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Direct and fast probabilistic assessment of long term monopile load distribution from combined metocean data and fully nonlinear wave kinematics

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Abstract. A novel method is introduced to determine the long-term extreme value distribution of variables with an associated short-term distribution. The method is applicable to e.g. the extreme value with a return period of 10.000 years for wave height, crest height of waves as well as wave-induced response and loads on offshore wind turbine monopiles. The extreme values are determined by a combination of a joint probabilistic description of the met-ocean environment and of a recently developed database of fully nonlinear wave kinematics computations. For two benchmark monopile structures, representative for the conditions at Dogger Bank and the German Bight in the North Sea, the one-hour max value of crest height, inline force and overturning moment are computed via the Rainey slender-body force model. Convolution with the joint probability of the sea state parameters in the nondimensional space of wave steepness and Ursell parameter leads to the marginal probability distribution for these parameters up to a 10.000 year return period and properly accounts for the uncertainty of the extreme value parameters in also the short-term distributions. It is found that the best extreme value fit is generally obtained with a third-order polynomial fit within the space of steepness and Ursell parameter. Compared to the Forristall crest height distribution, the inclusion of full nonlinearity leads to larger crest heights at low return period levels. However, due to its realistic treatment of the breaking limitation, lower crests are predicted at the 10.000 year level for the two positions considered in the North Sea. With further verification of the wave kinematics in combination with load models and a thorough comparison to present engineering practice, the proposed methodology provides a robust future solution for directly estimating extreme value distributions of loads and response of offshore wind turbine monopiles.

1. Introduction

Offshore wind turbines may collapse or be damaged beyond repair due to excessive wind or wave loading. This is usually expressed in terms of an annual failure probability. An acceptable failure probability is a trade-off between high construction costs of a very safe turbine and a high risk of losing the turbine in a severe storm during the operational phase.

A probability of failure is usually achieved by following a design code recipe such as (IEC61400-3 [1] or DNV-RP-C205 [2]). The wave load design format used in these codes are rooted in the deep-water oil and gas industry and is based on either nonlinear regular waves or linear representations of irregular waves (HSE RR087 [3]). An underlying assumption in the codes is that there is a deterministic relationship between wave height and wave load. The largest load is assumed associated with the highest wave and the long-term distribution of wave loading is therefore deduced from the long-term distribution of individual wave heights. The kinematics of these extreme waves is usually represented by a single, nonlinear stream function wave [4]. By applying a force model, as the Morison load model [5], it is possible to derive a characteristic design load. The more recent extensions from Rainey [6] and Kristiansen and Faltinsen [7] add some extra terms to the Morison formulation, to improve the physical accuracy. The acceptable probability of failure is then supposedly achieved by applying partial load...
factors to the computed load, taken in the offshore wind industry as the wave load arising from the wave with a wave height corresponding to a 50-year return period.

However, smaller, steeper waves can generate larger loads than larger, longer waves, if they are for example able to drive the resonant motion of the structure. Moreover, the shape of the waves is not regular or symmetric, especially when the waves are close to or fully breaking, see f.ex. Schloer et al. [8], Wang et al. [9] and Ghadirian et al. [10]. To provide more physically sound wave kinematics, a large database of nonlinear waves has recently been developed [11].

In addition to these quasi-static loads, especially in steep sea states, the largest waves may break, generating impulsive slamming loads on the structures. Several models to simulate loading from breaking waves on fixed offshore structures are available, e.g. Goda [12], Wienke Oumeraci[13], WiFi JIP [14], Hansen and Kofod-Hansen [15], Ghadirian and Bredmose[16], Pierella et al. [17].

Both the non-breaking and breaking wave load formulas mentioned here provide a deterministic description of the wave load given the input parameters. However, due to the randomness of the problem, every load level is associated with a probability of being exceeded. In fact, each sea state has a certain probability \( P \) of arising every \( N \) years, where \( N \) is the return period. When computing the probability of observing a particular wave load, this long-term probability needs to be considered together with the short-term probability of observing certain loads in that particular sea state.

There is the need for a comprehensive design procedure that can consider all of the above random variations, which we aim to describe in the current paper. The method presented herein for evaluating the long-term distribution of a maximum short-term response (e.g. the wave loading) starts with an extreme value analysis of the slowly-varying sea state parameters. The tail of the distribution of the dominant parameters (e.g. the zeroth moment of the wave spectrum \( H_{m0} \)) is then estimated, together with the distributions of the secondary parameters (e.g. peak period \( T_p \)) conditional on the extremes of the dominant parameters. This method, referred to as JEVA (Joint Extreme Value Analysis) in this paper, was applied by Hansen et al. [18] to compute the joint statistics of severe sea states in the North Sea. The long-term distribution of any short-term response variable (e.g. base shear load) can then be obtained through convolution of the short-term response conditional on the sea state with the long-term distribution of sea states.[18]

Reliable formulations of short-term distributions are generally limited to relatively few variables and distributions, such as Forristall [19,20] for wave height and wave crest height. In this paper, we present a method that uses the recently developed fully nonlinear wave kinematics database by Pierella et al. [11] to compute the short term distributions of the response variables. In combination with Froude scaling and a slender-body load model, we create a large number of realizations of one-hour maxima of fully nonlinear maximum crest and wave height, inline force and overturning moments (OTM) for a static response, specific to two sites. We then use covariates to derive short-term Generalized Extreme Value (GEV) distributions of these variables, including the dependence of the GEV parameters on the wave steepness and the Ursell parameter \( U_r \). When this short-term distribution is used for the convolution with the JEVA approach and its joint extreme value analysis of slowly-varying metocean parameters, design-case specific long-term distribution of response variables are derived directly, e.g. the value of a 10,000 year return period OTM for the static response. The Markov Chain Monte Carlo (MCMC) method applied in Hansen et al. [18] can be extended for the proposed methodology to consistently handle the statistical uncertainty associated with the fit of the GEV parameters for the short-term parameters when performing the convolution with the long-term joint distributions.

The quantitative application of the newly proposed methodology in detailed design is limited by the accuracy of its subcomponents. In this work, performed in the framework of the DeRisk Danish innovation project [21], we focus on the methodology and the estimation of site-specific short-term distributions, while [11] discusses the validation of the DeRisk database.

2. The long-term sea state distribution: Metocean data and the JEVA approach

The parameters typically applied as input for metocean extreme value analysis are wind speed and direction, significant wave height \( (H_{m0}) \), peak period \( (T_p) \), peak wave direction \( (\theta_p) \), wave spreading
water level and ocean current speed and direction. Since observational records in most cases are too short and lack representation of variability across the wind farm sites, numerical metocean models simulating atmospheric, wave and hydrodynamic parameters are normally configured and then calibrated and validated against in situ and remotely sensed data.

The used wind dataset is adopted from the Climate Forecast System Reanalysis (CFSR) atmospheric model [22], established by the National Centre for Environmental Prediction (NCEP) [23]. The CFSR data used for this study were available on an hourly basis from 1 January 1979 to 31 December 2018. We derive wind speed and direction at 10m for the metocean analysis and use the same dataset for forcing both the spectral wave and hydrodynamic models presented below. The domain covered by the two models includes the North Sea and has a resolution of about 3 km at the sites analyzed in the paper.

Water level, depth-integrated ocean current data and spectral wave data were established for the same 40-year period through numerical modelling using the models, MIKE 21 Flow model FM by DHI [23] and the MIKE 21 Spectral wave model by DHI. The models were validated against a large number of in-situ observation across northern Europe as well as satellite altimeter data [35]. The wave model output, used for the analysis, include the integral parameters mentioned above \((H_{m0}, T_p, \theta_p, \theta_s)\).

The long-term distribution of sea states is derived using the method of Hansen et al. [18]. The tail of an equivalent storm peak significant wave height is estimated using a non-stationary extreme value model. Significant wave height may vary with storm direction and with season and hence location, scale and shape parameters of the extreme value distribution is non-stationary by being allowed to vary with storm direction and season as well. The model is fitted to data from the 40 years hindcast data set, and the epistemic uncertainty related to the extrapolation to events with return periods far beyond 40 years is accounted for by integration over the posterior distribution of model parameters. Joint distributions are estimated for all relevant variables conditional on the equivalent \(H_{m0}\).

Monte-Carlo simulation is used to generate long samples of storm events. A storm model is used to generate time series with values of the relevant sea state parameters every hour within each storm event, as described in Hansen et al. [18]. Because a consistent set of metocean parameters are sampled for every event, the 1-hour maximum of the short term variables like monopile overturning moment can be sampled as well if the dependency on the sampled variables (e.g. \(H_{m0}, T_p, \) current speed) can be described. The DeRisk database is used to derive such distributions, as shown in Sections 3, 4 and 5.

3. The short-term distribution of wave height and loads: the DeRisk database

The DeRisk database [11] is a large collection of long-crested extreme wave kinematics, with the main purpose of computing ultimate loads from large waves on offshore structures. The kinematics are computed via the fully nonlinear potential flow model OceanWave3D [24]. The model is run on a 25 km long domain, with a gentle 1:85 slope. Long-crested linear irregular waves with different combinations of a zeroth moment of the power spectrum \(H_{m0}\) and peak period \(T_p\) are generated in the offshore section with maximum depth of \(h_{\text{max}} = 250\) m and travel to the outlet section, where \(h_{\text{min}} = 12.5\) m. The nonlinear kinematics is then sampled on vertical lines from the surface to the sea bottom at about 130 locations in the shallow section of the domain. The kinematics are stored in a large online database which is publicly available [25], together with routines to access and rescale the data to suit the target scale. A simple wave breaking model was used in order to avoid instabilities in the simulation, which smooths the free surface and the free surface potential when the downward free surface acceleration is larger than \(\beta g\), where \(g = 9.80665\) m/s\(^2\) is the gravitational acceleration and \(\beta = 0.5\). The validity of the database can be extended to the scale required by the designer by up- or downscaling the kinematics by the Froude hypothesis. [11]

To compute the hydrodynamic force on the cylinder from the wave kinematics, the Rainey [6] force model was used. The model can be regarded as an extension of the Morison [5] force model. The expression for the force is

\[
P_x^{xyl} = \int_{-H}^{H} \left[ \frac{1}{2} \rho C_D Du|u| + \rho (1 + C_m) \frac{\pi}{4} D^2 \frac{du}{dt} + \rho \frac{\pi}{4} D^2 C_m w_x u \right] dz - \frac{1}{2} \rho \frac{\pi}{4} D^2 C_m \eta_x u^2
\]  

(1)
where $C_D$ is the drag coefficient, $(u, w)$ are the wave velocities along the streamwise ($x$) and vertical ($z$) axes, $C_M = 1 + C_m$ is the added mass coefficient, $D$ is the cylinder diameter. The quantity $\frac{du}{dt}$ is the total (kinematics plus convective) acceleration, $\rho$ is the fluid density and $\eta$ is the free surface elevation. A subscript indicates derivation with respect to the subscripted variable.

The mass and drag coefficients were chosen with the standard values of $C_M = 2.0$ and $C_D = 1.0$ [26]. As for the OTM, the distributed force in the integral in equation (1) is multiplied by $z$ and then integrated up to $\eta$, while the point force at the surface is multiplied by the time-varying moment arm $\eta + h$. For the current study, no wind force was applied on the structure, and the structure was considered stiff, therefore only static loads are computed. Wind loads and structural flexibility can be included by using appropriate physical models as the QuLA [27], while the overall workflow of the methodology would remain unchanged.

4. The proposed model: GEV fit of short-term distribution and convolution with slowly varying metocean parameters

The short-term distributions are next estimated for fitting the one-hour maxima of wave height, crest height as well as static response inline force and OTM calculated for each of the two sites. Data for the short-term distribution modelling is taken from the DeRisk database coupled with the load modelling described Section 3, which allows to generate a large number of one-hour maximum load realizations.

The fits allow wave steepness ($H_m k_p$) and the Ursell Number ($H_m k_p^{-2} h^{-3}$) to be covariates meaning that the GEV parameters (location, scale and shape) are expressed as polynomial functions of these two covariates, named $X_1$ and $X_2$. Polynomial coefficients are named $\beta_X$. The polynomial expressions examined are summarized in Table 1.

For each of these polynomial expressions and each response parameter, the MCMC technique is used to estimate the distribution of each $\beta_X$ coefficient for each of the GEV parameters. Hence, sea state and depth dependent short-term GEV distributions are estimated, including their estimation uncertainty.

The long-term distribution of the maximum loading, $P(X_{\text{max}})$ is then solved through Monte-Carlo simulation. The long-term distribution of sea states, $p(\Omega)$, has already been simulated and the integral is therefore solved by sampling $X_{\text{max}}$ from $P(X_{\text{max}}|\Omega)^{-1}$ for all the simulated sea states, where $P(X_{\text{max}}|\Omega)^{-1}$ is the inverse cumulative distribution function of the sea state maximum response, conditional on the sea state $\Omega$.

### Table 1 Polynomial expansions of covariates examined.

<table>
<thead>
<tr>
<th>ID</th>
<th>Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$f(x, \beta) = \beta_0$</td>
</tr>
<tr>
<td>Linear</td>
<td>$f(x, \beta) = \beta_0 \pm \beta_1 x_1 + \beta_2 x_2$</td>
</tr>
<tr>
<td>Order 2</td>
<td>$f(x, \beta) = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^2$</td>
</tr>
<tr>
<td>Order2CT</td>
<td>$f(x, \beta) = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^2 + \beta_5 x_1 x_2$</td>
</tr>
<tr>
<td>Order3CT</td>
<td>$f(x, \beta) = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_1^3 + \beta_4 x_2 + \beta_5 x_2^2 + \beta_6 x_1 x_2 + \beta_7 x_1 x_2^2$</td>
</tr>
</tbody>
</table>

The main steps to perform this computation are summarized here.

1. Loop over all the years in the long-term simulation and for each year do
   a. Sample a set of $\beta$-coefficients from MCMC chain originating from the fitting of the response surfaces, which corresponds to sampling $\beta$ coefficients from the distribution that MCMC returns as part of its parameter estimation.
   b. Calculate $X_1, X_2$ for every hour of simulated events for the specific year and compute the GEV-parameters (different values for every hour as function of $X_1, X_2$) from the response surfaces, see under the point (a)
c. Draw the one-hour maximum response \( X \) for every hour from the GEV-distributions

2. Retain only the maximum response from every simulated year. This gives us an empirical estimate of the distribution of the annual maximum response.

3. Compute the extreme values as the \( \exp(-1/T_R) \) quantile in the annual maximum response distribution, where \( T_R \) is the return time.

5. Application study: wave crest and maximum loads estimates

5.1. The sites

The two sites considered are the Dogger Bank with 20m depth and the German Bight with 33m depth. These are selected to represent typical environmental metocean condition met when developing offshore wind energy plants in the North Sea.

As described in Section 2, a total of 40 years of accurate metocean data were simulated by the hindcast models, [28][23][22][29]The following parameters in the metocean data set are used, with a time step of 1 hour: the zeroth moment of the wave spectrum \( (H_{m0}) \) the peak wave period \( (T_p) \), the mean wave period \( (T_{02}) \), the mean wave direction \( (MWD) \), the10m wind speed and direction \( (WS \ and \ WD) \), the depth-averaged current speed and direction \( (CS \ and \ CD) \), the still water level \( (wL) \). Using the JEVA methodology presented in Hansen et al. [18], joint metocean parameter probability distributions were fitted for slowly varying long term metocean parameters. The fitted models are used to generate large samples of extreme events. This is done using Monte Carlo sampling of events from the models as described in Section 2. Two simulations are generated for each site: \( 2 \cdot 10^4 \) years including all sampled storm events, and \( 2 \cdot 10^5 \) years including only those events where \( H_{m0} \geq 6.0 \) m.

The requirement for 10,000 year conditions is related to the acceptable annual probability of failure. Please note that the extrapolation from 40 years of validated hindcast data to conditions with return periods of 10,000 years, is associated with a very large uncertainty. The uncertainty in the metocean environment \( (H_s, T_p \ etc.) \) is not the main topic of this paper, but this important element is dealt with in more detail in the referenced paper by Hansen et.al. (2020).

For illustration purpose, representative scatter plots for the \( 2 \times 10^5 \) years simulation are shown in Figure 1 for Dogger Bank with 20m water depth. In black, we report the data points from the hindcast time series, while the colored dots are sampled from the fitted distribution.

![Figure 1](image.png)

**Figure 1** Representative JEVA scatter plots for Dogger Bank (20m), \( 2 \cdot 10^5 \) years. The black dots are from the hindcast dataset.

5.2. The two structures

The two monopile foundations are designed for the DTU 10MW turbine [30], with a hub height of 119 m. The rotor diameter of the turbine is \( D_{rot} = 178.3 \) m, with a \( v_{rated} = 11.4 \) m/s. For the purpose of the present computations, we do not consider any aerodynamic force from the rotor, nor any dynamic excitation of the structure. Therefore, the only parameter that impacts the loads is in fact the outer
monopile diameter. For the \( h = 20 \text{ m} \) depth, we consider a monopile with a \( D = 7 \text{ m} \), while for the \( h = 33 \text{ m} \) depth the pile has an outer diameter of \( D = 7.5 \text{ m} \) [30].

5.3. Short-Term response data

In this section, we present a subset of the short-term load computations that can be extracted from the DeRisk database, and we perform a quality assurance of the simulations.

In Figure 2, the 16,000 realizations of free surface elevation that compose the DeRisk database are represented, together with the contour lines of 10 and 100-year return period joint occurrence of nondimensional depth and significant wave height, extracted from the results of the long term extreme value analysis as shown in Figure 1. We can see how the DeRisk database includes sea states well beyond the 100-year contour line and getting quite close to the breaking limits from Goda [12].

In the next step, we verify that the simulation is able to represent physically sound crest elevations. We produce the analysis for the 33 m depth, but similar conclusions can be drawn for the 20 m depth. We first extract all the hourly maximum wave heights from the dataset and the associated wave period \( T \), by taking the time difference between the two closest down-crossings delimiting the wave with the largest height. For each wave, we also registered whether it was breaking, according to OW3D’s breaking filter. The filter smooths a 3-point region of the surface elevation and surface potential when the downward acceleration overcomes \( 0.5g \), where \( g = 9.80665 \text{ m/s}^2 \).

A maximum wave height of around 26 meters was registered for \( h = 33.0 \text{ m} \).

In Figure 3, we plot the data mentioned above on a nondimensional depth and nondimensional steepness axes. We then bin the waves in 50x50 bins, and we compute the ratio between the number of breaking waves over the total number of waves. Together with the hourly maximum wave heights, we plot two dashed lines indicating the breaking wave limit for irregular waves, from equation (6) in the work of Goda [12]. In their work, Goda hypothesized that single waves in the nondimensional spaced marked by the two lines obtained have a linearly increasing probability of breaking \( P_b \), from \( P_b = 0 \) for \( A = 0.12 \) to \( P_b = 1 \) for \( A = 0.18 \). Consistently with our expectations, the closer the waves get to the upper breaking limit (\( A = 0.18 \)), the closer the ratio approaches one. We conclude that the maximum waves extracted from the database accurately capture the breaking wave limit.

Examples of 1-hour short-term computations that can be extracted from the DeRisk database are in Figure 4 for the Dogger Bank sea state, close to a 10 year storm (see SS20 in Figure 2). We plot the free surface elevation statistics in the top subplots, and the overturning moment in the bottom ones. In the left subplot, we plot a 100s excerpt of the time series, which contains the largest crest measured in the 1-hour segment, and the relative force on the right. In the central subplot we plot the exceedance...
probability of the 1-hour maximum wave crests and OTM 1-hour maxima. On the right subplots we report the power spectral densities for the whole 1-hour time series, smoothed with a running average with a frequency band of $\Delta f = 0.0025 \text{ Hz}$.

Figure 4 Free surface elevation and static moment for the h=20.0 m case (SS20). On top, the free surface elevation $\eta$ is plotted. At the bottom, the static moment $M_{stat}$ is plotted.

In the top left subplot we observe a maximum wave crest of around 12 meters. In this particular case, on the bottom left subplot, we see how this largest wave crest also yields the largest overturning moment. However, this is not the case for all of the sea states. Similar considerations are valid for the association between max overturning moment and the wave height. For the 20 m depth, it is computed that only in 46% of the 1-hour sea states the maximum overturning moment was associated with the highest wave, while the same figure is 49% for the 33 m depth. The spectrum, in the upper right subplot, peaks at around $T_P = 11.2 \text{ s}$, while the significant wave height is $H_{m_0} = 6.6 \text{ m}$. A significant amount of energy is observed in the frequency range around $f = 0.2 \text{ Hz}$, likely due to nonlinear interactions.

5.4. Short-term distribution model

To illustrate the short term convolution Figure 5 and Figure 6 show the distribution of the DeRisk realizations as grey dots and the fitted GEV parameters (rainbow contour lines) assuming linear and Order3CT2 model for the covariates for wave crest height.

The JEVA joint probability lines are shown as red contours going from 1-year to 1000-year return period inside-out. These indicate the part of the short term fit that will ultimately play a role when convoluted with the long term metocean statistics. In Figure 5, the linear fit strategy is evident in the parallel arrangement of the contour lines marking the average values of the parameter distributions. We can also see how the points from the hourly maxima derived from the DeRisk database are well distributed in the nondimensional space, allowing for a satisfactory fit. However, the density of the hourly maxima seems to be lower in the area around $H_{m_0} k_p \approx 0.1$. This is due to a lack of simulations in that range of steepness and Ursell number from the DeRisk database. This may increase the uncertainty of the fit for sea states with a low Ursell number.

In Figure 6, the third-order polynomial expansion is visible. A more complex pattern of the contour lines suggests a more refined fitting strategy. The differences between the 3rd order and the linear model are visible in all of the GEV parameters. In particular, in the region of Ursell number above 0.4 the location parameter contour lines seem to follow an opposite trend, for which the location parameter is larger for larger sea state steepness, while the contrary was true for the linear model, where the contour lines suggest a less complex pattern of variation. A similar consideration holds for the shape parameter. Moreover, in the 3rd order model, there is a large area of the parameter space where its magnitude is between 0.1 and 0.2. In the linear model, a sharp gradient was on the contrary visible, mainly correlated with the steepness parameter.

Despite the higher order of the fit, as a general trend, we can conclude that all the three distribution parameters are more clearly influenced by the average steepness $H_{m_0} k_p$ than by the Ursell number, as the predominantly vertical orientation of the contour line suggests.
To illustrate the quality of the fit and to highlight the differences between the linear and the 3rd order model, the resulting GEV distribution is shown for two selected points in the covariate space in Figure 7. The distribution is compared to the distribution of the 1-hour max wave crest realization from the 50 points in the DeRisk database that are nearest to the evaluation point in the covariate space.

In the top subplot, we observe a comparison between the GEV fitted curve and the points originating from the database for a sea state on the 1000 year return period contour line. The third-order model approximates much better the simulated values than the linear model, and is able to follow the data up to a quite high cumulative probability level. On the other hand, the linear fit underestimates the probability level quite dramatically, especially for the largest values of the nondimensional crest height.

The same conclusions can be drawn for the bottom plot, which is produced for a sea state with a return period close to 10 years. The presented plots seem to confirm that the third order model outperforms the linear model consistently in different locations of the nondimensional space. For the sake of completeness, in the next section all the models in section 4. will be used to compare the results.

Figure 5 Site: Dogger Bank (20m). Fitted GEV parameters (rainbow contour lines), location, scale and shape (left to right) and JEVA joint probability lines (red contours going from 1 year to 1000-year return period inside-out) for crest height as function of wave steepness (x-axis) and Ursell number (y-axis). Linear covariates.

Figure 6 Site: Dogger Bank (20m). Fitted GEV parameters (rainbow contour lines), location, scale and shape (left to right) and JEVA joint probability lines (red contours going from 1 year to 1000-year return period inside-out) for crest height as function of wave steepness (x-axis) and Ursell number (y-axis). Order3CT2 covariates.

6. Results and discussion
The results of the convolution of the slowly varying metocean parameters and the response variables are presented in this section. The resulting convoluted extreme value distribution of one-hour maxima of short-term responses are presented below for the two locations. In Figure 8 and Figure 9, we report the maximum hourly values on the x axis, as a function of the return period on the y axis, expressed in years.
In Figure 8(a), we plot the crest height distribution for the deeper location \((h = 33.0 \, \text{m})\) with all the models in Table 1. We add the Forristall [20] distribution and the more recent model from Schubert et al. [31], which includes a higher order of wave non-linearity. It is visible how the different proposed models tend to agree up to a return period of ca. 1000 years, except the linear model which starts to deviate from the others already for 10 years return time. Between 1000 and 10000 years, the third order model predicts the lowest crests. The proposed model estimates higher crests for the lower return period than both the Forristall and the Schubert distribution, while they agree quite well for the longest return period. This is interpreted as being due to the fully represented nonlinearity of the OW3D wave model, which therefore predicts higher crests than the Forristall distribution and even the Schubert distribution. For larger storms with longer return periods, the breaking from the current kinematics model limits the crest height, achieving a closer agreement with the Forristall and the Schubert distributions, but with a more restricted trend of lower crest height at even higher return periods effectively allowing wave breaking to be represented in the extrapolation.

In Figure 9(a), the plot is produced for \(h = 20.0 \, \text{m}\). While the tendencies are overall similar to the shallower depth, we first note that the maximum crest height is around 14 meters, against a maximum crest of around 16 meters for \(h = 33.0 \, \text{m}\). Moreover, we observe that the current model estimates moderately larger crests than the Forristall distribution up until 10 year return period. This may be counter-intuitive, as one would expect more nonlinear enhancement of the crests at lower depths. However, as it is signaled by the sharp decrease of the maximum hourly wave crest with an increasing return period after 10 years, there is a decisive increase in breaking that is registered at lower depths. The third order model for the present formulation, which provides the best agreement with the simulated short-term distributions, predicts a 20% lower crest for the 10000 year return period with respect to the Forristall and the Schubert distributions.

In Figure 8(b), we plot the statistics for the maximum inline static force for the 33m German Bight location. While all of the higher-order models tend to agree on the peak force distribution up until the 10000-year return period level, the linear model predicts lower peaks for return periods larger than 10 years. This confirms that the added complexity of the second-order model has a quite definite effect while adding cross-terms and the third-order does not seem to influence the results significantly. This can also be observed in Figure 9. As for the 20m Dogger Bank location, in Figure 9(b) the picture is slightly different. First, the 10000-year return period maximum inline static force is around \(9 \sim 11 \, \text{MN}\). This can be explained by the smaller water submerged depth of the cylinder, which ultimately leads to
lower peak loads. Moreover, in this case it seems like adding the third order term does influence the statistics quite significantly, with a ca. 10% difference on the 10000 year inline force peak with respect to the second-order model. From the above analysis, the inline force seems less sensitive to the model choice, except for the values with the highest return period.

Figure 8 Site: German Bight (33m). The responses considered are one-hour maximum crest height with respect to still water level, the maximum static force and maximum overturning moment.

Figure 9 Site: Dogger Bank (20m). The responses considered are one-hour maximum crest height with respect to still water level, the maximum static force and maximum overturning moment.

The same analysis can be repeated for the overturning moment, as in Figure 8(c) and Figure 9(c). The 10000 year overturning moment for the 33m German Bight location is three times the one that is found for the 20m Dogger Bank location. This is explained by the different moment arm that is associated with the wave forces, and also with the largest probability of observing a larger $H_{m0}$ at 33.0 meters depth.

We see how the difference between the models for the OTM is similar to what was shown in for the inline force. Also Figure 9(c) exhibits the same trends of Figure 8(c), where the third order model predicts the largest overturning moment.

7. Conclusion and perspectives
In this paper, a methodology for deriving the extreme values of response parameters was presented. It handles sea state dependence of response variables and enables direct probabilistic treatment of critical response parameters like inline force and overturning moment (OTM) by the convolution of long-term distribution of sea state parameters and short-term distributions of responses. Different models for the correlation of the shape, location and scale parameters with the chosen covariates (the Ursell number and the mean sea state steepness) were analyzed. The third-order model gave the best agreement with the simulated short-term distribution.

Finally, we analyzed the results of the new methodology in estimating the wave crest, inline force and overturning moment for two monopiles at two different depths, one monopile with a diameter $D = 7.0$ m at $h = 20.0$ m and a $D = 7.5$ m monopile at $h = 33.0$ m. Due to the full nonlinearity included in the model, the new methodology results in higher crest heights than the traditional Forristall distribution for sea states that are far from breaking, while it results in lower wave heights when the sea state has an increased probability of breaking, the effect of which is included in the DeRisk database.

As for the force, it was shown that the models predict reasonable static peak force values for the 10000-year return period level. In particular, the model predicts larger forces and overturning moments
for the deeper location and lower for the shallower location, as expected. The maximum hourly force and moment estimates were less dependent on the degree of the polynomial expansions, contrarily to the crest statistics.

The model was shown to produce sensible estimates of static force even at very large return periods. A natural next step consists of adding a dynamic structural model to the computations, to improve the physical description of the system and adding wave breaking to the load model. Especially in large storms where the turbine is idling, the total forcing on the foundations strongly depends on the excitation of the structural eigenfrequencies and by the decay of these vibrations due to the low structural and aerodynamic damping. A correct modeling of these two effects is key to achieve physically correct estimates of the long-term loads, and it will be attempted in future works. Also, the sensitivity of results to the uncertainty in underlying the metocean data sample (40 years) as well as its implicit modelling errors need further analysis and quantification.

Moreover, a full treatment of handling breaking wave loads, the consideration of the interplay between model limitations and the statistical approach adopted and a comparison to present engineering practice is left for investigation in future work.

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