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Analysis of the design of experiments of offshore wind turbine fatigue reliability design with Kriging surfaces

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Abstract

The fatigue design of Offshore Wind Turbines (OWT) is one of the most resource demanding tasks in the OWT design process. Techniques have been developed recently to simplify the amount of effort needed to design to structural fatigue. This is the example of the usage of Kriging surrogate models. These may be used in OWTs design not only, to reduce the computational effort needed to analyse an OWT, but also to allow their design to be robust.

Due to the stress variability and its non-linear character, the short-term fatigue damage variability is high, and converging the stochastic field approached by the surrogate model in relation to the real observations is challenging.

A thorough analysis of the different components that load an OWT and are more critical for the tower component fatigue life is required, and therefore, presented and discussed in the current paper.

The tower, jointly with the foundation, are particular components of the OWT regarding the fatigue analysis process.

Statistical assessments of the extrapolation of fatigue loads for the tower and the influence of the environmental parameters in the short-term damage are presented in this paper. This sets a support analysis for the creation of the Kriging response surfaces for fatigue analysis. NREL's 5MW monopile turbine is used due to its state of the art character. Five environmental variables are considered in the analysis. A sensitivity analysis is conducted to identify which variables are most prominent in the quantification of the short-term damage uncertainty in the tower. The decoupling of the different external contributions for the fatigue life is a major contribution of the work presented. Preliminary guidelines are drawn for the creation of surrogate models to analyse fatigue of OWT towers and the most relevant conclusions are presented in an industry-oriented design outline regarding the most critical random variables that influence OWT short-term fatigue calculation.

Keywords: Offshore wind turbine; Reliability; Kriging surrogate model; Sensitivity anaysis; Short-term fatigue damage;

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1. Introduction

The calculation of fatigue of OWT is a resource demanding process. The design lifetime of an OWT is quite long, and can be expected to be as high as 20 years. It is straightforward to perceive that reproducing in the design phase to the full extent this period of time of operation of such a complex system without some simplifying assumptions is an unfeasible task.

In this context the IEC guidelines to design OWT, (IEC, 2005) and (IEC, 2009), set fatigue to be analyzed with a semi probabilistic framework. Assuming that the high load ranges will contribute the most for the fatigue damage, the load range is recommended to be extrapolated from a load set referring to a time *t* to the whole lifetime period T considered. The extrapolation considers fitting the exceedances over a pre-specified quantile (A *Q95%* is recommended for extrapolation purposes in (IEC, 2005)) and taking the cycles below the specified quantile to repeat deterministically over the OWT lifetime T. To assess the loading ranges, means and number of cycles a rainflow counting scheme should be implemented.

The full lifetime damage level is then assessed with the widely known Palmgren-Miner rule of linear damage sum.

$$D_T = \sum_{i=1}^{N_T} D_{SH\,i}$$

where D_{SH} is the damage accumulated in the reference period of time *t* (usually 10 minutes), D_T is the damage accumulated during the considered lifetime *T*, N_T is the number of D_{SH} cycles that occur during the considered lifetime period *T*.

Even considering that extrapolation techniques are used, a high computational effort is still demanded to produce accurate results. Reliability based optimization techniques are then difficult to apply to these systems.

A good example of the effort needed in the analysis is found in (Moriarty, Holley, & Butter, 2004), where the probabilistic analysis of OWT and extrapolation of loads are analyzed for both, the extreme loading and the fatigue design. For extrapolation purposes, and considering two variables as the main design variables, wind velocity (U) and turbulence intensity (I), 4725 simulations were needed for the full integration technique and to fully characterize the tail region of the load distribution. Important to highlight that even considering this large number of simulations and large computational effort needed (for reference; considering that each FAST software 10 minutes simulation may take a average time of 20 minutes in a i7-4790 CPU supported by 16GB of RAM) to complete these simulations, only approximately a single month of fully continuous operation is covered by these. The results are then compared with the extrapolation based on 197 simulations without the binning of *I*.

Additionally, (Moriarty, Holley, & Butter, 2004) highlight that using very high quantiles for extrapolation may not be adequate for low slope of the S-N curve, which is the case of the tower materials. This fact motivates the development of alternative methodologies to assess the reliability of the tower.

The complexity of the coupled codes to model OWTs is related to the many variables that influence the operation of these, and that make a probabilistic framework very complex to develop. One of the most relevant works on the probabilistic analysis of wind turbine fatigue is presented in (Veldkamp, 2008). In this work a very extensive review of the uncertainties and random variables that affect the fatigue design of wind turbines and their effect is discussed in detail and a methodology for probabilistic fatigue analysis is proposed. To notice that it is of particular interest when dealing with OWT design to know which variables may be more prominent in the turbine fatigue behavior.

The current paper addresses then, in the framework of applying Kriging surrogate models for reliability, the influence of the different random variables that are expected to contribute the most to the fatigue of the tower component of OWTs. When implementing a Kriging surrogate model is then important to assess which will be the variables that contribute the most to D_{SH} in order not to introduce complexity in the Kriging that does not comprise relevant information, and additionally to optimize the computational effort spent in the process of defining the most accurate response surface. To achieve this, the remaining of Section 1 presents some works of reliability with Kriging surfaces. Section 2 introduces then these models, their theoretical background, and the motivation for their application in the context of OWT tower fatigue analysis. Section 3 discusses the influence of the different variables on short term damage, presenting also some initial conclusions. Finally, the main conclusions are drawn in the final Section.

1.1. Probabilistic design of OWT with Kriging surrogate models

The Kriging models or Gaussian process models are of interest for the topic of reliability analysis due to their interpolation capacity, the flexibility to approximate arbitrary functions with a high level of accuracy and the capability of accounting for a local uncertainty measure.

Several examples of application and discussion of Kriging surrogate models as a tool for reliability and probabilistic structural analysis are found in (Bichon, Eldred, Swiler, Mahadevan, & McFarland, 2008) , (Echard, Gayton, & Lemaire, 2011), (Echard, Gayton, Lemaire, & Relun, 2013), (Gaspar, Teixeira, & Guedes Soares, 2014), and (Zhang, Lu, & Wang, 2015).

For OWT analysis the Kriging surrogate models gained particular attention with the work developed in (Yang, Zhu, Lu, & Zhang, 2015) where a tripod structure is optimized supported by results from the Kriging surrogate models. In this work a Finite Element model is used to generate very accurate Design of Experiments (DoE) points and then the Kriging is used to extend the responses calculated to the full response of the system. A methodology of reliability based design optimization is then developed to optimize the support structure to extreme responses from Normal operating conditions and Seismic conditions.

Later, in (Morató, Sriramula, & Krishnan, 2016), the support structure probability of failure under extreme events is computed using a Kriging surrogate model to simulate the loading response of the system. Two limit state function are considered in the analysis. In a similar way than the previous work, the support points are picked using a Latin Hypercube Sampling technique.

It was mentioned that, when dealing with complex models it is important to not compromise efficiency by introducing additional complexity in the surrogate model that does not accomplish improved stochastic accuracy. In (Gaspar, Teixeira, & Guedes Soares, 2014) it was shown that the usage of higher order polynomials do not improve the accuracy of the reliability predictions in the particular case of the structural reliability.

In the case of OWT towers the quantity of external variables that will influence the loads in the tower is high due to the complex behavior of the turbine on its own but mainly due to the number of environmental loading variables. (Echard, and Gayton, & Bignonnet, 2014) analyse the specific case of fatigue failure in a probabilistic basis using Kriging surrogate models. The surrogate model is used to approach directly the limit state equation of fatigue and then to estimate the probability of failure. (Teixeira, O'Connor, Nogal, Nichols, & Spring, 2017) applies these in the analysis of OWT towers fatigue, using the Kriging surrogate model to approximate the OWT model. Samples generated from the surrogate model represent therefore short term operation of the OWT.

2. Probabilistic damage calculation of OWT with Kriging surrogate models

The probabilistic calculation of fatigue damage relying on Kriging surrogate models uses the capacity of these surrogate models to interpolate a Gaussian field. Assuming that $g(x)$ represents a real function of $D_{SH}(\varphi_p)$ which is function of p $\varphi_p$input parameters, a Kriging surrogate model $\mathrm{G}(x)$ that approximates $\mathrm{g}(x)$ can be written as follows:

$$G(x) = f(\beta; x) + z(x),$$

$$f(\beta; x) = \beta_1 \, f_1(x) + \cdots + \beta_p \, f_p(x),$$

where $f(\beta; x)$ is a deterministic component determined by a regression model defined by p basis functions $f_p(x)$ and β_p regression coefficients. The Gaussian stochastic uncertainty of the model is introduced by $z(x)$, which is a stochastic Gaussian process with mean 0 and covariance between two points *i*, and *j* in space given by:

$$cov(z(x_i), z(x_j)) = \sigma_z^2 \, \Omega(\theta; x_i, x_j),$$

$$with \ i, j = 1,2,3, \dots, m$$

with σ_z^2 as the constant process variance and Ω a correlation function that represents the correlation between two arbitrary points in space x_i and x_j. A wide application of an exponential correlation function can be identified in previous works for structural reliability, producing efficient results.

The process of creating the Kriging metamodel requires a sample of M support points. This sample is frequently called DoE; $DoE = [x_k, == g(x_k)]$ for $k = 1,2,..,M$; and has the particularity of being the exact prediction of the real function *g(x)* in the respective DoE point.

A more extensive description of the theory that backs the usage of Kriging surrogate models in the context of reliability analysis, with further discussion of the different parameters involved in the calculation of these surrogate models (e.g. regression models; autocorrelation functions), is presented in (Dubourg, 2011).

3. Influence of random variables in short-term (SH) fatigue on OWT tower

To analyse the influence of the different variables that may be considered in the DoE a one-factor-at-time (OFAT) approach is used. The OFAT approach involves setting a reference point, changing then one parameter at the time and evaluating the output results.

A very common local method for sensitivity analysis involves calculating the partial derivatives of the output variable D_{SH} in relation to an input variable X_i of the DoE in a reference fixed point of the space of input variables X_0. The sensitivity in this case is then defined as:

$$S_{D_{SH_i}} = \left.\frac{\partial D_{SH}}{\partial X_i}\right|_{X_0}$$

where $S_{D_{SH_i}}$ is the sensitivity of the short term damage to a variation in the variable X_i. Eight reference states (X_0) represented by a combination of environmental variables were considered for the OFAT analysis. These consider four different states of operation of the OWT and are set to ensure more robust results. Complementing hence potential limitations introduced by the OFAT methodology and the way it covers the space of the variables.

3.1. Setting the Reference Cases

When developing a sensitivity analysis of such complex systems, which depend on many variables, the computational effort needed to cover the entire space of possible events can become unreasonably high. This is the case of OWT towers, where the structural behavior depend on many external variables. These computational requirements complicate even further when a probabilistic analysis is being developed and many simulations are needed to characterize the statistical moments of the variables.

In the present case five are considered, the mean wind speed (U_w), the significant wave height (H_s), the wave peak period (T_p), the turbulence intensity (I) and wind misalignement (θ_w). To address these five variables, a global and a local analysis to the system's behavior is implemented. This allows a general overview over the system to be analysed and then to work locally in some specific points. In the present case the methodology implemented follows the approach developed in (Martinez-Pastor, Nogal, & O'Connor, 2016) and (Martinez-Pastor, Nogal, O'Connor, & Caulfield, 2016), where a hybrid global-local approach was applied for transport networks.

It is noted that the effort needed for the analysis is highly reduced, comparatively to what would be expected to cover a full analysis of five variables, by the fact that in this case the variables are highly correlated between them. The waves are correlated with the period, and the wind with the turbulence intensity and the direction. In this way, a problem that involves five dimensions can be reduced to two main dimensions of analysis, one related to the wind variables and another related to the wave variables. The wind and the waves are on their own correlated. Assuming that wind and wave occur with coherence, these two main dimensions of analysis are then separated in states of high energy and low energy, or high and low wind speed and turbulence intensity and high and low significant wave heights and peak periods, as depicted in Figure 1. Even attending to the high non-linearity of a fatigue analysis, and attending to the fact that a real system is being considered where no discontinuities in D_{SH} are expected and that most environmental variables have vary less inside an energy state, it is assumed that within the combinations of environmental states of energy the system will experience similar statistical loads and damage.

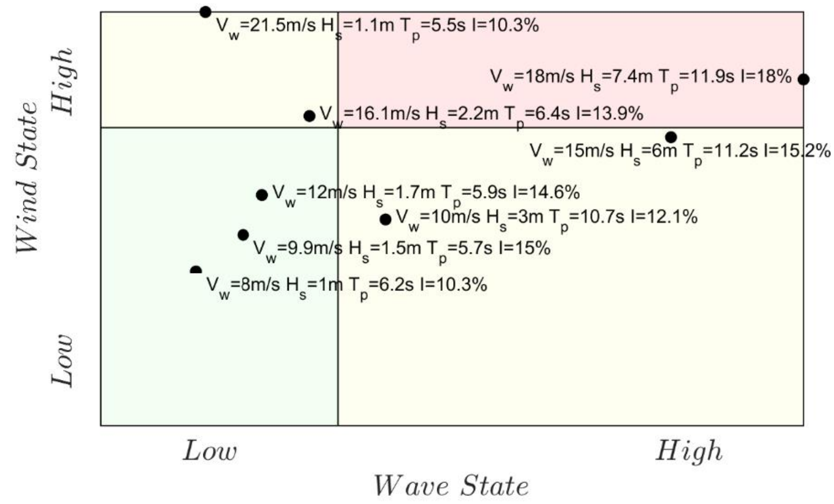

Figure 1 – Space of variables and reference cases for local sensitivity analysis.

High energy states are not very frequent but they represent a higher number of combinations of variables. Low energy states, which occur more often, represent much smaller intervals of occurrences among the variables considered. To cover the most of the space of variables and having as reference the data from (Fischer, de Vries, & Schmidt, 2010), the energetic states of wind and waves are divided between high and low energy. For the wind, the high energy threshold represents approximately 10% of the whole data, with U_w bigger than 15.5m/s, and with turbulence intensity depending on this value. For the waves, it corresponds to the wave states with higher energy than the combination of H_s bigger than 2.5m and T_p bigger than 9s, which also represents approximately a bit more than 10% of the total occurrences.

The global reference points X_0 are sampled in Figure 1. These are analysed globally in order to understand global trends in the data. Local analysis is conducted in each reference point.

NREL's Baseline 5MW monopile OWT was used in the analysis (Jonkman, Butterfield, Musial, & Scott, 2009). A total of 15 simulations for each reference case were run to analyse the OFAT results, performing a total of 720 simulations. Variations of 20% were implemented for H_s, T_p, U_w and I. For the case of θ_w, misalignments of 5° relative to the rotor horizontal axis were considered to study the sensitivity in all the reference cases. The misalignment is particular in the sense that in practice variations in wind directions are compensated by the control system. In this case the control system is neglected and the interest is to infer if small misalignments influence the OWT tower damage.

The value of 20% can be considered quite significant in a sensitivity analysis. In the presented case the aim of the analysis was to have a description of the operational D_{SH} depending on the DoE within a Kriging surface framework with a reasonable amount of computational effort. Considering very small changes of the parameters would demand an ever higher number of simulations due to the fact that for most of the cases a change smaller than 20% is not significant enough to introduce a relevant change in the environmental state. This is more prominent in the case of environmental states that are located in the *Low-Low* region. The final goal was then to analyse the variations of the damage considering that it would behave like a surface, and covering most of its surface.

3.2. Results of OFAT analysis

Figure 2 shows the results for the changes of environmental variables in the DoE. The wind velocity U_w and the turbulence intensity I are the most influent variables in the short term damage D_{SH} in seven of the eight cases analysed. D_{SH} is not significantly influenced by changes in H_s and T_p. The waves do not interact directly with the tower, only with the foundation, and their influence is deeply connected with damping effects from the tower interaction with the air. These did not prove, on operating conditions, of major importance for the tower fatigue mean values when compared with the variables associated with the wind.

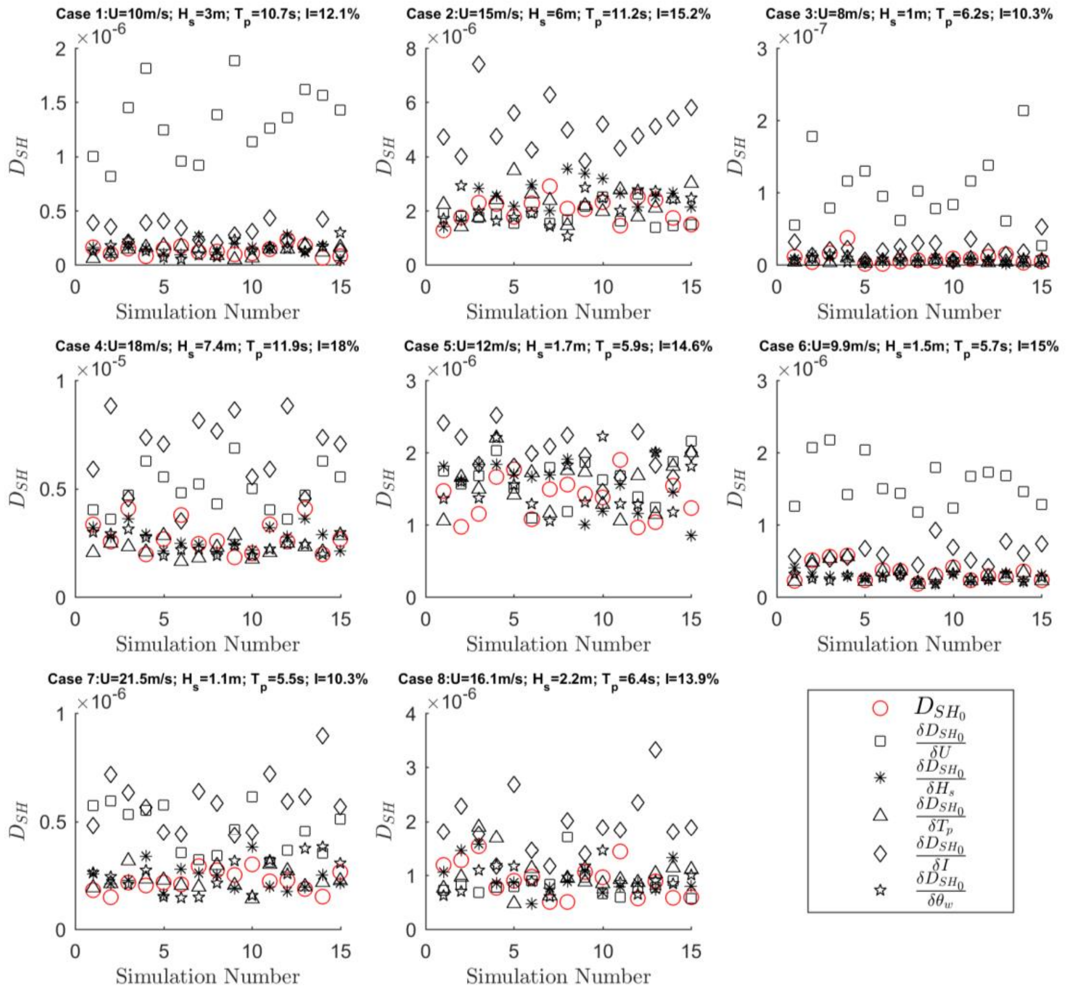

Figure 2 - Results of the OFAT for the environmental variables.

In Table 1 are presented the results for the statistical variations in the mean and standard deviation of the samples modeled. U_w and I dominate the major global statistical variations in the tower damage and cause the major variations in the sample statistical moments relatively to X_0. Regarding the wind speed, the results indicate that two local maximums of averaged damage should then be expected in operation, one near the rated wind power and another near the shut-down wind speed. (Cheng, van Bussel, van Kuik, & Vugts, 2003) showed that extreme loading of OWT occurs close to the rated power, therefore, the same may occur for fatigue damage as the biggest load range has major contribution to decrease the fatigue life. For operating speeds over the rated power I seems to influence the most the short term damage sensitivity in the tower. The maximum values of D_{SH} are obtained for the highest values of I within operating conditions. Despite not being a common occurrence, this finding is relevant when designing the OWT as the current Design Load Cases (DLC) of OWT do not consider the effect of the occurrence of high I values during operation for fatigue calculations. It is common during the design phase to use the Normal Turbulence Model (NTM).

In the sample of Case 1, dU_w causes a variation of 820% in μD_{SH} while dI causes a variation of μD_{SH} of 124%. In this case the damage was already expected to increase closer to the rated U_w. For the simulated Case 2 the influence of the U_w diminishes significantly, indicating that above the rated power the sensitivity of D_{SH} to the mean wind speed decreases. The variation in the mean of the damage is mainly influenced in this case by I. For the cases 3 and 4 this pattern in $d\mu_{D_{SH}}$ repeats, although a relevant local sensitivity to U_w can be identified also in Case 4. This indicates that near the shut-down U_w an increase in the average damage should be expected as dU_w in Case 4 approaches the shut-down wind speed of 25 m/s. The Cases 5 and 6 share similar environmental variables, but in the Case 5, the wind is already over the rated-speed, and therefore the local sensitivity is lower. The Case 7 and 8 confirms the trends identified before.

Table 1 – Variation of the sample mean and standard deviation properties function of the parameter modified in the DoE.

$\mu D_{SH_{X_0}}$	$\frac{d\mu D_{SH_{X_0}}}{dU_w}$	$\frac{d\mu D_{SH_{X_0}}}{dH_s}$	$\frac{d\mu D_{SH_{X_0}}}{dT_p}$	$\frac{d\mu D_{SH_{X_0}}}{dI}$	$\frac{d\mu D_{SH_{X_0}}}{d\theta_w}$
Case 1	$1.16 \times 10^{-6}(820\%)$	$0.11 \times 10^{-7}(7.9\%)$	$-0.18 \times 10^{-7}(-12\%)$	$0.12 \times 10^{-6}(124\%)$	$0.05 \times 10^{-7}(3.7\%)$
Case 2	$-0.17 \times 10^{-6}(-8.5\%)$	$0.28 \times 10^{-6}(13.8\%)$	$0.85 \times 10^{-7}(4.18\%)$	$2.93 \times 10^{-6}(143\%)$	$0.12 \times 10^{-6}(5.7\%)$
Case 3	$9.63 \times 10^{-8}(1138\%)$	$-0.21 \times 10^{-8}(-24\%)$	$-0.34 \times 10^{-8}(-40\%)$	$1.07 \times 10^{-8}(218\%)$	$-0.15 \times 10^{-8}(-18.7\%)$
Case 4	$2.3 \times 10^{-6}(84.3\%)$	$-1.1 \times 10^{-7}(-4\%)$	$-5.3 \times 10^{-7}(-19\%)$	$3.98 \times 10^{-6}(146\%)$	-3.9×10^{-7} (-14.3%)
Case 5	$2.52 \times 10^{-7}(18.3\%)$	$1.75 \times 10^{-7}(12.7\%)$	$1.66 \times 10^{-7}(12.1\%)$	$6.19 \times 10^{-7}(45.1\%)$	1.82×10^{-7} (13.3%)
Case 6	$1.26 \times 10^{-6}(370\%)$	$-6.2 \times 10^{-8}(-18.4\%)$	$-0.11 \times 10^{-7}(-3.2\%)$	$2.42 \times 10^{-7}(71.3\%)$	-0.73×10^{-7} (-21.5%)
Case 7	$2.39 \times 10^{-7}(107\%)$	$1.60 \times 10^{-8}(7.2\%)$	$0.5 \times 10^{-8}(2.2\%)$	$3.63 \times 10^{-7}(163\%)$	2.74×10^{-8} (12.3%)
Case 8	$8.4 \times 10^{-8}(-9.2\%)$	$3.2 \times 10^{-8}(3.5\%)$	$9.7 \times 10^{-8}(10.6\%)$	$1.00 \times 10^{-6}(110\%)$	2.4×10^{-8} (2.6%)
$\sigma D_{SH_{X_0}}$	$\frac{d\sigma D_{SH_{X_0}}}{dU_w}$	$\frac{d\sigma D_{SH_{X_0}}}{dH_s}$	$\frac{d\sigma D_{SH_{X_0}}}{dT_p}$	$\frac{d\sigma D_{SH_{X_0}}}{dI}$	$\frac{d\sigma D_{SH_{X_0}}}{d\theta_w}$
Case 1	$2.41 \times 10^{-7}(495\%)$	$1.79 \times 10^{-8}(36.6\%)$	$-7.4 \times 10^{-9}(-15.2\%)$	$7.69 \times 10^{-8}(158\%)$	$1.32 \times 10^{-8}(27.15\%)$
Case 2	$1.9 \times 10^{-9}(0.40\%)$	$1.55 \times 10^{-7}(31.8\%)$	$8.88 \times 10^{-8}(18.2\%)$	$5.35 \times 10^{-7}(110\%)$	4.85×10^{-8} (9.96%)
Case 3	$3.79 \times 10^{-8}(483\%)$	$-4.4 \times 10^{-9}(-55.9\%)$	$-5.2 \times 10^{-9}(-66.6\%)$	$6.9 \times 10^{-8}(88.3\%)$	-5.1×10^{-9} (-65.1%)
Case 4	$2.20 \times 10^{-7}(29.2\%)$	$-2.62 \times 10^{-7}(-34.7\%)$	$-3.43 \times 10^{-7}(-45.5\%)$	$9.89 \times 10^{-7}(130\%)$	-2.78×10^{-7} (-36.9%)
Case 5	$1.29 \times 10^{-8}(4.42\%)$	$5.56 \times 10^{-8}(19\%)$	$5.84 \times 10^{-8}(20\%)$	$6.4 \times 10^{-9}(2.17\%)$	8.2×10^{-8} (28%)
Case 6	$1.94 \times 10^{-7}(156\%)$	$-6.66 \times 10^{-8}(-53.3\%)$	$-3.4 \times 10^{-9}(-2.7\%)$	$2.97 \times 10^{-8}(23.8\%)$	-8.21×10^{-8} (-65.7%)
Case 7	$6.41 \times 10^{-8}(137\%)$	$1.31 \times 10^{-8}(27.9\%)$	$0.97 \times 10^{-9}(2.1\%)$	$8.11 \times 10^{-8}(1.73\%)$	3.25×10^{-8} (69.3%)
Case 8	$-6.97 \times 10^{-8}(-20.6\%)$	$-3.40 \times 10^{-8}(-10.1\%)$	$2.85 \times 10^{-7}(8.4\%)$	$2.34 \times 10^{-7}(69.4\%)$	-9.4×10^{-8} (-27.8%)

The sample standard deviation σ is a statistical moment that converges slower than the sample mean μ. The precise analysis of results is then more difficult when the variation of the standard deviation is not very substantial. In this case it is difficult to weight the contribution from the sensitivity itself and from the stochastic convergence of the standard deviation. σD_{SH} converges significantly more slowly than the μD_{SH}. This convergence depends highly on the sample. In all the case the major variations of standard deviation occur in the same case where the variation of $\mu D_{SH}$is higher, indicating that an offset of μD_{SH} is very likely to be accompanied by a change of the whole population distribution moments. As recommendations from the indicators obtained in the results, when building a Kriging surface, are:

- Uncertainty of the short-term damage is quite significant, and standard deviations are in average between 25-30% of the mean over the rated speed. For lower wind speeds, below rated power, where the damage generated is less important for the structure, this value ascends to almost 50%.
- U_w and I should always be considered in the DoE of a Kriging surrogate surface to assess the reliability of an OWT tower. Making this the dimension of the Kriging surface at least 2.
- As the variation of statistical parameters is quite high for low number of simulations, assessing the uncertainty introduced by the wave parameters can be taken as redundant in comparison to the intrinsic uncertainty of the D_{SH}. For severe sea states and states where the wind is not prominent in the D_{SH} results these can be important. Therefore it may be reasonable to model these variables in the DoE or to truncate the Kriging to account for the uncertainty in the regions of interest in the cases where the wave parameters show influence on D_{SH}.
- The θ_w influence over D_{SH} is limited. The yaw control system was not modeled, still the results obtained indicate that for small wind directions the damage the change in D_{SH} are not relevant.

It is important to emphasize that the complexity that affects the OWT is high and other parameters (e.g. structural model, tower diameter or thickness, among others) may be included in the analysis. Nevertheless, these are not the main focus of the Kriging surface as a tool for reliability because they are usually seen as design variables to be set in order to comply with the environmental loading requirements. In particular, the OWT tower thickness and diameter are expected to have a relevant influence in the fatigue life.

4. Conclusions

Motivated by the fact that the current methodologies implemented tend to inaccurately extrapolate the damage for the OWT life-time, a methodology involving Kriging surrogate models was proposed to account for the uncertainty that affects these type of structures.

The current paper discusses then, within the framework of underpinning the development of Kriging surrogate models for the reliability analysis of OWT towers, the influence of environmental variables on the short term damage generated in the tower when a rainflow counting analysis is applied together with the Palmgren-Miner rule.

For the case of the monopile OWT, which is a fixed foundation, the variables associated with the wind dominate the short term damage sensitivity in the tower component. Among the variables analysed, the wind speed and turbulence intensity stand out as the most relevant. The wind direction is the least influent parameter, if small wind directions are considered. The waves, despite carrying high amount of energy, are significantly less influent in the short-term damage generated in the tower. Recommendations were presented based on the indicatons found to create Kriging surfaces to model fatigue. Depending on the context of application, the balance between the number of variables to consider in the DoE and the amount of information carried by each variable should be equated. If very low computational time is pursued, the wave variables should not be accounted in the Kriging surface DoE and the focus should be set in the wind variables, speed and turbulence. This may be the case of optimization problem during OWT operation. Nevertheless, in the future the analysis of the coupled influence of variables needs to be addressed in order to guarantee full robustness of the results.

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