Improving the Self-Explaining Performance of Czech National Roads

Jiří Ambros, Veronika Valentová, Ondřej Gogolin, Richard Andrásík, Jan Kubeček, and Michal Bil

Improving the road network according to the principles of self-explaining roads is a promising way to increase the level of safety; however, there are no universal guidelines on how to measure and improve the self-explaining performance of existing roads. To apply this approach on Czech national roads, the present study was conducted, consisting of five steps: (a) automated segmentation into tangents and horizontal curves; (b) collection of floating car data and calculation of speed; (c) development of multivariate speed models for estimation of speed, including on segments not covered by floating car data; (d) networkwide application of the models and evaluation of speed consistency, such as differences in speeds on tangents and following curves; and (e) identification of substandard curves, and categorization and proposal of optimization for consistent placement of traffic control devices or reconstructions. The paper describes all the steps as well as several checks conducted along the way, such as comparison of profile speed and floating car speed, interpretation of regression models, and validation of predicted speed consistency against long-term average crash frequency. The methodology has been certified for use in practice and will be applied by the Czech national road agency.

The level of road traffic safety on Czech roads is unsatisfactory. In 2011, the National Road Safety Strategy was established, with goals to reduce the number of fatalities by 60% and serious injuries by 40% by 2020. A variety of countermeasures have been proposed and continuously applied, such as infrastructure improvements, increased police enforcement, and improved traffic safety education. Despite these efforts, annual evaluations of the fulfillment of the strategy show that the goals have not been met (1).

In this critical situation, new solutions and measures need to be adopted. An option that is mentioned in the strategy is to improve the road network based on the principles of self-explaining and forgiving roads. A self-explaining environment is a traffic environment that simply elicits safe behavior by its design (2). The concept involves designing a road system in which drivers’ expectations created by the road environment are implicitly in line with safe behavior. According to an international review (3), the self-explaining road concept and principles have been used worldwide and often in situations that differ from the original. For example, in the United Kingdom, self-explaining roads are mentioned as those where drivers naturally adopt the correct speed (4). In New Zealand, the concept was extended to an areawide approach to traffic calming and speed management (5). In the United States, the term “self-enforcing design” was introduced, which reinforces established speed limits and reduces speeding opportunities; such roads should induce drivers to adopt operating speeds that are within limits (6). In summary, there are no universal definitions or guidelines on how to measure and improve the self-explaining performance of the existing roads.

This paper summarizes a research project that focused on improving the self-explaining performance of Czech national roads. The project was conducted by the Transport Research Centre according to the needs of the national road agency (Road and Motorway Directorate). The following sections describe the data collection, development of the methodology, and application on rural sections of national roads, followed by a discussion and conclusions.

THE STUDY

According to Gitelman et al. (7), the tools that are applicable for creating self-explaining roads include (a) setting a correct functional hierarchy of the road system, (b) providing consistency in road design, and (c) measuring a link between road characteristics and travel speeds. The second and third options were adopted in the present project.

The idea behind the concept of consistency (also design consistency, alignment consistency, or speed consistency) is as follows: drivers are more likely to make fewer errors in the vicinity of geometric features that fit their expectations than in the vicinity of features that violate their expectations (8). Consistent design ensures that successive geometric elements are coordinated in a manner that minimizes variability in vehicle speeds, prevents critical driving maneuvers, and reduces crash risk (9). Consistent operating speeds are a product of consistent design (10); therefore, the variables for evaluating design consistency are usually defined in terms of an operating speed (10). Various consistency measures have been used. The most used measure, which was developed by Lamm et al., evaluates consistency in the magnitude of speed reduction between successive design elements. Design is regarded as good if the magnitude of the difference in the 85th speed percentile is less than 10 km/h; as fair if the difference is between 10 and 20 km/h; and as poor if the difference is greater than 20 km/h (11–13).

The following subsections describe the five study steps:

1. To divide the studied network (rural sections of national roads) into tangents and horizontal curves, a novel method of automated segmentation was developed and applied.
2. Floating car data were purchased and processed to obtain free-flow speed.
3. Since the floating car data did not cover the whole analyzed network, multivariate regression models (relationships between speed and explanatory variables) were built. The purpose of these models was to enable future network-wide application, without forcing users to collect their own data. To prove the models' quality, the validity of differences of estimated (predicted) speeds (i.e., speed consistency) against long-term average of crash frequency was checked.

4. The models were applied to the entire Czech road network. Speed was estimated for each segment and consistency was evaluated.

5. Substandard curves were identified. Consistency assessments were categorized into five classes; a specific optimization was proposed for each class.

Step 1. Segmentation

Various authors have used different approaches to obtain alignment parameters and make segments of tangents and curves (14–16). Nevertheless, each method has its disadvantages, such as limited accuracy or dependence on manual processing. Often a combination of manual and automatic identification is used. A novel, fully automated segmentation methodology was recently developed [see Andrášik and Bill (17) for details]. The methodology consists of four steps:

1. Preprocessing with the Douglas-Peucker algorithm for data generalization;
2. Calculation of geometrical explanatory variables;
3. Classification of tangents and curves with the use of a classification tree, based on explanatory variables; and
4. Postprocessing with the least-squares method for radii computation.

The average error of identification is less than 5%, which is more precise than commonly used techniques. The method was applied in the present study to distinguish between tangents and curves. Since several segments were relatively short, two rules were considered:

- Lamm et al. (11) marked tangents shorter than 200 m as dependent; speeds on such tangents are influenced by speeds on previous segments.
- For crash-based analyses (i.e., also for planned validation), the AASHTO Highway Safety Manual (18) recommends using minimal segment length of 0.1 mi (160.9 m). In a similar vein, Czech hotspot identification guidelines (19) use a length of 250 m.

Based on these two criteria, a minimal length of 200 m was chosen; shorter segments were discarded.

Step 2. Determination of Speed

The floating car data (FCD) were purchased from a private company, Princip a.s. The data set consisted of GPS data points from 1,172 company vehicles, collected over eight months (October 2014 to May 2015). The speed was calculated from the GPS location and the time interval between the points, given by the recording frequency 4 times/s. This way, speed was assigned to the data points of each individual drive.

To analyze relationships between speed, road geometry, and traffic safety, it is necessary to use free-flow speed (FFS), which is speed that is not constrained by congestion, traffic devices, or adverse weather conditions. The traditional approach to estimating FFS relies on field studies, where speeds of single (uninfluenced) vehicles are detected with handheld speed guns, roadside traffic counters, and fixed loops or tubes (20). However, with area-wide collected FCD, a different approach is necessary. Typically, the data from off-peak hours are believed to represent FFS (21–23); however, since company vehicles often travel during peak hours, this approach could lead to enormous data loss. A different method was therefore applied, consisting of the following steps:

1. Each data point was assigned to the nearest vertex of the road centerline.
2. For each vertex, speed values were calculated and divided into two groups (influenced and uninfluenced speed) based on cluster analysis.
3. FFS was calculated as the 85th percentile of uninfluenced speed.
4. The weighted average of FFS per segment was used, with the weight given by the number of data points assigned to each vertex.

To obtain representative information, data from more drives in selected sections were needed. A TRB Synthesis (20) reports the parameters of operating speed studies, including the number of observations; many of the parameters used the criterion of at least 100 per site. The same criterion was applied in this study; segments with fewer than 100 drives were discarded (in case there were 100 or more drives in both directions, both were used).

The representativeness of speed estimated from FCD was compared with spot speed, which was measured by a statistical radar SR 4. In seven profiles, FCD speed was on average 2 km/h greater than the radar speed.

Step 3. Development and Validation of Speed Models

Given the traditional links between geometric design and operating speed studies, speed models are usually simple, only introducing horizontal curve radii (or some of the derivatives, such as degree of curve or curvature change rate (CCCR) as predictors. However, speed is a complex issue, influenced by several environmental effects, such as cross section, roadside, road marking, or roadside vegetation density (24–27). Recent studies have indicated that speeds are affected by several characteristics that are normally neglected in operating speed models (28, 29).

Values of the following explanatory variables (potential speed choice attributes) were assigned to each segment:

- Traffic volume (half of bidirectional annual average daily traffic),
- Road geometry (CCCR, curve radius, length, vertical grade, and visibility of segment end),
- Cross section (climbing lane, road width, shoulder width, cross slope, and overtaking possibility), and
- Road equipment and roadside (road signing, guardrails, delineator posts, and vegetation).

Some variables were extracted from national road agency databases; some were manually identified in Google Maps; and cross slope was measured by an instrumented vehicle. An effort was made to filter out the segments with nonstandard parameters, such as multiple lanes, medians, intersections, bus stops, pedestrian crossings, tunnels,
and railroad level crossings. The goal was to obtain a sample of two-lane, undivided rural segments (potentially with climbing lanes), where speed should only be influenced by the listed attributes. In total, 296 segments (168 tangents and 128 curves) were obtained.

Before modeling, the frequencies of the categorical variables were studied. In cases where some category was present in fewer than 10% of the segments, the variable was discarded. This was the case for delineator posts and road signing. In addition, intercorrelations of explanatory variables were checked. In case they were high (with Pearson correlation coefficient above 0.5), for example, between road width and shoulder width, only one of such variables entered the model. Descriptive characteristics of the explanatory variables that were used for modeling are presented in Tables 1 and 2, separately for tangents and curves.

The following common model form was adopted (20):

\[ V_{55} = b_0 + \sum b_i x_i \]  

where

\[ V_{55} = 85\text{th speed percentile}, \]
\[ x_i = \text{explanatory variables (in Tables 1 and 2), and} \]
\[ b_i = \text{regression coefficients to be estimated.} \]

Models were calibrated separately for tangents and curves. Multivariate regression modeling in IBM SPSS was used, in backward-stepwise manner, keeping the variables with significance level below 0.05 (5%).

Inspired by previous studies (20, 30, 31), the following steps were taken:

1. Development of a model for tangent speeds (with the above-mentioned potential explanatory variables) to obtain predictions \( V_t \) and
2. Development of a model for curve speeds (with the above-mentioned potential explanatory variables, including predictions \( V_t \)) to obtain predictions \( V_c \).

The modeling results are shown in Table 3. Column B presents a vector of unstandardized regression coefficients, that is, the values of the intercept \( b_0 \) and coefficients \( b_i \) from Equation 1. The next columns include standard errors (SEs), standardized regression coefficients (B), and achieved levels of statistical significance (Sig.).

The internal validity of the models may be illustrated by the signs of the regression coefficients:

- Increasing length, road width, visibility, and enabled overtaking and climbing (which have positive coefficient signs) are associated with an increase in speed; the same positive relationship holds for the influence of the preceding tangent speed on speed in the following curve.
- An increase in traffic volume, cross slope, or CCR (with negative coefficient signs) is associated with a decrease in speed.

These associations are generally logical and consistent with the literature (20): increasing segment length, road width, as well as the possibility of overtaking, using a climbing lane, or visibility through the segment, allow higher driving speed. The increased tangent speed is then translated into the following curve. By contrast, higher curvature, cross slope, or traffic volume leads to a decrease in speed.

The coefficients of determination \( R^2 \) of the models were .271 for tangents and .398 for curves. To ensure that they are sufficient and the model predictions make sense, an external validity test was conducted. Validation against crash indicators as objective safety was chosen, following many previous applications of this approach (30, 32, 33). The validation was based on a comparison of speed differences (calculated from predicted speeds) against objective safety, expressed in the empirical Bayes (EB) estimate of expected
TABLE 3  Estimated Regression Coefficients of Speed Prediction Models

<table>
<thead>
<tr>
<th>Tangent</th>
<th>$B$</th>
<th>SE</th>
<th>Sig.</th>
<th>Curves</th>
<th>$B$</th>
<th>SE</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>92.119</td>
<td>3.376</td>
<td>0.000</td>
<td>(Intercept)</td>
<td>50.704</td>
<td>15.316</td>
<td>0.001</td>
</tr>
<tr>
<td>Traffic volume</td>
<td>−0.001</td>
<td>0.000</td>
<td>0.023</td>
<td>$V_c$</td>
<td>0.559</td>
<td>0.158</td>
<td>0.001</td>
</tr>
<tr>
<td>Length</td>
<td>0.004</td>
<td>0.001</td>
<td>0.001</td>
<td>CCR</td>
<td>−0.070</td>
<td>0.011</td>
<td>0.000</td>
</tr>
<tr>
<td>Cross slope</td>
<td>−2.169</td>
<td>0.838</td>
<td>0.011</td>
<td>Shoulder width</td>
<td>−1.660</td>
<td>0.794</td>
<td>0.039</td>
</tr>
<tr>
<td>Road width</td>
<td>1.611</td>
<td>0.741</td>
<td>0.031</td>
<td>Climbing lane</td>
<td>4.399</td>
<td>1.904</td>
<td>0.023</td>
</tr>
<tr>
<td>Overtaking</td>
<td>3.962</td>
<td>1.200</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visibility of segment end</td>
<td>3.026</td>
<td>1.283</td>
<td>0.020</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Climbing lane</td>
<td>10.347</td>
<td>2.232</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: $B$ = unstandardized regression coefficients; SE = standard error; sig. = achieved levels of statistical significance; $V_c$ = predicted speed in preceding tangent.

crash frequency (for details, see Hauer et al. [34]), EB estimates the long-term average as a combination of the following:

1. Expected crash frequency according to the crash prediction model (safety performance function):

$$N = b_0 \cdot I^{a} \cdot L^{b}$$  \hspace{1cm} (2)

where

$N$ = crash frequency,
$I$ = traffic volume,
$L$ = length, and
$b_i$ = estimated regression coefficients.

2. Recorded crash frequency based on police data.

Consistent with other studies (35, 36), only single-vehicle crashes were used for the validation, since they are more clearly linked to road geometry and speed. Crash frequencies were summed over a six-year period (2009–2014) and for all severity levels (property damage only, light injuries, serious injuries, and fatalities) for each curve. The model was calibrated with the use of generalized linear modeling with negative binomial error structure in IBM SPSS.

The validation results, in absolute values of speed difference (consistency), are displayed in Figure 1. The categories were chosen so that each bin contains at least 10 values. The values of the EB averages form a clear rising trend, with the last bin ($\Delta V > 6 \text{ km/h}$) being more than 50% higher than the first bin ($\Delta V < 2 \text{ km/h}$). This result also confirms that self-explaining roads (with minimal speed differences, that is, maximal speed consistency) are the safest.

Step 4. Networkwide Determination of Speed Consistency

As described in Step 3, the regression models were based on a reduced sample, and thus the model results (predictions) do not cover the complete network. A model extension was conducted in the following steps:

1. Selection by length of tangents $\geq 200 \text{ m}$ (as already used in Step 3) and curves $\geq 50 \text{ m}$ (as opposed to the previously used 200 m), and

![Figure 1](image_url)  \hspace{1cm} FIGURE 1  Results of the validation of absolute speed difference against empirical Bayes (EB) estimates of expected crash frequency.
2. Filtering out nonstandard segments (multilane, bus stops, and so forth), similar to Step 3.

After filtering, there were 992 tangent-curve pairs, that is, approximately a quarter of the original road network (609 km, roughly 380 mi). The values of the explanatory variables in Table 3 were assigned to the segments. The model equations were used to obtain predictions and calculate the speed differences in all the tangent-curve pairs:

\[
\Delta V = V_p - V_c
\]

where

\( \Delta V \) = speed consistency,

\( V_p \) = predicted speed in curve, and

\( V_c \) = predicted speed in preceding tangent.

**Step 5. Categorization and Optimization**

The following criteria were used to develop a ranked list of curves:

1. Ascendant ranking of speed differences \( \Delta V < -4 \) km/h.
2. Ascendant ranking of curve radii \( < 400 \) m [critical value based on Elvik (37)].
3. Descendant ranking of CCR differences \( > 180 \) gon/km [threshold value based on Lamm et al. (11)].

As a result, 117 curves were identified as substandard (inconsistent), that is, requiring subsequent optimization. Optimization may be done through consistent placement of traffic control devices or redesign and reconstruction (e.g., curve flattening). Decisions on these strategies should ideally be based on some form of risk hierarchy. The following are some examples:

- The U.S. Manual on Uniform Traffic Control Devices (38) selects the type of signs based on a difference between speed limit and advisory speed. Advisory speed may be selected based on accelerometer measurement, design speed equation, or use of a Ball Bank indicator.
- In Queensland, Australia (39), curves are considered substandard if advisory speed is at least 15 km/h lower than the 85th speed percentile on the preceding tangent. A four-step hierarchy is formed based on approach (tangent) speed and advisory speed (measured by a Ball Bank indicator).
- In the European research project SAFESTAR (40), a five-step hierarchy was proposed that used the 85th percentile of tangent speed (predicted by a regression model) and curve design speed. The approach was adopted in several European countries (Denmark, the Netherlands, and Poland), as well as in the Texas Horizontal Curve Signing Handbook (41), where 85th percentiles of curve and tangent speeds were used; the former needs to be measured, and the latter may be predicted by software.
- Portuguese research (30) employed prediction models for tangent and curve speeds. Based on differences between these speeds, consistency classes of signing were proposed.

The original intention was to use the SAFESTAR approach in the present project. However, the determination of curve design speeds was difficult, since in the Czech Republic they are unavailable network wide and their calculation was unreliable due to nonexistent or inaccurate information on super-elevation and friction. Therefore, it was decided to develop an approach inspired by the Portuguese example, that is, to use speed consistency calculated from predictions of curve and tangent speeds (as described in Step 3).

The proposed approach not only considers the assessment of speed consistency but also the assessment of relation design. Relation design means that sequences of design elements (i.e., tangents and curves) are formed such that the elements following one another are subject to specific relations ([1]). In many guidelines, these relations are more or less qualitative or broadly defined. For example, AASHTO's Green Book (42) suggests a generally accepted ratio of the radii for two successive curves below 1.5, and avoidance of sharp curves at the ends of long tangents. In contrast, German design guidelines (43) introduce two fundamental graphs: (a) relationship of tangent length and following curve radius \( L \) and \( R \), and (b) relationship of two consecutive curve radii, \( R_2 \) and \( R_1 \) (in case the intermediate tangent length does not exceed 300 m). Conforming to these relation design rules ensures that single design elements are not put together arbitrarily.

The proposed assessment approach consists of the following four steps:

1. Single element assessment based on empirically set thresholds of speed consistency (Figure 2a).
2. Relation design assessment based on speed consistency, adapted according to the graphs from the German guidelines (Figure 2, b and c).
3. Field inspection of the assessed curves to investigate other influences, such as sight conditions, vertical alignment, vegetation, road surface, and so forth. Historical crash records may also be considered.
4. Combined assessment based on Steps 1 to 3. For example, when a curve is categorized as A class (in Steps 1 and 2), but an adverse condition is identified during Step 3, the class is changed to B.

Two examples are given in Table 4:

- Curve 1 is assessed as A class in speed consistency. The relation design assessment applies to the relationship of tangent length \( L \) and following curve radius \( R \) (A class); there is no following curve (within 300 m), so the consecutive curve radii assessment \( (R_1 + R_2) \) does not apply. The crash history contains one crash in six years, which is below average in the analyzed sample (two crashes in six years). However, field inspection revealed the presence of a visual trap caused by a combination of horizontal and vertical alignment. In summary, the final assessment was downgraded from A to B.
- Curve 2 is assessed as C class in speed consistency. The relation design is applied in both ways \( (L + R_1 + R_2) \); since another curve follows within 300 m after the current curve; the result is C class. During a field inspection, negative cross slope was identified as well as excessive crash history (four crashes in six years, which is double the average). The final assessment was thus downgraded from C to D.

For A to C classes, consistent application of traffic control devices (signing and marking) is proposed (see Table 5); for D class, reconstruction is recommended.

In addition, advisory speeds on warning signs and spacing of delineator posts and chevrons were recommended based on the curve radius. The details are listed in newly developed guidelines (44).
FIGURE 2. Three assessment steps: (a) speed consistency, (b) tangent length and following curve radius, and (c) radii of two consecutive curves (when intermediate tangent length does not exceed 300 m).

TABLE 4 Two Examples of Assessment

<table>
<thead>
<tr>
<th>Curve 1</th>
<th>Curve 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Speed consistency</td>
<td>$\Delta V = -2$ km/h</td>
</tr>
<tr>
<td>2. Relation design</td>
<td>$L = 471$ m, $R = 392$ m</td>
</tr>
<tr>
<td>3. Field inspection</td>
<td>Combination with vertical curve</td>
</tr>
<tr>
<td>4. Combined assessment</td>
<td>A downgraded to B</td>
</tr>
</tbody>
</table>
TABLE 5 Proposal of Traffic Control Devices for Each Consistency Class

<table>
<thead>
<tr>
<th>Class</th>
<th>Traffic Control Devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Broken centerline</td>
</tr>
<tr>
<td>B</td>
<td>Warning sign, chevrons, solid centerline</td>
</tr>
<tr>
<td>C</td>
<td>Retroreflective warning sign with advisory speed, retroreflective chevrons, double solid centerline</td>
</tr>
</tbody>
</table>

**NOTE:** Default traffic control devices (not listed in the table) consist of delineator posts and solid edge line.

**DISCUSSION OF ISSUES**

A methodology for the identification of substandard curves and their optimization toward improving self-explaining performance was described. Nevertheless, each of the five steps is open to discussion and potential improvement in the future; this section comments on some issues.

**Issue 1. Disregarding Transition Curves**

Transition elements provide a smooth connection between tangents and curves and are thus commonly used in road design. Some authors concluded that transition curves do not significantly influence speed (45), while others found that the presence of transition curves ensures greater speed consistency in more limited speed variations between design elements (46). This study disregarded transition curves during segmentation the procedures, as is common in most studies (45).

**Issue 2. Choice of the Consistency Speed Indicator**

Several studies recommended not to rely on a simple indicator of the difference in 85th percentiles of speeds, aggregated per segment, as was used in this study, since such an indicator may underestimate the real speed reduction (4). Other indicators, such as the 85th percentile of maximum speed reduction, may circumvent this issue (47). Speed profiles could also be used, which take into account more locations within segments.

**Issue 3. Excess FCD Speed over Radar Speed**

There may be various reasons for the reported difference between speeds based on FCD and radar measurements:

- Different driver samples. Company drivers (captured in FCD speed) are usually professionals, who may tend to drive faster than common drivers (radar speed).
- FFS definition. FFS from FCD and radar data have different definitions. In addition, when using radar, various headway thresholds may lead to different results (48).

Excess FCD speed was also found in a Belgian study (23), where it reached almost 10 km/h. Thus, a difference of 2 km/h in this study should not have severely biased the analyses.

**Issue 4. Explanatory Power of Speed Models**

The coefficients of determination ($R^2$) of the developed speed regression models are relatively low. However, their magnitudes are similar to the ones obtained in other studies based on FCD (31, 49). This finding may be explained by the characteristics of FCD: the traditional studies were based on samples collected in more or less controlled conditions (daytime, season, weather, and so forth), and may thus yield homogeneous results with high $R^2$ values. By contrast, FCD studies use an anonymous sample collected during various days, seasons, and weather conditions, leading to heterogeneous results with low $R^2$ values. A TRB Synthesis (20) lists other potential reasons for insufficient models, such as a limited sample size and number of observations, consideration of passenger cars only, or flawed assumption of data independence. Low explanatory power may lead to insufficient reliability in cases when models are applied in different time and space from the original conditions. Therefore, the models could benefit from improvement, for example, by adding potential additional explanatory variables and considering vehicle and driver characteristics using random effect models (29).

**Issue 5. Size of Speed Differences**

The thresholds of the speed differences (5 and 10 km/h), which were obtained and used for assessment and categorization in Step 5, may appear low, for example, compared with French (50) or Spanish (51) guidelines, which use threshold values of 40 or 45 km/h. However, when the relative proportions of curves and specific speed difference ranges are compared, the values are relatively close. For example, Suffiscau (52) reported differences up to 16 km/h for 85% of curves in the French review, which is comparable to 83% in the Czech sample in this study.

In addition, there may be a difference attributed to the fact that the network analyzed in this study consisted of national roads, which are of relatively high standard, as opposed to secondary roads, which are often a target of similar foreign studies. [A local road sample in a Polish study (31) had an average curvature change rate that was approximately 3.5 times higher than that in the national road sample in this study.] This difference highlights that it would be valuable to adapt the described methodology to lower road categories, which have more challenging horizontal alignment with higher speed differences, as shown in the pilot study (53).

**CONCLUSIONS**

Improving the road network according to the principles of self-explaining roads is a promising way to increase the level of safety; however, there are no clear guidelines on how to measure and improve the self-explaining performance of the existing roads. This study applied this approach on Czech national roads. The paper describes all the steps that were conducted, from data collection and processing to the final categorization and optimization proposal. Although several checks were done in the process (including validation of predicted speed consistency), the procedure is far from perfect. Several open questions, which have been summarized, call for further improvement of the methodology.

The methodology was certified for practical use and will be applied by the Czech national road agency. After the real-life application, a follow-up study may focus on an evaluation of the effectiveness of
the proposed placement of traffic control devices. Further practical extension could consider wider applications of the concept of self-explaining and forgiving roads, such as setting a functional hierarchy of the road network, optimized speed limits, or innovative cross-section configurations, such as 2+1 roads.

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REFERENCES


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