Probabilistic traffic load model for short-span city bridges

L. Hellebrandt [1], C.B.M. Blom [2,3], R.D.J.M. Steenbergen [1,4]

[1] TNO, Structural Reliability, Delft, the Netherlands

[2] TU Delft, Concrete Structures, Delft, the Netherlands

[3] Ingenieursbureau Rotterdam, Rotterdam, the Netherlands

[4] Ghent University, Department of Structural Engineering, Ghent, Belgium

In the coming years numerous existing traffic bridges in cities are subject to re-evaluation. In this paper a new probabilistic traffic load model for short-span bridges is proposed. As an example, site-specific weigh-in-motion data from Rotterdam, the Netherlands, is included in the model. The method proposed in this paper allows for a very efficient computation and at the same time takes into account the stochastics in axle loads and distances. For a simply supported 6 m single lane bridge the probabilistic load model provides a design load effect that is slightly lower than currently prescribed EN 1991-2 and the Dutch Guidelines for existing structures NEN 8700 and NEN 8701. This indicates that there is possible potential for a small reduction of the traffic load for short-span city bridges compared to the current standards. However, given the questionable quality of recorded measurements, a more extensive measurement campaign using WIM measurements is needed to get an adequate quantification of the traffic load parameters for city traffic conditions.

Key words: traffic load, probabilistic, weigh-in-motion (WIM), short-span bridge

1 Introduction

Several countries face the problem of aging infrastructure assets. Due to increasing weight of commercial vehicles and density of traffic in the last decades, the reliability level of bridges and viaducts may drop below the required target. This holds especially for municipalities where the load used in the design of the bridges may have been based on a lower load class than for bridges in the highway network. Since most bridges in urban areas are rather small, the focus in this paper is on short span bridges. Traffic load models, used for both design and re-evaluation of bridges according to European standards, are based on measurements on highways in the 1980's [Sedlacek *et al.*, 2008] and in the case of for example The Netherlands also calibrated to recent measurements on Dutch highways.[Steenbergen, Morales-Nápoles, & Vrouwenvelder, 2012]. The question arises whether these load models are representative for inner city areas. Traffic load data obtained by weigh-in-motion (WIM) measurements has been a typical and accepted method of assessing traffic loading in the past decades, however a correct calibration of the measurement system is required.

In this paper we focus on load effects in the ultimate limit state (ULS). In this case, the load parameter of interest for evaluation of the structural reliability is the maximum load effect for a certain reference period. We will therefore search for the statistical distribution of this load effect, which can be either directly included in a full probabilistic analysis, or can serve as input for determining a design load in a semi-probabilistic calculation.

Traffic load models based on WIM data have been developed and used in the past, for example by Enright [2010], Steenbergen, Morales-Nápoles, & Vrouwenvelder [2012] and Kozikowski [2009]. A both practical and sufficiently accurate method to interpret WIM data for short-span bridges is currently not available.

In a "traditional" approach load effects, such as bending moment or shear force, are directly calculated based on the measured traffic data, for example by evaluating the load effects under the measured "stream" of traffic (using the axle loads, axle distances, vehicle distances as registered). Hereafter, block maxima values of the resulting load effects are gathered. As measurement campaigns are limited to a few months or maximum one year, this set of values usually consists of daily or weekly maxima, based on which a statistical distribution for the daily (or weekly) maximum can be determined. To calculate characteristic values of the load effect for the reference period of several years, one must extrapolate from these daily or weekly extreme value distributions. This extrapolation requires assumptions and although the extreme load effect can be determined, the loading scenario (i.e. the parameters of the "extreme" vehicle or vehicles and their location on the bridge) expected to cause this most extreme load effects cannot be identified.

A second approach, adapted by Enright & O'Brien [2013], [O'Brien *et al.*, 2012] is a long-run traffic simulation model, which eliminates the need of extrapolation. The simulation is carried out based on probability distributions fitted to relevant parameters of WIM data, such as axle distances, axle weights, vehicle distances. There are several methods proposed for the statistical description of the vehicle parameters. An overview of related literature is given for example by Enright & O'Brien [2013]. Correlations between relevant parameters of a vehicle are modelled as well. Traffic is then generated using Monte Carlo simulation for several thousands of years. Based on the simulated traffic flow, load effects are calculated and, as the simulation is long-run, a set of values of the maximum load effect for a reference period (e.g. 50 years) can be determined. This can be used for calibrating design loads or as a direct input to a full probabilistic analysis. In the above mentioned research, 1000 years of traffic has been simulated.

The second approach of traffic loading analysis described above [Enright & O'Brien, 2013] has the advantage that the typical loading scenarios causing the extreme load effect(s) can be identified. However, a major disadvantage of this approach, when considering application for a site-specific load model on short-span city bridges, is the complex correlation structure which has to be set up in order to simulate traffic. Furthermore, the procedure necessary to set up this load model is very time-consuming. Besides, detailed modelling of vehicle distances and traffic flows is not expected to significantly increase the accuracy of load effect calculation on short-span inner-city bridges. It is therefore interesting to search for a more practical and fast way to describe local traffic loading conditions using WIM data.

According to the code for existing structures in The Netherlands, NEN 8700, a minimum reference period of 15 years should be used. The background is described in [Steenbergen & Vrouwenvelder, 2010]. The remaining service life is chosen by the owner, the municipality, in this case for existing bridges this is also 15 years. For inner city bridges of EN 1990 Consequence Class 2, the required reliability for the life time in NEN 8700 is β = 2.5; this corresponds to a maximum allowed failure probability of 6 10-3 in the remaining life time. The use of this β = 2.5 is still under discussion, but here it is chosen as a typical example. These values, compared for example to a new design by Eurocode (50 or 100 years reference period with larger reliability indices), are advantageous when looking for the design values of a load, as the corresponding maximum exceedance probabilities are relatively low. There is therefore potential for applying a traffic simulation model.
In this paper we propose a novel traffic load model for short-span city bridges . This approach, similarly to that of Enright & O'Brien [2013], has the advantage that several hundred years of traffic can be simulated in a relatively short time, avoiding the need to extrapolate daily or weekly maximum distributions.

In this paper, we first give an overview of the relevant attributes of traffic for bridge loading in the ultimate limit state and present the proposed traffic simulation model in Section 2. In Section 3 we elaborate on the traffic simulation and the process of determining load effects (i.e. bending moment), derived from the previously simulated traffic. Herein, a load-effect maxima distribution is determined for the reference period. In Section 4, load effects based on the standard Eurocode load model (LM 1) are compared to those determined from the probabilistic traffic load model. A summary and conclusions are provided in Section 5. The traffic load model is illustrated on calculations for a 6 m span beam.

2 Traffic load model

2.1 Weigh-in-motion data

The WIM database used in this research was collected in the city of Rotterdam. Expecting that traffic loads in the city are lower than on highways, the Municipality of Rotterdam initiated a measurement campaign to determine traffic loading on its local bridges. In typical WIM systems today piezo-electric sensors are applied, which are based on the principle of converting stress or strain to proportionate electrical energy. In this measurement campaign a WIM HESTIA measurement system was used, which is capable of determining speed, vehicle length, inter-axle distance, axle weight and gross vehicle weight (GVW). For each passing axle two measurements are registered.

Two relatively heavily loaded (maximum allowed GVW: 80 tons) locations within the city (local road) were chosen, where WIM systems were installed in 2013. The first location was on a descending road directly before traffic lights; the decelerating vehicles distorted the measurements greatly because of the sensitivity of the measurement system for horizontal forces. The second location also suffered from accelerating and braking vehicles. For this reason data from only the second locations was taken into account; also there the calibration of the WIM measurements was questionable but the values were considered to be conservative. The campaign resulted in a database of heavy vehicles corresponding to two months of traffic. A heavy vehicle is defined as a vehicle with a GVW of 3.5 tons or higher. Vehicles with a lower weight are expected not to significantly contribute to the extreme loading situations on the bridge, therefore they are not considered in the data analysis. After pre-processing measurement data, information of 48 586 heavy vehicles, corresponding to two months of measurements, was used.

The same number of vehicles per unit time is used for the traffic load model developed in this paper, corresponding to about 300 000 heavy (> 3.5 tons) vehicles per year.
Figure 1 and 2 give the distribution functions of axle and vehicle weight. In these Figures also the values from the Dutch highway RW16-L from April 2008 are plotted since these were used for the calibration of the National Annex of EN-1991-1-4. However this calibration was not done for short spans and only for spans of 20 m, 50 m, 100 m and 200 m.

2.2 *Approach for traffic load modelling*

The first of two main aspects within the traffic load modelling is to describe a sequence of heavy vehicles, each characterised by axle loads and axle distances. The second is to determine life-time maxima load effects caused by the sequence of the previously simulated vehicles on a given structure. In the following, we describe this method briefly, while in Section 1 the various steps of the process are discussed in detail.
We restrict ourselves to a one-lane bridge or a main girder of a bridge affected by traffic load in one direction. The most relevant principle behind the proposed model is that the governing load effect on a short-span bridge will result from one single heavy-weight

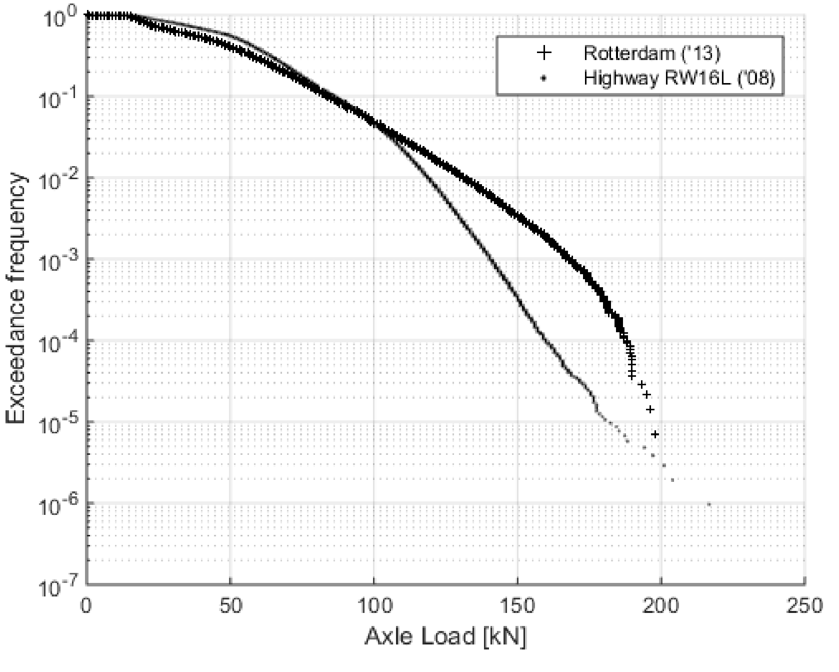

Figure 1. Axle load distributions in Rotterdam and RW16-L

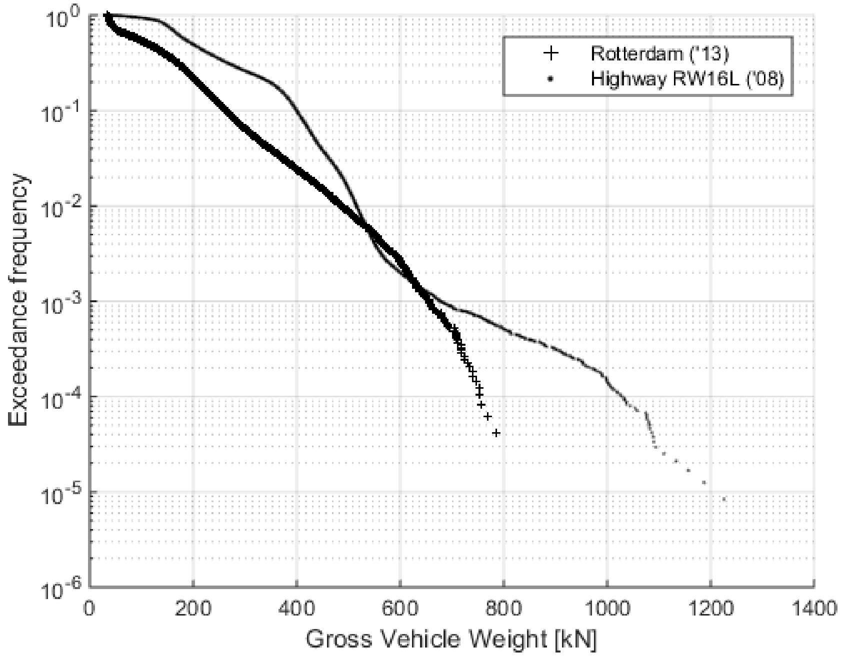

Figure 2. Vehicle load distributions in Rotterdam and RW16-L

vehicle on the bridge since the bridge (order of magnitude 6-10 m) is small with respect to one truck. As a result, the "sequence" (i.e. order) of vehicles, as well as the inter-vehicle distance can be neglected and the modelling consists of individual heavy vehicles that may pass over the bridge in the reference period.

The basis of the traffic simulation is the data obtained from WIM measurements. With help of this data, relevant truck properties can be described by random variables. Similarly to other traffic load models, such as that of Caprani [2005], the main strategy is to use *vehicle categories*, which we define here by the number of axles. Data analysis and simulation will be carried out within these vehicle categories. We assume that the ratio of various vehicle categories in the traffic stays constant in the reference period.

In the proposed method, vehicles with a GWV possibly higher than the recorded values (2 months) will be simulated, while it is assumed that (significantly) different axle configurations than registered in the measurement period will not appear. The 4-step process is described in the following.

1. The GVW within each category is described using a Gaussian mixture distribution, fitted to the measured data. Within each vehicle category (based on

number of axles), vehicle weights are simulated based on the distribution fitted to the measured GVW datasets.

2. We define the *vehicle property* (1), which represents the ordered distance of axles and the ratio of the gross vehicle weight carried on each axle.

$$R_{n,i} = [d_1, d_2, ...d_{n-1}, a_1, a_2, ...a_n] , \tag{1}$$

where n is the vehicle category; i is the index of the registered WIM measurement; d_j is the axle distance between axles j and j+1 and a_j is the *relative load* on axle j. The relative load is defined as that fraction of the total weight that is carried by the axle under consideration. Vehicle properties can directly be determined from WIM measurements. Vehicle properties are sampled randomly from the empirical data and "coupled" to the simulated vehicle weights. This process is carried out separately for vehicle categories.

3. After having obtained a set of vehicles within each vehicle category, we determine and analyse the maximum load effects. In case of using a linear model to describe the relation between load and load effect, we can simplify the process of determining a large number of load effects by calculating the maximum load effect in an arbitrary cross section of a bridge for each vehicle property. The load effect caused by a simulated vehicle can then be obtained as described in (2).

$$LE_{sim,Ri} = \frac{GVW_{sim}}{GVW_{unit,Ri}} LE_{Ri} \tag{2}$$

Here $LE_{sim,Ri}$ is the load effect from a simulated truck; LE_{Ri} is the load effect from a unit-weight truck with the vehicle property Ri; GVW_{sim} is the simulated GVW and $GVW_{unit,Ri}$ is the unit GVW.
The principle behind the load-effect simulation is that it is sufficient to know only the GVW and property index of each simulated vehicle and the load effect caused by unit weight trucks of all possible vehicle properties. Instead of calculating a load effect caused by each passing vehicle, significant reduction in the necessary computation time is reached by doing this only for the measured vehicle properties and then 'scaling' the result with the vehicle weight.

4. Finally, to determine the reliability of a structure for the (remaining) service life, the extreme (maximum) value of the load effect within the reference period

should be known. This value is a stochastic quantity itself. With the help of long-run simulations, multiple extreme values for a reference period can be found. Based on these results, the load effect maximum can be approximated by a statistical (extreme value type) distribution.

The resulting extreme value distribution of the life-time maxima load effect can be used to determine design values of the load or to carry out a level II or III reliability analysis on the cross section.

3 Traffic- and load effect simulation

3.1 ***Simulating vehicle weights***

As basis for the Monte Carlo simulation is it chosen to group vehicles with identical number of axles in one category, defined in 2.2. Per category an analytical distribution function is fitted to the empirical distribution function of the GVW and from that analytical distribution function the GVW is sampled in the Monte Carlo simulation. In the past, statistical distributions of measured GVW-s have been described by bi- or tri-modal normal distributions, for example when calibrating the Eurocodes [Sedlacek *et al*., 2008]. To each category of GVW data multi-modal normal distributions are fitted using the built-in function of MatLab® '*fitgmdist*', the number of components varying between four and ten.

Vehicles with a number of axles above 8 were not included in the model, because only a few of these were recorded, therefore a distribution fit to the GVW-s in these categories could not be done. We investigate whether this may introduce a significant error in the extreme load effect prediction. The heaviest vehicles measured were not the ones with the highest axle number (9, 11 axles). This influence is depicted in Figure 3, where exceedance probability diagrams are plotted for the GVW of all vehicles, based on Gaussian mixture distribution fits. The continuous line is based on measurements of up to 8 axles, while the dashed line corresponds to the total measured population, thus including a few 9 and 11-axle vehicles as well. It can be seen that the influence of these measurements is negligibly small.

3.2 ***Determining axle loads***

Besides the GVW, the axle loads and position of axles have a significant influence on extreme load effects especially for short bridges. For the load effect, here we choose the

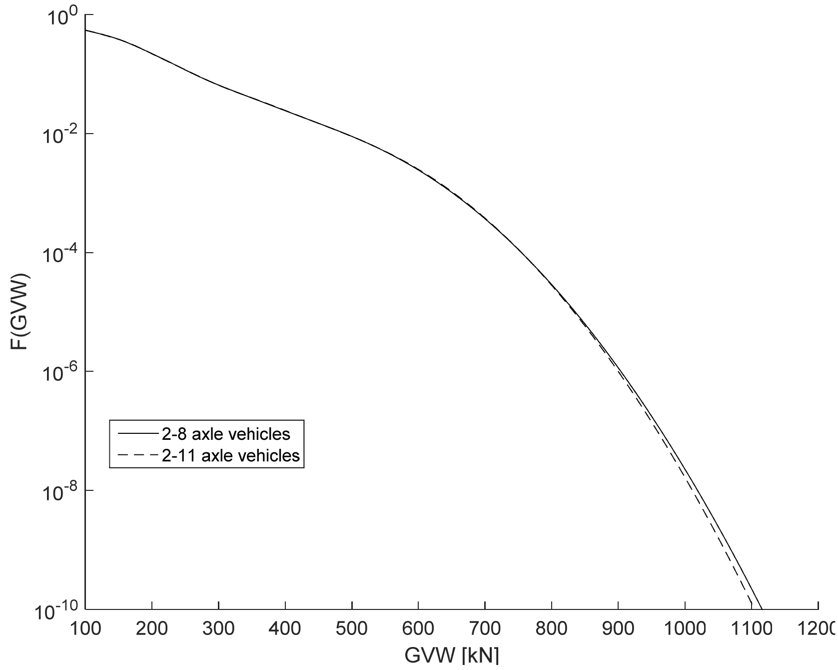

Figure 3. Exceedance probability of GVW based on statistical distribution of all measurements

bending moment in the middle of a simply supported short span beam.

It is assumed that the ratio of vehicles with a certain number of axles is and will remain constant for the reference period. Furthermore, it is assumed that the recorded vehicle types give a good description of the expected traffic in the reference period with respect to axle distances and weight distribution among the axles.

It is assumed that the WIM measurements record all vehicle properties that will appear in the reference period of the load with a sufficient precision, i.e. no vehicles with significantly different axle composition or distribution of total weight over the axles will occur. It should be taken into account that the closer two axles are, the larger the correlation is between the magnitude of the load on these axles [Enright, 2010]. By adopting vehicle properties, this aspect is accounted for, in a simplified way.

The output of a typical traffic simulation model, which will serve for determining load effects on a bridge, is a set of heavy vehicles described by axle loads and distances. As described in the introduction section, it can be reasonably assumed that on a short bridge (with a span of up to 20 m) of one traffic lane, the inter-vehicle distance will not play a significant role in the loading for the ultimate limit state. The output of the traffic simulation proposed for short bridges is therefore a "matrix" of heavy vehicles, described by their axle loads. To determine the load effects caused by the vehicles, it is sufficient to consider only the vehicle weight and "property index" of each simulated vehicle. The relevance of this step is saving computational capacity. The method proposed in this paper allows for efficient computation and at the same time takes into account the variability in axle loads and distances.

The main idea behind the simulation model is to couple vehicle properties simulated based on the above mentioned empirical sample space with the GVW-s simulated from the fitted statistical distributions, within each vehicle category. However, the weight distribution amongst the axles is not fully independent of the total weight of the vehicle. An example of this dependence can be seen in Figure 4, within the Vehicle Category 5, where the largest relative axle load is plotted against the GVW for each recorded vehicle. A negative correlation structure can be recognised when visualizing a bi-variate tri-modal Gaussian mixture distribution fit to the data, such as in Figure 4. In practice, this means that the higher the GVW, the lower the fraction of the load on the heaviest loaded axle of the vehicle will be. This can be explained by a more even load distribution amongst axles of

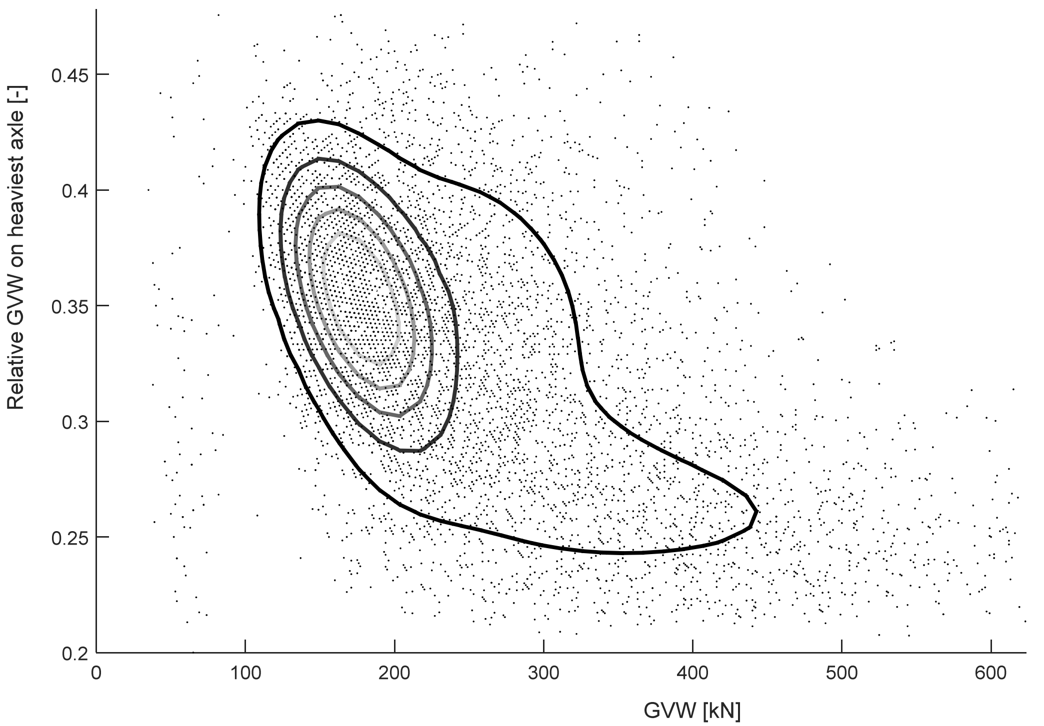

Figure 4. Scatter plot of measured GVW against highest relative axle load per vehicle, with contour of fitted tri-modal Gaussian mixture. All recorded 5-axle vehicles

fully loaded trucks. The proposed model will account for this dependence, as described below.

In the traffic simulation, first, vehicle weights have been simulated based on the previously defined Gaussian mixture distributions fitted to the GVW datasets, using the Monte Carlo method.

When coupling the simulated vehicle weight with a randomly simulated vehicle property, the relation of the maximum relative axle weight to the magnitude of the GVW should be taken into account, for the reasons explained above.

The following approach is proposed: vehicle properties are divided to sub-categories within each vehicle category, based on the GVW they had appeared with in the measurements. These sub-categories will ensure that for example a simulated GVW of 40 tons does not get "coupled" with a vehicle property that was determined from a vehicle of 5 tons. Thresholds of 100 kN (GVW) are chosen for the sub-categories. An example is visualised in Figure 5: within Vehicle Category 5 a GVW of 345 kN is simulated. The second parameter describing this vehicle, the vehicle property, is then simulated from a sub-category of properties. A subcategory can be the interval where the GVW originally belongs to, in this case the interval [300;400[. The other option, allowing for example for a simulated GVW of 301 kN to be coupled with a vehicle property that was measured on a vehicle of 299 kN, is to sample for a given GVW from the "neighbouring" sub-categories as well. In the case of the GVW of 345 kN this would mean the intervals [200;400[or [200;500[. The disadvantage of this approach is that due to the different number of measurements in each block, the ratio of various vehicle properties will be distorted in the simulated traffic.

In order to check the influence of the procedure described above, as an example, in Figure 6 the simulated axle loads for Vehicle Category 5 (5 axle vehicle) are compared to the measurements. This vehicle is the most frequent vehicle in the database. In the figure the exceedance probability of the axle loads is plotted. It can be seen that in the tail of the distribution the simulated axle loads overestimate the measurements, indicating a slightly conservative estimate using simulations. It is noted that the simulation does not directly give the value of axle loads, this is calculated simply by multiplying the simulated GVW with the relative axle load fractions belonging to the coupled vehicle property.

*3.3 **Load effects from simulated traffic***

The approach proposed in this paper allows for an easy simulation of several hundred years of traffic. As the life-time maximum of the load effect is a stochastic quantity in itself,

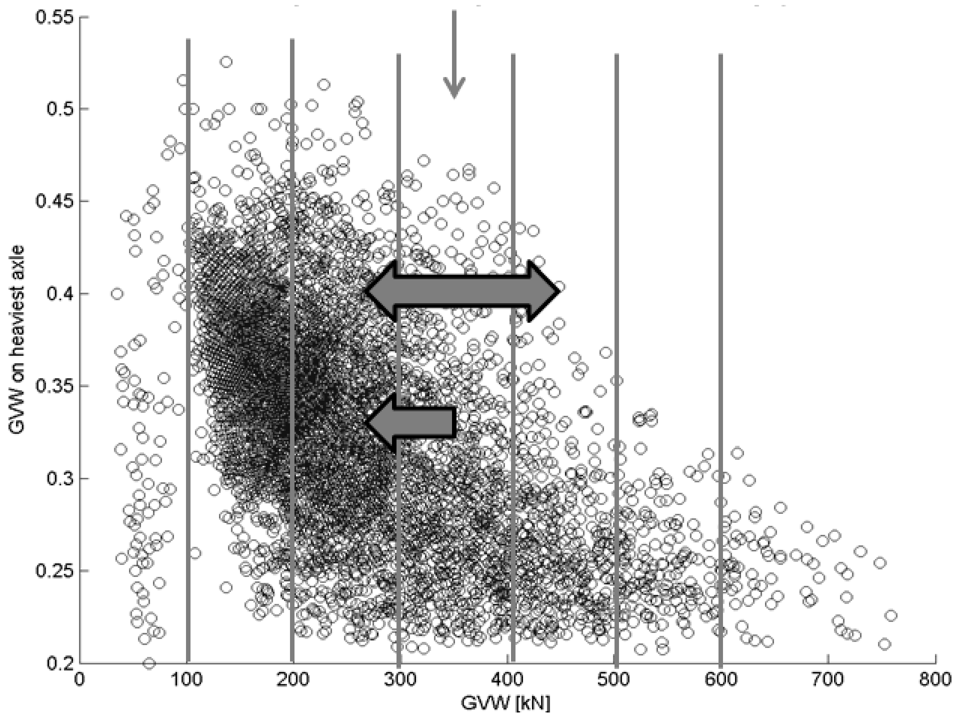

Figure 5. Sub-division of vehicle properties to sub-categories by highest relative axle load. 5-axle vehicles

we carry out the simulation for the reference period multiple times. Then, using block-maxima method, 15-year extreme values can be found.

As described in 2.2, we determine load effects caused by the simulated traffic by taking the load effect resulting from a unit-weight vehicle with same vehicle property as that of the simulated truck, and multiplying it with the (simulated) GVW. The main advantage of this approach is the reduction of computation time, allowing for simulation of several hundred years of traffic. Using each vehicle property that has appeared in the measurements, a load effect calculation for 48586 cases is needed. If all passing vehicles were to be calculated separately, for only one single simulation of the 15-year reference period the load-effect calculations would be 4.37 million. To obtain 500 15-year maxima values, 2.18 billion evaluations on the load effect would be required. Herein, the maximum bending moment in the mid-span is determined, nevertheless the algorithm could be adjusted for maximum load effect on the whole beam or for another load effect such as shear.

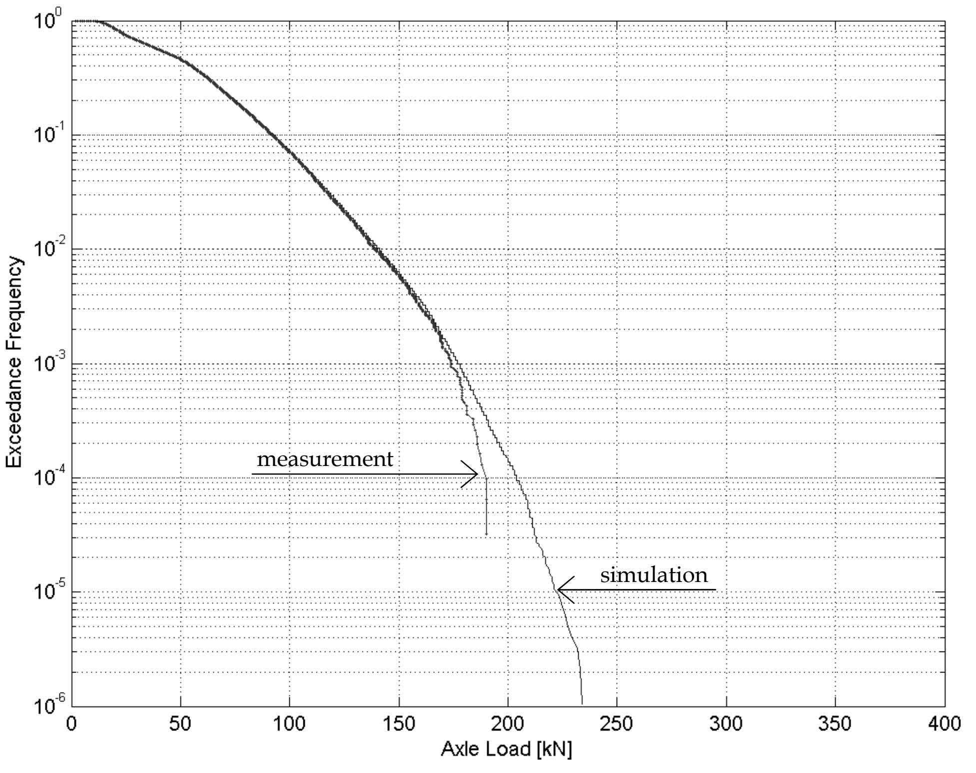

Figure 6: Comparison of measurements and simulated axle loads, category 5

3.4 Statistical distribution of extreme load effects

The final step of the traffic load modelling is analysis of the simulated load effects. In Figure 7 a histogram of 500 values of 15-year maximum bending moment can be seen, determined at mid-span of a 6 m span simply supported beam.

A statistical distribution is fitted to the set of extreme values which were derived from the simulations. The chosen distribution should model the *tail data* accurately, as structural failure is expected to occur due to the most extreme loads. The type of the distribution as well as the parameters should be estimated. The type is likely to be an extreme value distribution. Both a generalized extreme value distribution and a specific type of it, a Gumbel distribution is fitted to the results as well as Gaussian mixture distributions of 10 and 20 components.

In Figure 8 the exceedance-probability of the fitted distributions is plotted together with the exceedance frequency plot of the set of 15-year maxima load effect values. The Gumbel distribution appears to be an adequate fit, and is preferred because to many components in

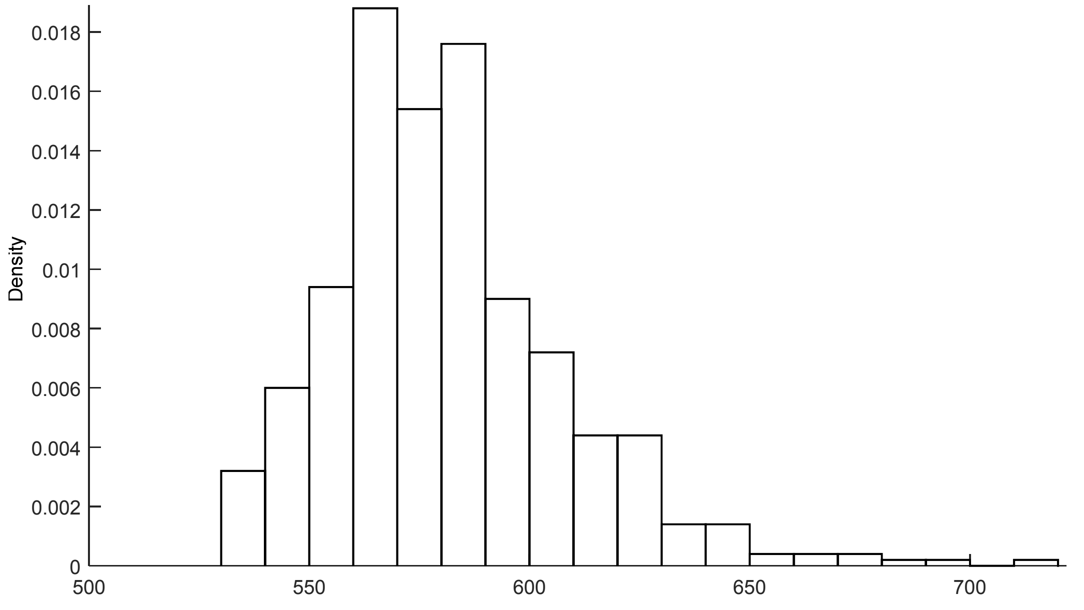

Figure 7. Histogram of 15-year maxima bending moment [kNm]; 6m span simply supported beam

a Gaussian mixture make no physical sense. However we point out that the range of the design value of the maximum load effect is expected in a Level I probabilistic calculation at an exceedance probability of $\Phi(2.5 \times -0.7) = 0.04$, therefore determining a highly accurate fit in a range corresponding to significantly lower exceedance probabilities is not necessary. Similarly as when fitting distributions to the GVW data points gained from the WIM measurements, parameters of the distribution are determined using a maximum likelihood algorithm. A Gumbel distribution is described by two parameters, in this case a mean value of 581 kNm and standard deviation of 27.6 kNm result.

The parameters of the fitted (Gumbel) distribution are statistical variables themselves, see e.g. [Kottegoda & Rosso, 2008]. One strategy to quantify their uncertainty is to assign a standard error (i.e. standard deviation of the parameter) to each. These standard deviations correspond to confidence intervals, a range in which the parameter of our estimated distribution falls with a given probability, and therefore give an indication of the reliability of the fit, assuming that the chosen distribution is correct. For the Gumbel distribution, the standard error of the mean is 1, while for the standard deviation 0.7. These correspond to coefficients of variation of 0.002 and 0.02, relatively low values. For a more accurate procedure, confidence bounds should be observed in all steps and uncertainties should be propagated through the model.

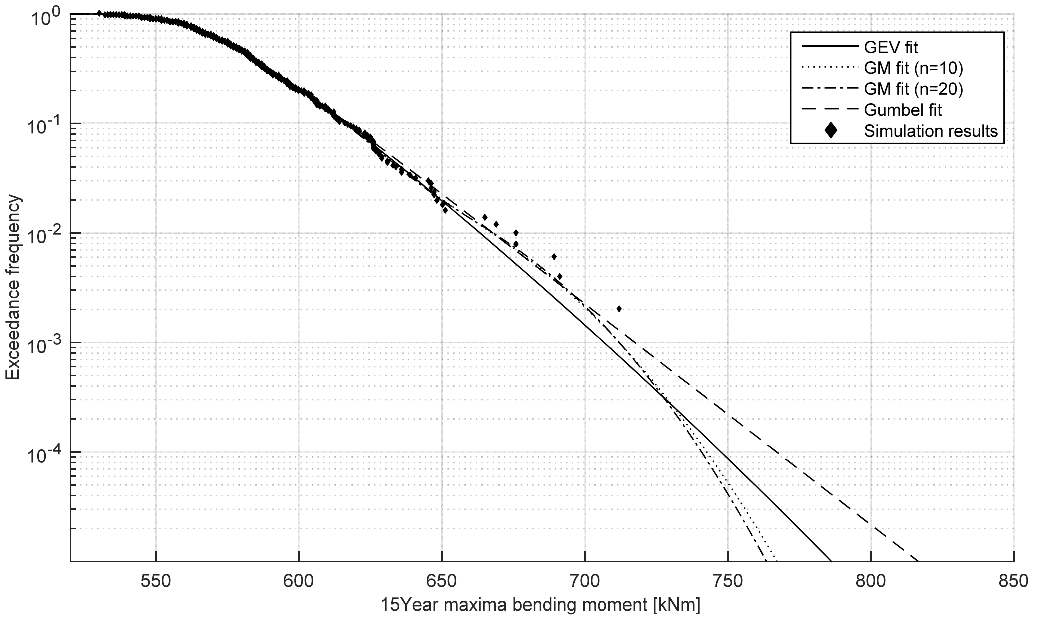

Figure 8: Exceedance-probability plot of various distribution types fitted to 15-year bending moment maxima values (6 m span simply supported beam)

4 Comparison to load effects from Eurocode and Dutch national guidelines

To give an indication of the possible benefit of the probabilistic model with local data, we compare the resulting load effects (in this case bending moment) to those calculated using the standard Eurocode load models, the Dutch National Annex and the Dutch Guidelines for existing structures [NEN-EN 1991-2; NEN 8700; NEN 8701]. For global analysis, the load model LM 1 of EN 1991-2 is considered.

For the comparison a 6 m span bridge is chosen, with one traffic lane, modelled as a simply supported beam. The width of the traffic lane is 3 m. The bending moments at the middle cross section will be compared, both originated from the Eurocode and from the probabilistic traffic load model.

4.1 Some specifics of the Dutch building code for existing structures

In the Netherlands, as an extension to the rules of the Eurocodes, further regulations apply to existing structures. These are laid down in the codes NEN 8700 (Basis of designs) and NEN 8701 (Actions) and contain safety levels for existing structures, based on an economic optimum as well as a basic requirement for human safety. The background of the adjustment is described by Steenbergen and Vrouwenvelder [2010]. In these codes, accepted probabilities of failure are defined for structures of the three consequence classes that are indicated in Eurocode EN 1990, for two different situations, 'disapproval' and 'repair'. For engineering practice, the reliability levels are translated into a partial safety factor format.

A typical short-span city bridge outside of the main highway network belongs to Consequence Class 2. For this case, the above mentioned Dutch regulations allow, for 'disapproval', for a reliability index of β = 2.5 for a reference period of 15 years. In Table 1 the corresponding partial factors and reliability indices are given. The safety format 6.10 a/b of EN 1990 is applied here.

Table 1. Required reliability and partial factors for existing structures at "rejection" level, according to NEN 8700

Load combination/ consequence class (CC)	Required reliability	Permanent loads		Traffic load
		Favourable	Unfavourable	
	β	$\gamma_{gj,sup}$	$\gamma_{gj,inf}$	γ_T
Case 6.10a				
CC 1	1.8	1.0	0.9	1.0
CC 2	2.5	1.1	0.9	1.1
CC 3	3.3	1.25	0.9	1.25
Case 6.10b				
CC 1	1.8	1.0	0.9	1.0
CC 2	2.5	1.1	0.9	1.1
CC 3	3.3	1.15	0.9	1.25

Specifications in the Netherlands (National annex to EN-1991-2 and NEN 8701) allow for taking into account a shorter reference period as well as the lower influence of traffic trends for a shorter remaining working life. The first load-reduction factor, Ψ_t, accounts for the fact that the actual reference period *t* is not equivalent to the standard reference period for new structures (100 years for the case of bridges). In NEN-8701 a recommendation for these values is given, for 15 years reference period on a short-span bridge this is Ψ_t = 0.98. The second factor takes into consideration that load models were calibrated considering an increasing rate of heavy traffic in time, up to 2060. This means that when the remaining service life ends earlier than 2060, a reduction is allowed for compared to the calibrated load value. The multiplier accounting for this trend effect α_{trend} , depends on the influence length and on the year when the remaining working life ends, ranging from 0.9 (2015) to 1.0 (2060) for bridges of 20 m influence length and from 0.775 (2015) to 1.0 for 200 m influence length. Finally, a reduction is allowed for a lower number of vehicles per year (300 000), in this case ψ = 0.98.

In order to compare the results of the proposed probabilistic traffic load model to the load effects which would be used in practice for this case, we adapt the above mentioned reduction factors as multipliers of LM1 from EN-1991-2. The following section will give information on their values, considering the specifics of the case.

4.2 Design load based on Eurocode load model with national guidelines

To make a realistic comparison, one should consider the load that would be used in practice to check an existing structure. Therefore the Load Model 1 of Eurocode will be multiplied by the reduction factors described in 4.1. The resulting design load is given in Table 2. Since in the proposed probabilistic load model no 'trend' is considered, to make a realistic comparison, we will also reduce the LM1 load according to NEN 8701 so that there is no trend accounted for. The bending moment at mid span from the LM1 load model, including the reduction factors can now be calculated, the results are summarized Table 3. In case we consider a traffic lane loaded on 3.6 m width, as for example in [Steenbergen *et al.*, 2012], the total bending moment including factors increases slightly, to 867 kNm. The difference between the two cases is marginal, for the comparison we will use the more narrow lane.

Table 2. Reduction factors for EN-NEN load model

Length	[m]	6
Design life	[years]	100
Reference period	[years]	15
heavy traffic / 2 months		4.86E+04
heavy traffic / year		2.92E+05
	Factors	
Factor for lower number of trucks	ψ	0.98
Factor to account for no trend	α_{trend}	0.967
Shorter time (NEN 8701)	Ψ_t	0.98
Total reduction factor		**0.929**

Table 3. Design bending moment at mid-span, neglecting effect of trend [kNm]

Moment from loads	[kNm]	
Tandem loads - Characteristic		720
Distributed load (3m width) - Characteristic		121.5
Total characteristic		841.5
Partial factor for traffic load (NEN8701)	[-]	1.10
Reduction factors	[-]	0.929
Moment including factors	[kNm]	860

4.3 Design load based on probabilistic traffic load model

To obtain the design load effect from the proposed probabilistic traffic load model, additional stochastic parameters should be considered. These are described in the following paragraphs and it is shown how to include these variables when determining the design load.

The dynamic response of the structure amplifies the effect of vehicle loading. A commonly used, simplified model to account for this behaviour is the dynamic amplification factor (DAF), a multiplier of the static load. The load effect values resulting from the traffic simulation model do not account for this effect, which therefore has to be included in the further steps. The dynamic amplification is considered to be a stochastic parameter. Multiple studies address the topic of the DAF [Caprani, González, Paraic, & O'Brien, 2011; Gonzalez et al., 2009; Steenbergen *et al.*, 2012]. In this paper, we adapt the results of the literature study carried out for a research project of TNO, commissioned by the Dutch Ministry of Infrastructure [Steenbergen *et al.*, 2012]. We consider a normally distributed DAF with a mean value of 1.1 and a variation coefficient of 0.1.

The model uncertainty for the load effect, θ_M, takes into account the difference between the model and reality when converting a load to load effect. The recommended value from [Vrouwenvelder, Marková, & Holický, 2001] is a normal distribution N(1.0, 0.1). A small statistical uncertainty θ_{Stat} is accounted for, since the design value of the traffic load (see Table 5) is still within the empirical distribution function of the simulated 15-year maxima. The values of the variables are given in Table 4.

The design value of the total extreme load must be determined including these variables. For this, a semi-probabilistic approach is adopted, assuming the standard importance factor $\alpha = 0.7$ for the load. The acceptable maximum exceedance probability of the load is described by (3). For the required reliability $\beta = 2.5$, the corresponding exceedance probability is $P_d = 0.04$.

$$P_d = \phi(-\alpha\beta) \tag{3}$$

The value of the traffic load corresponding to P_d is determined with the help of Prob2B® reliability software. First, the limit state equation (4) is defined. When the design load S_d is exceeded, the limit state equation assumes a negative value. Therefore, in the second step we search for the value of S_d which results in a failure probability equal to the allowed exceedance probability P_d .

$$Z = S_d - S_{\mathrm{T}}\theta_{\mathrm{Stat}}\theta_{\mathrm{M}}DAF \tag{4}$$

The resulting design load is S_d = 818 kNm. This is marginally, 5% lower than the load allowed for according to the standards (see Table 3) , $S_{\text{NEN-EN}}$ = 860 kNm. The design values of the random variables are summarized in Table 5.

Table 4. Model factor for probabilistic load model

Variable	Sign	Distribution	Mean	Stand. Dev.
Dynamic amplification	DAF	Normal	1.1	0.10
Statistical uncertainty	θ_{T}	Normal	1.0	0.05
Model uncertainty - load effect	θ_{M}	Normal	1.0	0.10

Table 5. Design value of random variables resulting from probabilistic calculation

Variable	Sign	Design value
Dynamic amplification	DAF	1.2
Statistical uncertainty	θ_{T}	1.03
Model uncertainty - load effect	θ_{M}	1.11
Traffic loading	S_{T}	595.90
Design traffic load	S_d	818.00

5 Summary and conclusions

In this paper, a probabilistic traffic load model for short-span bridges has been presented and demonstrated for a case of a 6 meter span bridge. We proposed a method that uses local WIM data and is capable of simulating several thousands of years of traffic as well as the resulting load effects. Measurement data was analysed and categorized by number of axles. Gross vehicle weights were described by statistical distributions (Gaussian mixture). As a basis of the proposed method, we have defined the *vehicle property* and described traffic by coupling this attribute to simulated vehicle weights. The proposed model accounts for a practical relationship between the weight of a vehicle and the distribution of total weight among the axles. By assigning a load-effect multiplier to each vehicle property, a series of load effects caused by the simulated traffic could directly be obtained from the model. The maximum load effect values for the reference period of interest, for example 15 years according to the Dutch regulations for existing structures, were collected from the results, and the statistical distribution of this maximum load effect was estimated. Calculations were carried out for a 6 m span bridge. The design value of the load effect was determined, considering dynamic amplification and model uncertainties. The acceptable exceedance probability of the load corresponds to the reliability index $\beta = 2.5$, based on national standards for existing structures in the Netherlands. The obtained design value was compared to the design value according to the Eurocode supplemented by regulations for the Netherlands (Dutch National Annex and NEN 8700 and NEN 8701 codes for existing structures). Having considered the reduction factors allowed for in the above mentioned norms, the probabilistic load model using WIM data from a recent measurement campaign gave a design load effect that is marginally (5%) lower than prescribed by the current standards.

Two domains for future research are on the one hand studying validity of the assumptions, on the other hand extending the model. The main assumptions to verify and possibly further develop the model based on these, are: (a) validity of the sub-categorization within vehicle categories for GVW-sampling; (b) further study inclusion of vehicles with over 8 axles; (c) investigate whether truck configurations are an adequate representation of a population within a vehicle category. Valuable extension to the traffic load model could be: (d) consider lateral load distribution in an upgraded traffic load effect model; (e) observe multiple cross sections of the beam instead of only the middle one; (f) study different influence lines, e.g. for the shear force near the supports; (g) investigate the influence of weight-limitation and law-enforcement on the maxima load–effect distribution. Furthermore, considering multiple spans and possibly locations, more generic conclusions could be drawn about the magnitude of traffic loading on short-span city bridges. Finally, given the questionable quality of recorded measurements, a deeper investigation into the WIM system adequate for city traffic conditions should be carried out.

Literature

Caprani, C. C. (2005). Probabilistic Analysis of Highway Bridge Traffic Loading. National University of Ireland, University College Dublin.

Caprani, C. C., González, A., Paraic, R., & O'Brien, E. J. (2011). Assessment dynamic ratio for traffic loading on highway bridges. *Structure and Infrastructure Engineering*, 8, 295–304. http://doi.org/15732471003667645

Enright, B. (2010). Simulation of Traffic Loading on Highway Bridges. Dublin Institute of Technology.

Enright, B., & O'Brien, E. J. (2013). Monte Carlo simulation of extreme traffic loading on short and medium span bridges. *Structure and Infrastructure Engineering*, 9(12), 1267–1282. http://doi.org/10.1080/15732479.2012.688753

European Commission. (2003). EN 1991-2 Eurocode 1: Actions on Structures Part 2: Traffic loads on bridges [from Dutch].

European Committee for Standardisation. (2002). EN 1990. European Committee for Standardisation.

European Committee for Standardisation. (2005). EN 1991 - Annex A2: Application for bridges. European Committee for Standardisation.

Gonzalez, A., Znidaric, A., Casas, J. R., Enright, B., Obrien, E., Lavric, I., & Kalin, J. (2009). Recommendation on dynamic amplifcation allowance, *Deliverable D10*.

Hellebrandt, L. (2014). Structural Reliability of Existing City Bridges - Analysis with Monte Carlo simulation including a load model based on weigh-in-motion measurements [unpublished thesis]. Technical University of Delft.

Kottegoda, N. T., & Rosso, R. (2008). *Applied Statistics for Civil and Environmental Engineers*. John Wiley & Sons, Inc.

Kozikowski, M. (2009). WIM Based Live Load Model for Bridge Reliability. University of Nebraska at Lincoln.

Normcommissie 351001. (2011a). NEN 8700 - [Assessment of existing structures in case of reconstruction and disapproval - Basic rules] Dutch. Delft: Nederlandse Normailsatie-instituut.

Normcommissie 351001. (2011b). NEN 8701 - [Assessment of existing structures in case of reconstruction and disapproval - Actions] Dutch. Delft: Nederlandse Normailsatie-instituut.

O'Brien, E. J., Enright, B., & Getachew, A. (2010). Importance of the Tail in Truck Weight Modeling for Bridge Assessment. *Journal of Bridge Engineering*, 15(2), 210–213. http://doi.org/10.1061/(ASCE)BE.1943-5592.0000043

O'Brien, E. J., Hajializadeh, D., Sheils, E., & Enright, B. (2012). Estimation of Lifetime Maximum Distributions of Bridge Traffic Load Effects. In F. Biondini & D. . Frangopol (Eds.), *6th International Conference on Bridge Maintenance, Safety and Management* (pp. 1482–1488). Stresa: Taylor & Francis.

Sedlacek, G., Merzenich, G., Paschen, M., Bruls, A., Sanpaolesi, L., Croce, P., … Hanswille, G. (2008). Background document to EN 1991- Part 2 - Traffic loads for road bridges - and consequences for the design.

Steenbergen, R. D. J. M., Morales-Nápoles, O., & Vrouwenvelder, A. C. W. M. (2012). General safety consideration and modeling of traffic load for bridge constructions, TNO-060-DTM-2011-03685-1814. Dutch.

Steenbergen, R. D. J. M., & Vrouwenvelder, A. C. W. M. (2010). Safety philosophy for existing structures and partial factors for traffic loads on bridges. *Heron*, 59 (2/3), 123–139.

Vrouwenvelder, A. C. W. M., Marková, J., & Holický, M. (2001). JCSS Probabilistic Model Code.