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The Effect of Traffic Growth on Characteristic Bridge Load Effects

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Abstract

Freight traffic in the European Union is increasing with time. This paper describes a method for considering this growth when assessing traffic loading on bridges and examines the effect of this growth on characteristic load effects. The Eurocode Load Model 1 is used for the design of new bridges. As this model can be overly conservative for the assessment of existing bridges, a scaled down version can be used by applying α–factors to the load model. This is usually done by modelling the traffic loading on the bridge using site-specific weigh-in-motion data and calculating the α–factors in accordance with the results. In this paper, weigh-in-motion data from a site in the Netherlands is used to demonstrate the proposed approach. 40-year simulations of traffic loading are performed on various bridges. The simulations consider year-on-year growth in both the volume and weight of trucks. Time-varying generalized extreme value distributions are then fitted to the simulated data and used to calculate the characteristic load effects. The results are then compared with the load effects generated by Load Model 1 in order to calculate the associated α–factors. It is found that an increase in truck weights has the most significant 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.

Nomenclature

GEV	generalised extreme value
GVW	gross vehicle weight
IL	influence line
LE	load effect
LM1	(Eurocode) load model 1
WIM	weigh-in-motion

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1. Introduction

The Eurocode load model for normal traffic, Load Model 1 (LM1), is applicable for the design of new bridges (EC1, 2009). 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 vehicles 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 (Getachew and OBrien, 2007; Miao and Chan, 2002) and for the development of bridge design codes (EC1, 2009; Nowak, 1993). 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 (Nowak, 1993) . The Generalized Extreme Value (GEV) distribution has also been used by many authors, both for site-specific assessment (Getachew and OBrien, 2007; Miao and Chan, 2002) and for the development of bridge design codes (EC1, 2009; Nowak, 1993). 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 (OBrien et al., 2015).

As an alternative to direct extrapolation from measured data, Monte Carlo simulation can be used (Enright and OBrien, 2013; OBrien et al., 2013). 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 (OBrien et al., 2010). 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 (Enright and OBrien, 2013).

These previously mentioned studies (Enright and OBrien, 2013; OBrien et al., 2013, 2010) 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 (Capros et al., 2008). This will likely result in an increase in the frequency of trucks but also the weight of these trucks, although the latter is hard to predict as it is somewhat restricted by legal weight limits. 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 for Deliverable 3.2 (Leahy et al., 2015) 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 OBrien et al. (2014) 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 (Žnidarič et al., 2015).

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 (Enright and OBrien, 2013; OBrien and Enright, 2012). 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 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 OBrien (2011) 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 (EC1, 2009) which is outside the scope of this work. These trucks are removed using filtering rules proposed by Enright et al. (2015).

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 (OBrien and Enright, 2011) 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 (OBrien and Enright, 2011). This approach varies the GVW, the in-lane gaps and the inter-lane headway – see Figure 1.

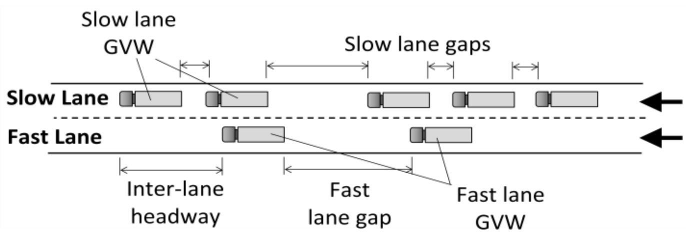


Figure 1. Sample scenario showing the properties which are varied in Scenario Modelling.

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 hogging moment over the central support of two-span continuous bridge are plotted alongside those of the measured 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.

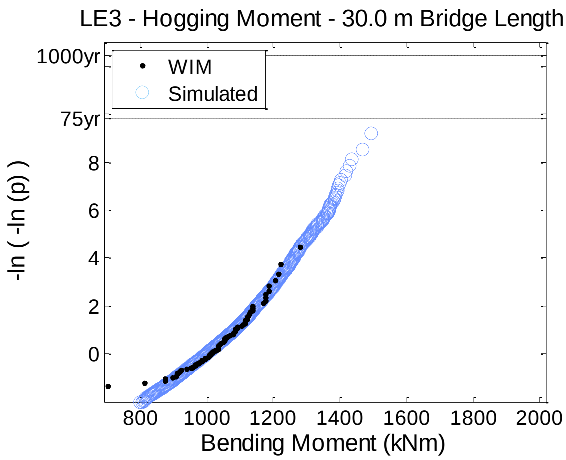


Figure 2. Maximum daily hogging moment over the central support on a 30 m (2 × 15m) bridge for a 40 year traffic simulation with the corresponding values from the WIM data.

3.2. Modelling traffic growth

Increased freight transport can be divided into both 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. 1% annual growth in truck weights is examined but is unlikely to occur without significant changes in legislation for allowable axle configuration and axle weights. Nevertheless, it is examined here for illustration purposes. The increases in the flow of trucks are more likely to represent the true situation.

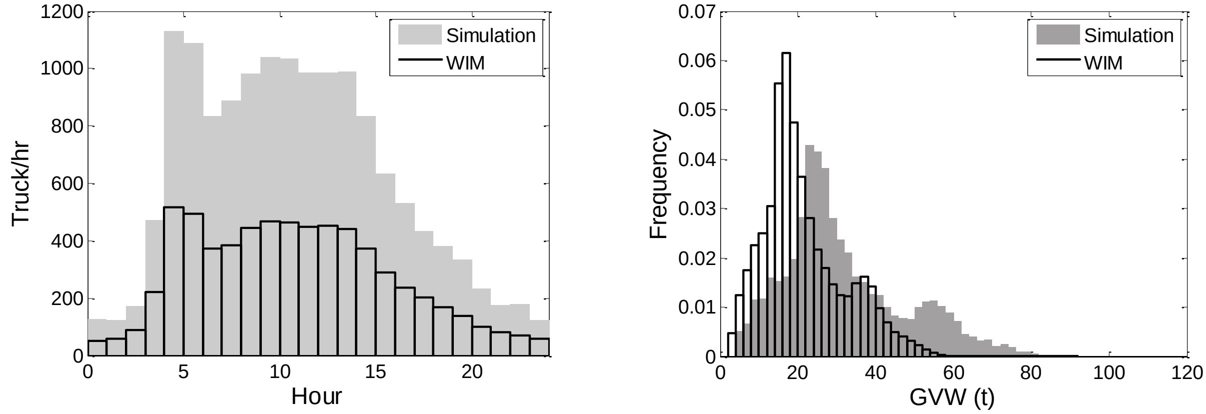
Table 1. Growth Rates Examined.

		Annual Flow Growth		
		0%	1%	2%
Annual Weight Growth	0%	✓[1]	✓	✓
	0.5%	✓	✓	✓
	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(a). 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 all the measured 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(a) 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 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. To increase the weight of a truck in a scenario, it is replaced with another truck randomly selected from the appropriate higher weight band.



(a) Flow at the WIM site and at the end of the simulation.

(b) GVW histograms for the WIM data and for the simulated traffic at the end of the simulation.

Figure 3. Traffic characteristics at the WIM site and at the end of a 40 year simulation period with 2% yearly flow growth and 1.0% yearly GVW growth.

In general, the new truck will be expected to have the same or more axles than the truck it replaced. This allows weight increases to be simulated by replacing lighter trucks with heavier trucks that have been measured in the current traffic.

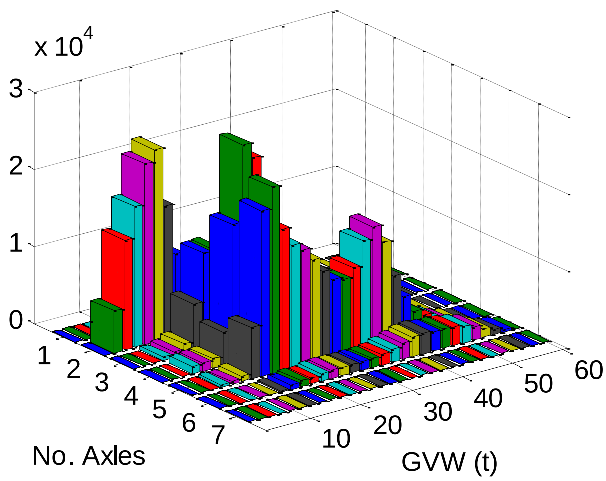


Figure 4. 3D histogram with the number of axles on the trucks in 2 t weight bands.

In the simulation, measured trucks can only be replaced by heavier trucks from the WIM data up to a certain GVW 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 3(b). 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.

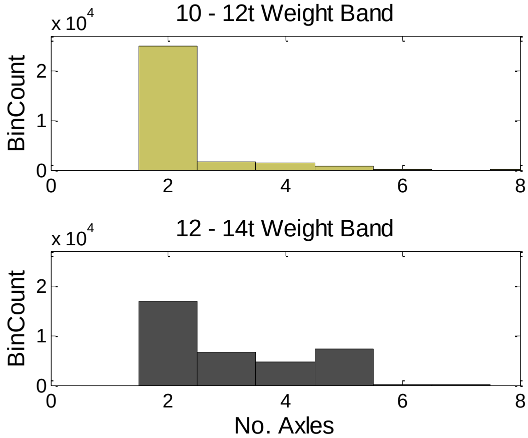


Figure 5. Histogram of the number of axles in the 10-12 t and 12-14 t weight bands.

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. 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.

It is acknowledged that this approach for increasing the weight of trucks over 50 t is not ideal as it is increasing axle weights which are governed by legal limits. Such increases are unlikely to occur without future changes to legislation. This assumption needs to be considered when reviewing the results of the simulations.

Figure 6 shows a 40 year simulation with the maximum growth rate examined (annual increases of 2.0 % in flow and 1.0 % in weight). When compared with the equivalent simulation with no growth in Figure 2, the effect of traffic growth in clear.

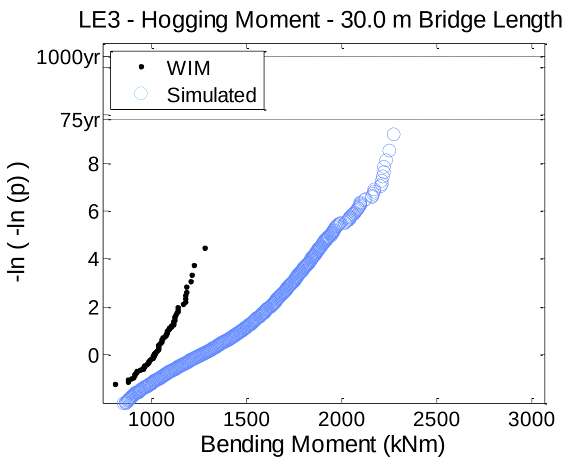


Figure 6. Maximum daily hogging moment over the central support on a 30 m (2 × 15m) bridge for a 40-year traffic simulation with annual growth of 1% in weight and 2% in flow.

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 analyzed using a simple influence line. The transverse stiffness of the bridge is allowed for by using lane factors (Enright and OBrien, 2013). 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 7.

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.

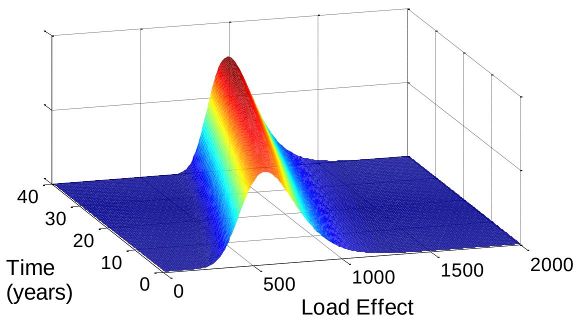
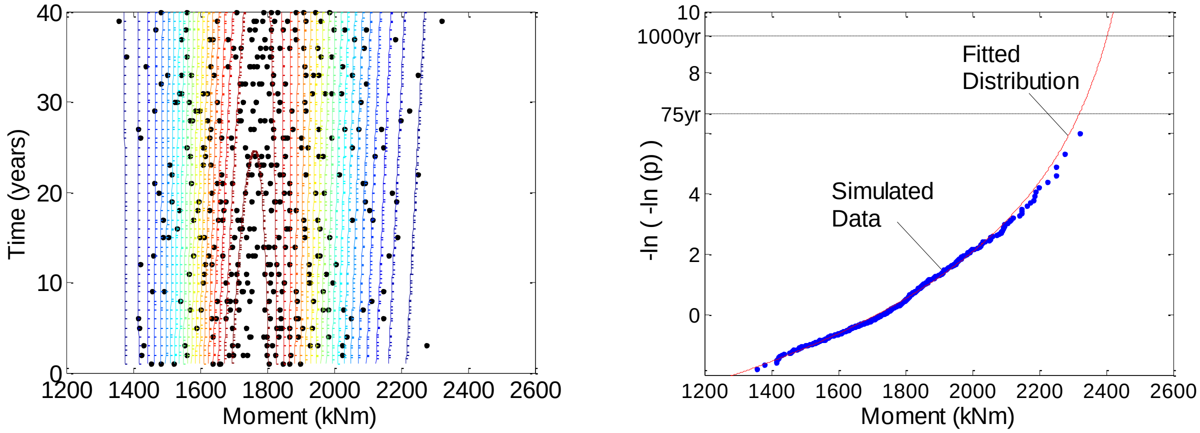


Figure 7. Non-stationary GEV distribution.

Figure 8 (a) shows the simulated maximum 25-day load effects increasing with time and a contour plot of the fitted non-stationary GEV distribution. Figure 8 (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 8 plots the maximum 25-day load effects used in the analysis, unlike Figure 2 which shows maximum daily load effects.



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

Figure 8. 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.

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 (Minervino et al., 2003).

3.5. Determining α-Factors

The simulated 1000-year load effects are compared with those given by the basic Eurocode Load Model 1 (EC1, 2009) . This ratio is referred to here as the α-factor and is given in Equation (1).

$$\alpha\ factor = \frac{Simulated\ 1000yr\ load\ effect}{Basic\ LM1\ load\ effect} \tag{1}$$

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.

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 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

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 with the results for an annual weight growth rate of 1%. 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 growth in traffic data measured at a Netherlands WIM site. A time-varying GEV distribution is fitted to the simulation data in order to determine characteristic load effects and corresponding α–factors. Different annual growth rates of truck volumes and weight 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 a 40-year service life. In comparison, a 1% annual growth in truck weight results in an increase in α–factors of 43%. Although growth in truck weights results in much higher increases in α–factors, it should be considered that such growth is restricted by legislation and most growth is likely to occur in the frequency of trucks. Consequently, the results are sensitive to the assumptions used for growth in weight. It should also be noted that the Netherlands experiences very heavy loading compared with other European countries and therefore the results presented here may not be applicable to all European traffic. However, it is believed that the results are indicative of the general trend.

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.

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