Ocean Engineering 169 (2018) 19–37

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Effects of parameter estimation method and sample size in metocean design conditions

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ARTICLE INFO

Keywords:
Block maxima method
Sample size
GEV distribution
Wind speed design values
Parameter estimation methods
ERA-20C

ABSTRACT

The accurate estimation of extreme values for metocean parameters (wind speed, wave height, etc.) plays a crucial role in marine renewable energy industry and in coastal and offshore engineering applications. The most fundamental approach for extreme value analysis is the annual maxima approach that is directly related to the Generalized Extreme Value (GEV) distribution. Since the performance of the GEV parameter estimation methods is dependent on both the method and the available sample size, the exploration of these issues is analytically performed. Firstly, a simulation study is implemented based on the Maximum Likelihood (ML), the L–moments (LMOM), the Elemental Percentile and the Maximum Product of Spacings methods for different sample sizes. It is concluded that the ML should not be taken for granted since LMOM method performs better in many respects. Afterwards, both methods are applied for the estimation of the GEV parameters of wind speed annual maxima series. LMOM method provided the best fits for the overwhelming majority of cases considered. Finally, the 50- and 100-year wind speed return levels are estimated. With respect to the relative confidence intervals of the return level estimates, no solid conclusions can be drawn since there is lack of a systematic behaviour.

1. Introduction

Extreme value analysis (EVA) of metocean characteristics, such as wind speed, wave height, sea-level, etc., is of significant importance for engineers and environmental scientists. One of the main objectives of EVA refers to the estimation of design values (return levels) and associated return periods of the random variable of interest. See, for example, (Kharin and Zwiers, 2000), (Ronold and Larsen, 2000), (Engeland et al., 2004), (Chen et al., 2004), (An and Pandey, 2005), (Caires and Sterl, 2005), (Stefanakos et al., 2007), (Larsén and Mann, 2009), (Chen and Huang, 2010), (Vinoth and Young, 2011), (Jonathan and Ewans, 2013), (Panchang et al., 2013), (Gouldby et al., 2014), (Sarkar et al., 2014), (Anastasiades and McSharry, 2014), (Cannon et al., 2015), (Su et al., 2017), (Manis and Bloodworth, 2017), (Pes et al., 2017), (Wang, 2017), where various applications of EVA in ocean, environmental and civil engineering can be found.

Design parameters corresponding to environmental loads implied by wind, waves, etc. are used in practice to evaluate the resistance of an offshore structure in the ultimate limit state. In addition, the accurate estimation of design values greatly facilitates the analysis of different serviceability limit states, (Fujino et al., 2012), (Kasperski, 2013). A variety of applications of EVA in wind energy assessment and wind turbine/offshore platform structural design are provided by (Viselli et al., 2015), (Mo et al., 2015), (Kang et al., 2015), (Chiodo et al., 2015), (Patlakas et al., 2016), (Su et al., 2017), (Ali et al., 2017), (Wang et al., 2015), (Wei et al., 2016), and (Pop et al., 2016).

The most widely used EVA methods are the block maxima (BM) and the peaks over threshold (POT). BM and POT methods utilize extreme type data, fitting a distribution function based on solid theoretical grounds. Since the results of these methods are of asymptotic nature, in practice, limited sample sizes may limit, or even render impossible, their applicability. A discussion and comparison of BM and POT methods has been provided in (Ferreira and de Haan, 2015). Particular applications regarding the estimation of metocean extremes can be found in (Soukissian and Kalantzi, 2006, 2009), (Soukissian et al., 2006), (Sartini et al., 2015), (Caires, 2016), (Orimolade et al., 2016). A mathematical introduction to the statistics of extremes has been made in (Beirlant et al., 2004).

In order to implement the BM method, the grouping of data into blocks of equal length and the selection of the maximum of each block is required. According to the main theoretical result of EVA, these maxima follow asymptotically the Generalized Extreme Value (GEV) distribution; see (Coles, 2001), Ch. 3. Though some theoretical restrictions apply (e.g. the block maxima should be realizations of

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https://doi.org/10.1016/j.oceaneng.2018.09.017
Received 26 October 2017; Received in revised form 4 September 2018; Accepted 6 September 2018
0029-8018/

independent and identically distributed random variables), an important advantage of the BM method is that it still works when the maxima are not exactly independent and identically distributed (iid), provided that the long range dependence of high level exceedances is weak (Ferreira and de Haan, 2015). Some important issues of debate as regards the application of the BM method (and other EVA methods as well) to measured data are the following:

1. The available sample size: Some of the parameter estimation methods of the GEV distribution perform marginally fair with small sample sizes; for example, the performance of the widely used Maximum Likelihood (ML) method can be extremely erratic for small samples, i.e. $N \leq 25$, see (Katz et al., 2002), especially with respect to the estimation of extreme quantiles of the GEV distribution. Long time series are generally required for the accurate estimation of extremes; however, there is no consensus with regards to the required length of the time series. In (Cook, 1985) it is suggested that the BM method (with 1-year block size) can produce reliable results, when the available records have a duration of 20 years at least; see also (Palutikof et al., 1999). In the discussion of (Dukes and Palutikof, 1995) with particular reference to wind speed annual maxima (AM) time series, it has been noted that it is difficult to identify the effects of the length of time series on the maximum return period in order to safely consider the obtained estimates as reliable. Using GEOSAT wave measurements (Panchang et al., 1998), concluded that extreme value estimations from five years and 14 years of data are very close. Some authors, e.g. (Jeong and Panchang, 2008), also accept that extrapolations to return periods three or four times the data length are appropriate. In (Devis-Morales et al., 2017) the authors claim that 35 years of data are enough to predict the 100-year wave height, while in (Perrin et al., 2006) 30 years of wind speed data have been used for the estimation of 50 and 100-years design winds; see also (Polnikov et al., 2017) for a similar approach as regards wave height. On the other hand, in (Vanem, 2017), it has been suggested that "*at-site analyses based on 30 years of data are reasonably accurate for return periods up to about 20 years, but not much more than this*". A method introduced by (Cai and Hames, 2011) can be used to determine the minimum sample size required for the estimation of the GEV distribution parameters based on the asymptotic properties of the ML method. Nevertheless, the sample size issue related with the BM approach still remains open.

2. The choice of the block size: As already mentioned, the most pronounced problem in EVA, and in particular of the BM approach, refers to the appropriateness of the available sample size for a rational design value estimation. This issue is directly connected with the choice of the block size. A small block size may lead to large bias while a large one may lead to large estimation variance; see, e.g. (Coles, 2001). For most environmental parameters the one-year block size has been established.

3. The parameter estimation technique: For the estimation of GEV parameters, a widely used method is the ML, mainly due to its well-developed asymptotic properties; see (Coles, 2001), (Katz et al., 2002). A detailed review, assessment and evaluation of the performance of nine different estimation methods for the GEV distribution parameters has been provided by (Soukissian and Tsalis, 2015). The analysis has been based on a simulation study with a constant sample size $N = 30$, while an application to real wind speed data has been also presented. In the same work, it was concluded that ML, Maximum Product of Spacings (MPS) and Elemental Percentile (EP) methods outperform with respect to bias, variance and mean squared error.[1] However, the potential effects of the available sample size to the estimation of the GEV parameters were not considered since the simulation study was based on random samples with constant size.

Regarding the performance of the GEV parameter estimation methods with respect to the available sample size, various works assessed different estimation methods. In (Madsen et al., 1997) the ML and the methods of L-moments (LMOM) and moments (MOM) have been evaluated through a simulation study. The evaluation has been based on the standardized RMSE with respect to the $T-$ year event estimator (for T=10, 100 and 1000 years) for sample sizes 10, 30, 50. Although the performance of each method was dependent on the value of shape parameter, the considered return levels and the sample sizes, it has been shown that the MOM estimators are preferable. In (Kysely, 2002) LMOM and ML methods have been assessed for EVA of temperature; it was concluded that the individual return values were affected by the choice of the estimation method although there was no sensitivity as regards the estimated parameters by any of the methods. MPS, ML and LMOM methods for small sample sizes (10, 20, 50) have been evaluated through simulation by (Wong and Li, 2006). The evaluation for each parameter estimate has been based on the mean absolute error; the authors concluded that the MPS performs better than ML method, while the first is more stable compared to ML and LMOM methods for small sample sizes (Diebolt et al., 2008). have introduced and evaluated the Generalized Probability-Weighted Moments (GPWM) method and compared it with ML and LMOM for small and medium samples (15, 25, 50 and 100). A recent joint evaluation of MPS, ML and EP methods (along with the quantile least squares method) can be found in (Ashoori et al., 2017), where the average scaled absolute error criterion has been used for the evaluation of the obtained fits.

Another important issue refers to two types of uncertainty that are associated with extreme value estimation problems, namely: i) the aleatory (inherent) uncertainty, that is due to the randomness of environmental processes and cannot be reduced, and ii) the epistemic uncertainty that can be reduced provided that sufficient data for the examined process are available. According to (Orimolade et al., 2016), the components of epistemic uncertainty are data uncertainty, (probability) model uncertainty, climatic uncertainty and statistical uncertainty. The latter is mainly raised by the limited statistical information (e.g. limited sample size) and the parameter estimation method. Epistemic uncertainty may be reduced by increasing sample size and/or reducing sample measurement error (Wada et al., 2016), while the uncertainty raised by the sample can be quantified using bootstrapping (Orimolade et al., 2016). Taking into consideration that in metocean applications EVA is based on sample sizes less than 50 (Wada et al., 2016), examined the effects of the epistemic uncertainty on the estimates of return values. After a simulation study, it was concluded that the Likelihood-Weighted method (LW) provides better estimates of epistemic uncertainty from small samples of poor quality. Uncertainties related with wind and wave analysis have been discussed by (Bitner-Gregersen et al., 2014) while a discussion on wind measurement errors can be found in (Soukissian and Papadopoulos, 2015).

Under the condition that the BM method is selected and the GEV distribution model is adopted, the primary aim of this paper is the identification of the combined effects of i) the sample size of AM, and ii) the GEV parameter estimation method to the EVA of wind speed time series. Accordingly, this work is structured in two parts: in the first part, after a short introduction to the asymptotic extreme value theory of iid random variables and a description of the considered GEV parameter estimation techniques (Section 2), in Section 3 a simulation study and the comparison of ML, MPS, EP and LMOM estimators is performed for different sample sizes in the range [20,50].[2] The LMOM method is also included since its suitability has been suggested by other authors especially for small sample sizes; see, e.g. (Hosking et al., 1985), (Hosking, 1990), (Katz et al., 2002). Regarding the assessment of each estimation method performance, different statistical criteria are adopted for the evaluation of: i) each GEV parameter estimate and ii)

[1] According to bias, the MPS method performs better, while according to the mean squared error, the EP, MPS and ML methods seem to outperform.

[2] The considered small to medium sample sizes roughly correspond to the usually available sample sizes in relevant met-ocean applications.