14th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP14
Dublin, Ireland, July 9-13, 2023

Relevance of Uncertainty Modelling for Wind Turbine Lifetime Estimations

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ABSTRACT: For the fatige design of wind turbines, the determination of so-called lifetime "damage equivalent loads" (DELs) is essential. Lifetime DELs highly depend on the environmental conditions acting on the turbine. Although environmental conditions are in most cases highly uncertain, their uncertainty is only modelled implicitly by using a quasi-deterministic approach according to the industry standard. One reason why non-deterministic simulation approaches are rare is their high computing time. However, as there has recently been significant progress in using meta-models for the DEL approximation, more advanced, explicit uncertainty modelling becomes a current research focus. In this work, four different uncertainty models – namely quasi-deterministic, probabilistic, interval and p-box – are applied to wave height data. Subsequently, for all uncertainty models, lifetime DELs are calculated for a generic 5 MW offshore wind turbine based on a meta-model. As a result, it is shown that the differences in the resulting DELs are relatively small. Hence, if sufficient data of environmental conditions are available, less advanced uncertainty models can be applied.

For the design of wind turbines, the determination of the fatigue lifetime is essential. Frequently, so-called lifetime "damage equivalent loads" (DELs) are used as a measure for the fatigue lifetime (Dimitrov et al. (2018); Hübler and Rolfes (2021)). Lifetime DELs are calculated by combining and weighting several short-term DELs, i.e., DELs for periods of several minutes. The short-term DELs can be determined by analysing time series calculated using aero-elastic simulations. To take uncertainties of environmental conditions (ECs) – which always exist due to scattering of wind and wave conditions but also due to long-term changes in ECs – into account, usually a large number of stochastic aero-elastic simulations is carried out for different combinations of wind speeds, wave heights and wave periods (and possibly other ECs). Subsequently, the short-term DELs of all simulations are combined resulting in a lifetime DEL (Dimitrov et al. (2018); Hübler and Rolfes (2021)). However, this more or less deterministic procedure, which is recommended by the current standards (International Electrotechnical Comission (2019)), considers uncertainty only implicitly. Other non-deterministic approaches taking uncertainties explicitly into account, e.g., probabilistic approaches based on Monte Carlo simulations (MCSs) and joint statistical distributions of all relevant ECs, are available (Müller and Cheng (2018); Muskulus and Schafhirt (2015)) but neither state of the art nor industry standard. One reason why non-deterministic simulation approaches are rare is their high computing time (Hübler et al. (2018)). However, recently there was significant progress in using meta-models, e.g., Gaussian Process Regressions (GPRs) or Artificial Neural Networks (ANNs), for the short-term DEL approximation (Dimitrov et al. (2018); Schröder et al. (2018); Müller et al. (2021)). Since short-term DELs can be quickly approximated using meta-models and, therefore, a huge number of short-term DELs can be taken into account when computing a lifetime DEL, the computational effort of non-deterministic approaches is manageable by now. This is why different explicit uncertainty models – e.g., probabilistic, interval or p-box – become more popular in the context of fatigue lifetime estimations of wind turbines (Hübler and Rolfes (2021); Müller and Cheng (2018); Hübler et al. (2020)). However, until now, the relevance of advanced, explicit uncertainty modelling has not been analysed in detail. Therefore, in this work, four different uncertainty models – namely quasi-deterministic, probabilistic, interval and p-box – are applied to measurement data of ECs. To keep the analysis simple, in this work, the wave height is the only EC being assumed to be uncertain. All other ECs are set to deterministic values depending on the wave height. For all uncertainty models, lifetime DELs are calculated for a generic 5 MW offshore wind turbine based on a GPR meta-model. The differences in the resulting DELs are compared to judge the relevance of the uncertainty modelling approach.

1. GENERAL METHODOLOGY

To determine the relevance of uncertainty modelling for wind turbine lifetime estimations, four aspects have to be considered: suitable uncertainty models, data for ECs which are used to derive the uncertainty models, a measure for the lifetime and a model to determine the lifetime or its measure based on the uncertain ECs.

The different uncertainty models are explained in detail in Section 2.

Data are taken from the FINO3 measurement platform in the North Sea. The measurement mast delivers a large amount of high-quality measurements of ECs. Inter alia, wind speeds v_s, air densities ρ (or more specifically humidity, air pressure, air temperature that are required to calculate the air density), significant wave heights H_s and wave peak periods T_p are measured. The FINO3 platform has been measuring continuously since 2009. Here, a measurement period of 7 years (1st Dec. 2010 to 30th Nov. 2016) and three hour mean values are considered to guarantee stationary wave conditions. More detailed information regarding the measurements at FINO3 can be found, for example, on the website (https://www.fino3.de/en/). The post-processing of the raw data, e.g., the reduction of tower shadow effects or the computation of air densities, is explained in Hübler et al. (2017).

A measure for the fatigue lifetime is the lifetime DEL (Dimitrov et al. (2018)), which is based a combination of short-term DELs. A short-term DEL represents a load signal with a constant frequency and amplitude (S_{eq}). It yields the same damage according to the Palmgren-Miner rule as an investigated (realistic) short-term load signal with various frequencies and amplitudes (S_i):

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

where $N_{\text{ref}} = 600$ to set the frequency of the DEL to 1 Hz for a 10-minute period. S_i and n_i are different amplitudes and the corresponding number of cycles in the original load signal, when applying a rainflow counting. The material exponent is chosen as $m = 3$. Short-term DELs give us a representative measure of fatigue for a short-time period (e.g., ten minutes). However, to gain knowledge about fatigue lifetimes, DELs have to be calculated in the long term. For this purpose, a lifetime DEL can be defined:

$$S_{\text{LT}} = \left(\int S_{\text{eq}}(\mathbf{x})^m f(\mathbf{x}) d\mathbf{x} \right)^{1/m}, \tag{2}$$

where $\mathbf{x}$ is the input vector of ECs, i.e., $\mathbf{x} = [v_s \quad H_s \quad T_p \quad \rho]^{\text{T}}$, and $f(\mathbf{x})$ is the joint probability density function of $\mathbf{x}$. In this work, only operating conditions are considered. This means that, for example, no ECs are considered, for which the wind speed exceeds the cut-off wind speed of 25 ms^{-1}.

To determine the short-term DELs in Eq. (1), load signals for specific positions at a turbine are required. In this work, only a single exemplary load and position is considered: the overturning moment in wind direction at mudline of the NREL 5 MW reference wind turbine (Jonkman et al. (2009)) with the OC3 monopile as substructure (Jonkman and Musial (2010)). For this position, the load time series could be simulated using an aero-hydro-servo-elastic simulation code. However, as stated in the introduction, meta-modelling replacing aero-elastic simulations by directly correlating ECs and short-term DELs have become available recently. This is why in this work, the GPR meta-models ($g(\mathbf{x})$) of Hübler and Rolfes (2021), is used:

$$\hat{S}_{\text{eq}}(\mathbf{x}) = g(v_s, H_s, T_p, \rho). \tag{3}$$

For more information regarding the meta-model and/or the considered turbine and load, the reader is referred to Hübler and Rolfes (2021).

Finally, to keep the analysis simple, in this work, the number of uncertain ECs is reduced to one. This means that the wave height H_s is considered as uncertain. The wave period is defined as a function of the wave height $T_p(H_s) = 12.7 \times \sqrt{0.102\,\text{s}^2\text{m}^{-1} \times H_s}$ following current standards (International Electrotechnical Comission (2019)). The air density has a negligible influence on the fatigue lifetime (Hübler and Rolfes (2021)). Hence, it is set to a constant value: $\bar{\rho} = 1.225\,\text{kgm}^{-3}$. For the wind speed, eleven bins of 2 ms^{-1} are defined within the operational range of the turbine, i.e., 3 to 5 ms^{-1}, ..., 23 to 25 ms^{-1}. For each bin, the DEL calculation is done separately. The wind speed is assumed to be constant in each bin, e.g., 4 ms^{-1}, etc. This simplification leads to the following equation for the lifetime DEL calculation:

$$S_{\text{LT,simp}} = \left(\sum_{i=1}^{11} g(\bar{v}_{s,i}, H_s, T_p(H_s), \bar{\rho})^m P_i \right)^{1/m}, \tag{4}$$

where P_i and $\bar{v}_{s,i}$ are the occurrence probability of and the mean wind speed in bin i, respectively.

2. UNCERTAINTY MODELS

In the previous section, the general methodology to approximate lifetime DELs based on uncertain ECs and a meta-model correlating ECs and short-term DELs was briefly outlined. In Equation (4), the only variable is the wave height H_s. In the following subsections, four different uncertainty models to model H_s are presented and applied to the available EC data measured at FINO3.

2.1. *Quasi-deterministic approach*

The quasi-deterministic approach is a slightly simplified version of the method recommended by current standards (International Electrotechnical Comission (2019)). For this approach, a constant wave height in each wind speed bin is assumed. Hence, first, the entire wave height data is clustered according to the wind speed. Second, for each wind speed bin, the mean wave height $\bar{H}_{s,i}$ is determined using all wave data in this bin. Finally, $\bar{H}_{s,i}$ and the GPR meta-model ($g(\mathbf{x})$) – visualised in Figure 1 – are used to determine the lifetime DEL:

$$S_{\text{LT,qd}} = \left(\sum_{i=1}^{11} g(\bar{v}_{s,i}, \bar{H}_{s,i}, T_p(\bar{H}_{s,i}), \bar{\rho})^m P_i \right)^{1/m}. \tag{5}$$

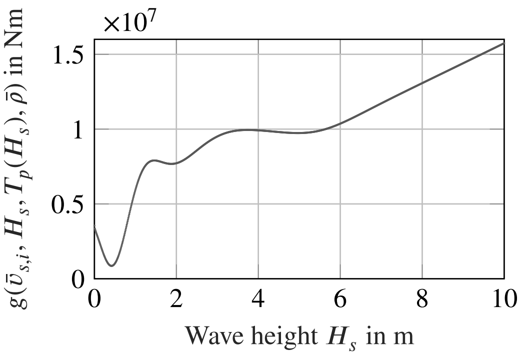

Figure 1: Functional relationship between wave height and short-term DEL for $\bar{v}_{s,i} = 6ms^{-1}$.

The probability of the bin P_i is:

$$P_i = \frac{N_i}{\sum_{j=1}^{11} N_j}, \tag{6}$$

where N_i is the number of measurements in bin i. Within the seven-year measurement period, about 15 000 valid three hour measurements are available within the operating range of the wind turbine, i.e., $\sum_{j=1}^{11} N_j \approx 15\,000$. All bin probabilities and mean wave heights are summarised in Table 1.

Table 1: Mean wind speeds, mean wave heights and probabilities of each bin i.

$\bar{v}_{s,i}$ in ms^{-1}	4	6	8	10	12	14	16	18	20	22	25
$\bar{H}_{s,i}$ in m	0.87	1.0	1.2	1.5	1.8	2.1	2.7	3.2	3.8	4.7	5.1
P_i in %	12	16	17	18	16	10	6.2	2.9	1.1	0.44	0.21

2.2. *Probabilistic approach*

For the probabilistic approach a theoretical statistical distribution is fitted to the available wave height data in each wind speed bin using a maximum likelihood estimation. Hübler et al. (2017) showed that different distributions, e.g., Weibull or extreme value distribution, fit wave data best in the various wind speed bins. Here, it is abstained from using different distributions for each bin, but a Weibull distribution is fitted in all bins:

$$f(x|a,b) = \begin{cases} \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-\left(\frac{x}{a}\right)^{b}} & \text{for } x \geq 0 \\ 0 \quad \text{for } x < 0. \end{cases} \tag{7}$$

The corresponding probability density functions (PDFs) are shown in Figure 2 and the distribution parameters a and b are given. To calculate the lifetime DEL in case of a probabilistic approach, MCS is applied. Based on the distributions determined, $N_{\text{MCS}} = 10^5$ random samples of the wave height $H_{s,j}$ are generated for each bin. Subsequently, the lifetime DEL can be computed as follows:

$$S_{\text{LT,prob}} = \left(\sum_{i=1}^{11} \left(\frac{P_i}{N_{\text{MCS}}} \sum_{j=1}^{N_{\text{MCS}}} g(\mathbf{x}_j)^m \right) \right)^{1/m}, \tag{8}$$

where $g(\mathbf{x}_j) = g(\bar{v}_{s,i}, H_{s,j}, T_p(H_{s,j}), \bar{\rho})$.

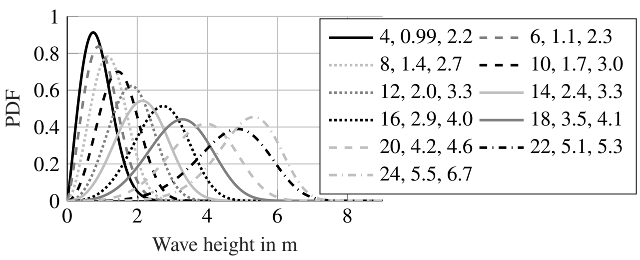

Figure 2: Illustration of the wave height distributions. Legend: $\bar{v}_s$, a and b (i.e., distribution parameters).

2.3. *Interval approach*

A probabilistic approach assumes that sufficient data to fit a distribution is available in each bin. This assumption might not be valid for bins of high wind speeds, where data are be scarce. An interval approach – just defining a maximum and minimum for each bin – might be an alternative, as less data are required. In general, maxima and minima can be determined using different approach, e.g., the largest/smallest measured or small/large quantiles can be used. In this work, limits of the intervals are chose in such a way that 68.3 % of the measurement data lie within the interval. This corresponds to the $\pm\sigma$ rule. The resulting limits of H_s, i.e., $\left[H_{s,\min,i}, H_{s,\max,i}\right]$, in each bin are summarised in Table 2. Since the functional relationship between wave height and short-term DELs is non-linear (cf. Figure 1), the lowest wave height does not necessarily yield the smallest short-term DEL. Therefore, a minimisation and a maximisation is conducted:

$$S_{\text{max,i}} = \max\left(g(\mathbf{x}_i)\right) \quad \text{and} \tag{9}$$

$$S_{\text{min,i}} = \min\left(g(\mathbf{x}_i)\right) \tag{10}$$

with $g(\mathbf{x}_i) = g(\bar{v}_{s,i}, H_s, T_p(H_s), \bar{\rho})$ and $H_{s,\min} \leq H_s \leq H_{s,\max}$. For the optimisations, in this work, a genetic algorithms is applied. After having determined the minimum/maximum long-term DEL in each bin, the lifetime DEL can be determined by weighting the bins according to their probability:

$$S_{\text{LT,int,max}} = \left(\sum_{i=1}^{11} \left(P_i \, S_{\text{max,i}}^m \right) \right)^{1/m} \quad \text{and} \tag{11}$$

$$S_{\text{LT,int,min}} = \left(\sum_{i=1}^{11} \left(P_i \, S_{\text{min,i}}^m \right) \right)^{1/m}. \tag{12}$$

2.4. *Probability-box approach*

A p-box is an imprecise probability distribution which is used to model data which feature aleatory

Table 2: Wave height intervals each bin i.

Bin	1	2	3	4	5	6	7	8	9	10	11
$H_{s,\min,i}$ in m	0.48	0.58	0.74	0.96	1.2	1.4	2.0	2.5	3.0	3.7	4.1
$H_{s,\max,i}$ in m	1.3	1.4	1.7	2.0	2.5	2.9	3.4	4.1	4.7	5.6	5.8

and epistemic uncertainty. A p-box can be represented by the bounds on its cumulative distribution function (CDF). A reason for the epistemic uncertainty can be statistical uncertainty due to limited data. If this uncertainty is reduced towards zero, e.g., if a large amount of data is available, the bounded CDF converges to a single CDF and the p-box becomes a classical distribution. In general, several methods are suitable to determine imprecise distributions based on measurement data (Zhang et al. (2013)). In this work, Weibull distributions with interval parameters are used, i.e., the distribution parameters a and b are modelled as intervals, e.g., $a_{\min} \leq a \leq a_{\max}$. The intervals are determined using the 95 % confidence intervals for a and b and are given in Table 3. Obviously, the intervals widen for bins with less data, i.e., high wind speeds.

Based on the intervals, the bounds of the wave height CDFs $F(H_s)$ can be determined as follows:

$$F_{\min}(H_s) = \min(F(H_s|a,b)) \quad \text{and} \tag{13}$$
$$F_{\max}(H_s) = \max(F(H_s|a,b)) \tag{14}$$

with $a_{\min} \leq a \leq a_{\max}$ and $b_{\min} \leq b \leq b_{\max}$. Similarly, for a given percentile $p \in [0,1]$, the corresponding limits for the wave height are:

$$H_{s,\min} = \min(F^{-1}(p|a,b)) \quad \text{and} \tag{15}$$
$$H_{s,\max} = \max(F^{-1}(p|a,b)) \tag{16}$$

with F^{-1} being the inverse of the wave height CDF. Minimisations and maximisations are conducted using a genetic optimisation method. Two exemplary imprecise wave height CDFs for different wind speed bins are shown in Figure 3.

To calculate the lifetime DEL in case of a p-box approach, MCS in combination with optimisation is applied. For each bin i, first, $N_{\text{MCS}} = 10^5$ random percentile values $p \in [0,1]$ are generated. For each of these values, $H_{s,\min,i,p}$ and $H_{s,\max,i,p}$ are determined using Equation 15 and 16. And second, a

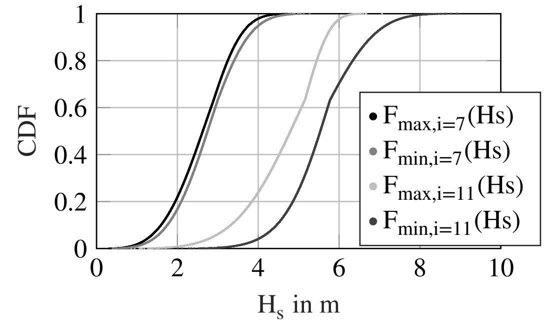

Figure 3: Illustration of two exemplary wave height p-boxes ($15\,ms^{-1} \leq v_s \leq 17\,ms^{-1}$ and $23\,ms^{-1} \leq v_s \leq 25\,ms^{-1}$).

minimisation and a maximisation are conducted for each of the percentile values p in each bin i:

$$S_{\text{max,i,p}} = \max\left(g(\mathbf{x}_{i,p})\right) \quad \text{and} \tag{17}$$
$$S_{\text{min,i,p}} = \min\left(g(\mathbf{x}_{i,p})\right) \tag{18}$$

with $g(\mathbf{x}_{i,p}) = g(\bar{v}_{s,i}, H_s, T_p(H_s), \bar{\rho})$ and $H_{s,\min,i,p} \leq H_s \leq H_{s,\max,i,p}$. As before, for the optimisations, a genetic algorithm is applied in this work. After having determined the minimum/maximum short-term DEL for each sample p in each bin i, the overall lifetime DEL can be determined by weighting the bins according to their probability:

$$S_{\text{LT,pBox,max}} = \left(\sum_{i=1}^{11}\left(\frac{P_i}{N_{\text{MCS}}}\sum_{j=1}^{N_{\text{MCS}}} S^m_{\text{max,i,p}}\right)\right)^{1/m}, \tag{19}$$

$$S_{\text{LT,pBox,min}} = \left(\sum_{i=1}^{11}\left(\frac{P_i}{N_{\text{MCS}}}\sum_{j=1}^{N_{\text{MCS}}} S^m_{\text{min,i,p}}\right)\right)^{1/m}. \tag{20}$$

3. RESULTS

3.1. *Quasi-deterministic approach*

The quasi-deterministic approach assumes a constant wave height in each wind speed bin. Based on this mean wave height, DELs for each bin can be

Table 3: Intervals for distribution parameters for the Weibull p-boxes in all bins.

Bin	1	2	3	4	5	6	7	8	9	10	11
$a_{\min}$	0.97	1.1	1.3	1.6	2.0	2.3	2.9	3.4	4.0	4.8	5.2
$a_{\max}$	1.0	1.2	1.4	1.7	2.1	2.4	3.0	3.6	4.3	5.3	5.8
$b_{\min}$	2.1	2.2	2.6	2.9	3.2	3.2	3.8	3.8	4.1	4.3	5.1
$b_{\max}$	2.2	2.4	2.8	3.1	3.4	3.5	4.2	4.4	5.2	6.4	8.7

calculated (cf. Equation 5). Results are summarised in Table 4. It becomes apparent that bins for high wind speeds do not contribute significantly to the lifetime DEL. This is the case, although the DELs of these bins are quite high. However, the occurrence probability of these bin is too low (cf. Table 1) for a significant influence.

3.2. *Probabilistic approach*

For the probabilistic approach, $N_{\mathrm{MCS}} = 10^5$ random samples of the wave height $H_{s,j}$ are generated for each wind speed bin. For each sample, the GPR meta-model is evaluated. Finally, the lifetime DEL is computed using Equation 8. Results are summarised in Table 5. In addition, Figure 4 shows exemplarily the distribution of the DELs $(g(\bar{v}_{s,i}, \bar{H}_{s,j}, T_p(\bar{H}_{s,j}))$ in the fifth bin.

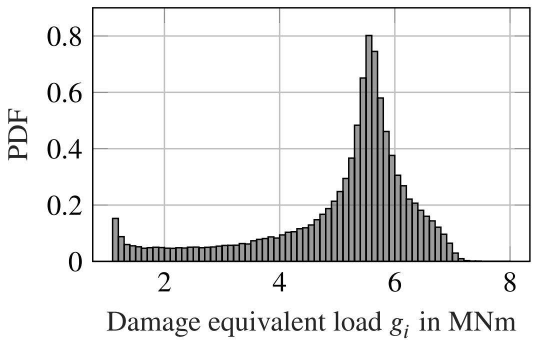

Figure 4: Distribution of DELs $(g(\bar{v}_{s,i}, \bar{H}_{s,j}, T_p(\bar{H}_{s,j}))$ in bin $i = 5$, i.e., 11 ms^{-1} $\leq v_s \leq$ 13 ms^{-1}.

The results clarify that low to medium wind speed bins contribute most to the lifetime DEL. However, it has to be mentioned that DELs scatter significantly within each bin. Hence, on the one hand, for the probabilistic approach a sufficiently high number of samples has to be used. On the other hand, the use of a probabilistic approach compared to a quasi-deterministic approach – applying the mean value of each bin – might be valuable.

3.3. *Interval approach*

For the interval approach, a maximum and a minimum for the DEL in each bin and, subsequently, for the lifetime DEL is determined using Equation 9 to 12. Results are summarised in Table 6. As expected, there is a significant difference between the minimum and the maximum lifetime DEL. In order to be conservative, the maximum value is probably the better choice for a design. Interestingly, not only the lifetime DEL is different for the interval bounds, but the contributions of the various wind speed bins as well. When considering the maximum DELs, the influence of bins with low wind speeds increases. Probably, this is due to the nonlinear correlation of wave heights and DELs (cf. Figure 1) and the higher probabilities of these wind speeds.

3.4. *Probability-box approach*

For the p-box approach, imprecise distributions for the DELs in each bin are determined using a combination of MCS and optimisation. Subsequently, minimum and maximum lifetime DELs are determined using Equation 19 and 20. Results are summarised in Table 7. Two exemplary imprecise DEL CDFs for different wind speed bins are shown in Figure 5. The difference between the minimum

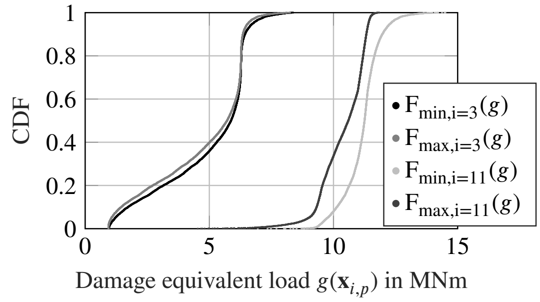

Figure 5: Illustration of two exemplary DEL p-boxes (7 ms^{-1} $\leq v_s \leq$ 9 ms^{-1} and 23 ms^{-1} $\leq v_s \leq$ 25 ms^{-1}).

Table 4: Summary of the results for the quasi-deterministic approach. 1) DELs $g_i = g(\bar{v}_{s,i}, \bar{H}_{s,i}, T_p(\bar{H}_{s,i}), \bar{\rho})$ in each bin and overall. 2) Percentage share $p_{\%,i} = ((g_i)^m\, P_i)\, S_{LT,qd}^{-m}$ of each bin i.

Bin	1	2	3	4	5	6	7	8	9	10	1	overall
g_i in MNm	5.4	6.0	5.9	5.5	5.5	6.1	6.9	7.9	8.7	9.7	11	6.00
$p_{\%,i}$ in %	8.5	16	16	14	12	11	9.3	6.7	3.4	1.9	1.3	100

Table 5: Summary of the results for the probabilistic approach. 1) DELs in each bin and overall: $\bar{g}_i = \left(1/N_{MCS} \sum_{j=1}^{N_{MCS}} g(\bar{v}_{s,i}, H_{s,j}, T_p(H_{s,j}), \bar{\rho})^m\right)^{1/m}$. 2) Percentage share $p_{\%,i} = ((\bar{g}_i)^m\, P_i)\, S_{LT,prob}^{-m}$ of each bin i.

Bin	1	2	3	4	5	6	7	8	9	10	1	overall
$\bar{g}_i$ in MNm	6.3	6.1	5.5	5.3	5.6	6.1	7.0	7.9	8.6	9.7	11	6.04
$p_{\%,i}$ in %	13	16	13	13	12	11	9.8	6.6	3.3	1.8	1.2	100

Table 6: Summary of the results for the interval approach. 1) Maximum/minimum DELs $S_{min,i}$ and $S_{max,i}$ in each bin and overall. 2) Percentage share $p_{\%,min,i} = \left(S_{min,i}^m\, P_i\right) S_{LT,int,min}^{-m}$ and $p_{\%,max,i} = \left(S_{max,i}^m\, P_i\right) S_{LT,int,max}^{-m}$ of each bin.

Bin	1	2	3	4	5	6	7	8	9	10	11	overall
$S_{\mathrm{min,i}}$ in MNm	0.78	1.5	2.7	3.9	4.7	5.2	6.1	7.2	8.0	8.5	9.8	4.33
$S_{\mathrm{max,i}}$ in MNm	8.6	7.9	6.3	6.1	6.3	6.9	7.8	8.7	9.2	10	11	7.21
$p_{\%,min,i}$ in %	0.07	0.61	4.2	14	19	18	18	14	7.1	3.3	2.4	100
$p_{\%,max,i}$ in %	20	21	12	11	10	9.0	8.0	5.3	2.4	1.3	0.8	100

Table 7: Summary of the results for the p-box approach. 1) Maximum/minimum DELs in each bin and overall: $\bar{S}_{min,i} = \left(1/N_{MCS} \sum_{j=1}^{N_{MCS}} S_{min,i,p}^m\right)^{1/m}$ and $\bar{S}_{max,i} = \left(1/N_{MCS} \sum_{j=1}^{N_{MCS}} S_{max,i,p}^m\right)^{1/m}$. 2) Percentage share $p_{\%,min,i} = \left(\bar{S}_{min,i}^m\, P_i\right) S_{LT,pBox,min}^{-m}$ and $p_{\%,max,i} = \left(\bar{S}_{max,i}^m\, P_i\right) S_{LT,pBox,max}^{-m}$ of each bin i.

Bin	1	2	3	4	5	6	7	8	9	10	11	overall
$S_{\mathrm{min,i}}$ in MNm	6.1	6.0	5.4	5.3	5.5	6.0	7.0	7.8	8.5	9.4	10	5.95
$S_{\mathrm{max,i}}$ in MNm	6.4	6.2	5.5	5.4	5.6	6.2	7.1	8.0	8.9	10	11	6.13
$p_{\%,min,i}$ in %	13	16	13	13	12	11	10	6.6	3.3	1.7	1.1	100
$p_{\%,max,i}$ in %	13	16	13	12	12	11	10	6.7	3.4	1.9	1.3	100

and the maximum lifetime DEL is relatively small for the p-box approach. A reason for that is the small epistemic uncertainty for those bins that contribute most to the lifetime DEL, i.e., bins of small to medium wind speeds. These bins contain a lot of data. On the one hand, this reduces the epistemic uncertainty (cf. Figure 5). On the other hand, it increases the probability P_i (cf. Table 4) and, therefore, the contribution to the lifetime DEL of these bins.

3.5. *Comparison*

Comparing the results in Table 4 to 7, it becomes apparent that the differences between the various uncertainty models are relatively small. The quasi-deterministic and the probabilistic approach only differ by about 1 %. The p-box yields a range of $\pm$ 1.5 % compared to the probabilistic approach. Both differences are negligible. Only the interval approach leads to different results by predicting a range of approximately $\pm$ 25 % compared to the other approaches. However, this is not surprising, as the interval approach does not focus on mean values but includes 68 % of the data in its interval (one σ rule). Hence, the upper limit of the interval is always conservative (here, approximately 20 % higher compared to the other approaches). Therefore, an interval approach might not be suitable in the context of lifetime calculations or at least other limits have to be chosen for the interval to reduce conservativity.

4. CONCLUSIONS

In this work, four different uncertainty models in the context of lifetime estimations for wind turbines have been analysed and compared. On the one hand, it was shown that the use of more advanced, explicit uncertainty models is feasible when applying meta-models for the short-term DEL estimation. On the other hand, the results clarify that more advanced uncertainty models might not be required if sufficient measurement data are available. However, this hypothesis is only valid for the simplified approach of this work, i.e., the wave height being the only uncertain variable. If other ECs are modelled as uncertain as well, the statistical uncertainty will increase for the same amount of measurement data. Hence, in this (more realistic) case, it can be presumed that more advanced uncertainty models will make a difference. Therefore, future work should analyse the effect of the presented uncertainty models when considering several ECs as uncertain. Moreover, the influence of the uncertainty models on other DEL – not only the DEL for the overturning moment at mudline – should be investigated in future, as especially DEL for blade loads might behave differently.

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