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Using Weigh-In-Motion Data to Determine Aggressiveness of Traffic for Bridge Loading

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Abstract

This paper presents results based on the analysis of an extensive database of weigh-in-motion (WIM) data collected at five European highway sites in recent years. The data are used as the basis for a Monte Carlo simulation of bridge loading by two lane traffic, both bidirectional and same-direction. Long runs of the simulation model are used to calculate characteristic bridge load effects (bending moments and shear forces), and these characteristic values are compared with design values for bridges of different length as specified by the Eurocode for bridge traffic loading. Various indicators are tested as possible bases for a "Bridge Aggressiveness Index" to characterize the traffic measured by the WIM data in terms of its influence on characteristic bridge load effects. WIM measurements can thus be used to determine the "aggressiveness" of traffic for bridges. The mean maximum weekly gross vehicle weight is proposed as the most effective of the indicators considered and is shown to be well correlated with a wide range of calculated characteristic load effects at each site.

Subject headings: Bridge loads; Assessment; Simulation models; Weight; Load factors.

Introduction

Methods of assessing the load carrying capacity of existing bridges are well established in the literature and play an important role in the Bridge Management Systems of bridge owners and operators. The applied traffic loading is an equally important issue in any bridge safety calculation and has received increasing attention in recent years (see, for example, Kulicki at al. 2007). One approach to the assessment of a characteristic bridge load effect is (OBrien and Enright 2011):

- to fit statistical distributions to measured traffic data;
- to simulate vehicle crossing/meeting/overtaking events on the bridge;
- to identify block maximum load effects (e.g., maximum moment per day);
- to fit the block maximum data to an Extreme Value statistical distribution and hence
- to find the characteristic maximum load effects.

This procedure is computationally demanding and simpler methods have been proposed. One such method is that proposed by Ghosn and Moses (1986) who suggest a formula for the median value of the 50-year maximum bending moment as:

$$M_{median} = amW^{*}H \qquad (1)$$

where:

a = One of two possible (span-dependent) deterministic values – one value for short single-unit trucks which tend to dominate shorter spans (up to 18 m), and one for semi-trailers on longer spans. The term aW^{*} gives the mid-span moment for a given truck type with a given Gross Vehicle Weight (GVW) with fixed % of GVW per axle;

m = random value reflecting variations in truck geometry (related to span);

W^{*} = 95th percentile of GVW for this truck type (calculated from WIM data);

H = random value reflecting multiple presence (dependent on traffic volume and span) and extreme tail of GVW.

This is based on just two classes of trucks – single-unit (rigid) trucks and semi-trailers.

Another method is that proposed by Moses (2001) who suggests that the traffic load factor (γ) for the assessment of a single-lane bridge can be reduced from the standard value of 1.8 using the following formula based on measured WIM data:

$$\gamma = 1.8 \frac{\overline{W}_{20} + t_{(ADTT)} \sigma_{20}}{54.4} > 1.30 \qquad (2)$$

where:

$\overline{W}_{20}$ = the average truck weight in tonnes for the top 20% of the weight sample of trucks;

σ_{20} = the standard deviation of the top 20% of the truck weight sample;

$t_{(ADTT)}$ depends on Average Daily Truck Traffic (ADTT), ranging from 4.0 at 100 trucks per day to 4.9 at 5000 trucks per day.

This assumes that the maximum expected lifetime load is 54.4 t (120 kips) which is related to the legal maximum of 80 kips applicable in most states of the United States. Moses (2001) recommends that traffic be measured for a period of 1 to 2 days, and proposes a similar formula for two-lane bridges. Moses also refers to the use of the 95th and 99th percentile GVW in characterizing the maximum live load.

Getachew and OBrien (2007) propose an alternative simplified approach using French and Dutch WIM data from 1996 and 2003. This load model consists of two 5-axle trucks whose weights are the 1000-year and 1-week characteristic values. The model is shown to correlate well with a more sophisticated calculation of a range of characteristic load effects.

The aim of this study is to develop a rating system for traffic as measured by WIM data in terms of its “bridge aggressiveness”. This is similar to developing a simplified approach to bridge load assessment. However, the Bridge Aggressiveness Index (BAI) is intended for pre-screening purposes rather than direct use in accurate bridge assessments. The aim of the Index is to provide an approximate measure, based only on WIM data collected at a site, which will give an indication of

the relative magnitudes of the characteristic load effects on bridges. Furthermore, it is a rating system for the traffic only – it is not intended to provide a measure of the overall safety of a bridge which depends on the load carrying capacity as well as the traffic load.

An examination of recent WIM data from various sites throughout Europe shows the presence of significant numbers of extremely heavy vehicles with many crane-type vehicles and low loaders weighing more than 100 t (220 kips). The development of a Bridge Aggressiveness Index requires that the critical characteristics of such traffic be identified. This study uses the results from a Monte Carlo simulation model to estimate characteristic loading for different bridge lengths and load effects based on WIM data collected at five European sites. The characteristic load effects are expressed as "alpha factors" which give the ratio of the estimated characteristic load effects to the design load effects for the basic load model specified in the Eurocode for bridge traffic loading (O'Connor et al. 2001). Various candidate statistics calculated from the WIM data are tested to see how effective they might be as indicators of characteristic loading. This study focuses on short to medium span bridges, up to 45 m long, where free-flowing traffic with dynamics is taken to govern (Bruls et al. 1996; Flint and Jacob 1996).

WIM Data

A large database of WIM measurements was collected for trucks weighing 3.5 t (7.7 kips) or more at five European highway sites between 2005 and 2008, as detailed in Table 1. WIM systems are calibrated against statically weighed trucks to remove possible bias due to dynamic rocking or bouncing motions of the passing vehicles. Four of the sites used piezo-electric sensors embedded in the pavement of the lane so no inaccuracies were introduced by side-by-side combinations of vehicles.. At these sites, the sensors are not necessarily placed near any particular bridge, and in this study the WIM measurements are assumed to be typical of highway traffic in each region. In assessing a particular bridge, the traffic would ideally be measured directly at the bridge location, using either Bridge-WIM or pavement sensors on the approach to the bridge. The fifth site, at Vransko in Slovenia, used a Bridge WIM system which, according to the data suppliers, calculated the weights of each vehicle in side-by-side situations. The legal limits for standard trucks (with 5 axles or more) are 50 t in the Netherlands, 42 t in the Czech Republic and 40 t in the other three

countries. Above these limits, trucks would be expected to have special permits, but it is not possible to identify from the WIM data whether an extremely heavy vehicle has a special permit or is illegally overweight. The recorded data were cleaned to remove unreliable observations. This cleaning is essential in identifying and removing incorrect vehicle data that would otherwise distort the subsequent analysis (Sivakumar and Ibrahim 2007, Sivakumar et al., 2011). There are cameras at the WIM site in the Netherlands which photograph unusually heavy trucks, and photographs of trucks of particular interest were examined to verify the high GVWs observed and to assist in the formulation of rules for data cleaning at all sites. A range of criteria were used to remove dubious records including: (a) vehicles traveling below 40 km/h or above 120 km/h, (b) vehicles with less than two axles, (c) vehicles where the gap to the following vehicle is 0.1 seconds or less, (d) vehicles where the length as found from the induction loops is less than the wheelbase found by the WIM sensors, (e) vehicles where the gross weight is not equal to the sum of the axle weights, (f) vehicles with an axle spacing less than 0.4m. Full details are provided in an online report (Enright and OBrien 2011) which also describes a sensitivity analysis which shows that the criteria chosen for removing vehicles do not unduly influence estimated annual maxima for bridge load effects. Between all sites, an average of 1.5% of recorded vehicles were removed as a result of data cleaning. For accurate modeling of very small inter-vehicle gaps, a precision of 0.01 seconds or better is preferable when recording vehicle arrival times; although a lower precision of 0.1 seconds is still acceptable. At the site in Poland, the precision of 1 second made it difficult to fully calibrate the simulation model for small inter-vehicle gaps.

It can be seen from Table 1 that some extremely heavy vehicles were recorded, with the maximum GVW at each site being in excess of 100 t, and it is these extremely heavy vehicles that govern the maximum loading likely to occur in the lifetime of a bridge. Measurements at four of the sites were for two same-direction lanes, while at the site in Slovakia, traffic was measured in two opposing-direction lanes. At all four same-direction sites, between 92% and 96% of trucks were recorded in the slow lane, with relatively few trucks using the fast lane.

Table 1. WIM Data

Country	Netherlands (NL)	Slovakia (SK)	Czech Republic (CZ)	Slovenia (SI)	Poland (PL)
Site	Woerden	Branisko	Sedlice	Vransko	Wroclaw
Road number	A12 (E25/E30)	D1 (E50)	D1 (E50/E65)	A1 (E57)	A4 (E40)
Number of measured lanes	2	2	2	2	2
Number of directions	1	2	1	1	1
Total trucks (cleaned)	646 548	748 338	729 929	147 752	429 680
Time period	Feb to Jun 2005	Jun 2005 to Dec 2006	May 2007 to May 2008	Sep to Nov 2006	Jan to Jun 2008
Number of weekdays with full traffic record	77	290	148	39	87
Average Daily Truck Traffic (ADTT) in one direction	7 102	1 100	4 751	3 293	4 022
Time stamp precision (s)	0.01	0.1	0.1	0.001	1.0
Maximum number of axles	13	11	12	12	9
Average GVW (t)	21.8	19.9	20.7	25.1	13.4
Number over 60 t	1,716	556	376	15	587
Number over 70 t	892	78	169	3	35
Number over 80 t	609	37	66	3	15
Number over 100 t	238	8	12	1	1
Maximum GVW (t)	165.6	117.1	129.0	131.3	105.9

Monte Carlo Simulation

Vehicles

In Monte Carlo simulation, the parameters for each individual truck, and for the arrangement of trucks in each lane, are generated using statistical distributions derived from the traffic measured at each site. A detailed description of the methodology adopted is given elsewhere (Enright 2010), and is summarized here. For gross vehicle weight and vehicle class (as defined here by the number of axles on the vehicle), a semi-parametric approach is adopted (OBrien et al. 2010). This involves using a bivariate empirical frequency distribution in the regions where there are sufficient data points. Above a certain GVW threshold value, the tail of a bivariate normal distribution is fitted to

the observed frequencies which allows vehicles to be simulated that may be heavier than, and have more axles than, any measured vehicle.

Bridge load effects for the spans considered here are sensitive to wheelbase and axle layout. Within each vehicle class, empirical distributions (bootstrapping directly from histograms) are used for the maximum axle spacing for each GVW range. Axle spacings other than the maximum are less critical and trimodal normal distributions are used to select representative values. The proportion of the GVW carried by each individual axle is simulated in this work using bimodal normal distributions fitted to the observed data for each axle for each vehicle class. The correlation matrix is calculated for the proportions of the load carried by adjacent and non-adjacent axles for each vehicle class, and this matrix is used in the simulation using the technique described by Iman and Conover (1982).

Traffic flows measured at each site are reproduced in the simulation by fitting Weibull distributions to the daily truck traffic volumes in each lane at each site, and by using hourly flow variations based on the average weekday traffic patterns in each lane. Any temporal variations in the distribution of vehicle weights are not modeled in the simulation. A year's traffic is assumed to consist of 250 weekdays, with the very much lighter volumes of weekend and holiday traffic being ignored. This is similar to the approach used by Cooper (1995). In some jurisdictions, special-permit trucks may be more likely to operate at weekends when traffic volumes are light, but at the sites considered this was not found to be the case.

The traffic has been assumed to be statistically stationary, i.e., no allowance has been made for growth in the volumes of freight during the lifetime of the bridge. Even a modest growth assumption of 3% per annum results in more than a quadrupling of freight over a 50 year lifetime. Such levels of growth, if sustained, would likely generate unrealistic levels of congestion and are considered beyond the scope of this study.

Lateral Distribution of Loading

This study focuses on two-lane bridges, with two different lane configurations – two opposing-direction lanes, and two same-direction lanes of traffic. In simulation, many millions of loading events are analyzed, and for efficiency of computation it is necessary to use a reasonably simple model for transverse load distribution on two-lane bridges. This is achieved by calculating load effects for each vehicle assuming the bridge is a simple beam, and then multiplying these load effects by a lane factor to account for transverse distribution. The lane factors used are based on finite element analyses which were performed on concrete bridges of different lengths (from 12 to 45 m), and different construction methods (solid slab for shorter bridges, and beam-and-slab for longer bridges). One lane is identified as the "primary" lane and the lane factor for vehicles in this lane is always taken as 1.0. When a vehicle is also present in the other "secondary" lane, its contribution to the maximum stress is calculated by applying a factor less than or equal to 1.0. This factor depends on the load effect considered and the type of bridge deck construction. Two sets of lane factors are used in the simulation runs, one at either end of the ranges identified in the analysis – "low" and "high". The factors used are shown in Table 2, together with the three types of load effect that are examined in all simulation runs.

Table 2. Lane Factors for Secondary Lane

	Load Effect	Lane Factors	
		Low	High
LE1	Mid-span bending moment, simply supported	0.45	1.0
LE2	Support shear, simply supported	0.05	0.45
LE3	Central support hogging moment, 2-span continuous	0.45	1.0

Spatial Layout of Traffic

Bidirectional traffic is simulated by generating two independent lanes of traffic, one in each direction. The distribution of inter-vehicle gaps within each lane is modeled using the method described by OBrien and Caprani (2005). The observed gap distributions up to 4 seconds are

modeled using quadratic curves for different flow rates, and a negative exponential distribution is used for larger gaps.

Modeling two same-direction lanes requires a different approach. Three types of gap are required to define the spatial layout of vehicles in this case – two in-lane and one inter-lane gap distribution. These three distributions are inter-dependent – if any two are known, the third is automatically determined. However, simulating two of the gap distributions independently does not give satisfactory results. For example, if the gap distributions in each lane are simulated independently, the resulting inter-lane gap distribution does not match the observed distribution.

For short to medium span bridges with same-direction traffic, loading events featuring one truck in each lane (either side-by-side or staggered) are particularly important. To assess if there is any dependence between the weights of these vehicles, each fast-lane truck in the measured data is notionally paired with the nearest truck in the slow lane, and the gap is measured in seconds between the front axles of the two vehicles. The majority of trucks are present in the fast lane only when there is another truck nearby in the slow lane – i.e. they are normally passing another truck. There is a significant peak in the average fast lane GVW when the inter-lane gap is around zero, i.e., when the trucks are very close, and a similar pattern is evident in the Czech Republic. It appears that a high percentage of overtaking trucks are relatively heavy whereas the smaller number of trucks that remain in the fast lane when there is no truck nearby in the slow lane tend to be light.

In order to model the gap distributions and patterns of dependence between two same-direction lanes, a multi-dimensional smoothed bootstrap approach is adopted, as described in OBrien & Enright (2011). The principle of bootstrapping is to repeatedly draw random samples from the observed data (Efron and Tibshirani 1993). In this case, the samples used are “traffic scenarios”, with each scenario consisting of between five and eight slow-lane trucks in succession, with any adjacent fast-lane trucks. In preparation for simulation, the WIM data are analyzed and all scenarios are identified. The parameters recorded for each scenario are flow rate, gaps, GVWs and speeds. The gaps needed to define the scenario are the gaps within each lane, and one inter-lane headway which positions the first fast-lane truck relative to the leading slow-lane truck in the scenario, as shown in Fig. 1. Correlations between parameters are implicitly included in each

scenario. The aim in setting up the scenarios is to keep them reasonably small (between five and eight slow-lane trucks) so as to maximize the variability in the simulation, but also to have them large enough to capture patterns that may be significant for bridge loading.

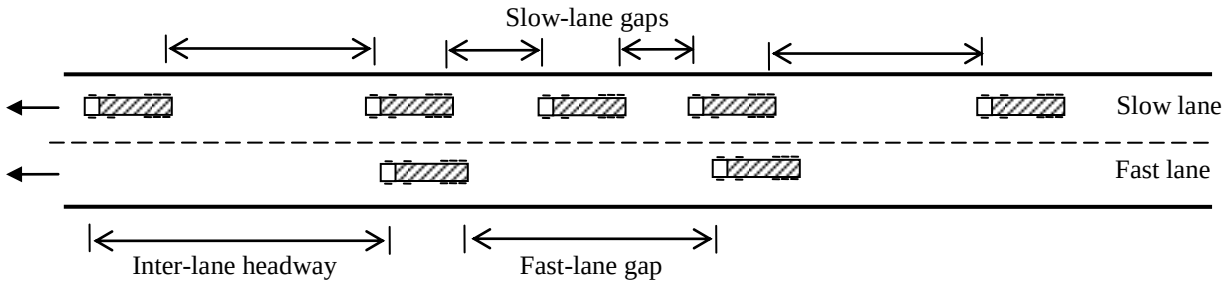


Fig. 1. Traffic scenario.

In the simulation process, a flow rate is determined for the time of day, based on average measured values for all weekdays. A scenario is selected at random from all scenarios corresponding to this flow rate. For a given traffic flow rate, each scenario has an equal probability of selection which means that the relative frequencies of the parameters defining the scenarios are reproduced in the simulation. The trucks in the selected scenario are added to the stream of traffic, the time is advanced, and another scenario is selected.

This bootstrap process would be expected to produce bridge loading very similar to the measured traffic. The measurements have been collected over a number of months, but in order to estimate characteristic bridge loading, many years of traffic must be simulated. A key part of this process is to extend the simulation to incorporate scenarios that have not been directly observed. Of particular interest is the modeling of vehicles heavier than, and with more axles than, any measured vehicles. Different gap combinations than those observed also need to be allowed to occur. Variations from the observed scenarios are introduced in a number of ways. Each time a scenario is selected in the simulation, the GVWs, gaps and speeds that define it are modified using variable-bandwidth kernel density estimators, as described below. When a GVW has been selected for a particular vehicle, the number of axles is randomly chosen from the measured distribution for that weight. The axle spacings, and distribution of the GVW to individual axles, are also generated randomly from

measured distributions for vehicles with different numbers of axles. The approach used for vehicle modeling is described in more detail by Enright (2010).

The term "kernel density estimator" describes the use of kernel functions to provide a better estimate of a probability density function from sample data (Scott 1992). A simple histogram gives an estimate of the density at discrete points, but is influenced by the choice of the bin size and origin. Replacing each data point by a kernel function and summing these functions gives a better estimate. Different kernel functions can be used – they are typically symmetric unimodal functions such as the normal density function. In Monte Carlo simulation, for each random variable, some estimate of its probability density is required. This estimate can be a parametric fit to the data or some non-parametric density. One non-parametric method is to use interpolation on the empirical cumulative distribution, but using a kernel density estimate gives a better coverage of the design space which is important for generating traffic loading scenarios that will be critical for bridges. As Hormann & Leydold (2000) point out, the "smoothed bootstrap" method – re-sampling the observed data and adding some noise – is the same as generating random variates from the kernel density estimate, but without needing to compute the estimated density. In this study, the smoothed bootstrap is applied to three variables – GVW, gaps and speeds. Each value x_i taken from the observed traffic scenarios is modified by adding some noise:

$$X_i = x_i + K\left[h(x_i)\right] \tag{3}$$

where K is a kernel function, centered at zero with a variable bandwidth h which depends on the value of x_i. For each random variable being modeled, a suitable bandwidth must be chosen – if the bandwidth is too small, not enough variability is introduced to the empirical data, whereas too large a bandwidth oversmooths the data. Bandwidths were selected by engineering judgment in each case. For example, Fig. 2 shows the smoothing effect of different bandwidths for one of the random variables – the speed of the vehicles in the slow lane at the site in the Netherlands.

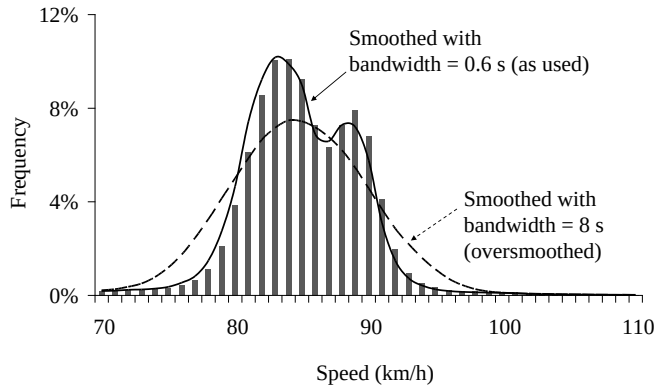


Fig. 2. Smoothing effect of different bandwidths on the distribution of vehicle speeds in the slow lane in the Netherlands

Estimation of Characteristic Loading

The Eurocode (EC1, 2003) specifies a characteristic load effect value for bridge design as that value which has a 5% probability of being exceeded in 50 years. This is equivalent to the value with a return period of approximately 1,000 years. Extrapolating from simulation runs which cover a short number of years produces estimates of the characteristic value with relatively high variability. The Monte Carlo simulation model used here has been optimized (by using parallel processing and by ignoring lighter vehicles) to make it possible to run many thousands of years of traffic, and this greatly reduces the variability of the estimates. The approach described here does not however remove the uncertainty inherent in estimating characteristic loading from data collected over time periods which are much shorter than the bridge lifetime.

The magnitudes of load effect vary with effect type, span, etc. In order to test candidates for a BAI, it is necessary to normalize all characteristic load effects against a common benchmark, and the Eurocode is adopted for this purpose. Results for bidirectional traffic are calculated for all sites, but for two-same direction lanes, results are calculated for just two of the sites – the Netherlands and the Czech Republic.

Comparison of results for each site with Eurocode Load Model 1

Eurocode Load Model 1 ("LM1") is intended to cover most of the effects of truck and car traffic and is also intended to cover flowing, congested or traffic jam situations with a high percentage of heavy trucks (EC1, 2003). It is shown schematically in Fig. 3.

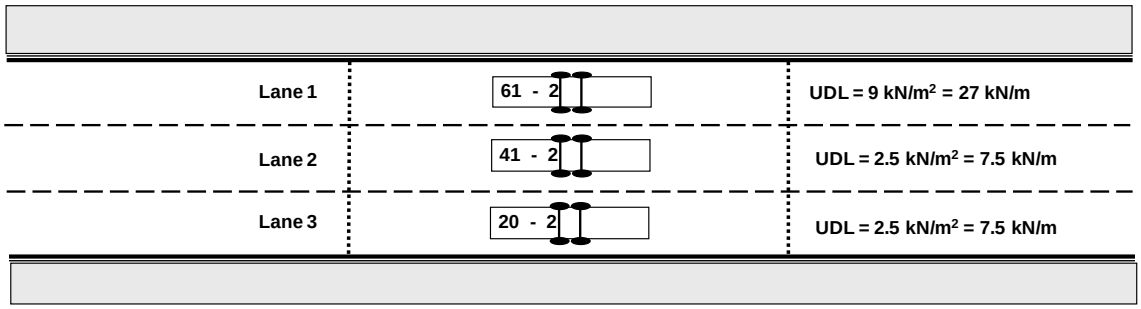


Fig. 3. Eurocode Load Model 1.
Note that for each tandem, the gross weight in tonnes and the number of axles are shown, e.g., "61 – 2".

For a two-lane bridge, an overall carriageway width of 9 m is assumed, and according to the Eurocode this gives three notional lanes, each 3 m wide. The load model consists of a tandem (i.e., 2 axles) in each lane, with axle loads of 300 kN in lane 1, 200 kN in lane 2 and 100 kN in lane 3. This gives GVWs of 61, 41 and 20 t respectively. The axles are spaced 1.2 m apart. The load model also includes uniformly distributed loads of 9 kN/m^2 in lane 1, and 2.5 kN/m^2 in lanes 2 and 3. For the purposes of comparison with the results from simulation, the lane factors listed in Table 2 are applied to the Eurocode loading in lanes 2 and 3. The Eurocode model includes a span-dependent dynamic amplification factor (Dawe 2003) which, for 2 loaded lanes as used in the simulation, reduces linearly from 1.3 for very short bridges (notionally a span of zero) down to a factor of 1.1 for spans of 50 m. The load effects calculated for the Eurocode model are divided by the appropriate dynamic factors so that all comparisons are based on static load effects. The load effect values thus calculated for the lane factors and types of load effect listed in Table 2 are given in Table 3 for four different bridge lengths (15, 25, 35 and 45 m). Sample results from simulation runs at all five sites are shown in Fig. 4 for mid-span moment in a simply supported 35 m bridge with low lane factors. The simulated annual maximum bending moments for each site are sorted by value and plotted as

cumulative distributions on Gumbel probability paper which uses a log-log scale for the probability axis.

Table 3. Load Effects for Two-Lane Bridges - Eurocode Load Model 1

Lane Factors	Bridge Length (m)	LE1: Mid-span moment (kNm)	LE2: Shear at bridge support (kN)	LE3: Hogging moment (kNm)
High	15	4,291	875	917
	25	8,684	1,058	1,874
	35	14,286	1,245	3,119
	45	21,224	1,444	4,685
Low	15	3,186	653	683
	25	6,511	800	1,412
	35	10,793	952	2,370
	45	16,133	1,112	3,583

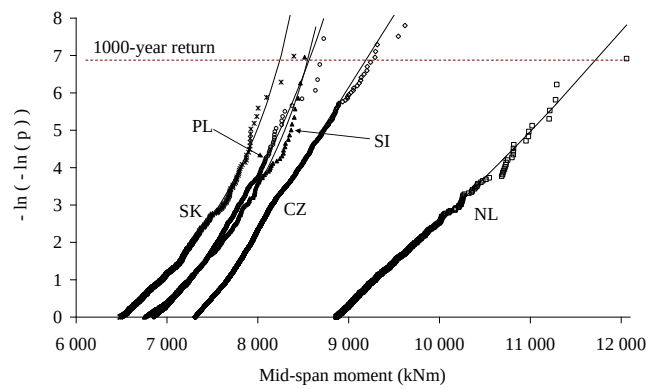


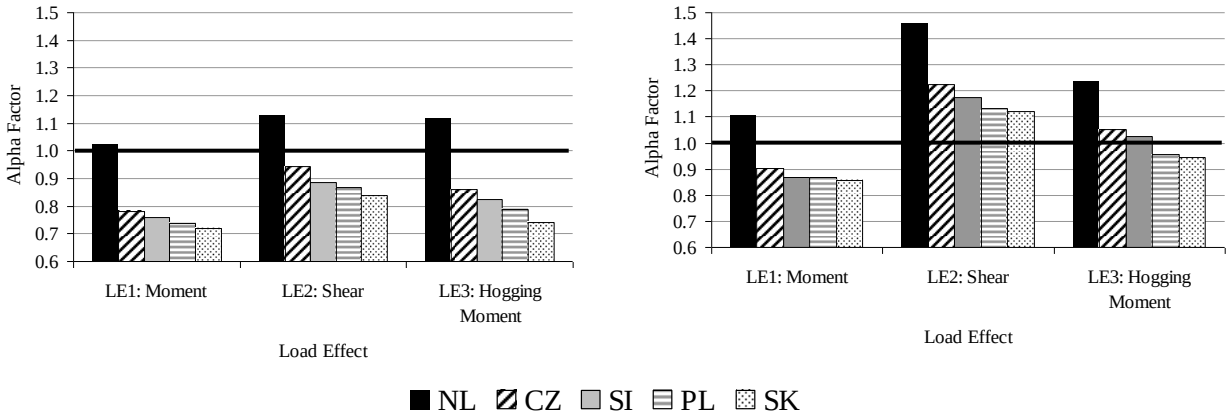
Fig. 4. Annual maximum bending moments from simulation for a 35 m bridge with low lane factors

Note: NL=Netherlands, CZ=Czech Republic, SI=Slovenia, PL=Poland, SK=Slovakia

These load effects are compared with the characteristic values calculated using the simulation model for bidirectional and same-direction traffic at each site, and alpha factors are calculated as the ratio of the characteristic value to the Eurocode value. Hence, an alpha factor of greater than one implies that the estimated characteristic loading is greater than the design values specified by Load Model 1. It can be argued that Eurocode Load Model 3 for special permit vehicles might be more appropriate

for design, but for the purposes of calculating the Bridge Aggressiveness Index described below, Load Model 1 (LM1) provides a reasonable benchmark.

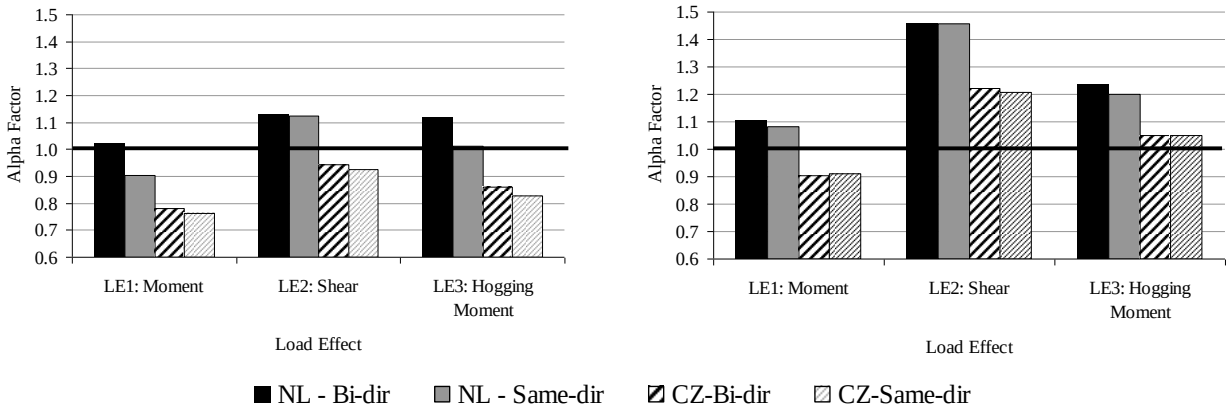
For each site the maximum alpha factor from the four bridge lengths are shown for bidirectional traffic in Fig. 5(a) for high lane factors and Fig. 5(b) for low lane factors. The variation between bridge lengths at a given site is quite small. As can be seen, the estimated characteristic loading for the site in the Netherlands is significantly in excess of the Eurocode LM1, with an alpha factor of up to 1.46. The Eurocode model has significant loading in both lanes, and simulated load effects which are dominated by the loading in one lane tend to show the largest excesses. The four central European countries have fairly similar results, and are 20 to 30% lower than the Netherlands, but there are still significant excesses over the Eurocode LM1, particularly for bridges with low lateral distribution.



(a) High lane factors (b) Low lane factors

Fig. 5. Comparison of characteristic loads with Eurocode Load Model 1, bidirectional traffic.

Note: NL=Netherlands, CZ=Czech Republic, SI=Slovenia, PL=Poland, SK=Slovakia



(a) High lane factors (b) Low lane factors

Fig. 6. Comparison of characteristic loads with Eurocode Load Model 1, for bidirectional and two same-direction lanes of traffic.

The comparisons with Eurocode LM1 for two same-direction lanes are shown in Fig. 6 for the sites in the Netherlands and the Czech Republic. The corresponding figures for bidirectional traffic are also shown. It can be seen that the only significant difference in loading between bidirectional and same-direction traffic at these two sites arises for bending moment on bridges with high lateral distribution. In these cases, the characteristic loading for two same-direction lanes is up to 10% lower than for bidirectional traffic. When lateral distribution is low, the characteristic load effects are dominated by single truck loading in one lane, and this means that there is little or no difference between the bidirectional and same-direction cases.

Bridge Aggressiveness Index

The aim of a Bridge Aggressiveness Index is to provide an approximate measure, based only on WIM data collected at a site, which will give an indication of the relative magnitudes of the characteristic load effects on bridges. For this study, the more conservative bidirectional case is used as the basis for testing different BAI's. As noted already, the same-direction case will tend to give between zero and 10% lower load effects. Different statistics from the GVW distributions at each site are tested as possible BAI's by calculating how well the values are correlated with the average alpha factors for each site, where the average is calculated over four bridge lengths, three load

effects and two lane factors. The correlation for the candidate BAI's are shown in Table 4. For example, the coefficient of correlation for the mean weekly maximum GVW is calculated from the data in the first two rows of Table 5.

Table 4. Correlation with Average Alpha Factor (5 Sites)

Candidate BAI	Correlation
1,000-year GVW	97.90%
Mean daily maximum GVW on weekdays	96.29%
Mean weekly maximum GVW	96.22%
99.999 percentile GVW	94.67%
99.99 percentile GVW	94.43%
Max observed GVW (variable time period)	94.61%
99.9 percentile GVW	81.47%
99 percentile GVW	17.66%
95 percentile GVW	20.92%
90 percentile GVW	9.05%

Table 5. Alpha Factors and BAI for Five Sites

Site:	NL	CZ	SI	PL	SK
Average alpha factor – all load effects, spans and lane factors	1.13	0.93	0.89	0.86	0.84
Mean weekly maximum GVW (t)	133.1	89.2	70.4	81.0	74.9
BAI	1.17	0.95	0.85	0.91	0.87

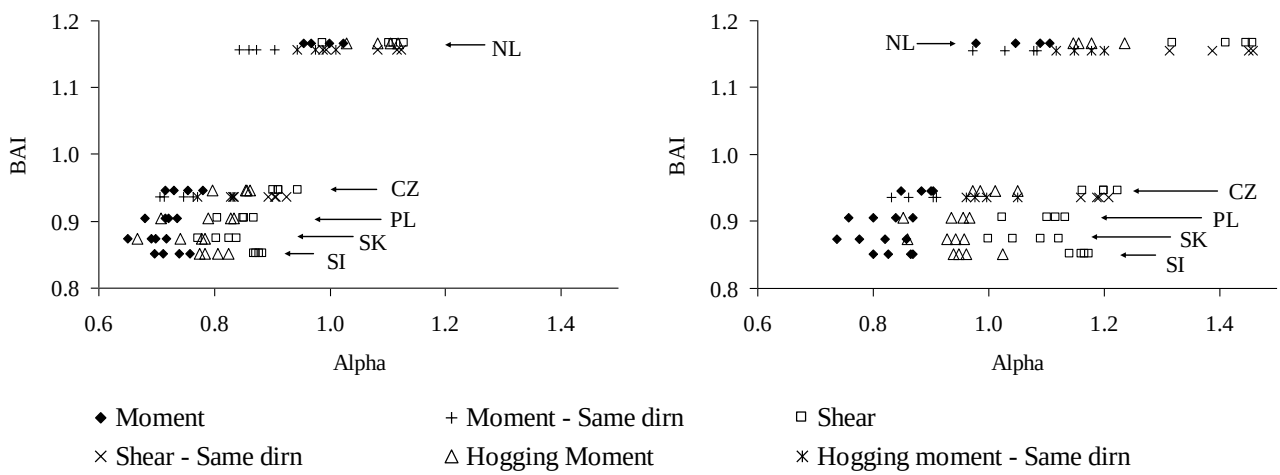
The 1,000-year GVW is the characteristic GVW at each site – the value with a 5% probability of being exceeded in 50 years, i.e., with a return period of approximately 1,000 years. While it gives the best correlation with the characteristic load effects, it is relatively difficult to calculate, and requires some judgment in fitting the tail of a normal distribution to the tail of the GVW distribution, as described by OBrien et al. (2010). The mean daily or weekly maximum GVWs are easy to calculate, and are the next best indicators. They also incorporate some element of traffic volumes. The mean weekly maximum is chosen as the basis for a BAI. It allows for daily variation

in traffic, and should be a better indicator of characteristic loading than the mean daily maximum GVW. On the other hand, if limited WIM data are available (less than perhaps 3 months), then the mean daily maximum may be more appropriate. The proposed index is based on a linear fit to the average alpha factors and the mean weekly maximum GVW values for each site. The coefficients calculated in the linear fit are rounded slightly for simplicity:

$$\text{BAI} = 0.5 + [\text{Mean weekly maximum GVW (t)}] / 200 \qquad (4)$$

The calculated BAI values for each of the five sites are shown in Table 5.

The BAI is plotted against alpha factors for each bridge length, load effect and site in Fig. 7(a) for high lane factors, and Fig. 7(b) for low lane factors. The alpha factors are shown for bidirectional traffic at the five sites, and for same-direction traffic for the Netherlands and the Czech Republic.



(a) High lane factors (b) Low lane factors

Fig. 7. Bridge Aggressiveness Index and corresponding Eurocode alpha factors.

Note: The same-direction points are moved down slightly for clarity.

It can be seen that, within each site, the Eurocode alpha factors vary significantly, indicating that this model does not result in fully consistent levels of safety for all load effects, spans, etc.. The variations are more pronounced for cases with low lane factors, i.e., where load sharing between

lanes is low. As these variations are for load effects derived from the same WIM site, no BAI can improve the situation.

Despite the variation within each site, there are clear differences in the alpha factor ranges between sites. For example, the Dutch site is clearly much more aggressive for bridges than the others. Hence, while it can only be viewed as an indicator, the BAI based on mean weekly maximum GVW does provide useful information about the safety of bridges subject to that traffic.

Conclusions

Various statistics calculated from measured WIM data at five sites are tested as possible indicators of characteristic maximum loading. It can be seen that anything lower than the 99.9 percentile GVW is not a good indicator for the traffic at the sites considered. This points to the dominance of extremely heavy vehicles at these sites. The mean maximum weekly GVW is proposed as the basis for a Bridge Aggressiveness Index. It is easy to calculate this statistic from measured WIM data; it incorporates variations in traffic flows over the typical week; and it incorporates some element of the average truck volumes at the site. More importantly, it shows good correlation with characteristic bridge loading.

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