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Equitable Testing and Evaluation of Marine Energy Extraction Devices in terms of Performance, Cost and Environmental Impact

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Extremes and Long Term Extrapolation

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Extremes and Long Term Extrapolation

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Summary

This report examines methods that may be applied to assessment of extreme sea states for the purposes of marine energy resource assessment. Single parameter (univariate) techniques including block maxima and storm maxima methods. I-FORM, a multivariate extreme extrapolation technique is also discussed.

CONTENTS

1 INTRODUCTION

In the reliability-based design of marine structures, long term extrapolation aims to provide engineers with metocean conditions

- which induce loadings and response of the structure capable to conduct to its failure
- with a probability of exceedence during the operational life of the structure sufficiently low to correspond to an acceptable risk

The low level of probability of exceedance considered makes that generally these metocean conditions have not been encountered during the duration of observation of the metocean parameters.

Classically, the probability of exceedence of a level is expressed as a return period. This return period is the time duration during which this level is exceeded once on average (e.g. 50-year return period). The level is called a return value (e.g. 50-year H_{m0} return value). This return period is sometimes artificial (e.g. 1000-year return period) and in this case refers simply to a very low probability of exceedance.

The calculation of wave or sea state parameters return values is challenging due to the typically short duration of physical measurements and the possible bias in long duration hindcasts. It is therefore necessary to apply extrapolation techniques using empirical distributions fitted to the available data to obtain the higher return values. As with all techniques of extrapolation, the result is very sensitive to the model of extrapolation. The model must be chosen based on robust physical or statistical considerations.

Extreme value theory and models provide tools for this extrapolation to events more extreme than those observed in a shorter period of time.

2 THE CONTEXT

There are *three* main considerations when determining the optimum extrapolation methodology:

- *The available observations: In situ*, satellite, numerical (hindcast)
- *The time scale to consider:* Individual waves, sea-states, gust wind, …
- *The environmental parameters*: The load or response of a structure is dependent of one or several parameters, of various type (intensity, frequency, direction, ...)

2.1 AVAILABLE OBSERVATIONS

The sources of physical measurement are numerous but few are practically usable for long term extrapolation.

- *In situ:* the duration of *in situ* measurements are generally short, with missing data, and expensive. Moreover if they concern a new site, the duration is the time the project is ready to wait before proceeding with deployement and is inevitably short. *In situ* data is mainly used for validation of other sources and may not be used for long term extrapolation.
- *Satellite:* there is now a long duration (~10 years) observations with altimeters and SAR (Synthetic Aperture Radar). Their advantage is their extensive world coverage, but their principal drawback is the coarse sampling in time and space (depending of the satellite). Due to the sampling in time, a lot of storms are missing, capital information for the extreme extrapolation. The information on sea-states is also limited, only H_s is usable from the altimeters, directional spectrum is partially (in frequency and direction) measured with the SAR. As with *in situ* measurements, satellite data can be used for calibration and have recently assimilated in numerical models.

Numerical: The numerical models avoid the two problems of *in situ* and satellite measurements. They provide information on long durations for global models (e.g. 45 years ERA40 [1], 12 years free NOAA-WW3 [2]), but also for regional models (e.g. ANEMOC [3], grid 2-3km, 24 years, no current, no tide). An example of H_s time series from 45 years of ERA40 hindcast, offshore Portugal, is given in Figure 2.1. In complicated situations (islands, complex bathymetry, strong tide and currents) long durations are too computing time expensive. Methods of space propagation by learning techniques (e.g. neural network) are necessary to obtain long historical datasets. Due to approximations or simplifications of the numerical model, bias is present and must be corrected as much as possible, for example in using *in situ* measurement. In Figure 2.2, the comparison of the H_s given by the hindcast model and buoy measurements show a quite good agreement. However, when looking at a quantile-quantile plot (Figure 2.3) a slight bias is clear, giving lower high values for the model than for the buoy.

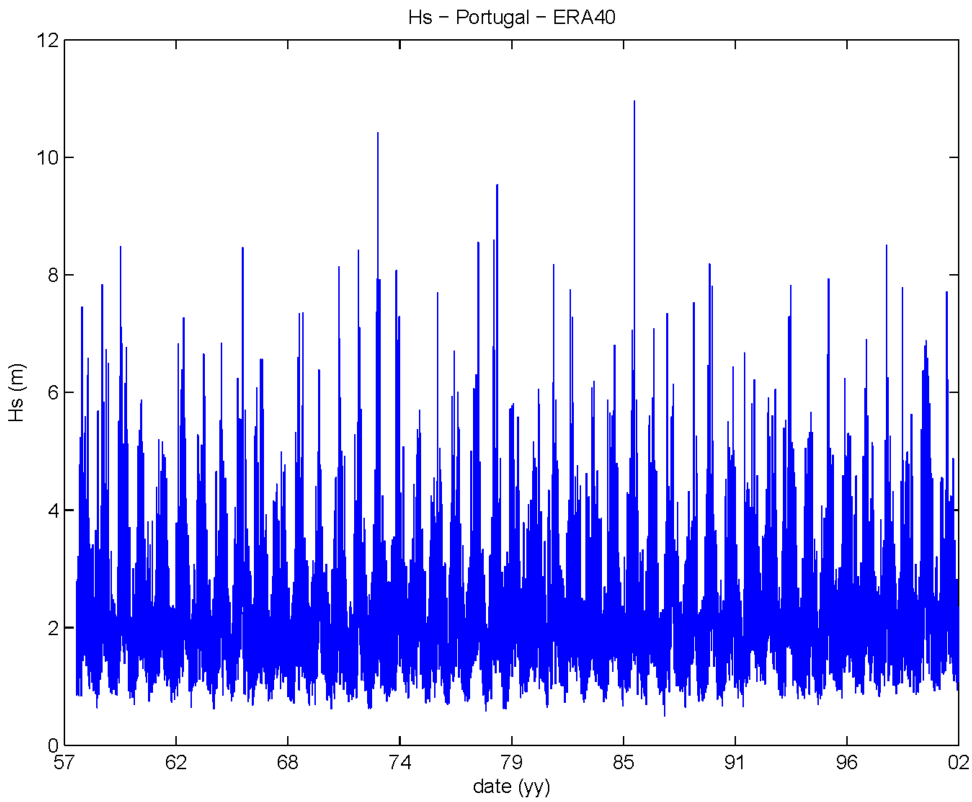

Figure 2.1 Hs time series offshore Portugal

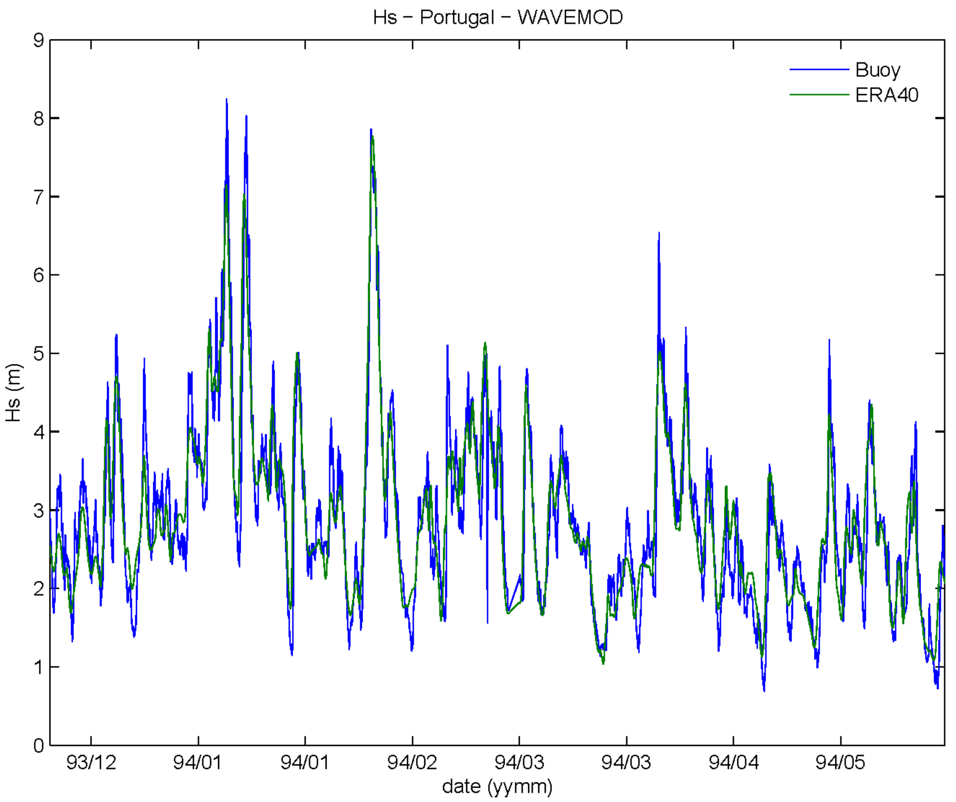

Figure 2.2 Hindcast vs in situ data

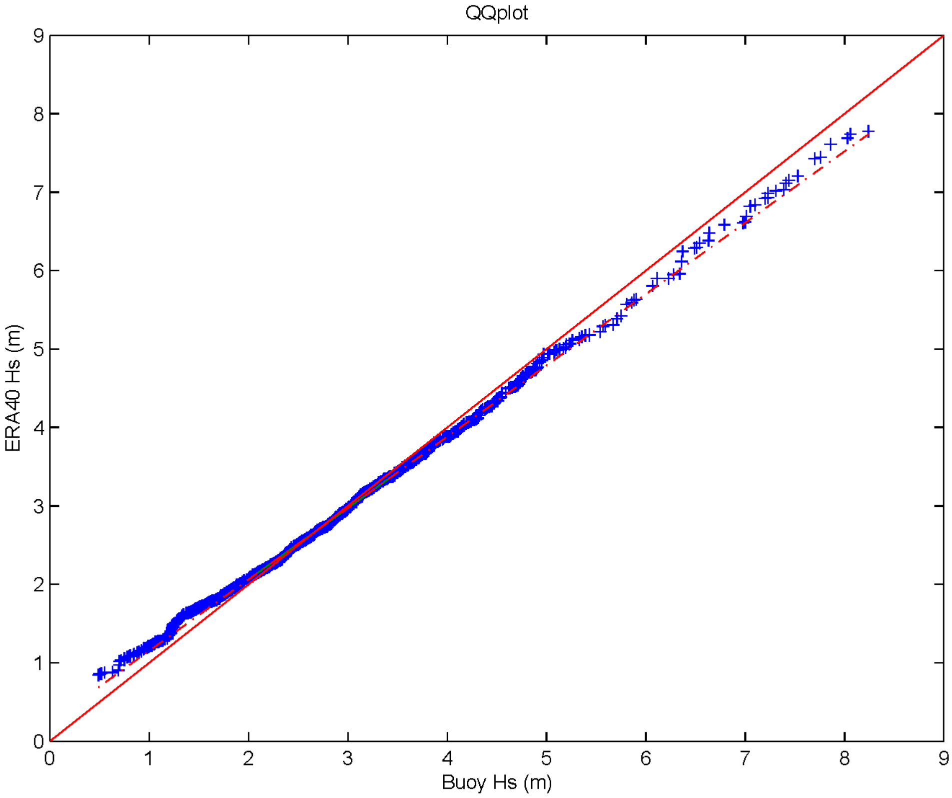

Figure 2.3 QQ-plot Hindcast vs *in situ* data

2.2 THE TIME SCALE

Two different time scales are generally considered in design for waves: the **individual wave** or the **sea-state**. For wind, **gust** and **mean wind** speed. The short scale is rarely available in database constructed from measurements (very often restricted to the maximum value inside a longer scale) and not available with satellite and hindcast models. Extrapolation on a short scale parameter will be based on previously fitted statistical models.

2.3 THE ENVIRONMENTAL PARAMETERS

The design criteria, based on stress, displacement, depend on one or several parameters of various types. The induced loading and response could be considered dependent of

- one parameter - one metocean phenomena (e.g. significant wave height, wind speed, …)
- several parameters - one metocean phenomena (e.g. significant wave height, mean period, mean direction, …)
- one parameter - several metocean phenomena (
- several parameters

A parameter can be of different kind

- intensity (e.g. wave height, H_s, wind or current speed) with induces loading or response increasing monotonically with the parameter
- other type (e.g. wave period, direction) with induces loading or response maximum in a specific range

In the case of several parameters

- it could exist a dominant intensity variable (for ex ; H_s-T_p) and the second variable is taken as the most probable value
- it could not exist dominant intensity variable (for ex. H_s-Wind speed)

As numerous will be the parameters, as complicated will be the extrapolation. As much as possible the problems must be decoupled to minimize the number of parameters.

The definition of a return value (e.g. 100-year H_s) corresponding to a time length (here 100 years) has a meaning when considering only one intensity parameter.

3 EXTRAPOLATION METHODS

3.1 MONO-PARAMETER

3.1.1 Extreme theory

The parameter for which a return value is required is usually an annual maximum. The first phase, therefore, is to estimate the distribution of this annual maximum from time series classically sampled to 20min, 1h or 3h. The return value x_N is then simply obtained by

$$P(X_{\max\_year} \leq x_N) = 1 - \frac{1}{N} \quad (1)$$

where P is the distribution of the annual maximum, N is the number of years. E.g. N = 100, for the hundred-year H_{m0} return value H_{m0100}.

Two general techniques are available for the calculation of the distribution of the annual maximum. The **block maxima** and the **storm maxima** methods. Other techniques are also used such as the *r-largest* (see [21]) or *Total Sample* methods (use of all the values, e.g. 3-hour H_s).

3.1.1.1 The block maxima methods

If the database is sufficiently long (several 10 years, e.g. 45 years for the ERA40 ECMWF hindcast), the empirical distribution of the annual maximum can be obtained directly from the sample of the 45 annual maxima. Generally, it is better to consider a smaller block size (e.g. a month) that remains sufficiently large to respect independence between maximum values. In that case the distribution of the annual maximum is obtained from the monthly maximum by

$$P(X_{\max\_year} \leq x) = P(X_{\max\_month} \leq x)^n \quad (2)$$

with n = 12, the number of months in a year

After the estimation of the empirical distribution, it is necessary to fit an analytical distribution to the empirical to be able to extrapolate to very high levels and to calculate x_N with formulae (1).

The statistical theory of extremes says that the maximum of n i.i.d (independent identically distributed) random variables X_i, as n is high, is a random variable with a distribution of only three types which have a unified under the GEV (Generalized Extreme Value Distribution) formulation.

$X_1, X_2, \ldots, X_n$, n random variables, **same law**, **independent**:

Let $X_{max,n} = \max(X_1, X_2, \ldots X_n)$ then:

$P(X_{max,n}<x) = P(X_1<x \;\&\; X_2<x \;\&\; \ldots \;\&\; X_n<x) = P(X_1<x)\, P(X_2<x) \ldots P(X_n<x)$

so

$$P(X_{\max,n}<x) = P(X_i<x)^n \quad (3)$$

when, $n \to \infty$, then $P(X_{max,n}<x)$ tends to a GEV (Generalized Extreme Value) distribution

$$P(X_{\max\_n}<x) = G(x) = \exp\left(-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-1/\xi}\right) \quad 0$$

ξ = 0, corresponds to a Gumbel law.

E.g. in the case of Gaussian, Rayleigh, exponential, Weibull, Gumbel distributions for the X_i, the GEV is a Gumbel law. The convergence with n can be very slow (e.g. for Gaussian law)

It is generally recommended that the Gumbel GEV be the default choice of distribution. The use of other distributions must be grounded in theoretical or physical consideration.

Figure 3.1 shows an example of empirical distribution of Hs yearly maximum (blue crosses) and the fitting of a Gumbel distribution (red line). The 20, 50 and 100-year return values are calculated with (1) and plotted. 90% and 95% confidence intervals are also illustrated (dashed lines). This shows the effect of sample variability on return value estimation. E.g. here, in spite of a long duration database, the 100-year return value has a probability 0.9 to be between 10.2m and 12.8m.

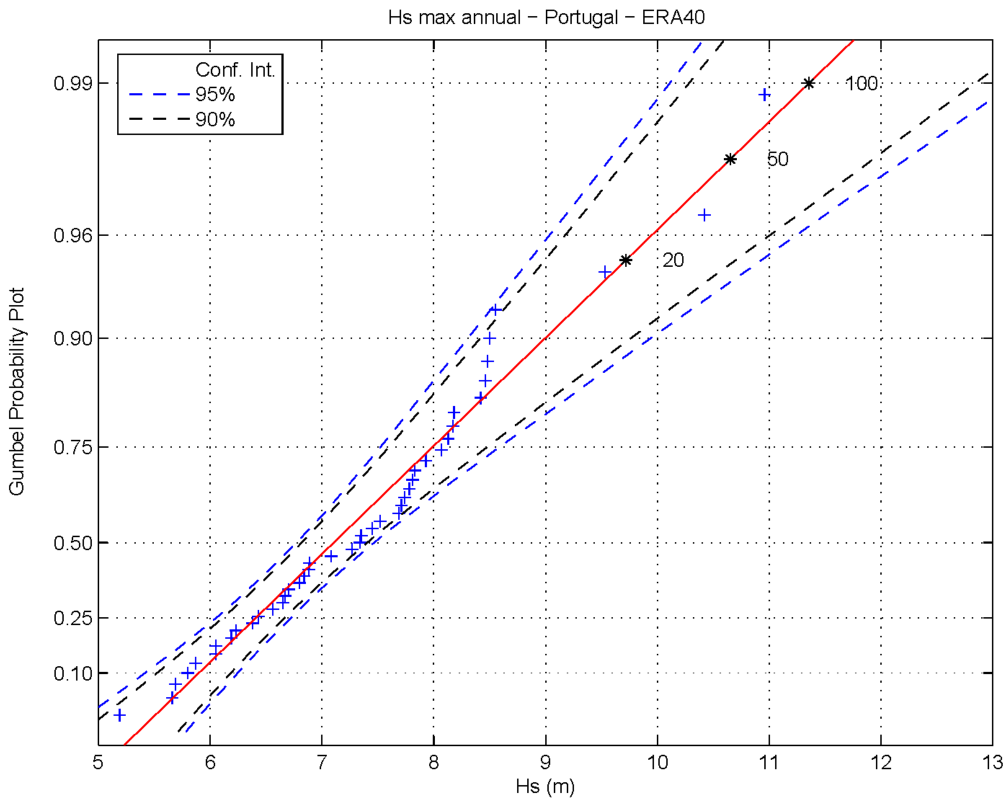

Figure 3.1 Fitting and extrapolation

The choice of non-Gumbel GEV extreme distributions can be based on statistical tests or physical considerations (e.g. saturated wave height due to breaking). It is important to consider that the fit of a 3-parameters non-Gumbel GEV, if not justified, will increase the effect of sample variability on the return value uncertainty compared to the 2-parameter Gumbel GEV. Figure 3.2 compares the confidence intervals obtained from Gumbel and general GEV fitting if the sample follows a Gumbel law (red line). Choosing a model with three parameters enlarged the confidence intervals, mainly for the long return periods. The GEV fit gives 90% confidence interval on 100-year return value 1.5m larger than Gumbel fit.

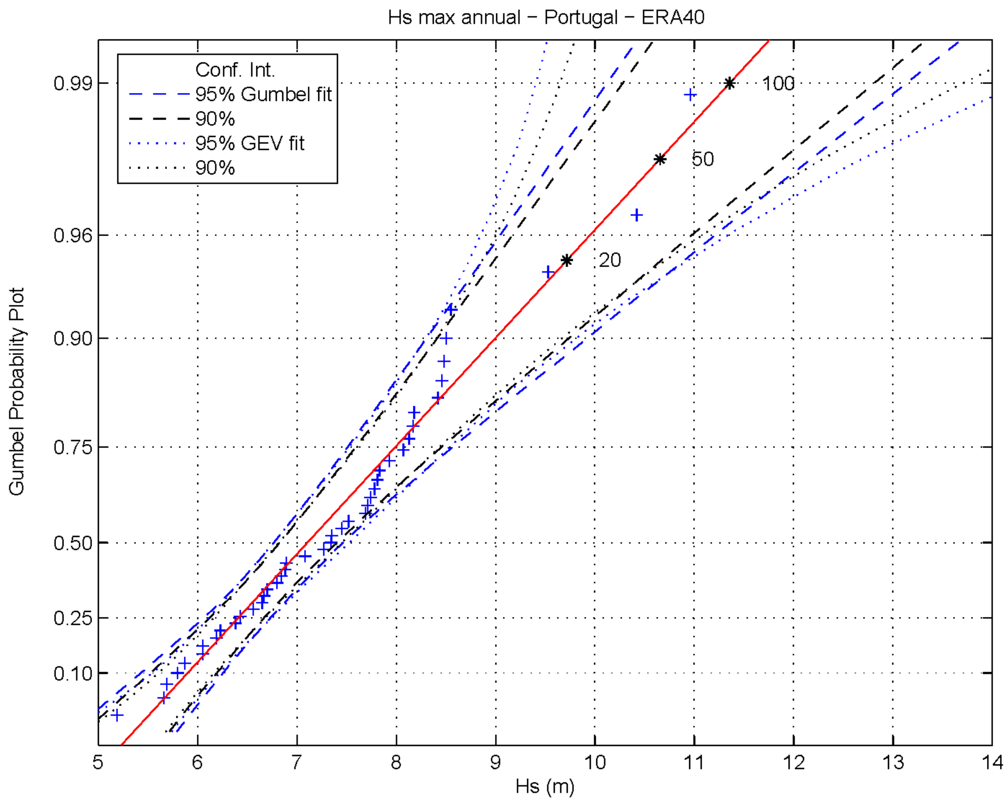

Figure 3.2 Confidence intervals, GEV vs Gumbel fit

The results of extreme theory given in (3) and 0 are based on two assumptions: the random variables follow the **same law** and are **independent**.

Independency. If we consider $X_{max,n}$ the H_s annual maximum

- if X_i represents H_s each hour (n = number of hours per year), independency is generally not verified and (3) is not true (however, it is the base of the Total Sample method)
- if X_i represents weekly maximum (n = number of weeks per year), independency is generally verified. The choice of the block length must be made with caution on site with swell climatology, as the swell H_s evolves very slowly.

In general, 0 stays true in case of dependence.

Equation (3) is applied to obtain yearly maximum empirical distribution from the empirical distribution of block maxima of 6 hours, one day, one week. It is clear that the hypothesis of independence between maxima is only valid when considering week block duration. “red” and “green” distribution are the same as indicated by (3).

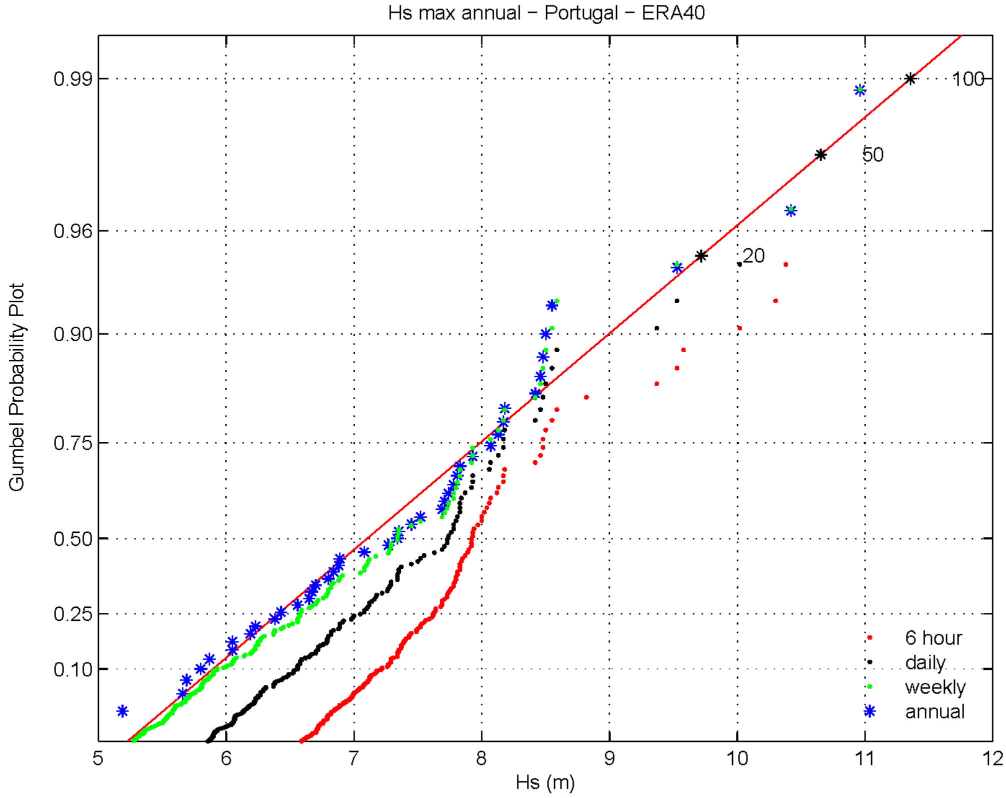

Figure 3.3 Effect of dependence on yearly maximum distribution

One way to overcome the problem of independence is to introduce the concept of "extremal index" (see [10])

Seasonality. The seasonality feature of all metocean phenomena is in contradiction with "**same law**" hypothesis. One way to overcome this problem is to fit an extreme GEV, $G_i(x)$ on each empirical distribution of monthly maximum.

The annual maximum distribution is then given by

$$P(X_{\max\_year} < x) = P(X_{\max\_jan.} < x) P(X_{\max\_feb.} < x) \ldots P(X_{\max\_dec.} < x) = G_1(x) G_2(x) \ldots G_{12}(x) \qquad (4)$$

which takes into account the seasonality

Taking into account the seasonality is illustrated in Figure 3.4. A Gumbel law is fitted for each month and annual maximum distribution calculated with (4). The distribution obtained for the extrapolation is plotted in black. It gives higher return values than those obtained with considering globally the yearly maximum, 12.2m in place of 11.4m.

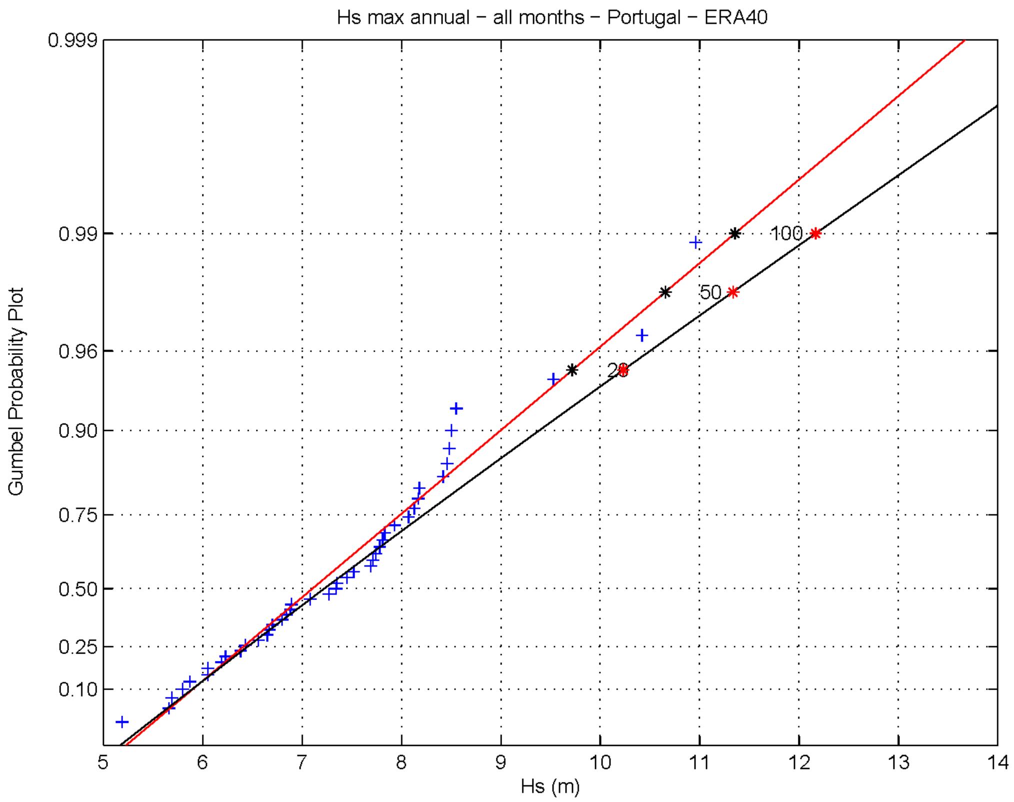

Figure 3.4 Taking into account seasonality

3.1.1.2 The storm maxima methods

Storm maxima methods allow the analysis of more information compared to the annual block maxima technique. This is particularly useful when the datasets are small (as is usually the case when quantifying annual maxima). The predominant method is the Peaks Over Threshold (POT) method. The POT method involves extracting a number of samples from the time series which are sufficiently separated in time to be considered as independent storm maxima. In contrast to block maxima methods these are not the maximum values over a particular time period (i.e. the monthly or annual maxima). Instead the samples are chosen based on their exceedance of a particular threshold. An asymptotic result of the theory of extremes states the conditional distribution of a random variable $P(X_{storm}<x|x>u)$, for high threshold u, tends only to three types, unified in the GP (generalized Pareto) distribution.

> if X is a continuous random variable, for high enough u, the conditional distribution of X given $X > u$ is taken to be of Generalized Pareto distribution (GPD) form
>
> $$P(X>x|X>u)=H(x)=(1+\xi\frac{x-u}{\sigma})^{-1/\xi} \quad (5)$$
>
> let $X_1, X_2,..., X_i,..., X_n$, n random variables, **same law** H(x), **independent**, where index i stands for a time t_i
>
> if the times of occurrence t_i follow a Poisson process.
>
> Considering the mean number of occurrence per year is m
>
> $$P(X_{\max\_year}<x)=\exp(-mH(x))=\exp(-m(1+\xi\frac{x-u}{\sigma})^{-1/\xi}) \quad (6)$$

Rem. annual maxima method is fully consistent with POT, but that threshold method makes fuller use of the data (if m is sufficiently higher than 1)

It is clear there are here two difficulties. First, a good construction of the storm sample (see [10] for techniques of optimised declustering), secondly the good choice of the threshold u which must be high enough, but not too much to permit a good fit of the GP distribution.

The selection of this threshold is, however, not trivial and is potentially difficult for the non-expert to apply effectively. There are two possibilities for that

- a linear regression on «Mean residual life» or «expected exceedance over threshold»

$$E(X>x|X>u)=\left(\frac{-\xi}{1+\xi}\right)u+\frac{\sigma}{1+\xi}\Big)^{-1/\xi} \quad (7)$$

an example is given Figure 3.5. The part to consider for the linear regression is, very often as here, not very clear.
- analysis of parameters of fitted GPD for increasing thresholds
An example is given Figure 3.6. Again the zone of stability is not very clear.

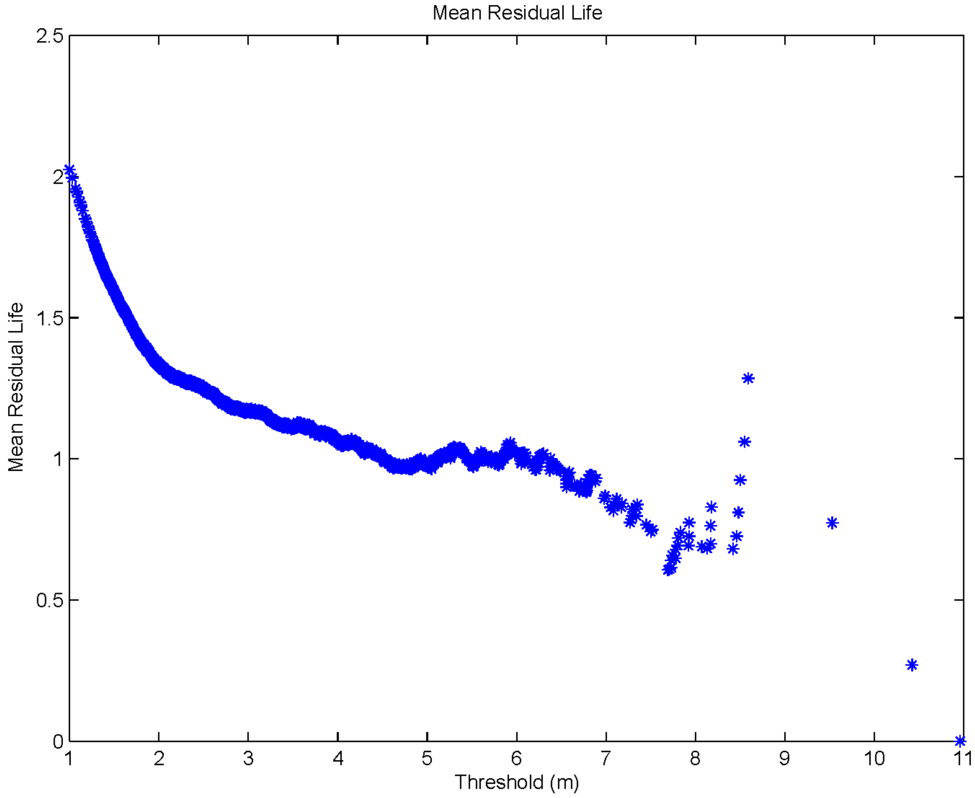

Figure 3.5 Mean residual life

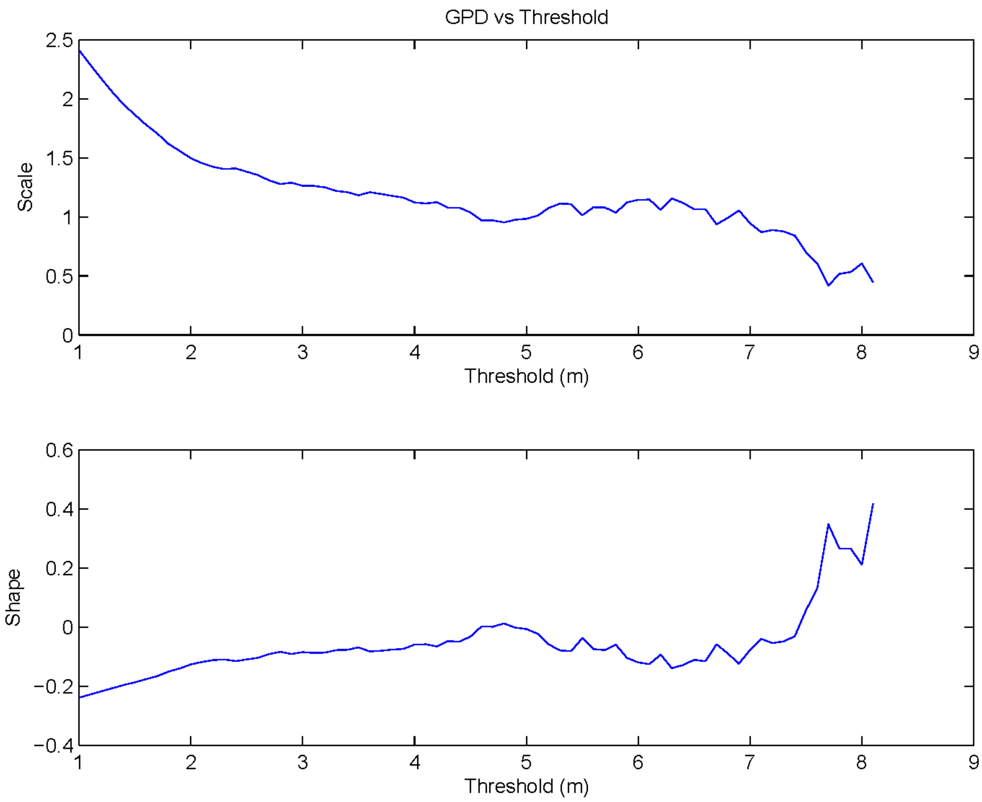

Figure 3.6 Fitted GPD parameters vs increasing threshold

In a last step, based on the hypothesis of a storm event Poisson process, the distribution of annual maximum is easily obtained from the fitted GP distribution (Eq. (6)). The final distribution will again be of the GEV type.

Steps of the POT method:

- determine a threshold over which a storm is defined
- decluster the storms (gather storms too close in time (Poisson process))
- from the empirical distribution of storm, find the threshold u for which the GPD hypothesis is valid (Mean residual life or analysis of parameters of fitted GPD for increasing thresholds)
- fit a GPD $H(x)$, (Maximum Likelihood method)
- calculate m, the mean number of storm per year
- calculate the annual maximum distribution for extrapolation $P(X_{\max\_year}<x)=\exp(-mH(x))$

Previous comments for Block Maxima Methods, on using other fitting distributions or 2-parameter vs 3-parameter GP distribution stay the same for POT.

Rem. Seasonality can be also introduced in POT, but makes makes the selection of a suitable threshold more difficult.

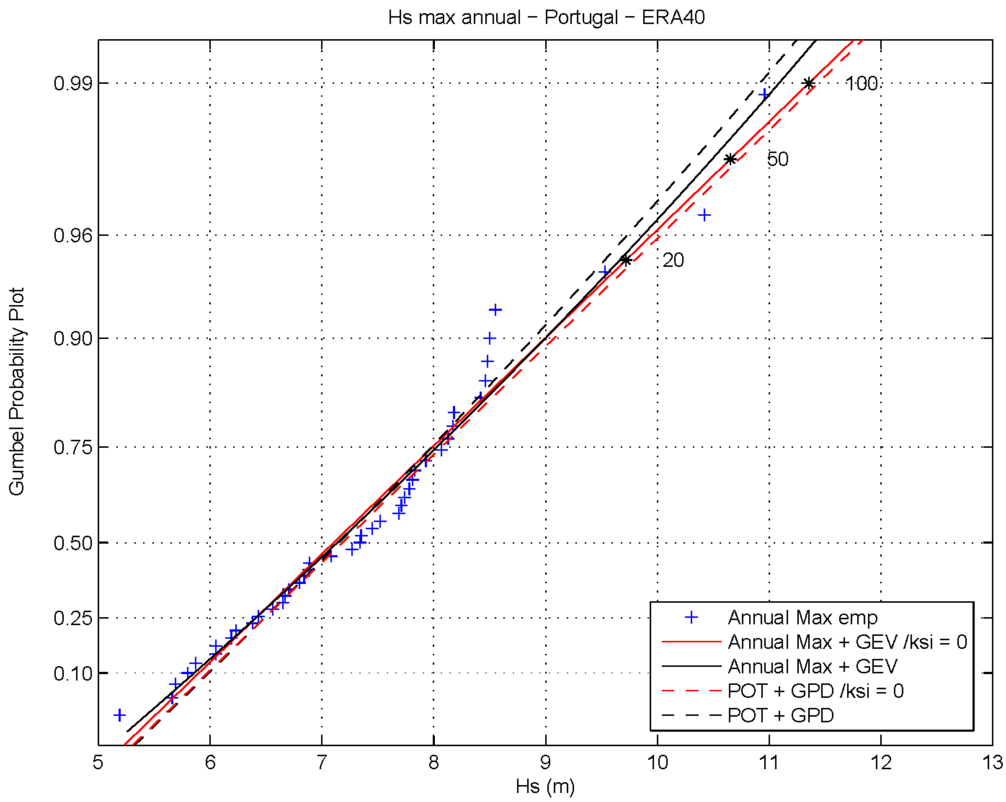

Figure 3.7 Annual block maxima vs POT

3.1.2 Short scale parameter – the n-year wave height

Time series of wave height or sea-state maximum wave height are rarely available over long periods and are absolutely unavailable from hindcasts. Different methods can be used, all based on the knowledge of the conditional distribution (to H_s and a mean period T_m) of the sea-state maximum wave height. See for example (Vinje [23]) fo wave height, (Prevosto & Forristall [20]) for crest height.

- The simplest solution is to associate to the H_s return value the most probable period or the period given by the breaking limit relationship. Then to use wave or crest height distribution given in [23] or [20] and apply (3) with *n* the mean number of waves in the duration of the sea-state (with a hypothesis of independence between waves) to obtain the distribution of the maximum wave or crest height. The crest or wave height return value is then the mode or a quantile (see Baarholm *et al* [4]) of this distribution.
- In using the same models as previously, for each H_s of the database, calculation of the most probable (mode of the distribution) maximum wave or crest height. Then Block Maxima or Storm methods can be applied to the new database of maximum wave or crest height to obtain the return values.
  Rem. In the first method, the return wave height is obligatory inside the sea-state with return Hs. In the second one, each sea-state participates to the wave height return value with only its most probable maximum wave height.
- So a last method is to take into account the distribution of the maximum wave height for all the sea-states. The wave height maximum distribution all sea-states considered is obtained by applying the law of total probability

$$P(H_{\max\_\ sea-state} \le h) = \int P(H_{\max\_\ sea-state} \le h \mid H_S, T_m) . f_{H_S,Tm}(h_s,t_m) . dH_S . dT_m \quad (8)$$

The joint distribution of significant wave height and period is generally given in the form

$$f_{Hs,Tm}(H_s,T_m) = f_{Hs}(H_s) . f_{Tm|Hs}(T_m \mid H_s) \quad (9)$$

Then a Total Sample method is applied to the distribution (8) of the sea-state maximum. This last method faces the problem of independence between sea-states inherent in Total Sample method.

3.1.3 Conclusions

Extreme values are typically extrapolated using a GEV distribution yearly maxima approach (e.g. Gumbel distribution of annual maxima) if the time series is sufficiently long (several tens of years).

When only short-term datasets are available (several years), the Peaks Over Threshold (POT) method may be used. POT examines values exceeding a certain threshold, thereby making fuller use of the data than the annual maxima approach. The selection of this threshold is, however, not trivial and is potentially difficult for the non-expert to apply effectively. The distribution should not be overly sensitive (e.g. in terms of scale and shape parameter) to changes in the chosen threshold (i.e. the distribution is stable). Achieving this stability may be difficult. It is therefore recommended that the Block Maxima method (week or month duration) be employed where possible.

The choice of extreme distribution must be grounded in theoretical and physical considerations (e.g. saturated wave height due to breaking). Using a non-Gumbel GEV distribution (Type II/III), or non-GPD, also needs strong justifications due to the increased variability in the resulting distributions.

The comparison between results of Block Maxima method and POT method on the ERA40 data base (Figure 2.1) is given in Figure 3.7. It shows that using GEV in place of Gumbel (ξ=0) leads to relatively lower return values (here slightly). The difference between the two methods is quite small, but other choices for thresholds in POT method would greatly change the results.

Some results of processing of the ERA40 database are presented in (Caires & Sterl [6],[7]).

The confidence intervals on the return values are continuously decreasing with the length of the database. We can consider that a database of duration 1/5 of the return period (e.g. 20 years for a 100-year value) is a minimum for a reasonable use of the return values in the design. The preferred approach is to include in the results confidence intervals to quantify the underlying uncertainties. Overly short durations will not include inter-annual variability, which induces bias on the estimated return values, bias which is not informed by the confidence intervals.

A typical representation of H_s return values, associated with its confidence interval, is given in Figure 3.8. The information on return values can be complemented by the distribution of the maximum Hs during a specified period of time. Figure 3.9 shows these distributions for durations one to hundred years. For example the magenta curve indicates that the maximum H_s value encountered during 20 years has a probability 10% to exceed 12m. This is to compare to 9.7m, the 20-year return value In addition, the intersections between the black curve and the distributions give on this graph the return values as plotted in Figure 3.8.

For all the methods, storm and block maxima, seasonality can and should be taken into account as it can change significantly the result of the extrapolation. In the same way climate change could be introduced (see [9] for more details) provided that robust models of such an evolution exists on sea-state or wind storm severity.

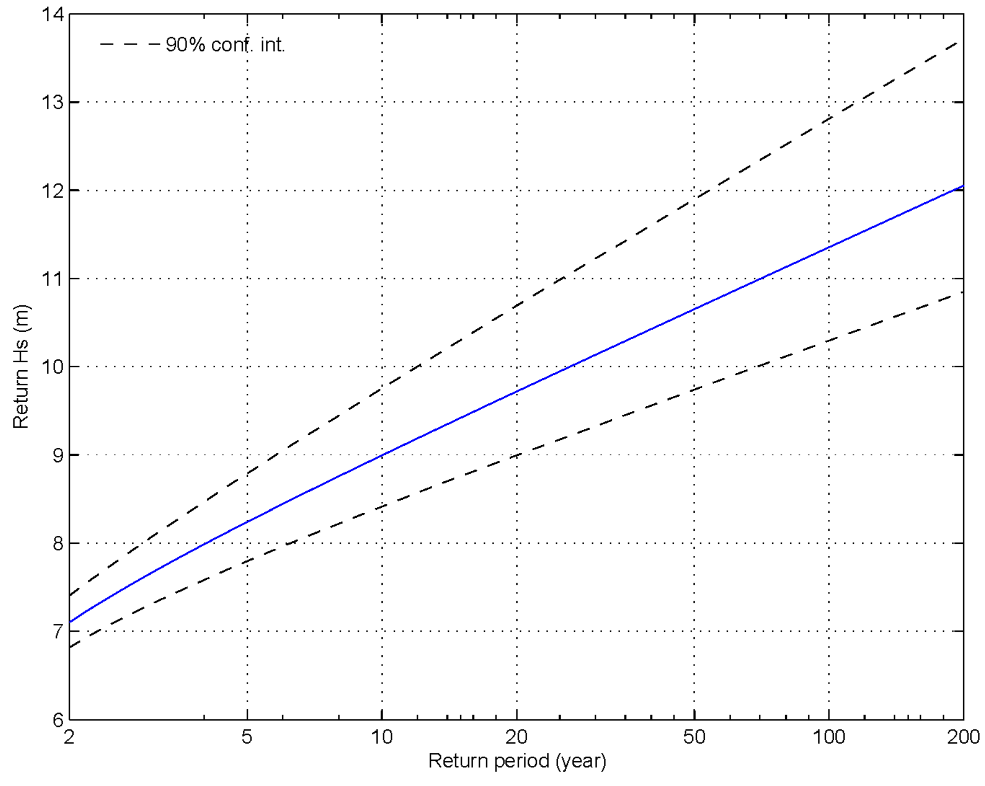

Figure 3.8 Typical representation of return values with confidence intervals

All methods described hereunder to waves can be applied to wind or current speed, and other short-term parameters (crest height, gust wind for ex.).

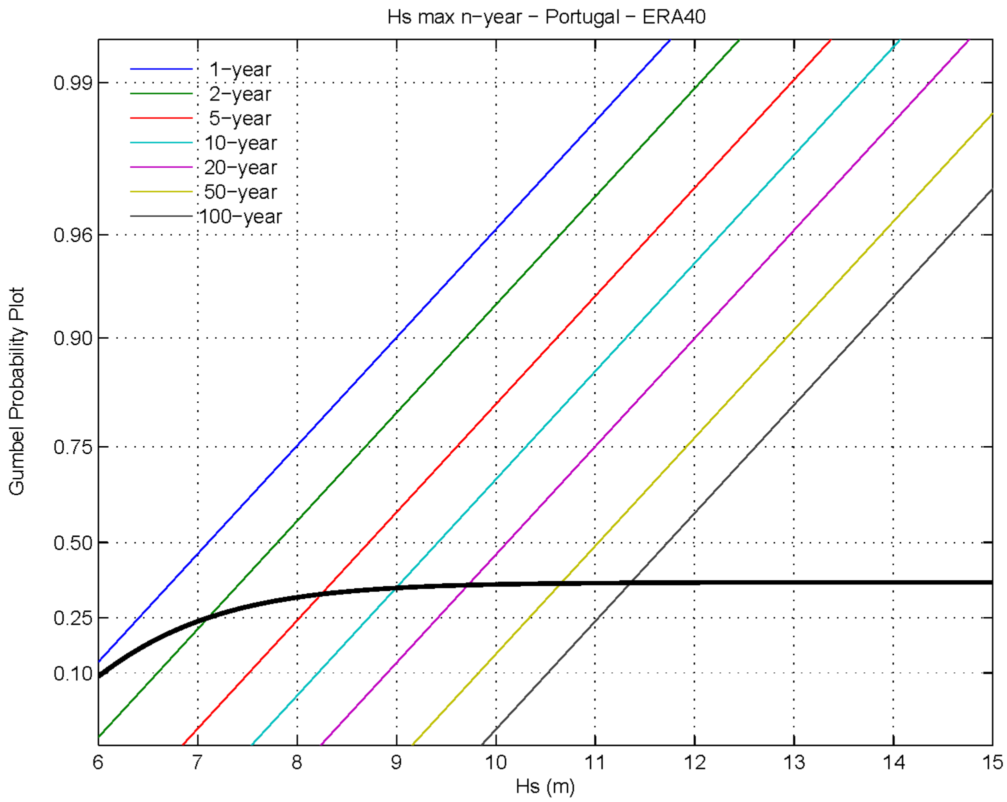

Figure 3.9 Distribution of the n-year maximum Hs

Figure 3.10 is an example of maps of return values that could be obtained with a block maxima method from a hindcast database.

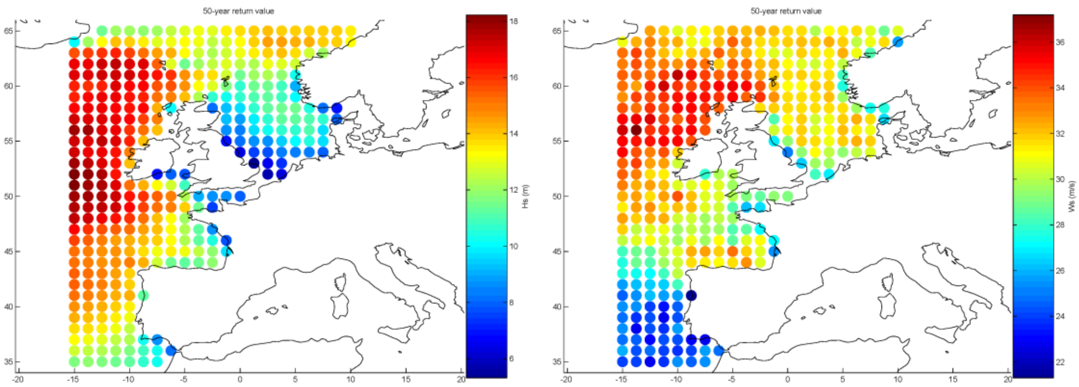

Figure 3.10 50-year H_s and wind speed return values

3.2 MULTI-PARAMETERS

3.2.1 Multivariate extreme extrapolation

The examination of multivariate extreme statistics is more complex. If, for example, waves, wind and current intervene simultaneously in extreme loadings, the definition of a centennial condition is not possible, only a condition which induces a centennial response has a meaning.

The crudest approach is to associate 100-year wave, wind and current return values. Of course this is generally over-conservative as the different phenomena are not strongly correlated. The simplest way to deal with is to associate different return values to define the n-year conditions, e.g. 100-year H_s associated with 20-year Wind speed associated with 10-year Current speed. The choice of the set of return periods is based on experience and is depending of the design criteria.

3.2.1.1 RBD methods

RBD (Response Based Design) methods are not based only on the description of metocean conditions but integrate in determination of design environmental conditions a modelling or a simulator of the structural response. These techniques include Direct Simulation Approach (DSA), Storm method (Tromans [22]), splitting methods, FORM/SORM (First/Second Order Reliability Method), …

3.2.1.2 I-FORM environmental contours

To provide a pure metocean answer to the issue of multi-parameter extremes, a suggested approach is to apply the Inverse-First Order Reliability Method (I-FORM). The method transforms the multivariate distribution of environmental parameters (e.g. H_{m0}, T_p, Wind speed,…) from the physical space to the standard Gaussian space, thus allowing by inverse transform to calculate a n-year contour in the physical space along which the n-year response will occur (in fact the maximum response on the contour).

In practical terms, any point of a 100-year Inverse-FORM contour is likely to induce a system response with a probability of exceedance of once every 100 years. It is important to note that the knowledge of the structure in itself is not needed to build a contour valid for any type of system response.

For more explanations and applications see (Baarholm *et al* [4]), (Forristal & Cooper [11]), (François *et al* [12]), (Haver & Kleiven [14]), (Nerzic *et al* [19]).

I-FORM contours have the advantages to be

- able to specify environmental conditions for long term return values
- valid for all the design criteria, only dependent of the statistical properties of the environment

but its drawbacks are that

- in case of 3D-parameters, the I-FORM contour is a 3D surface
- the FORM (first order approximation) methodology must be valid
- if H_s is H_s 6h for ex., the time dependence will overestimate the return values

Some examples of I-FORM contours are illustrated in Figure 3.11 for the couple (H_s,T_p) and (Wind speed, Surface current speed). Each contour corresponds to a return period (0.03-year, 0.1-year, 1-year, 10-year, 100-year) on the left in the normalized space and on the right in the physical space which will be used by the engineer to determine the design conditions.

(These results have been graciously supplied by Total E&P Angola and its Block 17 partners, more details in (Nerzic *et al* [19]))

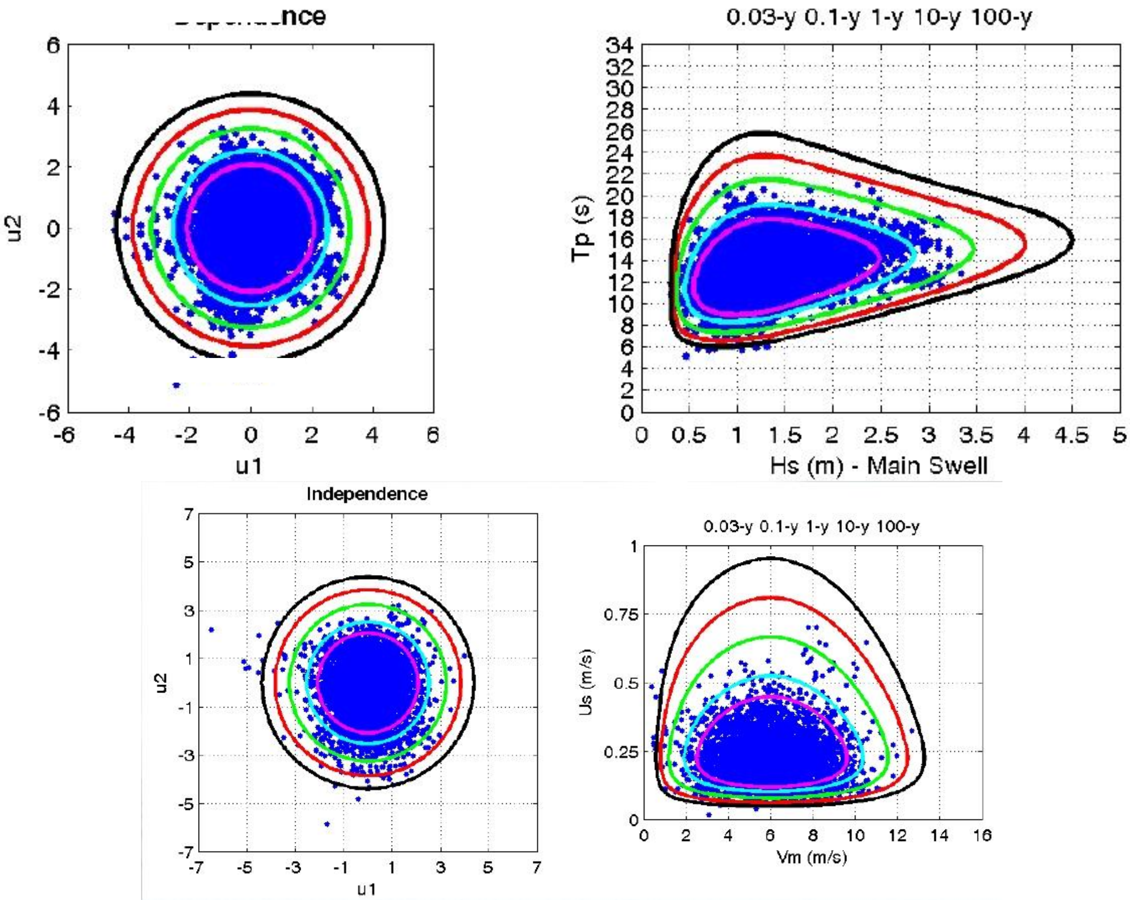

Figure 3.11 I-FORM contours in Normalized and Physical space

3.2.1.3 Joint distribution for extrapolation

All these methods need a good description of the extreme tail of the joint distributions as the extrapolation, like in the mono-parameter case, is completely dependent of this part of the distribution. This is a critical problem for which some authors have explored some solutions

- in using correlation coefficients and marginal distributions (like Nataf technique in FORM/SOM)
- by the fitting of analytical functions on conditional parameters and extrapolating them (see for example (Haver [15]) or (Nerzic *et al* [19])).
- by a conditional approach, more solidly based on extreme theory (Heffernan and Tawn [16], Ledford and Tawn [18])

This issue has not a definite solution and will need progress before integrating robust methods in industrial procedures.

3.3 SOFTWARE

Some software is freely available for extrapolation to extreme conditions. Some propose methodologies and help to process a database, others are simple toolboxes.

- Extremes Toolkit (extRemes): "Weather and Climate Applications of Extreme Value Statistics" in R.
- EVIM: "A Software Package for Extreme Value Analysis" in Matlab©.
- ISMEV : R functions to support the computations carried out in `An Introduction to Statistical Modeling of Extreme Values' by Stuart Coles [9].
- WAFO "Wave Analysis for Fatigue and Oceanography" in Matlab©.
- FERUM 4.1 "Finite Element Reliability Using Matlab" in Matlab©.

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