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Extrapolation of traffic data for development of traffic load models: assessment of methods used during background works of the Eurocode

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ABSTRACT: This paper reviews several extrapolation methods (for example fitting a distribution to the upper tail of the data and Rice's formula) implemented in the background study of the normal load model, LM1, in Eurocode 1, Part 2. Recent extensively used extreme value theory (EVT) based methods (block maxima method and peaks over threshold method) in other domains such as meteorology (for flood levels, quantity of rain, etc) are also reviewed. The methods are applied on weigh-in-motion (WIM) data to extrapolate characteristic values of long return period. Two different types of comparisons are made on extrapolating extreme gross vehicle weight (GVW), the total load on lane (TLL) and the induced traffic load effect (TLE). The first focuses on differences between the various prediction methods, and the other on changes between past and recently recorded data in France. The results show that the EVT based method is the better one for extrapolation.

KEYWORDS: extrapolation (prediction) method, gross vehicle weight, total load on lane, traffic load effect, characteristic value.

1 INTRODUCTION

Transport demand is growing worldwide. Indeed the road freight transport has increased in Europe by 45.7% between 1995 and 2008 and this strong growth trend seems likely to keep continuing at the same rate of about 2.7% per year (European Commission 2010). It is important to ensure that the European transport network, which has been mainly designed using the national codes, can sustain this continuing growth in demand.

The currently used normal load model, LM1, in Eurocode 1, Part 2 was first calibrated with a two weeks heavy traffic dataset from Auxerre (A6 motorway, Paris to Lyon, France) in the late 1980s; it was then re-calibrated by O'Connor et al (2001) with several representative European traffic datasets recorded at France weigh-in-motion (WIM) sites. The increasing traffic load effect has been found as the augmentation of traffic flow and probability of multiple trucks on bridge simultaneous. Therefore, the load model needs to be periodically re-assessed by current traffic, because of the wide changes in traffic volume, composition of traffic, vehicle weights and sizes, to ensure a satisfactory safety level for the design of new bridges; and also the quality of WIM data has increased greatly in the last decade

due to improved technologies and the development of specifications regulating accuracy levels. Accurate prediction of extreme load effects expected during the proposed or remaining lifetime of a structure is a key issue for the design or assessment of highway bridges.

This paper reviews several methods to obtain these extreme effects: the extrapolation methods (fitting distribution to the upper tail data and Rice's formula) implemented in the background study of the normal load model, LM1, in Eurocode 1 Part 2, and recently extensively used methods (block maxima method and peaks over threshold method). The methods are applied on WIM recorded traffic to extrapolate characteristic values of long return period. Comparisons are made on the extrapolated extreme gross vehicle weight, total load on lane, and induced traffic load effect. We compare the difference between various prediction methods and between past and recent recorded data in France.

This paper is organized as follows: Section 2 reviews the methods. Section 3 describes the WIM data used in this study. Section 4 compares the extrapolation of GVWs, TLLs and TLEs with different methods based on the three sets of WIM data and gives some comments and section 5 gives some conclusions.

2 REVIEW OF EXTRAPOLATION METHODS

In bridge engineering, the GVW of a heavy truck is particularly important to assess load effects on structures, as a single-heavy-truck combined with common trucks governs the traffic loading scenarios for short- to medium-span bridges; while multiple trucks on bridge simultaneously governs the traffic loading scenarios for medium-span to large span bridges. The extreme traffic load effects induced by these loading events should be obtained by extrapolating.

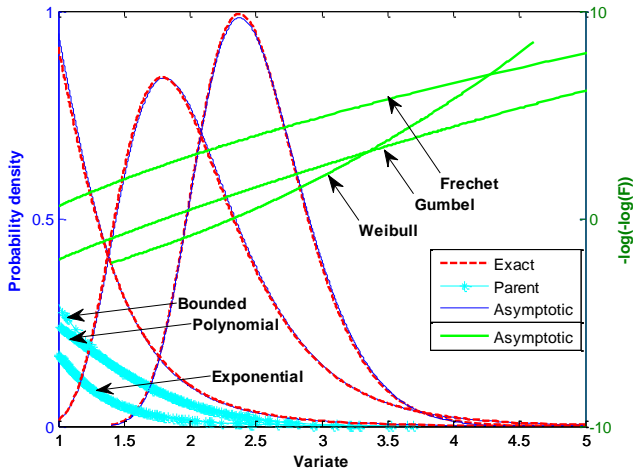


Figure 1 Comparison of extreme value distributions.

Let X be a random variable with distribution F , and x_1, \dots, x_n , an identically and independent distributed sample from X . The maximum value over the "n-observation" period is $M_n = \max x_1, \dots, x_n$. Then the distribution of M_n can be derived by $\Pr M_n < z = [F(X < z)]^n$, see Figure 2. This distribution has a well known limit, given in Figure 1 (Weibull, Gumbel, Fréchet).

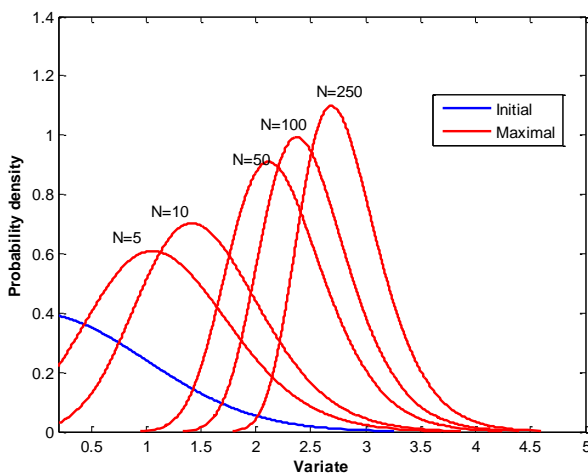


Figure 2 Extreme value distribution PDF for varying n

2.1 Prediction methods used in the background studies of Eurocode

In the background studies for the development of the Eurocode for bridge loading (EC1.2 2003), Bruls et

al. (1996) and Flint & Jacob (1996) consider several methods of extrapolation, including: a half-normal curve fitted to the histogram tail; a Gumbel distribution fitted to the histogram tail; Rice's formula for a stationary Gaussian process. O'Connor et al (2001) perform a study on the normal load model in ENV 1991-3 to validate the adequacy by a number of newly collected representative WIM data, and Rice's formula is adopted to extrapolate the characteristic load effects.

2.2 Basic of theory

The methods of statistical inference used in the literature to predict extreme traffic load effects are numerous. The following critique of the literature distinguishes four types of methods: those fitting distribution to the upper tail data, those extrapolating traffic load effects by Rice formula, those dealing with the generalized extreme value distribution based block maximum method and those fitting generalized Pareto distribution to peaks over threshold.

2.2.1 Fitting a Gaussian distribution to the upper tail

The distribution of M_n can be derived exactly according to the parent distribution function F of the sample (Coles 2001). However, raising an initial distribution function to a power leads to various types of extreme value distribution (see Figure 1), because of the tail of the initial distribution function. Only the upper tail of parent distribution function seriously contributes to the maximum distribution function (Bailey 1996) which is obtained by raising F to a power (see Figure 2).

Jacob (1990) fits a half normal distribution and Gumbel distribution to the high tail in order to predict the characteristic load and load effects of longer return periods. To calibrate AASHTO and develop a new load model, Nowak et al. (1994) fits a normal distribution to the upper tail of the ratio of load effect to HS20 load effect to extrapolate the average 75-year maximum load effect. However, neither the plotting position method nor the rules of threshold selection are described. Fu & You (2009) fit a Gumbel distribution to extrapolate load effects for long return periods.

There is a common agreement on using multimodal normal distribution to fit the curve of the GVW: O'Brien et al. (2010) fit normal distribution to the high upper tail, O'Connor & O'Brien (2005) use trimodal, while Mei and Qin (2004) utilize bimodal to fit GVW data. Thus a normal distribution is adopted to fit the upper tail of GVW for prediction. Its cumulative distribution function is:

$$F(x; \theta) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \quad (1)$$

where the parameter vector is $\theta = \mu, \sigma$, the mean and standard deviation values, respectively. The R-year return level, z , corresponding to exceeded probability of α is:

$$z = \mu + \sigma \cdot \Phi^{-1} 1 - \alpha \quad (2)$$

where Φ^{-1} is the generalized inverse of the normal distribution function.

2.2.2 Rice formula

Jacob (1996) considered Rice's formula to predict longer term return level of the load effect for the case of free traffic and congested traffic. To apply Rice's formula, the load effect should be assumed to Gaussian stationary process. Ditlevsen (1994) proved that a load effect from a long traffic load (several days) on a large bridge with slowly and smoothly varying influence lines could be modeled as a Gaussian random process.

Then, under the Gaussian hypothesis, the mean rate $v(x)$ of exceedences of a level $x > 0$ (number of times the level x is crossed with increasing values) during a reference period T_{ref} can be expressed by Rice formula,

$$v(x; \theta) = \frac{\dot{\sigma}}{2\pi\sigma} \exp\left[-\frac{x-m^2}{2\sigma^2}\right] \quad (3)$$

where θ is the vector of parameters: m is the mean of the process, σ is its standard deviation and $\dot{\sigma}$ is the standard deviation of the differentiated process.

Then the characteristic value for a long return period R can be extrapolated based on the definition of return period which is the mean period between two occurrences. Therefore the corresponding value is:

$$z = v^{-1} R, \theta \quad (4)$$

The critical issue in using the Rice formula is to estimate the parameters. Cremona (2001) provided an approach to obtain the optimal extrapolation of traffic load effect. By taking the logarithm of the Rice formula, the parameter estimation problem is simplified to the identification of the parameters of a second order polynomial function. The same as in fitting a distribution to the upper tail, only the upper tail of the level crossing histogram is important to extrapolate the R-year return level. Cremona (2001) suggested determining the optimal number of class intervals of the level-crossing histogram to use for fitting the Rice formula via Kolmogorov test. Getachew (2005) adopted Cremona's approach to analyze traffic load effects on bridge induced by both surveyed and Monte Carlo simulated traffic data. O'Connor & O'Brien (2005) compared the predicted extremes of simply supported moment for span lengths of 5, 10, 20, 50, 100 and 200 m by the Rice formula, classic Gumbel and Weibull extreme

value distribution. There is approximately a 10% difference between Rice and others. It demonstrates the importance of appropriate selection of an extreme value prediction method.

2.2.3 Block maxima method

As shown in Figure 2, the higher power to which we raise the initial distribution function, the less data that contributes to the maximum distribution function. In other words, very small discrepancies in the estimate of F can lead to substantial discrepancies for F^n . Fu & You (2009) states that 500 million data entries are needed to accurately predict a 75 year maximum with 4000 average daily truck traffic (ADTT): it is obviously impossible to obtain accurate extreme values in that way.

However, statisticians have found that F^n asymptotically tends to three classical extreme value distributions: Gumbel, Frechet and Weibull, which correspond to three different tail behaviors of the initial distribution function F , exponential, polynomial and bounded, see Figure 1 (Kotz & Nadarajah, 2000; Castillo et al., 2004). A unification of the three families of extreme value distribution into a single family known as generalized extreme value (GEV) distribution has been widely used in recent years to avoid choosing which of the three families is most appropriate for the data at hand. Moreover, reducing the power will increase the stability of prediction. So the block maximum method may be the best method that fits the GEV distribution to periodic, thus the GEV distribution is fitted to the daily maxima in this paper. Its cumulative distribution function is:

$$G(z; \theta) = \exp\left\{-\left[1 + \xi \left(\frac{z - \mu}{\sigma}\right)^{-1/\xi}\right]\right\} \quad (5)$$

where the parameter vector is $\theta = \xi, \sigma, \mu$, the shape, local and scale parameters, respectively. The R-year return level, z , corresponding to a probability α of exceedance is:

$$z = \mu - \frac{\sigma}{\xi} \left[1 - (-\log 1 - \alpha)^{-\xi}\right] \quad (6)$$

2.2.4 Peaks-over-threshold method

In hydrology, finance and wind engineering disciplines, it is extensively agreed that the way of using information is rather uneconomical and unreasonable in the block maxima method. The discarding of some of the largest observation in the block, given that only the block maximum is considered, represents a loss of information. Peaks-over-threshold (POT) method is an approach that can avoid deciding distribution type and efficiently using upper tail data. Crespo-Minguillon and Casas (1997) use POT approach to study weekly maximal traffic load effects. James (2003) analyzes traffic load effects on

railway bridges by POT approach. Asymptotic theory reveals that the excesses over sufficiently high threshold have an approximate distribution following generalized Pareto (GP) family which is:

$$H(y; \theta) = 1 - \left(1 + \frac{\xi y}{\sigma} \right)^{-1/\xi} \quad (7)$$

where $y = x - u$ is the excess of x over threshold u , and the parameter vector is $\theta = \xi, \sigma$, the shape and scale parameters, respectively. The R-year return level, z , corresponding to m observations over R-year is:

$$z = u + \frac{\sigma}{\xi} \left[m \zeta_u^{\xi} - 1 \right] \quad (8)$$

where ζ_u is the proportion of data over the threshold u .

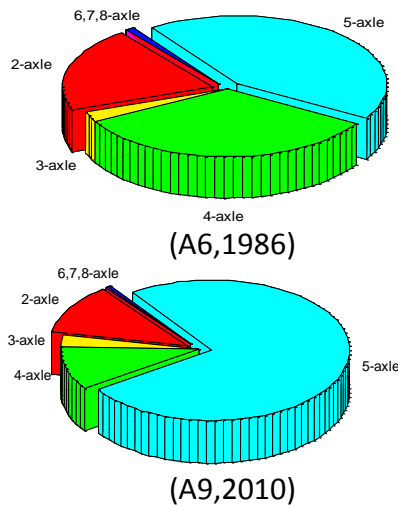


Figure 3 Proportion of vehicle types

3 WIM DATA USED

For this study two sets of WIM data are studied to extrapolate the extreme value of GVW and traffic load effect on a given bridge. One was recorded in the 1986, and the other consists of modern data that was recorded in 2010. In order to eliminate possible measurement errors, these data were scrubbed first before processing with cleaning rules (Sivakumar et al., 2010; Getachew 2005; Enright 2010), such as GVW greater than 3.5t, vehicle speed in the range of 35 km/h to 160 km/h etc..

The first set was recorded by the same WIM station on A6 highway at Auxerre in France, and this site has 4 lanes of traffic (2 in each direction). However, two lanes were recorded for one week from 26th May to 2nd June 1986. It contains 46049 trucks after filtration. The second set of data was from a piezo-ceramic weigh-in-motion system on the A9 motorway near Saint Jean de Védas, South-East of France in 2010. Only the upstream traffic lanes are recorded. In total 835468 trucks from January 2010

to May 2010 (GVW greater than 3.5 t) were recorded in the three lanes, with an average daily truck flow of 6217 trucks.

Tables 1 and 2 show the traffic remarkably evolved from 1986 to 2010. The average daily truck traffic (ADTT) has more than doubled in these 24 years; the average yearly growth rate is about 4.5% that is larger than the average growth rate of 2.7%. The composition of traffic has also hugely changed as shown in Figure 3, the proportion of 5-axle truck increases by about 30%, while the proportion of 4-axle truck decreases by about 20%, it is caused by an increase in the gross vehicle weight limit from 36 to 40t in 1992. 4-axle tandem trucks were replaced by 5-axle trimdem trucks.

Table 1 The basic information

Name of road	A6	A9
Time of recording	May, 1986	Jan. – May, 2010
Site location	Auxerre	St Jean-de-Vedas
No. of measured lane	2	3
Record period (days)	7	138
No. of trucks recorded	46049	835468
Av. hourly flow per lane	107	259
Av. daily flow per lane	2558	6217

Table 2 Proportion of vehicle types (classified by no. of axles)

No. of axles	A6, 1986		A9, 2010	
	No. of trucks	Percent (%)	No. of trucks	Percent (%)
4	14306	31.07	82926	9.93
5	19835	43.07	628709	75.25

4 EXTRAPOLATIONS AND COMMENTS

To re-assess the load model of Eurocode, three types of extrapolation have been done in this paper, which are the prediction of extreme GVWs, TLLs and TLEs. The prediction of GVW is based on single truck weight, the prediction of TLL is based on total loads on a single lane with length 50m, and the TLE is the induced mid-span moment of a simply supported structure. The influence lines are illustrated in Figure 4, and the time history of TLL and TLE are illustrated in Figure 5 (It is a double y-axis figure, on which the left y-axis is mid-span moment and the right is total traffic load on lane). As proved in the authors' paper (Zhou et al 2012), stable prediction can be achieved based on weekday's traffic, all extrapolations are based on weekday WIM data.

In order to demonstrate the efficiency of extrapolation, three different R-year return levels have been extrapolated: 1000-year return for each data set, 24-year return level for the data of 1986 and 1-year return level for the data of 2010. Because of the very short measured period, the number of daily maxima were not enough to ensure to obtain reasonable ex-

trapolation, the hourly maxima has been used to apply block maxima method.

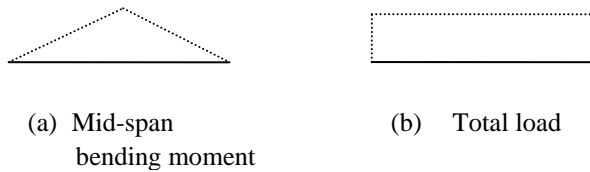


Figure 4 Influence lines used in calculation

The predictions are compared with those in previous background studies. The differences between characteristic values for the past and this study are given.

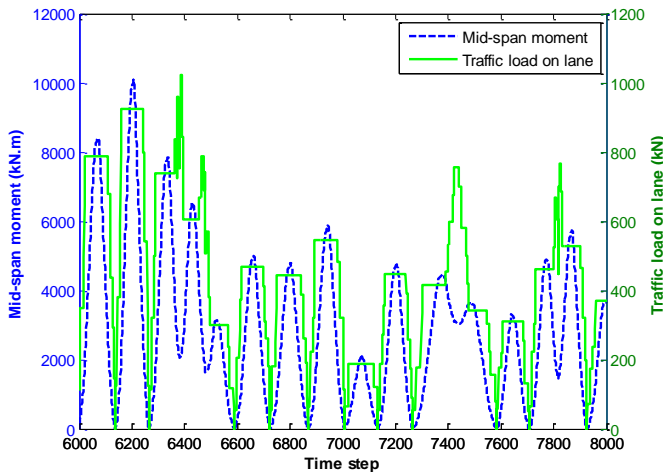


Figure 5 Time history of total load and induced load effect

Table 3 Gross vehicle weight statistics (in tons)

	A6,1986	A9,2010
Max of all trucks	76.1	74
Mean of all trucks	31.865	26.603
COV of all trucks (%)	0.436	0.407
Mean of daily maxima	62.120	57.543
COV of daily maxima (%)	0.084	0.127
Mean of second mode	41.387	36.505
COV of second mode (%)	0.148	0.093

4.1 Gross vehicle weight

The GVWs were analyzed for the purpose of extrapolating the extreme traffic load and calibrating the traffic load model.

Figure 6 shows the GVW histogram for these three sites' data. As shown, the modal has moved from right to left as time goes on, more details are given in Table 3, which shows summary statistics for the data. The mean GVW of all trucks has decreased from 31.9 t to 26.6 t; and the same phenomena has been found on events like daily maxima and top 5% trucks. While this phenomenon is in contradiction with the continuous trend of truck load increase, some explanations are: (i) a better precision of WIM sensors and stations (more efficient calibration), (ii) more effective enforcement above all since 2008 in France with the WIM based scanning

(Marchadour and Jacob, 2008), and (iii) two different sites.

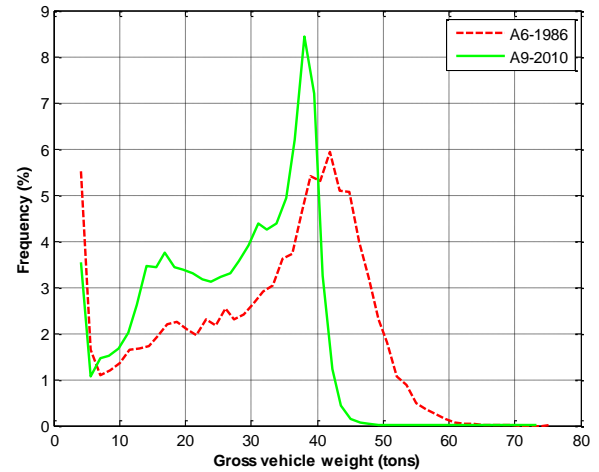


Figure 6 GVW histogram

Table 4 Extrapolated characteristic value of GVW (in tons)

Site	Method	Distribution parameters			Return period (years)	
		Shape	Scale or standard deviation	Location or mean	1000	Short*
A6 1986	Normal		8.71	28.28	79.99	74.37
	GPD	-0.09	2.57		78.42	75.56
	GEV	-0.23	4.54	53.44	72.51	71.79
A9 2010	Normal		8.64	47.68	100.3	94.69
	GPD	-0.20	5.57	-	81.61	75.76
	GEV	-0.10	4.85	44.62	82.12	72.41

*24-year, 1-year return levels for A6-1986 and A9-2010 data respectively.

Using the previously mentioned prediction methods on GVW as the basis for comparing the impact of the models and the evolution of traffic, the R-year return levels of GVWs are given in Table 4. From these sources some general observations can be made:

- Firstly, as expected, the extrapolated values increase from 1986 to 2010 as the traffic flow and the proportion of maxi-code 5-axle trucks increase.
- Secondly, the simply fitting of a normal distribution to upper tail data almost provides much higher estimates than the other two EVT based methods. This is surely due to the selected normal distribution: the shape parameters of the two EVT based methods are negative, which means the underlying parent distribution has a bounded tail, while the normal shape has exponential infinite bound. This shows once again the efficiency of the EVT based methods.
- Finally, the comparison of characteristic values for 24-year return period of the data of 1986 and 1-year return period of the data of 2010 show that these values are quite similar for the same methods. This means that the extrapolation can predict well the future events, i.e. the return levels can be

assessed as well with the data of the 1980s as with the data of 2010.

The GEV method brings about the Weibull distribution which is bounded (the bounds for Table 4 are 73.17 t for 1986 and 93.12 t for 2010). So, there is a discussion that must take place about whether the GVW is bounded or not. This discussion was made in the Joint Committee on Structural Safety (JCSS) in the 80s. Ditlevsen claimed that because the whole truck population is finite, the GVW distribution must be bounded. Jacob and Rackwitz inclined for a non upper bounded distribution, because the GVW possible values are infinite, and no upper limit may be chosen without truncating some abnormal loads, or imposing an arbitrary asymptotic value much too high. The question is not fully decided, and the choice should carefully take into account the available information and the consequences on the extrapolation.

4.2 Total load on a lane length

The objective of this section is to predict the maximum of the total load on a lane length for a typical medium span bridge of 50 m. As shown in Figure 5, process of total load on lane is a square-wave; therefore the Rice formula and fitting a Gaussian to upper tail are not a good choice. The block maxima method is chosen to perform the extrapolation. Table 5 summarizes the distribution parameters and characteristic values for different cases. The extrapolated values are compared with those of past studies, see Table 5. Indeed, in the last four columns of Table 5, several extrapolations of past studies are given: column “A6-1” gives the difference between our extrapolated values and those originally extrapolated

by Calgaro in the background studies for Eurocode 1 (traffic data is from the A6 highway in 1986); column “A6-2” is the difference between our extrapolated values and those obtained by Alan O’Connor (O’Connor et al, 1998) in his benchmark on extrapolation methods (the traffic is that of highway A6 in 1998). The last column, called “LM1 Design effects”, gives the difference between our extrapolated values and the design effects of the load model 1 of Eurocode 1. Some comments can be made:

- Firstly, stable predictions have been obtained due to the large size of the samples.
- Secondly, we note that the extrapolated values are lower than the effects of load model 1 of Eurocode 1, in any cases. If we consider the recent WIM data (of 2010), we see that the 1000-year return level calculated with this data is between 40% and 50% inferior to that obtained with the load models of Eurocode 1, which is on the safe side.

4.3 Traffic load effect

The load effect considered in this part is the bending moment of a simple supported bridge of 50 m length. The partial conclusions that can be made based upon the results given in Table 6 are:

- First, the Rice’s formula provides larger estimates than other methods, and it states that the total load on a lane length is bounded, which is reasonable as the traffic flow, distribution of GVW is stationary.
- Secondly, generally the characteristic load effects provided by modern data are similar to those for the 1980s’ data.

Table 5 Extrapolated characteristic value of load on lane (in kNs)

Site	Method	Distribution parameter			Return period		Difference (%)		
		Shape standard deviation or standard deviation	Scale or standard deviation of differentiate process	Location or mean	Short	1000 (years)	A6-1* ¹	A6-2* ²	LM1 Design effects
A6 1986	GEV (see 2.2.3)	-0.56	149.2	808	1072	1072	-35.58	-42.74	-45.03
A9 2010	GEV	-0.31	126.1	661.6	1033	1055	-36.61	-43.64	-45.90

*¹: value extrapolated by Calgaro (quoting from O’Connor et al, 1998)

*²: value extrapolated by O’Connor (quoting from O’Connor et al, 1998)

Table 6 Extrapolated characteristic value of single lane’s traffic load effect (in kN.m)

Site	Method	Distribution parameter			Return period		Difference (%)		
		shape	Scale	Location	Short	1000 (years)	A6-1	A6-2	LM1 Design effects
A6 1986	Rice	-31973	96892456	4470372.9	16262	19873	99.84	41.67	26.12
	GPD	0.20	292.5	-	14826	26385	123.17	58.20	40.84
	GEV	-0.13	517.7	5629	8829	9178	2.87	-27.08	-35.08
A9 2010	Rice	10229.3	3821.8	2689502	8563	10229	-7.70	-34.57	-41.75
	GPD	-0.13	591.7	-	9128	9631	31.46	-6.81	-17.04
	GEV	-0.10	599.2	4764.5	8226	9455	-4.92	-32.60	-39.99

- Thirdly, among the three methods, the GP distribution based POT approach provides better extrapolations.
- Finally, the extrapolated characteristic values assessed based on short measurements are more prone to variations. This is the case for the return levels assessed by means of the traffic of 1986.

5 CONCLUSIONS

In this study, various prediction methods are applied to extrapolate the characteristic GVWs, TTLs and TLEs for long return periods. The results show that it is very important to choose the adapted prediction method for the considered effect: for example, POT is the optimal for bending at mid-span of a single-span structure of 50m. In generally, the EVT based method is the better one in the studied cases. Moreover, a bigger size of sample gives more stable extrapolations, while Monte-Carlo simulation or the Bootstrapping method could be a useful method to reduce the variation of a sample by expanding the size of sample. The comparisons between extrapolations and LM1 design effects show that the normal load model LM1 is sufficient for modern traffic.

6 ACKNOWLEDGEMENT

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