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Comparison of Italian and Hungarian black spot ranking

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Abstract

Black spot ranking is an important tool for finding the sites with potential safety improvement on the road network. The EU Directive on Road Infrastructure Safety Management also demands the ranking of high accident concentration sites. This paper gives an introduction to localizing high accident concentration sites and the indicators used by Italy and Hungary. Accident and traffic volume data are gathered for motorway sections from both countries. Safety ranking is made using two conventional indicators, absolute number of accidents and accident rate. A more sophisticated ranking using the Empirical Bayes method is applied. Expected average crash frequency with Empirical Bayes adjustment is calculated. Based on the estimation of the crash frequency, the Critical Crash Rate (CCR) was added to identify and rank black spots. This additional performance measure is able to take into account traffic volume as required by the EU Directive. Results of the Empirical Bayes method are compared with the conventional procedures. It is concluded that the results are not comparable; inasmuch as there are modifications in the order of black spots. Based on the comparison of results recommendations are given to change the practice in both countries.

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Keywords: road safety; safety ranking; Empirical Bayes method

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1. Introduction

One of the four pillars of the EU Directive 2008/96/CE of the European Parliament on Road Infrastructure Safety Management is the ranking of high accident concentration sites that is based on the number of fatal accidents related to traffic volume. Details of the ranking procedure are not given in the Directive; therefore, several methods can be defined by different countries in the implementation of the procedure.

Elvik (2008) gave an overview of the definition of hazardous road locations in eight European countries and concluded that all of the countries except one identify these locations in terms of the recorded number of accidents. None of these countries apply the state-of-the-art approach to estimate the expected number of accidents using the Empirical Bayes method despite for several years many researchers (e.g. Persaud et al., 1999; Cheng and Washington, 2005) demonstrated that the Empirical Bayes method identifies hazardous locations more accurately than other traditional techniques.

The Empirical Bayes method combines the observed crash frequency with a predicted value. The latter one can be derived from the Safety Performance Function (SPF). Safety performance functions have been widely used in the traffic safety field for analyzing how the safety performance of road facilities is related to various road characteristics. In the beginning of the 1980s researchers started to demonstrate problems associated with conventional regression techniques used for accident prediction (e.g. Maycock and Hall, 1984; Hall, 1986; Hauer et al., 1988; Miaou and Lum, 1993). The limitation of the more appropriate Poisson regression technique was already known in 1984 by Maycock and Hall who used negative binomial modelling techniques for accident prediction models. Miaou and Lum (1993) used four regression models and demonstrated that the conventional linear regression models are not appropriate to make probabilistic statements about vehicle accidents, and that if the vehicle accident data are found to be significantly overdispersed relative to its mean, then using the Poisson regression models may overstate or understate the likelihood of vehicle accidents on the road. To overcome these problems later on the negative binomial modeling method became a widely accepted modeling technique and was recommended by many researchers (e.g. Abdel-Aty and Radwan, 2000; Sawalha and Sayed, 2001).

In the EB estimate the joint use of the observed and predicted crash frequencies is implemented by a weighted average, where the weight depends on the variance of the SPF. The EB Method combines the observed crash frequency with the statistical model estimate using Equation 1. This weight depends on the goodness of the SPF, that is, as overdispersion increases, the weight decreases and as a result less emphasis is placed on the predicted value than on the observed one.

$$N_{expected} = w \times N_{predicted} + (1 - w) \times N_{observed} \qquad (1)$$

where:
$N_{expected}$ = expected average crash frequency
$N_{predicted}$ = predicted average crash frequency using a SPF
$N_{observed}$ = observed crash frequency
w = weighted adjustment to be placed on the SPF prediction

The weighted adjustment factor is a function of the SPF's overdispersion parameter calculated according to Equation 2.

$$w = \frac{1}{1 + k \times (N_{predicted})} \qquad (2)$$

where:
k = overdispersion parameter of the SPF

The above method is illustrated graphically in Fig. 1 where the difference between the observed crash frequency, crash frequencies predicted by the SPF and the expected number of crashes with the EB adjustment are shown. The same figure highlights that these estimates can be used to calculate the Potential for Safety Improvement (PSI), which is the difference between the EB estimate (expected crash frequency) and the predicted crash frequency given by the

SPF. The magnitude of the PSI excess gives an idea about the potential safety savings at particular locations, therefore it is used for preparing ranked lists of sites for safety interventions.

In their research on black spot ranking techniques based on the Potential Safety Improvement (named "Potential Accident Reduction" in their paper) Maher and Mountain (1988) showed that due to the frequent lack of precision of the models, the Potential Accident Reduction does not necessarily outperform more traditional methods.

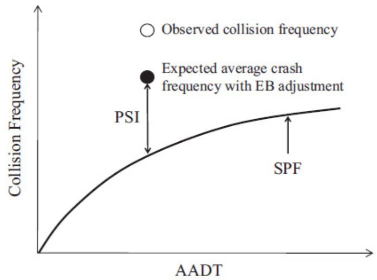

Fig. 1. EB estimation (Kwon et al., 2013).

When calibrating the SPF, the segmentation itself is also a crucial issue. There are a few methodologies and there is no preferred one, however, some basic rules can be identified. Cafiso et al. (2013) did a comprehensive study on the application of five different methods and the influence of segmentation on the performance of safety performance functions in terms of goodness of fit and the variables that could be modeled. They concluded that the best results were obtained for the segmentation based on having two curves and two tangents in each segment and the segmentation with fixed length. They also highlighted that a segmentation technique using constant values of all variables, therefore resulting in very short segments, led to the poorest model.

The Highway Safety Manual (AASHTO, 2010) recommends the use of homogeneous segments with respect to a number of parameters, such as the AADT (Annual Average Daily Traffic), number of lanes, lane width, shoulder width, shoulder type, curvature, driveway density, roadside hazard rating, median width and clear zone width. According to the HSM a minimum segment length of 0.10 miles (0.16 km) is recommended. Fitzpatrick et al. (2006) pointed out that in practice, this type of segmentation is not always easy to achieve as not all the variables are available. Koorey (2009) arrived at similar conclusions, namely that variable-length road segments seem intuitively more useful than fixed-length segments, because of the mixed attributes contained in the latter. He added that this advantage is less when shorter lengths are used, and fixed-length segments are computationally easier to create from constant-interval raw data.

The aim of this research is to introduce what procedure and indicators are used in Italy and Hungary to identify and rank high accident concentration sites and to investigate the effectiveness of these approaches when compared to the procedures based on the EB approach. First the conventional methods used are introduced briefly then the EB method is applied to two motorway sections in Hungary and Italy. The aim of the investigation is bifold: firstly to investigate how the ranking of sites with promise changes with the different approaches in both countries, secondly to determine the level of correlation between the rankings.

2. Methods currently used in Italy and Hungary

The current approaches used in Italy and Hungary for black spot ranking are conventional ones. In Italy three classes of indicators are used for ranking based on: frequency, density (variable/unit of length) and rate (variable/vehicle kms traveled) using the number of injured and/or killed persons or fatal plus injury crashes. The three classes of indicators have to be evaluated for a period of three years using homogenous segments in terms of traffic condition and geometry. The Italian regulation suggests the use of performance measures based on crash rate, however, at the same time provides alternative performance measures (the one based on frequency or density) to be used if traffic data are not available, which is often the case for local or secondary rural roads.

In Hungary the currently used black spot ranking is done by a software (Win-Bal). For the ranking the sliding window technique is used. For rural roads including motorways a 1000 m long window is moved forward with a 10 m increment and indicates sections where accident frequency reaches a pre-set value (normally 4 personal injury accidents within 3 years). The length of black spots or accident concentrations varies (can be shorter than 1000 m) depending on the exact locations of accidents. As a next step the software calculates three indicators for the selected locations: weighted number of accidents, crash rate and weighted crash rate (crashes are weighted depending on their severity). Depending on the position of the section in the three rankings a combined indicator is calculated and a final ranking is made. This procedure is fully automated, however, the user can modify the input parameters including the length of the window, the threshold value as well as the weights.

The EU directive requires the identification of high accident concentration sites for the TERN network which comprise mainly motorways. In Italy it is planned to extend the scope of the directive to all national and local rural roads after 2020. In Hungary road infrastructure safety management applies not only to the trans-European road network, but all national main roads since 1 January 2014 as well as to all the roads with more than 10,000 PCU/day since 1 January 2015.

The above detailed approaches have quite a few disadvantages, below some of them are mentioned briefly. All of the approaches are using historical observed accident data, therefore they don't take into account the random nature of crashes. In addition to that, previous researches (e.g. Elvik, 2007; Hauer et al., 1993) also proved that the use of the sliding window technique greatly inflates the number of false positives, i.e. the recorded number of accidents are above the critical threshold, whereas the expected number is below. The units of analysis should be ideally homogenous road sections with respect to all factors that exert an influence on safety, i.e. constant traffic volume, lane widths, speed limit etc. The Italian approach works with homogeneous sections, whereas the Hungarian one using the sliding window technique leaves it out of consideration.

3. Methodology

For an international comparison the subject of the analysis should be comparable. Access controlled motorways as the most uniform road design class can be the basis of an international comparison for two reasons. Firstly, motorway design is quite similar in both countries in terms of speed limit (130 km/h), width of cross-section elements (for instance lane width: 3.75 m and emergency lane width: 3.00 in both countries). Secondly, a motorway cross-section rarely changes along its length (except additional lanes at rest areas, grade-separated intersections or climbing lanes) and so it is perfect for fitting accident prediction models since the number of variables that can affect safety is much lower than in other road categories.

3.1. Data collection and segmentation

Accident and traffic volume data were gathered for two motorways (M1 in Hungary and A18 in Italy). Accident data cover 5 years for the Hungarian section (2010–2014) and 4 years for the Italian section (2009–2012). For the segmentation the following technique was used:

- The area of grade-separated intersections were taken out in order to avoid having intersection related crashes in the data. The area of the intersection was defined as a section starting from 50 m before the exit deceleration lane and ending 50 m after the entry acceleration lane.
- Sections with a cross-section of 2x2 lanes were taken into account, any other segments with additional lanes such as climbing lanes were taken out.
- Homogenous sections were formulated according to AADT and horizontal curves. (Vertical alignment was not used for two reasons: data were missing or inaccurate and as sections with climbing lanes were taken out, it was assumed to be not an influential parameter.)
- As it is indicated elsewhere in the literature (Cafiso et al., 2013; Koorey, 2009) too short segments can be biased due to the inaccurate identification of accident locations, therefore, after segmentation, segments shorter than 200 m were eliminated from the sample.

3.2. Descriptive statistics

As a result of the segmentation 105 homogeneous road sections were formed in Hungary, and 37 in Italy. Descriptive statistics of the data can be seen in Table 1, which points out that the two samples are quite comparable.

Table 1. Descriptive statistics.

Country		Italy	Hungary
AADT (veh/day)	Min	22275	23395
	Max	53229	47368
	Mean	27647	36201
	Standard deviation	9691	4868
Number of crashes	Total	308	291
	Min	0	0
	Max	23	12
	Mean (Σ Inc/Σ km)	5.37	2.90
Homogeneous sections	Min length (km)	0.230	0.200
	Max length (km)	5.097	3.053
	Average length (km)	1.548	0.957
	Total length (km)	57.280	100.532
	Number of sections	38	105

3.3. Modeling

For the EB method an SPF is needed in order to predict crash frequency and calculate the expected number of crashes. For the accident prediction model the Generalized Linear Modeling approach (GLM) assuming a negative binomial error structure was used, modeling was done in the R and SAS statistical software. The prediction equation form is given in Equation (3):

$$E(Y) = e^{\alpha_0} \cdot l \cdot AADT^{\alpha_1} \cdot e^{\sum_{j=1}^{m} \beta_j x_j} \tag{3}$$

where:
E(Y) = estimated accident count/year
l = segment length (in kilometers)
AADT = Annual Average Daily Traffic (veh/day), scaled to an annual value (multiplied by 365, divided by 10^7)
x_j = any of m-additional variables
α_1 = parameter describing the shape between traffic volume and number of accidents,
α_0 = constant and
β_j = coefficients to be estimated.

4. Results

4.1. Comparison of SPFs

Accident prediction models for both samples were fitted, first using AADT and horizontal alignment data. Horizontal curve as a predictor turned out to be highly significant for the Italian sample, however for the Hungarian sample not. Therefore AADT only models were calibrated and used for further analysis. Table 2 shows the model parameters for both countries. The shape parameters of AADT are highly significant and close to one, but with a slightly decreasing trend for Italy (α_1<1) and an increasing one for Hungary (α_1>1). Since with increasing AADT an increase in multiple crashes can be expected, these results indicate that multiple crashes are more relevant than single ones in Hungary, the opposite in Italy.

In the comparison of the crash prediction models, the most significant results are related to the constant term that is about two times higher in the Italian model. This means that the predicted crash frequency is on the average twice as much for the Italian motorways as for the Hungarian ones (Fig. 2). The 2015 ETSC report (ETSC 2015) draws similar values for road deaths per million inhabitants for Italy (56) and Hungary (60). The road deaths per vehicle billion kilometer is available only for Italy with a value of 7.8 over the EU average (5.8).

These results could be explained by a selection of motorways with exceptional crash rates (higher for A18, lower for M1) than the country average. This is partially true for the Italian A18 with a rate of 11.6.

Table 2. Model parameters for the AADT models.

Categories		Italy	Hungary
Intercept	Coefficient	1.5460	-0.8462
	p value	<0.0001	<0.0001
AADT	Coefficient	0.9852	1.1024
	p value	0.0015	0.0129
k		0.1583	0.0125

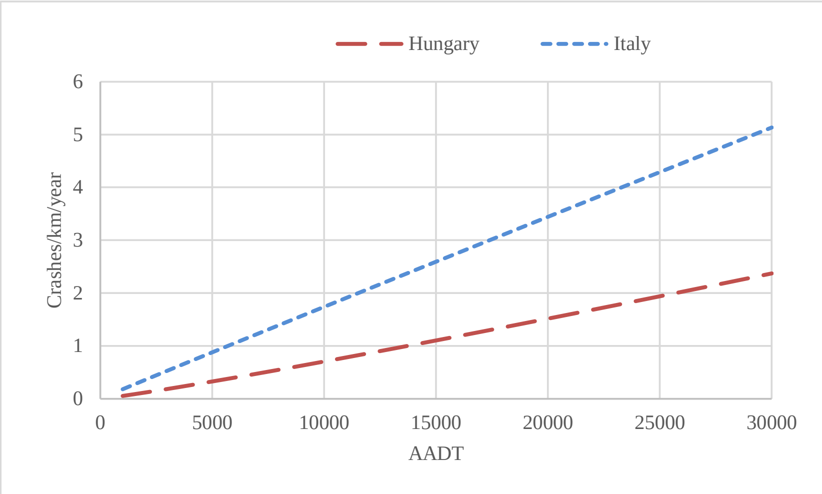

Fig. 2. AADT only SPFs for Italian and Hungarian motorways.

4.2. Comparison of rankings

The ranking of sites was done according to the indicators requested in the national guidelines:

- crash frequency (crashes/unit of length) (CF),
- crash rate (crashes/vehicle kms traveled) (CR),

and, for comparison, to the following performance parameters:

- expected number of accidents calculated by the EB method (EB),
- potential safety improvement (difference between the expected and predicted number of crashes) (PSI),
- Critical crash rate (CCR).

The critical crash rate is calculated making use of methods originally developed for quality control in the industry. Following this approach the critical crash rate for a given level of confidence is computed according to Equations (4) and (5):

$$CCR_{\delta i} = x_r + k_\delta \cdot \sqrt{\frac{x_r}{E_i} + \frac{1}{2 \cdot E_i}} \tag{4}$$

$$x_r = \frac{\sum_i OB_{si}}{\sum_i E_i} \tag{5}$$

where:
CCR_δ = crash rate upper limit for the *i*th site of the sample for level of confidence δ,
x_r = mean crash rate of the sample,
δ = level of confidence,
k_δ = normalized normal distribution values associated to the levels of confidence,
E_i = exposure at *i*th site (million vehicles × km), and
OB_{si} = observed crash frequency of the *i*th site (yearly crash).

Since the sliding window technique in Hungary provides a different sectioning approach and site identification, it cannot be compared with the above mentioned approaches. In order to select the sites with the highest expected crash frequency for the comparison of the different ranking criteria, sites that exceed the 70th percentile of the Negative Binomial distribution given by the SPF were identified and ranked in descending order based on the previously mentioned indicators (Table 3 and 4).

For each section, the percentile was estimated from the NB distribution with mean E(μ) and variance (Equation 6):

$$\sigma_y^2(\mu) = E_y(\mu) + E_y(\mu)^2 \cdot k \tag{6}$$

Only segments with expected crash frequency over the 70th percentile were considered for the ranking. For the Italian dataset about 45% of the EB estimation exceeds the 70th percentile (16 of 37) and were included in the ranking comparison while just 14 segments were included in the ranking comparison from the Hungarian dataset (about 13% of 105 sites).

Table 3. Ranking of the Italian dataset for different performance measures (the segments considered for ranking were selected based on the percentile of the EB estimation).

CF [Crash/km/year]		**EB/L [Crash/km/year]**		**PSI [Crash/km/year]**		**CR [Crash*10^6/ (365*AADT*km)/year]**		**CCR [Crash*10^6/ (365*AADT*km)/year]**	
Rank	Variable value	Rank	Variable value	Rank	Variable value	Rank	Variable value	Rank	Variable value
9	3.39	1	2.34	9	1.20	9	0.42	9	0.92
1	2.96	2	2.28	12	0.78	12	0.31	12	0.90
12	2.54	3	1.90	14	0.60	14	0.26	1	0.78
2	2.44	4	1.90	15	0.54	15	0.25	8	0.71
4	2.39	5	1.78	8	0.43	8	0.21	5	0.69
5	2.38	6	1.39	16	0.36	16	0.21	4	0.61
14	2.17	7	1.26	1	0.35	4	0.15	15	0.52
15	2.06	8	1.26	4	0.28	1	0.15	2	0.47
8	2.02	9	1.20	5	0.27	5	0.15	16	0.39
16	1.69	10	1.18	2	0.09	2	0.13	14	0.32
6	1.45	11	1.15	7	-0.09	7	0.10	7	0.27
7	1.23	12	1.04	10	-0.15	6	0.09	10	0.23
10	0.94	13	0.97	6	-0.19	10	0.09	6	0.23
11	0.82	14	0.94	11	-0.20	11	0.08	11	0.17
13	0.36	15	0.92	13	-0.43	13	0.03	13	0.12
3	0.00	16	0.92	3	-1.12	3	0.00	3	0.07

Table 4. Ranking of the Hungarian dataset for different performance measures (the segments considered for ranking were selected based on the percentile of the EB estimation).

CF **[Crash/km/year]**		**EB/L** **[Crash/km/year]**		**PSI** **[Crash/km/year]**		**CR** **[Crash*10^6/ (365*AADT*km)/year]**		**CCR** **[Crash*10^6/ (365*AADT*km)/year]**	
Rank	Variable value	Rank	Variable value	Rank	Variable value	Rank	Variable value	Rank	Variable value
9	2.40	1	4.01	7	0.14	13	1.15	13	0.55
7	1.40	2	3.95	9	0.13	7	0.44	7	0.53
2	1.20	3	3.93	13	0.10	1	0.31	9	0.52
8	1.20	4	3.88	8	0.06	8	0.30	8	0.51
12	1.20	5	3.88	12	0.03	9	0.30	1	0.51
11	0.80	6	3.83	11	0.03	10	0.27	12	0.51
3	0.60	7	3.55	1	0.02	11	0.27	11	0.51
4	0.60	8	3.45	10	0.01	12	0.26	10	0.50
13	0.60	9	3.45	2	0.00	2	0.23	2	0.50
14	0.60	10	3.45	3	-0.01	3	0.21	3	0.50
1	0.40	11	3.45	5	-0.03	14	0.15	5	0.49
10	0.40	12	3.44	14	-0.06	4	0.14	14	0.49
5	0.20	13	3.39	4	-0.08	5	0.13	4	0.49
6	0.20	14	3.37	6	-0.10	6	0.07	6	0.48

In order to compare the different rankings the Spearman's rank-correlation was used to determine the level of correlation between the rankings. Spearman's rank-correlation coefficient is a measure of association between the rankings of two variables measured on N individuals. In contrast to the more common Pearson correlations, the Spearman coefficients are computed from the ranks of the data values rather than from the values themselves. Consequently, they are less sensitive to outliers than the Pearson coefficients. This characteristic is useful in the present application where outliers can be expected in the list (e.g. sites with very high crash frequencies). The correlation coefficient is calculated as in Equation 7:

$$\rho_s = 1 - \frac{6 \times \sum_{i=1}^{n} d_i^{\,2}}{n \times (n^2 - 1)} \tag{7}$$

where:

ρ_s = Spearman's rank-correlation coefficient;
d_i = differences between ranks;
n = number of paired sets.

A score of 1.0 represents perfect correlation and a score of zero indicates no correlation. The t-approximation for this statistic, T, is valid for samples of size 8 upwards, and is calculated by Equation 8:

$$T = \rho_s \times \sqrt{\frac{n-2}{1-\rho_s^{\,2}}} \tag{8}$$

It has approximately a t-distribution with n-2 degrees of freedom, and can be used for a test of the null hypothesis of independence between samples.

Tables 5 and 6 show Spearman's rank correlations between each pair of variables. These correlation coefficients range between -1 and +1 and measure the strength of the association between the variables. Also the P-values testing the statistical significance of the estimated correlations is showed. P-values below 0.05 indicate statistically significant non-zero correlations at 95% significance level. The only pair of variables with P-values below 0.05 is the crash rate and crash frequency for the Hungarian rankings. That was expected for the Hungarian motorway given the negligible differences in traffic for the segments with higher crash frequency. A similar correlation, however only at 90% significance level, can be observed for the Italian sample.

From the correlation results it is possible to assume that none of the performance measures has significant correlation with the EB methodology, which represents the most suitable methodology to address regression to the mean effects. The results pointed out that when a performance measure is chosen the expected ranking is different.

In general crash rate gives a different evaluation of crash risk, not directly comparable with frequency because it is calculated for unit of exposure. Therefore, it cannot be considered as an alternative to crash frequency as a performance measure of safety but it should be used as a complementary measure taking into account both the total number of crashes (which represents a social cost) and the risk for individual travel unit (which identifies the individual cost). In this framework, the CCR parameter should be chosen in order to mitigate the regression to the mean bias due to the use of the observed crashes in the crash rate calculation. In the field of crash frequency measures, the use of EB technique (EB/L, PSI/L) as a black spot identification methodology is the only way to mitigate the regression to the mean bias due to the use of the observed crashes in the crash rate calculation.

Table 5. Ranking comparison for motorway A18 (Italy).

	EB/L	**PSI**	**Crash rate**	**CCR**
Crash frequency	0.0824	0.0941	0.4676	0.0176
P-value	(0.7498)	(0.7155)	(0.0701)	(0.9455)
EB/L	--	-0.1176	-0.2118	0.2912
P-value	--	(0.6486)	(0.4121)	(0.2594)
PSI	--	--	0.1559	0.4206
P-value	--	--	(0.5460)	(0.1033)
Crash rate	--	--	--	-0.1882
P-value	--	--	--	0.4660

Table 6. Ranking comparison for motorway M1 (Hungary).

	EB/L	**PSI**	**Crash rate**	**CCR**
Crash frequency	-0.1516	0.3231	***0.6747***	-0.1736
P-value	(0.5845)	(0.2441)	***(0.0150)***	(0.5313)
EB/L	--	-0.0813	-0.2484	-0.4110
P-value	--	(0.7694)	(0.3705)	(0.1384)
PSI	--	--	0.3846	0.0330
P-value	--	--	(0.1655)	(0.9054)
Crash rate	--	--	--	0.1824
P-value	--	--	--	(0.5107)

5. Conclusions

This paper presented what procedure and indicators are used in Italy and Hungary to identify and rank high accident concentration sites. The conventional methods used in both countries are introduced and, as a case study, along with these indicators the EB method is applied to two motorway sections. Rankings were set up using crash frequency, crash rate, expected number of accidents calculated by the EB method, potential safety improvement (difference between the expected and predicted number of crashes) and critical crash rate. As an input for the EB procedure SPF functions for Italy and Hungary were calibrated and compared. Finally, the correlation between the rankings were tested.

The investigation pointed out how the ranking of sites with promise changes with the different approaches in both countries. The rankings gave different results in both countries, as expected. As it is known from previous work the state-of-the-art approach to estimate the expected number of accidents using the Empirical Bayes method identifies and ranks different hazardous locations than the traditional naïve techniques. Having tested the correlation between the various ranking methods it was concluded that none of the performance measures has significant correlation with the EB and PSI methodologies providing the most suitable approach to address regression to the mean effects. Specifically, observed crash frequency and crash rate are not correlated with EB and PSI. Crash rate showed no agreement also with the critical crash rate (CCR) that is the simplest approach to mitigate RTM in crash rate computation. In this framework, the chance to make wrong decisions in the selection of sites to be treated based on the performance measure of safety suggested by the Italian and Hungarian regulation is high, with an uncontrolled over and underestimation of the safety performance of sites. Therefore, it is recommended to revise and update the black spot ranking methodologies in both countries and move forward in the direction of more up-to-date and rational solutions.

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