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# **MATHEMATICAL TRAFFIC LOAD MODELLING AND FACTORS INFLUENCING THE ACCURACY OF PREDICTED EXTREMES**

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**ABSTRACT:** Design and assessment of highway bridge structures requires accurate prediction of the maximum load effects, i.e. shear forces and bending moments etc., which may be expected during the proposed or remaining life of the structure. Traditionally these effects are calculated using conservative deterministic loading models prescribed by codes of practice. The inherent conservatism of these models lies in their need to be widely applicable. While this conservatism is relatively insignificant in design, it may be critical in assessment. In recent years advances in Weigh-in-Motion (WIM) technology have led to the increased availability of accurate and unbiased site-specific traffic records. These records have been successfully employed in the derivation of site-specific loading models and in calculation of load effects in assessment of bridge structures. The results of these assessments are accepted to be less conservative than those performed using generalised codified loading models. Given this reduction in the conservatism of the calculation it is important to quantify the implication of factors such as data inaccuracy or traffic growth on the calculated maximum load effects. This paper briefly describes the mathematical modelling involved in traffic simulation using WIM statistics. The results of direct simulations performed using WIM data are compared with those obtained through the statistical simulation technique termed Monte Carlo simulation, which is regularly employed where insufficient measured data exists. The implications of the accuracy of the recorded WIM data and the duration of recording on the predicted load effect are assessed along with the sensitivity of the extreme to the method of prediction. The effect of traffic evolution with time in terms of increased volumes of flow and weight limits are also explored.

**Keywords:** bridge, load effects, characteristic values, simulation, traffic flow, Monte Carlo, weigh in motion

## **INTRODUCTION**

Of the load effects to be determined in bridge assessment by far the most variable are those termed traffic loads. Traditionally, these effects have been determined in calculations employing deterministic loading models. Deterministic loading models have in the past been derived based on practical experience or more recently in model calibration studies. In both cases the parameters of the model, traditionally a uniformly distributed load and a concentrated load component are selected such that they will provide in excess of the predicted maximum loading effects which a broad range of structures may be expected to experience during their design life. In the calibration studies performed for the normal loading model for Eurocode 1 (CEN 1994) maximum lifetime effects were calculated for span ranges from 5 – 200m for 1 – 4 lanes and for structural forms ranging from simply supported to multiple continuous spans to fixed-fixed beams etc (O'Connor et al. 2001). It is apparent therefore that the requirement to be widely applicable results in considerable conservatism in deterministic loading models. This added conservatism is relatively unimportant in the design of new highway structures when considered from a cost perspective. However, in the assessment of existing structures it can be significant, particularly if it leads to a specified requirement for unnecessary rehabilitation/replacement of a serviceable structure. In recognition of this, increasingly in assessment practitioners and researchers alike have attempted to take account of site-specific traffic data in the determination of maximum load effects (Enevoldsen 2001; Bailey 1996; Jacob et al. 1989; Nowak 1994).

Whereas in the past the results of manual traffic surveys were employed in traffic flow simulations (Nowak 1993; Nowak 1994) in recent times advances in WIM technology has provided real time traffic statistics for simulation.

Weigh-in-Motion is the process of weighing trucks while they are travelling at full highway speeds (Dempsey 1997). There are three principal means by which trucks can be weighed while in motion:

- (i) sensors based on piezoceramic technology or electrical capacitance can be embedded in a groove in the road,
- (ii) a steel plate (about 2m×1m) encased in a frame can be embedded in a pit excavated in the pavement or,
- (iii) strain gauges attached to the soffit of an existing road bridge can be used to measure the flexure in the bridge and hence the weight of the truck on it.

There can be little argument that maximum load effects determined from site-specific data will provide a better indication of the serviceability/safety of a structure than effects determined from generalised loading models. In reducing the conservatism in the process however it is important to have some understanding of how factors such as the accuracy of the recorded data or the duration of recording etc. influence the predicted extremes.

This paper discusses the mathematical models and statistical techniques commonly used in flow simulation and investigates the factors which influence the accuracy of the extremes predicted in these simulations. The results of direct simulations performed using recorded data are compared to those calculated using the commonly used *Monte Carlo* method. Thereby validating its appropriateness for use in such simulations and in the studies performed in this paper.

Monte Carlo simulation is a statistical technique often employed where it is desirable to randomly generate data using known or assumed statistical distributions, in this case for vehicle and axle weight, speed and spacing etc. within assumed vehicle classes. The technique is used to increase the amount of data available, i.e. from 1 weeks continuously recorded data to 10 weeks

simulated data, or to generate different loading scenarios, i.e. congested flow, flow following an accident/lane closure etc. which may not have been directly recorded.

The results of studies performed to assess the sensitivity of calculated load effects to the mathematical models employed in prediction of extreme load effects are presented. Monte Carlo simulation is used to generate large duration theoretical traffic records permitting assessment of the sensitivity of the extremes to the quantity of available data. The use of the Monte Carlo technique permits studies to be performed with respect to the implications of the accuracy of WIM data on predicted characteristic load effects and an assessment of the influence of growth on the predicted extremes. Ultimately conclusions regarding the sensitivity of load effects determined in both direct and Monte Carlo simulations are drawn. These conclusions are of interest to anyone employing actual data or statistically derived site-specific loading models rather than deterministic codified loading models in the determination of maximum load effects in bridge assessment.

## **MATHEMATICAL TRAFFIC MODELS**

The traffic data employed in this paper may broadly be broken into two distinct groups:

- (a) those describing the traffic as a whole, i.e., proportion of vehicles in each lane, proportion of vehicles in each vehicle class, vehicle spacing etc.
- (b) those describing the vehicles within each class, i.e., gross vehicle weight, axle weight, vehicle geometry, speed, etc.

Models of these random variables are required for Monte Carlo simulation of theoretical traffic records. Many statistical models exist to describe the random variables governing traffic flow. Those employed in this paper are briefly discussed in the following sections.

## **TRAFFIC CHARACTERISTICS**

Theoretical traffic flow simulations may only be performed where knowledge of the site-specific traffic characteristics are known. In the past, parameters were estimated through subjective decisions or limited surveys of traffic flow (Nowak 1993, Nowak 1994, Agarwal and Cheung 1978). The availability of WIM data permits traffic characteristics to be directly determined from continuous traffic flow measurements.

### **Vehicle Proportions and Classification**

Accurate traffic flow simulation requires determination of the proportions of the total vehicle flow in each simulated lane, which are site-specific random variables. Estimation of these proportions may be made through traffic counting exercises or from available WIM records (Agarwal and Cheung 1987; Agarwal and Wolkowicz 1976; Bakht and Jaeger 1988; Prat 1991; Bruls et al. 1996a,b; Calgaro 1997, O'Connor et al. 2001).

A vehicle classification system is required for Monte Carlo generation of traffic records. Table 1 illustrates the vehicle classification system adopted for this paper (O'Connor 2001) which is based on the French national system. This system permits determination of the vehicle class proportions in addition to the statistical moments for each class describing the distributions of gross weight, individual and group axle weight etc.

## **Inter-Vehicle Spacing**

In many traffic studies, the distribution of inter-vehicle spacing (i.e., headway) is of interest and is modelled by a form of exponential distribution because traffic flow is idealised as a Poisson process (Harman and Davenport 1979). The Gamma distribution, which is a natural generalisation of the exponential distribution, is adopted in this study to model inter-vehicle spacing.

## **VEHICLE CHARACTERISTICS**

In generating vehicle flow simulations it is important to accurately describe the random variables of gross vehicle weight, axle weight, axle spacing, length, speed etc. The availability of WIM records permits accurate modelling of the controlling distributions within each vehicle classification outlined in Table 1.

Figure 1 demonstrates the twin peaked bimodal distribution of Gross Vehicle Weight (GVW) for class A113 defined in Table 1, i.e., 5 axle vehicles with rear tridem axle. This form of distribution is typical for gross weight (Harman and Davenport 1979; Jacob 1991; Nowak 1993; Bailey 1996; O'Connor et al. 2001). The first mode contains the partially loaded trucks while the second involves the fully loaded trucks.

## **TRAFFIC FLOW SIMULATION**

The governing variables of the statistical distributions chosen to represent the traffic and vehicle characteristics, i.e., mean values and standard deviations etc. are calculated using the WIM data recorded on site. Recognising that the WIM records may not have recorded all possible traffic situations, a technique such as Monte Carlo simulation may then be employed to regenerate



traffic records for any chosen scenario. The procedure will make use of the site-specific vehicle characteristics of vehicle and axle weights etc. but can modify traffic flow distributions to simulate any chosen situation. For example, if mixed flow conditions are required, i.e., a combination of free flowing and congested lanes, the speed and headway distributions for congested lanes will be almost deterministic whilst they will remain statistically variable for lanes with free flow.

The scenarios selected for Monte Carlo generation should be representative of those expected for the structure during its lifetime. In the recalibration studies performed for the Normal loading model of Eurocode 1 (CEN 1994), a range of scenarios were chosen representing normal, congested, mixed flow and accident/emergency flow situations (O'Connor et al. 2002).

For the purpose of this paper three flow scenarios are considered. The scenarios hereafter denoted Mixed4, Mixed2 and Free2, represent four and two lanes of mixed flow and two lanes of free flow respectively. Mixed flow is taken here to mean one lane congested with the remaining lanes free flowing. These scenarios have been selected as they are considered representative of the majority of traffic flow conditions to which typical four and two lane bridges are subjected. Neither hazard conditions nor full congestion are considered in this paper. It is important to point out that for two lane structures, the maximum load effects will be experienced by free flowing conditions for span lengths less than about 30m and by mixed flow conditions for spans in excess of this (O'Connor 2002; Nowak 1993; Bailey 1996). The threshold span length of approximately 30m is a function of the load effect under consideration. The explanation of this crossover in governing scenario comes from the inclusion of a dynamic amplification factor in the results of free flowing simulations to account for interaction between vehicles and the structures they

traverse. For span lengths less than 30m the governing load case is provided by two fully loaded articulated vehicles or axle groups side by side at or near the critical influence ordinate independent of the flow scenario considered. Consequently, when the dynamic factor is applied to the results of the free flowing scenario it governs the extreme. For span lengths >30m more than two vehicles are present on the span in the extreme and so the mixed flow case governs. For four lane structures, the load effects provided from mixed flow are generally in excess of those induced by four free flowing lanes. It is noted that in mixed flow cases, dynamic amplification is only applied to the free flowing lanes.

The WIM traffic records used in both direct simulation and in Monte Carlo simulation are taken from those used in the re-calibration of the Normal load model of Eurocode 1 (O'Connor 2002). The specific data was recorded over a 7-day period in 1997 on two carriageways of a main motorway on mainland Europe from Paris to Lille. During this period continuous WIM measurements were taken on four lanes, two in each direction. A total of 86,455 trucks were recorded, where a truck is classified as a vehicle with gross weight > 3500kg.

The load effects considered for comparison in this paper are the midspan moment in a simply supported beam, the continuous support moment in a two span beam and the total load on the span; the respective influence ordinates are denoted  $I_{SS}$ ,  $I_{CTM}$ ,  $I_{UNI}$ . These effects are chosen as they are often found to govern in the calibration of traffic load models (Jacob et al. 1989; O'Connor 2002). For simplicity in this study the influence surfaces were generated ignoring transverse distribution effects. In the recalibration of the Normal load model of Eurocode 1 transverse effects were modelled (O'Connor 2002).

## EXTREME LOAD EFFECTS

The results of traffic load simulations are employed in statistical extrapolation to determine the extreme load effects which the specific structure is predicted to experience during its remaining life. Three statistical distributions are considered in the following to determine the sensitivity of the predicted extreme load effect to the extrapolation chosen.

The first technique considered is based upon fitting an exponentially decaying function to the computed Level Crossing Histogram of load effect. The Level Crossing Histogram is computed by counting the number of times a specified level of load effect is exceeded in simulation and storing the results in the form of a histogram. An example is illustrated in Figure 2. Extrapolation to determine the characteristic values is performed using Rice's formula. Rice's formula is not itself Normal but has a Normal tail, which governs the extrapolation (Cremona 1995). This distribution is given as:

$$[1] \quad p(x) = \frac{1}{2\pi} \frac{\sigma_x}{\sigma_x} \exp\left(-\frac{\left(\frac{x - \bar{x}}{\sigma_x}\right)^2}{2\sigma_x^2}\right) = k \cdot \exp\left(-\frac{(x - m)^2}{2\sigma^2}\right)$$

The distribution is fit to the tail of the Level Crossing Histogram at the optimal censoring level (i.e., optimal number of class intervals to be used in the fit) which may be determined by the Kolmogorov K-test to a specified confidence level. Having satisfied an appropriate statistical test for suitability, the distribution may be used for extrapolation of a given load effect to predict the maximum values to a specified probability of exceedance.

To compare with the extremes predicted by fitting Rice's distribution, the extreme value distributions of the Gumbel family were also employed. A Weibull (i.e., Gumbel type III) distribution results when the maximum values are sampled from a parent frequency distribution having a finite upper bound. An alternative distribution is the Gumbel I distribution. In this case, the maximum values are sampled from a parent distribution with no upper bound (Gumbel 1958).

The principle of tail equivalence (Castillo 1991; Maes 1995) is employed in determining an appropriate extreme value distribution. The extreme value and parent distributions,  $G(x)$  and  $F(x)$  respectively, are considered tail equivalent if:

$$[2] \lim_{x \rightarrow \infty} \frac{1-G(x)}{1-F(x)} = 1$$

where the extreme value distribution  $G(x)$  is modelled by either the Gumbel I or Weibull distribution, given by Equations 3 and 4 respectively.

$$[3] G(x) = \exp \left[ -\exp \left( \frac{-(x-\lambda)}{\delta} \right) \right] \quad -\infty < x < \infty \quad \delta > 0$$

$$[4] G(x) = \exp \left[ -\left( \frac{\lambda-x}{\delta} \right)^\beta \right] \quad -\infty < x \leq \lambda$$

The threshold,  $\lambda$ , and scaling parameters,  $\delta$  and  $\beta$ , of the Gumbel law,  $G(x)$ , are estimated by the maximum likelihood approach (Castillo 1992).

The suitability of either the Gumbel or Weibull distribution is assessed by plotting the extreme data on probability paper where linearity indicates the appropriateness of the mathematical model (Gumbel 1958; Castillo 1991). The extreme values for simply supported moment in 5, 50 and 200 m spans were plotted on Gumbel I and Weibull probability paper, along with the Gumbel I and Weibull approximations (O'Connor 2001). For the shortest span length of 5 m neither distribution is superior, due to the lack of linearity in the extreme. However, the Weibull distribution is considered more appropriate as it implicitly recognises a physical upper limit for the maximum load effect on short spans as a function of the maximum possible axle and group of axle load (Bailey 1996, O'Connor 2001). For a 50 m span it is found that either distribution is appropriate. However for medium to long span bridges, i.e.  $> 50$  m, a convex trend is observed in the right hand tail of the Weibull distribution. As the tail region is of prime importance in extrapolation, clearly the Gumbel distribution is more appropriate for such cases.

It is also important to consider the characteristic load effect being determined. It is found that the choice of either extreme value distribution is dependent not only upon the span length but also upon the load effect being considered (O'Connor 2001).

## **COMPARISON OF METHOD OF PREDICTION OF THE EXTREMES**

Figure 3 illustrates, in ascending order, the predicted extremes of simply supported moment for scenario Mixed4 (i.e., 4 lanes of mixed flow) for span lengths 5, 10, 20, 50, 100 and 200 m. It should be noted that the extremes predicted by Rice extrapolation were performed from the simulations using real WIM data. On the other hand, those calculated using the Gumbel I and Weibull extreme value distributions were from Monte Carlo simulations. The relative errors, with

respect to the Rice extrapolations, are listed in Table 2. It is apparent that differences exist in the maximum load effects predicted by the various methods. This may be explained in terms of the use of direct and artificially regenerated data and when the different extrapolation techniques are considered. It is therefore important to ensure that adequate statistical tests are performed to ensure the most appropriate technique/distribution is selected in the prediction of extremes and that care is exercised in the use of the Monte Carlo method.

### **SENSITIVITY OF THE PREDICTED EXTREME TO STATISTICAL PARAMETERS**

The use of WIM data to determine maximum load effects through direct and Monte Carlo simulation has been demonstrated. Increasingly of interest are the implications of variation in the governing statistical parameters on these predicted extremes. In this section, the implications of variation in the accuracy of recorded WIM data, analysis for time and seasonal trends and the implications of traffic growth will be addressed in an attempt to estimate their implication for the accuracy of predicted characteristic extremes.

#### **Implications of WIM Data Accuracy**

Although in recent years, there have been great advances in the technology of weighing trucks while they are travelling at full highway speeds (Moses 1979), many weigh-in-motion sensors still give quite an inaccurate estimate of static weights, particularly on medium or rough pavements. This is due in considerable part to the dynamic motion of trucks and axles. In addition, factors such as pavement inclination, sensor inaccuracy and location of weighing station all influence the accuracy of the recorded WIM data (Dempsey and O'Brien 1995). A typical example of test results illustrated in Figure 4 shows a substantial scatter in measured gross weights relative to the corresponding static values (O'Brien et al. 1996).

In addition to sensor accuracy and site issues, the effects of calibration drift and longitudinal offset on the accuracy of recorded WIM data can be significant (Hallenback 1995a,b, c). It is important to determine the influence of errors in WIM data on the predicted maximum load effect values. The European specification on Weigh in Motion of Road Vehicles (COST 323 1997; Jacob et al. 2000; Jacob 2000) is employed for the purpose of this study. In summary, the accuracy classification prescribed by the specification is based on the width of the interval within which the required percentage of the recorded sample results falls. If the required number of GVW records are within 5% of the static values, the system is classified as Class A(5). Similarly, systems are classified as Class B(10), C(15), D(25) or E if the required number of records are within 10%, 15%, 25% or more than 25% of the static values respectively.

### **Influence of WIM Data Accuracy on Characteristic Extremes**

In accordance with the accuracy requirements of the European specification on Weigh in Motion of Road Vehicles (COST 323 1997), a varying random error was applied to a recorded WIM data file such that the resulting traffic files were classed from A(5) to E. This error was randomly imposed by Monte Carlo simulation. In total 50 files were generated from the parent in each class. Simulations were performed for the critical Mixed4 scenario (i.e., 4 lanes of mixed flow) for influence surfaces  $I_{SS}$ ,  $I_{CTM}$ ,  $I_{UNI}$  (i.e., midspan moment in a simply supported structure, continuous support moment in a two span structure and total load on a span) with spans lengths varying from 5 to 200m. In total 11,200 simulations were performed. The average error and standard deviation in the predicted characteristic extreme for load effects  $I_{SS}$  are illustrated in Figures 5 and 6 respectively. In the figures it should be noted that MC50 implies the results obtained from the average of 50 Monte Carlo generated traffic files while MC5 represents the

average from 5 Monte Carlo generated files. Similar analysis was performed for the influence surfaces denoted  $I_{CTM}$ ,  $I_{UNI}$ .

For short spans, where axle rather than vehicle loads govern the characteristic load effect, the accuracy of the WIM data has a significant influence on the predicted extreme. However, it is apparent that for longer spans, where the gross weight is far more important, the influence of the inaccuracy attenuates in the mean with corresponding reduction in standard deviation. This is caused by compensation in the randomly generated axle error due to the presence of multiple vehicles longitudinally and transversely on the influence surface. Also apparent, was the sensitivity of the error to the characteristic effect being determined (O'Connor 2001).

A degree of sensitivity with respect to the number of data files within a given classification is also apparent. For total influence surface lengths  $>50$  m (i.e., where mixed flow scenarios govern the extreme) the mean and standard deviation appear relatively insensitive to the number of data files. As such, a reasonable estimate of the characteristic extreme ( $\pm 5\%$ ) is obtained from 5 files of classification D(25) for spans  $>50$  m provided no apparent bias with respect to the error exists in the data. However, for total spans  $< 50$  m (i.e., where free flow is important) confidence in the predicted extreme is directly related to both the data classification and the number of data files employed. As such 5 files of D(25) are no longer sufficient. However, 5 C(15) files provide a reasonable estimate ( $\pm 5\%$ ) once again provided no apparent bias with respect to the error exists in the data.

Thus a suitable recommendation for the required accuracy of WIM data to be used in the prediction of extremes load effects in assessment might require a minimum class C(15) system



for spans <50 m, but permit less accurate data to be used for spans >50 m, whilst specifying a minimum number of WIM recording locations on site (O'Connor 2001).

### **ASSESSMENT OF TIME AND SEASONAL TRENDS**

The WIM data used in the assessment for time and seasonal trends was taken from a large-scale test of six WIM systems and four additional sensors on an urban roadway in Zurich, Switzerland (Caprez et al. 2001). Gross weights from some thousands of statically weighed vehicles were used to determine the levels of accuracy for each system with reference to the European specification on WIM (COST323, 1997). The accuracy of axle weights was not tested. The WIM sensors, which included one prototype, were tested with the assistance of a recording and processing device supplied by the organiser (ETH Zurich). Most systems encountered some problems, failures and faults, under the carefully controlled conditions of the 30-month test. However, the suppliers generally solved these after some delay.

Data from four WIM systems, A1 to A4, was analysed to examine the relationship between WIM accuracy and time or season. Two analyses were carried out. For the first, accuracy was calculated by month in chronological order. For the second analysis, three types of season were identified and accuracy was calculated once for each season type. A full account of the analysis is presented in (Caprez et al. 2001). Overall no time or seasonal trends could be definitively identified for any of the systems analysed.

### **ASSESSMENT OF THE INFLUENCE OF TRAFFIC GROWTH**

A central assumption in the extrapolation to determine extreme load effect values for design and assessment is that of stationarity of traffic (Leadbetter et al. 1983; Jacob et al. 1989; Flint and

Jacob 1996). This assumption, although necessary, is questionable. Vehicle traffic is a non-stationary phenomenon with variation in both vehicle proportions and weights experienced over time as a function of economic and technological developments. As such it is important to determine the sensitivity of predicted extreme load effects to changes in the composition of road traffic.

It is evident from studies performed in the recalibration of the normal load model of Eurocode 1 (CEN 1994) that over a period of 10 years, a significant shift in the composition of road traffic was experienced on a particularly heavily trafficked route in France. A substantial increase in the number of 5-axle vehicles (O'Connor et al 2001) was recorded. However, the results of the simulations performed in the recalibration indicated that, although this shift has taken place in the composition of traffic, there is little apparent effect on the characteristic extremes as variation in composition has been compensated for by increased accuracy in WIM records. However, given the current accuracy of WIM systems it is important to consider what influence future changes in traffic composition might have on extreme load effects.

For the purpose of this study a change in the traffic composition was simulated by instituting a theoretical increase in the proportion of class A113 (i.e., 5 axle semi-trailers with a rear tridem axle) vehicles by 5, 10, 25 and 50% with a corresponding reduction in the proportions of the other classes. These increases in the proportion of 5-axle vehicles lead to consequent increases in the volume of their flow by 0.75, 1.96, 7.3 and 25.2% respectively.

In addition to changes in the flow characteristics it is important to assess what influence changes in regulatory policy for vehicle weight will have on the predicted characteristic extreme. To this

end a sensitivity study has been performed where vehicle gross weights were increased by 5, 10 and 25%.

Monte Carlo simulations were performed for the revised characteristics of vehicle weight and flow proportion. Simulations were performed for influence surfaces  $I_{SS}$ ,  $I_{CTM}$ ,  $I_{UNI}$  for two and four lanes of traffic flow. As previously, for two lanes of flow, free (Free2) and mixed (Mixed2) simulations were performed resulting in an envelope of characteristic extremes. For four lanes, the characteristic extremes were determined for the mixed flow scenario (Mixed4). Statistical extrapolations were performed for a period of 50 years with a 5% fractile.

It is found that variation from the predicted extreme is far more dependent upon increase in gross vehicle weight than upon increases in the proportion of heavy vehicles in the flow (O'Connor 2001). It is apparent that up to 50% growth in the proportion of heavy vehicles in the flow has a small influence of approximately 10% (maximum) for  $I_{SS}$  for spans less than 50 m and that this change attenuates with increasing span length. The standard deviation on this error for  $I_{SS}$  is also highest for shorter spans, again attenuating with increasing span length. The influence of growth for  $I_{CTM}$  is found to be negligible (approx. 5%) for short spans, approaching 0% with increasing span length. Also again the standard deviation is found to be a function of span length.

In conclusion it is noted that the factor which could have major influence on predicted extremes in the future is a change in regulatory policy regarding allowable gross vehicle weight. On the other hand, increases of up to 50% in the volume of heavy vehicles in the flow have a much less significant effect. This finding is borne out by a US study, in which it was found that ‘...

Changes in traffic volume have less effect on the  $\beta$ -safety level than those in enforcement type...’ (Fu and Hag-Elfasi 1995).

### **ASSESSMENT OF THE INFLUENCE OF DURATION OF RECORDING**

The influence of the duration of recorded traffic in WIM files to be used in determination of characteristic values is of concern with regard to code calibration and assessment. As discussed, it has been assumed that traffic actions over a period of one year are taken as a stationary process. It was considered that 1 week in time could be taken as the representative period and therefore 1 week was taken as the basic simulation period for calculation of extremes (O’Connor et al. 2001). However, some authors have questioned such assumptions claiming that a longer recording period within each year (to allow for variability from week to week and to model seasonal variation) and/or in consecutive years is required to fully model the huge range of loading cases to which a structure will be subjected during its design lifetime. Comparisons are drawn with the determination of maximum wind or flood loading in a region where detailed records of maxima for previous decades are employed for extreme value modelling.

There is merit in such argument and ideally continuous records of traffic recorded over a range of seasons and for a number of years would be used in bridge assessment and code calibration. However, unfortunately in practice continuously recorded detailed and reliable traffic records are unavailable. Therefore a degree of engineering judgement is required to determine the optimal time and duration of traffic recording. Although, as previously discussed, in the re-calibration of the Eurocode it was considered that 1 week of continuously recorded data would provide

sufficient, the results of a study into the sensitivity of these extremes to the recording period are presented here.

Monte Carlo techniques have been employed to regenerate traffic records for recording periods varying from 1 to 4 weeks. A continuously recorded WIM file of 1-week provided statistical moments for the resulting load effect values. It is intended to attempt only to generate an increased number of load combinations to which the structure will be subjected through increasing the physical number of traffic records. In this generation it is assumed that the underlying distributions of weight and spacing are stationary. These assumptions are considered reasonable when taken in the context of previously presented results for studies in data accuracy and variation in traffic characteristics.

A comparison of the mean and standard deviation on the extreme load effects for influence surface  $I_{SS}$  and flow scenario Mixed4 is presented in Figure 7 with the percentage difference in characteristic extremes for simulated WIM data of duration 2, 3 and 4 weeks, relative to 1 week in Table 3. Results are presented in Figure 7 for span lengths 5, 10, 20, 50, 100 and 200 m. It is clear from Figure 7(a) that increasing the number of possible load combinations to which the structure is subjected has little effect on the extreme. The load effect values for each duration of recording are practically the same, as evidenced by the fact that, for each span length, the mean values are superimposed on each other when plotted. This fact is further evidenced in reference to Table 3, which demonstrates the largest percentage difference as 6%, with the average percentage difference of approximately 1.4%. Figure 7(b) demonstrates no apparent link between quantity of records and standard deviation of load effect.

## **CONCLUSIONS**

The aim of this paper is to present commonly used traffic flow simulation models, and to determine their appropriateness for bridge assessment. It was also intended to determine the factors influencing the accuracy of the extreme load effects predicted by these models. Although theoretical models are unable to exactly reproduce the load effects induced by actual traffic data, they do provide reasonable estimates of the extremes and the accuracy of these estimates are seen to be dependent upon the load effect considered. The accuracy of the generated files are seen to increase with increasing span length in inverse proportion to the variance in the extreme. A comparison between various extrapolation techniques demonstrates the importance of appropriate selection of an extreme value distribution. The influence of the accuracy of recorded WIM data is demonstrated to be a function of span as well as of load effect with accuracy more critical for shorter span lengths while the effects of increasing inaccuracy were seen to attenuate with span. The time-dependent and seasonal analysis do not provide any clear proof of a seasonal trend and, in some cases, there is evidence of an absence of such a trend. In performing an analysis for the effects of future growth it is determined that the factor which could have major influence on predicted extremes in the future is a change in regulatory policy regarding allowable gross vehicle weight. On the other hand increases of up to 50% in the volume of heavy vehicles in the flow have a much less significant effect. Finally the characteristic extremes are found to be relatively insensitive to variations in recording period from one to four weeks.

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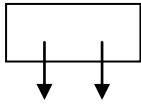
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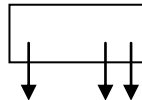
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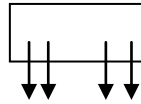
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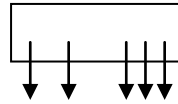
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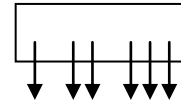
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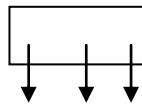
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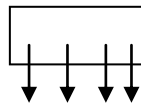
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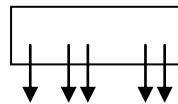
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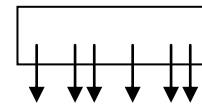
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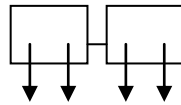
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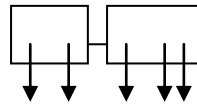
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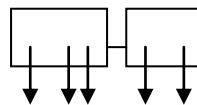
**A1212**



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**A11-12**



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**Table 2 - Extrapolation results**

Return Period Span [m]	<b>1 Year</b>	<b>20 Years</b>	<b>100 Years</b>	<b>I<sub>ss</sub></b>
<b>5</b>	<b>-11.1</b> (-14.6)	<b>-11.0</b> (-12.6)	<b>-11.1</b> (-10.7)	-5.5
<b>10</b>	<b>10.1</b> (-1.1)	<b>12.4</b> (1.1)	<b>14.1</b> (2.9)	-18.0
<b>20</b>	<b>-9.1</b> (-5.9)	<b>-9.1</b> (-3.7)	<b>-9.1</b> (-1.7)	-15.7
<b>50</b>	<b>3.5</b> (6.9)	<b>4.1</b> (9.1)	<b>4.5</b> (10.9)	-6.4
<b>100</b>	<b>10.1</b> (13.7)	<b>10.8</b> (15.9)	<b>11.3</b> (17.7)	2.6
<b>200</b>	<b>4.4</b> (10.4)	<b>4.2</b> (12.2)	<b>4.0</b> (13.7)	3.3

**Bold** : % Difference between Rices and Gumbel

**()** : % Difference between Rices and Weibull

**Table 5 – % Difference in characteristic extremes (Mixed4 I<sub>SS</sub>) for simulated WIM data duration 2, 3 and 4 weeks, relative to 1 week.**

RP	MC5			MC10			MC20			MC50			MC100			MC200		
	1-2	1-3	1-4	1-2	1-3	1-4	1-2	1-3	1-4	1-2	1-3	1-4	1-2	1-3	1-4	1-2	1-3	1-4
<b>1 wk</b>	0.6	0.2	0.7	0.0	3.8	3.2	6.2	2.4	2.1	1.7	1.6	2.4	0.5	1.9	2.4	0.8	1.6	0.5
<b>2 wks</b>	0.5	0.2	0.7	0.0	3.6	3.1	6.0	2.4	2.1	1.7	1.6	2.3	0.6	1.9	2.3	0.8	1.5	0.5
<b>3 wks</b>	0.5	0.2	0.7	0.0	3.5	3.0	5.8	2.3	2.1	1.7	1.5	2.2	0.6	1.8	2.2	0.8	1.5	0.5
<b>1 mth</b>	0.3	0.2	0.6	0.1	2.8	2.4	5.1	2.0	1.9	1.7	1.1	1.6	0.6	1.4	1.7	0.8	1.2	0.4
<b>6 mths</b>	0.3	0.2	0.6	0.1	2.7	2.2	4.9	1.9	1.9	1.7	1.1	1.5	0.6	1.3	1.6	0.8	1.2	0.4
<b>1 yr</b>	0.1	0.2	0.5	0.0	2.2	1.8	4.4	1.7	1.7	1.7	0.8	1.2	0.6	1.0	1.3	0.7	1.0	0.3
<b>20 yrs</b>	0.1	0.2	0.4	0.0	2.1	1.7	4.3	1.7	1.7	1.6	0.8	1.1	0.6	1.0	1.2	0.7	1.0	0.3
<b>50 yrs</b>	0.0	0.1	0.4	0.0	2.0	1.6	4.1	1.6	1.7	1.6	0.8	1.0	0.6	0.9	1.2	0.7	1.0	0.3
<b>100 yrs</b>	0.0	0.1	0.4	0.0	1.9	1.4	3.9	1.5	1.6	1.6	0.7	0.9	0.6	0.8	1.0	0.7	0.9	0.3

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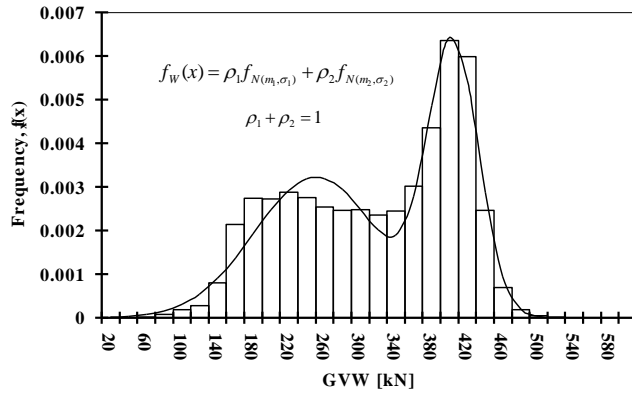
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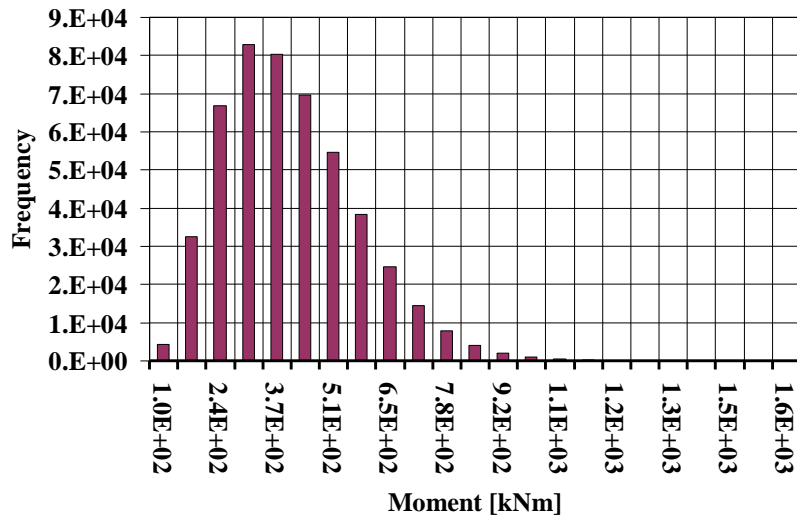
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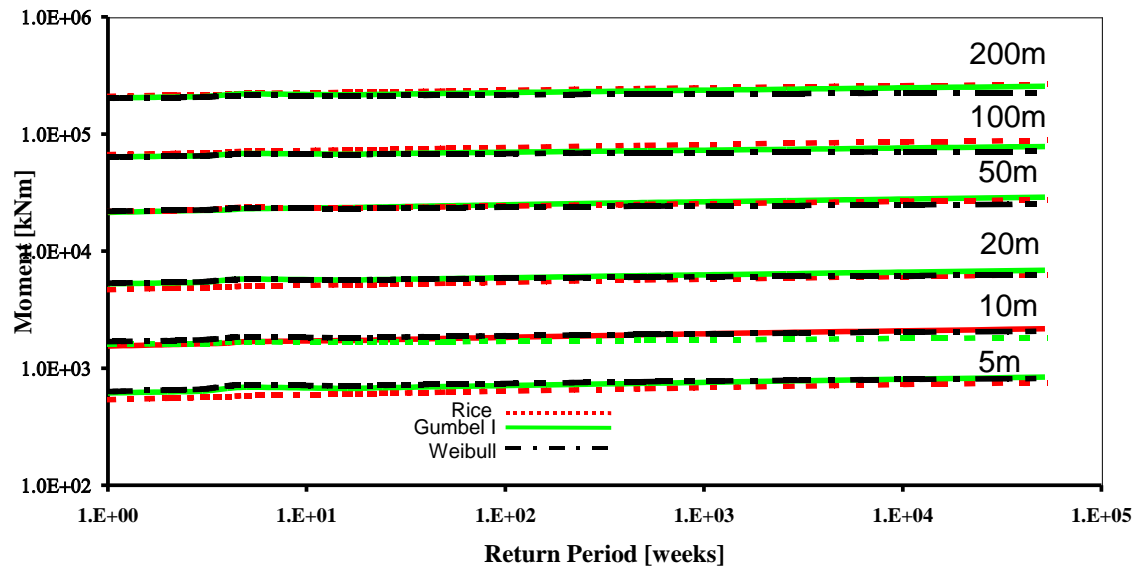


**Figure 1** - Gross weight distribution class A113

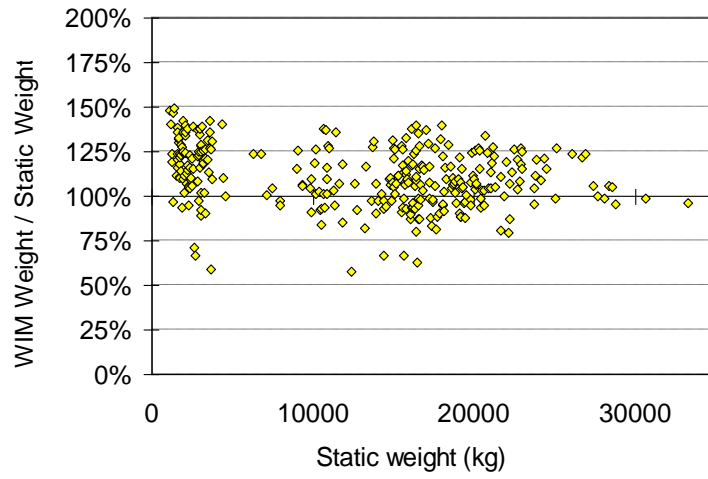




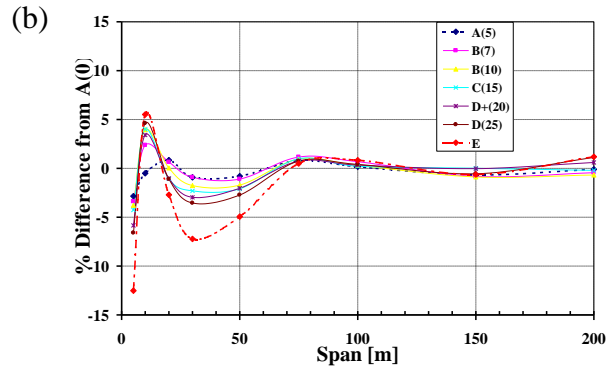
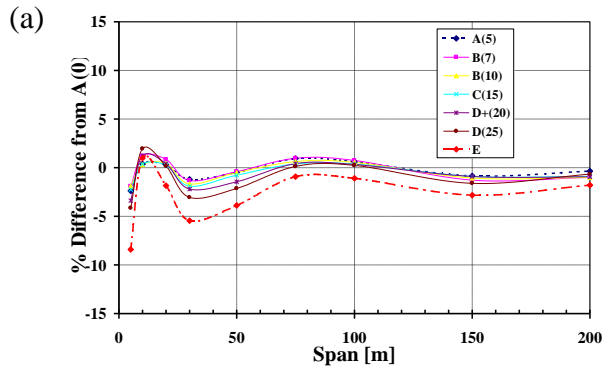
**Figure 2 - Level Crossing Histogram (DDN)**



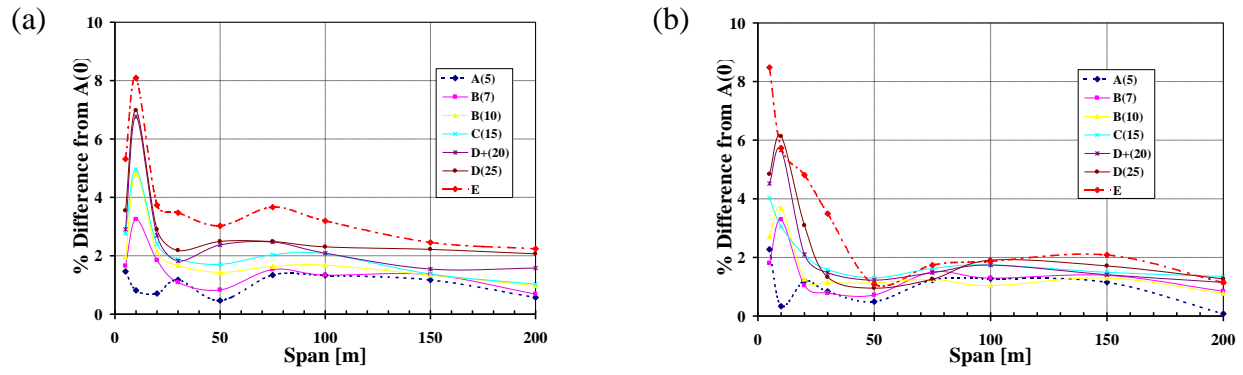
**Figure 3** – Comparison of characteristic extreme prediction methods



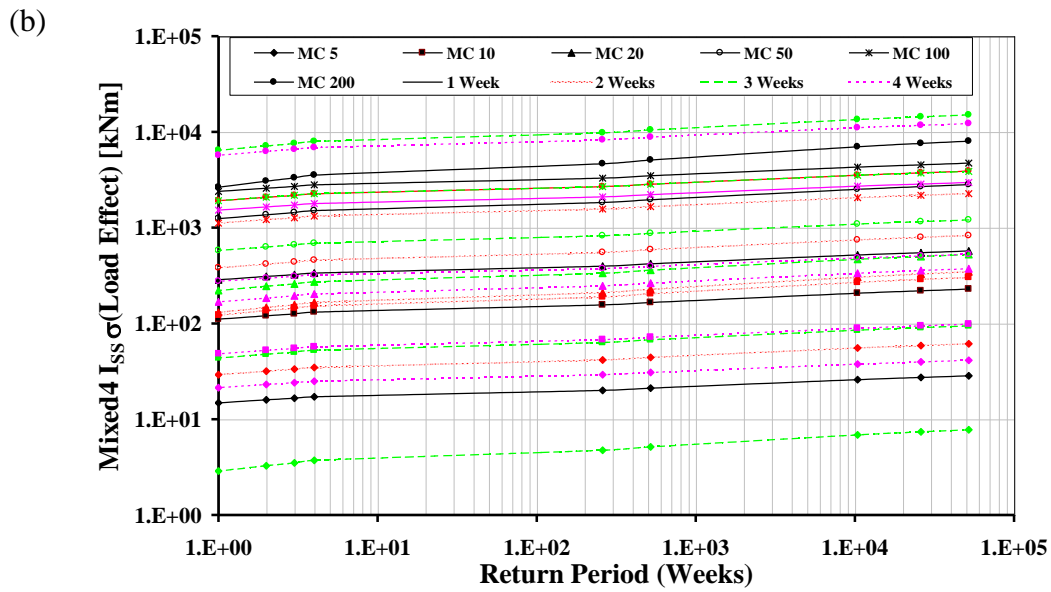
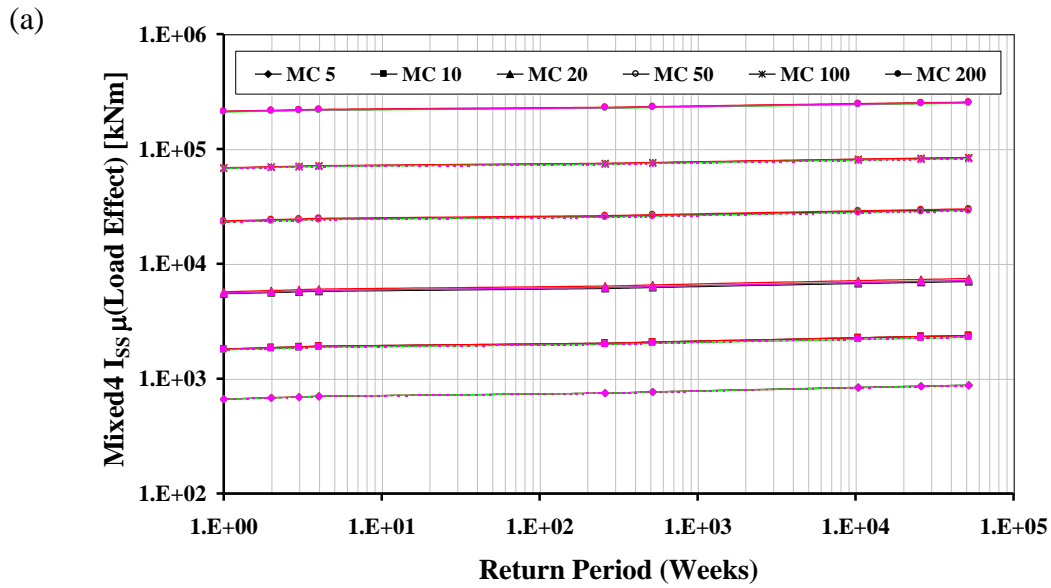
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