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Investigating the influence of segmentation in estimating safety performance functions for roadway sections

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HIGHLIGHTS

- The paper investigates how the approach to segmentation affects the model form and the goodness of fit of safety performance functions for road sections.
- Four different segmentation alternatives are tested in relation to data sets usually available.
- Statistical variability and time trend were addressed using the generalized estimating equation procedure with the negative binomial error distribution.
- The different segmentation approaches are compared based on the goodness of fit of the model.
- Best and worst approaches to segmentation are identified empirically and the results seem to be logically supported.

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ABSTRACT

Safety performance functions (SPFs) are crucial to science-based road safety management. Success in developing and applying SPFs, apart data quality and availability, depends fundamentally on two key factors: the validity of the statistical inferences for the available data and on how well the data can be organized into distinct homogeneous entities. The latter aspect plays a key role in the identification and treatment of road sections or corridors with problems related to safety. Indeed, the segmentation of a road network could be especially critical in the development of SPFs that could be used in safety management for roadway types, such as motorways (freeways in North America), which have a large number of variables that could result in very short segments if these are desired to be homogeneous. This consequence, from an analytical point of view, can be a problem when the location of crashes is not precise and when there is an overabundance of segments with zero crashes. Lengthening the segments for developing and applying SPFs can mitigate this problem, but at a sacrifice of homogeneity. This paper seeks to address this dilemma by investigating four approaches for segmentation for motorways, using sample data from Italy. The best results were obtained for the segmentation based on two curves and two tangents within a segment and with fixed length segments. The segmentation

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characterized by a constant value of all original variables inside each segment was the poorest approach by all measures.

1. Introduction

Safety performance functions (SPFs) are crucial to science-based road safety management using, e.g., the methods prescribed in the Highway Safety Manual (AASHTO and FHWA, 2010). These functions are statistical models used to estimate the expected crash frequency for a facility (Hauer, 1997) based on its characteristics, mainly traffic volume, which accounts for the majority of the variability in crash frequency, and geometric variables (Milton and Mannering, 1998). These functions are developed from data for a number of similar sites. Success in development or application of an SPF for road segments depends strongly on how well the data can be organized into distinct homogeneous entities, i.e., on the approach to segmentation.

Segmentation, when based on multiple variables, may lead to very short homogeneous segments (Resende and Benekohal, 1997). For example, when using the segmentation approach proposed by the Highway Safety Manual (HSM), the presence of very short segments does not allow proper statistical inference for several reasons. The most important are the non-perfect identification of the location of crashes, which is often taken from police reports (Quin and Wellner, 2012), and the fact that crashes are rare events resulting in a great number of segments with zero crash. Lengthening segments to avoid these issues will sacrifice homogeneity.

In the literature there are a number of different approaches to segmentation. Miaou and Lum (1993) suggested that including short segments less than or equal to 80 m in the calibration data could create bias in the estimation of linear models, but not when using Poisson models. Similarly, Ogle et al. (2011) demonstrated that short segment lengths less than 160 m cause uncertain results in crash analysis. Cafiso and Di Silvestro (2011) showed that to increase performance in identifying correct positives as black spots, segment length should be related to AADT with lower AADT values requiring longer segment lengths. Quin and Wellner (2012) studied the relationship between segmentation and safety screening analysis using different lengths of sliding windows to identify hazardous sites, and concluded that short segments as well as those that are too long create a bias in the identification of these sites.

Some studies focused on the relationship between crashes and road geometry in addressing segmentation. For example, Cenek et al. (1997), who investigated this relationship for rural roads data, used a fixed segment length of 200 m. A similar study was done by Cafiso et al. (2010) using homogeneous segments with different lengths on a sample of Italian two lane rural roads, while aggregating variables related to curvature and roadside hazard. They concluded that the model that contained geometry and design consistency variables were more reliable than others. Other studies suggested different ways to aggregate segment data to avoid lengths that are too short. For example, Koorey (2009) proposed the aggregation of curves and tangents when the radius of curves exceeds a predetermined threshold value. D'Agostino (2014) analyzed the performance of two different approach to segmentation using homogeneous segments with different lengths based on HSM or IHSDM approach on a sample of Italian motorways.

The Highway Safety Manual (AASHTO and FHWA, 2010) recommends the use of homogeneous segments with respect to AADT, number of lanes, curvature, presence of ramp at the interchange, lane width, outside and inside shoulder widths, median width and clear zone width. There is no prescribed minimum segment length for application of the predictive models, but there is a suggestion of a segment length not less than 0.10 miles (0.16 km).

Given the variety of concepts and methods, and the fact that there is no apparent preferred one, this paper seeks to investigate alternative approaches for segmentation, including the HSM procedures, using sample data from Italian motorways. The litmus test is how well SPFs can be estimated with calibration datasets that result from each approach. All but one of these approaches aggregate and redefine variables over longer segments while seeking to retain the geometric and exposure characteristics of a segment as best as possible. SPFs calibrated for different segmentations are compared in terms of goodness of fit and the variables captured. At each stage a variable was added or removed and there are several variations on exactly how this can be done. The way followed was to test the *p*-value of the variable, or a combination of them, and the correlation between the final set of variables.

In addition, for each segmentation concept, two simpler models were estimated and compared, a base model and curvature-based model that is described later.

2. Materials and methods

This section describes the dataset used for the elaboration, the variables used, the segmentation approaches evaluated, and the models investigated, before presenting the results.

2.1. *Data description*

The data used for this investigation pertain to an Italian rural motorway, the “A18” Messina-Catania, which is approximately 76 km (47.2 miles) long. The cross section is made up of 4 lanes, 2 in each direction, divided by a median with barriers and a presence of a service lane, one for each direction on the right side. The analysis period is for the 8 years from 2002 until 2009, during which 831 severe (fatal plus injury) crashes according to the official statistics on motor vehicle collisions provided by the Italian National Institute of Statistics (ISTAT, 2010). Table 1 shows basic statistics for this dataset. As it expected for the road category a great percentage of ran-off road crashes were present.

Only the road segments between intersections (interchanges) were analyzed, so the part of segment directly influenced by the presence of intersection was discarded. Segments were considered separately for each direction in the segmentation approach and combined in the same dataset for the calibration of the SPFs, in a way to have more detailed information about roadway features and avoid problem related to the possible difference of AADT in the left or right service lanes. Every segment contiguous to an intersection starts from a distance of 50 m (164 ft) from the bevel for the insertion of the service lanes for exit from, and entry into the main flow. The available data, in addition to AADT, were radius of curvature, vertical gradient, type of section, and roadside features (presence and typology of the lateral and median barriers). Unfortunately, no other information was available about the roadside condition.

With this wide variety of variables, it was impossible to achieve segmentation with perfectly homogeneous segments; thus, it was necessary to use variables as appropriate to characterize the segment features.

2.2. *Variables*

In order to divide the sample into homogeneous segments, it was necessary to combine all variables into a usable form, paying attention to the final form of the equation used for developing the SPFs for each segmentation approach. The average annual daily traffic (AADT), which describes the exposure to crash risk, was the only variable with a constant value for each segment in segmentation. Other variables were aggregated over segments in which they may not be constant for one or more segmentation approaches. The variables considered, apart from AADT, are related to geometry. The original data were curvature, gradient of each segment and barrier condition. The aggregated variables pertaining to these data are described below.

Table 1 – Details of the database used (length = 145.08 km for two directions).

Year	Range AADT	Total crashes (Fatal + Injury)	Ran-off road crashes (Fatal + Injury) [perc. on total]
2002	8696–24,904	94	47 [50%]
2003	9082–26,123	95	55 [58%]
2004	9423–26,947	100	68 [68%]
2005	10,944–26,882	104	42 [40%]
2006	7792–26,414	113	59 [52%]
2007	7917–27,001	119	62 [52%]
2008	7651–26,783	113	59 [52%]
2009	9066–26,743	93	55 [59%]
Total		831	447 [54%]

- Curvature change rate (CCR) (Lamm and Choueiri, 1987) describes the curvature of the segment, and is calculated as follow

$$\mathrm{CCR} = \frac{\sum_i |\gamma_i|}{L}[\mathrm{gon/m}] \tag{1}$$

where γ_i is the deflection angle for a contiguous element (curve or tangent) i within a segment of length L;

- Slope change rate (SCR) describes the vertical profile of the road segment, which represents the variation of the slope inside a single segment, and is calculated as follow

$$\mathrm{SCR} = \frac{\sum_i |\delta_i|}{L}[\mathrm{gon/m}] \tag{2}$$

where δ_i is the deflection angle for a slope related to the horizontal alignment within a segment of length L;

- I, defined as the weighted average of the vertical gradient (up and down) with the reference length within each segment;
- I_d, defined as the weighted average of the vertical gradient (down) with the reference length within each segment;
- Roadside hazard (RSH) along a motorway, which is based both on type of section (trench, embankment, viaduct) and on the type of barrier with reference to the European standard (EN 1317-1: 1998) (Cafiso et al., 2017b). Unfortunately, no other information was available about roadside condition and given the high importance of that parameter (Cafiso et al., 2016) (Table 1) a variable which take into account the different barrier typologies and hazard needed to be considered in the elaboration. RSH assumes 6 possible values (from 1 to 6, in increasing order of potential hazard), defined as follows. First, we considered only the conditions of the outer margin, assigning 1 to a trench, 2 to an embankment with adequate barriers (complying with EN 1317-1: 1998), 3 to the viaduct with adequate lateral barrier, 4 to an embankment where the side dam is not adequate, and 5 to the viaduct with inadequate lateral barrier. A value of 6 is considered if the median barrier is not adequate. For this variable, the percentage of the length of a segment in which the RSH value was 6 (RSH6) or 5 and 6 (RSH56) was used;
- TUN, defined as the percentage of the length of segment that is a tunnel.

2.3. *Segmentation approaches*

In order to assess the influence of the organization of the data into segments on the goodness of fit of an SPF, four different segmentation approaches were considered, taking as reference, the traffic (AADT) and the curvature. Specifically, these are

- Segmentation 1: homogeneous segments with respect to AADT and curvature, as suggested by HSM, using AADT and curvature as explanatory variables;
- Segmentation 2: data organized to have within each segment 2 curves and 2 tangents, avoiding having short segments when using a single curve;

Table 2 – Range of values of variables for segmentation approaches investigated.

Variable	Seg_1 (curve based)	Seg_2 (2 curves, 2 tangents)	Seg_3 (fixed length)	Seg_4 (homogeneous)
Length (m)	100.1–1563.4	234.7–3307.6	650.0	12–979.1
SCR (gon/m)	0–0.31	0–0.10	0–0.28	0–0.35
CCR (gon/m)	0–0.031	0–0.014	0–0.024	0–0.33
RSH6 (%)	0–70.23	0–55	0–66.03	–
RSH56 (%)	0–100	0–100	0–100	–
RSH	–	–	–	1–6
TUN (%) (Categ.)	0–100	0–75.4	0–100	0–1
I (gon)	−0.042–0.045	−0.031–0.031	−0.038–0.038	−0.042–0.045
I_d (gon)	0–0.043	0–0.031	0–0.038	0–0.043
N of segments	481	122	236	544

- Segmentation 3: segments with constant length. Specifically, a length of 650 m was chosen, coinciding with the maximum length of an interchange area, and selected to be just longer than the longest horizontal curve. This length was chosen to minimize the problem of incorrect location of crashes on Italian motorways.
- Segmentation 4: all the variables used in the stepwise procedure are constant within each segment with their original value.

For the segmentation based on curvature and AADT, very short segments were eliminated in order to have segments longer than 100 m. Using different segmentation approaches also changes the range of variation of the variables used to estimate the model, as shown in Table 2. For Segmentation 4, which is characterized by the value of the original data being constant inside each segment, it was not possible to use an aggregated variable for RSH and TUN, so these were used as categorical variables with their original value.

3. Theory/calculation

The generalized estimating equation (GEE) (Lord and Persaud, 2007) procedure was used to estimate SPF coefficients, using the Statistical Analysis System (SAS) software package (SAS, 2012) useful also for other application in road safety analysis (Cafiso et al., 2016, 2017a). The GEE procedure is classified as a multinomial analog of a quasi-likelihood function. The GEE procedure incorporates time trend, so is well suited to modeling data for longer time periods, such as the 8-year period used in this study. Specifically, it accounts for the temporal correlation that results when data for long periods are disaggregated into separate observations for each year to account for time trends. Consistent with the state of research in developing these models, the negative binomial error distribution was assumed for the count of observed crashes (Hauer, 1997). To evaluate the goodness of fit of the models, two different methodologies were applied: the Quasi-likelihood under the Independence Model Criterion (QIC) (Hardin and Hilbe, 2003; Pan, 2001) and the cumulative residuals (CURE) plot (Hauer and Bamfo, 1997).

The QIC statistic is analogous to Akaike's Information Criterion (AIC) statistic used for comparing models fit with likelihood-based methods. Since the generalized estimating equations (GEE) method is not a likelihood-based method, the AIC statistic is not applicable. The QIC has the following form

$$\mathrm{QIC} = -2\mathrm{Q}(\hat{u}; V) \tag{3}$$

where V represents the independent covariance structure used to calculate the quasi-likelihood and $\widehat{u} = g^{-1}(x\widehat{\beta})$, $g^{-1}()$ is the inverse of the link function. When using QIC to compare two structures, or two models, the model with the smaller statistic is preferred (Hardin and Hilbe, 2003; Pan, 2001; SAS, 2012). The smaller the value of QIC, the better is fit of the model to the data. Therefore, QIC can be used to compare and rank different models. For the present study, another advantage of QIC is that the goodness of fit of models with different numbers of parameters can be compared.

The CURE plot is used for the examination of residuals, i.e., the difference between the number of crashes observed at a site and the expected value from the SPF. It is used to examine whether the chosen functional form indeed fits each explanatory variable along the entire range of its values represented in the data. Assuming that residuals are normally distributed with expected value equal to 0 and a variance equal to σ (Hauer and Bamfo, 1997), it is possible to calculate the variance of the expected value as the square of the cumulate residuals. The trend in the residuals with respect to AADT (or other variables) can be evaluated relative to the variance to qualitatively assess goodness of fit. An upward or downward drift in the plot is a sign that the SPF consistently predicts fewer or more crashes, respectively, than were counted. Thus, it is desirable that the plot of cumulative residuals should stay flat or at least oscillate between over and under prediction and not stray beyond the $\pm 2\sigma$ boundaries.

The selection of the explanatory variables to be included in the model was made using a stepwise methodology, inserting at first all variables available, and testing for each of the four segmentation approaches in order to keep only the variables that were statistically significant (Cafiso and D'Agostino, 2015, 2016). This method was applied using different set of variables, and avoiding problems due to correlation of variables. In the end, one model was calibrated with different combinations of variables for each segmentation approach (Model A). Two other models were calibrated, one using only curvature (CCR) and AADT (Model B), and one as a base model for each approach, using AADT (Model C) as the only explanatory variable. For all of the models the segment length is included as an offset variable. In summary, Models A, B and C assume,

Table 3 – Values of regression parameters, (p-value) and [standard error] for different segmentation approaches and model forms.

	Seg_1 (curve based)	Seg_2 (2 curves, 2 tangents)	Seg_3 (fixed length)	Seg_4 (homogeneous)
Multiple variable models from stepwise procedure (Model A)				
Inter. ($\alpha_{0S}+\alpha_{tS}$)	−20.4439 (<0.0001) [1.0820]	−21.7516 (<0.0001) [1.4295]	−20.1429 (<0.0001) [1.3529]	−20.7288 (<0.0001) [1.2874]
AADT (α_{1S})	1.3652 (<0.0001) [0.1124]	1.4797 (<0.0001) [0.1417]	1.3475 (<0.0001) [0.1358]	1.4273 (<0.0001) [0.1307]
CCR (β_{iS})	2508.331 (0.0054) [9.0223]	484.9824 (0.0042) [169.5507]	262.6808 (0.0066) [96.7806]	0.2111 (0.0003) [0.0585]
I (β_{iS})	–	–	−14.3209 (<0.0001) [3.5159]	−6.0280 (0.0500) [3.1112]
I_d (β_{iS})	5.1423 (0.0010) [1.5671]	–	−16.2616 (0.0050) [5.7890]	–
Tunnel (β_{iS}) (Categ.)	0.0058 (0.0015) [0.0018]	0.0050 (0.0087) [0.0019]	0.0046 (0.0097) [0.0018]	−0.4540 (<0.0001) [0.0981]
RSH6 (β_{iS})	–	−0.0263 (0.0001) [0.0069]	–	–
RSH56 (β_{iS})	−0.0031 (<0.0001) [0.0008]	–	−0.0037 (<0.0001) [0.0009]	–
SCR (β_{iS})	–	−2.3927 (<0.0001) [0.2561]	8.4648 (<0.0001) [2.10570]	–
QIC	3322.00	1081.65	2706.95	4510.73
Model with AADT and CCR (Model B)				
Inter. ($\alpha_{0S}+\alpha_{tS}$)	−18.9141 (<0.0001) [1.3226]	−20.7128 (<0.0001) [1.6767]	−20.3723 (<0.0001) [1.6194]	−19.7873 (<0.0001) [1.3327]
AADT (α_{1S})	1.2075 (<0.0001) [0.1364]	1.3713 (<0.0001) [0.1667]	1.3476 (<0.0001) [0.1613]	1.2891 (<0.0001) [0.1358]
CCR (β_{iS})	23.7961 (0.0021) [7.7267]	489.8783 (0.0031) [165.8877]	291.9741 (0.0020) [94.3059]	0.2022 (0.0006) [0.0588]
QIC	3325.57	1109.89	2593.60	4580.81
Base model (Model C)				
Inter. ($\alpha_{0S}+\alpha_{tS}$)	−19.1467 (<0.0001) [1.3216]	−18.8182 (<0.0001) [1.3281]	−19.1993 (<0.0001) [1.3039]	−18.9870 (<0.0001) [1.2908]
AADT (α_{1S})	1.2358 (<0.0001) [0.1353]	1.2000 (<0.0001) [0.1363]	1.2403 (<0.0001) [0.1328]	1.2163 (<0.0001) [0.1321]
QIC	2947.62	1103.22	2583.40	4410.09

respectively, the following form

Model A

$$E(Y) = \exp(\alpha_{0S} + \alpha_{tS}) \times L \times AADT^{\alpha_{1S}} \times \exp\left(\sum_{i=1}^{n} \beta_{iS} Var_{iS}\right) \tag{4}$$

Model B

$$E(Y) = \exp(\alpha_{0S} + \alpha_{tS}) \times L \times AADT^{\alpha_{1S}} \times \exp\left(\sum_{i=1}^{n} \beta_{iS} CCR\right) \tag{5}$$

Model C

$$E(Y) = \exp(\alpha_{0S} + \alpha_{tS}) \times L \times AADT^{\alpha_{1S}} \tag{6}$$

where $E(Y)$ is the expected annual crash frequency of random variable Y, L is the length of road segment (m), AADT is average annual daily traffic (veh/d), α_{0S}, α_{tS} are exponents of constant term of the model, and time trend, the subscript S indicates the segmentation approach number, α_{1S} is exponent of AADT, β_{iS} is the set of regression parameters for different set of variables, with S indicating the segmentation approach number, and i ($i = 1, 2, \ldots, 7$), Var_{iS} is the set of variables resulting from the stepwise procedure, for each segmentation approach (S), and CCR is the curvature change rate (gon/m).

4. Results and discussion

The model calibration results are presented in Table 3, while the plots of the cumulative residuals are presented in Figs. 1–3.

As is evident from Table 3, for the primary Model A, which allows consideration of all available data, more variables could be included for Segmentation 3, which has constant segment length, than for the other approaches. For both the segmentation based on curvature and AADT (Segmentation 1) and the one achieved by inserting 2 curves and 2 tangents in each segment (Segmentation 2), five of eight variables considered in the stepwise procedure could be included in the model. However, the value of QIC is lower for the SPF based on Segmentation 2. The segmentation that gives the worst results in terms of number of variables that could be included in the model is Segmentation 4 for which all variables are constant within each segment. Not surprisingly, this model also has the highest value of QIC.

Some results in Table 3 indicate differences in the sign of the coefficients, suggesting opposing influences for some variables and segmentations on the expected number of crashes estimated by the SPF.

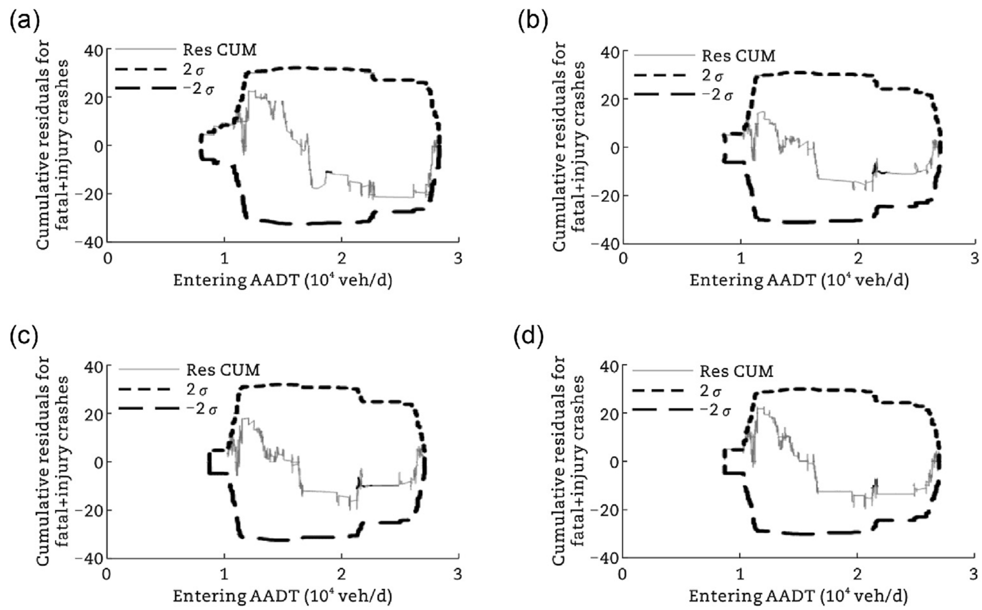

Fig. 1 – CURE plots with ± 2σ for Model A. (a) Segmentation 1. (b) Segmentation 2. (c) Segmentation 3. (d) Segmentation 4.

In general, Segmentation 2 gives the best results for the primary Model A, based on both QIC and the CURE plots in Fig. 1, which oscillates closer to the value of zero than the plots for the other segmentations. For Model B, in terms of the CURE plots, the best model is estimated from Segmentation 3, as is shown in Fig. 2. For Model C, based only on AADT, the plot that oscillates closest to the value of zero is based on Segmentation 4. No one plot exceeds the $\pm 2\sigma$ boundary. However, Segmentation 4, characterized by constant value of variables inside each segment, gives the poorest results, consistent with the earlier observation based on QIC. Furthermore, given the high percentage of ran-off road crashes, and the oscillation of the residual plot on the x-axis one of the way to improve crash prediction using the base model may be to consider different model forms at different ranges of AADT. As it is clear from Fig. 3 there is a general underestimation of crashes for AADT lower than 15,000 veh/d and an overestimation for larger value of AADT.

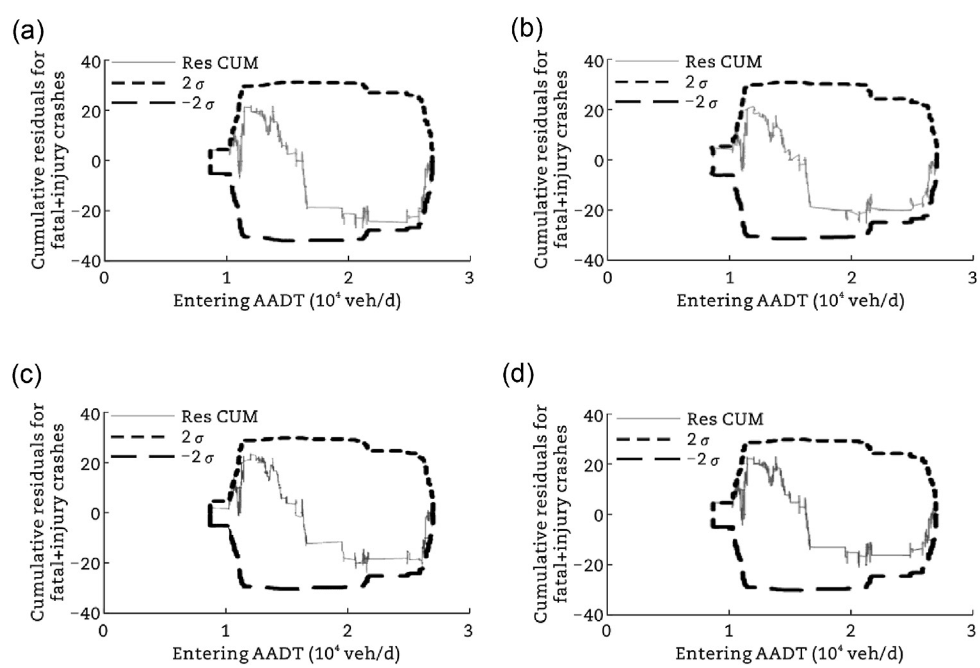

Fig. 2 – CURE plots with ± 2σ for Model B. (a) Segmentation 1. (b) Segmentation 2. (c) Segmentation 3. (d) Segmentation 4.

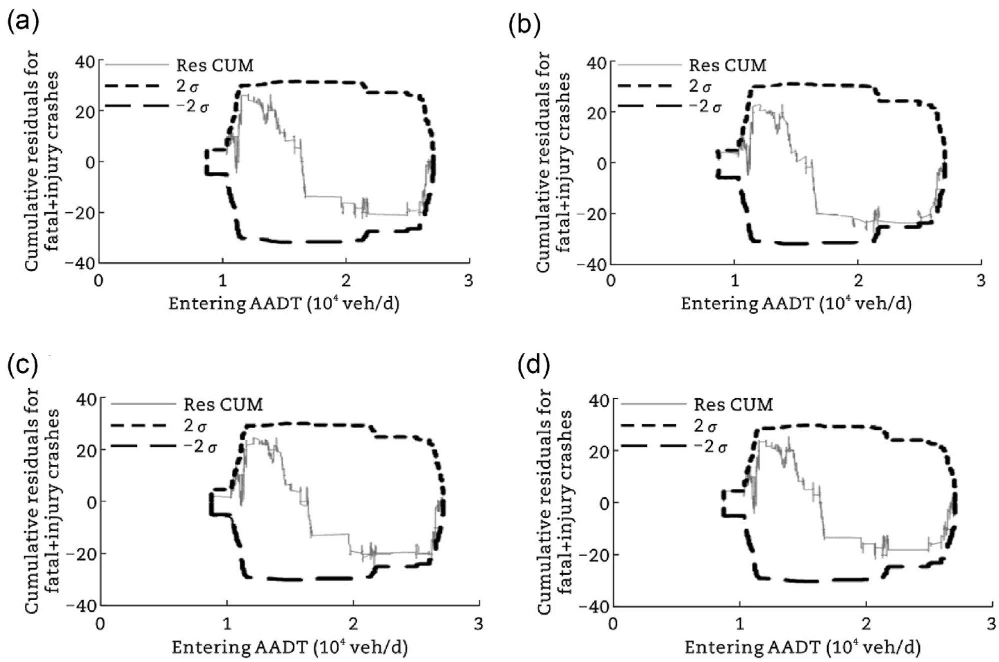

Fig. 3 – CURE plots with $\pm 2\sigma$ for Model C. (a) Segmentation 1. (b) Segmentation 2. (c) Segmentation 3. (d) Segmentation 4.

5. Conclusions

The purpose of this paper was to investigate the influence of highway segmentation on the performance of safety performance functions (SPFs), in terms of goodness of fit and the variables that could be modeled. To do this, it was necessary to sometimes aggregate variables into a usable form, characterized by a constant value of each modeled variable in each segment.

Four different segmentation approaches were evaluated with three different model forms. One approach is based on the Highway Safety Manual (HSM) method, using curvature and AADT as the basis, one has two curves and two tangents inside each segment, one has a fixed length of each segment, and one has all the variables constant within each segment relative to their original value.

One model was calibrated with different combinations of variables for each segmentation approach. Two other models were calibrated for each approach, one using only curvature and AADT, and one as a base model, using AADT as the only explanatory variable. The models were estimated for a sample of rural motorways segments in Italy, using data for the years 2002 through 2009. The generalized estimating equation (GEE) procedure was applied to develop the SPFs, which were evaluated using cumulative residual (CURE) plots and the Quasi-likelihood under the Independence Model Criterion (QIC) value.

The best results were obtained for the segmentation based on two curves and two tangents (Segmentation 2) and the segmentation with fixed length (Segmentation 3). Segmentation 4, characterized by a constant value of all original variables inside each segment, was the poorest approach by all measures. This is likely because it yields very short segments, resulting in non-perfect identification of the location of crashes and in a large number of segments with zero crashes. Both factors create difficulties in making sound statistical inference.

The results are promising in that fixed length segmentation may be the most flexible in practical applications because the segment length can be determined by data availability and quality and other factors to optimize the SPF calibration, while variables are considered inside each fixed length segment with an "exposure factor" to show their lengths. The length chosen for this research was based on pragmatic reasoning. Given the promise shown by the results, further research can explore alternative considerations for determining the length of fixed length segments used for SPF development. Similarly, the segmentation approach (Segmentation 2) based on two curves and two tangents in each segment, which also showed promise, could be further explored by considering different numbers of curves and tangents in a segment.

Given that it is not possible to test or quantify the uncertainty associated with a given the location accuracy of crashes, longer segments can mitigate this issue; however, the use of shorter segments is wide spread according to the literature. If longer segment can give good results in terms of goodness of fit, and they are still of engineering interest for safety analysis, the conclusion is that using longer segment can be the better solution for segmentation of a road network.

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