



2011

# Modelling of Highway Bridge Traffic Loading: Some Recent Advances

Bernard Enright

*Dublin Institute of Technology*, [bernard.enright@dit.ie](mailto:bernard.enright@dit.ie)

Colin C. Caprani

*Dublin Institute of Technology*, [colin.caprani@dit.ie](mailto:colin.caprani@dit.ie)

Eugene J. O'Brien

*University College Dublin*

Follow this and additional works at: <https://arrow.dit.ie/engschcivcon>

 Part of the [Civil Engineering Commons](#), and the [Structural Engineering Commons](#)

## Recommended Citation

Enright, Bernard, Caprani, Colin C., O'Brien, Eugene J. (2011), Modelling of Highway Bridge Traffic Loading: Some Recent Advances. 11th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP11), Zürich, Switzerland.

This Conference Paper is brought to you for free and open access by the School of Civil and Structural Engineering at ARROW@DIT. It has been accepted for inclusion in Conference papers by an authorized administrator of ARROW@DIT. For more information, please contact [yvonne.desmond@dit.ie](mailto:yvonne.desmond@dit.ie), [arrow.admin@dit.ie](mailto:arrow.admin@dit.ie), [brian.widdis@dit.ie](mailto:brian.widdis@dit.ie).



# Modelling of highway bridge traffic loading: some recent advances

B. Enright & C.C. Caprani

*Dublin Institute of Technology, Dublin, Ireland*

E.J. OBrien

*University College Dublin, Dublin, Ireland*

**ABSTRACT:** The accurate estimation of site-specific lifetime extreme traffic load effects is an important element in the cost-effective assessment of bridges. In recent years, the improved quality and increasing use of weigh-in-motion technology has meant that better quality and larger databases of vehicle weights are now available. This has enabled measurements of the regular occurrence of extremely heavy vehicles, with weights in excess of 100 t. The collected measurements have been used as the basis for building and calibrating a Monte Carlo simulation model for bridge loading. The computer programs written to implement this model generate simulated traffic in two lanes – for both the same direction and the bidirectional cases – and calculate load effects for bridges of various spans. The research focuses on free-flowing traffic on short to medium-span bridges. This paper summarizes recent advances and their contribution to the highway bridge traffic loading problem

## 1 INTRODUCTION

In recent years, the improved quality and increasing use of weigh-in-motion (WIM) technology (Jacob & OBrien 2005) has meant that more accurate measurements of vehicle weights are now available for periods covering many months or even years of traffic at selected locations. These extensive measurements can be used to refine probabilistic bridge loading models for the assessment of existing bridges, and to monitor the implications for bridge design of trends in vehicle weights and types. Site-specific bridge assessment, based on measured traffic, can lead to very significant cost reductions for maintenance (O'Connor & Enevoldsen 2009), and the application of site-specific models for bridge assessment has been widely studied (Moses 2001, Sivakumar & Ibrahim 2007).

European and North American codes are based on relatively small amounts of data collected some years ago (Nowak 1993, O'Connor et al. 2001). Changing truck weights, composition of traffic, and vehicle sizes all have implications for bridge loading, and codes need to be periodically re-calibrated based on current traffic. The characteristics of highway traffic in Europe can be seen in WIM data collected between 2005 and 2008 for 2.7 million trucks at five European sites. It is evident that special vehicles, with gross weights well in excess of legal limits, are frequently observed as part of normal highway traffic. These vehicles, which would be

expected to have special permits, are very important for bridge loading (Moses 2001, Sivakumar et al. 2007), and recent models incorporate these in the estimation of lifetime maximum bridge loading.

It is necessary to estimate as accurately as possible the probable maximum bridge load effects (bending moments, shears) over a selected lifetime. For assessment, this can be 5 to 10 years (Nowak et al. 1993), whereas for design the U.S. AASHTO code is based on the distribution of the 75-year maximum loading (Nowak 1993). The Eurocode (EC1, 2003) for the design of new bridges is based on the distribution of the 50-year maximum, and the characteristic load is calculated as the value with a 5% probability of being exceeded in the 50 year lifetime, which is approximately equivalent to the value with a return period of 1000 years. Even with the relatively large amounts of truck data gathered in recent years, it is still necessary to extrapolate from the measured data to calculate estimates of lifetime maximum bridge loading. This is true regardless of the particular method adopted. One approach is to fit a statistical distribution to the calculated load effects for the measured traffic, and to use these distributions to estimate characteristic lifetime maximum effects (Nowak 1993, Miao & Chan 2002). This process requires a significant degree of engineering judgment and subjectivity, as noted by Miao & Chan (2002) and by Gindy & Nassif (2006) who report variations in estimated lifetime maxima of up to 33%. An alternative approach adopted by many au-

thors is to use Monte Carlo (MC) simulation (Bailey & Bez, 1999, O'Connor & OBrien 2005), and this is the approach described here.

In the MC simulation approach, statistical distributions for vehicle weights, inter-vehicle gaps and other characteristics are derived from the measurements, and are used as the basis for the simulation of traffic, typically for some number of years. It is thus possible to simulate vehicles and combinations of vehicles that have not been observed during the period of measurement. Lifetime maximum load effects have usually been estimated by extrapolating from the results of the simulation. Cooper (1997) uses the Gumbel extreme value distribution for extrapolation, whereas the Generalized Extreme Value (GEV) distribution is applied by Caprani et al. (2008) for simulations of up to five years of traffic. One approach, described here, is to optimize the MC model so as to make it practical to simulate thousands of years on a conventional desktop computer, and if the simulation is run for a sufficiently long time, the lifetime maximum load effects can be found directly from the results of the simulation. Using long-run simulations avoids the problems of extrapolating from short simulation runs, and gives much more consistent results compared with existing MC simulation approaches. More sophisticated statistical techniques have also been applied to the problem of extrapolation, and some of these are also described here. Segregating loading events according to the number of trucks on the bridge and combining these with composite distribution statistics has been found to improve extrapolation results.

In order to simplify the simulation process, various restrictions are often placed on the traffic model used – some authors specify a maximum value for vehicle weights, and many use a limited set of vehicle classes with a fixed maximum number of axles (Bailey & Bez 1999, Buckland et al. 1980, Grave et al. 2000). Some employ limited modelling of inter-vehicle gaps (Nowak 1993, Buckland et al. 1980). Vehicle models are typically based on existing vehicle types only, without attempting to extrapolate for vehicle types other than those recorded (Cooper 1997). The approach described here is to build a detailed MC model, without any restrictive assumptions, and to calibrate it against extensive WIM data collected at different sites. The model is designed to

extrapolate both vehicle weights and types (axle configurations).

Estimating lifetime loading from short periods of measured or simulated data does not give a clear idea of what types of trucks are likely to be involved in lifetime maximum loading events. Long-run simulations provide examples of the types and combinations of vehicles that might be expected to feature in extreme bridge loading. This is useful in identifying the relative importance of factors such as gross vehicle weight (GVW), the weights of individual axles and of groups of axles, wheelbase, and axle layout. This in turn may help in identifying useful legal restrictions on truck types.

A widely-used approach has been to assume that the combination of static and dynamic load effects produced by free-flowing traffic governs loading for short to medium span bridges of up to 45 m in length. In longer spans, static loading produced by congested traffic has generally been considered to be more critical (Flint & Jacob, 1996). Recent work has critically examined this assumption, and the dynamic allowance for heavy vehicles may be much lower than previously thought. A probabilistic estimate of dynamic amplification at extreme loading levels has been developed which is considered more appropriate than the simpler dynamic allowance factor for individual vehicles.

## 2 MONTE CARLO SIMULATION

### 2.1 WIM data and vehicle types

Details are shown in Table 1 for WIM measurements collected at five European sites between 2005 and 2008. The GVW histogram for the site in Slovakia is shown in Figure 1. It can be seen that some extremely heavy vehicles were recorded, with the maximum GVW at each site being in excess of 100 t. An analysis of the WIM data for extremely heavy vehicles, supported by photographic evidence, shows that two types of vehicle tend to become dominant as GVW increases above 50 t – mobile cranes and low loaders. Cranes have very closely-spaced axles, which causes the weight to be concentrated over a relatively short wheelbase whereas low loaders have a much longer wheelbase, with a large

Table 1. WIM Data

Country	Netherlands	Slovakia	Czech Republic	Slovenia	Poland
Site	Woerden	Branisko	Sedlice	Vransko	Wroclaw
Total trucks	646 548	748 338	729 929	147 752	429 680
Time period (weeks)	20	83	51	8	22
Average daily truck traffic (ADTT) in one direction	7 102	1 100	4 751	3 293	4 022
Maximum number of axles	13	11	12	12	9
Maximum GVW (t)	165.6	117.1	129.0	131.3	105.9
Number over 70 t	892	78	169	3	35

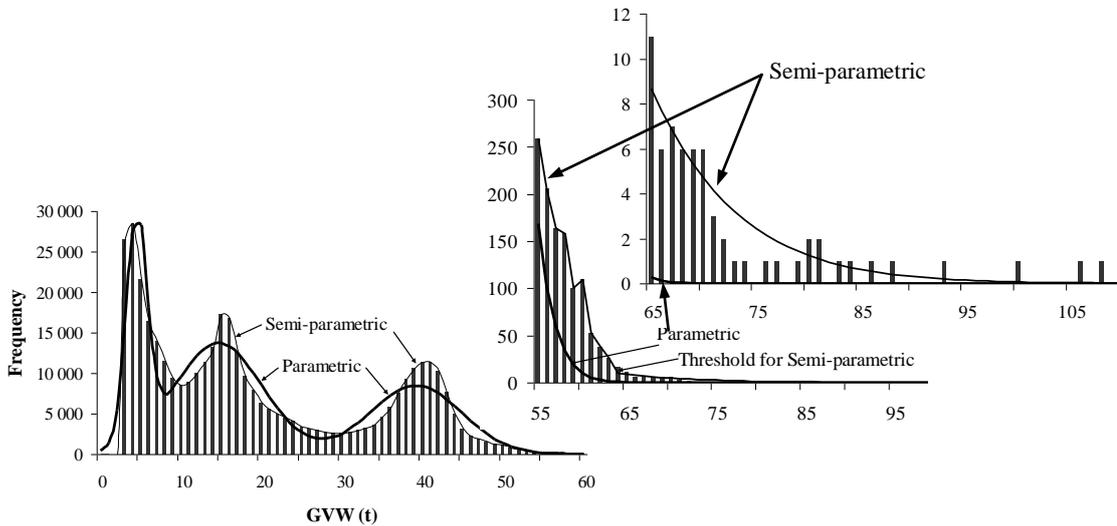


Figure 1. GVW Histograms for Slovakia with parametric and semi-parametric fits (close ups of tail region inset).

spacing between groups of axles. The correct modelling of these types of vehicles is important in estimating bridge loading.

## 2.2 GVW tail modelling

For Monte Carlo simulation, it is necessary to use a set of statistical distributions based on observed data for each of the random variables being modelled, and gross vehicle weight (GVW) is particularly important. Perhaps the most widely used approach has been a parametric one (O'Connor & OBrien 2005), which fits the measured histogram to a multimodal Normal (Gaussian) distribution, i.e., to a linear combination of a number of Normal distributions. As can be seen in Figure 1, this gives a moderately good fit for most of the GVW range, but significantly underestimates the probabilities in the critical upper tail. Non-parametric fitting uses the measured (empirical) histogram directly as the basis for simulating GVW. This is a reasonable method for the range of commonly observed GVWs, but the method presents problems in the upper regions of the histogram where observations are few and there are gaps with no measured data (Figure 1). A “semi-parametric” method proposed by OBrien et al. (2010) uses the measured histogram in the lower GVW range where there are sufficient data, and models the upper tail with a parametric fit. This ensures much greater accuracy of the probabilities in the tail region (Figure 1), allows for interpolation between sparse data points and provides a non-zero probability of GVWs above the highest observed value. The curve chosen here is the tail of a Normal distribution which is asymptotic towards zero probability and has been found by the authors to fit well to extreme truck weight data.

Simulation results show that the parametric and non-parametric methods produce estimates for characteristic loading, as defined in the Eurocode (EC1

2003), that are as much as 30% lower than those calculated using the semi-parametric approach. The semi-parametric approach is considered to give more realistic results and has been extended to model both GVW and number of axles on each vehicle. 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, and this 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 very sensitive to wheelbase and axle layout. In the simulation model described by Enright (2010), empirical distributions are used for the maximum axle spacing within each vehicle class (as determined by the number of axles). The axle position at which this maximum spacing occurs varies, and is also modelled using empirical distributions. Axle spacings other than the maximum are less critical and parametric trimodal Normal distributions are used for simulation. The proportion of the GVW carried by each individual axle is simulated 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 & Conover (1982). This approach to modelling axle configuration can be extended to characterize the axle layout for any vehicle, including those with more axles than observed in the WIM data.

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. A year's traffic is assumed to consist of 250 weekdays, with the very much lighter weekend and holiday traffic being ignored. This is similar to

the approach used by Caprani et al. (2008) and Cooper (1995).

### 2.3 Lateral distribution

In simulation, many millions of loading events are analysed, and for efficiency of computation it is necessary to use a reasonably simple model for transverse load distribution on two-lane bridges. One approach is to calculate load effects for each vehicle based on a simple beam, and then multiply these load effects by a lane factor to account for transverse distribution. Enright (2010) describes the use of lane factors based on finite element analyses which were performed on bridges with different spans (from 12 to 45 m), and different construction methods (solid slab for shorter spans, and beam-and-slab for longer spans). One lane is identified as the “primary” lane and the lane factor for vehicles in this lane is always taken as unity. When a vehicle is also present in the other “secondary” lane, the location of maximum stress is identified in the finite element model, and the relative contributions of each truck is calculated. In some cases the maximum stress occurs in a central beam, and the contribution from each truck is similar, giving a lane factor close to 1.0 for the secondary lane. In other cases, the maximum stress occurs in a beam under the primary lane, and the lane factor for the secondary lane is significantly reduced. In the case of shear stress at the supports of a simply supported bridge, the maximum occurs when each truck is close to the support, and the lateral distribution is very much less than for mid-span bending moment. As a result of this analysis, two sets of lane factors are used in the simulation runs, one at either end of the calculated ranges – “low” and “high”. The factors used are shown in Table 2, together with the three types of load effect that are examined in simulation.

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 Central support hogging moment, 2-span continuous	0.45	1.0
LE3 Support shear, simply supported	0.05	0.45

### 2.4 Simulated vs. measured load effects

The availability of relatively large amounts of WIM data make it practical to compare daily maximum load effects estimated from simulation with those calculated from the measured traffic. A sample comparison is shown Figure 2 for different load effects on a 35 m bridge using data for bidirectional traffic in Slovakia, with one lane in each direction. Results are plotted on Gumbel probability paper

which shows a re-scaled cumulative distribution function on which the Gumbel extreme value distribution appears as a straight line (Ang & Tang 1975). Four event types are shown – the one and two-truck same-lane events (denoted by “1” and “2” respectively), the two-truck meeting event, with a truck in each lane (“1+1”), and the three-truck meeting event, with two trucks in one lane (“2+1”).

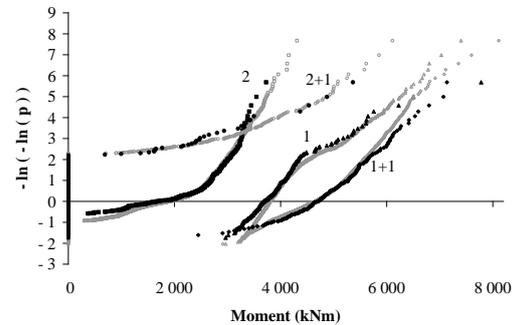


Figure 2 Slovakia, bi-directional traffic: Daily maximum bending moment, simply supported bridge, length = 35 m

Results for load effects from the simulation show good agreement with those calculated from measured data. The slight divergence of some of the measured values at the upper end of the curves can be attributed to the random nature of extreme events, and the principal objective of the simulation is to ensure that the model matches the main trends in the observed data.

### 2.5 Correlation in same-direction traffic

For short to medium span bridges with two same-direction lanes of traffic, loading events featuring one truck in each lane (either side-by-side or staggered) are particularly important. An analysis of the WIM data shows that there tends to be significant increase in the average GVW in the fast lane for trucks which are overtaking trucks in the slow lane.

It is well established that the distribution of same-lane gaps between vehicles varies with traffic flow rate (OBrien & Caprani 2005); in general gaps are less for higher flows. It is evident from the WIM data that there is also some slight dependence between gaps and GVW, and that successive gaps are not independent. The axle to axle gap observed behind vehicles tends to increase as the GVW increases. This can be attributed partly to driver behaviour, perhaps greater overhang (axle to bumper) distances, and also to the fact that many trucks in excess of the normal legal weight limit are followed by escort vehicles. The idea that successive gaps are not independent is reasonably intuitive. The platooning effect commonly observed on highways means that smaller gaps tend to occur in groups.

As might be expected, there is a tendency for heavier vehicles to travel at slightly lower speeds, although most extremely heavy vehicles are travelling at around 80 km/h which would be regarded as a

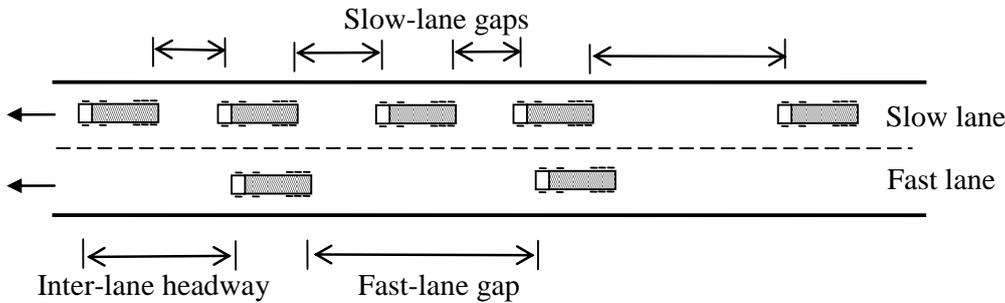


Figure 3. Traffic scenario.

normal highway speed for any truck. Speeds of successive vehicles in the same lane show a relatively high degree of correlation when the inter-vehicle gaps are small.

These various patterns are difficult to model using conventional techniques for simulating correlated data, particularly with two same-direction lanes. An alternative multi-dimensional smoothed bootstrap approach has been developed (Enright 2010) which avoids many of the difficulties associated with existing approaches, and in principle can quite easily be extended to more than two lanes.

The principle of bootstrapping is to repeatedly draw random samples from the observed data (Efron & 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 analysed 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 gap (or headway) which positions the first fast-lane truck relative to the leading slow-lane truck in the scenario, as shown in Figure 3. Correlations between parameters are implicitly included in each scenario. A bootstrap process with these scenarios 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 lifetime maximum 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. 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 by adding some “noise” using variable-bandwidth kernel functions (Scott 1992). 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.

For comparison purposes, two simulation models – one using a smoothed bootstrap technique and the other assuming no correlation – were run for 2000 days, and the simulated and measured results plotted on Gumbel paper. An example is shown in Figure 4 for side-by-side loading events on a 35 m two-span bridge in the Netherlands, and this illustrates that the smoothed bootstrap gives a significantly better fit to the measured data.

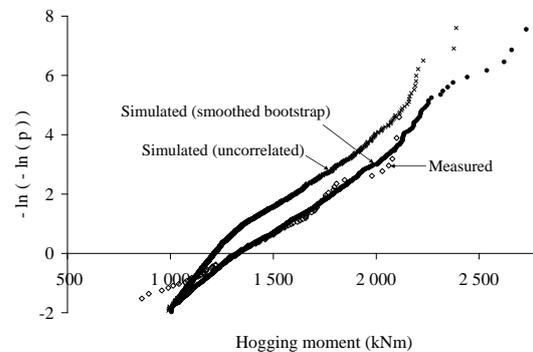


Figure 4. Simulated and measured daily maximum load effects.

## 2.6 Long-run simulations

Optimization of the simulation process described by Enright (2010) is achieved through program design in C++, parallel processing, and by focussing on significant loading events. Parallel processes generate simulated traffic in each lane, while other processes calculate load effects and gather periodic maxima for all event types on bridges of different spans. Focussing on significant loading events reduces the amount of calculation by ignoring individual trucks and groups of trucks where the combined GVW is less than some chosen span-dependent threshold (for example 40 t on a 15 m bridge).

The simulation process has been optimised to allow very long runs to be done, in excess of 1000 years, and this greatly reduces the variability of results and largely avoids issues about the selection of suitable statistical distributions for extrapolation purposes. Estimates with low bias and variance can be calculated for characteristic 1000-year load effects and for the distributions of 50- and 75-year lifetime maxima that can be used for reliability-based design and assessment.

The long-run simulations make it possible to examine in detail the types of loading events that give rise to the characteristic load effects. Bridge loading for the spans and sites considered is governed by single-truck and 2-truck events. The 1-truck events often feature trucks significantly heavier than any observed.

### 3 STATISTICAL TECHNIQUES FOR EXTRAPOLATION

Extrapolation directly from measured data or from short simulation runs remains a valuable technique for predicting lifetime maximum loading. Extreme value statistics are applied to block maximum data – typically daily maximum load effects. Recent work (Caprani et al. 2008) has concluded that bridge traffic load effect is not a single statistical generating mechanism. As is intuitively reasonable, the distribution of load effects caused by a 2-truck event (two trucks concurrently present on the bridge) differs to that of a 3-truck event. When each loading event-type is isolated, it is found that the GEV distribution is appropriate to model the daily maximum load effects that result (Caprani 2005). Thus a composite distribution of daily maximum load effect is required as a basis for extrapolation. Caprani et al. (2008) show that an appropriate model is the composite distribution statistics (CDS) model,  $GC(\cdot)$ :

$$G_c(s) = \prod_{i=1}^N G_i(s) \quad (1)$$

where  $G_i(\cdot)$  is any extreme value distribution.

This model has been shown to exhibit greater fidelity in fitting distributions of load effect, and meets minimum requirements for a good extrapolation model (Caprani 2005).

#### 3.1 Predicting the Lifetime Load Effect

Extrapolations to a return period result in a single value of load effect. Since repeating the process would generally yield a different result, there should be a means of acknowledging both this variability and the variability that arises from the modelling process itself. Since many codes define characteristic values as a probability of exceedance in the design life of the structure (for example, the Eurocode's 5% probability of exceedance in 50 years definition), it is not a distribution of characteristic values that is of interest, but the distribution of lifetime load effect. Therefore focus should be centred on the estimation of the lifetime distribution of load effect, from which the characteristic value can then be derived. Of significant further value would be a means by which allowances for modelling uncertainties, such as parameter confidence intervals, could be included.

Predictive likelihood is a method for estimation which allows both for sampling and modelling uncertainties. It is based on the maximization of the likelihood of both the data and a predictand (possible prediction value):

$$L_p(z|y) = \sup_{\theta} L_y(\theta; y) L_z(\theta; z) \quad (3)$$

where  $L_p(z/y)$  is the predictive (joint) likelihood of the predictand  $z$ , given the data vector,  $y$ ;  $L_y(\theta; y)$  is the likelihood of the parameter vector  $\theta$  given the data  $y$ , and;  $L_z(\theta; z)$  is the likelihood of the parameter vector  $\theta$  given the predictand  $z$ . Since the likelihoods are jointly maximized,  $L_p$  gives an indication of the relative likelihood of the data giving rise to the predictand. Application of Equation (3) for a range of predictands allows a probability density function of predictands to be determined. See Caprani (2005) for a more detailed explanation.

Caprani & OBrien (2010) have applied this method to the bridge loading problem and showed that the traditional return period approach yields different results to the direct estimate of the characteristic value from the lifetime distribution of load effect (Caprani & OBrien 2006b). The method has also been shown Caprani & OBrien (2006a) to be effective in predicting extreme vehicle weights.

### 4 ALLOWING FOR DYNAMIC INTERACTION

The dynamic amplification factor (DAF) is defined as the ratio of total to static load effect, where total load effect results from the truck and bridge interacting dynamically. Allowances for dynamic interaction are made in bridge loading codes, based on the notion of the DAF. Usually however, the worst possible DAF is applied to the critical static load effect and this approach does not take into account the reduced likelihood of these events coinciding. Indeed it is intuitively reasonable that grossly overloaded vehicles are not as dynamically lively as unloaded vehicles, for example. Furthermore, it is also reasonable that critical static loading events, involving many vehicles, will have destructive interference of the dynamic behaviour, resulting in lower levels of dynamic interaction, on the average.

#### 4.1 Dynamic Interaction at the Lifetime Load Effect

##### 4.1.1 Statistical Background

Total and static load effects are related through the DAF, which is not constant as all loading events differ both dynamically and statically. However, there remains a degree of correlation between these statistical variables. The recent statistical theory of multivariate extreme values has been applied to this problem to extrapolate these correlated variables to their

design lifetime values (Caprani 2005). Their ratio at this level is therefore the level of dynamic interaction applicable for the bridge design lifetime. This has been termed the assessment dynamic ratio (ADR) in recognition that it does not arise from any one single loading event.

#### 4.1.2 Sample Application

The Mura River bridge in Slovenia is used to provide a sample application of the statistical analysis for ADR. Monthly maximum mid-span bending stresses were identified from static simulations. These events then modelled to determine the level of dynamic interaction, as explained in González et al. (2008). The population of total and static load effects were analysed using a Gumbel Bivariate Extreme Value Distribution (BEVD). Parametric bootstrapping was then used to determine the lifetime BEVD, from which the relationship between characteristic total and characteristic static load effects was determined, the ratio of which is defined as the ADR, shown in Figure 5 (Caprani 2005). As can be seen, the expected level of lifetime dynamic interaction, for this site and bridge, is a DAF of about 1.06. This is significantly less than the DAF allowed for in the Eurocode of about 1.13 for such a bridge and load effect.

#### 4.2 Implications for the General Bridge Traffic Load Effect Problem

The findings, just outlined, have significant implications for the assessment of lifetime bridge traffic load effect, as well as the direction that future research into the area should take. The ADR finding has particular importance given that the majority of bridges are of short- to medium-length since it is currently assumed that the governing loading scenario for these bridges is that of free-flowing traffic with associated dynamic effects. The low level of lifetime dynamic allowance found for the Mura River bridge, if found to be general, will alter the governing loading scenario for the vast majority of bridges.

#### 4.3 The Governing Form of Traffic

To determine for what load effects and bridge lengths the different traffic regimes govern, it is useful to consider the value of DAF (or equivalently ADR) which is required in order for free-flowing traffic regimes to govern (Figure 6). Thus, as knowledge about lifetime DAF values becomes more available, it is easier to assess the governing form of traffic. As a simplification, we take the average load effect predictions for different traffic compositions. Dividing the congested model results by the free-flow model results gives us this 'Required DAF'. Figure 6 shows the values of Required DAF for each

load effect, along with the Eurocode values DAF for comparison. In this figure, once the required DAF is larger than the design DAF, congested traffic governs. Thus, from Figure 6, congested traffic governs above lengths of about 52 m, 33 m and 45 m, for Load Effects 1, 2 and 3 respectively. (Refer to Table 2 for a description of load effects).

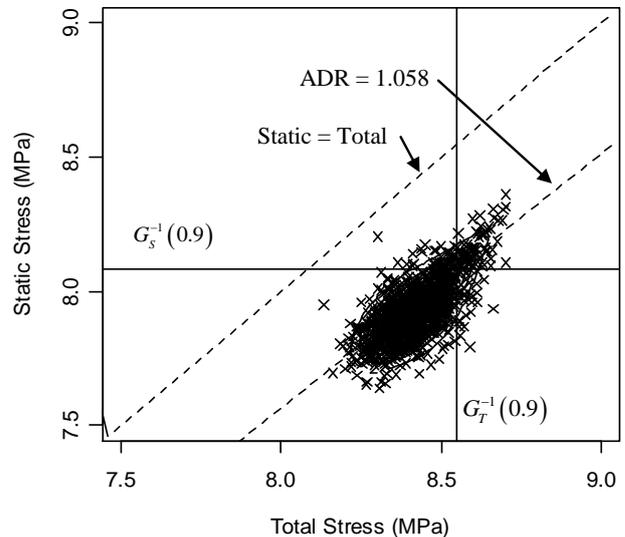


Figure 5. Lifetime total and static load effect.

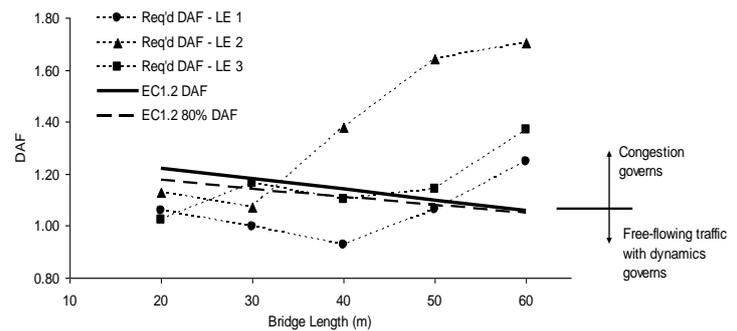


Figure 6. Identification of governing traffic state through required DAF.

It is also possible to assess the impact of a postulated reduction in the dynamic increment of 20%, as shown in Figure 6. For example, the DAF of 1.20 has an increment of 20% which, when reduced by 20% results in a DAF of 1.16 – called EC1.2 80% DAF in the figure. Depending on the slopes of the various lines, this change may have small or significant impact. Applying this 20% reduction in DAF, results in congestion governing for bridge lengths of about 50 m, 32 m and 38 m, for Load Effects 1, 2 and 3 respectively. Thus the governing traffic loading scenario for Load Effect 2 is sensitive to the value of DAF used.

## 5 CONCLUSIONS

More sophisticated statistical and simulation approaches to the problem of estimating lifetime maximum bridge loading have been developed in re-

cent years. Large quantities of good quality WIM data are now available and can be used for the calibration and testing of simulation models. It is possible to run simulations for thousands of years, thus reducing the variability of results. Extrapolation from short-term data has been improved by more rigorous statistical analysis. A probabilistic approach to maximum lifetime dynamic amplification indicates that lower dynamic amplification factors may be more appropriate. The minimum bridge length for which congested traffic governs depends on load effect, and may be lower than previously thought.

## REFERENCES

- Ang, A. H.-S. & Tang, W. H. (1975), *Probability concepts in engineering planning and design*, New York: Wiley.
- Bailey, S. F. & Bez, R. (1999), 'Site specific probability distribution of extreme traffic action effects', *Probabilistic Engineering Mechanics*, 14, 19-26.
- Buckland, P. G., Navin, F. P. D., Zidek, J. V. & McBryde, J. P. (1980), 'Proposed vehicle loading of long-span bridges', *Journal of the Structural Division, ASCE*, 106 (No. ST4), 915-932.
- Caprani, C. C. (2005), *Probabilistic analysis of highway bridge traffic loading*, PhD Thesis, School of Architecture, Landscape and Civil Engineering: University College Dublin, Ireland.
- Caprani, C. C., O'Brien, E. J. & McLachlan, G. J. (2008), 'Characteristic traffic load effects from a mixture of loading events on short to medium span bridges', *Structural Safety*, 30 (5), 394-404, doi: [10.1016/j.strusafe.2006.11.006](https://doi.org/10.1016/j.strusafe.2006.11.006).
- Caprani, C. C. & O'Brien, E. J. (2006a), 'Finding the Distribution of Bridge Lifetime Load Effect by Predictive Likelihood', *ASRANet*, Glasgow.
- Caprani, C. C. & O'Brien, E. J. (2006b), 'Statistical Computation for Extreme Bridge Traffic Load Effects', In: B. H. V. Topping, ed. *Proc. 8th Int. Conf. on Computational Structures Technology*, Civil-Comp Press, Stirling, Scotland, Paper No. 139.
- Caprani, C. C. & O'Brien, E. J. (2010), 'The Use of Predictive Likelihood to Estimate the Distribution of Extreme Bridge Traffic Load Effect', *Structural Safety*, 32 (2, March), 138-144, doi: [http://dx.doi.org/10.1016/j.strusafe.2009.09.001](https://dx.doi.org/10.1016/j.strusafe.2009.09.001).
- Cooper, D. I. (1995), 'The determination of highway bridge design loading in the United Kingdom from traffic measurements', In: Jacob B. et al., ed. *First European Conference on Weigh-in-Motion of Road Vehicles*, ETH, Zurich, 413-421.
- Cooper, D. I. (1997), 'Development of short-span bridge-specific assessment live loading', in *Safety of bridges*, P. C. Das, ed., London: Thomas Telford, 64-89.
- EC1. (2003), *Eurocode 1: Actions on structures, Part 2: Traffic loads on bridges*, Brussels: European Standard EN 1991-2:2003: European Committee for Standardization, TC250.
- Efron, B. & Tibshirani, R. (1993), *An Introduction to the Bootstrap* Chapman and Hall/CRC.
- Enright, B. (2010), *Simulation of traffic loading on highway bridges*, PhD Thesis, School of Architecture, Landscape and Civil Engineering: University College Dublin, Ireland.
- Flint, A. R. & Jacob, B. (1996), 'Extreme Traffic Loads on Road Bridges and Target Values of Their Effects for Code Calibration', *Proceedings of IABSE Colloquium*, Delft, The Netherlands, IABSE-AIPC-IVBH, 469 - 478.
- Ghosn, M. & Moses, F. (1986), 'Reliability calibration of bridge design code', *Journal of Structural Engineering, ASCE*, 112 (4), 745-763.
- Gindy, M. & Nassif, H. H. (2006), 'Comparison of traffic load models based on simulation and measured data', *Joint International Conference on Computing and Decision Making in Civil and Building Engineering*, Montréal, Canada, [online] available from: <http://www.icccbexi.ca/html/en/AutIndex.htm#G>, accessed 8 May 2007
- González, A., Rattigan, P. H., O'Brien, E. J. & Caprani, C. C. (2008), 'Determination of bridge lifetime dynamic amplification factor using finite element analysis of critical loading scenarios', *Engineering Structures*, 30 (9), 2330-2337.
- Grave, S. A. J., O'Brien, E. J. & O'Connor, A. J. (2000), 'The determination of site-specific imposed traffic loadings on existing bridges', in *Bridge Management 4*, M. J. Ryall, G. A. R. Parke, & J. E. Harding, eds., London: Thomas Telford, 442-449.
- Iman, R. L. & Conover, W. J. (1982), 'A distribution-free approach to inducing rank correlation among input variables', *Communications in Statistics - Simulation and Computation*, 11 (3), 311 - 334.
- Jacob, B. & O'Brien, E. J. (2005), 'Weigh-In-Motion: Recent developments in Europe', In: E. J. O'Brien, B. Jacob, A. González, & C.-P. Chou, eds. *Fourth International Conference on Weigh-In-Motion (ICWIM4)*, Taipei, Taiwan, National Taiwan University.
- Miao, T. J. & Chan, T. H. T. (2002), 'Bridge live load models from WIM data', *Engineering Structures*, 24, 1071-1084.
- Moses, F. (2001), 'Calibration of load factors for LRFR Bridge Evaluation', *NCHRP Report No. 454*. Washington D.C.: Transportation Research Board.
- Nowak, A. S. (1993), 'Live load model for highway bridges', *Structural Safety*, 13, 53-66.
- Nowak, A. S. (1994), 'Load model for bridge design code', *Canadian Journal of Civil Engineering*, 21, 36-49.
- Nowak, A. S., Nassif, H. H. & DeFrain, L. (1993), 'Effect Of Truck Loads On Bridges', *Journal of Transportation Engineering (ASCE)*, 119 (6), 853-867.
- O'Brien, E. J. & Caprani, C. C. (2005), 'Headway modelling for traffic load assessment of short- to medium-span bridges', *The Structural Engineer*, 83 (16), 33-36.
- O'Connor, A. & Enevoldsen, I. (2009), 'Probability-based assessment of highway bridges according to the new Danish guideline', *Structure and Infrastructure Engineering*, 5 (2), 157-168.
- O'Connor, A., Jacob, B., O'Brien, E. J. & Prat, M. (2001), 'Report of current studies performed on normal load model of EC1 Part 2. Traffic loads on bridges', *Revue Française de Génie Civil*, 5 (4), 411-433.
- O'Connor, A. & O'Brien, E. J. (2005), 'Traffic Load Modelling and Factors Influencing the Accuracy of Predicted Extremes', *Canadian Journal of Civil Engineering*, 32 (1), 270 - 278.
- O'Brien, E. J., Enright, B. & Getachew, A. (2010), 'Importance of the Tail in Truck Weight Modeling for Bridge Assessment', *Journal of Bridge Engineering, ASCE*, 15 (2), 210-213, doi: [http://dx.doi.org/10.1061/\(ASCE\)BE.1943-5592.0000043](https://dx.doi.org/10.1061/(ASCE)BE.1943-5592.0000043)
- Scott, D. W. (1992), *Multivariate density estimation : theory, practice, and visualization*, New York: Wiley.
- Sivakumar, B. & Ibrahim, F. I. S. (2007), 'Enhancement of bridge live loads using weigh-in-motion data', *Bridge Structures*, 3 (3-4), 193-204.
- Sivakumar, B., Moses, F., Fu, G. & Ghosn, M. (2007), 'Legal truck loads and AASHTO Legal Loads for Posting', *NCHRP Report 575*.