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Meta-models for fatigue damage estimation of offshore wind turbines jacket substructures

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Abstract

One of the main structural components of offshore wind turbines is the substructure which bridges the gap between seabed and tower foot. One possible concept employed in intermediate water depths for turbines with high-rated power is the jacket. This structure is excited by several environmental impacts like wind and wave loads or centrifugal loads from the rotor motion. In order to reach competitive costs of energy, it is crucial to minimize the lifetime capital expenses by means of robust and reliability-based design. However, a simulation-based optimization approach on the full scale model requires high numerical capacity. In this work, the problem of numerically expensive fatigue life evaluation is addressed by the utilization of a meta-model approach. The performance of two meta-models solutions, namely Kriging and Interval Predictor Model, is compared. In particular, the different behavior of the probabilistic confidence intervals of the Kriging regression and the interval bounds of the IPM is discussed.

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Keywords: offshore wind turbine; fatigue; extreme loads; robust optimization; reliability; imprecise probability

1. Introduction

According to the state of the art, the structural design of substructures for offshore wind energy converters involves commonly thousands of time-domain simulations in order to cover all occurring combinations of environmental parameters. On the way to a robust design optimization of these structures, methods for computationally efficient fatigue damage evaluation are highly desirable. In a robust design optimization, the model needs to be evaluated repeatedly. As an example, for each design and the corresponding set of optimization parameters, a full uncertainty propagation must be carried out. It is necessary to propagate the uncertainties found in stochastic and imprecise parameters. When the outputs are computed from numerically demanding computer models, the total number of required simulations

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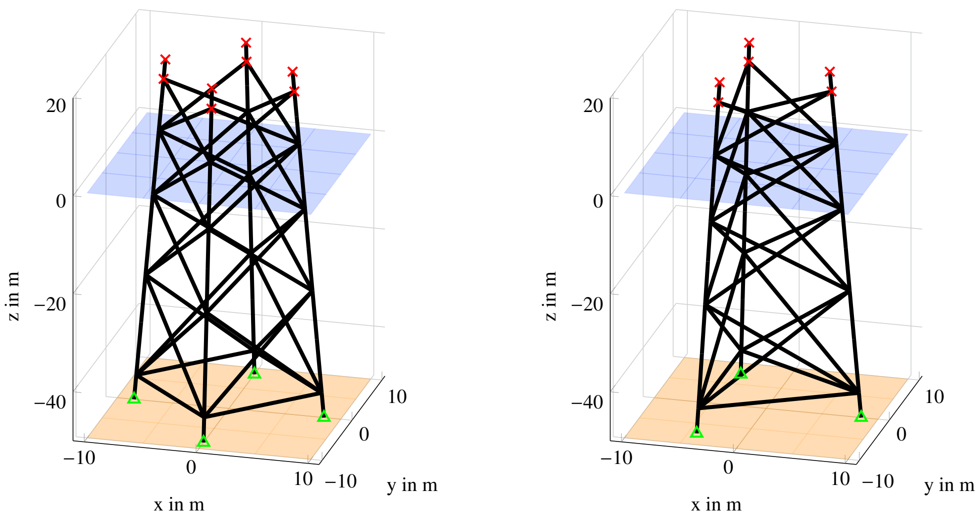

(a) Four-legged jacket.

(b) Three-legged jacket.

Fig. 1. Topology of test jackets used for reduction study. × indicates interface and △ base joints. Damage assessment is performed at all X- and K-joints.

makes the computation infeasible. In this work, the problem of numerical demanding fatigue damage evaluation is addressed by the utilization of two meta-models.

To avoid the inclusion of subjective and often unjustified hypotheses, the imprecision and vagueness of the data can be treated by using concepts of imprecise probabilities. Imprecise probability combines probabilistic and set theoretical components in a unified theory allowing the identification of bounds on probabilities for the events of interest [1].

2. Simulation and Design Load Cases

In order to utilize meta-modelling techniques for lifetime estimation of jacket substructures, two test structures for the NREL 5 MW reference turbine [2] are examined in the following. In general, the rough topology and geometry of the OC4 jacket [3] is the basis for both structures, depicted as four-legged design in Fig. 1(a) and three-legged design in Fig. 1(b), to cover all relevant structure types present to date. As the OC4 jacket has some drawbacks with respect to fatigue damage calculation, the jacket model already proposed in [4] is used. The procedure for fatigue damage calculation is as follows: Firstly, a transient simulation of the entire wind turbine is conducted in time domain for each design load case. The aero-servo-hydro-elastic simulation framework FAST is used for this purpose. Then, the stress signals of critical fatigue hot spots (tube-to-tube connections in K- and X-joints) are gained by stress concentration factors according to DNV GL [5]. Finally, the resulting hot spot stresses are evaluated by an S-N-curve approach and linear damage accumulation to obtain structural damages for all joints. It is referred to [6] for further details concerning this procedure or the parameters and boundaries of the problem.

The present study is performed on the research platform FINO3 located 80 km west of the island Sylt in the German North Sea. To create conditional probability distributions, dependencies among the environmental conditions have to be defined. These are shown in Table 1. To incorporate dependencies in the statistical distributions, the data of dependent parameters is separated in bins. For example, the wave peak period is fitted in several bins of significant wave height in 0.5 m steps. Kolmogorov-Smirnov tests (KS-tests), chi-squared tests (χ^2-tests), and visual inspections are used to identify the best fitting distribution for all regarded parameters. Moreover, it was decided to match all bins of one parameter with the same distribution type, because this is more reasonable in a physical way. If several distributions fit the data equally well, data from the measurement platform FINO1 is used as a comparison to find the most suitable solution.

Table 1. Statistical distributions for different dependent parameters.

Parameter	Statistical distribution	Dependencies
Wind speed	Weibull	Wind speed
Wind direction	Nonparametric	Wind speed
Significant wave height	Gumbel	Wave height
Wave peak period	Bi-modal log-normal	Significant wave height
Wave direction	Nonparametric	Wind direction
Yaw error	Normal	-

The statistical distributions are input for a load set that comprises 2048 design load cases, resulting in 4096 simulations (for two test structures) conducted for this study. A maximum fatigue damage is associated with each load case which is used as initial point for the following study.

3. Meta-models for robust analysis and uncertainty quantification

Meta-models are a mathematical representation of a complex relation, where the outputs are predicted using basic algebraic operations and the model parameters are tuned by existing input/output pairs. However, it is necessary to associate a measure of uncertainty with each prediction, because a meta-model will inevitably introduce an approximation error. This is especially important during robust optimization analysis. Not all meta-models can directly provide an error estimation of the predicted output, e.g., they will only give a deterministic prediction. In this case, multiple meta-models must be trained with a bootstrap procedure in order to estimate the prediction error.

Other meta-models will instead provide a prediction error together with the output. Thus, such meta-models are particularly useful in an uncertainty quantification and robust design framework. In this work, two meta-models particularly suitable for their bounded prediction will be compared, namely the Gaussian process meta-model, also known as Kriging, and the Interval Predictor Model.

3.1. Kriging

The Kriging meta-model predictor is composed by the sum of 2 terms:

$$\hat{y}(x) = f(\beta, x) + \zeta(x; \theta), \tag{1}$$

where the term f is a regression model and ζ represents a stochastic process. Usually, the regression model is a polynomial and the stochastic process is a stationary homogeneous Gaussian process. Thus, a Kriging model is uniquely identified by the degree of the polynomial regression and the covariance function $R(\theta, x_i, x_j)$. Covariance models (also known as kernels) that are usually employed are exponential, gaussian, linear, etc. [3].

The supervised learning procedure of the Kriging model is the optimization problem

$$\min_{\theta} \left\{ \psi(\theta; x_{i,i=1,\cdots,N}) \equiv |R|^{\frac{1}{N}} \cdot \sigma^2 \right\}, \tag{2}$$

where $|R|$ is the determinant of the covariance matrix of the training points, and N is the number of training pairs. The Kriging model computes also the variance of the prediction, thus Kriging associates a Gaussian random variable with each prediction. Therefore its possible to use a probabilistic approach and associate confidence intervals to the prediction (e.g., $\pm 2\sigma$). For this reason, probabilistic-based robust optimization frameworks can clearly exploit a Kriging prediction, e.g., in the reliability-based constraints of an optimization.

Finally, it can be demonstrated that the Kriging predictor is exact for the training samples, and the variance will increase when far from calibration points.

3.2. Interval Predictor Model

The Interval Predictor is a meta-model that returns an interval as the dependent quantity. By contrast to standard models, which yield a single predicted output at each value of the models inputs, IPM yields an interval into which the unobserved output is predicted to fall. Thus, a set of output values is assigned to each input x such that

$$I_y(x,P) = \left[\underline{y}(x,p_{max},p_{min}), \overline{y}(x,p_{max},p_{min})\right] = \left\{y = \phi(x)^T \cdot p, p_{min} \le p \le p_{max}\right\}, \tag{3}$$

where ϕ is any arbitrary basis function, p are the model parameters, p_{min} and p_{max} are called *defining vertices* of the hyper-rectangular parameter space P. $\underline{y}$ and $\overline{y}$ are defined as

$$\begin{aligned} \underline{y}(x,p_{max},p_{min}) &= \phi(x)^T \cdot m_p - \frac{1}{2}\left|\phi(x)^T\right| \cdot \delta_p \\ \overline{y}(x,p_{max},p_{min}) &= \phi(x)^T \cdot m_p + \frac{1}{2}\left|\phi(x)^T\right| \cdot \delta_p \end{aligned} \tag{4}$$

with $m_p = (p_{min} + p_{max})/2$ and $\delta_p = (p_{min} - p_{max})$. Two particular basis types, namely polynomial and radial, are usually considered.

The IPM calibration consists of providing input/output pairs. Then, p_{min} and p_{max} are determined with an optimization procedure such that the interval built around the average prediction of minimum width includes all the outputs.

4. Numerical Example

Before training the meta-models, a global sensitivity analysis has to be performed with the real data to identify the input parameters providing the largest contribution in the variance of the desired output. This is an important step, since it allows to reduce the input parameters taken into account in the meta-models, thus simplifying the models by ignoring the least important inputs. OpenCossan [7,8], a MATLAB toolbox for uncertainty quantification and reliability analysis jointly developed by the Institute for Risk and Uncertainty[1] and the Institute for Risk and Reliability[2], was employed for both the global sensitivity analysis and the meta-model calibration and prediction presented here.

4.1. Global Sensitivity Analysis

The focus of this work lies in the comparison of the prediction of the fatigue damage given by the two meta-models. To capture a better understanding of the load case parameters effects on the damage, it has been decided to keep only the most important parameters in the approximate function and exclude the less important. As a matter of fact, the less important parameters introduce an increase in the complexity of the problem without adding to the overall knowledge. Therefore first-order Sobol' indices [9] of the six load case parameters with respect to the damage are calculated. Fig. 2 shows the results for the three-legged jacket (Fig. 2 (a)) and four-legged jacket (Fig. 2 (b)). The indices were computed using the Random Balance Design algorithm [10]. The sensitivity shows very similar results for both structures allowing to unequivocally identify the unimportant inputs. Thus, the wind and wave directions, as well as the yaw error, can be safely ignored from the meta-model I/O calibration data.

Additionally, it can be seen that the wave height shows the highest first order effect for both jackets, and a clear effect is also caused by the wind speed, the wind turbulence and the wave period, though of different magnitude and relative importance concerning the two jackets. Therefore, only these four parameter have been chosen as input parameters for both meta-models.

The meta models are built based on measurement data for 2048 load cases for each jacket, where 75 % of the data are used for calibration and 25 % for validation.

4.2. Results of the Kriging Model

The Kriging meta-model class included in OpenCossan is linked to the DACE toolbox [11]. This toolbox provides polynomials regression models of different orders, as well as multiple correlation (e.g., exponential, gaussian, linear).

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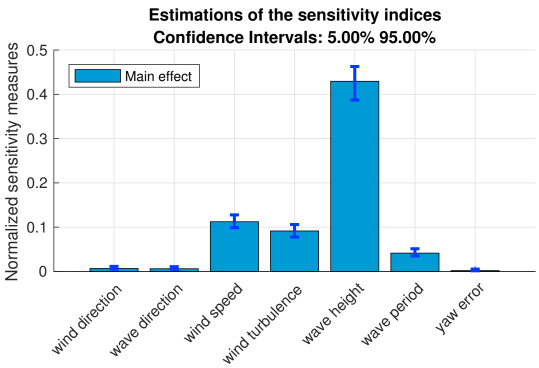

Fig. 2. Main effect of the load case parameters on the damage of the (a) Three-legged jacket & (b) Four-legged jacket.

In this application, the best predictions, measured by means of the regression error R^2 were obtained by the quadratic regression and an exponential correlation model.

In order to assure that leaving out the unimportant inputs doesn't affect the accuracy of the approximation, a Kriging model with all seven inputs is calibrated at first. The regression error for this meta-model predictions is $R^2 = 0.934$. In a second step, only the four most important inputs are used. Fig. 3 (a) shows the predicted bounds of the Kriging approximation of the maximum damage as a function of the wave height compared to the simulated outputs. The regression error of the validation data is $R^2 = 0.956$; this proves that the four parameter model is not only less complex to build but also more accurate.

The prediction bounds have a good coverage of the real outputs, even though less training points are available for high levels of wave height. This is clearly represented by an increase in the prediction bounds, corresponding to a much wider uncertainty. This increase of uncertainty in the prediction for high wave heights is clearly represented in Fig. 3 (b), where the difference between the upper bound of the prediction and the real output is plotted. Finally, despite the increase in prediction uncertainty, 97% of the real data is correctly included in the 2σ confidence interval.

4.3. Results of the Interval Predictor Model

The Interval Predictor Model was implemented in OpenCossan. Both approaches, the polynomial and radial basis function, are available. However, the best predictions, measured by means of the regression error ($R^2 = 0.972$) were obtained with a power of 4 polynomial basis function.

Fig. 4 shows the predicted bounds of the IPM approximation of the maximum damage as a function of the wave height compared with the simulated outputs and the difference between the upper bound of the prediction and the real output. In contrast to the Kriging meta-model, the IPM shows no increased uncertainty for high wave heights. Instead, the difference between the upper bound and the simulated maximum damage is contained in a small, almost constant interval. Additionally, high wave height is predicted as well as lower wave height using a significantly less samples.

5. Conclusions and further work

This work has shown the feasibility of a meta-model prediction with uncertainty bounds for fatigue damage estimation. Two competitive meta-model solutions were tested. The results show that both meta-models can accurately predict the mean behavior of the maximum fatigue damage of the jackets using only four out of the seven available input parameters.

However, when the prediction bounds are included in the analysis, the Kriging model might lead to an excessive and over-conservative prediction, provided that limited training data is available. This will be especially the case when this approach is expanded to a complete design optimization, since very few load cases will be computed for each test design due to computational constraints.

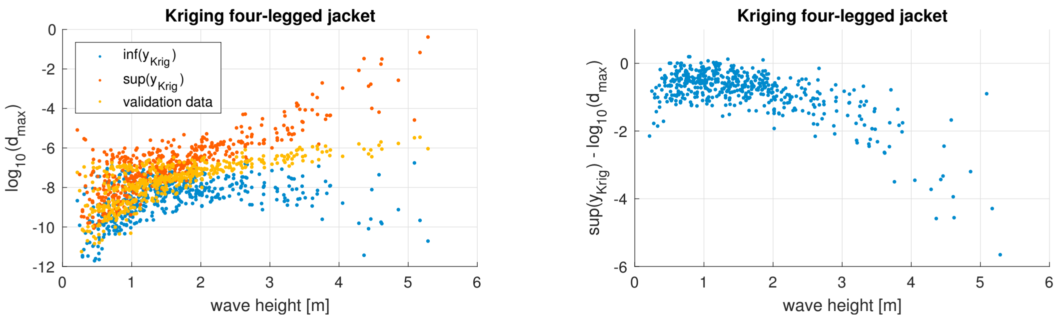

Fig. 3. (a) Prediction of the Kriging model for the validation input data; (b) Distance between the predicted upper bound and the simulated damage.

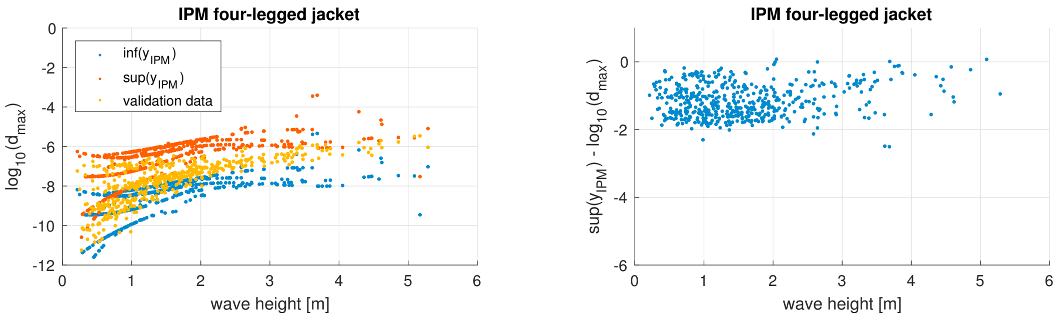

Fig. 4. (a) Prediction of the IPM for the validation input data; (b) Distance between the predicted upper bound and the simulated damage.

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