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# SITE SPECIFIC MODELLING OF TRAFFIC LOADING ON HIGHWAY BRIDGES

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## **Abstract**

Accurate traffic loading models based on measured weigh-in-motion (WIM) data are essential for the accurate assessment of existing bridges. Much work has been published on the Monte Carlo simulation of single lanes of heavy vehicle traffic, and this can easily be extended to model the loading on bridges with two independent streams of traffic in opposing directions. However, a typical highway bridge will have multiple lanes in the same direction, and various types of correlation are evident in measured traffic, such as groups of very heavy vehicles travelling together and heavy vehicles being overtaken by lighter ones. These traffic patterns affect the probability and magnitude of “multiple presence” loading events on bridges, and are significant for the maximum lifetime loading on the bridge.

This paper analyses traffic patterns using multi-lane WIM data collected at four European sites. It describes an approach to the Monte Carlo simulation of this traffic which seeks to replicate the observed patterns of vehicle weights, same-lane and inter-lane gaps, and vehicle speeds by applying variable bandwidth kernel density estimators to empirical traffic patterns. This allows the observed correlation structure to be accurately simulated but also allows for unobserved patterns to be simulated. The process has been optimised so as to make it possible to simulate traffic loading on bridges over periods of 1,000 years or more, and this removes much of the variability associated with estimating characteristic maximum load effects from shorter periods of either measured or simulated data. The results of this analysis show that the patterns of correlation in the observed traffic have a small but significant effect on bridge loading.

**Keywords:** Bridge, correlation, simulation, traffic loading, weigh-in-motion

## **1. Introduction**

Much work has been done on modelling bridge loading due to two-lane same-direction traffic. In the work by Nowak (1993), a number of simplifying assumptions were made – for example that one in 15 heavy trucks has another truck side-by-side, and that for one in 30 of these multiple truck events, the two trucks have perfectly correlated weights. A heavy truck was defined as one with a gross vehicle weight (GVW) in the top 20% of measured truck weights. As Kulicki et al. (2007) note, the assumptions used were based on limited observations, and the assumptions on weight correlation were entirely based on judgment, as almost no data were available. Moses (2001) presents a simple traffic model for estimating multiple presence probabilities as a function of average daily truck traffic (ADTT), and then selects conservative values, some being based on subjective field observations, for calibrating load factors

for bridge assessment. Sivakumar et al. (2007) refine the definition of side-by-side events to include two trucks with headway separation of  $\pm 18.3$  m (60 ft), and also consider the influence of the bridge length. Sivakumar et al. (2008), citing Gindy and Nassif (2006), extend this further by classifying multiple-presence events as side-by-side, staggered, following or multiple. They present statistics, derived from weigh-in-motion (WIM) measurements, for the frequency of occurrence of these events for different truck traffic volumes and bridge spans. They describe a method for estimating site-specific bridge loading which uses multiple-presence probabilities calculated either directly from WIM data or estimated from traffic volumes using reference data collected at other sites. It is assumed, surprisingly enough, that the GVW distribution is the same in both lanes, and that there is no correlation between weights in adjacent lanes.

In the development of the Eurocode for bridge loading (EC1 2003), characteristic load effects were estimated by extrapolating directly from results for measured traffic, and also by extrapolating from Monte Carlo simulation of traffic, with each lane being simulated independently (Bruls et al. 1996; O'Connor et al. 2001).

Croce and Salvatore (2001) present a theoretical stochastic model based on a modified equilibrium renewal process of vehicle arrivals on a bridge and note that while existing numerical models are particularly efficient when single-lane traffic flow is considered, they are unsatisfactory for multi-lane traffic, and have often employed drastic simplifications. In their model, convolution is used to combine load effect distributions for traffic in multiple lanes.

This study is based on WIM data collected at four European sites. A detailed analysis of the data reveals that for groups of adjacent vehicles in both lanes, there are patterns of correlation and interdependence between vehicle weights, speeds and inter-vehicle gaps. A Monte Carlo simulation model has been developed for evaluating bridge loading due to traffic in two same-direction lanes. This simulation seeks to reproduce the sometimes subtle patterns of correlation that are evident in measured traffic while also adding an element of randomness so as to vary the 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).

## **2. Observed traffic**

### **2.1. WIM data**

The WIM data used as the basis for this study were collected at four European motorway sites, as summarized in Table 1. At each site, traffic in two same-direction lanes was measured. As would be expected, the volumes of truck traffic in the fast lane are much lower than in the slow lane, with the percentage of trucks travelling in the fast lane varying from 3.8% in Slovenia to 7.7% in the Netherlands. A notable feature of the data at all sites is the number of extremely heavy vehicles.

**Table 1 – Summary of WIM data**

Country	Netherlands		Czech Republic		Slovenia		Poland	
Time period	Feb to Jun 2005		May 2007 to May 2008		Sep to Nov 2006		Jan to Jun 2008	
Lane	Slow	Fast	Slow	Fast	Slow	Fast	Slow	Fast
Total Trucks	596 568	49 980	684 345	45 584	142 131	5 621	398 044	31 636
ADTT*	6 545	557	4 490	261	3 158	135	3 708	314
Maximum GVW	165.6	75.2	129.0	128.0	131.3	58.4	105.9	69.9
No. over 60 t	1680	36	322	54	15	0	584	3
No. over 100 t	238	0	10	2	1	0	1	0

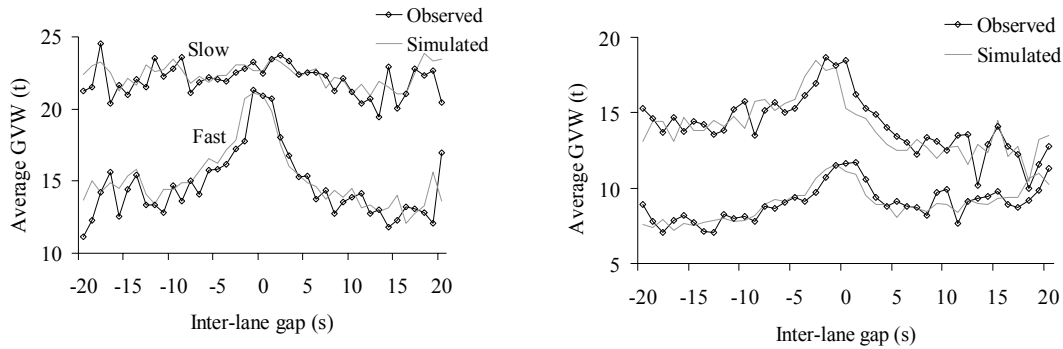
\* Average daily truck traffic per lane on week days

## 2.2. Patterns in measured traffic

There are distinctive patterns observable in the measured traffic. Similar patterns occur at each site, to a greater or lesser degree, and the challenge of reproducing these site-specific patterns in simulation is the focus of this paper. For short to medium span bridges, loading events featuring one truck in each lane 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. At all sites, many fast-lane trucks are within 2 seconds of a slow-lane truck – 75% in the Netherlands, 72% in the Czech Republic, 55% in Slovenia and 46% in Poland. The differences between sites may be attributable to driver behaviour at each location. The average GVW of the truck in the fast lane and of the nearest truck in the slow lane are plotted against the inter-lane gap for the Netherlands in Figure 1(a). There is a significant peak in the fast lane GVW when the 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 heavy truck in the fast lane tends to be associated with a nearby truck in the slow lane, i.e. it is passing another truck. In Poland (Figure 1(b)), there is a peak in the fast-lane GVW and also in the slow-lane GVW when the trucks are close, suggesting that both the passing truck and the truck being passed are heavier than average. The Slovenian data suggest that the passing truck tends to be lighter than the average for the fast lane. The graphs in Figure 1 show results for both the observed data and for simulated traffic where the simulation uses the methods outlined in this paper. At all sites, the simulated traffic reproduces the observed site-specific patterns very well.

There is also some correlation between the weights of successive trucks in the same lane, particularly in the slow lane where most trucks are found. The coefficient of correlation between the GVW of all leading trucks and all following trucks is typically in the range 5% to 10%. The correlation tends to increase as the weights of both trucks increases. In Figure 2, pairs of successive trucks are selected if both their weights are above a certain threshold (25 t, 30 t, etc.), and the correlation coefficient calculated for all such pairs is plotted against the threshold value. The trend is

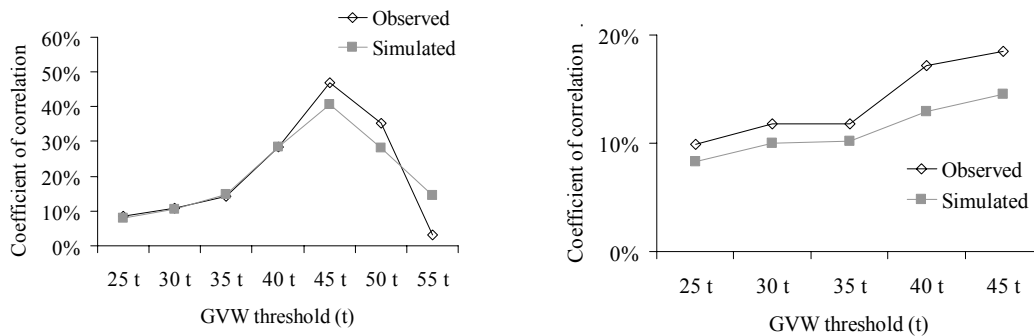
particularly pronounced in the Czech Republic (Figure 2(a)) and in the Netherlands. In Slovenia (Figure 2(b)) and Poland, the trend is present, but less obvious. There are widely-used techniques for modelling correlation in Monte Carlo simulation, such as that described by Iman and Conover (1982), and the use of copula functions (Nelsen 1999). In the authors' experience, it is very difficult to simulate the correlations evident in Figure 1 and Figure 2 using these techniques. The simulation method described in this paper successfully reproduces the observed correlations.



(a) Netherlands

(b) Poland

**Figure 1 – Inter-lane GVW correlation**



(a) Czech Republic

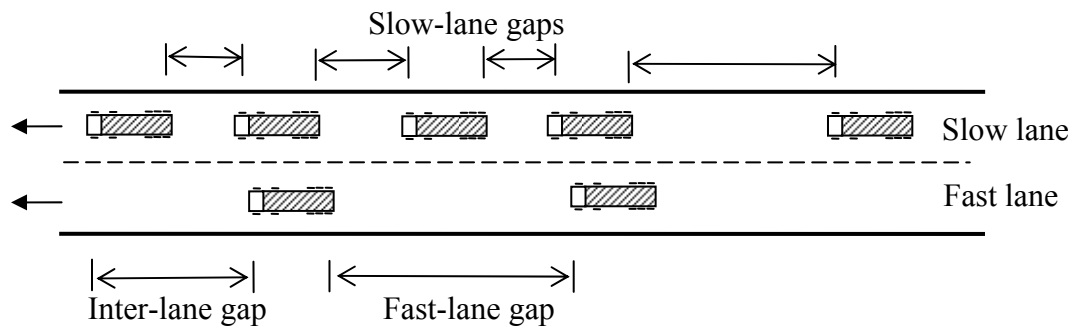
(b) Slovenia

**Figure 2 – Slow-lane GVW correlation**

Other patterns evident in the observed data include a relationship between speed and GVW, with heavier trucks tending to travel at slightly lower speeds. There is some evidence of larger gaps behind heavier trucks. It is also apparent that successive inter-vehicle gaps are not independent, particularly at lower traffic volumes where platooning causes small gaps to occur in clusters. The simulation of the spatial layout of traffic in two same-direction lanes requires the correct modelling of three inter-dependent gap distributions – the in-lane gaps in each of the slow and fast lanes, and the inter-lane gaps. If the in-lane gaps are simulated independently for both lanes, the resulting inter-lane gap distribution will be a poor match for the observed. Similarly, if the slow-lane and inter-lane gaps are simulated based on the observed data, the resulting fast-lane gaps will not match the observed.

### 3. Simulation of traffic

The principle of bootstrapping is to draw random samples repeatedly 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 analysed and all scenarios are identified. The parameters recorded for each scenario are flow rate, gaps, GVWs and speeds. The flow rate is represented by the number of slow-lane trucks in the current hour, rounded to the nearest 10 trucks/hour. The gaps needed to define the scenario are the gaps within each lane, and one inter-lane gap which positions the first fast-lane truck relative to the leading slow-lane truck in the scenario, as shown in Figure 3. The number of parameters needed to describe a single scenario (i.e. the dimensionality of the problem) varies with the size of the scenario, but in the typical scenario shown in Figure 3, a total of 21 different parameters are needed – the GVWs and speeds of seven trucks, six gap values and a flow rate. Correlations between parameters are implicitly included in each scenario.



**Figure 3** – Traffic scenario

In the simulation of traffic, the traffic flow rate at any time is based on the measured average hourly flow rate. Traffic scenarios appropriate to the current flow rate are drawn randomly from the observed traffic. This bootstrap process would be expected to produce bridge loading very similar to the measured traffic. 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 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, 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

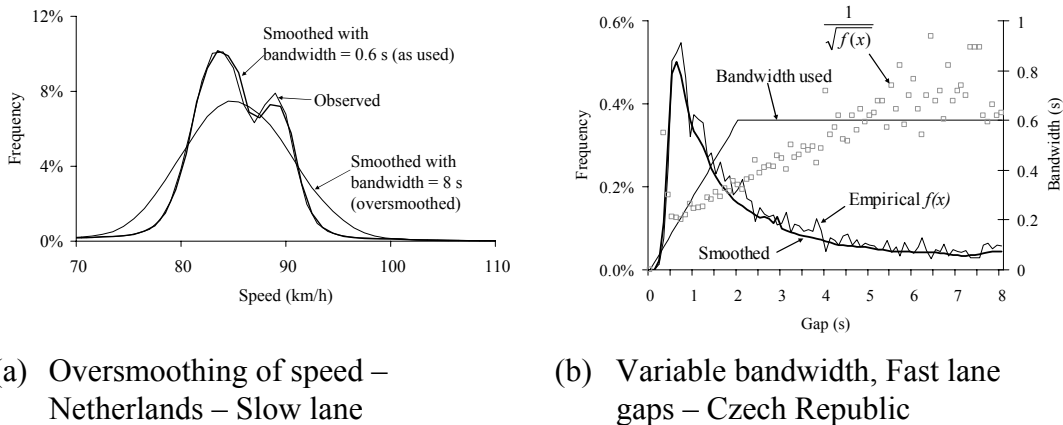
three variables – GVW, gaps and speeds. Each value  $x_i$  taken from the observed traffic scenarios is modified by adding some noise:

$$X_i = x_i + K[h(x_i)] \quad (1)$$

where  $K$  is a kernel function, centred at zero with a variable bandwidth  $h$  which depends on the value of  $x_i$ . For each random variable being modelled, a suitable bandwidth must be chosen – if the bandwidth is too small, not enough variability will be introduced to the empirical data, whereas too large a bandwidth will oversmooth the data, as shown for example in Figure 4(a). Scott (1982) discusses adaptive smoothing where the bandwidth of the kernel function is varied and cites the approach developed by Abramson (1982):

$$h_i(x_i) = \frac{h}{\sqrt{f(x_i)}} \quad (2)$$

where  $f(x_i)$  is the empirical density function. This approach is adopted here, and allows for additional smoothing where the observed data are sparse, as illustrated in Figure 4(b) for fast-lane gaps in the Czech Republic. The choice of bandwidth  $h$  is somewhat arbitrary, and is based on the avoidance of oversmoothing (as in Figure 4(a)).



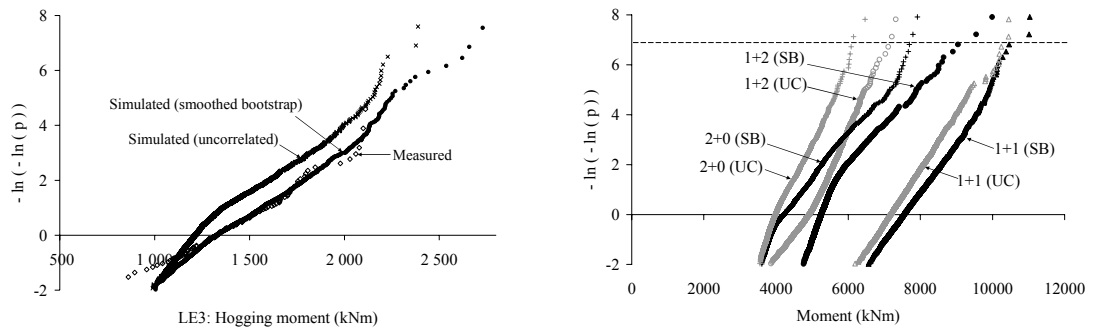
**Figure 4** – Kernel bandwidth

## 4 Results

To assess the effects of correlation, an uncorrelated simulation model was also developed in which GVWs, slow-lane gaps, inter-lane gaps, and speeds are drawn independently for each truck from the observed distributions. In order to compare the simulation models, comparison is made between bridge loading by measured traffic and by simulated traffic on bridges of different lengths – 15, 25, 35 and 45 m. Daily maximum values are calculated for each loading event type for three load effects – mid span bending moment on a simply supported bridge (LE1), support shear at the entrance to a simply supported bridge (LE2), and for bridges which are 35 m or longer, hogging moment over the central support of a two span continuous bridge (LE3). Loading events are classified according to the number of trucks present in each lane on the bridge when a maximum load effect occurs.

For comparison purposes, the two simulation models – smoothed bootstrap and uncorrelated – were run for 2000 days, and the simulated and measured results plotted

on Gumbel paper. An example is shown in Figure 5(a) for events with one truck in each lane on a 35 m bridge in the Netherlands, and this illustrates that the smoothed bootstrap gives a significantly better fit to the measured data. An analysis of all spans, load effects and event types described above shows that in general the smoothed bootstrap gives a better fit to the measured data for multi-truck events. For one-truck events, both methods perform equally well.



(a) Goodness of fit

(b) Lifetime loading – 35 m bridge, Czech Republic

**Figure 5** – Daily and annual maximum load effects – Smoothed bootstrap (SB) vs. uncorrelated (UC) models

To see what effect the different modelling assumptions have on the characteristic maximum loading, both methods were used to simulate 2500 years of traffic. In the Eurocode for bridge loading (EC1 2003), the value with a 5% probability of exceedance in 50 years is specified for design which is approximately the value with a return period of 1000 years. Sample results are plotted in Figure 5(b) which shows simulated annual maxima on a 35 m bridge in the Czech Republic with high lateral distribution. Three event types are shown –one truck in each lane (1+1), two trucks in the slow lane (2+0), and one truck in the slow lane with two trucks in the fast lane (1+2). For single-truck events (not shown), both models give the same results, but for events involving two or more trucks there are significant differences between the two simulation models, with the smoothed bootstrap method giving more conservative results than the uncorrelated model. The increases in characteristic maximum load effects due to correlation in models were calculated for the four spans and three load effects considered at the sites in the Netherlands and the Czech Republic. Correlation effects were found to account for an increase in 1000-year loading of up to nearly 8%, with typical values of around 5%, particularly when lateral distribution is high. Confidence intervals estimated using a parametric bootstrap indicate that these differences are statistically significant.

## 5 Conclusions

There are subtle patterns of correlation evident in measured traffic data. This interdependence between weights, speeds and inter-vehicle gaps for adjacent trucks affects the estimation of lifetime maximum bridge loading. A multi-dimensional smoothed bootstrap approach is presented here which re-samples observed traffic scenarios and uses kernel functions to introduce additional variation. The traffic scenarios are defined so as to capture patterns that may be significant for bridge loading, and to maximise variability in the simulation. The method is relatively simple to implement for any new site, and could be extended to three or more lanes. It is effectively the



same as sampling from empirical distributions (for GVW, gaps and speed), but with correlation and some additional smoothing and randomness. It potentially could be used to model congested or partly congested traffic, if sufficient data were available. The choice of bandwidth for the kernel smoothing functions is somewhat arbitrary, although results for characteristic bridge loading are, within reason, not too sensitive to this choice. The model presented provides a better fit to measured data across the range of key loading event types than is obtained with a model which does not include any correlation effects. The effects of correlation on characteristic maximum loading may be as high as 8% for the range of bridge spans considered.

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