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Lifetime reassessment of offshore wind turbines considering different operating conditions using Kriging meta-models

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Abstract. To extend the lifetime of an offshore wind turbine, a lifetime reassessment is required to determine the remaining lifetime. In this case, the lifetime is recalculated using the combinations of environmental parameters (wind and wave effects) that actually occurred during the lifetime and which normally differ from the assumed conditions during design. The computational effort of such a lifetime reassessment is significant, as a very large number of aeroelastic simulations has to be carried out. Therefore, according to the state of the art, the number of considered combinations of environmental parameters is reduced similar to the design procedure. In this work, an alternative approach for the lifetime reassessment is investigated in detail. It keeps the full set of combinations of environmental parameters and also considers normal operation as well as idling. The challenge of the high computational effort is resolved by using Kriging meta-models instead of aeroelastic simulations. The meta-model-based approach is compared to two other methods for lifetime reassessment: First, the reference method, i.e., a full lifetime reassessment using aeroelastic simulations where all actually occurred combinations of environmental parameters are considered. And second, the approach according to IEC 61400-3. The results show that it is possible to use meta-models instead of the original simulation model for the lifetime reassessment. The computing time can be significantly reduced compared to the other two methods, while maintaining a high approximation quality in the prediction of the lifetime fatigue loads.

1 Introduction

Offshore wind turbines are usually designed for 25 years. After this period, there are various options regarding the further use of the wind turbines, e.g., decommissioning of the wind turbines, repowering or lifetime extension. In the case of a lifetime extension, the operation of the wind turbine is extended beyond its originally intended lifetime. However, to extend the lifetime, the remaining lifetime of the wind turbine must first be determined. This can be done using a lifetime reassessment or recalculation. Here, the lifetime is recalculated using the environmental conditions (wind and wave effects) that actually occured during the lifetime. However, this means that a large number of combinations of environmental parameters, i.e., aeroelastic simulations, must be taken into account. Due to the resulting large number of simulations required (approximately 1,000,000 simulations), it is hardly possible to perform an exact lifetime reassessment using an aeroelastic simulation model.

One option for significantly reducing the calculation effort is to reduce the number of considered combinations of environmental conditions. This is the approach according to the standards (IEC 61400-1 (IEC, 2019a) and IEC 61400-3 (IEC, 2019b)) and

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was carried out, for example, by Stewart (2016), Ziegler and Muskulus (2016), Bouty et al. (2017), Velarde et al. (2020), and Katsikogiannis et al. (2021). However, this method does not take into account all combinations of environmental parameters that may have occured, so that this and the extrapolation to the lifetime using the probability of occurence of each input parameter combination creates an uncertainty in the prediction of the lifetime.

An alternative to a reduction of input parameter combinations is the use of meta-models as surrogates of the original aeroelastic simulation model. Due to the significant reduced computing time of meta-models, all combinations of environmental parameters that actually occured can be calculated, although each calculation is only an approximation compared to the original aeroelastic simulation model. Due to the low computing time of the meta-models, another advantage of using meta-models is that changes during the lifetime of the wind turbine can be taken into account quickly. For example, the lifetime may have to be calculated several times because a new wind farm has been built nearby during the lifetime which changes the wind conditions in the existing wind farm. Another reason could be an adjustment of the control strategy of the wind turbine during its lifetime. In these cases, if a meta-model is used, only a new calculation with the meta-model is necessary or (in the second case) a new meta-model needs to be created. In contrast, without a meta-model, it is not possible to re-simulate the complete lifetime with the original simulation model due to the high amount of required simulations.

Meta-models or surrogate models for fatigue load prediction, such as Kriging or Gaussian Process regression (e.g., Dimitrov et al. (2018), Slot et al. (2020), Wilkie (2020), Avendaño-Valencia et al. (2021), Müller et al. (2022), Singh et al. (2024)), artificial neural networks (ANNs; e.g., Müller et al. (2017), Schröder et al. (2018), Müller et al. (2021), Haghi and Crawford (2024)), polynomial chaos expanson (PCE; e.g., Dimitrov et al. (2018), Murcia (2018), Schröder et al. (2018), Slot et al. (2020)), or mixture density networks (e.g., Singh et al. (2024), Singh et al. (2025), have been comprehensively investigated in recent years for operating conditions for onshore and offshore wind turbines. This involved both more detailed investigations of meta-models and comparative studies (e.g., Dimitrov et al. (2018), Schröder et al. (2018), Slot et al. (2020), Müller et al. (2021), Singh et al. (2024)) in which several meta-models were compared with each other. For idling conditions, the use of meta-models for predicting fatigue loads was recently investigated by Schmidt et al. (2025a). In all these studies, it turned out that the use of meta-models for both onshore and offshore wind turbines offers a good opportunity regardless of the operating status of the wind turbine to calculate fatigue loads with a feasible computational effort compared to the use of the original aeroelastic simulation model.

However, there are only a few studies in which the lifetime of wind turbines has been calculated using meta-models and compared with other methods for the lifetime calculation. For example, Stewart (2016) investigated different methods for the reduction of the simulation size for the lifetime calculation of a floating wind turbine. Among other things, he investigated the use of response surface methods and genetic programming. These results were compared with lifetime DELs which were calculated from about 30,000 aeroelastic simulations. It turned out that the used response surface method is not able to capture all important effects for predicting fatigue loads while genetic programming lead to good results. Dimitrov et al. (2018) compared the predicted lifetime DELs of an onshore wind turbine using five different meta-models with the lifetime DELs determined using 1,000 aeroelastic simulations created with a quasi Monte Carlo sampling for seven different reference sites plus the standard reference classes from IEC 61400-1 (IEC, 2019a). The results show that the PCE and the Kriging approach both

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show a good accuracy in prediction of the site-specific lifetime DELs, whereas Kriging is slightly more accurate but requires more computing time. Schmidt et al. (2023) conducted a lifetime reassessment for an offshore wind turbine using Kriging meta-models considering 100,000 input parameter combinations which correspond to approximately 1.9 years and compared it to the results of aeroelastic simulations using the same 100,000 input parameter combinations. Additionally, a comparison with the approach according to IEC 61400-3 (IEC, 2019b) was performed. It turned out that the used Kriging meta-models are suitable to conduct a lifetime reassessment compared to the other two methods, as a high degree of accuracy and a low computational effort can be achieved by using the meta-models instead of the aeroelastic simulations. All mentioned studies have in common that only normal operation was investigated. However, according to IEC 61400-1 (IEC, 2019a), in addition to normal operating, idling must also be taken into account when calculating the lifetime of an (offshore) wind turbine. To the authors' knowledge, a lifetime reassessment using meta-models considering different operating conditions (e.g., normal operating and idling), has not yet been investigated. Furthermore, although the number of considered simulations in the different studies is partly very high, they remain well below the number of input parameter combinations that will affect an (offshore) wind turbine over its 20 to 25-year lifetime.

For this reason, in this study, a lifetime reassessment is performed using Kriging meta-models, taking into account the entire lifetime of the wind turbine and considering not only normal operation but also idling conditions. This lifetime calculation is then compared with two other methods for calculating the lifetime, which use aeroelastic simulations: First, a full lifetime calculation, where the same input parameter combinations were used to calculate the lifetime as for the meta-model-based method. And second, a lifetime calculation according to the standard IEC 61400-3 (IEC, 2019b). The aim is to find out to what extent the Kriging meta-models are suitable for the lifetime calculation compared to other methods and to identify the differences between the three methods. It has to be mentioned that all considered methods can be used both for the design of an offshore wind turbine and for the lifetime reassessment. In the following, the terms lifetime reassessment or lifetime calculation are used.

The paper ist structured as follows. First, in Sect. 2, the three methods for lifetime reassessment are detailed described. In Sect. 3, in a first study, the three different methods for lifetime reassessment are compared. Among other things, this involves investigating how much computational effort the individual methods require for the lifetime calculation. In a second study (Sect. 4), the impact of the wind turbine availability on the lifetime DELs is investigated. At the end (Sect. 5), a conclusion is drawn.

2 Method

2.1 Simulation model and settings for the aeroelastic simulation model

The time-domain simulations for the investigations in this work are conducted using the aero-hydro-servo-elastic code FASTv8 from the National Renewable Energy Laboratory (Jonkman, 2013). The FASTv8 code was enhanced by introducing soil-structure-interaction (Häfele et al., 2016; Hübler et al., 2018). As wind turbine model, the NREL 5 MW reference wind turbine (Jonkman et al., 2009) with the OC3 monopile and soil (Jonkman and Musial, 2010) is used. As in Hübler et al. (2017a) and

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Hübler et al. (2018), the required soil matrices for the soil model are based on the lateral soil model of Kallehave (2012) and on the axial soil model of FUGRO (API, 2007). Initial conditions were used for the calculation of the soil matrices in accordance with Häfele et al. (2016), i.e., no loads were applied.

The turbulent wind field is calculated using TurbSim (Jonkman and Kilcher, 2016). Here, the Kaimal turbulence model is used, which is one of the turbulence models recommended in the IEC 61400-1 guideline (IEC, 2019a) and which is frequently used, for example, by Yang et al. (2015), Slot et al. (2020), and Wilkie (2020). The irregular waves are calculated using the JONSWAP spectrum. The JONSWAP spectrum is commonly used for offshore wind turbine simulations, e.g., by Velarde et al. (2019), Stieng and Muskulus (2020), and Wilkie (2020).

The simulation length of each simulation is 10 minutes. In addition, a run-in time is taken into account, which is cut off to remove the influence of the initial transients resulting from the abrupt loading at the beginning of the simulation. As previously mentioned, the simulations in the time domain are carried out, both for normal operation and idling. Due to the different structural behaviour of the wind turbine during normal operation and idling caused by the lower aerodynamic damping and an associated greater impact of the wave loads for the idling wind turbine, different run-in times must be taken into account for the two operating states (Schmidt et al., 2025a). For normal operation, 240 seconds run-in time is taken into account in this work. According to Hübler et al. (2017b), this additional simulation time should be sufficient for the calculation of fatigue loads for the NREL 5 MW reference turbine on a monopile for normal operation. For idling, run-in times between 60 and 800 seconds are considered depending on the wind speed according to Schmidt et al. (2025a).

Five scattering environmental parameters (mean wind speed v_s, turbulence intensity TI, significant wave height H_s, wave peak period T_p, and wind-wave-misalignment θ_{mis}) are considered in this work. Hübler et al. (2017a), Murcia (2018) and Velarde et al. (2019) identified theses parameters as significant in sensitivity analyses for operating wind turbines. Due to their significant impact on the fatigue loads of operating wind turbines, it is assumed that these parameters also have a significant influence on the fatigue loads of an idling wind turbine. Additionally, for idling load cases, the initial rotor position ψ (azimuth angle) is considered as scattering parameter. In an earlier study (Schmidt et al., 2025a), it was found that for idling wind turbines, the variation of this parameter is relevant for determining the fatigue loads at the rotor blade root. For the five environmental parameters mentioned, the statistical distributions by Hübler et al. (2017b) are used, which were fitted to the measured environmental conditions at the FINO 3 research platform in the German North Sea. For ψ, for each input parameter combination, a random value between 0° and 360° is chosen.

The simulated loads in the time domain are transformed into short-term damage equivalent loads (DELs) according to Palmgren-Miner rule. The short-term DELs are calculated as follows:

$$S_{eq} = \left(\sum \frac{n_i S_i^m}{N_{ref}} \right)^{\frac{1}{m}} \quad (1)$$

Here, n_i is the corresponding number of cycles for each load amplitude S_i determined by a rainflow counting according to the standard ASTM E1049-85 (ASTM, 2017). N_{ref} = 600 is the number of equivalent cycles for a frequency of 1 Hz for a 10-minute time series and m is the Wöhler exponent. The Wöhler exponent m = 3 is chosen for steel and m = 10 for the composite material of the rotor blade. The load amplitude S_i is corrected according to Goodman (1914).

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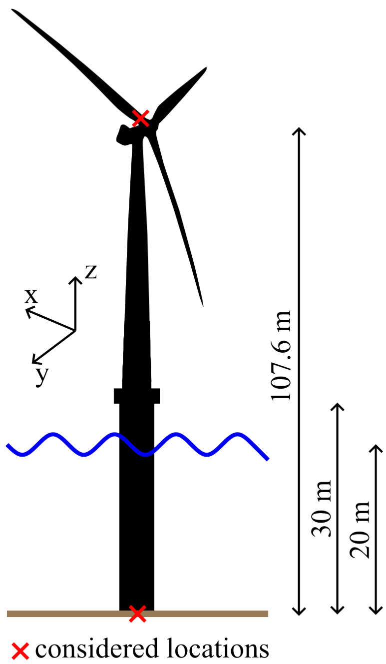

Figure 1. Visualisation of the NREL 5 MW reference turbine on the OC3 monopile (not to scale) with markings indicating the locations at which the internal forces are evaluated.

Table 1. Considered internal forces for the lifetime reassessment

Internal forces	Description
F_x	shear force at mudline in wind direction
M_y	overturning moment at mudline in wind direction
F_y	shear force at mudline perpendicular to wind direction
M_x	overturning moment at mudline perpendicular to wind direction
$M_{x,Root}$	edgewise moment at the blade root
$M_{y,Root}$	flapwise moment at the blade root

The lifetime reassessment in this work is carried out for the internal forces at the monopile and at the rotor blade root. A visualisation of the considered locations and a list of the internal forces can be found in Fig. 1 and Table 1.

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2.2 Kriging meta-models

In this work, Kriging meta-models are used for the lifetime reassessment of an offshore wind turbine. Kriging, also known as Gaussian Process regression, is chosen because it has shown promising results in previous work, in terms of approximation quality and computational effort required to create the meta-models (Slot et al., 2020; Wilkie, 2020). Furthermore, for the offshore wind turbine considered in this study (NREL 5 MW reference wind turbine on the OC3 monopile), Kriging meta-models already exist for normal operation and idling conditions (Müller et al., 2022; Schmidt et al., 2025a) so that they can be easily used.

Kriging combines a regression equation to model the mean or general trend in the data and a Gaussian Process (GP) with a zero mean to model the deviations from the general trend (Santner et al., 2018). The mathematical equation is composed as follows (Rasmussen and Williams, 2006):

$$g(\mathbf{x}) = f(\mathbf{x}) + \mathbf{h}(\mathbf{x})^T \beta. \tag{2}$$

Here, $\mathbf{h}(\mathbf{x})^T \beta$ represents the general trend in the data with known regression or basis functions $\mathbf{h}(\mathbf{x})$ and unknown regression coefficients β. $f(\mathbf{x})$ is a Gaussian process with a zero mean and the covariance function or kernel function $k(\mathbf{x},\mathbf{x}')$:

$$f(\mathbf{x}) \sim GP(0, k(\mathbf{x},\mathbf{x}')). \tag{3}$$

As mentioned before, by using the Gaussian process, the deviations from the general trend, also called residuals, are modelled. The covariance function $k(\mathbf{x},\mathbf{x}')$ describes the similarity between different data points ($\mathbf{x}$ and $\mathbf{x}'$). Here, it is assumed that data points whose input values are close to each other, i.e., are similar, also have similar output values. The covariance functions used can be isotropic or anisotropic. While isotropic covariance functions use the same correlation length for each input parameter, anisotropic covariance functions use a separate correlation length for each input parameter. For more information on Kriging, the reader is referred to Santner et al. (2018) and Rasmussen and Williams (2006).

The Kriging meta-models used in this work are surrogate models of the offshore wind turbine described in Sect. 2.1. The Kriging meta-models are used to predict the short-term DELs S_{eq} as defined in Eq. 1 for the internal forces summarised in Table 1. For normal operation and idling, separate meta-models from previous work (Müller et al., 2022; Schmidt et al., 2025a) are used or newly created based on the findings in the aformentioned work.

For normal operation, for the internal forces and moments at the monopile, the Kriging meta-models investigated in Müller et al. (2022) are used. The meta-models are trained using a pure quadratic basis function and the anisotropic matern 3/2 covariance function. Since the current study aims to recalculate the lifetime for the edgewise and flapwise bending moments at the rotor blade root but Müller et al. (2022) only investigated in-plane and out-of-plane bending moments, the meta-models for the edgewise and flapwise bending moments are created in the same way as in Müller et al. (2022) for the in-plane and out-of-plane bending moments. . For idling, the Kriging meta-models created by Schmidt et al. (2025a) are used. These were trained using a linear basis function and the anisotropic matern 3/2 covariance function.

The input parameters of the meta-models are the five environmental parameters mentioned previously in Sect. 2.1 (v_s, TI, H_s, T_p, θ_{mis}). In addition, as described in Schmidt et al. (2025a), for the rotor blades in idling conditions, ψ and the mean

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rotor speed ω are taken into account as additional input parameters. All meta-models used were created with 8,500 training samples, and an additional 1,500 test samples were used to test the meta-models. The training and test samples were created using Halton sequences and the statistical distributions of Hübler et al. (2017b) of the FINO 3 research platform. For more information regarding the used Kriging meta-models, the reader is referred to Müller et al. (2022) and Schmidt et al. (2025a). Kriging meta-models generally predict a mean and a corresponding standard deviation for each short-term DEL. For the prediction of the short-term DELs in this work, only the predicted mean values are used.

2.3 Lifetime reassessment

In this work, three different methods for a lifetime reassessment of offshore wind turbines are investigated and compared. The first method is a full lifetime reassessment using aeroelastic simulations. This method represents an accurate lifetime calculation and is therefore used as a reference solution within the scope of this work. The second method is a lifetime reassessment according to IEC 61400-3 and the third method is a lifetime reassessment using Kriging meta-models. The three methods are compared to identify differences and to find out whether the use of meta-models is suitable for a lifetime reassessment of offshore wind turbines. In the following, the three methods are discussed more in detail.

2.3.1 Full lifetime reassessment

For the full lifetime reassessment, i.e., the reference solution, aeroelastic simulations are carried out using the simulation model and settings described in Sect. 2.1. As described in Sect. 2.1, normal operation and idling are considered. Idling is taken into account for wind speeds outside the wind speed range of normal operation ($v_s < 3\,ms^{-1}$ and $v_s > 25\,ms^{-1}$). In addition, an availability of the wind turbine of 90 % is assumed in accordance with IEC 61400-3 (IEC, 2019b). This means that 10 % of all occuring load cases during the lifetime of the wind turbine are idling load cases due to the non-availability of the wind turbine. These 10 % are assumed to be independent of the wind speed. The lifetime reassessment is therefore divided in two cases: The wind turbine is available, i.e., normal operation for $3\,ms^{-1} \leq v_s \leq 25\,ms^{-1}$ and idling for $v_s < 3\,ms^{-1}$ and $v_s > 25\,ms^{-1}$, and the case where the wind turbine is not available, i.e., idling for the entire wind speed range.
The input parameter combinations for the aeroelastic simulations are created with the help of the Monte Carlo method using the statistical distributions of the environmental parameters of the FINO 3 research platform from Hübler et al. (2017b). According to Dimitrov et al. (2018), the resulting short-term DELs from the aeroelastic simulations are then converted into lifetime DELs using the following equation:

$$S_{eq,lifetime} = \left[\sum_{i=1}^{N} \left[S_{eq}(\mathbf{x}_i) \right]^m p(\mathbf{x}_i) \right]^{\frac{1}{m}} \tag{4}$$

Here, $\mathbf{x}_i$ is the ith vector of input variables. For normal operation and for idling for the internal forces and moments at the monopile, $\mathbf{x}_i = [v_s \; TI \; H_s \; T_p \; \theta_{mis}]^T$ and for idling for the rotor blades, $\mathbf{x}_i = [v_s \; TI \; H_s \; T_p \; \theta_{mis} \; \psi]^T$. N is the number of simulations and $p(\mathbf{x}_i)$ is the probability of occurence of each simulation. Here, due to the Monte Carlo sampling, the probability of occurence of each simulation is $p(\mathbf{x}_i) = 1/N$. A separate lifetime-DEL is calculated for each of the two cases

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'wind turbine is available' and 'wind turbine is not available'. These are then weighted and added together as shown in Eq. 5.

$$S_{eq,lifetime,total} = \left(S^m_{eq,lifetime,avail} \times p_{avail} + S^m_{eq,lifetime,unavail} \times p_{unavail}\right)^{\frac{1}{m}} \quad (5)$$

The case for the available wind turbine is weighted with $p_{avail} = 0.9$ and the case of the unavailable wind turbine with $p_{unavail} = 0.1$.

To consider the complete lifetime of 25 years, the conduction of 1,314,900 10-minute simulations would be necessary. However, as previously mentioned, the simulations are sampled from probability distributions of the environmental parameters using the Monte Carlo method. Therefore, it is first analysed whether it is necessary to simulate the entire 25 years or whether the lifetime DELs may already converge with fewer simulations. To analyse this, the number of simulations used to calculate the lifetime DELs is increased step by step. As described above, a distinction is made during the investigation as to whether the wind turbine is generally available (combination of normal operation and idling load cases, 90 % of the lifetime) or whether the wind turbine is not available (only idling load cases for all wind speeds, 10 % of the lifetime). Based on this categorisation, the maximum number of simulations for the available case is 1,183,410, and for the unavailable case 131,490. For the convergence studies, initially, 440,000 simulations are performed for the case where the wind turbine is available, which corresponds to approximately one third of the total number of simulations of 1,314,900. For the convergence study of the unavailable wind turbine, however, only 150,000 simulations are performed, as the total number for this case is already 131.490 simulations and therefore no further simulations are required.

The results are shown in Fig. 2(a) for the avabilable wind turbine and in Fig. 2(b) for the unavailable wind turbine. The lifetime DELs are normalised for each internal force using the lifetime DELs for the maximum number of simulations investigated (440,000 for the available case, 150,000 for the unavailable case). It is assumed that the lifetime DEL is converged if the deviation is less than 0.5 %.

From Fig. 2, it becomes clear that, for the available case, the normalised lifetime DELs for each of the internal forces investigated converge after just over 100,000 simulations. For the unavailable wind turbine, the normalised lifetime DELs converge after less than 100,000 simulations, except for $M_{x,Root,lifetime}$. The convergence behaviour of $M_{x,Root,lifetime}$, however, is significantly worse. The curve shows clear jumps, even with a comparatively high number of simulations around 100,000. These jumps are caused by some few simulations in which the wave peak period has values of approximately 4 s or 8 s and the resulting short-term DELs of $M_{x,Root}$ are very large. One possible explanation for this large values of the resulting short-term DELs is that in these simulations, the wind turbine is excited at its natural frequency, causing the rotor blades to vibrate strongly, which is why the short-term DELs have very high values. To investigate whether these outliers only occur for very specific wind and wave conditions that might not even occur in reality (i.e., numerical artefacts in the aeroelastic code), the corresponding simulations are simulated again with changed wind and wave seeds (all other input parameters kept unchanged). The results for $M_{x,Root,lifetime}$ with changed wind and wave seeds for the outliers are shown in Fig. 3 together with the original curve of $M_{x,Root,lifetime}$ from Fig. 2(b). It becomes clear that only by changing the random seeds in the corresponding few simulations that previously predicted very large short-term DELs the convergence behaviour is significantly improved. This leads to the conclusion that, in these few simulations, it is not the combination of input parameters itself but rather the combination of the

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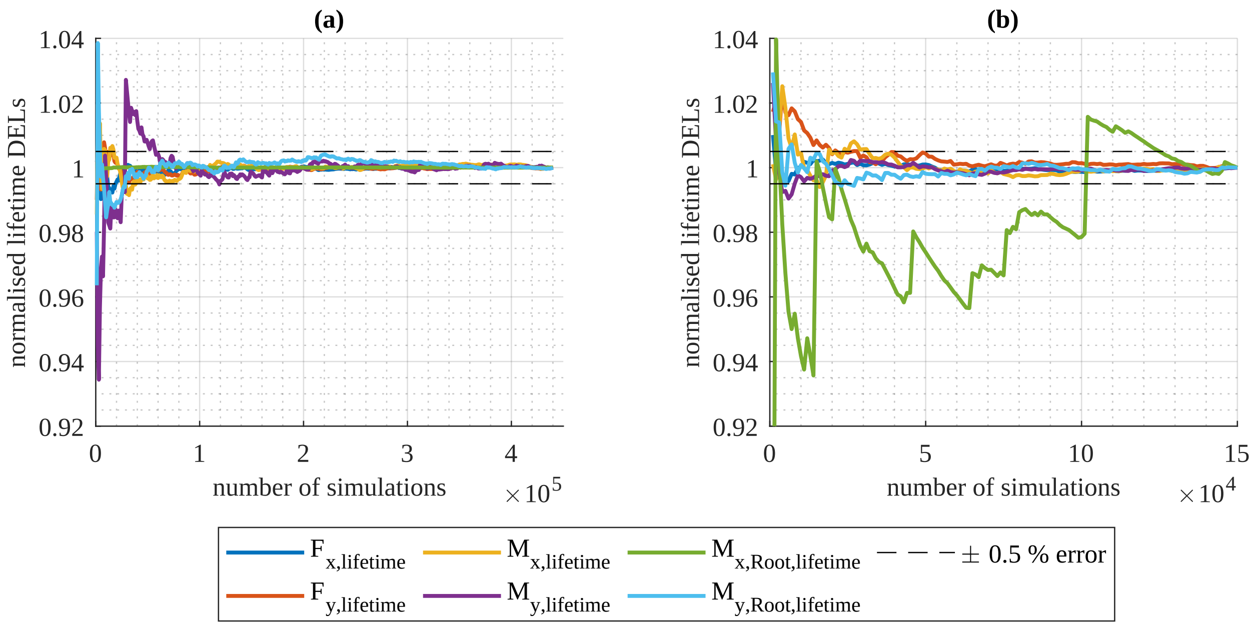

Figure 2. Normalised lifetime DELs of the reference solution depending on the number of simulations. (a) wind turbine is available (normal operation and idling conditions for wind speeds outside the wind speed range of normal operation), (b) wind turbine is not available (only idling). The lifetime DELs are normalised using the lifetime DELs determined with the maximum number of simulations.

input parameters in conjunction with the random seeds that can, in some rare cases, lead to very high short-term DELs due to the strong vibration of the wind turbine. It is assumed that this strong oscillation of the wind turbine rotor blades does not occur in reality, but is rather an effect of FAST resulting from the simplified modelling of the wind turbine. However, it is still the case that the lifetime DEL of $M_{x,Root}$ with the changed random seeds only shows a deviation of less than 0.5 % from the lifetime DEL determined with 150,000 simulations when using approximately 130,000 simulations. For this reason, in the further course of the work, the lifetime DELs for the unavailable wind turbine are determined using the maximum number of 131,490 simulations. For the available wind turbine, 200,000 simulations are chosen to be on the safe side as the lifetime DELs are better converged using 200,000 simulations instead of 100,000 simulations.

2.3.2 Lifetime reassessment according to the standard IEC 61400-3

For the lifetime reassessment according to the standard IEC 61400-3 (IEC, 2019b), the input parameters v_s, H_s, and T_p must be considered as scattering parameters. Additionally, the wind and wave direction can be taken into account. In this work, the wind wave misalignment θ_{mis} is considered instead. This is consistent with the work of Stewart (2016) and with our previous work (Schmidt et al., 2023). According to IEC 61400-1 (IEC, 2019a), the 90 % percentile of the corresponding probability

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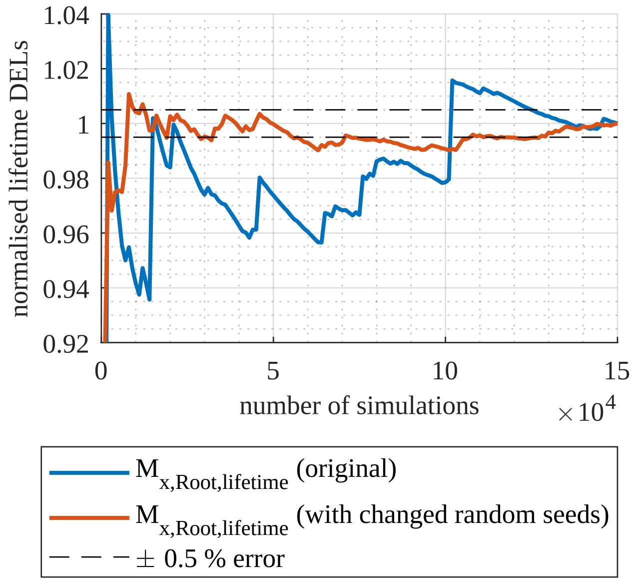

Figure 3. Normalised lifetime DELs of the reference solution of $M_{x,Root}$ depending on the number of simulations for the unavailable wind turbine. Comparison of original curve of Fig. 2(b) with curve with changed random seeds for the outliers. The lifetime DELs are normalised using the lifetime DELs determined with the maximum number of simulations.

distribution should be used for TI. Since the use of the 90 % percentile for TI can lead to significantly higher lifetime DELs compared to the other methods used in this work, where TI is considered as scattering parameter (Schmidt et al., 2023), instead of the 90 % percentile for TI, in this study, the mean value for TI is taken into account.

To create the load case set, the probability distributions of the four input parameters are divided according to the bin sizes given in Table 2. For each bin of each input parameter, the probability of occurence is determined. Then all possible combinations of the four input parameters are determined and for each input parameter combination the probability of occurence is calculated by multiplying the probabilities of occurence of each of the four parameters. If all possible combinations of the four input parameters are considered, for the statistical distributions of the FINO 3 research platform (Hübler et al., 2017b) this results in 263,520 simulations. Additionally, according to IEC 61400-3, six 10-minute simulations with different seeds or one 1-hour simulation must be carried out. In the case of six different seeds, this results in a number of 1,581,120 simulations.

The computational effort to conduct these number of simulations is very high. However, by taking into account all possible combinations of the input parameters, combinations are also considered that do not or only very rarely occur in reality, such as a low wave height in combination with a high wind speed. To reduce the computing time, combinations with a very low probability of occurence are therefore not considered. For these load cases it can be assumed that the probability of occurence of these load cases is so small that the impact on the lifetime of the wind turbine is negligible, even if the damage they cause

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Table 2. Considered bin sizes according to IEC 61400-3 and ranges of the input parameters

Input parameter	Bin size	Range
v_s	2 ms^{-1}	1 – 35 ms^{-1}
H_s	0.5 m	0.25 – 9.75 m
T_p	0.5 s	0.25 – 30.25 m
θ_{mis}	30°	-180° – 180°

is high. Only those parameter combinations are taken into account for which the probability of occurence is so high that they occur at least once during the lifetime of the wind turbine, i.e.,

$$p_{min} = \frac{1}{25 \times 365.25 \times 24 \times 6} = 7.6 \times 10^{-5}\,\%. \quad (6)$$

By introducing p_{min} as the minimum probability of occurence, the number of simulations can be reduced to 16,214 simulations per seed, i.e., 97,284 simulations in total. Although only about 6 % of all possible combinations are simulated, the computed combinations sum up to $p_{IEC,total}$ = 99.7 % of the real lifetime. This shows that the number of simulations can be significantly reduced without neglecting significant combinations of input parameters.

In this work, the case 'available wind turbine' and 'unavailable wind turbine' are considered. This is taken into account by conducting the resulting 97,284 simulations once for the available case and once for the unavailable case. This results in a total of 194,568 aeroelastic simulations. As for the full lifetime reassessment, the resulting short-term DELs from the 97,284 simulations for each case (available and unavailable wind turbine) are then separately converted into lifetime DELs according to Eq. 4. In contrast to the full lifetime reassessment, $p(\mathbf{x}_i)$ here corresponds to the probability of occurence of each input parameter combination whereby the probabilities of occurence of each input parameter combination were corrected with the sum of all occurence probabilities $p_{IEC,total}$ = 99.7 %. This ensures that the sum of all occurence probabilities is 1, as it is the case with the reference solution. The resulting lifetime DELs are then weighted and added together as shown in Eq. 5. Again, the lifetime DELs for the available wind turbine are weighted with $p_{avail} = 0.9$ and the lifetime DELs of the unavailable wind turbine with $p_{unavail} = 0.1$.

2.3.3 Lifetime reassessment using Kriging meta-models

For the lifetime reassessment using Kriging meta-models, the meta-models described in Sect. 2.2 are used. To calculate the lifetime DELs with the meta-models, the same input parameter combinations used for the full lifetime reassessment described in Sect. 2.3.1 are used. The only difference is that, in addition to ψ, the mean rotor speed ω is taken into account as an additional parameter for the accurate prediction of the bending moments at the rotor blades in idling conditions. The short-term DELs returned for the 200,000 (available) and 131,490 (unavailable) input parameter combinations by the meta-models are then converted separately into lifetime DELs for the available and the unavailable case using Eq. 4. Due to the con-

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Table 3. Normalised calculated lifetime DELs for the available and unavailable case and under a consideration of 90 % availability. The lifetime DELs are normalised for each case using the reference solution.

	available wind turbine			unavailable wind turbine			90 % availability		
Load	Reference	IEC	meta-model	Reference	IEC	meta-model	Reference	IEC	meta-model
$F_{x,lifetime}$	1.000	0.996	0.993	1.000	0.997	0.978	1.000	0.996	0.993
$M_{y,lifetime}$	1.000	1.008	0.917	1.000	0.936	0.892	1.000	0.960	0.900
$F_{y,lifetime}$	1.000	1.017	0.987	1.000	1.048	0.990	1.000	1.019	0.987
$M_{x,lifetime}$	1.000	1.004	0.908	1.000	1.129	0.924	1.000	1.009	0.908
$M_{x,Root,lifetime}$	1.000	0.999	1.000	1.000	0.967	0.688	1.000	0.999	1.000
$M_{y,Root,lifetime}$	1.000	0.925	1.002	1.000	0.997	1.027	1.000	0.925	1.002

sideration of ω as an additional input parameter, in Eq. 4, $\mathbf{x}_i$ for idling conditions for the rotor blades changes as follows: $\mathbf{x}_i = [v_s\ TI\ H_s\ T_p\ \theta_{mis}\ \psi\ \omega]^T$. The calculated lifetime DELs are then weighted and added together, using $p(\mathbf{x}_i) = 1/N$ as probability of occurence of each prediction as described in Sect. 2.3.1. Again, the resulting lifetime DELs are weighted and added together as shown in Eq. 5. Here, too, the case for the available wind turbine is weighted with $p_{avail} = 0.9$ and the case of the unavailable wind turbine with $p_{unavail} = 0.1$.

3 Results

3.1 Comparison of different methods for lifetime reassessment

In Table 3, the normalised lifetime DELs calculated with the described methods are shown for three different cases: the available case, the unavailable case and the case of an availability of the wind turbine of 90 %.

For the method according to IEC 61400-3 it becomes clear that the deviations of the lifetime DELs from the reference solution are small with less then 10 % deviation from the reference solution with the exception of $M_{x,lifetime}$ for the unavailable, idling case. Here, the deviation is approximately 13 %. However, assuming a typical availability of 90 % as also shown in Table 3, it is apparent that although the deviation of the lifetime DEL for M_x for the unavailable, idling case is approximately 13 %, the total lifetime DEL under a consideration of 90 % availability is almost unaffected by this deviation.

The lifetime DELs predicted using the meta-models also show, with two exceptions, only small deviations with less than 10 % compared to the reference solution. Only in the case of the unavailable, idling wind turbine, the deviations for two internal forces ($M_{y,lifetime}$ and $M_{x,Root,lifetime}$) are larger than 10 %. One possible explanation for the poorer approximation by the meta-models is that the meta-models may not represent all the important effects that occur in the simulation model. Although the meta-models have been comprehensively validated (Müller et al., 2022; Schmidt et al., 2025a), it is possible that, due to the large number of combinations of environmental conditions considered in this study, there are input parameter combinations

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Table 4. Comparison of the normalised lifetime DELs predicted by the Kriging meta-models for the available case and for normal operation. The lifetime DELs are normalised using the reference solution for the available case and for normal operation.

Load	available case	only normal operation
$F_{x,lifetime}$	0.993	0.996
$M_{y,lifetime}$	0.917	0.985
$F_{y,lifetime}$	0.987	0.988
$M_{x,lifetime}$	0.908	0.910
$M_{x,Root,lifetime}$	1.000	1.000
$M_{y,Root,lifetime}$	1.002	1.002

that the meta-models are not able to accurately represent. Therefore, possible causes will be discussed in more detail.

At 11 %, the deviation for $M_{y,lifetime}$ for the unavailable case is of a similar magnitude to $M_{y,lifetime}$ in the available case and the 90 % availability case and $M_{x,lifetime}$ for all considered cases. It therefore seems that there are overall effects on the bending moments at the monopile that cannot currently be represented by the meta-models. Since the available case includes normal operation and idling (for wind speeds outside the wind speed range for normal operation), the lifetime DELs resulting from taking only normal operation into account are now being investigated to further determine the cause of the poorer approximation quality for the bending moments at the monopile. The resulting normalised lifetime DELs are shown in Table 4. It becomes clear that the predicted lifetime DELs for the available case and for normal operation are generally very similar. Only for $M_{y,lifetime}$, the differences between the normalised lifetime DELs are larger. Here, in contrast to the current study, the meta-model for M_y can predict the lifetime DELs for normal operation with a small deviation of less than 2 % compared to the reference solution. The deviation of $M_{y,lifetime}$ for the available case therefore mainly arises from the prediction of the idling meta-model. During normal operation, the fore-aft direction (M_y) is significantly more damped than the side-side direction (M_x) of the offshore wind turbine. However, during idling, this aerodynamic damping is no longer present due to the very slow rotor speed resulting in a significant lower damping in fore-aft direction. This different structural behaviour and the resulting larger impact of the wave loads caused by the lower damping seem to be something that the meta-models cannot really deal with right now. Furthermore, as described in Schmidt et al. (2025a), M_x and M_y for idling show greater seed-to-seed variation than, for example, F_x and F_y. This makes accurate predictions using meta-models even more difficult. However, a deviation of around 10 % of the lifetime DELs of the reference solution is considered acceptable within the scope of this study.

For the meta-model of $M_{x,Root}$, it can be assumed that not all important effects are taken into account in the meta-model. This becomes clear when looking at the predicted short-term DELs of $M_{x,Root}$ as a function of individual input parameters, e.g., as a function of v_s or T_p as shown in Fig. 4. Across the entire wind speed range and also across a large range of the peak period, the meta-model underestimates the short-term DELs calculated by the simulation model. In contrast to the bending moments

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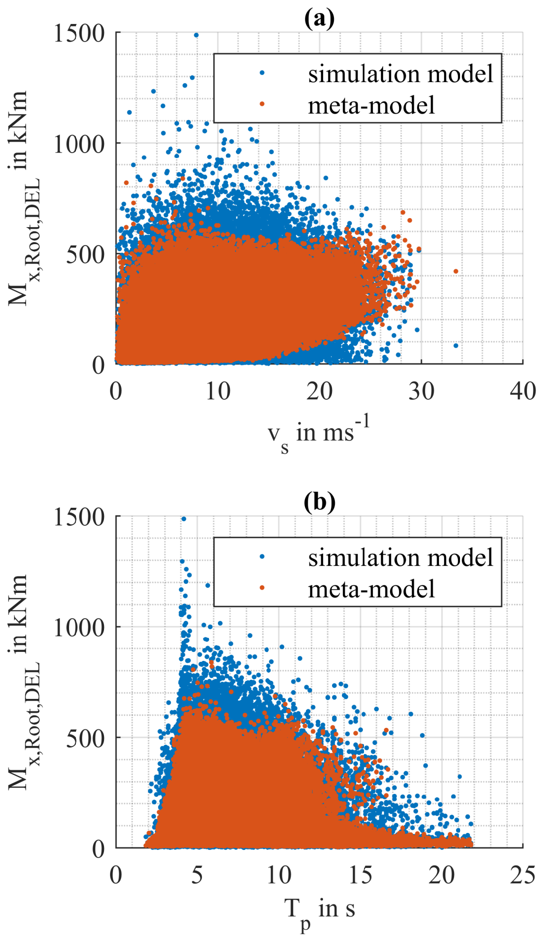

Figure 4. Comparison of the short-term DELs of $M_{x,Root}$ calculated by the aeroelastic simulation and the Kriging meta-model (a) depending on v_s and (b) depending on T_p.

at the monopile, however, the deviation of $M_{x,Root,lifetime}$ is, significantly higher at approximately 31 %. This is a very large deviation, which is not acceptable at first glance. Nevertheless, since the idling conditions at the rotor blades have only a very minor impact on the overall lifetime DEL at 90 % availability of the wind turbine (see Table 3) and the focus of this work is not only on idling conditions, this problem will not be addressed further in this paper. However, this is an issue that should be investigated more closely in future work, particularly if idling is the focus of an investigation.

Another point that becomes apparent when looking at the lifetime DELs predicted with the meta-models in Table 3 is that, with a few exceptions, the predicted lifetime DELs are smaller than the lifetime DELs of the full lifetime reassessment. The calcula-

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tion with the meta-models is thus not conservative. However, to use the meta-models as a surrogate for aeroelastic simulations for the lifetime calculations, they should rather be conservative compared to the original aeroelastic simulation. Therefore, this is a point that will be discussed in more detail in the further course of this study. However, even the lifetime DELs determined according to IEC 61400-3 are not conservative for all considered internal forces. As shown by Schmidt et al. (2023), these only become conservative if the 90th percentile is chosen for TI instead of the mean value as in the current study.

3.2 Impact of the number of simulations used for the determination of the lifetime DELs

For the lifetime DELs shown in Table 3, for the method according to IEC 61400-3, 194,568 aeroelastic simulations were conducted. For the meta-model-based method, 17,000 aeroelastic simulations for the training of the meta-models (8,500 simulations for each, normal operation and idling) were conducted as no more aeroelastic simulations need to be conducted for the determination of the lifetime DELs. In this section, it is investigated to what extend these numbers of simulations can be reduced. This is an important point, as each simulation with a simulation time of 10 minutes also requires around 10 minutes of computing time.

3.2.1 Required number of simulations for lifetime reassesment using the method according to IEC 61400-3

Figure 5 shows the lifetime DELs for the case of 90 % turbine availability as a function of the simulations performed to determine the lifetime DELs to clarify how many simulations are used to calculated the lifetime DELs. Here, a constant number of simulations is used for the reference solution and the calculation with the meta-models. In contrast, the number of simulations for calculating the lifetime DELs according to IEC 61400-3 is stepwise increased to a maximum of 194,568, to find out how many simulations are required to achieve a good approximation of the reference solution. The stepwise increase of the number of simulations is achieved by decreasing p_{min} from $p_{min} = 0.1\,\%$ until $p_{min} = 7.6 \times 10^{-5}\,\%$. This is done for the input parameter combinations for the available case. For the unavailable case, for each step, the same input parameter combinations are used as for the available case. Subsequently, for each step, the lifetime DELs are calculated for the available and the unavailable case. As in Sect. 2.3.2, the probability of occurence of each considered input parameter combination is corrected by the sum of all probabilities of occurence. This ensures that the sum of all probabilities of occurence considered in each step is equal to 1. Finally, the resulting lifetime DELs are weighted and added together according to Eq. 5. As before, the lifetime DELs for the available wind turbine are weighted with $p_{avail} = 0.9$ and the lifetime DELs of the unavailable wind turbine with $p_{unavail} = 0.1$.

From Fig. 5, it becomes clear that the number of simulations used for the method according to IEC 61400-3 influences the lifetime DELs of all considered internal forces. In particular for $F_{y,lifetime}$, $M_{x,lifetime}$ and $M_{y,Root,lifetime}$ the number of simulations has a significant impact on the lifetime DELs. At least 70,000 simulations must be carried out to ensure that the deviation from the reference solution is less then 10 % for all considered internal forces ($M_{y,Root,lifetime}$ is the decisive factor). Thus, the computational effort can be reduced to around 20 % compared to the reference solution. This is a significant reduction of the computational effort. However, for the prediction of the lifetime DELs using the meta-models, only 17,000 simulations

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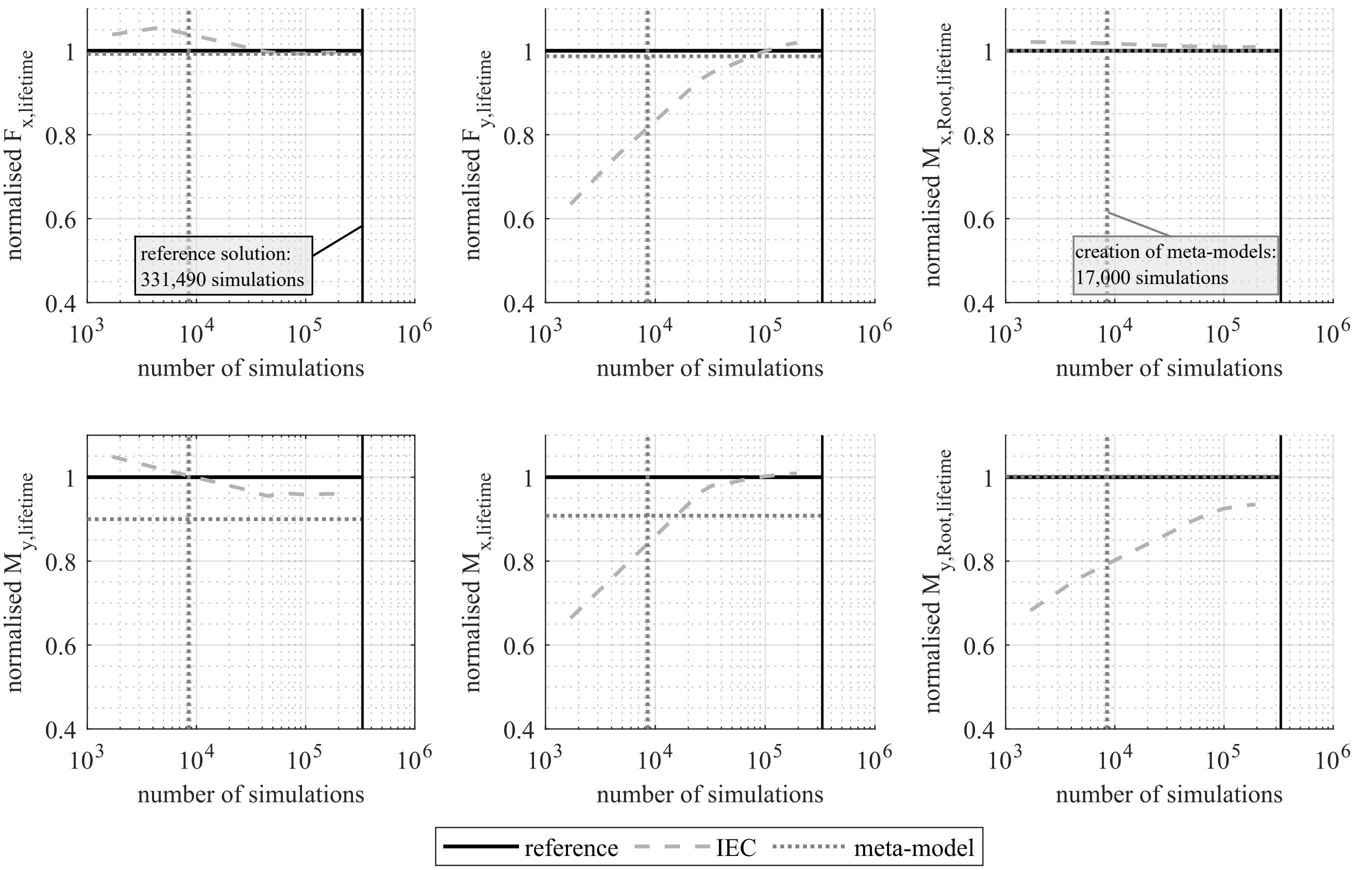

Figure 5. Normalised lifetime DELs of the three methods for the case of an availability of the wind turbine of 90 % versus the number of simulations used for the calculation of the lifetime DELs. The lifetime DELs are normalised with the lifetime DELs of the reference solution.

were conducted for the training of the meta-models. Thus, compared to the reference solution, when using meta-models, the computing time can be reduced to around 5 % of the computational effort for the full lifetime reassessment. Nevertheless, there might still potential for optimisation with regard to the computational effort required to determine the lifetime DELs using the Kriging meta-models. During setting up the meta-models, it was checked that the number of simulations used to train is sufficiently high to predict the short-term DELs with sufficient accuracy. However, for a good prediction of lifetime DELs, probably, fewer simulations to train the meta-models are required, as small errors can be averaged out. It is therefore possible that the dotted vertical line in Fig. 5, which represents the number of simulations used to create the meta-models, can be shifted further to the left and the lifetime DELs will still be predicted well while additional computing time is saved. This will be investigated in more detail in the next section.

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3.2.2 Required number of training samples for a lifetime reassessment using Kriging meta-models

To determine the required number of training samples for a lifetime reassessment using the Kriging meta-models, convergence studies are conducted where the number of simulations used to create the Kriging meta-models are increased successively and the lifetime DELs are then compared with the lifetime DELs of the reference solution. Two convergence studies are carried out here: one for the meta-models for normal operation and one for the meta-models for idling. For the convergence study for the meta-models for normal operation, the input parameter combinations of the available case for normal operation ($3ms^{-1} \leq v_s \leq 25ms^{-1}$) are used to determine the lifetime DELs. These are 190,306 input parameter combinations. The remaining 9,694 input parameter combinations ($v_s < 3\,ms^{-1}$ and $v_s > 25\,ms^{-1}$) are removed, as these represent idling conditions. For the convergence study for the meta-models for idling, the 131,490 input parameter combinations for the unavailable case can simply be used.

The results are shown in Fig. 6. It becomes clear that the lifetime DELs for normal operation converge at a significantly lower number than 8,500 training samples previously used for the generation of the meta-models. Only 600 training samples are needed for the creation of the meta-models to achieve a normalised lifetime DEL with a deviation of less than 5 % compared to the use of 8,500 training samples. For idling conditions, it can be seen that the lifetime DELs for the internal forces at the monopile and $M_{y,Root}$ also converge very quickly. To achieve normalised lifetime DELs with a deviation of less than 5 % compared to the lifetime DELs predicted with the meta-models generated with the maximum number of 8,500 training samples, only 700 training samples are required. For the meta-model for $M_{x,Root}$, it takes longer for convergence to occur. Here, only after 4,400 training samples there is a deviation of less than 5 % from the lifetime DEL determined with the meta-model with the maximum number of 8,500 samples. However, it has already been shown in Sect. 3.1 that if an availability of 90 % is assumed, the idling conditions of the rotor blades are of very minor importance. Therefore, if, as in this case, a typical wind turbine availability is assumed and the focus is not on idling conditions, very good predictions of the lifetime DELs can also be made for $M_{x,Root}$ with the meta-model for idling trained with 700 samples. However, if the focus lies on idling conditions, the larger number of 4,400 training samples should be used to create the meta-models.

Using the recommended 600 or 700 training samples leads to errors below 5 %. However, a full convergence is not yet achieved. Hence, to stay more conservative, more training samples for the generation of the meta-models can be used. For example, to achieve a maximum error of 2 % compared to the predicted lifetime DELs using the meta-models with the maximum number of training data of 8,500, 4,700 samples are needed for normal operation and 2100 samples (without considering the meta-model for $M_{x,Root}$) are needed for the generation of the meta-models. If the prediction for $M_{x,Root,lifetime}$ for idling shall also converge with an error of less than 2 %, 5,500 training samples are required here.

Assuming a typical availability of the wind turbine and therefore negligible impact from $M_{x,Root}$ during idling, it can be summarised that the number of training samples required can be signficantly reduced to a total of 1,300 training samples compared to the 17,000 samples used previously. In this case, the predicted lifetime DELs for both operating states deviate with less than 5 % from the lifetime DELs predicted using the meta-models with the maximum number of training samples of 8,500. This means that the computing time can be reduced by using meta-models even further from previous 5 % of the

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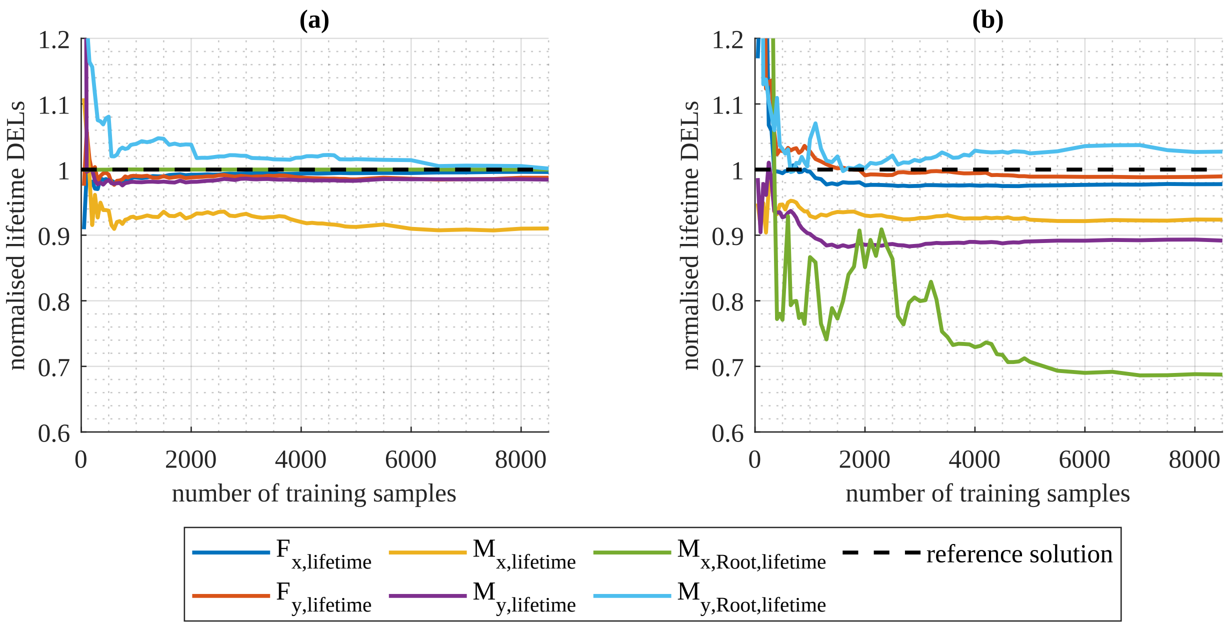

Figure 6. Predicted normalised lifetime DELs using the Kriging meta-models depending on the number of training samples used for the generation of the meta-models for (a) normal operation and (b) idling conditions. The lifetime DELs are normalised with the lifetime DELs of the reference solution for normal operation and idling.

computing time of the reference solution to less than 0.5 % of the computing time of the reference solution. If higher accuracy is desired, the number of training samples can be reduced to a total of 6,800, in which case the deviation from the lifetime DELs predicted using the meta-models with 8,500 training samples for each operating status is only 2 %. In this case, using the meta-models reduces the computational effort to approximately 2 % of the computing time required for the reference solution. In the final step of this investigation, the lifetime DELs for 90 % availability of the wind turbine are calculated using the meta-models created with the recommended training sample sizes. These are then compared with the lifetime DELs for 90 % availability from Table 3. The results are shown in Table 5. It becomes clear that the differences between the three different training sample sizes are only minor. Only $M_{y,lifetime}$ predicted by the meta-models using only 1,300 training samples in total deviates slightly more. This can be explained by the fact that the idling meta-model for M_y in particular has not yet converged (see Fig. 6), but the operating status idling for this internal force has a significant impact on the total lifetime DEL. However, this deviation is considered acceptable, meaning that both training set sample sizes remain recommended.

3.3 Conservative prediction of lifetime DELs using meta-models

As shown in Sect. 3.1, the lifetime DELs predicted by the meta-models are not yet conservative compared to the reference solution. One way to make the prediction of the meta-models more conservative is to adjust each prediction of the meta-

Table 5. Predicted normalised lifetime DELs using the meta-models for 90 % availability considering different training sample sizes. The first row of the table shows the training sample sizes for normal operation + training sample size for idling. The lifetime DELs are normalised using the reference solution.

Load	8,500 + 8,500 samples	600 + 700 samples (5 % deviation)	4700 + 2100 samples (2 % deviation)
$F_{x,lifetime}$	0.993	0.997	0.991
$M_{y,lifetime}$	0.900	0.979	0.893
$F_{y,lifetime}$	0.987	0.995	0.985
$M_{x,lifetime}$	0.908	0.911	0.912
$M_{x,Root,lifetime}$	1.000	1.000	1.000
$M_{y,Root,lifetime}$	1.002	1.020	1.016

models. As already mentioned in Sect. 2.2, the Kriging meta-models used generally predict a mean value and a corresponding standard deviation for each short-term DEL. The meta-models used in this work so far only use the mean value to predict the short-term DELs. Since the Kriging prediction for each short-term DEL follows a normal distribution, percentile values for each short-term DEL value can easily be calculated, e.g., the 60th percentile as shown in the following equation:

$$P_{60} = \Phi^{-1}(0.6) \times \sigma + \mu. \qquad (7)$$

Here, Φ is the standard normal distribution and μ and σ are the predicted mean value and standard deviation of the Kriging meta-model. The use of another percentile for the prediction instead of the mean value has the advantage that the prediction becomes more conservative, while the already trained meta-models can still be used. Therefore, it will be investigated to what extent a conservative prediction of the lifetime DELs can be achieved by considering a different percentile value instead of the mean value of the Kriging meta-model. While, to the author's knowledge, percentile values are not currently used to make preditions of fatigue loads using meta-models more conservative, percentile values such as the 90th percentile for TI are used in the IEC 61400-1 to make predictions conservative.

For this study, the 50th percentile (mean value) to the 95th percentile are taken into account. Here, the Kriging meta-models created with 8,500 training samples are used. As in the previous section (Sect. 3.2.2), two studies are conducted, one for the meta-models for normal operation and one for the meta-models for idling. Furthermore, the same 190,306 input parameter combinations for the determination of the lifetime DELs for normal operation and the same 131,490 input parameter combinations for the determination of the lifetime DELs for idling are used for each investigated percentile.

The results shown in Fig. 7(a) clearly indicate that, when using the 65th percentile of the Kriging prediction, all meta-models for normal operation make a prediction of the lifetime DELs on the safe side (normalised lifetime DEL is greater than 1). For the meta-models for the idling wind turbine (Fig. 7(b)), this is only achieved from the 90th percentile onwards. Here, $M_{x,Root,lifetime}$ is decisive. However, it is noticeable that the results of $M_{x,Root,lifetime}$ deviate signficantly from the results

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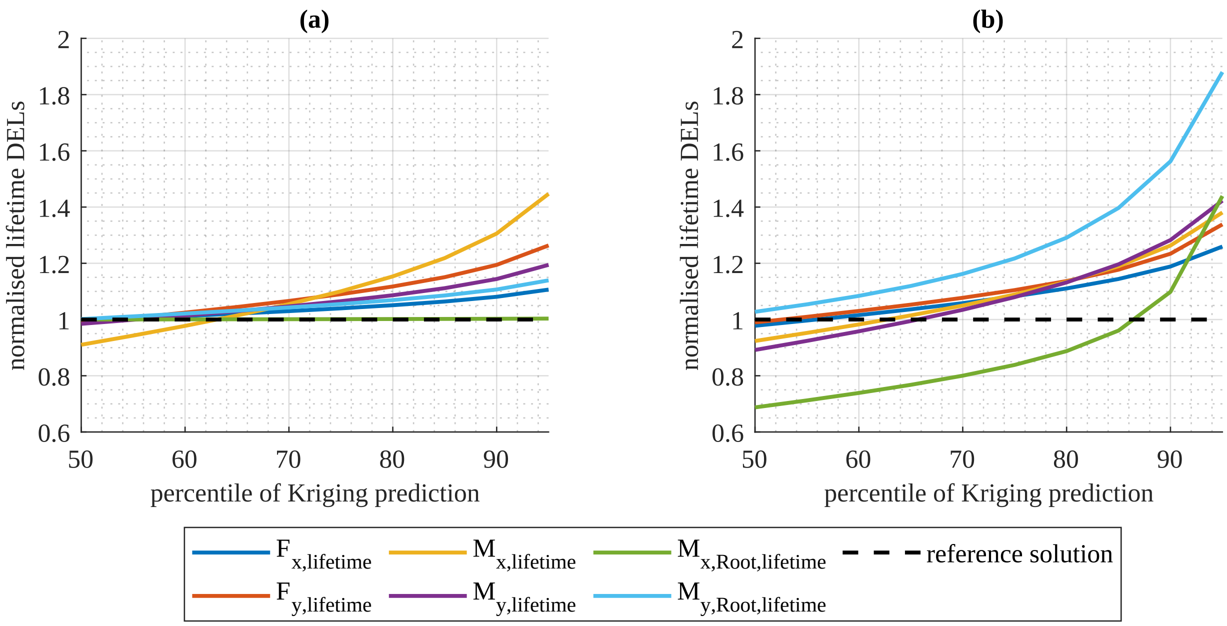

Figure 7. Normalised lifetime-DELs using the Kriging meta-models depending on the percentile of prediction of the Kriging meta-models for (a) normal operation and (b) idling conditions. The lifetime DELs are normalised with the lifetime DELs of the reference solution for normal operation and idling.

of the other internal forces investigated. For the remaining internal forces, the use of the 70th percentile would be sufficient to achieve a value of the normalised lifetime DELs larger than 1. One reason for the large deviation of the curve of $M_{x,Root,lifetime}$ is that the lifetime DEL is not approximated as well by the meta-model as already described before. However, as mentioned in Sect. 3.1, idling has only a very minor impact on the overall lifetime DELs of the rotor blade root bending moments, assuming a typical availability. Thus, for 90 % availability, even when using the mean value for the prediction with the meta-models, the prediction for both rotor blade root bending moments is greater or equal to 1 (see, for example, Table 3). From this, it can be concluded that if typical availability is assumed, a non-conservative prediction of the idling meta-model of $M_{x,Root}$ still leads to a conservative total lifetime DEL.

Assuming typical availability of the wind turbine, the use of the 65th percentile is recommended for the meta-models for normal operation, and the use of the 70th percentile is recommended for the meta-models for idling for the prediction of conservative lifetime-DELs for all considered internal forces. However, if the focus is on idling, the 90th percentile should be used for the meta-models of idling.

If the percentiles described above (65th percentile for normal operating and 70th percentile for idling) are used for the predictions with the meta-models, the total lifetime DELs for an availability of the wind turbine of 90 % shown in Table 6 are obtained. It becomes clear that all meta-model predictions are now conservative compared to the reference solution. Hereby,

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Table 6. Normalised total lifetime DELs for 90 % availability using the recommended percentiles for the meta-model predictions (65th percentile for normal operation and 70th percentile for idling) compared to the normalised total lifetime DELs using the mean values for the meta-model prediction from Table 3. The lifetime DELs are normalised using the reference solution.

Load	prediction using mean value	conservative prediction
$F_{x,lifetime}$	0.993	1.027
$M_{y,lifetime}$	0.900	1.049
$F_{y,lifetime}$	0.987	1.014
$M_{x,lifetime}$	0.908	1.024
$M_{x,Root,lifetime}$	1.000	1.001
$M_{y,Root,lifetime}$	1.002	1.033

the deviation of the reference solution is for all considered internal forces below 5 %. This shows that only by using other percentiles of the Kriging predictions instead of the mean values, it can be ensured to predict conservative lifetime DELs compared to the reference solution.

4 Impact of wind turbine availability on lifetime DELs

In the previous study, a wind turbine availability of 90% was assumed. This section briefly investigates the impact to which availability influences the lifetime DELs of the considered offshore wind turbine. For this, the availability of the wind turbine is varied between 80 % and 100 %. To determine the total lifetime DELs for the different availabilities, the lifetime DELs determined for the available case and the unavailable case are weighted according to Eq. 5 with the availabilities $p_{avail} = [0.8, 0.85, 0.9, 0.95]$ and $p_{unavail} = [0.2, 0.15, 0.1, 0.05]$. For each investigated availability, the lifetime DELs for all considered internal forces and moments are calculated using the simulated lifetime DELs of the full lifetime reassessment (reference).

The results are shown in Fig. 8. It becomes clear that for $F_{x,lifetime}$ and $M_{y,lifetime}$, a reduction in availability leads to an increase in lifetime DELs. This impact is particularly strong for $M_{y,lifetime}$, so that at 80% availability, the lifetime DEL is approximately 1.6 times greater than at 100% availability. One possible explanation for the increase in the lifetime DELs is that the turbine is less damped in the fore-aft direction during idling due to the lack of or very slow rotation of the rotor. Thus, the wave loads have a greater impact on the structural behaviour of the turbine. For the remaining internal forces and moments, however, a reduction in availability leads to a reduction of the lifetime DELs. The side-side direction is, in contrast to the fore-aft direction, significantly less damped during normal operation resulting in a minor impact of the aerodynamic damping in this direction. Accordingly, the structural behaviour in this direction does not change as signficantly as in the fore-aft direction. The fact that the lifetime DELs decrease in side-side direction with decreasing availability could be explained by the fact that during idling, the loads on the turbine resulting from the rotation of the rotor are lower. For the rotor blades, the loads on the

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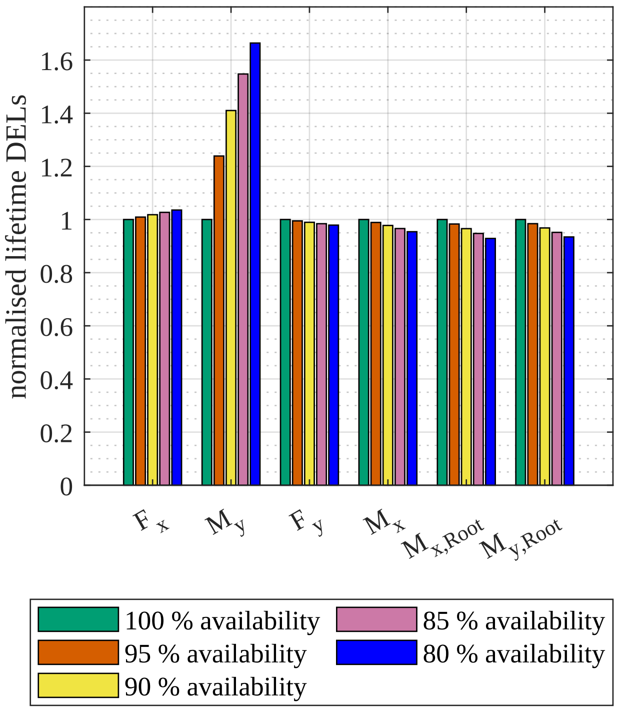

Figure 8. Normalised lifetime DELs for all considered internal forces depending on the availability of the wind turbine. The lifetime DELs are determined using the full lifetime reassessment. The lifetime DELs are normalised with the lifetime DELs for the case of 100 % availability of the wind turbine.

rotor blades are also significantly lower due to the very slow rotation of the rotor compared to normal operation. Therefore, the decrease in availablity leads to an decrease in the lifetime DEL and therefore an increase in the lifetime.

5 Conclusions

In this study, a lifetime reassessment was performed using meta-models considering different operating conditions, namely normal operation and idling. This lifetime calculation was then compared with two other methods using aeroelastic simulations: a full lifetime reassessment which served as a reference soluation and a lifetime calculation according to IEC 61400-3. The simulation model used was the NREL 5 MW reference turbine on the OC3 monopile. Within the lifetime calculations, the lifetime DELs at the monopile at the mudline in wind direction and perpendicular to the wind direction, as well as the blade root moments, were determined. In summary, it can be said that both, the method according to IEC 61400-3 and the meta-

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model-based method lead to good results regarding the lifetime reassessment. The most important findings of the investigations of the three methods for lifetime reassessment are summarised below:

1. The determined lifetime DELs using the method according to IEC 61400-3 deviate less than 15 % compared to the lifetime DELs of the reference solution. By reducing the number of simulations from 194,568 to 70,000, the computational effort for this method could be significantly reduced to around 20 % of the computational effort of the reference solution whereby at the same time ensuring that the deviation from the reference solution is less then 10 % for all considered internal forces.

2. For the meta-model-based method, the deviations of the lifetime DELs are, with a few exceptions, generally small with less than 10 % compared to the lifetime DELs of the reference solution. Only for $M_{y,lifetime}$ and $M_{x,Root,lifetime}$ for the unavailable (idling) case, the deviations are larger. While for $M_{y,lifetime}$ the deviation is 11 %, the deviation for $M_{x,Root,lifetime}$ is approximately 31 %. However, assuming a typical availability of 90 %, these deviations are not critical for the prediction of the total lifetime DELs of M_y and $M_{x,Root}$.

3. For the prediction of the lifetime DELs using the meta-models, the used Kriging meta-models were trained using 17,000 aeroelastic simulations (in total for both operating conditions). A convergence study showed that the number of training samples needed for the generation of the Kriging meta-models can significantly be reduced for the prediction of the lifetime DELs. Assuming a typical availability of the wind turbine, to achieve a deviation of less than 5 % compared to the lifetime DELs predicted using the meta-models with the maximum number of training samples of 8,500 for each operating status, only a total of 1,300 training samples for both operating conditions are required. This means a reduction of the computational effort to less than 0.5 % of the computational effort to determine compared to the reference solution.

4. The predicted lifetime DELs using the meta-models are not conservative using the mean value of the prediction of the Kriging meta-models. However, using the 65th percentile for normal operating and the 70th percentile for idling conditions, leads to a conservative prediction of the lifetime DELs.

The results showed that the use of meta-models could be an alternative option to the approach according to IEC 61400-3 of reducing the number of considered input parameter combinations. By using meta-models, it is possible to consider all actually occured combinations of input parameter combinations with an acceptable computational effort. The predicted lifetime DELs of both methods are of the same order of magnitude, although the computational effort for the meta-model-based method is by more than an order of magnitude lower.

In addition to comparing the three methods for calculating the lifetime, the impact of the availability of the wind turbine on the lifetime was investigated. This investigation showed that for $F_{x,lifetime}$ and $M_{y,lifetime}$ (internal force and the moment at the monopile in wind direction) a reduction in availability leads to an increase in lifetime DELs and a resulting decrease of the remaining lifetime. In particular for $M_{y,lifetime}$ this impact is strong, so that at 80 % availability, the lifetime DEL is approximately 1.6 times greater than at 100 % availability. This shows that it is very import to take idling into account when calculting the lifetime. For the remaining internal forces and moments, however, a reduction in availability leads to a reduction

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of the lifetime DELs.

Nevertheless, there are still a few points that are still open. The prediction of the lifetime DELs using the meta-models for the unavailable case for $M_{y,lifetime}$ and in particular for $M_{x,Root,lifetime}$ show a larger deviation to the reference solution compared to the remaining considered internal forces. Here, it is assumed that these meta-models are not capable of mapping the relationshiop between all input parameter combinations that occur and the associated short-term DELs. This is an issue that should be investigated more closely in further research in order to improve the predictive quality of the corresponding meta-models. Furthermore, the lifetime reassessment using meta-models has only been investigated in this work for the FINO 3 site and the NREL 5 MW reference turbine on the OC3 monopile for six different internal forces at two locations of the offshore wind turbine. Further work should therefore be carried out to investigate the transferability of the results of this work for other sites and other types of wind turbines and/or other support structures. Additionally, in this work only Kriging meta-models were used to predict the lifetime DELs. Future work should also consider different meta-models to find out if the choice of another meta-model type will lead to a better prediction of the lifetime DELs or / and a further reduction of the required computational effort. However, Kriging has the benefit of direct uncertainty estimation, which is essential for making the meta-model conservative. It should also be noted that the use of short-term and lifetime DELs for the lifetime calculation is in particular for the rotor blades a simplification. Although this is a simplification, it is nevertheless the current state of research and also in line with industry standards with regard to lifetime reassessments and global aeroelastic simulations in the time domain.

Data availability. The simulated short-term DELs as well as the corresponding input parameters for the full lifetime reassessment and the lifetime reassessment according to IEC 61400-3 are published as an open-access data publication within the Research Data Repository of the Leibniz University Hannover: https://doi.org/10.25835/ubouf7p2 (Schmidt et al., 2026b). The data are published as text files.

The Kriging meta-models as well as the training and test data for the generation of the meta-models have previously been published as open-access data publications within the Research Data Repository of the Leibniz University Hannover: https://doi.org/10.25835/vfc4xy34 (Schmidt et al., 2025b) and https://doi.org/10.25835/eydp1nl2 (Schmidt et al., 2026a). The meta-models are published as MATLAB files and the training and test data are published as text files.

Author contributions. FS did the main research work, conducted the aeroelastic simulations for the full lifetime reassessment and the lifetime reassessment according to the IEC standard and carried out the lifetime reassessment using the meta-models. Through discussion and feedback, CH and RR contributed to the interpretation and discussion of the results. The paper was revised and improved by all authors.

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https://doi.org/10.5194/wes-2026-38
Preprint. Discussion started: 23 February 2026

References

American Petrolium Institute (API): Recommended Practice for planning, designing and constructing fixed offshore platforms - working stress design - Errata and supplement 3: RP 2A WSD, https://www.api.org/publications-standards-and-statistics/standards-addenda-and-errata/standards-addenda-and-errata/ /media/f86ed982222e44c3b6ee42dc9ba39833.ashx (last access: 6 February 2026), 2007.

American Society for Testing and Materials (ASTM): Standard practices for cycle counting in fatigue analysis, ASTM E1049-85, https://doi.org/10.1520/E1049-85R17, 2017.

Avendaño-Valencia, L. D., Abdallah, I., and Chatzi, E.: Virtual fatigue diagnostics of wake-affected wind turbine via Gaussian Process regression, Renew. Energy, 170, 539-561, https://doi.org/10.1016/j.renene.2021.02.003, 2021.

Bouty, C., Schafhirt, S., Ziegler, L., and Muskulus, M.: Lifetime extension for large offshore wind farms: Is it enough to reassess fatigue for selected design positions?, Energy Procedia, 137, 523-530, https://doi.org/10.1016/j.egypro.2017.10.381, 2017.

Dimitrov, N., Kelly, M. C., Vignaroli, A., and Berg, J.: From wind to loads: wind turbine site-specific load estimation with surrogate models trained on high-fidelity load databases, Wind Energy Science, 3, 2, 767-790, https://doi.org/10.5194/wes-3-767-2018, 2018.

Goodman, J.: Mechanics applied to engineering, Longmans, Green & Co., London, UK, https://archive.org/details/cu31924004025338/mode/2up (last access: 06 February 2026), 1914.

Haghi, R. and Crawford, C.: Data-driven surrogate model for wind turbine damage equivalent load, Wind Energy Sci., 9, 2039-2062, https://doi.org/10.5194/wes-9-2039-2024, 2024.

Häfele, J., Hübler, C., Gebhardt, C. G., and Rolfes, R.: An improved two-step soil-structure interaction modeling method for dynamical analyses of offshore wind turbines, Appl. Ocean Res., 55, 141-150, https://doi.org/10.1016/j.apor.2015.12.001, 2016.

Hübler, C., Gebhardt, C. G., and Rolfes, R.: Hierarchical four-step global sensitivity analysis of offshore wind turbines based on aeroelastic time domain simulations, Renew. Energy, 111, 878-891, https://doi.org/10.1016/j.renene.2017.05.013, 2017a.

Hübler, C., Gebhardt, C. G., and Rolfes, R.: Development of a comprehensive database of scattering environmental conditions and simulation constraints for offshore wind turbines, Wind Energy Science, 2, 2, 491-505, https://doi.org/10.5194/wes-2-491-2017, 2017b.

Hübler, C., Häfele, J., Gebhardt, C. G., and Rolfes, R.: Experimentally supported consideration of operating point dependent soil properties in coupled dynamics of offshore wind turbines, Marine Structures, 57, 18-37, https://doi.org/10.1016/j.egypro.2017.10.381, 2018.

International Electrotechnical Commission (IEC): Wind energy generation systems - part 1: Design requirements, International standard IEC 61400-1, https://webstore.iec.ch/en/publication/26423 (last access: 6 February 2026), 2019a

International Electrotechnical Commission (IEC): Wind energy generation systems - part 3-1: Design requirements for fixed offshore wind turbines, International standard IEC 61400-3-1, https://webstore.iec.ch/en/publication/29360 (last access 6 February 2026), 2019b

Jonkman, B. J.: TurbSims User's Guide v2.00.00, National Renewable Energy Laboratory, Golden, Colorado, USA, 2016.

Jonkman, J., Butterfield, S., Musial, W., and Scott, G.: Definition of a 5-MW Reference Wind Turbine for Offshore System Development, National Renewable Energy Laboratory, Golden, Colorado, USA, https://doi.org/10.2172/947422, 2009.

Jonkman, J. and Musial W.: Offshore Code Comparison Collaboration (OC3) for IEA Task 23 Offshore Wind Technology and Deployment, National Renewable Energy Laboratory, Golden, Colorado, USA, https://doi.org/10.2172/1004009, 2010.

Jonkman, J.: The New Modularization Framework for the FAST Wind Turbine CAE Tool, 51st AiAA Aerospace Sciences Meeting, including the New Horizons Forum and Aerospace Exposiotion, 7-10 January 2013, Dallas, Texas, USA, 1-26, https://doi.org/10.2514/6.2013-202, 2013.

Kallehave, D., Thilsted, C.L., and Liingaard, M.: Modification of the API P-y Formulation of Initial Stiffness of Sand, in: Offshore Site Investigation and Geotechnics: Integrated Technologies - Present and Future, 12-14 September 2012, London, UK, https://onepetro.org/SUTOSIG/proceedings-abstract/OSIG12/OSIG12/SUT-OSIG-12-50/3358?redirectedFrom=PDF (last access: 6 February 2026), 2012.

Katsikogiannis, G., Sørum, S. H., Bachynski, E. E., and Amdahl J.: Environmental lumping for efficient fatigue assessment of large-diameter monopile wind turbines, Marine Structures, 77, 102939, https://doi.org/10.1016/j.marstruc.2021.102939, 2021.

Müller, K., Dazer, M., and Cheng, P.W.: Damage assessment of floating offshore wind turbines using response surface modeling, Energy Procedia, 137, 119-133, https://doi.org/10.1016/j.egypro.2017.10.339, 2017.

Müller, F., Krabbe, P., Hübler, C., and Rolfes, R.: Assessment of meta-models to estimate fatigue loads of an offshore wind turbine, in: The Proceedings of the Thirty-First (2021) International Ocean and Polar Engineering Conference, Rhodos, Greece. 20-25 June 2021, 543-550, https://onepetro.org/ISOPEIOPEC/proceedings-abstract/ISOPE21/ISOPE21/ISOPE-I-21-1214/464471 (last access: 3 December 2025), 2021.

Müller, F., Hübler, C., and Rolfes, R.: Transferability of meta-model configurations for different wind turbine types, in: Proceedings of the ASME 2022 41st International Conference on Ocean, Offshore and Arctic Engineering, Vol. 8: Ocean Renewable Energy, OMAE 2022, Hamburg, Germany, 5-10 June 2022, 79698, https://doi.org/10.1115/OMAE2022-79698, 2022.

Murcia, J. P., Réthoré, P.-E., Dimitrov, N., Natarajan, A., Sørensen, J. D., Graf, P., and Kim, T.: Uncertainty propagation through an aeroelastic wind turbine model using polynomial surrogates, Renewable Energy, 119,910-922, https://doi.org/10.1016/j.renene.2017.07.070, 2018.

Rasmussen, C. E., and Williams, C. K. I.: Gaussian Processes for Machine Learning, Adaptive Computation and Machine Learning, MIT Press, Cambridge, Massachusetts, USA, https://doi.org/10.7551/mitpress/3206.001.0001, 2006.

Santner, T. J., WIlliams, B. J., and Notz, W. I.: The design and Analysis of Computer Experiments, Second Edition, Springer Series in Statistics, edited by: Diggle, P., Gather, U., and Zeger, S., Springer New York, New York, https://doi.org/10.1007/978-1-4939-8847-1, 2018.

Schmidt, F., Hübler, C., and Rolfes, R.: Lifetime reassessment of offshore wind turbines using meta-models, in: 14th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP14), Dublin, Ireland, 9-13 July 2023, http://hdl.handle.net/2262/103307 (last access 6 February 2026), 2023

Schmidt, F., Hübler, C., and Rolfes, R.: Kriging meta-models for damage equivalent load assessment of idling offshore wind turbines, Wind Energ. Sci., 10,3069-3089, https://doi.org/10.5194/wes-10-3069-2025, 2025.

Schmidt, F., Hübler, C., and Rolfes, R: Simulation data and Kriging meta-models of an offshore wind turbine, LUIS [data set], https://doi.org/10.25835/vfc4xy34, 2025.

Schmidt, F., Krabbe, P., Hübler, C., and Rolfes, R: Open-access database for meta-models for fatigue calculations of reference wind turbines, LUIS [data set], https://doi.org/10.25835/eydp1nl2, 2026.

Schmidt, F., Hübler, C., and Rolfes, R.: Simulation data for lifetime reassessment of an offshore wind turbine, LUIS [data set], https://doi.org/10.25835/ubouf7p2, 2026.

Schröder, L., Dimitrov, N. K., Verelst, D. R., and Sørensen, J. A., Wind turbine site-specific load estimation using artificial neural networks calibrated by means of high-fidelity load simulations, J.Phys.: Conf. Ser., 1037, 62027, 10.1088/1742-6596/1037/6/062027, 2018.

Singh, D., Dwight, R., and Viré, A.: Probabilistic surrogate modeling of damage equivalent loads on onshore and offshore wind turbines using mixture density networks, Wind Energ. Sci., 9, 1885-1904, https://doi.org/10.5194/wes-9-1885-2024, 2024.

https://doi.org/10.5194/wes-2026-38
Preprint. Discussion started: 23 February 2026

Singh, D., Haugen, E., Laugesen, K., Dwight, R. P., and Viré, A.: Data-driven probabilistic surrogate model for floating wind turbine lifetime damage equivalent load prediction, Wind Energy Sci., 10, 2865-2888, https://doi.org/10.5194/wes-10-2865-2025, 2025.

Slot, R.M., Sørensen, J. D., Sudret, B., Svenningsen, L., and Thøgersen, M. L.: Surrogate model uncertainty in wind turbine reliability assessment, Renewable Energy, 151, 1150-1162, https://doi.org/10.1016/j.renene.2019.11.101, 2020.

Stewart, G. M.: Design load analysis of two floating offshore wind turbine concepts, Ph.D. thesis, University of Massachusetts-Amherst, USA, 126 pp, 10.7275/7627466.0, 2016.

Stieng, L. E. S. and Muskulus, M.: Reliability-based design optimization of offshore wind turbine support structures using analytical sensitivities and factorized uncertainty modeling, Wind Energy Science, 5, 1, 171-198, https://doi.org/10.5194/wes-5-171-2020, 2020.

Velarde, J., Kramhøft, C., and Sørensen, J. D.: Global sensitivity analysis of offshore wind turbine foundation fatigue loads, Renew. Energy, 140, 177-189, 10.1016/j.renene.2019.03.055, 2019.

Velarde, J., Kramhøft, C., Sørensen, J. D., and Zorzi, G.: Fatigue reliabilty of large monopiles for offshore wind turbines, Int. J. Fatigue, 134(2020), 105487, 10.1016/j.ijfatigue.2020.105487, 2020.

Wilkie, D.: Advancing probabilistic risk assessment of offshore wind turbines on monopiles, PhD thesis, University College London, London, UK, https://discovery.ucl.ac.uk/id/eprint/10090835 (last access: 6 February 2026), 2020.

Yang, H., Zhu, Y., Lu, Q., and Zhang, J.: Dynamic reliability based design optimization of the tripod sub-structure of offshore wind turbines, Renew. Energy, 78, 16-25, 10.1016/j.renene.2014.12.061, 2015.

Ziegler, L. and Muskulus, M.: Fatigue reassessment for lifetime extension of offshore wind monopile substructures, Journal of Physics: Conference Series, 753, 092010, 10.1088/1742-6596/753/9/092010, 2016.