increases, with daytime speeds becoming lower. The maximum difference between daytime and nighttime speeds is approximately 1 mph, which occurs when the number of access points 300 feet before the PC is four.
Figure 7 Midcurve speed estimates by varying the number of access points 300 ft before the PC.

As Table 17 shows, the difference between the coefficients for the difference between the posted speed limit and advisory speed is 0.044 mph for every mile per hour increase in the difference. Speeds were 0.044 mph lower during the nighttime than daytime for every mile per hour increase in the difference, holding all other variables constant. As previously mentioned, one possible explanation is drivers may rely on traffic control devices during the nighttime since they have retro-reflective properties and it is harder to see and judge the curve during the night. Figure 8 shows a graphical representation of the three models by varying the difference between the posted speed limit and the advisory speed. The mean values for all of the independent variables, except
the difference between the posted speed limit and advisory speed were calculated and then multiplied by their respective coefficient, and then the models were plotted by varying the difference between the posted speed limit and advisory speed. The model shows that nighttime speeds are predicted to be higher regardless of the difference between the speed limit and advisory speed, but the difference between nighttime speeds and daytime speeds increases as the difference between the posted speed limit and advisory speed increases. The maximum difference between the daytime and nighttime speeds is approximately 1.5 mph, which occurs when the difference between the posted speed limit and advisory speed is 30 mph.
Figure 8 Midcurve speed estimates by varying the difference between the posted speed limit and advisory speed.

Overall, the coefficients of the independent variables had a larger magnitude during the nighttime than they did during the daytime. The models also depict that drivers may select their operating speed more on traffic control devices during the nighttime, and they may rely more on geometric features during the daytime. The coefficient had a larger magnitude during the nighttime for all of the traffic control variables: difference between the posted speed limit and advisory speed, chevrons indicator, speed limit of 40, 45, or 55 mph indicator, and approach speed. Also, the coefficient had a larger magnitude during the daytime for four geometric variables: the inverse
radius, number of access points 300 feet before the PC, the distance from the previous curve, and a paved shoulder width of two feet or less indicator. By comparing the coefficients it can be seen that there are differences between the model for predicting operating speeds during the daytime and the model for predicting speeds during the nighttime.

**Graphical Representation of Difference in Models Based on Operating Speeds**

As Table 17 shows, the difference between the coefficients for the approach speed is -0.173 mph for every mile per hour increase in the approach speed. Curve midpoint speeds were 0.173 mph higher during the nighttime than daytime for every mile per hour increase in the approach speed, holding all other variables constant. One possible explanation for this is drivers are not able to see the curve as clearly during the nighttime, so they misjudge the curve and maintain a speed through the curve that is closer to their approach speed. Figure 9 shows a graphical representation of the three models estimated by varying the approach speed. Depending on the approach speed, this is the variable that explains the biggest difference in the speed prediction between the daytime and nighttime. The mean values for all of the independent variables, except the approach speed were calculated and then multiplied by their respective coefficient, and then the models were plotted by varying the approach speed. The model shows that nighttime speeds are predicted to be lower at lower approach speeds, but around 40 mph nighttime speeds are actually predicted to be higher than daytime speeds. The figure shows that depending on the site characteristics, there may be less of a concern about design consistency during the nighttime at higher approach speeds since drivers are selecting a higher speed to travel through the curve. However, there may be more of a concern about drivers selecting a speed higher than the design speed, which has safety implications since vehicles might select a speed that exceeds driver comfort, or worse, the available friction, which may ultimately result in sliding off roadway. Depending on the specific site, there may be substantial differences in operating speeds and these
differences should be considered in the geometric design process to help promote design consistency and reduce the likelihood that drivers select a speed that may result in lose of control of the vehicle.

Figure 9 Midcurve speed estimates by varying the approach speed.
**Ratios of Daytime and Nighttime Coefficients**

Figure 10 shows the ratios of the coefficients from the daytime and nighttime models, which were calculated and shown in Table 17 above. As the figure shows, most of the ratios are between 0.5 and 1.5. The variable that has a ratio closest to 1.0 is the distance from the previous curve, with a ratio 1.05. The variable with the largest ratio is a paved shoulder width of two feet or less since the variable has a small coefficient in the nighttime and is not significant. The ratio for this variable is -36.31, which shows the sign of the coefficient was different between the two models.

As previously discussed, the majority of variables (8 of 12) had a coefficient with a larger magnitude in the nighttime model, which is shown by a ratio less than 1.0. The previous figures compared the 95 percent confidence intervals to each other, and it was determined that the daytime and nighttime intervals overlap each other for all the variables, but as Figure 10 shows, there are a differences between the models when just the point estimates (i.e. coefficients) are compared to each other.
Figure 10 Ratio of midcurve speed coefficients.
6.2 Comparison of Midcurve Standard Deviation Model

Table 18 shows a comparison between the model for estimating curve midpoint standard deviations that was estimated using daytime observations and the model that was estimated using nighttime observations. Most of the independent variables were significant in both the daytime and nighttime model. However, the variable indicating if sight distance was restricted from vegetation or a cutslope on the inside of the curve was not significant in the nighttime model, but it was significant in the daytime model. Also, the variable indicating a warning sign prior to the curve was not significant in the nighttime model, but it was significant in the daytime model.

Table 18 shows the differences in the coefficients, which were calculated by subtracting the coefficients in the nighttime model from the coefficients in the daytime model. The ratios of the coefficients are also shown in the table, which were calculated using the following equation:

\[
\text{Ratio of coefficients} = \frac{\text{Daytime coefficient}}{\text{Nighttime coefficient}}
\]

A value of 1.0 means the coefficients in the two models are the same, while a value exceeding 1.0 means the coefficient in the daytime model has a larger magnitude than the coefficient in the nighttime model, and a value less than 1.0 means the coefficient in the nighttime model has a larger magnitude than the coefficient in the daytime model.
Table 18 Comparison of daytime and nighttime midcurve standard deviation model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Day Observations</th>
<th>Night Observations</th>
<th>Difference in Coefficients</th>
<th>Ratio of Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve speed (mph)</td>
<td>0.221</td>
<td>0.207</td>
<td>0.014</td>
<td>1.07</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>0.143</td>
<td>0.205</td>
<td>-0.062</td>
<td>0.70</td>
</tr>
<tr>
<td>Speed limit of 55 mph (1 if present; 0 otherwise)</td>
<td>-4.683</td>
<td>-5.299</td>
<td>0.615</td>
<td>0.88</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-1.533</td>
<td>-0.974</td>
<td>-0.559</td>
<td>1.57</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-0.870</td>
<td>-1.770</td>
<td>0.900</td>
<td>0.49</td>
</tr>
<tr>
<td>Dirt or grass shoulder indicator (1 if present; 0 otherwise)</td>
<td>-1.288</td>
<td>-0.759</td>
<td>-0.529</td>
<td>1.70</td>
</tr>
<tr>
<td>Prior warning sign (1 if true; 0 otherwise)</td>
<td>-1.052</td>
<td>-0.384</td>
<td>-0.668</td>
<td>2.74</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if present; 0 otherwise)</td>
<td>-0.604</td>
<td>-0.845</td>
<td>0.241</td>
<td>0.71</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>0.832</td>
<td>0.722</td>
<td>0.111</td>
<td>1.15</td>
</tr>
<tr>
<td>Vegetation/cutslope indicator (1 if present; 0 otherwise)</td>
<td>1.930</td>
<td>0.414</td>
<td>1.516</td>
<td>4.66</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>-0.629</td>
<td>0.023</td>
<td>-0.653</td>
<td>-26.94</td>
</tr>
</tbody>
</table>

Adjusted R² 0.4959 0.5185

Comparison of Independent Variables Coefficients

Figures 11 through 13 shows graphical representations of the coefficients of the daytime and nighttime midcurve standard deviation models. For the indicator variables, the point estimate from the model, along with the 95 percent confidence intervals, is plotted against the speed
metric. For the continuous variables, the range of the independent variable is plotted along the horizontal axis while the estimated standard deviation from the model is plotted along the vertical axis. Figure 11 shows the coefficients for a posted speed limit of 55 mph.

As Table 18 shows, the difference between the coefficients for a posted speed limit of 55 mph indicator variable is 0.615 mph. The standard deviation was 0.615 mph lower during the nighttime than daytime at sites with a posted speed limit of 55 mph, holding all other variables constant. One possible reason for this difference is drivers rely more on traffic control devices during the nighttime and fewer drivers may exceed the speed limit during the nighttime because of the limited sight distance. However, as Figure 11 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

![Figure 11](image_url)

**Figure 11** Midcurve standard deviation 95 percent confidence intervals I.
Figure 12 shows the coefficients for a left-hand curve indicator, lane width nine or ten feet indicator, a dirt or grass shoulder indicator, a prior warning sign indicator, data collected in the upgrade direction indicator, paved shoulder width of two feet or less indicator, and if there was vegetation or a cutslope on the inside of the curve restricting sight distance indicator.

As Table 18 shows, the difference between the coefficients for the left-hand curve indicator variable is -0.559 mph. The standard deviation was 0.559 mph lower during the daytime than nighttime on left-hand curves, holding all other variables constant. One possible explanation for the difference is drivers are better able to judge the curve during the daytime, while more drivers may misjudge the curve during the nighttime, and as a result they may slow down more than required or not as much as they would have during the day. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 18 shows, the difference between the coefficients for the lane width of nine or ten feet indicator variable is 0.900 mph. The standard deviation was 0.900 mph lower during the nighttime than daytime at sites with a lane width of nine or ten feet, holding all other variables constant. One possible explanation for the difference is the retroreflectivity of the center- and edge-lines may have increased driver awareness to the narrower lane width, so more drivers slowed down during the nighttime. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 18 shows, the difference between the coefficients for the dirt or grass shoulder indicator variable is -0.529 mph. The standard deviation was 0.529 mph lower during the daytime than nighttime at sites with a dirt or grass shoulder, holding all other variables constant. One possible explanation for the difference is drivers are able to see the dirt or grass shoulder during the
daytime so the drivers who may typically select a higher speed may reduce their speeds to a more uniform speed as a result of the dirt or grass shoulder; whereas drivers may have a harder time seeing that the shoulder is unpaved during the nighttime, so they may not reduce their speeds to a more uniform speed. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 18 shows, the difference between the coefficients for a prior warning sign indicator variable is -0.668 mph. The standard deviation was 0.668 mph lower during the daytime than nighttime at sites with a prior warning sign, holding all other variables constant. Since drivers probably rely on traffic control devices more during the nighttime it was expected that the standard deviation would be lower during the nighttime. One possible reason for the difference is the data used in this thesis were collected on rural roadways, so the warning signs may have lost their retroreflectivity, but were not replaced because maintenance for these roadways may be less of a priority than more urban roadways. This may have caused the signs to be nearly invisible at nighttime, so many drivers may not have seen the warning sign, which made it so only some of the drivers slowed down; whereas most of the drivers probably saw the prior warning sign during the daytime and were able to adjust their speeds. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 18 shows, the difference between the coefficients for the data collected in the upgrade direction indicator variable is 0.241 mph. The standard deviation was 0.241 mph lower during the nighttime than daytime lower at curves that were located on an upgrade, holding all other variables constant. One possible explanation for the difference is drivers who travel at higher speeds during the daytime might not feel comfortable driving at those higher speeds during the nighttime on an upgrade because they do not want to “over drive” their headlights on the crest
vertical curve that they will eventually traverse. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 18 shows, the difference between the coefficients for a paved shoulder width of two feet or less indicator variable is 0.111 mph. The standard deviation was 0.111 mph higher during the daytime than nighttime at sites with a paved shoulder width of two feet or less, holding all other variables constant. One possible explanation for the difference is drivers are able to see the narrower paved shoulder during the daytime, so some drivers may slow down while others do not; whereas at nighttime drivers may have more difficulty seeing the narrower paved shoulder. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.

As Table 18 shows, the difference between the coefficients for the vegetation or a cutslope indicator variable is 1.516 mph. The standard deviation was 1.516 mph higher during the daytime than nighttime at sites that had limited sight distance from vegetation or a cutslope on the inside of the curve, holding all other variables constant. This variable was insignificant in the nighttime model and had very little predicting power for the standard deviation. One possible explanation for the difference is drivers are able to recognize that their sight distance is limited from the vegetation or cut slope, so some drivers may slow down to compensate for the limited sight distance, while others may ignore the limited sight distance; whereas sight distance is limited more by the headlights during the nighttime and the vegetation or cutslope may not be seen. However, as Figure 12 shows, the two 95 percent confidence intervals overlap each other, so the coefficients do not differ significantly.
Figure 12 Midcurve standard deviation 95 percent confidence intervals II.
As Table 18 shows, the difference between the coefficients for the difference between the posted speed limit and advisory speed is -0.062 mph for every mile per hour increase in the difference between the posted speed limit and advisory speed. The standard deviation was 0.062 mph higher during the nighttime than daytime for every mile per hour increase in the difference between the posted speed limit and advisory speed, holding all other variables constant. As previously mentioned, drivers probably rely on traffic control devices more during the nighttime, so some drivers may follow the recommended advisory speed, while others may ignore the advisory speed; whereas drivers are able to see the curve better during the daytime and more drivers may select a speed based on their judgment of the curve and not the advisory speed. Figure 13 shows a graphical representation of the three models by varying the difference between the posted speed limit and the advisory speed. The mean values for all of the independent variables, except the difference between the posted speed limit and advisory speed were calculated and then multiplied by their respective coefficient, and then the models were plotted by varying the difference between the posted speed limit and advisory speed. The model shows that nighttime standard deviations are predicted to be higher regardless of the difference between the posted speed limit and advisory speed, but the difference between the two estimates increases as the difference between the posted speed limit and advisory speed increases. The maximum difference between the daytime and nighttime standard deviations is approximately 2.5 mph, which occurs when the difference between the posted speed limit and advisory speed is 30 mph.
Figure 13 Standard deviation estimates by varying the difference between the posted speed limit and advisory speed.

Overall, the coefficients of the independent variables had a larger magnitude during the daytime than they did during the nighttime. As with the curve midpoint speed models, these models depict that traffic control devices may have more of an effect on the standard deviation at nighttime, and geometric features may have more of an effect during the daytime. The coefficient had a larger magnitude during the nighttime for two of the three traffic control variables, the difference between the posted speed limit and advisory speed, and speed limit of 55 mph indicator variable. Also, the coefficient had a larger magnitude for five of the six geometric
variables, paved shoulder width of two feet or less indicator, left-hand curve indicator, prior warning sign indicator, vegetation or cutslope on the inside of the curve indicator, and dirt or grass shoulder indicator. By comparing the coefficients it can be seen that there are differences between the model for predicting the standard deviation during the daytime and the model for predicting the standard deviation during the nighttime.

**Graphical Representation of Difference in Models Based on Operating Speeds**

As Table 18 shows, the difference between the coefficients for the curve midpoint mean speed is 0.014 for every mile per hour increase in the curve midpoint speed. The standard deviation was 0.014 mph higher during the daytime than nighttime for every mile per hour increase in the curve midpoint mean speed, holding all other variables constant. This difference is insignificant for practical purposes and the increase in the standard deviation is almost the same during the daytime and nighttime. Figure 14 shows a graphical representation of the three models estimated. The mean values for all of the independent variables, except the curve midpoint mean speed were calculated and then multiplied by their respective coefficient, and then the models were plotted by varying the curve midpoint speed. The figure shows that the predicted standard deviations are higher at nighttime for all curve midpoint speeds. There may be instances where the standard deviation is higher during the daytime, but based on the coefficients and Figure 14, the standard deviation will generally be higher during the nighttime. The increased standard deviation, along with the potentially higher predicted speeds at nighttime suggests that there may be more vehicles traveling at higher speeds that exceed side friction values for comfort, or worse, the design speed at nighttime.
Figure 14 Standard deviation estimates by varying curve midpoint speed.

Ratios of Daytime and Nighttime Coefficients

Figure 15 shows the ratios of the coefficients from the daytime and nighttime models, which were calculated and shown in Table 18 above. As the figure shows, most of the ratios are between 0.5 and 2.0. The variable that has a ratio closest to 1.0 is the curve midpoint mean speed with a ratio 1.07. The variable with the largest ratio is the vegetation or cutslope on the inside of the curve indicator variable since the variable has a small coefficient and is not significant in the nighttime; the ratio for this variable is 4.66. Also, the ratio was 2.74 for the prior warning sign indicator variable. As previously discussed, the coefficient for the majority of variables (6 of 10) had a
larger coefficient in the daytime model, which is shown by a ratio greater than 1.0. The previous figures compared the 95 percent confidence intervals to each other, and it was determined that the daytime and nighttime intervals overlap each other for all the variables, but as Figure 15 shows, there are differences between the models when just the point estimates (i.e. coefficients) are compared to each other.
Figure 15 Ratio of midcurve standard deviation coefficients.
6.3 Transferability Test

In addition to the comparison of the coefficients in the daytime and nighttime models, a transferability test was also done. A transferability test was performed to determine if there is a difference between the model estimated for nighttime speeds and the model estimated for daytime speeds. A transferability test can be used to determine if the estimated parameters are the same between the daytime and nighttime model. The models were estimated using 3SLS, so the transferability test determined if the combined models of speed and standard deviations of speed are different. The test uses log likelihoods at convergence with the general form:

\[ X^2 = -2[LL(\beta_A) - LL(\beta_D) - LL(\beta_N)] \]

where,

\[ LL(\beta_A) = \text{log likelihood at convergence of model using both day and night observations} \]
\[ LL(\beta_D) = \text{log likelihood at convergence of model using day observations} \]
\[ LL(\beta_N) = \text{log likelihood at convergence of model using night observations} \]

The degrees of freedom for \( X^2 \) in the transferability test is determined from the following equation:

\[ DF = (\text{Estimated parameters})_D + (\text{Estimated parameters})_N - (\text{Estimated parameters})_A \]

where,

\[ DF = \text{degrees of freedom} \]
\[ (\text{Estimated parameters})_D = \text{number of estimated parameters in day model} \]
\[ (\text{Estimated parameters})_N = \text{number of estimated parameters in night model} \]
\[ (\text{Estimated parameters})_A = \text{number of estimated parameters in all observations model} \]

The log likelihoods at convergence for the three models can be seen in Table 19 below.
### Table 19 Log likelihoods at convergence.

<table>
<thead>
<tr>
<th>Model</th>
<th>Log Likelihood (LL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Observations</td>
<td>-1147.504</td>
</tr>
<tr>
<td>Day Observations</td>
<td>-690.707</td>
</tr>
<tr>
<td>Night Observations</td>
<td>-448.109</td>
</tr>
</tbody>
</table>

The equation for $X^2$ is solved below.

$$X^2 = -2[LL(\beta_A) - LL(\beta_D) - LL(\beta_N)]$$

$$X^2 = -2[-1147.504 - (-690.707) - (-448.109)]$$

$$X^2 = -2[-8.688]$$

$$X^2 = 17.376$$

The equation for degrees of freedom is solved below.

$$DF = (\text{Estimated parameters})_D + (\text{Estimated parameters})_N - (\text{Estimated parameters})_A$$

$$DF = 13 + 13 - 13$$

$$DF = 13$$

Based on the degrees of freedom, it would be concluded that the two models are different at the 95 percent confidence level if $\chi^2$ was equal to or exceeded 22.362. $\chi^2$ was calculated to be 17.376, so it is not concluded that the estimated parameters between the daytime and nighttime models are significantly different at the 95 percent confidence level. However, it would be concluded that the two models are different at the 80 percent confidence level if $\chi^2$ was equal to or exceeded 16.985. Since $\chi^2$ was calculated to be 17.376, it is concluded that the estimated parameters between the daytime and nighttime models are significantly different at the 80 percent confidence level. $\chi^2$ is not large enough to conclude that the models are different at the 90 or 95 percent confidence level.
6.4 Summary of Results

The results of the models show that there are differences between the coefficients of the independent variables in the daytime and nighttime models when just the point estimates (i.e. coefficients) are compared. Unfortunately, the relatively small sample size resulted in higher standard errors, so as a result, there was not a statistically significant difference between many of the independent variables in the daytime and nighttime operating speed models. Figure 4 shows that the coefficients differ for many binary variables between the daytime and nighttime mean speed models, but the 95 percent confidence intervals of the variables for the daytime and nighttime overlap each other for all of the variables. The binary variables with the largest difference between the coefficients in the daytime and nighttime models are the lane width of 9 or 10 feet indicator, a paved shoulder width of two feet or less indicator, and the chevrons indicator. Figure 5 shows that nighttime operating speeds are predicted to be higher on tighter radii curves, while daytime operating speeds are predicted to be higher on larger radii curves, but the difference between daytime and nighttime speeds as a function of curve radius is nominal. Figure 6 shows that the curve midpoint speed is predicted to increase at approximately the same rate during the daytime and nighttime as the distance from the previous curve increases. Figure 7 shows that operating speeds are predicted to decrease more during the daytime than nighttime as the number of access points 300 feet before the PC increases. Figure 8 shows operating speeds are predicted to decrease more during the nighttime than daytime as the difference between the posted speed limit and advisory speed increases. As Figure 9 shows, the main variable that is associated with a difference between daytime and nighttime operating speeds is the approach speed. Drivers maintained a speed closer to their approach speed through the curve more so during the nighttime than daytime.
Figures 11 and 12 show that the coefficients differ for many binary variables between the daytime and nighttime standard deviation models, but the 95 percent confidence intervals of the variables for the daytime and nighttime overlap each other for all of the variables. The binary variables with the largest difference between the coefficients in the daytime and nighttime models are the lane width of 9 or 10 feet indicator, a prior curve/turn warning sign indicator, and the vegetation or cutslope on the inside of the curve indicator. Figure 13 shows that the standard deviation is predicted to increase more during the nighttime than daytime as the difference between the posted speed limit and advisory speed increases. Figure 14 shows that the standard deviation is predicted to increase at approximately the same rate during the daytime and nighttime as the curve midpoint mean speed increases. As shown in Figures 13 and 14, the standard deviation is typically predicted to be higher during the nighttime than daytime.

The coefficients for some of the independent variables are different in the daytime and nighttime models, but as the transferability test shows, the daytime and nighttime models are only marginally statistically significant. Based on these differences, recommendations are made in the next chapter describing how these differences can potentially be incorporated into geometric design policy and processes.
Chapter 7

Conclusions and Recommendations for Geometric Design Policy and Processes

7.1 Conclusions

This thesis considered the association among speed metrics, geometric design, and traffic control variables on two-lane rural highways. Models of mean speed and speed deviation were estimated for daytime and nighttime conditions to determine if the roadway features affected speeds differently at different times of the day. The findings suggest that there are differences in speed during daytime and nighttime conditions, and these differences can be explained by the geometric design features and traffic control devices present along the road. These differences may help explain why a disproportionate number of crashes occur during the nighttime, relative to the daytime, when considering vehicle-miles travelled by time of day. The models show drivers rely more on traffic control devices during the nighttime to select their speed, while they rely more on geometric features during the daytime, which is based on the magnitude of the coefficients of the regression models.

As discussed in the previous chapter, there are differences between operating speeds during the daytime and nighttime, and these differences should be accounted for during the geometric design process. There is also a difference in the models for predicting the standard deviation of operating speeds, and the results show that standard deviations are higher during the nighttime. This may result in more vehicles exceeding side friction values for comfort or the design speed during the nighttime, which has safety implications. Previous research has also shown that more crashes are expected when the standard deviation of operating speeds is higher (Garber and Ehrhart, 2000). The results of this thesis show there may potentially be significant differences
between the standard deviation of operating speeds during the daytime and nighttime, particularly when the difference between the posted speed limit and advisory speed is large. Since this is the case, the standard deviation of speeds should also be considered in future operating speed modeling, and in future design consistency research.

7.2 Recommendations for Geometric Design Policy and Processes

The regression parameters for each independent variable in the daytime and nighttime operating speed models differ in magnitude; however, this difference is often not statistically significant. As such, the recommendations developed in this section are based on the trade-off between design consistency (i.e., minimizing the speed difference between the approach tangent and midpoint of a horizontal curve) and lower operating speeds. Figure 9 shows that operating speeds are more uniform between the approach tangent and midpoint of a horizontal curve at night (i.e., better design consistency) relative to daytime operating speeds, yet predicted operating speeds are higher at night than during the daytime.

Sight distance is limited more during the nighttime from the limited distance that headlights can illuminate, especially on horizontal curves, and travelling at higher speeds increases the stopping distance of a vehicle, so the probability a driver has the required stopping sight distance increases by lowering operating speeds. Also, higher speeds result in more severe crash outcomes, if a crash occurs. As such, the recommendations were made, in part, based on the assumption that it is safer for drivers to reduce their speed rather than maintain a more consistent speed from the approach tangent to the midpoint of a horizontal curve.

- Current design practices suggest consideration of operating speeds when selecting geometric design speeds (which are then used to determine geometric design criteria), so it is desirable for daytime and nighttime operating speeds be
similar. The operating speed models estimated in this thesis show that there are several variables that cause nighttime and daytime speed predictions to differ. The main variable that causes nighttime speed predictions to be higher than daytime predictions is the approach speed at higher speeds. The difference between the coefficients for the approach speed is 0.173 mph, so for every mile per hour increase in approach speed, nighttime speed predictions will be 0.173 mph higher than daytime speeds, holding all other variables constant. This result matches engineering intuition and is most likely from drivers not being able to see the geometric layout of the curve as well at nighttime, which causes them to misjudge the curve and maintain a higher speed through the curve. If the desire is to reduce nighttime speeds and have them match daytime speeds more closely, one possible way to accomplish this is to reduce approach speeds. This may be achieved by creating a driving environment during the nighttime that is similar to the daytime. This can be done by increasing the amount of positive guidance that is installed, which may provide drivers with more information during the nighttime (i.e. more visible and frequent use of traffic control devices or illumination where nighttime speeds are high relative to the daytime, ensure centerline and edgelines are clearly visible at night and that the retroreflectivity is sufficient to clearly delineate the curve, ensure advisory speed signs are installed when appropriate, and alignment signs (e.g. chevrons, curve or turn warning signs, etc.) are installed when required).

- If the desire is to have nighttime speeds more closely match daytime speeds, tighter radii curves should be avoided since operating speeds are predicted to be higher at nighttime than during the daytime on tighter radii curves. Drivers
probably midjudge curves with tighter radii since they cannot see the geometric layout of these curves as well at night, which causes them to maintain a higher speed through the curve. By designing curves with larger radii, daytime and nighttime operating speeds would be closer together based on the result of this research. As with the previous recommendation, if speeds are already predicted to be above the design speed, designing curves with larger radii is not recommended since operating speeds typically increase as the radius increases.

- Again, if the desire is to reduce nighttime speeds and have them more closely match daytime speeds, narrower lanes widths should be considered. Mean operating speeds and the standard deviation of speed were lower during the daytime and nighttime when the lane width was nine or ten feet compared to wider lanes, but speeds were 1.391 mph lower, and the standard deviation was 0.900 mph lower, during the nighttime than daytime. By using narrow lane widths, nighttime operating speeds would be even lower than daytime speeds at lower approach speeds, and nighttime speeds would more closely match daytime speeds at higher approach speeds. Another advantage to designing roads with narrow lane widths is the standard deviation would also be lower during both the daytime and nighttime, which has been shown to improve safety (Garber and Ehrhart, 2000).

- If the desire is to have improved speed consistency between the daytime and nighttime, installing wider shoulders could make it so daytime and nighttime speeds more closely match each other. A paved shoulder width of two feet or less did not have a significant effect on nighttime operating speeds, but daytime operating speeds decreased by 1.436 mph relative to shoulder widths wider than
two feet. By paving shoulders with widths greater than two feet, daytime speeds may be higher so they are closer to nighttime speeds at higher approach speeds, but if operating speeds were predicted to be above the design speed then this should not be done. This recommendation would allow for more consistency between speeds during the daytime and nighttime at higher operating speeds. Having more speed consistency between the daytime and nighttime will allow drivers to have the same expectations under both conditions, without altering their driving behavior.

7.3 Recommendations for Future Work

While the results of this thesis show there are differences between how drivers select their operating speeds during the daytime and nighttime, future research should expand on these results. The research can be expanded in the following ways:

- The recommendations for geometric design policy and processes made in this thesis were based on the assumption that it is safer for drivers to slow down more entering a curve than maintain their speed since higher speeds result in more severe crash outcomes, if a crash occurs. This assumption should be verified in future work.

- Model the speed difference between the approach and curve midpoint during the daytime and nighttime. This explicitly focuses on design consistency and can produce a statistical model to show drivers change their speed between an approach tangent and horizontal curve.
• Use the mean speed and standard deviation models from this thesis to model the friction demand during the daytime and nighttime, and then determine if there is a higher probability that the friction demand exceeds the friction supply during the nighttime. This recommendation would require friction supply data to be available for the comparison.

• Collect the grade of the curve, rather than just identifying the curve as being located on a downgrade, level ground, or upgrade.

• Collect the maximum superelevation within the horizontal curves. If possible, collect the available sight distance. The roadside hazard rating (RHR) should also be determined for each site, since the roadside environmental likely affects how drivers perceive a roadway.

• Collect additional speed data at different sites to increase the number of observations available to estimate the operating speed models. Additional data collection efforts should focus on collecting more data at nighttime. An increased sample size would decrease the standard errors of the coefficients and reduce the width of the confidence intervals associated with each regression parameter. This may eliminate the confidence interval overlap in the present study.

• Only 27 sites were used to estimate the models in the present study, so data should also be collected at sites with different characteristics so that the models can be applied to a wider range of sites. Additional differences between daytime and nighttime operating speeds may be found by expanding the characteristics of
the sites used to estimate the models. Specifically, collect data at more sites that
have a 55 mph posted speed limit and no advisory speed.

• Collect additional speed data at different sites to verify that the models estimated
  in this thesis can be applied to other curves not included in the sample that was
  used to estimate the current models.
References


Charlton, S.G. The Role of Attention in Horizontal Curves: A Comparison of Advance Warning, Delineation, and Road Marking Treatments. *Accident Analysis & Prevention, 39*(5), September 2007, pp. 873-885.


Table 20 OLS midcurve mean speed model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>z-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve standard deviation (mph)</td>
<td>0.481</td>
<td>0.075</td>
<td>6.44</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Inverse radius (ft)</td>
<td>-2455.277</td>
<td>183.964</td>
<td>-13.35</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Number of access points 300 ft before PC</td>
<td>-1.316</td>
<td>0.197</td>
<td>-6.68</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>-0.228</td>
<td>0.026</td>
<td>-8.73</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Distance from previous curve (100's of ft)</td>
<td>0.054</td>
<td>0.017</td>
<td>3.12</td>
<td>0.002</td>
</tr>
<tr>
<td>Approach speed (mph)</td>
<td>0.496</td>
<td>0.054</td>
<td>9.20</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-2.245</td>
<td>0.495</td>
<td>-4.54</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if true; 0 otherwise)</td>
<td>-2.480</td>
<td>0.571</td>
<td>-4.34</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-1.660</td>
<td>0.487</td>
<td>-3.41</td>
<td>0.001</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>-1.091</td>
<td>0.370</td>
<td>-2.95</td>
<td>0.003</td>
</tr>
<tr>
<td>Chevrons indicator (1 if present; 0 otherwise)</td>
<td>1.450</td>
<td>0.415</td>
<td>3.49</td>
<td>0.001</td>
</tr>
<tr>
<td>Speed limit of 40/45/55 mph (1 if present; 0 otherwise)</td>
<td>2.397</td>
<td>0.455</td>
<td>5.27</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>23.597</td>
<td>2.537</td>
<td>9.30</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Number of observations = 280

R² = 0.8843
Adjusted R² = 0.8791
Root MSE = 2.2001
Table 21 OLS midcurve standard deviation model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
<th>z-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midcurve speed (mph)</td>
<td>0.230</td>
<td>0.020</td>
<td>11.48</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Difference between posted speed limit &amp; advisory speed (mph)</td>
<td>0.164</td>
<td>0.030</td>
<td>5.52</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Speed limit of 55 mph (1 if present; 0 otherwise)</td>
<td>-4.873</td>
<td>0.589</td>
<td>-8.27</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Left-hand curve indicator (1 if present; 0 otherwise)</td>
<td>-1.196</td>
<td>0.311</td>
<td>-3.85</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Lane width of 9 or 10 ft (1 if present; 0 otherwise)</td>
<td>-1.210</td>
<td>0.299</td>
<td>-4.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Dirt or grass shoulder indicator (1 if present; 0 otherwise)</td>
<td>-0.977</td>
<td>0.280</td>
<td>-3.5</td>
<td>0.001</td>
</tr>
<tr>
<td>Prior warning sign (1 if true; 0 otherwise)</td>
<td>-0.753</td>
<td>0.286</td>
<td>-2.64</td>
<td>0.009</td>
</tr>
<tr>
<td>Data collected in upgrade direction (1 if present; 0 otherwise)</td>
<td>-0.742</td>
<td>0.327</td>
<td>-2.27</td>
<td>0.024</td>
</tr>
<tr>
<td>Paved shoulder width ≤ 2 ft (1 if present; 0 otherwise)</td>
<td>0.829</td>
<td>0.268</td>
<td>3.10</td>
<td>0.002</td>
</tr>
<tr>
<td>Vegetation/cutslope indicator (1 if present; 0 otherwise)</td>
<td>1.325</td>
<td>0.309</td>
<td>4.29</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant (mph)</td>
<td>-1.070</td>
<td>0.961</td>
<td>-1.11</td>
<td>0.266</td>
</tr>
</tbody>
</table>

Number of observations = 280

$R^2 = 0.5125$

Adjusted $R^2 = 0.4943$

Root MSE = 1.6771