



Title	Traffic Load Effect Forecasting for Bridges
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Publication date	2015-09-23
Publication information	Leahy, Cathal, Eugene J. O'Brien, and Alan O'Connor. "Traffic Load Effect Forecasting for Bridges." International Association for Bridge and Structural Engineering, September 23, 2015. https://doi.org/10.2749/222137815818358231 .
Conference details	IABSE Conference on Structural Engineering: Providing Solutions to Global Challenges, Geneva, Switzerland, 23-25 September 2015
Publisher	International Association for Bridge and Structural Engineering
Item record/more information	http://hdl.handle.net/10197/9247
Publisher's version (DOI)	10.2749/222137815818358231

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Traffic Load Effect Forecasting for Bridges

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Abstract

Traffic flows, as well as truck weights, increase with time. This must be taken into account in order to accurately assess traffic loading on bridges. The Eurocode Load Model 1 is used for the design of new bridges but a scaled down version of the model can be used for the assessment of existing bridges. This scaling is usually done by applying α -factors to the load model. The effect of traffic growth on these α -factors is assessed in this paper. Weigh-in-motion data from the Netherlands is used as the basis for traffic models which simulate year-on-year growth of both traffic flow and truck weights. A time-varying generalised extreme value distribution is then used to calculate the characteristic load effects and determine the α -factors. The effect of different traffic growth rates on these α -factors is then examined. It is found that an increase in truck weights has the most influence on the α -factors but that increased flow also has a significant effect.

Keywords: bridge; loading; traffic growth; simulation; Generalised Extreme Value distribution; Eurocode; load model 1.

1 Introduction

The Eurocode load model for normal traffic, Load Model 1 (LM1), is applicable for the design of new bridges [1]. A scaled down version of LM1 may be a suitable notional load model for the assessment of existing bridges and this scaling is generally done by applying α -factors to the original model. The Eurocode model can be scaled by estimating the characteristic maximum load effects and comparing the results to LM1.

Characteristic maximum load effects can be calculated in a number of ways. A popular approach is to use Weigh-In-Motion (WIM)

technology to measure the weight of trucks as they travel along a road in normal traffic. Extrapolation from this measured WIM data to estimate the characteristic lifetime bridge load effects is an established procedure and has been used in many studies, both for site-specific assessment [2,3] and for the development of bridge design codes [1,4]. One commonly-used approach is to extrapolate using a statistical distribution fitted directly to the measured data. The Normal distribution has often been used for extrapolation, with the measured data being plotted on Normal probability paper [4]. The Generalized Extreme Value (GEV) distribution has also been used by many authors, both for site-

specific assessment [2,3] and for the development of bridge design codes [1,4]. This family of distributions contains the Gumbel (type I), Fréchet (type II) and Weibull (type III) distributions. With this extreme value approach the distribution is fitted to block maxima, e.g., maximum daily or maximum weekly values. Other extrapolation approaches have also been used and the accuracy of different extrapolation approaches is compared in [5].

As an alternative to direct extrapolation from measured data, Monte Carlo simulation can be used [6,7]. This involves fitting suitable distributions to the various measured parameters— axle weights, axle spacings, inter-vehicle gaps, traffic flow rates, etc. These distributions may be parametric, semi-parametric, or empirical [8]. Characteristic values can then be extrapolated from a number of years of simulated traffic, or long-run simulations representing thousands of years of traffic can be used to avoid the need for extrapolation [6].

These previously mentioned studies [6–8] generally assume that the characteristics of the traffic (i.e. truck weights, number of axles, flow, etc) are stationary and that future traffic will have the same characteristics as the currently measured traffic. However, road freight transport in the European Union is expected to grow by about 1.8% until 2030 due to economic growth and an increased flow of freight traffic between member states [9]. This will likely result in an increase in both the weight and frequency of trucks. Consequently, in order to obtain an accurate estimate of maximum lifetime characteristic load effects, it is important to consider future traffic conditions.

This paper describes work which was performed as part of the Re-Gen research project (www.re-gen.net) to examine the effect of traffic growth on Eurocode alpha factors. The traffic modelling approach proposed by O'Brien et al. [10] is used to

predict the characteristic load effects on two-lane same-direction bridges while allowing for traffic growth. WIM data from a road in the Netherlands is used as the basis for the simulations.

2 WIM data

The WIM data used in this study was collected between February and June 2005 on the A12 near Woerden in the Netherlands. This data was used as it contained two-lane same-direction traffic with time stamp records to an accuracy of one hundredth of a second for each vehicle. This time stamp accuracy is required in order to accurately determine the exact relative location of trucks on the bridge [11].

It should be noted that there is very heavy loading at this site. It has a large average flow rate of 6600 trucks per day and recent studies, which compared this site to other sites in Europe, showed the loading to be significantly greater than at the other European locations [6,12]. As a result the alpha factors calculated for this site will not be typical of sites across Europe. However, it is believed that the increases in alpha factors with traffic growth should be comparable with other sites.

All WIM databases contain a certain amount of erroneous data. This data must be identified and removed before any meaningful analysis can be performed. Erroneous data can be as a result of gross errors while weighing certain individual trucks. However, it can also be as a result of calibration drift or loss of calibration of the system which affects all records over a certain period. The cause of individual errors is not always known but can sometimes be caused by a vehicle straddling two lanes or by a long vehicle being recorded as two separate vehicles. Rules based on those proposed by Enright and O'Brien [13] are used here to filter erroneous records. These rules examine the recorded axle spacings and weights to identify and remove suspicious configurations.

Once the erroneous records have been removed, the remaining truck records are then filtered to remove permit trucks. Permit trucks are removed from the WIM analysis as permits trucks are covered by Load Model 3 [1] which is outside the scope of this work. These trucks are removed using filtering rules proposed by Enright et al. [14].

In addition, the database includes weekends and bank holiday traffic which is significantly lighter in volume and average Gross Vehicle Weight (GVW), in comparison to normal weekday traffic. Due to these different statistical properties, the weekend and bank holiday data is removed so the analysis can be applied to a homogeneous dataset.

3 Methodology

3.1 Traffic Simulation Model

A Scenario Modelling approach [15] is used to perform long run traffic simulations of two-lane same-direction traffic. With two-lane same-direction traffic, there are many important correlations between truck weights and inter-truck spacing which influence the results. These correlations must be considered in order to accurately simulate the traffic. With the Scenario Modelling approach, the measured traffic from the WIM data is perturbed to create new traffic. The modelling approach is concerned only with the trucks in the WIM data; the cars are ignored as they are considered insignificant for loading on the bridge lengths considered here (15 – 40 m).

The measured data is divided into a series of scenarios which are then randomly selected and joined together to simulate a stream of traffic. During this process the selected scenarios are perturbed using a smoothed bootstrap approach to generate new traffic [15]. This approach varies the GVW, the in-lane gaps and the inter-lane headway – see Figure 1.

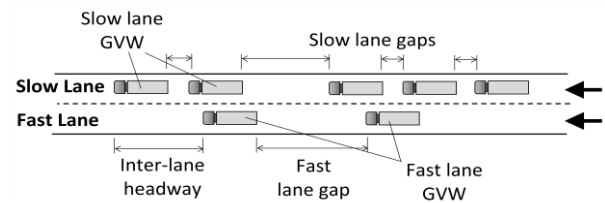


Figure 1. Sample scenario showing the properties which are varied in Scenario Modelling.

A 40-year simulation of traffic at the Netherlands WIM site is shown in Figure 2 with no traffic growth. The simulated maximum daily load effects for midspan bending moment on a 15-m bridge are plotted alongside those of the measured WIM data.

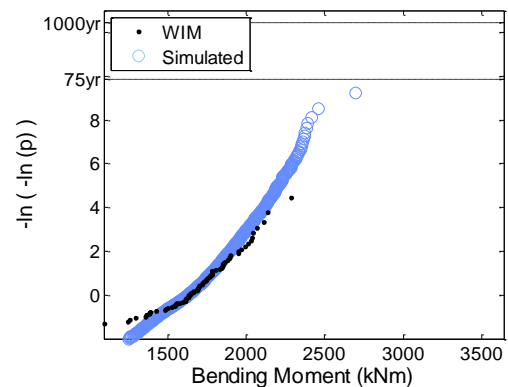


Figure 2. Maximum daily midspan bending on a 15m bridge for a 40 year traffic simulation with the corresponding values from the WIM data.

It can be seen that the simulated load effects are a good fit to those of the WIM data and that the trend in the measured data is effectively extrapolated beyond the measured data.

3.2 Modelling traffic growth

Increased freight transport can be divided into both a growth in flow and growth in the weights of trucks. As noted previously, an annual growth rate of 1.8% until 2030 has been predicted by the European Commission. This growth is likely to result in increases in both the frequency and weight of trucks. However, it is not known what proportion of each parameter will contribute to the total growth. As a result, a number of different

growth rates and combinations of growth rates are examined for the flow and weight of trucks – see Table 1.

Table 1. Growth Rates Examined.

		Annual Flow Growth		
		0%	1%	2%
Annual Weight Growth	0%	✓ ¹	✓	✓
	0.50%	✓	✓	✓
	1%	✓	✓	✓

¹ The reference dataset with which the cases with growth will be compared.

The increase in flow is modelled by assessing each hour of the day independently. This is done to preserve the variations in flow by time of day. This variation can be seen in Figure 3. Increased flow with time is modelled by first determining the flow associated with the hour of the day and the year being simulated. Scenarios are then randomly selected from scenarios with this flow rate. This results in a gradual increase in flow rate over the simulation period. The measured hourly flow is illustrated in Figure 3 along with the flow rate at the end of a 40-year simulation period with an annual traffic growth rate in flow of 2%.

Increases in the weight of trucks with time are also modelled. To realistically increase truck weights, the axle configurations must also change as it is not realistic as axle configurations are largely dependent on the load capacity, and hence weight, of the truck.

To increase truck weights, the measured traffic is separated into two tonne weight bands – see Figure 4. For each weight band, we have a distribution for the number of axles, with examples shown in Figure 5. It can be seen as the weight of the truck increases, the distribution for the number of axles changes.

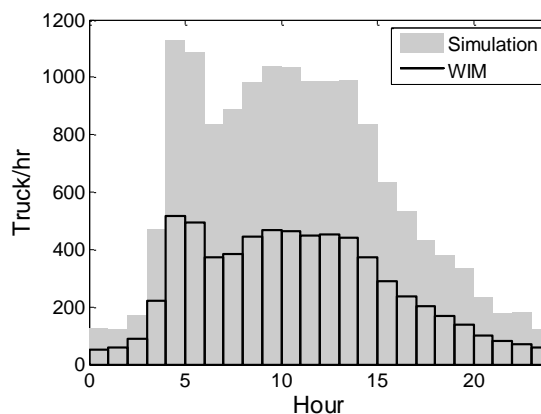


Figure 3. Flow variation at the WIM site and simulated flow rates at the end of 40 year simulation period with 2% yearly flow growth.

To increase the weight of a truck in a scenario, it is replaced with another truck randomly selected from the appropriate higher weight band. In general, the new truck will be expected to have the same or more axles than the truck it replaced.

In the simulation, measured trucks can only be replaced by heavier trucks from the WIM data up to a certain weight limit. Above a certain threshold there will not be any heavier trucks in the WIM data to randomly select to replace the measured truck – see right hand tail of

Figure 6. This is particularly relevant towards the end of the simulation period when large increases in truck weight may need to be simulated. As a result, it was decided that the random selection process for simulating heavier trucks would only be applied to trucks with a measured GVW of less than 50 t. This ensures that there is always a selection of heavier trucks to randomly select. Above 50 t, the original axle configuration is kept and the weights on the axles are increased to simulate growth in weights. However, it is not realistic to continue to increase the weight on an axle without imposing an upper limit. After examination of the trends in axle weights in the WIM data it was decided to impose an upper limit of 20 t above which the axle weights could not be increased.

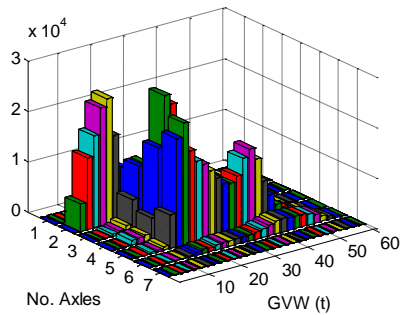


Figure 4. 3D histogram with the number of axles on the trucks in 2 t weight bands.

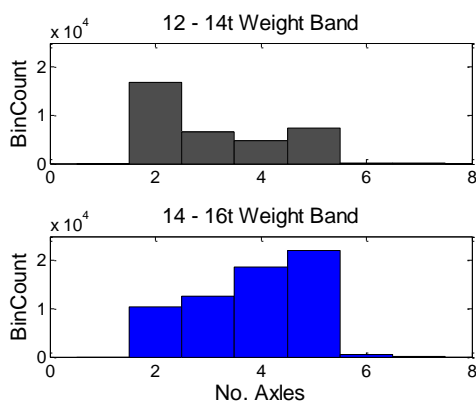


Figure 5. Histogram of the number of axles in the 14-16 t and 16-18 t weight bands.

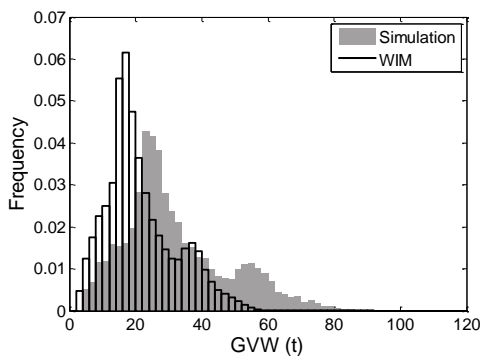


Figure 6. GVW histograms for the WIM data and for the simulated traffic at the end of the 40-year simulation period with 1.0% yearly growth.

It should be noted that there were a small number of measured axles which exceeded 20 t and these were allowed to remain in the data. Figure 7 shows a 40-year simulation with the maximum growth rate examined (annual increases of 2.0 % in flow and 1.0 % in weights). When compared

with the equivalent simulation with no growth in Figure 2, the effect of traffic growth in clear.

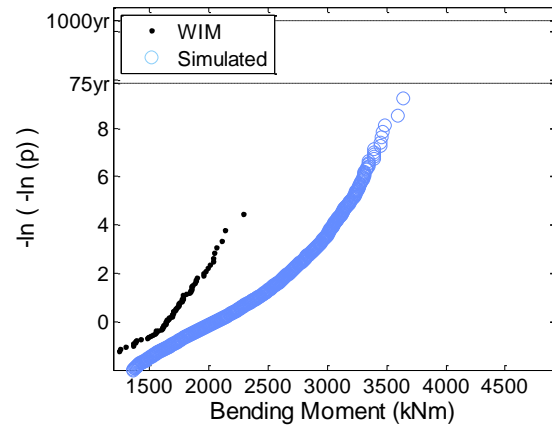


Figure 7. Maximum daily midspan bending on a 15m bridge for a 40-year traffic simulation with annual growth of 1% in weight and 2% in flow.

3.3 Influence Line Analysis

The simulated traffic is passed over influence lines to examine the following three load effects for bridge lengths of 15, 30 and 45 m:

- **LE1:** Midspan bending moment on a simply supported bridge.
- **LE2:** Shear at the support of a simply supported bridge.
- **LE3:** Negative bending moment over the central support of a two span continuous bridge.

It should be noted that for LE3, a 15 m two span (2 × 7.5 m) continuous bridges is not a common configuration and is not examined in this work.

When calculating load effects in two-lane same-direction traffic, each lane is analysed using a simple influence line. The transverse stiffness of the bridge is allowed for by using lane factors [6]. The primary lane contributes all of its calculated load effect whereas the contribution of the secondary lane is multiplied by a lane factor. The lane factors used are shown in Table 2 and are those which were found by Enright & OBrien

(2013) to represent stiff bridges where there is relatively large transverse distribution of load.

Table 2. Lane Factors for overtaking lane with high transverse stiffness.

Load Effect	Lane Factor
LE1: Mid-span bending moment, simply supported	1.0
LE2: Support shear, simply supported	0.45
LE3: Central support hogging moment, 2-span continuous	1.0

3.4 Non-Stationary GEV Method for Estimating Characteristic Load Effects

To account for traffic growth, OBrien et al. (2014) proposed the non-stationary GEV approach for estimating characteristic load effects. With this method, the parameters of the distribution are time dependent which allows the distribution to increase with traffic growth – see Figure 8.

To calculate the characteristic load effects for a bridge at the WIM site, a 40-year traffic simulation is performed for each annual growth rate for weight and flow. 40 years represents the remaining service life being assessed. The non-stationary GEV distribution is then fitted to the maximum 25-day load effects using maximum likelihood estimation. The 1000-year return period load effect can then be calculated. It is important to differentiate between the service life and return period. Service life is the period over which the traffic growth is occurring while return period is a level of safety.

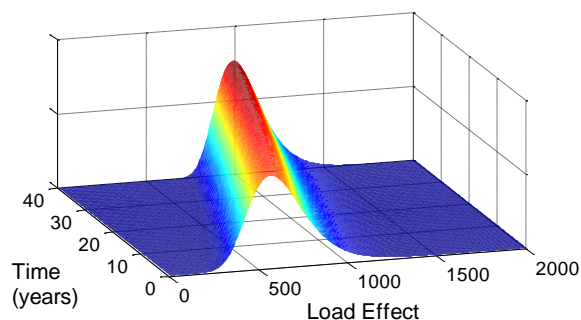
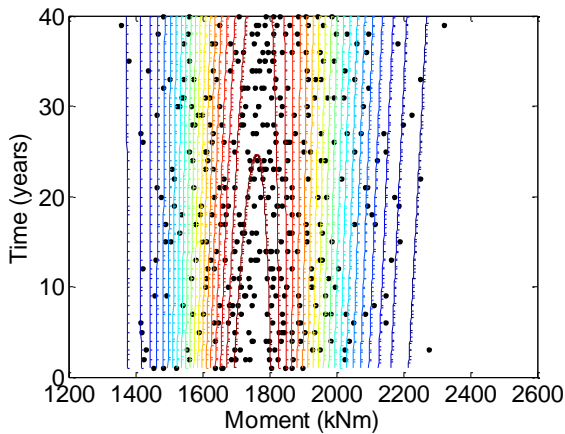


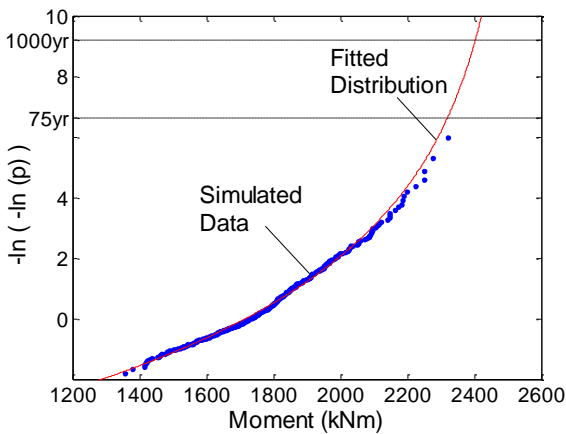
Figure 8. Non-stationary GEV distribution.

Figure 9 (a) shows the simulated maximum 25-day load effects increasing with time and a contour plot of the fitted non-stationary GEV distribution. Figure 9 (b) shows a Gumbel probability paper plot of the same data and the fitted distribution. The plot is effectively a cumulative distribution function (CDF) with the y-axis values plotted on a double log scale to allow the tail of the distribution to be easily examined. It shows that the fitted distribution is a good fit to the measured data and is effective in extrapolating the trend in the measured. It should be noted that Figure 9 plots the maximum 25-day load effects used in the analysis, unlike Figure 2 which shows maximum daily load effects.

A 1000-year return period was used in the calibration of the Eurocode LM1. This is predominantly used for the design of new bridges. For the assessment of existing bridges, the remaining service life is generally less than the design life and it may be more appropriate use a shorter return period, i.e., a lower level of safety. The 75-year return period is shown on some of the plots as an example of a smaller return period. A return period of 75 years is used in bridge design in the United States but a smaller return period can be used for assessment [16].



(a) Simulated data with contour plot of fitted distribution.



(b) Probability paper plot.

Figure 9. Non-stationary GEV distribution fitted to 25-day maximum load effects for a IL3 on a 30-m bridge for a 40-year simulation with 1% flow and 1% weight growth.

3.5 Determining α -Factors

The simulated 1000-year load effects are compared with those given by the basic Eurocode Load Model 1 [1]. This ratio is referred to here as the α -factor and is given in Equation (1).

$$\alpha \text{ factor} = \frac{\text{Simulated 1000yr load effect}}{\text{Basic LM1 load effect}} \quad (1)$$

4 Results

Table 3 shows the α -factors for the simulations with no traffic growth.

Table 3. α -factors with no traffic growth.

Bridge Length (m)	IL 1	IL 2	IL 3
15	0.58	0.66	n/a
30	0.61	0.67	0.60
45	0.57	0.60	0.54

Table 4 shows the increase in the α -factor for the simulation with maximum annual growth (2.0% flow growth and 1.0% weight growth). This produced an average increase in alpha-factor of 48% with a maximum increase of 64% occurring for hogging moment on a 45-m bridge. Hogging moment appears to be the most sensitive of the load effects to traffic growth.

It can also be seen that greater increases are evident for the longer bridge lengths. This is likely due to multiple truck presence events being more critical on longer spans. Increases in flow will have more influence on these events than on the single truck loading events which tend to govern for short bridge lengths.

Table 4. Percentage increase in α -factor with 2% flow + 1% weight annual traffic growth.

Bridge Length (m)	IL 1	IL 2	IL 3
15	36	45	n/a
30	44	49	52
45	46	49	64

Shear at the support (IL2), varies less than the other load effects with bridge length. IL2 has a lower lane factor as only a small proportion of the load in one lane causes shear at the support of the adjacent lane. The critical event in that case is more likely caused by a single truck loading event rather than side-by-side events. As a result, shear may be more dependent on individual axle

weights rather than growth in overall vehicle weight.

As axle weights were not allowed to increase above 20 t during simulation, there is an upper limit to axle weights but not to gross weight. This could explain the reduced influence of growth on shear (IL2). Table 5 shows the average increase in alpha factor across all influence lines examined for each combinations of growth rate examined.

Table 5. Average alpha factor increase for each combination of growth.

		Annual Flow Growth		
		0%	1%	2%
Annual Weight Growth	0%	-	6%	9%
	0.5%	19%	27%	31%
	1%	43%	51%	48%

It should be noted that there is a certain degree of random variation in simulations such as these which are based on random number generation. This is apparent in Table 5 where for the results for an annual weight growth rate of 1% where the result for 1% growth in flow (51%) is greater than for 2% growth in flow (48%). Ideally, the simulations would be repeated a number of times to average out this random variation but this is not feasible in this case as the simulations are quite time consuming. To simulate each combination of weight and flow growth, an overnight simulation is required.

5 Conclusions

As freight traffic is expected to grow significantly until at least 2030, traffic growth needs to be allowed for when modelling traffic loading on bridges. A scenario modelling traffic simulation approach is used to model traffic growth in data measured at a Netherlands WIM site. A time-varying GEV distribution is fitted to the simulation results in order to determine characteristic load effects and corresponding α -factors. Different

traffic growth rates are assumed over a 40-year service life.

The results show that growth significantly affects the α -factors for all bridge lengths and influence lines examined. Growth in weight has a much more significant effect than growth in flow, with a 1% annual growth in flow causing an average increase in α -factors of 6% over the 40-year service life. In comparison, a 1% annual growth in truck weight results in an increase in α -factors of 43%.

The results highlight the need to consider traffic growth when assessing site-specific traffic loading on an existing bridge. It also identifies the need for road owners to consider traffic growth when developing traffic load models for bridge design/assessment.

6 Acknowledgements

The research presented in this paper was carried out as part of the CEDR Transnational Road Research Programme Call 2013. The funding for the research was provided by the national road administrations of Denmark, Germany, Ireland, Netherlands, UK and Slovenia. The Ministry of Infrastructure and the Environment of the Netherlands (Rijkswaterstaat) are gratefully acknowledged for providing the WIM data used.

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