Surrogate infill criteria for operational fatigue reliability analysis

R. Teixeira, A. O'Connor, M. Nogal
Department of Civil, Structural and Environmental Engineering
Trinity College Dublin, Ireland.

ABSTRACT: Analysis of Offshore Wind Turbine (OWT) fatigue damage is an intense, resource demanding task. While the current methodologies to design OWT to fatigue are quite limited in the way and amount of uncertainty they can account for, they still represent a relevant share of the total effort needed in the OWT design process. The robustness achieved in the design process is usually limited. To enable OWT to be more robust, an innovative methodology that tackles current limitations using a balanced amount of designing effort was developed. It consists of generating a short-term fatigue damage (D_{SH}) using a Kriging surrogate model that accurately accounts for uncertainty using an adaptive approach.

The current paper discusses the application of a reinterpolation convergence to build a Kriging surrogate model that replicates D_{SH} in OWT tower components. Different variables involved in the convergence are discussed. The discussion extends then to how the design could be improved by using different convergence scenarios for the Kriging surface. Cross-validation is used to train and validate the surrogate surface. The main goal is to give the designer a rationale on the trade-off between computational time and accuracy using the mentioned approach to design robust OWT towers.

Results show that on a design basis two levels of approach may be efficient. In the first, if a very high computational cost is expected, a trade-off between accuracy and computational time must be considered and then, if the intention is to check how robust the current design is, a full convergence of the surface should be pursued.

1 INTRODUCTION

The current trends in the design of complex structures indicate that structural reliability is a topic of growing interest. A shift in the direction of how the current design practices are implemented can be identified with increasing requirements of structural reliability in the design process.

When it comes to fatigue design of OWT the current design practices are limited by the amount of statistical characterization they can account for. Currents practices to design OWT to fatigue are regulated by (IEC 2005, IEC 2009) or (DNV 2014). Calculation of the fatigue life during the design phase involves running multiple simulations, establishing a long-term characterization of loads and then, estimate the expected fatigue life for the component. In the limit case, the full life of the component could be estimated. Nevertheless, frequently fully evaluating the lifetime loads is not feasible, and fatigue life due to loading may be limited in uncertainty quantification.

OWT towers structural fatigue is neither dominated by high load ranges or small load ranges. This fact demands, when developing a probabilistic analysis for an OWT tower, the definition of both, the common occurrence as well as the tail statistical regions. As a result, the probabilistic characterization of an OWT tower requires a significant amount of designing effort which makes a complete comprehensive description practically not feasible.

The presented work builds on the methodology presented in Teixeira, O'Connor, Nogal, Nichols, & Spring (2017) to calculate probabilistically fatigue life of OWT towers. Improvements to the methodology previously introduced are presented in the current work. In particular, the non-deterministic character of the points in the Design of Experiments (DoE) is included and an infill convergence criteria is used and discussed to define the Kriging DoE iterations.

To achieve the presented goal of using a surrogate model that replicates OWT tower damage, Section 2 presents some of the works in the reliability with

Kriging, 3 discusses the methodology, 4 presents the results of the research undertaken and 5 presents the main conclusion of the work underpinned.

2 RELIABILITY ANALYSIS OF OWT TOWERS

There are limited works on reliability design of OWT towers. Moriarty et al. (2004) analysed the extrapolation of loads for extreme occurrences and fatigue loads, concluding that the current design practices for calculation of structural fatigue of the OWT tower component are not adequate due to the fact that, as a steel component, fatigue is not mainly dominated by high load ranges.

Veldkamp (2006) presents one of the most influential works in the design of OWT turbines to structural fatigue. In this work the author develops a comprehensive analysis of the different uncertainties that affect wind turbines. It is interesting to note that, for the tower component, the author refers that 98% of the structural fatigue life in the fore-aft direction occurs during operation of the turbine (at operational wind speeds). Nevertheless, this conclusion was not generalised to OWTs that are affected for additional environmental loads (sea).

Recently, Kriging surrogate models gained particular interest for reliability analysis due to their capability of interpolating functions accounting for the uncertainty in the interpolation process. The usage of Kriging surrogate models for reliability purposes appears in the field of OWT reliability analysis in the works presented by Yang et al. (2015), Morató et al. (2016).

In order to implement these surfaces as models for reliability, a Gaussian behaviour is demanded for the variable to be approximated with the Kriging surrogate model. In this regard, an important consideration for the application of Kriging surrogate models as valid approaches for fatigue design of OWT towers is the one given in Wirsching and Chen (1988) which states that the fatigue damage of OWT towers usually follows a normal or log-normal distribution.

3 NOISY KRIGING SURROGATE MODELS

Kriging surrogate models are interpolation models that consider Gaussian uncertainty in the predictions of the model. The main idea behind the Kriging surrogate model is to approximate a true state function $g(x)$ in a d dimension and with $x \in \mathbb{R}^d$ with an approximate mathematical model $G(x)$ that predicts $G(x)$ with Gaussian uncertainty in the points where no *a priori* information about x exists.

Assuming that $g(x)$ can be defined for $\forall x$ the process of establishing $G(x)$ demands a sample of k support points to be defined. This sample is usually designated as Design of Experiments (DoE); $DoE = [\boldsymbol{X}, \boldsymbol{Y} == g(\boldsymbol{X})]$ being $\boldsymbol{X} = [x_1, x_2, \ldots x_k]$ a vector

of realisations of x and y the respective true evaluations of $g(x)$ at $\boldsymbol{X}$,

Using a Kriging surrogate model the true response function $g(x)$ can then be approximated as a conditional function of the observations $\boldsymbol{X}$:

$$G(x|Y = g(\boldsymbol{X})) = G(x) = f(\beta; x) + Z(x) \qquad (1)$$

with,

$$f(\beta; x) = \beta_1 f_1(x) + \ldots + \beta_p f_p(x) \qquad (2)$$

where $f(\beta; x)$ is a deterministic function determined by a regression model defined by p ($p \in \mathbb{N} - 0$) basis trend functions $\boldsymbol{f}(x) = [f_1, \ldots, f_p]$ and p regression coefficients β; this term will define the order of the deterministic approximation and as such can have a vectorial or non-vectorial form. $Z(x)$ is a Gaussian stochastic process with zero mean and covariance between two points in the space given by:

$$\mathbf{C}(x_i, x_j) = \sigma^2 R(x_i, x_j; \theta), \qquad (3)$$

$with\ i,\ j = 1, 2, 3, ..., k$

here, $\mathbf{C}$ is the covariance matrix that defines the correlations between generic points in x; σ^2 is the constant process variance and $R(x_i, x_j; \theta)$ is a correlation function. Different $R(x_i, x_j; \theta)$ can be applied in the context of reliability analysis. Some of the main are presented in Roustant et al. (2012). For reliability applications it is common to find $R(x_i, x_j; \theta)$ in its *separable* form. In the *separable* form $R(x_i, x_j; \theta)$ depends on h, the distance between the two generic x points being computed with $R(x_i, x_j; \theta)$, Equation 4. Alternative correlation forms can be also implemented as described in Rasmussen (2004).

$$R(x_i, x_j; \theta) = \prod_{i=1}^{d} R(h_i; \theta_i),\ \theta \in \mathbb{R}^d \qquad (4)$$

As stated this correlation function depends on $h = [h_1, \ldots,\ h_d]$, an incremental difference between $x - x_i$, and depends on theta θ parameter. θ is to be fitted in the implementation using an optimization process. To note that θ has a vectorial form if $d > 1$.

The Maximum Likelihood (ML) method is commonly applied for finding θ. The idea behind the ML is to search for a set of parameters that maximize the likelihood of the $\boldsymbol{Y}$ observations.

For a given $\boldsymbol{Y}$, a new prediction can be obtained through a generalised least squares formulation, where two estimators, β and σ^2 depend on the third one, the θ hyperparameters.

With the knowledge of all the estimators of a Kriging model conditional on the y sample, a prediction $g(u)$ in a generic point u in the space is given by the built model expected value μ_G and variance σ_G^2:

$$\mu_G(u) = \boldsymbol{f}(u)^T \beta + \boldsymbol{c}(u)^T \mathbf{C}^{-1}(\boldsymbol{Y} - \mathbf{F}\beta) \qquad (5)$$

$$\sigma_G^2(u) = \sigma^2[1 + D^T(u)(\mathbf{F}^T\mathbf{C}^{-1}\mathbf{F})^{-1}D(u)$$
$$- \boldsymbol{c}^T(u)\mathbf{C}^{-1}\boldsymbol{c}(u)] \quad (6)$$

with,

$$D(u) = \mathbf{F}^T\mathbf{C}^{-1}\boldsymbol{c}(u) - \boldsymbol{f}(u); \quad (7)$$

where $\boldsymbol{c}(u) = c(u, x_i),\ i = 1, 2, \ldots, k$ is the correlation vector that relates the realisation to be evaluated with the known points and $\boldsymbol{f}(u)$ is the vector of trend functions evaluated at u.

3.1 Noisy Design of Experiments

In the particular case where the true realisations $\boldsymbol{Y}$ are not deterministic, some measure of uncertainty needs to be considered when building the DoE.

To account for uncertainty in $\boldsymbol{Y}$ the Kriging model needs can be modified to consider some measure of statistical characterization of $\boldsymbol{Y}$. this is achieved by introducing an additional variable in $\mathbf{C}$.

$$\boldsymbol{Y} = \boldsymbol{Y_E} + \zeta \quad (8)$$

with $\boldsymbol{Y_E}$ being the expected value of $\boldsymbol{y}$ and ζ is a Gaussian process with mean 0 and variance equal to $\sigma_{\boldsymbol{Y}}^2$, the variance of each true realisation of $\boldsymbol{Y}$. $\mathbf{C}$ becomes then

$$\mathbf{C}(x_i, x_j) = \sigma^2 R(x_i, x_j; \theta) + \boldsymbol{I}\sigma_{\boldsymbol{Y}}^2 \quad (9)$$

where $\boldsymbol{I}$ refers to the identity matrix.

3.2 Methodology

The methodology used to design OWT to fatigue was first implemented in Teixeira, O'Connor, Nogal, Nichols, & Spring (2017). In this work a Kriging surrogate without noise in the DoE was implemented to replace the expensive computational model of the OWT. A damage indicator, D_{SH} was defined in order to characterize the output of the computationally expensive code.

In the present work a similar methodology is used, including the same damage indicator D_{SH} defined as the short-term damage calculated using

$$D_{SH} = \sum_{L_i=1}^{L_n} \frac{n_{L_i}}{N_{L_i}} \quad (10)$$

where the n_{L_i} is the number of load cycles recorded for a load L_i in a predefined t period of operation of the OWT, and N_{L_i} is the allowed number of cycles accordingly to the specified material used in the component being analysed. The allowed number of cycles is given by a specified S-N curve. D_{SH} is highly dependent on the environmental conditions and needs to be calculated for multiple operational conditions. For

the current implementation a $t = 600s$ is applied to define D_{SH}. The value of $600s$ is used as staple in the OWT industry. It induces limited low frequency loading damage loss (Veldkamp 2006).

A simplified diagram of the proposed methodology is presented in Figure 1.
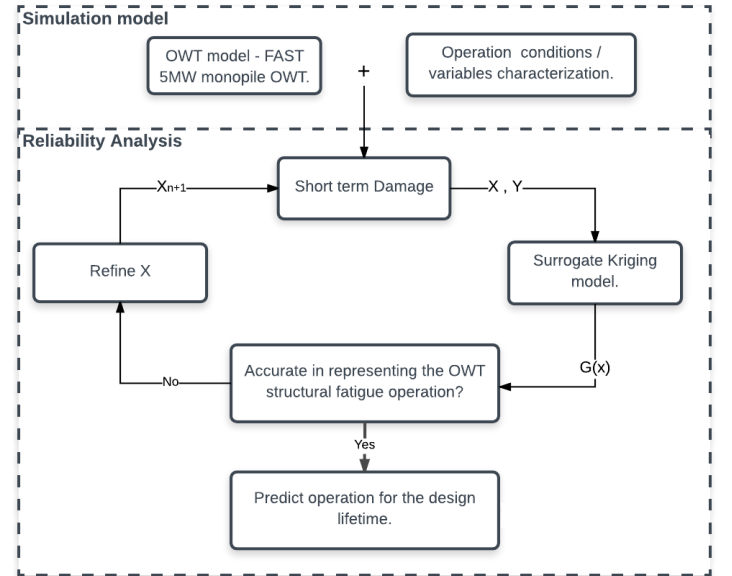

Figure 1: Diagram of the methodology based on Kriging surrogate models applied to assess OWT tower fatigue reliability.

Jonkman et al. (2009) is used in the analysis due to its baseline character. $600s$ simulations of OWT operation cost approximately $1200s$ to be completed when using the highest 4th generation i7 processor rated CPU. Parallel processing may be used to run multiple simulations. Nevertheless, it can be perceived the amount of computational time demanded to design OWTs to fatigue, where thousands of simulations are demanded to produce accurate results. As material the, S235 steel is used to compute the damage rates.

A Kriging surrogate model, when approaching well the simulation model of the OWT and predicting accurately the amount of short-term fatigue that is generated in the tower, contributes significantly to reduce computational time.

3.3 Infill criteria

When the DoE is of expensive evaluation as in the present case, new iterations of the DoE need to be carefully chosen. It is not feasible to expand the vector X without criteria if efficiency is pursued.

Picheny et al. (2013) analysed different design criteria used to establish $G(x)$ in the case where Y is not deterministic. Different state-of-the-art functions in computational analysis were studied to produce comparative results.

In the present work, and according to the specificity presented by the problem being tackled, an infill design criteria is used to select new points in the DoE. When using the Kriging to approximate a probabilistic field, areas of high uncertainty are to be avoided.

It is known that areas of high uncertainty are more likely to occur when the density of the DoE is smaller. It is important to highlight that the characteristics of the probabilistic problem of D_{SH}, are expected to be continuous and have small gradients [1], thus such behaviour is assumed in the current analysis.

Teixeira, O'Connor, Nogal, Krishnan, & Nichols (2017) investigated the sensitivity of five variables in the DoE (wind velocity, significant wave height, peak period, turbulence intensity and wind direction) of an OWT tower in operation conditions, concluding that both wind speed (U) and turbulence intensity (I) are expected to show the most significant influence in the fatigue life design. The sea state was set to have constant conditions for all the combinations of U and I. Figure 2 presents some simulations that consider the mean wind speed U and the turbulence intensity I in the DoE. It is possible to infer that there are no significant
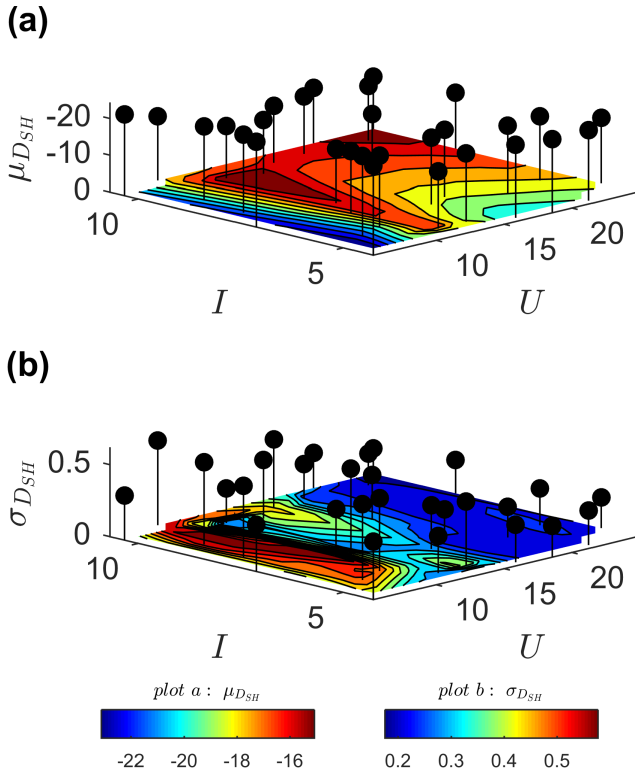
(a)

(b)

Figure 2: Map of the first two statistical moments of the D_{SH} space calculated based on 50 samples. Built based on 29 points (black dots).

nificant changes in the surface, and the gradient of change within the DoE is "coherent" (because fatigue is a cumulative process no significant local changes in the surface or discontinuities are expected). There is a peak in the $\mu_{D_{SH}}$ near the turbine rated power (11.4m/s). Cheng et al. (2003) identified that for a pitch control turbine the most significant loading occurred slightly above the rated power. Consequently this increase in the local fatigue damage rate may

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[1]By continuous and of small gradients, it is meant that in the DoE space adjacent points are expected to have similar statistical characteristics.

be connected to this fact. Despite small load amplitudes being important contributors of damage for steel structures, high load amplitudes are still the highest contributors to the reduction of the fatigue life. In Figure 3.3 it can be seen that a significant contribution of fatigue damage occurs in between 11-13m/s U, even for low values of I. In regard of changes in turbulence, as I increases, D_{SH} increases in almost all the U above rated power.

A reinterpolation, introduced in Forrester et al. (2006), is applied as infill criteria to select new points in the DoE. This infill criteria was designed to specifically deal with noisy Kriging optimization. The reinterpolation methodology consists in using two Kriging models in parallel, one main model and one auxiliary model. The main model is the model to be improved, or the target model, and the auxiliary model is used to select new points in the DoE. While the target model is a noisy Kriging surrogate, the auxiliary Kriging model should be non-noisy.

The support Kriging model is designed from the target noisy Kriging model. By using a non-noisy Kriging it is possible to use the Expected Improvement (EI) criteria to select the $n+1$ point to be added to the noisy Kriging model.

The EI algorithm is one of the most widely used methodologies for improving the accuracy of Kriging interpolation models and was first introduced in Jones et al. (1998). The selection of the $n+1$ point with the EI algorithm is based on solving the following function.

$$EI_n(x) = \mathbf{E}\left[\min(Y_n) - G(x)|G(X) = Y_n\right] \quad (11)$$

which can be re-written as,

$$EI_n(x) = (\min(\mathbf{Y_n}) - \mu_G(x))\Phi\left(\frac{\min(Y_n) - \mu_G(x)}{\sigma_G(x)}\right)$$

$$+ \sigma_G(x)\phi\left(\frac{\min(Y_n) - \mu_G(x)}{\sigma_G(x)}\right) \quad (12)$$

The EI is the expected ($\mathbf{E}$) difference between the minimum currently best known prediction $\mathbf{Y_n}$ at iteration n and the conditional $G(x)$ built on the assumption that $G(X) = Y_n$. n denotes the iteration index. Φ and ϕ are the Normal cumulative and probability density functions (CDF and PDF respectively).

The stopping criteria for the reinterpolation loop is the EI. Convergence is considered to be attained when the EI is very close to zero. A common alternative is to define a stopping criteria in terms of the computational budget available.

4 RELIABILITY OF OWT TOWERS USING ADAPTIVE NOISY KRIGING

A correlated Latin Hypercube Space (LHS) sample with 15 points was used to start building the surrogate

model. The 4 extreme combinations possible in the DoE are added before any infill criteria was implemented. Only combinations of operational environmental states were considered in the analysis. Figure 3 presents the position of the initial points in the DoE along with four alternate combinations of maxima.

The addition of the maxima was motivated by the need to improve the accuracy in approximating the true behaviour $g(x)$ of the OWT tower fatigue D_{SH}. The EI algorithm definition using the function minima was unlikely to define the maxima points as $n+1$ iteration for the maxima U of operation ($25m/s$). Furthermore, when fitting the noisy Kriging surface these "corner" points showed very inaccurate standard deviation prediction and thus their definition before any further iteration in the infill space was required. To validate the obtained results for $G(x)$ a
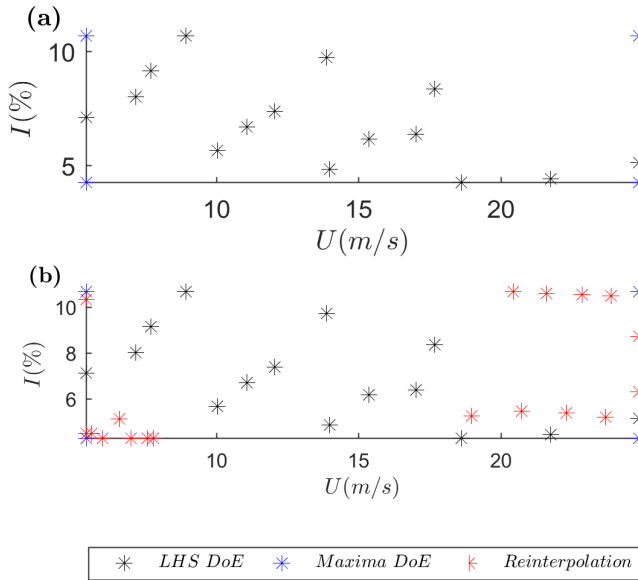
Figure 3: Reinterpolation evolution of the DoE. (a) Initial DoE sample. (b) DoE after reinterpolation

cross-validation was used for both, the mean and the standard deviation. The validation points were picked using Monte Carlo sampling from a set of possible combinations covering the space U and I (with 100 partitions for each variable). Figure 4 and Table 1 present and discuss the results of applying a cross-validation.

A challenge of using Kriging as surrogate models in the context described is related to the convergence of the model parameters used, constant process variance, θ hyperparameters and polynomial function. These parameters have a major role in the accuracy of the operational fatigue surface, and consequently in the estimated level of lifetime fatigue design. Commonly these parameters are selected using an optimization methodology for θ. Figure 4 presents results for the error depending on parametric changes of constant process variance and hyper-parameters. Five representative examples were used for reference.
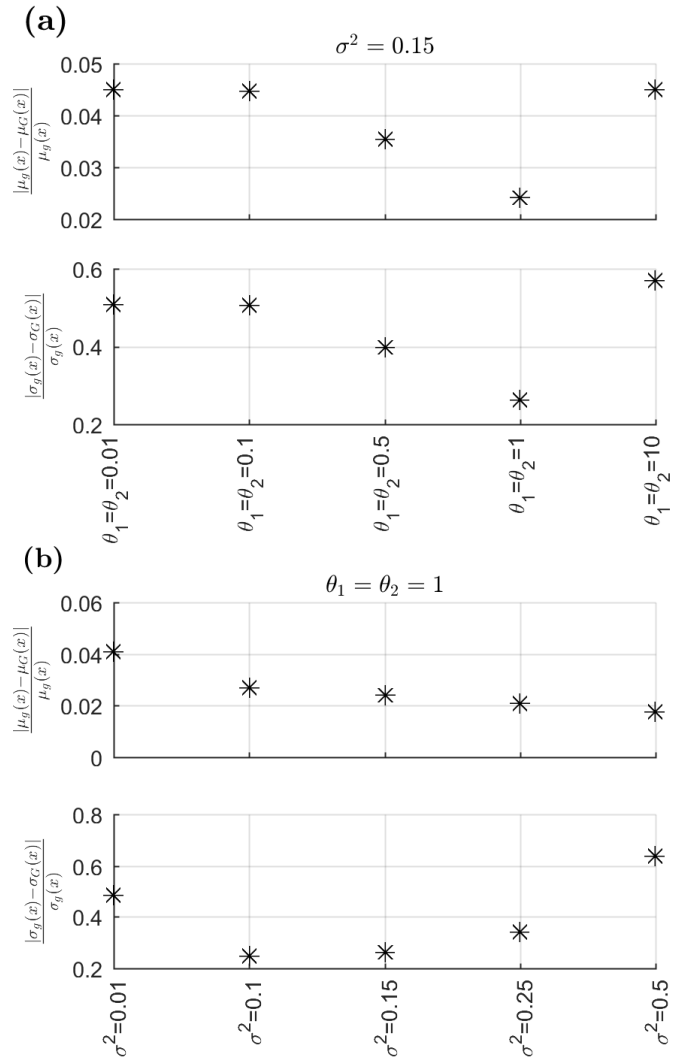
Figure 4: Influence of the constant process variance and its length scale θ parameters. A 4th polynomial was used to compute the results. (a) - Changes in accuracy using constant process variance. (b) - changes in accuracy using constant values for the θ parameters.

To highlight that the space to be covered during optimization is incomparably higher. The convergence of the predicted standard deviation is more difficult that the mean for all the cases. For sake of computational feasibility, a deviation in the standard deviation is assumed with the consideration that it, being a 2nd order moment, will have less impact in the computation of results than deviation of the mean.

In figure 4 a region where the error decreases can be identified for both cases. This local analysis can be of interest to help defining the region of interest for the search function. Additionally, the model parameters can be used to tune $G(x)$ in case the validation of the initial optimization is not satisfactory.

Different search functions are available to calculate the optimization parameters. To define the D_{SH} surface the optimization algorithm implemented in Roustant et al. (2012) is used.

Additionally to the surrogate convergence, a relevant step in a probabilistic analysis of $D_S H$ is related to the convergence of the statistical distribution mo-

ments before converging the surrogate model. This problem of converging the statistical distribution is an unavoidable problem that may significantly increase the cost of a probabilistic analysis. Some degree of uncertainty should be assumed in order for the analysis to have an efficient (computational) cost-accuracy. As example, if a reliability based design optimization (RBDO) is pursued, less points should be used to converge the statistical distribution; whereas if the goal is to have the most accurate results possible, relevant efforts should be allocated to the convergence of the probability density function (PDF). Greenwood & Sandomire (1950) analysed the number of samples required to characterize a statistical distribution. Using 50 samples, while the mean converged very fast, the same did not happen with the standard deviation. With a sample size of 50 points, 85% of the cases the estimation of the standard deviation is within 15% of its real value.

For the reinterpolation a 4th polynomial function was used to create the Kriging surface in each step of iterations. The convergence domain for θ was left relatively wide, varying for both hyper-parameters between 0.01 and 100. When setting the surrogate for prediction a smaller search domain presented more accurate results. A Gaussian correlation function was applied to define the correlation between points.

Table 1: List of points generated for cross-validation and respective results for the last solution of θ used to predict D_{SH}. A 4rd degree polynomial function was applied to generate the Kriging surface.

$U(m/s)$	$I(\%)$	$\frac{|\mu_{g(x)} - \mu_{G(x)}|}{\mu_{g(x)}}$	$\frac{|\sigma_{g(x)} - \sigma_{G(x)}|}{\sigma_{g(x)}}$
7.42	10.73	0.9	16.4
9.43	8.09	0.9	16.1
9.91	7.20	2.0	13.2
10.74	9.19	0.5	23.7
13.24	5.16	2.0	27.9
16.11	6.38	2.7	13
17.12	4.51	1.0	5.8
18.31	5.98	0.8	1.3
19.82	6.84	0.4	11.9
22.41	4.80	0.1	8.5

As mentioned, the cross-set of data can be used to train or tune the surrogate model in order to obtain the most accurate results. This may be achieved by training the model's θ hyper-parameters in order to minimize the error in cross-validation. In the current implementation the training process involved search for a local minimum of the error in σ. The cross-validation error in μ was below 5% $\forall \theta$.

In the presented study no maximum acceptable error in the standard deviation was considered. I is noted that 23.7% and 27.9% can be considered significant in multiple applications, which could demand refining the domain where there is a significant relative error. It is interesting to notice that for the second case this error occurs for values of $x = [U, I]$ space where a there is a very close point in the X used to create the Kriging model. The noisy Kriging prediction is more accurate when more information about the physical space is available, meaning that errors in predictions of points that are close to any $\boldsymbol{X}$ may be related to inaccuracy in the definition of the statistical distribution in that respective point. Future implementations should address the maximum acceptable error in a case-specific scenario, which means that the maximum acceptable error should depend on the end use or user.

Applications of a similar methodology may also consider some measure of statistical distance to evaluate the fitting. A statistical distance would allow a more sensitive measure on the accuracy of the Kriging prediction relative to a known distribution, and therefore, the probability of sampling the known distribution using the Kriging surrogate.

One of the particularities found in the reinterpolation process is that, even considering that using a reinterpolation model avoids the definition of a $n + 1$ point that already exists in X, in some circumstances the $n + 1$ calculated point will be very close to other point in X. This may be particularly concerning if computational time has significant importance. Therefore, in such cases, efforts should be maximized to cover well the domain of x.

In order to verify the results 1000 operation points where taken from a sample of real data taken from Teixeira et al. (2018). The simulation results are compared with the prediction in Figure 5. The predictions approximate well the true $g(x)$ function and reproduce the cumulative character of the D_{SH}.

Figure 5(a) presents the simulated points and Figure 5(c) presents the relative error for two samples taken from $G(x)$. This relative error would never be expected to be 0, but instead it would be expected to converge as the cumulative damage increases. Figure 5(b) compares the cumulated damage and its statistical variation. The real simulations are very close to the mean value. To calculate the statistical intervals as new points are added to the cumulative damage a random sample needs to be generated, one from $i \sum D_{SH}$ and another from the $i + 1$ point to be added.

The computational gains from using a Kriging surrogate model are substantial. There is computational cost in setting the Kriging surrogate model. In this example 1850 simulations were used to set the Kriging model before the reinterpolation was stopped. After setting the Kriging surrogate model, multiple simulations can be run at virtual no cost.

Simulating 20 years of operation demands more than 1 million samples of 10 minutes operation which are almost impossible to obtain if the OWT simulation model is to be ran every single time to extract the loads or a value of D_{SH}. Furthermore, to define the long term statistical behaviour multiple 20 years
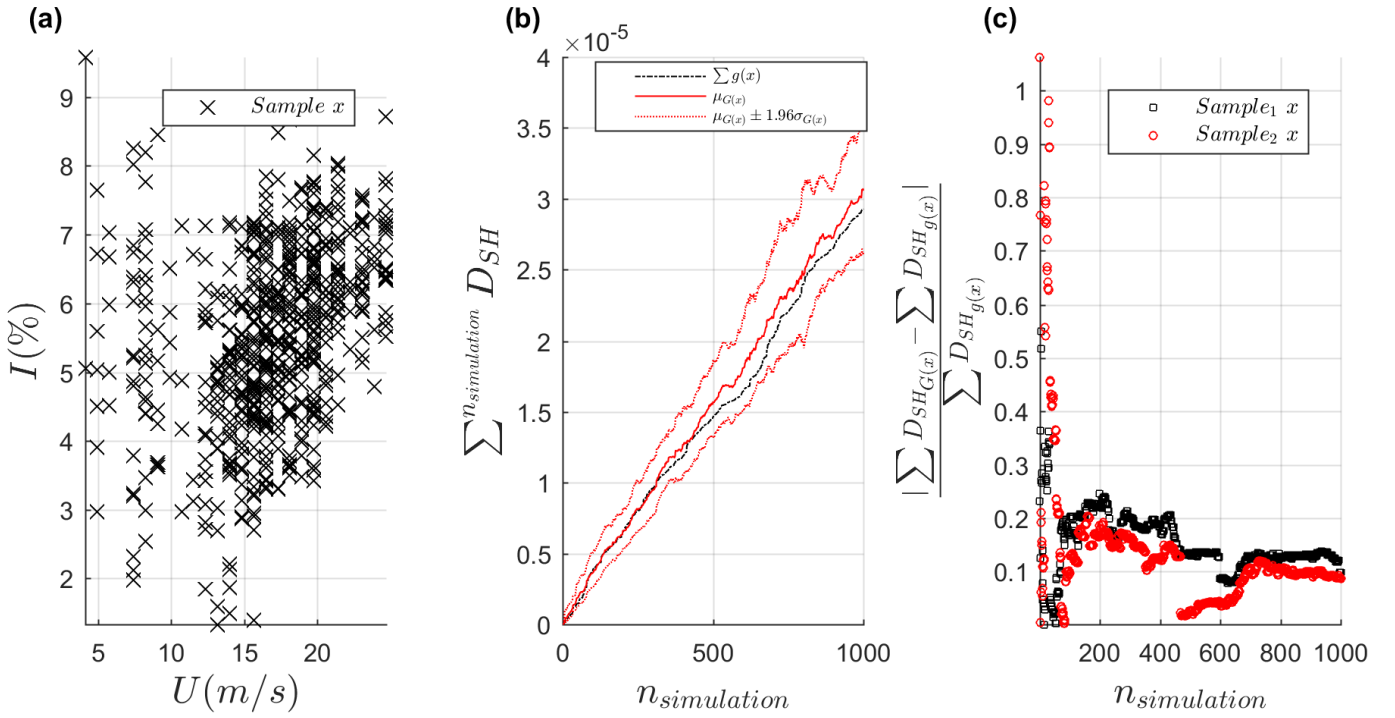
Figure 5: Convergence of the cumulative tower D_{SH} for 1000 points of operation between the Kriging prediction and a real sample extracted from NREL's 5MW turbine. (a) Simulated sample (b) Cumulated sample mean and statitical deviation. (c) Deviation of two extracted random samples at the (a) points and the simulated sample of 1000 points.

of operation need to be assessed. The number of simulations undertaken to achieve the Kriging surrogate can then be seen as a very low relative computational cost considering the gains it unlocks in terms of probabilistic analysis.

In order to access the reliability of the system a specified failure mode needs to be defined. As example (DNV 2014) defines 0.5 as the limit for fatigue cumulated damage. A lower limit can be considered with the level of reliability depending on the limit defined. Fatigue design using a linear damage sum tends to be conservative or non-conservative, and because of that the limit state should defined to accommodate this behaviour.

Nevertheless, it was identified that the mean of the cumulated damage increases significantly faster than the standard deviation and as a result the statistical behaviour of the cumulated damage remains relevant while the cumulated sample is relatively low, e.g. 1000 points. This implies that fatigue of the OWT can be faced as a problem of uncertainty in this convergence. As a result, from the loading variability, fatigue reliability is a problem of mean and how accurate is the assessed mean. This fact is also of interest when predicting fatigue design damage with Kriging models and can contribute to significant effort reduction when using these models as surrogate of D_{SH}. It would be of interest in the future to apply this methodology using probabilistic S-N curves.

5 CONCLUSIONS

An approach to assess fatigue reliability was discussed in the current paper. It involves using a oper-

ation fatigue surface to estimate the long-term probability of failure of an OWT tower to fatigue damage in the design phase. This fatigue surface is defined using a Kriging surrogate model, to be improved with a reinterpolation methodology. The main goal is to replicate the very expensive computational model using this operation fatigue probabilistic surface, taking advantage of the fatigue repetitive physical behaviour.

It is highlighted that the motivation of such a design scheme emerged from the difficulty in assessing the long-term fatigue life statistical behaviour. As a long-term cumulative process, with very significant computational burden, the current design methods do not require for fatigue to be translated into a target level of reliability, or probability of failure.

The results showed that accurate prediction of fatigue damage rates during operation can be achieved with relatively low computational cost. The true 20 years of operation of an OWT would represent more than 1 million 600-seconds simulations, which have an unbearable cost and therefore are not feasible. If the true reliability for 20 years is to be calculated, the number of simulations increase even further. In the current example the probabilistic behaviour of NREL's monopile OWT tower to structural fatigue was characterized using 1850 simulations. These are then used to predict any further number of operation contribution to to decrease the design fatigue life. Hence, the benefit of using the surrogate model is very relevant.

Nevertheless, some improvements are still required to achieve robust surrogate modelling. It may be of interest to introduce some criteria for the reinterpolation in order to avoid spending computational effort in

points that do not contribute significantly to improve the accuracy of the probabilistic field. Additionally, as for the current example the computational effort was relatively low and it may be interesting to add more points to the surrogate model as well to validate it. It was seen that some of the areas of the surrogate model after reinterpolation remained with a high relative error, which may contribute for an under or overestimation of the operational fatigue damage rates.

To conclude, the interest of the presented methodology fits not only optimization procedures, but also the assessment of fatigue life in the design phase. The main change that the designer should be aware in both procedures is the level of uncertainty that should be accepted in the fitting. For the first, some error should be accepted in the PDF convergence, while for the second, assuming it as a final design iteration, more computational effort should be allocated to generate the Kriging surface.

ACKNOWLEDGEMENTS

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