The final publication is available in: Accident Analysis and Prevention. 2019, August 2019, 1-6.
10.1016/j.aap.2019.05.002, ISSN 0001-4575

An analysis of factors influencing accidents on road bridges in Norway

Rune Elvik ¤, Fridulv Sagberg, Per Andreas Langeland

Institute of Transport Economics

Gaustadalleen 21, 0349 Oslo, Norway

ABSTRACT

Factors explaining systematic variation in the number of injury accidents on road bridges in Norway during 2010-2016 have been identified by means of negative binomial regression models. A total of 6824 bridges recording in total 1368 accidents were included. Although almost 90 % of the bridges recorded zero accidents, there is no evidence of an excessive number of zeros, often referred to as "zero-inflation". Traffic volume, stated as AADT (Annual Average Daily Traffic), was found to be the single most important factor influencing the number of accidents. It explained nearly 72 % of the systematic variation in the number of accidents. The number of accidents increased less than proportionately with traffic volume, meaning that accidents per million vehicle kilometres declined with increasing traffic volume. Long bridges were found to be safer than short bridges and recently built bridges were safer than older bridges. Based on in-depth studies, a more detailed analysis of factors associated with fatal accidents was performed.

¤ Corresponding author (re@toi.no)

Key words: bridge; accident prediction; negative binomial regression; in-depth study

1 INTRODUCTION

Many accident prediction models have been developed for a specific type of roadway element. Probably the largest number of models for a certain type of roadway element deal with intersections, see e.g. the review of accident prediction models for intersections by Nambuusi et al. (2008). There are also a number of accident prediction models for horizontal curves, see the synthesis in Elvik (2013) and the update in Elvik (2017). Accident prediction models for tunnels are still few (Lemke 2000, Caliendo et al. 2013, Lu et al. 2016).

Bridges are another roadway element for which it can be argued that developing separate accident prediction models is more informative than mixing bridges with other types of roadway elements in a single model. Traffic on bridges can be more exposed to high crosswinds than traffic on land. The road surface on bridges gets slippery more easily than the road surface on land (Khan et al. 2009), where the ground stores heat. Bridges, like tunnels, are an enclosed space with limited room for evasive manoeuvres. Space may not allow for providing separate facilities for walking or cycling. Bridges may have steep slopes to allow sufficient height for ships to pass under them. Horizontal curves at both ends of a bridge are not uncommon. Finally, bridges are comparatively rare and represent a small share of road length. Thus, statistical models that include both bridges and roads on land may not have enough power to detect any differences in safety between bridges and roads on land.

The first objective of this paper is to develop an accident prediction model for road bridges in Norway. This model will identify some of the factors that are associated with accidents on bridges and compare safety on bridges to safety on roads on land. A second objective of the paper is to identify factors contributing to fatal accidents on bridges, based on in-depth studies of fatal accidents that have been done routinely in Norway since 2005. In-depth studies give more insight into the mechanisms precipitating accidents than statistical modelling can do.

This may be particularly relevant for short-term factors, like weather events, whose contribution to accidents may be difficult to detect in a statistical model. The paper is based on a report published by the Institute of Transport Economics (Sagberg and Langeland 2017). Initially, the few previous models of safety on bridges that have been found will be reviewed.

2 PREVIOUS STUDIES

A search for relevant studies was made in ISI Web of Science, using "road safety" or "road accident" or "road crash" and "bridge" as search terms identified in the title, abstract or keywords of a paper. A total of 63 studies were identified. Most of these studies dealt with technical aspects of bridge construction and maintenance. Only a few studies have developed accident prediction models.

Turner (1984) developed a model to predict accident rates (accident per million vehicles passing a bridge) on two-lane, two-way bridges in Texas. A total of 25 variables influencing accident rates were tested. The three most important were AADT, relative bridge width (width of bridge minus width of approach road) and approach road width. Accident rates were particularly high on bridges that were narrower than the approach road.

Ranes (2000) studied accident rates (injury accidents per million vehicle kilometres of travel) on 758 bridges in Norway with a length of at least 50 metres. Accident rates were found to be highest on the last 50 metres of the approach road and lowest on the middle of the bridge. Accident rate declined as AADT increased. Accident rate was negatively related to the width of bridges. Recently built bridges had a lower accident rate than older bridges. The factors were studied one-at-a-time and multivariate techniques were not employed. Nevertheless, they show that accidents on bridges are related to AADT, the length of the bridge, the width of the bridge and the age of the bridge.

Retting, Williams and Schwartz (2000) studied accident rates of four bridges in New York, carrying between 68,000 and 133,000 vehicles per day. Three of the bridges had significantly higher accident rate than the approach roads. Rear-end collisions were the most common type of accident on the bridges. The Norwegian study quoted above (Ranes 2000) also found rear-end collisions to be the dominant type of accident.

Khan et al. (2009) used GIS-based software to identify clusters of ice-related accidents in the state of Wisconsin in the United States. Ice-related accidents were found to cluster at bridge locations, suggesting that low friction and ice on the road surface can be major contributing factors to accidents on bridges.

Lu et al. (2014) developed a safety assessment tool for a long bridge crossing the Yangtze river in China. They did not trust accident reporting, and therefore relied on a surrogate measure of safety (speed variance). Based on this, four risk classes were defined. For most combinations of mean speed and hourly volume, the bridge was found to operate at low or moderate risk.

Metha et al. (2015) developed accident prediction models based on data for 1122 bridges in the state of Alabama in the United States. According to the model that best fitted the data, the number of accidents was positively related to AADT, bridge length and shoulder width. The number of lanes was recorded, but not included as a predictor variable in any of the models developed.

3 DATA AND METHOD

The data used to develop accident prediction models were extracted from the inventory of bridges kept by the Norwegian Public Roads Administration. Only bridges that were at least 10 metres long were included. The bridge registry contains geometric data for the bridges, such as length, width, number of lanes and grade. Data on accidents, traffic volume and speed limit were taken from the national road data bank. Accident data refer to the years 2010-2016. Only the total number of accidents for this period was provided, not the number of accidents each year. All accidents are police reported injury accidents. Property-damage-only accidents are not recorded by the police in Norway. A total of 7569 bridges were included. Complete data were available for 6824 bridges. Table 1 shows the count of accidents on all 7569 bridges and on those with complete data.

Table 1 about here

All analyses were based on bridges with complete data. It is seen that most bridges had zero accidents, but that there was a long and thin tail, with very few bridges recording five or more accidents. The empirical distribution of accidents was compared to two theoretical distributions to assess the possible presence of an inflated number of zeros, i.e. more bridges having zero accidents than implied by the theoretical distributions. It is seen that there is no zero-inflation, i.e. the actual number of bridges recording zero accidents was not greater than expected according to the negative binomial distribution.

A negative binomial regression model was fitted to explain variation between bridges in the expected number of accidents. The negative binomial regression model had the following form:

$$\text{Predicted number of accidents} = e^{\beta_0} AADT^{\beta_1} L^{\beta_2} e^{\left(\sum_{n}^{i=1} \beta_n x_n\right)} \qquad (1)$$

The first term is the constant term. AADT is Annual Average Daily Traffic. L is bridge length (in metres). The final term is other characteristics of the bridge that may be related to the number of accidents. When fitting the model, AADT and length were entered as natural logarithms. An AADT value of 0 was treated as missing data; only bridges with AADT greater than 0 were included.

Goodness-of-fit was assessed by means of the Elvik index and by developing cumulative residuals plots. (Fridstrøm et al. 1995, Elvik et al. 2013). The Elvik index of goodness of fit is based on the over-dispersion parameter of a negative binomial regression model. The over-dispersion parameter is estimated as follows:

$$Var(x) = \lambda \cdot (1 + \mu\lambda) \qquad (2)$$

In equation 2, λ denotes the expected number of accidents and μ denotes the over-dispersion parameter. Solving equation 2 with respect to the over-dispersion parameter gives:

$$\mu = \frac{\frac{Var(x)}{\lambda} - 1}{\lambda} \qquad (3)$$

If the mean (λ) and variance (Var(x)) of the raw data (i.e. the empirical distribution of the count of accidents between bridges) are known, the over-dispersion parameter of the crude data can be estimated by applying equation 3. Denoting the over-dispersion parameter of the raw data as μ_{crude} and the over-dispersion parameter of the fitted model as μ_{model} the Elvik index is defined as follows:

$$\text{Elvik-index of goodness-of-fit} = 1 - \frac{\mu_{model}}{\mu_{crude}} \qquad (4)$$

It takes on values between 0 and 1 and shows the share of systematic variation in accident counts explained by the model.

The data source for the study of fatal accidents was reports prepared by multi-disciplinary investigation teams performing in-depth studies of all fatal accidents in Norway. These studies have been conducted since 2005. Each team consists of a highway engineer, a vehicle expert, a human factors expert and a medical doctor. The reports are fairly standardised. Key items of information are therefore easily coded for quantitative analysis. A total of 31 reports on fatal accidents associated with bridges were studied. The small number of reports precludes extensive statistical analysis, but the accidents have been classified according to road alignment, precipitating mechanism, type of accident, functioning of safety barriers and injury mechanism. In both the model-development study and the in-depth study, accidents recorded on the bridge as well as the last 50 metres of road before the bridge (both directions) have been included.

4 EXPLORATORY STATISTICAL ANALYSIS

Table 2 lists the variables that were included in the analysis. The number of accidents was the dependent variable, all other variables listed in Table 1 were independent variables.

Table 2 about here

It is seen that most bridges were short, as mean length is only 56 metres. Since the geo-coding of accidents can be somewhat imprecise, there may, for the shortest bridges, be ambiguity about whether an accident occurred on the bridge or on the approach road. As noted above, accidents were included for 50 metres of the approach road at both ends of the bridge. Clearly, for the shortest bridges, the lengths included for the approach road will by far exceed the length of the bridge. Therefore, separate models have been developed for bridges that are at least 100 metres long.

80 km/h is the most common speed limit. In the models developed, the dummy for this speed limit was omitted, as including all speed limit dummies would produce perfect collinearity.

For bridges with complete data, random variation (which is equal to the mean = 0.2007) made up 0.2005/0.5936 = 33.7 % of total variation in the count of accidents; systematic variation made up 66.3 %. Thus, the variation between bridges in the number of accidents is predominantly systematic.

A common problem in accident modelling is that predictor variables tend to be highly correlated. Table 3 shows the bivariate correlations (Pearson's r) between the predictor variables.

Table 3 about here

Most of the correlations in Table 3 are weak. The strongest correlation, 0.560, is between ln(AADT) and bridge width. To assess whether this correlation influenced results, coefficient estimates in models with both variables included were compared to coefficient estimates in models with just one of the variables included. If the estimated coefficients had similar values and standard errors, it was concluded that co-linearity was not a problem.

5 ACCIDENT PREDICTION MODELS

Table 4 shows estimated coefficients including all bridges and including only bridges with a length of at least 100 metres.

Table 4 about here

The results are similar for all bridges and bridges with a length of at least 100 metres. The number of accidents increases as traffic volume increases, but less than proportionately, meaning that bridges with a high AADT will have a lower accident rate per million vehicle kilometres of travel than bridges a low AADT, as previously found by Ranes (2000). The number of accidents increases with bridge length, but again not proportionately. This means that the longer a bridge is, the lower will be its accident rate per million vehicle kilometres of travel.

The coefficient for construction year is negative, showing that new bridges are safer than older bridges. The coefficient for width is positive, which is inconsistent with the report by Ranes

(2000), which found that wider bridges had a lower accident rate than narrow bridges. As noted, ln(AADT) and bridge width are positively correlated. When bridge width was omitted, the coefficient for ln(AADT) changed from 0.601 (0.0299) to 0.685 (0.0270), which suggests that it is not strongly influenced by the inclusion of bridge width. The over-dispersion parameter increased slightly, from 1.388 to 1.481, indicating a marginally poorer goodness-of-fit. However, when ln(AADT) was omitted, the coefficient for bridge width changed from 0.042 (0.0074) to 0.127 (0.0085) and the over-dispersion parameter changed to 2.565, indicating a much poorer model fit. Clearly, ln(AADT) is the most important of the two variables and omitting it leads to omitted variable bias, i.e. the coefficient for bridge width is biased by including part of the effect of ln(AADT). Thus, including both variables in the model is regarded as best. The coefficients for both variables had small standard errors.

The coefficients for low speed limits are positive, the coefficients for high speed limits are negative (using the speed limit of 80 km/h as reference). These results correspond to those found in an accident model for all national and county roads in Norway, see the columns to the right in Table 4, based on a report by Høye (2016). This does not mean that high speed improves road safety. It reflects the fact that speed limits are a proxy for road standard and roadside development. Thus, the speed limits of 90, 100 and 110 km/h are only found on motorways in Norway, i.e. access-free roads with a median, at least two lanes per direction and no at-grade junctions. The lower speed limits, from 60 km/h and below, are used when there is roadside development, i.e. in suburban and urban areas, where factors like a high density of junctions and more pedestrians and cyclists contribute to increasing the accident rate.

Providing a facility for walking or cycling, usually a sidewalk that may be protected by a fence improves safety, in particular on long bridges.

6 IN-DEPTH STUDY OF FATAL ACCIDENTS

Statistical models show the variables that may explain systematic variation in the number of accidents. This is useful for planning purposes, as some of the variables can be influenced by design or traffic management, like (within limits) bridge length, bridge width, the provision of facilities for walking, and speed limit. A statistical model does not give insight into the risk factors and mechanisms associated with each accident. In particular, the effects of temporary risk factors, such as weather-related factors, cannot be captured by a multivariate model unless very detailed weather data are available. The in-depth data are suitable for shedding light on these factors.

Figure 1 shows, a in chronological sequence, factors associated with the 31 fatal accidents. These factors were coded based on the reports of the investigating teams.

Figure 1 about here

The road was classified as either straight or curved. A curve was classified as sharp if its radius was less than 150 metres. It is seen that almost half the fatal accidents occurred in curves. These curves were found both on the approach road and on the bridge. Three fatal accidents occurred on bridges that were narrower than the approach road. The most common precipitating mechanism was skidding or other forms of loss of control. This is consistent with the tendency for slippery road surfaces to be more common on bridges than on roads on the ground. The friction coefficient was measured to a value of less than 0.2 in five of the fatal accidents. This is very slippery indeed and well below the lowest permitted friction on public roads according to standards for road maintenance.

Running off the road before reaching the bridge was the most common type of fatal accident. There was no safety barrier to prevent running off the road in 12 fatal accidents. In three cases, the guardrail failed to contain the vehicle (weak guardrail). These findings suggest that some fatal accidents can be prevented by measures to increase road surface friction and install or improve guardrails. Crushing was the most frequent injury mechanism, suggesting that many accidents involved steep and high slopes.

7 DISCUSSION

All models developed to explain systematic variation in the number of accidents are limited by the availability of data. It is never possible to obtain data on all potentially relevant variables. Omitted variable bias is therefore a potential source of bias in all such models.

The models developed in this paper fit the data quite well. That, obviously, is no insurance against bias due to omitted variables or use of the wrong functional form for the variables included in the analysis. Figure 2 show a cumulative residuals plot (Cure-plot) for the model including all bridges with complete data (6824 bridges).

Figure 2 about here

Most estimates are clustered in the left half of the plot, not surprising considering the fact that almost 90 % of the bridge had zero accidents. The cumulative residuals stay within plus or minus two standard errors and fluctuate around zero. They stray outside the standard errors to the far right, as the sum of the model-predicted number of accidents was 1360, whereas the total recorded number of accidents was 1368. On the whole, however, model predictions are unbiased.

The model based on all bridges explains about 86 % of the systematic variation in the number of accidents (based on the Elvik index). This is illustrated in Figure 3.

Figure 3 about here

The strongest predictor variable is traffic volume. A model including this variable only explained 72 % of the systematic variation in the number of accidents (based on the Elvik index). The other variables included in the full model added only 14 % to explained variance. 14 % of the systematic variation in the number of accidents was not explained by any of the variables included in the model.

One indicator of the presence of omitted variable bias is instability of regression coefficients as new variables are added to the model. Such instability indicates that the variables included are correlated with the new variables added to a model. The coefficient for traffic volume was 0.661 in the model only including this variable, 0.601 in the full model including all bridges, 0.685 in the model including all bridges but omitting bridge width and 0.562 in the model including bridges with a length of at least 100 metres. These estimates are close and do not suggest any major bias attributable to correlation between traffic volume and other variables included in the models.

With respect to width, width squared was added in order to test for a non-linear relationship between width and the number of accidents. The coefficient for width squared was negative, but not statistically significant. Estimates for widths between 3 and 13 metres indicated a monotonic relationship, with the predicted number of accidents increasing as a function of width. This relationship is somewhat counterintuitive, but speed is known to be positively related to road width. Speed is likely to be higher on wide bridges, for any speed limit, than on narrow bridges.

There are many statistical models to choose from when modelling accident data (Lord and Mannering 2010). A negative binomial regression model of the form developed in this paper is very common. A version of the model using a variable over-dispersion parameter was tested, but did not improve model fit. Further, to explore heterogeneity in the data, a finite mixture negative binomial regression model was tested. The model did not converge, suggesting that the data do not originate from two or more different populations of bridges.

8 CONCLUSIONS

The main conclusion of the study can be summarised as follows:

1. Negative binomial regression models have been developed to identify factors explaining systematic variation in the number of accidents on road bridges in Norway. Traffic volume was found to be the single most important factor.
2. The number of accidents increases less than proportionately with traffic volume, meaning that the accident rate per million vehicle kilometres of travel declines as traffic volume increases.
3. Long bridges are safer than short bridges and recently built bridges are safer than older bridges. In general, accident rate declines as speed limit increases. This reflects the fact that the highest speed limits are found on motorways of a high standard and the lowest speed limits found on urban roads with mixed traffic.
4. In-depth studies of 31 fatal accident indicated that curves, slippery road surface and weak or no guardrail were important contributing factors to these accidents.

ACKNOWLEDGEMENT

This study was funded by the Norwegian Public Roads Administration

REFERENCES

Caliendo, C., De Guglielmo, M. L., Guida, M. 2013. A crash-prediction model for road tunnels. Accident Analysis and Prevention, 55, 107-115.

Elvik, R. 2013. International transferability of accident modification functions for horizontal curves. Accident Analysis and Prevention, 59, 487-496.

Elvik, R. 2017. Can evolutionary theory explain the slow development of knowledge about the level of safety built into roads? Accident Analysis and Prevention, 106, 166-172.

Elvik, R., Fridstrøm, L., Kaminska, J., Meyer, S. 2013. Effects on accidents of changes in the use of studded tyres in major cities in Norway: A long-term investigation. Accident Analysis and Prevention, 54, 15-25.

Fridstrøm, L., J. Ifver, S. Ingebrigtsen, R. Kulmala and L. K. Thomsen. 1995. Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts. Accident Analysis and Prevention, 27, 1-20.

Høye, A. 2016. Utvikling av ulykkesmodeller for ulykker på riks- og fylkesvegnettet i Norge (2010-2015). Rapport 1522. Oslo, transportøkonomisk institutt.

Khan, G., Santiago-Chaparro, K. R., Qin, X., Noyce, D. A. 2009. Application and integration of lattice data analysis, network K-functions, and geographic information system software to study ice-related crashes. Transportation Research Record, 2136, 67-76.

Lemke, K. 2000. Road safety in tunnels. Transportation Research Record, 1740, 170-174.

Lord, D., Mannering, F. 2010. The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. Transportation Research Part A, 44, 291-305.

Lu, L., Wang, C., Zhang, Y., Chen, W. Du, X. 2014. Development of a safety assessment tool for long-span bridges. Transportation Research Record, 2451, 97-102.

Lu, J. J., Xing, Y., Wang, C., Cai, X. 2016. Risk factors affecting the severity of traffic accidents at Shanghai river-crossing tunnel. Traffic Injury Prevention, 17, 176-180.

Metha, G., Fields, R. T., Lou, Y., Jones, S. 2015. Safety performance function development for analysis of bridges. Journal of Transportation Engineering, 141, 8.

Nambuusi, B. B., Brijs, T., Hermans, E. 2008. A review of accident prediction models for road intersections. Report RA-MOW-2008-004. Hasselt University, Steunpunt Mobiliteit en Openbare Weken.

Ranes, G. 2000. Vegtrafikkulykker på bru. En analyse av vegtrafikkulykker på bruer på Europa- og riksvegnettet 1993-97. Rapport TTS 8 1999. Oslo, Statens vegvesen, Vegdirektoratet.

Retting, R. A., Williams, J., Schwartz, S. I. 2000. Motor vehicle crashes on bridges and countermeasure opportunities. Journal of Safety Research, 31, 203-210.

Sagberg, F., Langeland, P. A. 2017. Trafikkulykker på bruer i Norge 2010-2016. rapport 1606. Oslo, Transportøkonomisk institutt.

Turner, D. S. 1984. Prediction of bridge accident rates. Journal of Transportation Engineering, 110, 45-54.

LIST OF FIGURES AND TABLES

Figure 1:

A model of factors associated with 31 fatal accidents on bridges

Figure 2:

Cure-plot for main model predicting bridge accidents

Figure 3:

Contributions of main factors to explaining variance in the count of accidents on bridges

Table 1:

Distribution of bridges by count of accidents. Empirical distribution, Poisson distribution and negative binomial distribution

Table 2:

Key statistics for variables included in models

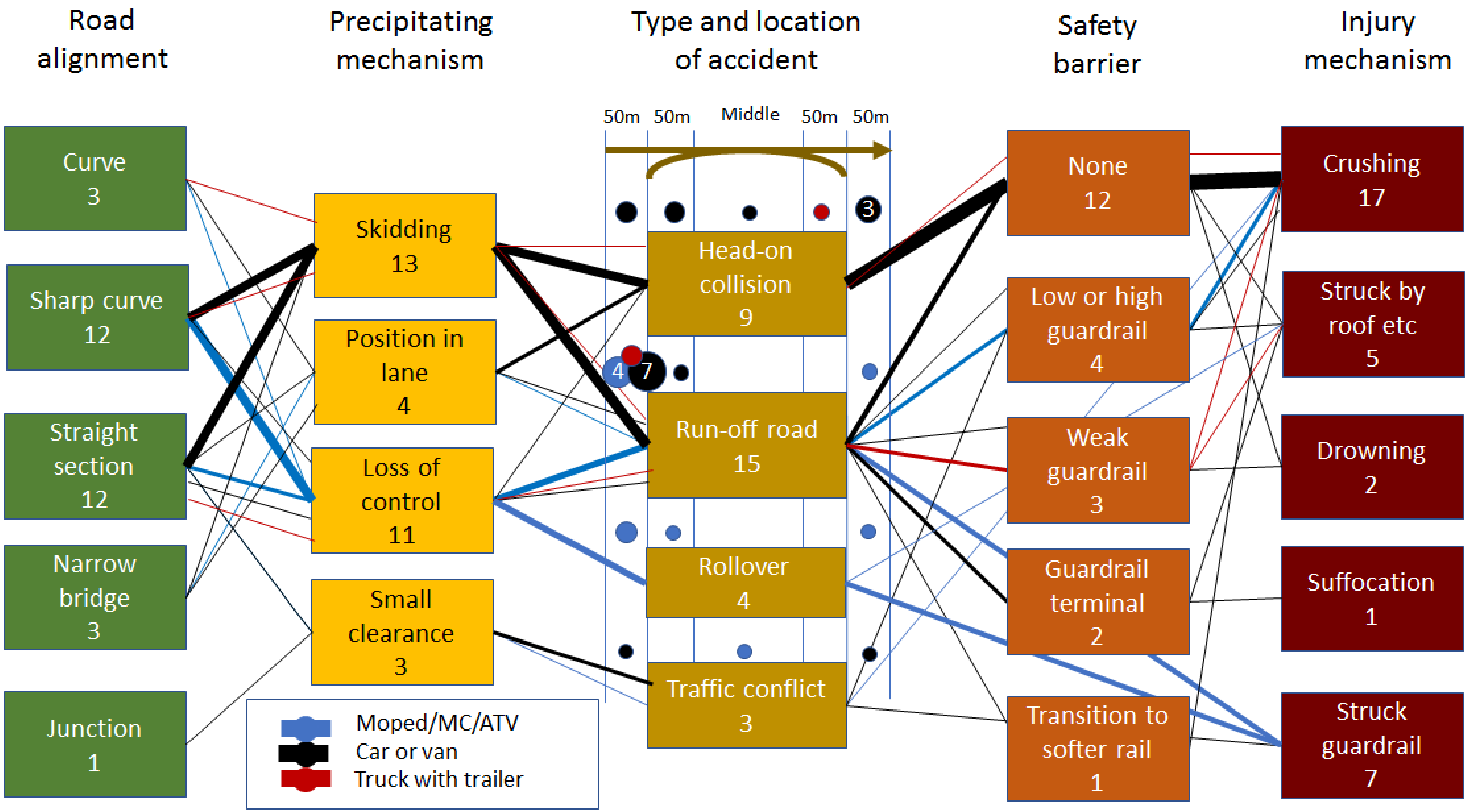
Table 3:

Correlations (Pearson's r) between independent variables

Table 4:

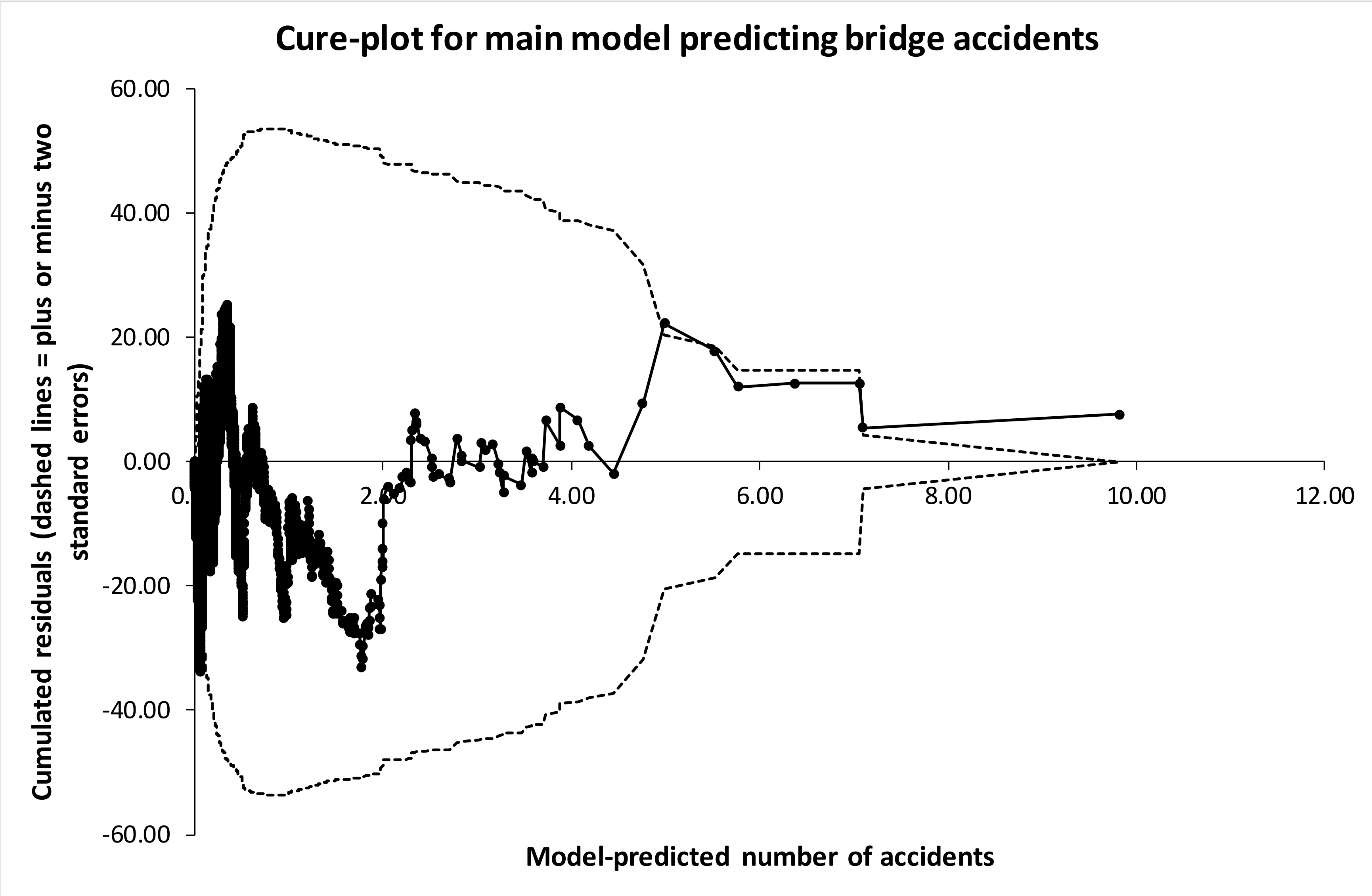
Estimated coefficients (standard errors in parentheses) Comparison with coefficients for accident prediction model for roads in general

Figure 1:



Road alignment
Precipitating mechanism
Type and location of accident
Safety barrier
Injury mechanism
Curve 3
Sharp curve 12
Straight section 12
Narrow bridge 3
Junction 1
Skidding 13
Position in lane 4
Loss of control 11
Small clearance 3
50m 50m Middle 50m 50m
Head-on collision 9
Run-off road 15
Rollover 4
Traffic conflict 3
3
4 7
None 12
Low or high guardrail 4
Weak guardrail 3
Guardrail terminal 2
Transition to softer rail 1
Crushing 17
Struck by roof etc 5
Drowning 2
Suffocation 1
Struck guardrail 7
Moped/MC/ATV
Car or van
Truck with trailer

Figure 2:



Cure-plot for main model predicting bridge accidents
60.00
40.00
20.00
0.00
-20.00
-40.00
-60.00
0.
2.00
4.00
6.00
8.00
10.00
12.00
Cumulated residuals (dashed lines = plus or minus two standard errors)
Model-predicted number of accidents

Figure 3:

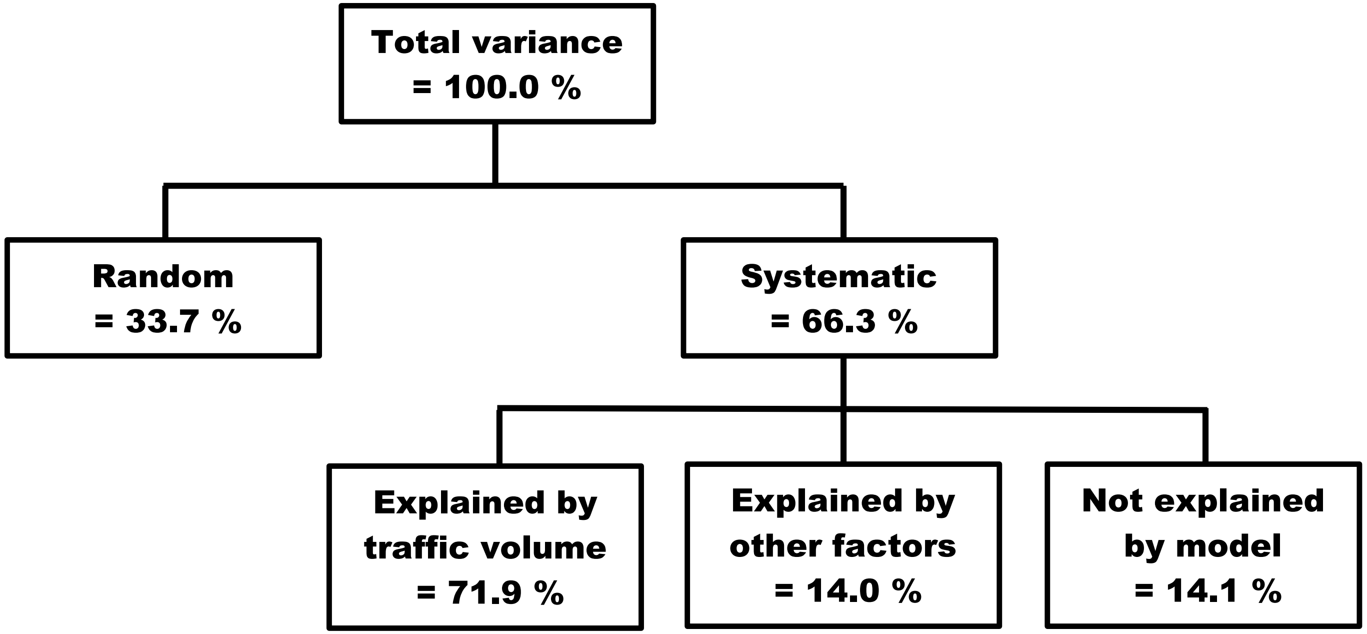

Total variance
= 100.0 %
Random
= 33.7 %
Systematic
= 66.3 %
Explained by
traffic volume
= 71.9 %
Explained by
other factors
= 14.0 %
Not explained
by model
= 14.1 %

Table 1:

	All bridges			Bridges with complete data		
Number of accidents	Empirical count	Poisson	Negative binomial	Empirical count	Poisson	Negative binomial
0	6702	6274	6710	5987	5584	5995
1	627	1177	549	604	1120	530
2	125	110	177	123	112	172
3	49	7	71	47	8	69
4	33		32	32		30
5	7		15	7		14
6	7		7	6		7
7	4		4	4		3
8	1		2	1		2
9	6		1	5		1
10	4			4		
11	1			1		
12	1			1		
13	0			0		
14	0			0		
15	0			0		
16	1			1		
17	0			0		
18	1			1		
Total	7569	7569	7568	6824	6824	6823
Mean	0.1876	$X^2 = 544.8$	$X^2 = 128.3$	0.2005	$X^2 = 475.5$	$X^2 = 51.9$
Variance	0.5612	Df=3; p<0.000	Df=9; p<0.000	0.5946	Df=3; p<0.000	Df=9; p<0.000

Table 2:

Variable	Minimum	Maximum	Mean	Standard deviation
Number of accidents	0	18	0.2005	0.7711
Construction year	1700	2017	1974.66	23.19
Length (metres)	10	1892	56.13	108.67
Width (metres)	0.5	62.0	8.68	4.13
AADT	0	99812	5601	10940
Dummy for speed limit 30 km/h	0	1	0.0152	0.1225
Dummy for speed limit 40 km/h	0	1	0.0317	0.1751
Dummy for speed limit 50 km/h	0	1	0.1499	0.3570
Dummy for speed limit 60 km/h	0	1	0.1615	0.3680
Dummy for speed limit 70 km/h	0	1	0.0614	0.2401
Dummy for speed limit 80 km/h	0	1	0.4620	0.4986
Dummy for speed limit 90 km/h	0	1	0.0297	0.1699
Dummy for speed limit 100 km/h	0	1	0.0265	0.1607
Dummy for speed limit 110 km/h	0	1	0.0229	0.1495
Dummy for pedestrian facility	0	1	0.2500	0.4350

Table 3:

	Ln(length)	Width	Ln(AADT)	Dum30	Dum40	Dum50	Dum60	Dum70	Dum90	Dum100	Dum110	P-facility
C-year	0.217	0.318	0.273	-0.050	-0.077	-0.082	-0.049	0.047	0.146	0.152	0.162	-0.098
Ln(length)		0.228	0.325	-0.019	-0.014	0.021	-0.013	0.022	0.072	0.127	0.136	0.287
Width			0.560	0.041	0.039	0.061	-0.003	0.098	0.131	0.152	0.096	0.187
Ln(AADT)				-0.005	0.037	0.040	0.001	0.194	0.144	0.250	0.227	0.142
Dum30					-0.023	-0.055	-0.056	-0.033	-0.023	-0.021	-0.019	0.070
Dum40						-0.072	-0.074	-0.043	-0.030	-0.027	-0.025	0.115
Dum50							-0.173	-0.100	-0.071	-0.064	-0.059	0.162
Dum60								-0.103	-0.073	-0.066	-0.061	0.078
Dum70									-0.042	-0.038	-0.035	0.028
Dum90										-0.027	-0.025	-0.059
Dum100											-0.023	-0.056
Dum110												-0.051

Table 4:

	Model including all bridges		Model including bridges with length > 100 metres		Model for road segments in general (Høye 2016)	
Term	**Coefficient (SE)**	**P-value**	**Coefficient (SE)**	**P-value**	**Coefficient (SE)**	**P-value**
Constant	20.053 (3.236)	0.000	36.295 (8.823)	0.000	-16.584	0.000
Ln(AADT)	0.601 (0.030)	0.000	0.562 (0.061)	0.000	0.928	0.000
Ln(length)	0.402 (0.035)	0.000	0.766 (0.109)	0.000	1.000	Offset parameter
Construction year	-0.014 (0.002)	0.000	-0.024 (0.005)	0.000		
Width	0.042 (0.007)	0.000	0.076 (0.017)	0.000		
Speed limit 30 km/h	0.454 (0.269)	0.091	-0.457 (0.751)	0.543	0.140	0.094
Speed limit 40 km/h	0.104 (0.193)	0.588	-0.539 (0.481)	0.262	-0.058	0.257
Speed limit 50 km/h	0.312 (0.103)	0.002	0.329 (0.210)	0.117	0.128	0.000
Speed limit 60 km/h	0.185 (0.104)	0.075	0.231 (0.207)	0.264	0.009	0.748
Speed limit 70 km/h	0.185 (0.126)	0.141	0.368 (0.263)	0.162	-0.021	0.527
Speed limit 90 km/h	-1.005 (0.239)	0.000	-0.597 (0.460)	0.194	-0.369	0.000
Speed limit 100 km/h	-1.103 (0.205)	0.000	-1.212 (0.342)	0.000	-0.785	0.000
Speed limit 110 km/h	-1.608 (0.278)	0.000	-1.593 (0.426)	0.000		
Pedestrian facility	-0.058 (0.083)	0.484	-0.337 (0.172)	0.050		
Dispersion parameter	1.388 (0.142)	0.000	1.091 (0.193)	0.000		
Elvik-index	0.859		0.831		0.942	
N	6824		827		76046	