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Hyperbox method: a design-oriented selection of fatigue load cases for offshore wind turbines

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Hyperbox method: a design-oriented selection of fatigue load cases for offshore wind turbines

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Abstract. In offshore wind engineering, efficient and well-targeted environmental condition sampling is key to strike the best compromise between accuracy in load assessment and number of simulations. This is even more challenging for floating offshore wind, because of the increased sensitivity to environmental directionality and wind-wave misalignments compared to fixed-bottom. For the fatigue analysis, the selection of the Design Load Cases (DLCs) for a mastered design process should both capture the synthetic information from large amount of data and remain representative of the environment, considering insights from system responses. Since standards do not provide a detailed approach to achieve the representativity goal, a fatigue DLC selection method answering the above challenges is thus proposed, based on direct exploitation of environmental wind and wave long-term time series. It proceeds through a sequence of iterative binning steps to define an appropriate set of boxes in hyperspace, here called *hyperboxes*, i.e. discrete multidimensional bins in the environment's descriptive parametric space. Representative metrics for each variable within the boxes can be either defined from conventional statistical indicators or determined as a function of the expected system fatigue responses. It ultimately produces a compact and representative fatigue DLC list for the integrated load analysis (ILA) task, accounting for system response sensitivities where relevant. Selection performance is assessed against the original distribution for a set of discretization choices, depending on the offshore wind turbine design characteristics. Project-wise, this method is flexible and adjustable for all design phases, allowing to make the most of a few tens up to several thousands of DLCs. Floating and fixed-bottom offshore wind system design iterations benefit from the presented approach from concept to detailed phases, increasing the efficiency of the engineering team and the chances of project success.

1. Introduction

Fixed-bottom and floating offshore wind turbine (FOWT) engineering requires time-domain coupled simulations of the entire system subjected to wind, waves, and currents, as part of the integrated load analysis (ILA). At a given site and throughout the asset's life, environmental components will vary all around the 360° directions relative to the system. For non-axisymmetric structures like FOWTs, dynamic responses will differ depending on the environment's heading;

fatigue loads deriving from different headings will be distributed over substructure components (pontoon, mooring line, etc.) as a function of directionality.

Therefore, a high representativity of the joint metocean parameters – intensities, directions and frequencies – is required for design; this is stated for instance in the IEC and DNV normative texts. The DNV-RP-0286 (1) recommended practice (RP) for "Coupled analysis of floating wind turbines" introduces the main principles behind the load cases set-up. It supposes that binning and grouping are necessary and refers to the lumping method exposed by Kühn (2). This methodology of fatigue load cases establishment, with *Hs*, *Tp* and wind speed parameters, was initially introduced for fixed-bottom offshore wind turbines and must be modified for FOWTs to take relative directions and misalignments into account, which is crucial for design. The IEC 61400-3 series (3) indicates that wind-wave misalignment cases require special attention and may be particularly important for load cases driving tower-base fatigue. At present, no precise directive or guideline is given for a practical application; however, the evolution expected with the upcoming floating international standard IEC 61400-3-2 includes guidance toward the type of approach proposed in this work.

This article focuses on the Design Load Cases (DLC) selection for the analysis of fatigue loads, used in the assessment of Fatigue Limit States (FLS). To carry out the related simulations, a long-term time series needs to be synthesized in a reduced and representative DLC list. Usually this is done by defining Normal Sea States (NSS). The fatigue cases are defined by the IEC 61400 suite of standards (3): family DLC 1.2 for a turbine in power production and family DLC 6.4 for a parked turbine.

The DLC selection method introduced in this paper has the following main objectives:

- Accurate representation of the metocean environment within a limited DLC budget, using the full information of the available hindcast time series;
- Exerting control on discretization parameters for a design-oriented DLC selection.

The first objective is addressed by grouping a larger number of parameters using a sequential multidimensional binning process; the second by selecting appropriate statistical values for the bins and their resolution, to make the output most representative for structural fatigue. It is shown how both objectives can be influenced by the responses of the studied system.

The paper is organized as follows: a detailed description of the DLC selection methodology is given in Section 2. Applied cases in a FOWT perspective are presented in Section 3, and the design-oriented aspects are discussed in Section 4.

2. DLC selection method

2.1 Definitions and conventions of metocean parameters

Dirp Wave peak direction of provenance [degN] in geographical convention clockwise from North.
Hs Significant wave height [m].
Tp Peak wave period [s].
WsHub 10-min average wind speed at hub height [m/s].
Wd Wind direction of provenance [degN] in geographical convention.
Misal Wind-wave misalignment [deg] defined as Wd-Dirp within the [-180°;180°] interval.

2.2. Objectives and overview

The goal of the DLC list definition is to find a limited but representative set of conditions to characterize the environment for fatigue analysis.

The full dataset with N_{param} parameters is used in the method. This allows better control on (a) the discretization resolution for each parameter, (b) the resulting number of selected DLCs (noted N_{DLC}) and (c) the choice of the characteristic bin values to be calculated for each parameter for all cases.

The process is based on sequential binning of the N_{param} parameters. A tuned discretization is carried out at each step, adding each time a new dimension to the bins. The result is the segmentation of the N_{param}-space dataset into multi-dimensional boxes, here also called *hyperboxes*.

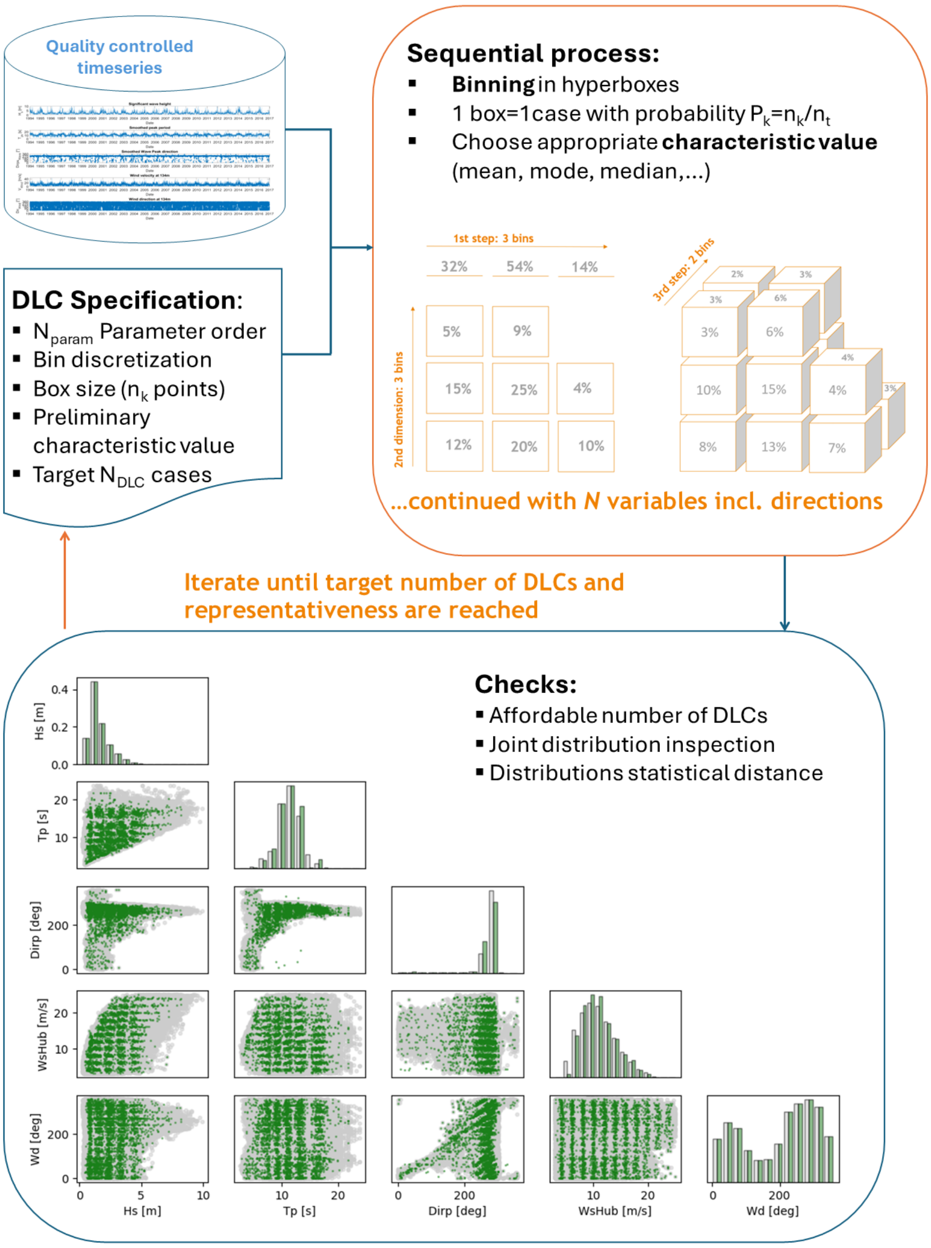

Figure 1. Overview of the iterative discretization process of N_{param} parameters into hyperboxes

Fit-for-purpose checks help to determine when a compromise between the number of DLCs and the representativity of the original distribution is reached. If necessary, the sequence of the binning steps can be reprocessed with refined bin discretization to converge to satisfactory results.

2.3 Iterative discretization steps (binning)

Time series of simultaneous variables are used as inputs. They are typically extracted from a specific hindcast study for the site, which might be a mesoscale reanalysis like the ECMWF ERA5 or a high spatial resolution model at the site of interest. Metocean parameters need not be limited to usual wind, wave and current parameters such as *WsHub*, *Hs*, *Tp*, and their directions, but can also extend to other information such as partitioned sea-state parameters, wind turbulence intensity, etc.

Once the time series is quality-controlled (no outlier, regular time steps, etc.), a set of key metocean parameters is defined and ranked for the iterative binning-grouping process summarized in Figure 1.

A sequence of discretizations is performed. The parameter order is set up by the user, according to the governing design drivers.

The first variable discretisation of DLC family 1.2 can be for instance the wind speed at hub height (*WsHub*), taken every 1 m/s from cut-in to cut-out. Alternatively, the wave direction (e.g. peak *Dirp*) can be prioritised to split properly the different wave directional regimes of the site.

The second discretisation, e.g. by *Hs*, adds a new dimension to the bins and results in two-dimensional rectangular boxes obtained for each *WsHub-Hs* delimitation.

3rd variable: e.g. *Tp* discretisation in main ranges of interest for the design analysis. A resulting three-dimensional rectangular cuboid box is obtained. This step is illustrated in Figure 2 as it is easy to represent in 3D, but the principle remains valid in higher dimensions.

4th variable: e.g. wind directions by macro sectors.

5th variable: e.g. wave directions by macro sectors.

The above binning description results in a set of hyperrectangles. These $\mathbb{R}^{Nparam}$ data point sets are called boxes or hyperboxes in this paper. The above discretization and lumping sequence is repeated and adjusted until an affordable number of load cases is obtained, and site conditions are well enough represented. The discretization sequence is to be adapted to the site specificities and the expected sensitivity of wind- and wave-induced response processes.

2.4. Binning specification

The discretisation choices are based on: the initial bin size; the variability of the parameter within that bin; the sensitivity of the structure to the parameter and its variability; the targeted number of DLCs.

Depending on these inputs, binning can be performed using regular bins (e.g. 30° sectors for wind direction) or parameter-tailored discretization (e.g. *Tp* refinement around a resonance period). One can typically specify the minimum allowable resolution, to cap lumping to an acceptable level.

2.5. Box percentage

The long-term probability of occurrence (P_k) associated to each case k is equal to the number of datapoints in the box (n_k), divided by the total data points in the reference time series (n_t): $P_k = n_k / n_t$. The sum of the percentage of all the selected N_{DLC} fatigue cases (from DLC families 1.2 and 6.4) should generally be equal to one when representing a full on-site operational life.

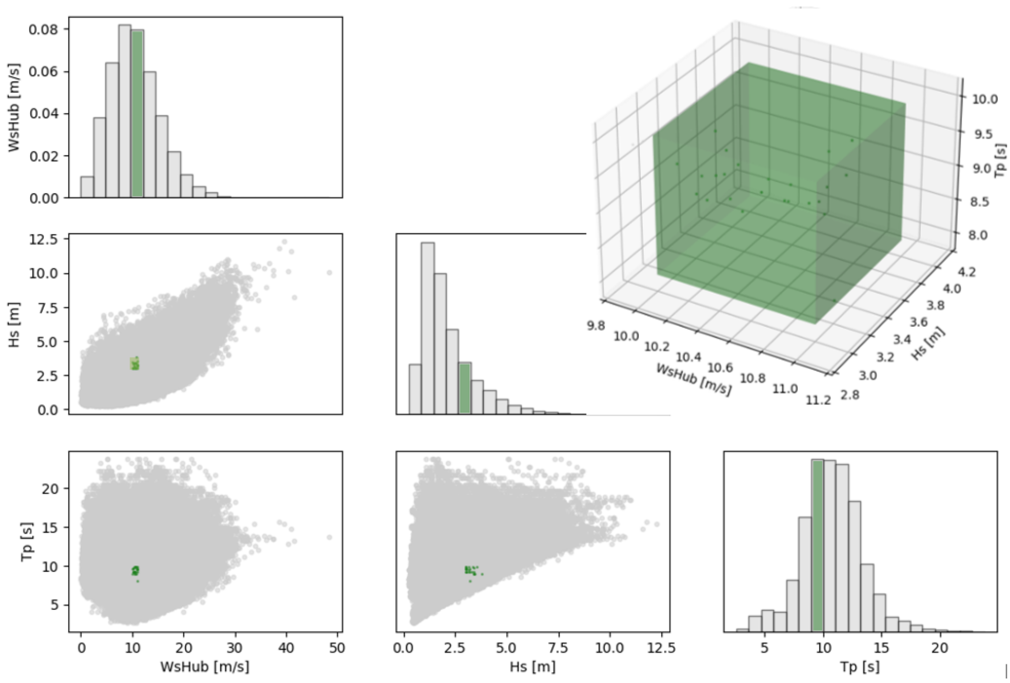

Figure 2. Histograms (diagonal), 2D scatter plots (lower left) of the full dataset (in grey) and selected data points for one selected box (in green) shown along with 3D scatter plot (upper right)

On one hand, attention should be paid to get balanced percentages. For instance, too large boxes may be avoided (e.g. P_k values no larger than 1-2%) and should lead to a finer discretization of one or several parameters within these boxes. Oppositely, if a minimum size of a box is imposed, merging of adjacent boxes is considered in the appropriate variable dimension. The included data points are grouped with the neighboring box. For instance, with specification of minimum P_k>0.01%, if the first [15°;30°[wave directional sector includes less than 0.01% of the time series data point, it will be merged with the next [30°;45°[interval.

On the other hand, merging should be used with expert awareness. For instance, small boxes can still be meaningful for high *Hs* and well separated *Tp* values, and in general where high short-term damage can be expected.

Boxes with mixed populations (and no consistent characteristic value) can be detected using intra-box variance statistics. In this case, new discretization settings can be tested.

2.6. Choice of characteristic bin values

Each hyperbox represents a combination of binned values of each parameter of interest. The final DLC list can be determined using characteristic values obtained for each box instead of the simple centre values of each (univariate) bin range. Such characteristic values are obtained by taking a representative metric (e.g. mean value, median, maximum, weighted average…) of the metocean events x_i contained in the box. This ensures that each DLC will better represents the distribution of points gathered inside a given bin, especially for large ones and if parameter variability is high within the bin.

An illustration of characteristic value computation is given in Figure 3. The selection is illustrated with two metocean parameters. The characteristic value (in green) is chosen to best reflect the joint distribution of points gathered within each box.

For each parameter, the choice of characteristic metric is usually the same for all the boxes. However, metrics might also be hyperbox dependent to better reflect the variability of the reference data and its impact on the design. For instance, for a hyperbox with high peak period values, it might be worth selecting a conservative value closer to a system natural period.

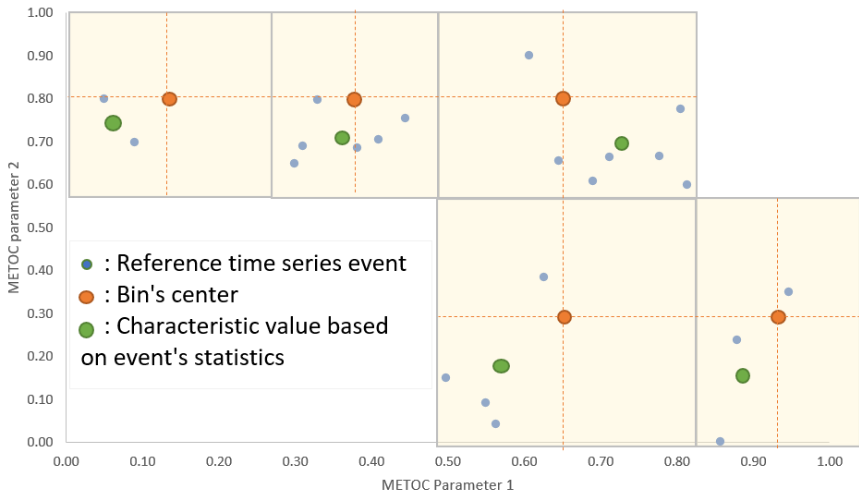

Figure 3. Illustration of binning-grouping and the choice of characteristic parameter values

Hence, the method remains flexible for a design-oriented choice of values. This advantage enables getting a characteristic value that better predicts the damage within a box. As an example, since the structural damage induced by the sea state may be considered roughly proportional to Hs^m, m being the inverse slope of the fatigue S-N curve of the considered material, a power mean (M_m) of Hs may be used instead of an arithmetic mean. In this case, the characteristic value of variable x for case k is calculated using all the n_k points in the box:

$$\boldsymbol{M_m(x)} = \left(\frac{1}{n_k}\sum_{i=1}^{n_k} x_i{}^m\right)^{1/m} \quad (1)$$

Depending on the considered component of the floating wind substructure (e.g. tower base flange, mooring), m can take values of 3, 4, etc.

2.7 Distribution check

With the primary objective of getting a reduced number of DLCs in agreement with the site environment, the obtained selection is compared to the initial time series. This is done using both comparative diagrams and calculation of multidimensional distribution distances.

A visual representation made of comparative histograms and superposed scatter plots can show the big picture of all parameters at once, in complement to detailed errors between distributions.

The deviation between the obtained selection and the original time series is numerically assessed using a measure of total distance (D_s) between the distributions. The distance may be calculated for univariate or multivariate frequency distributions as the difference of the discrete probabilities (in %) of the total dataset (p_t) and the selected dataset (p_s):

$$\boldsymbol{D_s(x) = abs(p_t(x) - p_s(x))} \tag{2}$$

3. Applications

3.1. Input data

The application case is the constitution of a DLC list (for ILA use) of a FOWT unit or cluster in a French South Brittany site of interest, having a harsh and very directional metocean environment.

Wind and wave data are extracted from the Ifremer ResourceCode wave hindcast over Northwest Europe (4). The 27-year environmental time series for the considered parameters are shown in Figure 4. The total number of time records in the dataset is n_t = 236688.

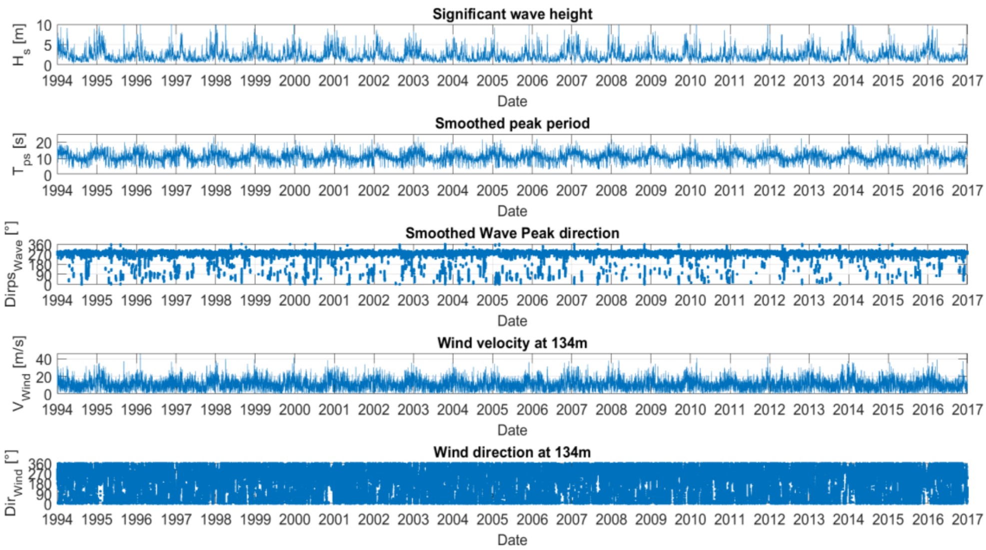

Figure 4. South Brittany time series of *Hs, Tp, WsHub* extracted from Ifremer ResourceCode hindcast point 117220 (47.3°N -3.7°W)

3.2. Application to three parameters

Considering a simple case to render a 3-parameter application (*WsHub, Hs, Tp*), the above South Brittany time series are used as input for the selection of DLCs of the 1.2 family. The same time-series is used for each example. A target of about 500 cases is set for a preliminary fatigue assessment.

The following specifications are considered for the sequential binning:

- First, the *WsHub* univariate histogram is calculated. The discretization of *WsHub* is made every 1 m/s from cut-in (3 m/s) to cut-out (25 m/s) wind speeds.
- Joint histograms with the second *Hs* variable are then calculated, using the following bin limits [0;1;2;3;4;6;8;12] in meters.
- The third discretization is performed along the *Tp* dimension, with the following bin limit values in seconds: [0;5;8;10;12;15;25]. The process results in a series of 3D boxes.

- In each box, the average *WsHub*, *Hs* and *Tp* are taken as characteristic values.

For comparison purposes, a typical industrial approach is replicated, considering bivariate *WsHub-Hs* distributions (scatter diagrams), using respectively bins of 1 m/s and 0.3 m, and *Hs-Tp* relationships with the same target of 500 design load cases.

The distributions of the DLCs produced by both approaches (typical and hyperbox) are superimposed on the full dataset in Figure 5. The compared probability distribution functions on the right show that the *Hs* and *Tp* are much better represented by the hyperbox approach than the typical one. This improvement is confirmed by the measure of *Hs* distance distributions of $D_{typical}(Hs)$=17% for a typical approach versus $D_{hyperbox}(Hs)$=2% for the hyperbox approach ([Table1]). The distances between the joint distributions *D(Hs,Tp)* and *D(WsHub,Tp)* are also significantly better for the hyperbox method.

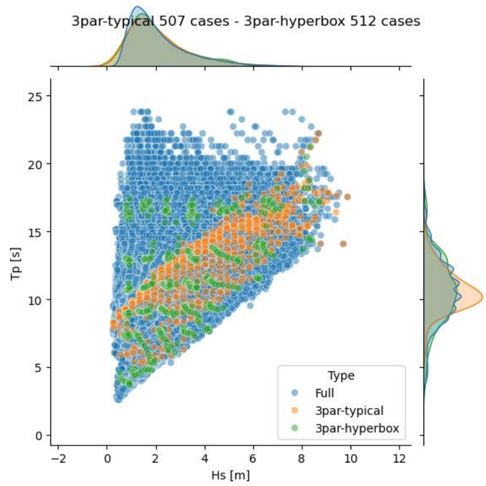

Figure 5. *Hs-Tp* joint scatter plots of superimposed full time series (blue), typical (orange) and hyperbox (green) approaches, with superimposed *Hs* and *Tp* probability distributions on top and to the right

Table 1. Distribution distance of full dataset versus a typical method and the hyperbox method, for univariate (*WsHub*, *Hs* and *Tp*) and bivariate (*WsHub-Hs* and *Hs-Tp*) distributions, three-parameter example

Parameter distribution	Resolution	Typical method (507 DLCs)	Hyperbox method (512 DLCs)
D(WsHub)	1 m/s	0 %	0 %
D(Hs)	1 m	17 %	2 %
D(Tp)	2 s	39 %	14 %
D(WsHub,Hs)	1 m/s – 1 m	17 %	2 %
D(Hs,Tp)	1 m – 2 s	58 %	15 %

3.3. Application to five parameters including wind and wave directions

Considering a more exhaustive application with 5 parameters, the same South Brittany time series is used for the selection of about 4000 1.2 DLCs including directionality information.

The following specifications are considered for the binning steps:

- Wind direction (*Wd*) bins are defined every 30°.
- 2D boxes with bins of *WsHub* defined every 2 m/s from cut-in to cut-out wind speed.
- 3D boxes with discretization along the wind-wave misalignment angle (*Misal*) every 45°.
- 4D boxes with discretization along *Hs*, using [0;1;2;3;4;12] bin limits in meters.

- 5D boxes with discretization along *Tp*, using [0;8;10;12;15;25] bin limits in meters.

The *WsHub*, *Misal*, *Hs* and *Tp* characteristic values are defined as the mean, whilst the mode is used for wind direction.

For comparison, a typical industrial approach is replicated again, considering the bivariate *WsHub-Hs* distributions (scatter diagram like), using 1 m/s and 0.3 m wide bins and *Hs-Tp* relationships, for each directional 30° wind sector. The average values of *Tp* and of the wind-wave misalignment angle are used for each *Wd-WsHub-Hs* bin. The same goal of 4000 individual DLCs is kept.

The distributions from both approaches (typical and hyperbox) are compared against the full dataset in Figure 6 and Table 2. As for the previous 3-parameter application, the distance between the *Tp* distribution selection and the original dataset shows a much better agreement with hyperboxes. Moreover, this method enables to get a better wind-wave misalignment representativity than the typical approach: wind directions are well selected by both whereas wave directions are in better agreement with the full dataset with the hyperbox approach. The distance of the peak wave direction distribution is $D_{hyperbox}(Dirp)$=23% versus $D_{typical}(Dirp)$=50%. Note that hyperbox scores could be further improved allowing for a higher number of cases and/or different discretization rules.

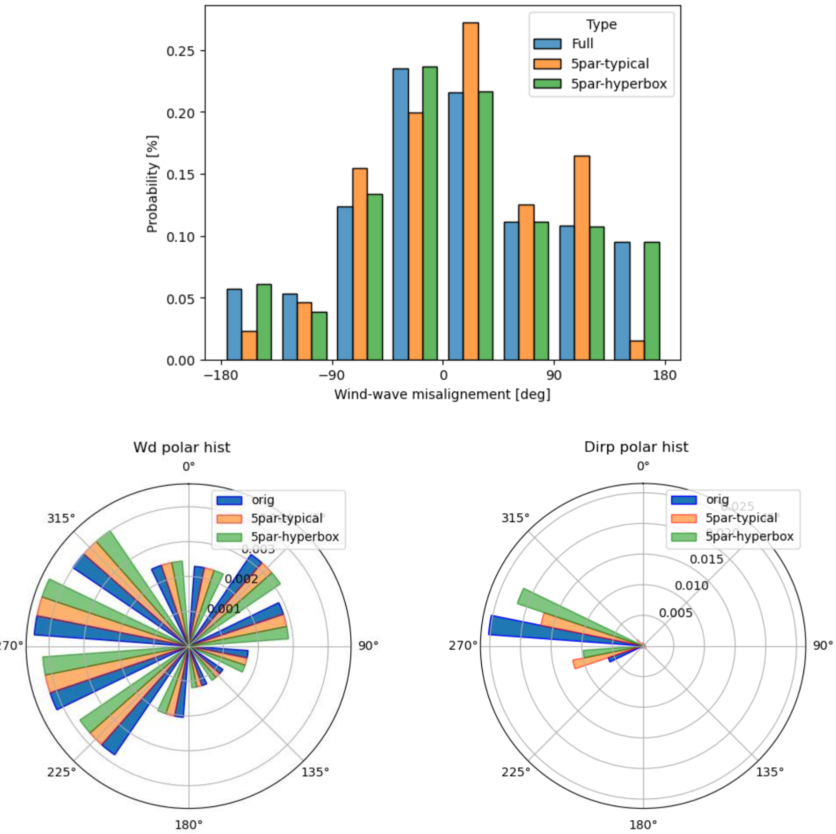

Figure 6. Juxtaposed histograms of wind-wave misalignment (top) and corresponding polar histograms of wind and wave directions (bottom plots)

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Table 2. Distribution distance of full dataset versus a typical method and the hyperbox method for univariate (*WsHub, Hs* and *Tp*) and bivariate (*WsHub-Hs* and *Hs-Tp*) distributions, five-parameter example

Parameter distribution	Resolution	Typical method (3848 DLCs)	Hyperbox method (3614 DLCs)
WsHub	2 m/s	0 %	0 %
Wd	30 deg	0 %	0 %
Hs	1 m	17 %	<1 %
Tp	2 s	32 %	12 %
Dirp	30 deg	50 %	23 %
Misal	45 deg	31 %	3 %
WsHub-Wd	2 m/s – 30 deg	< 1%	< 1%
WsHub-Hs	2 m/s – 1 m	17 %	2 %
Hs-Tp	1 m – 2 s	49 %	13 %
Hs-Misal	1m – 45deg	40 %	<1 %

3.4. Other parameters

The above examples are restricted to five wind and wave parameters. The hyperbox method lets the possibility of adding other variables such as current speeds and directions, wind turbulence intensity and vertical shear parameters, additional sea state spectral parameters, etc.

The above results show the advantages of the hyperbox method for an accurate statistical representation of the environmental parameters per sector. Nevertheless, the overarching goal of fatigue DLC selection for ILA is the best possible representation of long-term damage at the site. The next section provides insights on the incorporation of further design considerations in the hyperbox process.

4. Design-oriented considerations

4.1. Response-based choice of bin resolution

Hyperbox definition should be made with system responses in mind; more specifically, the binning resolution may be increased where it matters for design. An application consists in refining *Tp* around periods where the wave Response Amplitude Operators (RAO) of the structure reveal most damage.

Consider a substructure sensitive to *Tp* within a particular interval, say 6-10 s. For demonstration purposes, an idealized response function of normalized damage is built as a Gaussian distribution function of *Tp* with mean of 8 s and standard deviation of 4 s. This response model is combined with a) the full time series, b) 507 DLCs prepared using the typical approach of the three-parameter example and c) the 512 DLCs prepared with the hyperbox approach of the three-parameter example, which conveniently has a refined 2 s bin resolution around 8 s (§3.2). The estimated normalized long-term damage of the original data points is shown on Figure 7 (left) as a function of *Hs* and *Tp*.

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Figure 7 (right) indicates the resulting repartition of the normalized long-term damage (i.e. considering the occurrences of the sea states) per *Tp* range for a) full time series, b) typical approach, and c) hyperboxes. The overall error of idealized long-term damage between the typical method and the full dataset, given in Table 3, is about 7% whereas the error is reduced below 1% with hyperboxes. The repartition of damage per *Tp* is also better with the hyperbox method.

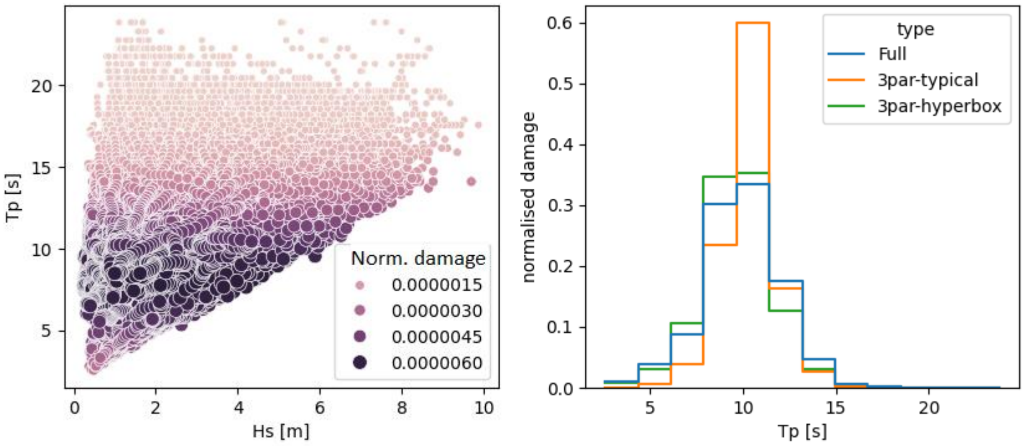

Figure 7. Normalized damage intensity against *Hs* and *Tp* (left), and damage repartition per *Tp* (right)

Table 3. Difference between estimated normalized damage of full dataset and DLC selection methods

Calculated difference	Typical method (507 DLCs)	3-parameter hyperbox method (512 DLCs)
Overall error of normalized long-term damage	6.8 %	0.3 %

4.2. Response-based choice of characteristic values

One of the key features of the hyperbox method is allowing an expert choice of characteristic parameter values. This decision should be made in agreement with the expected response of the system. The following example focuses on the sea state parameters.

The damage induced by the sea state can be seen as roughly proportional to Hs^m, where m is the negative inverse slope of the S-N curve. A new simplistic damage response model is defined here as function of Hs^m and gaussian law of *Tp*. This simplified model is applied here with m=4 on:

a) the full environmental time series, illustrated in Figure 8 (left) as a function of *Hs* and *Tp*.
b) the 3848 DLCs prepared using a typical approach as in the 5-parameter example of §3.3.
c) the 3614 hyperbox DLCs with mean *Hs* used as characteristic value, also for the 5-parameter §3.3.
d) a modified 3614 DLCs hyperbox variant (same binning as above) using for characteristic bin values: a power mean *Hs* (cf. Equation 1, m=4) instead of the arithmetic mean, and the mode instead of the mean for *WsHub*; this modification was performed in iterative fashion.

The overall estimated long-term damage error between the typical method and the full dataset, given in Table 4, is 16.6% whereas the error is -5.6% for the c) hyperbox approach, and only 1.9% for modified hyperboxes as in d).

Figure 8 (right) shows the normalized long-term damage repartition per wind speed range for a) full time series, b) typical approach, c) hyperboxes, and d) modified hyperboxes. The use of the mode for *WsHub* allows a more accurate repartition of long-term damage across wind speeds. In addition, the choice of the power mean for *Hs* enables a better estimation of damage for the high values associated with wind speeds around and above 20 m/s.

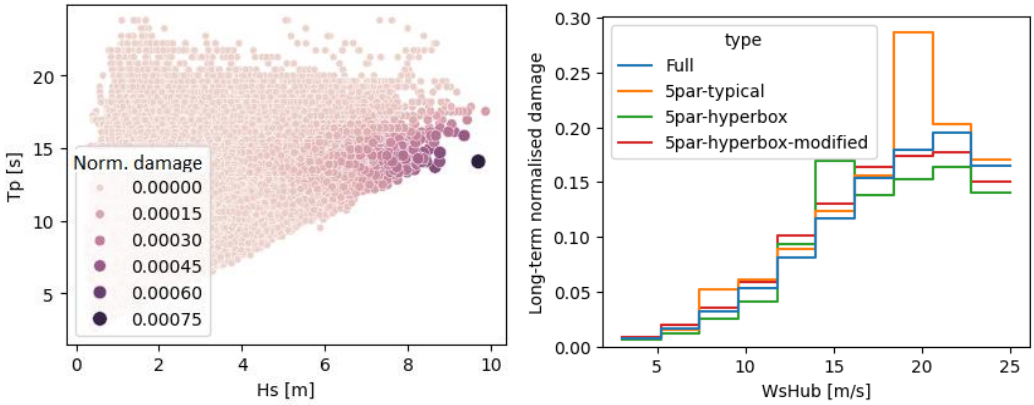

Figure 8. Normalized damage intensity against *Hs* and *Tp* (left), and damage repartition per *Tp* (right)

Table 4. Difference between estimated normalized damage of full dataset and DLC selection methods

Calculated difference	Typical method (3848 DLCs)	5-parameter hyperbox with mean *Hs* and mean *WsHub* (3614 DLCs)	5-parameter hyperbox with power mean *Hs* and mode *WsHub* (3614 DLCs)
Overall error of normalized long-term damage	16.6 %	-5.6 %	1.9 %

4.3. More response-based considerations

As highlighted in the two previous sections, response-based considerations are very useful to specify the bin resolution and define characteristic parameter values. This can be achieved either considering analytical formulae or based on empirical knowledge of the system's sensitivities.

An example of analytical considerations is proposed in (5) where first a power weighting similar to the one presented in section 4.2 is applied on *Hs*, to define a damage-equivalent *Hs* per bin. Then, an equivalent peak period is estimated based on the assumption that for slender structures like monopiles, dynamic fatigue loads are proportional to the wave spectrum energy at the first natural frequency. Thus, the weighting scheme is based on a power averaging of the spectral value at the natural frequency to assess an equivalent spectral value from which an equivalent *Tp* can be recalculated.

Another approach based on empirical considerations is proposed in (6). The idea is to derive damage-equivalent contour lines for the system, either based on dedicated frequency- or time-domain simulations. As mentioned in (6), contour lines refer in this example to (*Hs,Tp*) combinations that result in the same damage level at a given location along the structure. The basis of the method is then to find the combination that best represents the total fatigue damage for each bin.

Although the two given examples focus on monopile structures, similar approaches can be developed to address other fixed and floating foundation types.

5. Conclusion and further work

A flexible methodology for Integrated Load Analysis (ILA) fatigue Design Load Cases (DLC) selection is presented, based on multi-dimensional boxes with number of dimensions equal to number of parameters, denoted hyperboxes. A detailed description of the proposed process with design governing considerations is given, together with quantified benefits. Applied examples show that, compared to a typical industrial approach relying on scatter diagrams, the hyperbox method makes a better use of site data by:

a) preventing the loss of frequently discarded "joint" information, especially directionality which is key for floating systems;
b) enabling a reasoned adaptation of parameter space resolution and characteristic bin values to the actual design problem;
c) allowing thorough quality checks of candidate DLC selections;
d) producing a higher-quality DLC list better correlated to the original site data;
e) ultimately, limiting the error on long-term damage to a minimum, and thus avoiding under or over design of the system.

When applied to offshore wind turbines, especially floating, the hyperbox method facilitates design convergence from the early stage when the ILA computing budget is most limited, and beyond. Engineering efficiency and the chances of project success (feasibility, optimal sizing, on-time delivery) are increased, and conversely the risk of radical "midway" component redesign due to emerging fatigue issues is reduced. This de-risking effect is particularly valuable in the presence of vicious design cycles, a well-known eventuality in floating wind substructure engineering.

Of course, the proposed method expresses its best potential when paired with a calculation chain able to resolve fatigue damage into relevant structural details at a CPU and engineering man-hour budget compatible with all design stages, see e.g. (7).

Past experience with the hyperbox method in floating wind, spanning across preFEED and certified FEED-level works, shows us it is a valuable decision-making asset: its direct benefits on environment representativeness, together with the ability to leverage on designer experience, helps to make the right design decisions along the engineering path to project execution.

Further work will involve a more thorough incorporation of system response features into the DLC selection process, and a demonstration of the method's gains when applied to a design loop (ILA).

References

1. DNV-RP-0286 - Recommended practice - Coupled analysis of floating wind turbines. 2019.
2. Kühn MJ. Dynamics and Design Optimisation of Offshore Wind Energy Conversion Systems. 2001.
3. IEC-61400-3 - Wind energy generation systems – Part 3: Design requirements for offshore wind turbines. 2019.
4. Accensi M, Alday M, Maisondieu C, Raillard N, Darbyrian D, Old C, et al. ResourceCODE framework: A high-resolution wave parameter dataset for the European Shelf and analysis toolbox. In: Proceedings of the Fourteenth European Wave and Tidal Energy Conf. Plymouth, UK; 2021.
5. Seidel M. Wave induced fatigue loads on monopiles - New approaches for lumping of scatter tables and site specific interpolation of fatigue loads. In: International Wind Engineering Conference. 2014.
6. Katsikogiannis G, Sorum SH, Bachynski EE, Amdahl J. Environmental lumping for efficient fatigue assessment of large-diameter monopile wind turbines. Marine Structures. 2021.
7. Antonutti R, Martin A. Accurate FOWT fatigue assessment at all design stages. WindEurope annual event; 2022.