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Reliability analysis of fatigue damage extrapolations of wind turbines using offshore strain measurements

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Abstract. While substructures of offshore wind turbines become older and begin to reach their design lifetimes, the relevance of measurement based lifetime extension increases. To make well-founded decisions on possible lifetime extensions, damage extrapolations based on measurements are needed. However, although for all substructures, fatigue damage calculations were conducted during the design process, there is no consensus on how to extrapolate 10-minute damages to lifetime damages. Furthermore, extrapolating damages is an uncertain process and its actual reliability is unknown. Therefore, the current work uses data of offshore strain measurements to assess different approaches of extrapolating damages, and to investigate the reliability of damage extrapolations. For the present data, the most reliable lifetime estimations are possible, if the damage data is split up into wind speed bins. For each wind speed bin, the occurrence probability should be based on data rather than on design documents. Moreover, using mean damages in each bin is the best practice. Furthermore, our results suggest that strain measurements of about 9 to 10 months lead to a relatively representative and unbiased data set. Therefore, if there are no significant changes of the turbine or the environmental conditions over the lifetime, damage extrapolations based on such a time period are sufficiently accurate.

1. Introduction

By now, the oldest offshore wind turbines (OWTs) are operating for 20 years and more or are even already decommissioned [1]. Therefore, lifetime extension becomes a really important topic. Every year of additional operation beyond the expected lifetime can be fairly profitable, as all debts etc. are already paid back. A first standard for lifetime extension for wind turbines was recently introduced [2]. It proposes lifetime extensions based on a combination of inspections and renewed fatigue damage simulations using an updated design model. These simulation-based fatigue reassessments for OWT substructures are investigated, for example, by Ziegler and Muskulus [3, 4] and Bouty et al. [5]. However, if the load conditions - the OWTs were exposed to - are known, better approximations of the remaining lifetime can be made. Hence, the new standard [2] recommends to use measured load data if available. The first lifetime estimations based on measured strain data were already conducted in the 90s [6, 7]. However, due to the increasing relevance of lifetime extensions, measurement based damage extrapolations (i.e. lifetime calculations) became a research focus again [8, 9], as it is a valuable addition to simulation based analyses.

For all substructures of OWTs, fatigue damage calculations are conducted during the design process. Still, for measured loads, there is no consensus on how to extrapolate 10-minute damages to lifetime damages. Extrapolations based on measurements are rare, and if any, simplified. For example, damages are just linearly interpolated for longer time periods. Nevertheless, extrapolations are needed, if only limited measurement data is available being nearly always the case [7, 8, 9]. Furthermore, even for simulation-based extrapolations, it is not precisely known how reliable the state-of-the-art extrapolations are [10, 11]. Thence, in this work, the extrapolation process of substructural fatigue damages and the inherent uncertainty of it are investigated in more detail, while the focus is on measurement data. Strain measurements of two Belgian OWTs are utilised.

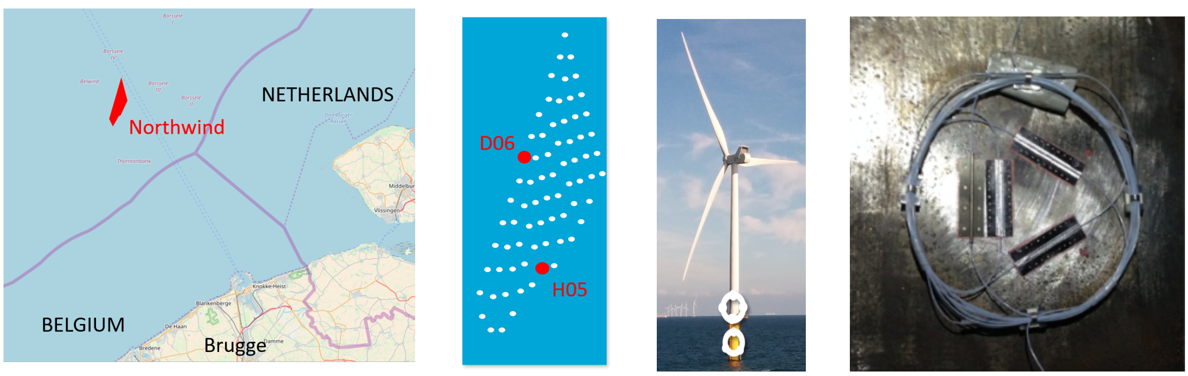
Firstly, the damage extrapolation procedure is investigated by analysing different methods. In this context, the use of different types of bins (wind speed bins, combined wind speed and wind direction bins, etc.), of design and data-based bin probabilities, and of mean damages or percentiles are possible alternatives that are analysed.

Secondly, for measurement-based damage extrapolations, the required measurement time for reliable lifetime calculations is of major interest, as in reality, only limited measurement data is available. A time-based bootstrapping algorithm is applied to determine the minimum amount of measurement data that is required to achieve acceptable uncertainties of the lifetime approximation.

2. Measurement setup

In this work, offshore data of a measurement campaign in the Belgian “Northwind” wind farm is utilised. Northwind consists of 72 Vestas V112-3 MW turbines being mounted on monopiles. The wind farm is located about 37 km off the Belgium coast (see Figure 1(a)), and has moderate water depths of 16 m to 29 m.

Since October 2014, strain measurements of two instrumented turbines H05 and D06 - both marked in Figure 1(b) - are available. 3 years of data from 1st November 2014 to 31th October 2017 are used. For D06, only data since 1st November 2015 was available. The two turbines, instrumented by OWI-lab, are positioned on both sides of the wind farm to enable an analysis of different wind conditions (free inflow conditions for different wind directions) and to cover different water depths. The varying water depths lead to slightly different monopile designs,



(a) Location of Northwind and the utilised metocean stations (adapted from “open street map”).

(b) Northwind with turbines marked.

(c) V112 with indication of measurment location.

(d) Welded FBG.

Figure 1. Illustration of the investigated, instrumented turbines, and the measurement setup.

Table 1. Properties of the investigated turbines (according to Ref. [9] and [12]).

Turbine	Location	Hub height	Water depths	Eigenfrequency	Diameter monopile
H05	Vestas V112	71 m	18.9 m	0.30 Hz	5.2 m
D06			26.9 m	0.27 Hz	

and therefore, to varying eigenfrequencies (see Table 1). Variations of the eigenfrequency can influence fatigue lifetimes. Both turbines are instrumented with, inter alia, 7 fiber Bragg gratings (FBG) as strain gauges positioned at two different heights (see Figures 1(c) and 1(d)). The moment level of the FBGs is calibrated using the thrust loading over the operational window of the OWT. Using yaw data it is possible to correct for offsets of both strain and (installation) heading. Sensor drift is typically not a problem associated with FBG measurements. The positions of the FBGs are at the interface between tower and transition piece (TP) and the interface between TP and monopile. Here, the measurement layer between TP and monopile is used, where the FBGs are welded to the wall. Through the welded connection, the strain transfer is not perfect. So, for welded FBGs, a correction due to reduced sensitivities is necessary [13]. Spreading three strain gauges around the circumference and an additional temperature compensation enable a determination of bending stresses at the TP-monopile interface.
In addition to the strain data, SCADA data of the two turbines is available so that wind speeds, turbulence intensities, etc. can be used to split up the damage data into bins. Wind data, especially turbulence intensities, measured by SCADA systems is not always very reliable, since the rotor disturbs the anemometer measurement. However, since SCADA data is only utilised for the binning procedure and not for the damage calculation itself, a moderate accuracy is sufficient. In fact, it is not even critical if, for example, the wind speed is not completely correct (e.g. no nacelle transfer function). Due to the damage calculation based on strain measurements, there is no damage per wind speed calculation, but rather a damage per "another parameter" binning. This "other parameter" does not even have to have any physical meaning and could be for example: "biased anemometer measurement". It is only important that the parameter is consistent.

3. Methodology

3.1. Damage calculation

To analyse the damage extrapolation, short-term (10 min) damages have to be calculated in a first step. As the short-term damage calculation is a relatively standardised procedure and is not the focus of this work, it is not explained in detail. It is referred to Figure 2 and some additional information are given: Firstly, the "static extrapolation" is a simplified procedure to extrapolate stresses from the measurement position to other positions (i.e. heights). It is based on the assumption that all significant loads are due to the thrust load. Hence, a linear relationship of heights and stresses is assumed (see Figure 2). This procedure is only valid for monopiles, and even for those, it can be problematic, if there are high wave loads. Secondly, correction factors are applied to calculate the "true", i.e. hot spot stresses. Examples for these correction factors are stress concentration factors (SCF) for the present details (according to the design; e.g. welds) or corrections for the reduced sensitivity of welded FBGs. Thirdly, for the slope of the S-N curve, values of 3 and 5 are applied. Using this methodology and the measured strains a dataset of about 160 000 damage values (3 years) is available for the monitored turbines.

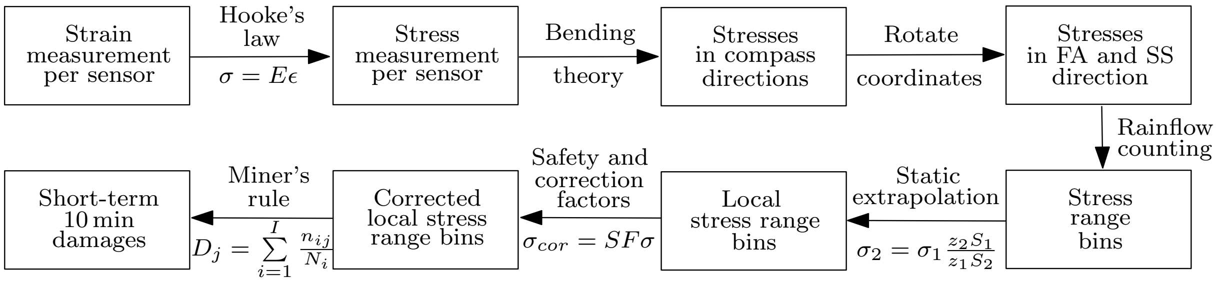


Figure 2. Flowchart presenting the short-term damage calculation procedure based on strain measurements (FA: fore-aft, SS: side-to-side).

3.2. Damage extrapolation

The first focus of this work is the extrapolation of short-term damages to lifetime damages, as this process is not sufficiently investigated and quite uncertain. An overview of the extrapolation process is given in Figure 3. There are four decisions to be made: bin type (1), empty bin filling (2), statistical damage parameter (3), and probability source (4). Hence, there are a lot of ways to extrapolate damages influencing the final outcome significantly. In a first step, all short-term damages (D_j) are sorted into several bins (M) of environmental conditions (ECs). The "dimension", discretisation, and the ECs of these bins can differ. For example, no bins (0d; linear extrapolation, i.e. the lifetime is just the inverse of the accumulated damage per year), wind speed bins (1d-bins), combined wind speed and direction bins (2d-bins), combined wind speed and turbulence bins (2d-bins-TI), or combined wind speed, direction and wave height bins

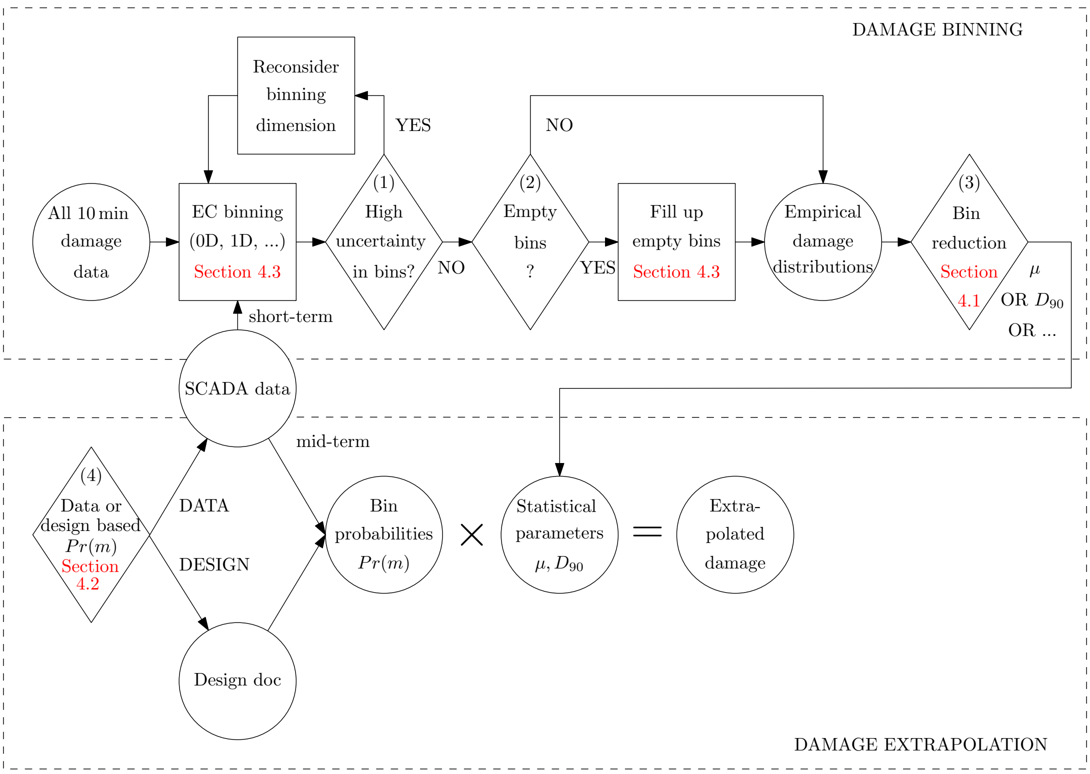


Figure 3. Illustration of different damage extrapolation techniques.

(3d-bins) are possible. Following the recommendations for bins of OWT simulations, the focus is on the first three bin types (0d to 2d). Still, for example, for wave dominated structures, other bin types can be more expedient.
Since, especially for bins of higher dimension, there are not always measurements in all bins (e.g. a certain combination of ECs might not occur), empty bins have to be filled up (2). Here, only one bin filling algorithm that fills up empty bins with the highest statistical damage value of the same wind speed is considered.
The choice of the statistical damage parameter is quite relevant (3). For each bin, the mean value of all $J(m)$ corresponding damage values can be calculated. However, as the mean value tends to underestimate damages for small data sets, a high percentile (e.g. the 90^{th}) can be used to be more conservative.
Finally, each bin has a certain occurrence probability ($Pr(m)$). $Pr(m)$ can either be determined by using measurement data (e.g. several years of SCADA data) or be given in design documents (4). On the one hand, probabilities given in design documents are typically based on long-term data (20 years and more) making them more reliable. On the other hand, even if site-specific OWT design is conducted, the EC distributions are normally not derived for the precise site of the considered OWT which might lead to biased results.
To calculate the lifetime damage (D_{LT}), the weighted damages of all bins are summed up and multiplied by a time factor. It follows (for using the mean):

$$D_{LT} = \frac{20\,\text{years}}{10\,\text{min}} \sum_{m=1}^{M} \left(Pr(m) \frac{1}{J(m)} \sum_{j=1}^{J(m)} D_j(m) \right). \tag{1}$$

There is no differentiation between operational and faulty conditions (see Section 5). The lifetime L in years is the inverse of the lifetime damage multiplied by the design lifetime of 20 years:

$$L = \frac{20\,\text{years}}{D_{LT}}. \tag{2}$$

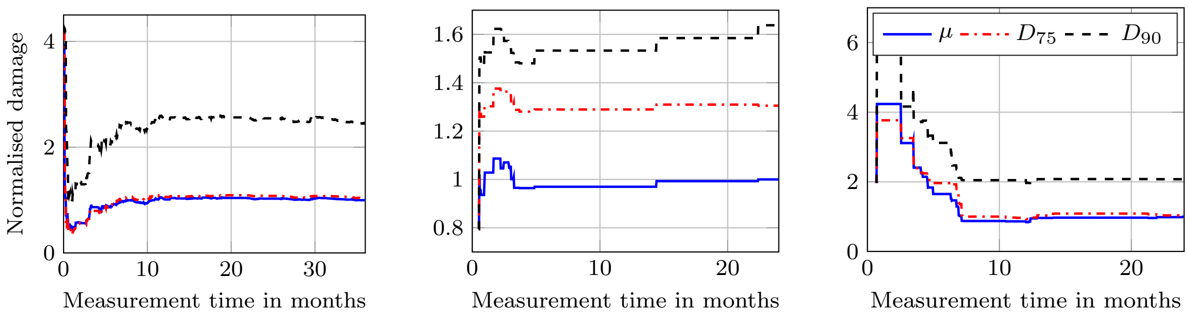
3.3. Time-based bootstrapping
In a second step, the minimum time period that is needed to achieve reliable lifetime estimations is determined. This time period can be determined by applying time-based bootstrapping (c.f. block bootstrapping with overlapping blocks [14]). Before explaining the idea of time-based bootstrapping, it has to be clarified why the knowledge of a minimum measurement time is essential. Why is it not possible to just use the current data (e.g. measurement data of two months) and estimate the uncertainty of this data by "traditional" sample based-bootstrapping [15]? The problem of applying sample-based bootstrapping on the whole available data is that it only gives an estimation of the uncertainty of the present data, but does not provide any information on the representativeness of the data itself. Hence, if these two months are calm summer months, then the scattering of damage values might be small, but the lifetime extrapolation is still significantly biased. Therefore, a minimum time period has to be found to guarantee representative periods. This is done by time-based bootstrapping. For classical bootstrapping, samples are generated by sampling from all available cases with replacement. For the time-based version, starting points of the time periods (e.g. 2 months) in the overall available 3 year time period are sampled with replacement. If the starting point is near the end of the available dataset, the selected period continues in the beginning of the available dataset. This procedure conserves seasonal effects by using consecutive data and is suitable to determine a minimum measurement length. However, the sampled time period has to be significantly smaller than the available time period in order to preserve mostly independent samples. If, for example, the sampled time period covers the full available period, all samples are exactly the

same and not independent (only the starting point changes). Hence, the maximum time period used is 18 months for H05 and 12 months for D06.

4. Results

4.1. Statistical damage parameter

At first, the statistical damage parameter selection (3) is analysed. By definition, for 20 years of data, the approach of using the mean value in each bin gives the correct lifetime estimation, if no bins are empty and bin probabilities are correct. However, due to the exponential correlation between stress amplitudes and cycle counts, the damage behaviour is dominated by some rare, extremely high cycles. Hence, for small data sets, the mean value tends to underestimate the real damage, as these rare events are not sufficiently covered. That is why high percentiles (e.g. the 90$^{\text{th}}$ percentile) are frequently used to be conservative.
In Figure 4, the convergence of the mean damage and two different percentiles (D_{75} and D_{90}) and different bins is shown to assess the usability of these different statistical parameters.



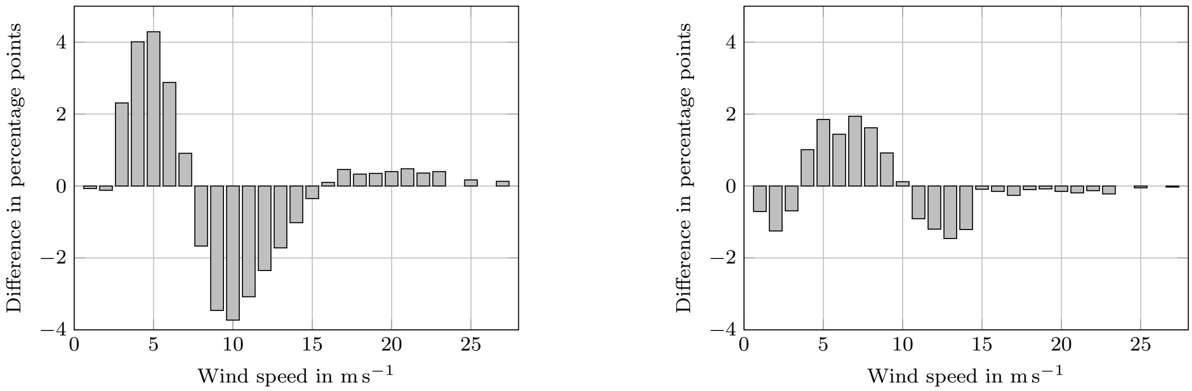
(a) H05: $5\,\mathrm{m\,s^{-1}} < v_s < 7\,\mathrm{m\,s^{-1}}$ (b) D06: $23\,\mathrm{m\,s^{-1}} < v_s < 25\,\mathrm{m\,s^{-1}}$ (c) D06: $17\,\mathrm{m\,s^{-1}} < v_s < 19\,\mathrm{m\,s^{-1}}$ and $0° < \theta < 30°$

Figure 4. Convergence of the normalised damage (mean value (μ) and 75$^{\text{th}}$ and 90$^{\text{th}}$ percentile (D_{75} and D_{90})) in different bins (wind speed v_s and direction θ) and both turbines.

It becomes apparent that the mean value converges within less than 12 months, while D_{90} results in significantly higher damages that are about twice the mean value. The relatively fast convergence of the mean damage is especially present for bins with high probabilities (cf. Figure 4(a); $>$ 1000 measurements), but even for rarely occurring bins (Figure 4(b)) or 2d-bins (Figure 4(c); $\sim$ 50 measurements) a converged mean value after 12 months is present.
Knowing that the mean value converges quickly in nearly all bins, the argument of it being non-conservative is not relevant. Furthermore, the 90$^{\text{th}}$ percentile leads to very conservative approximations. Hence, the use of mean values in each bin is recommended. Only if more conservativity is essential and the quality of the measurement data is limited, which can lead to biased mean values, high percentiles should be applied.

4.2. Probability source

Next, the source of the bin probabilities is investigated (4). There are two options: Firstly, probability distributions of design documents can be used being based on reliable long-term data. Secondly, data-based bin probabilities can be applied representing the conditions at the precise site of the turbine, but being - in most cases - only based on mid-term data. Figure 5 shows the differences of wind speed probabilities. In Figure 5(a), design probabilities are compared to the distribution derived using 3 years of SCADA data. Figure 5(b) shows the difference between the data of two consecutive years.



(a) Difference of design and data (3 years).

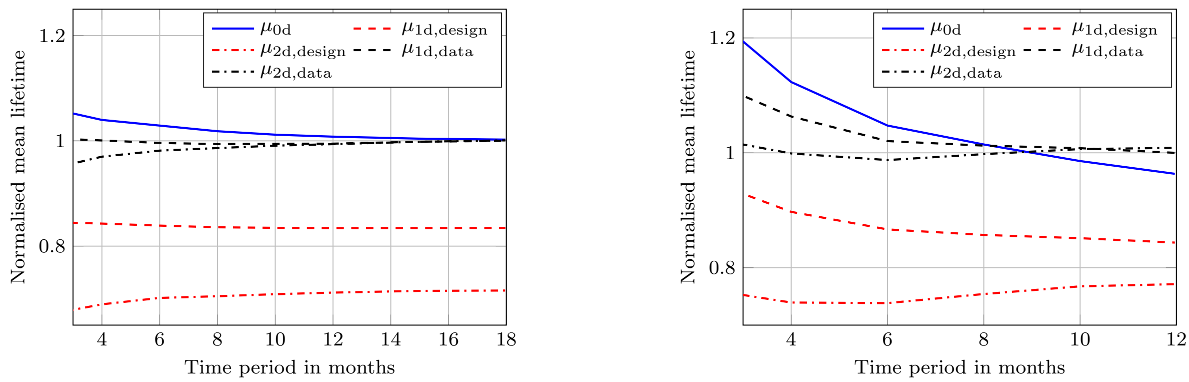
(b) Difference of the year one and two.

Figure 5. Differences of wind speed probability distributions (H05).

The difference between data and design is more pronounced than deviations in short-term data. Hence, at least for the current application, the data-based approach is recommended, if sufficient data (at least one year but preferably several years) is available.
This suggestion is supported by the results of the lifetime convergence with increasing measurement periods presented in Figure 6. For the determination of the bin probabilities, the full 3 years of SCADA data independent of the considered measurement period (strain data) are used. This approach is not only feasible, as normally SCADA data of the full previous lifetime is available (i.e. more SCADA than strain data), but essential. If the same data period was used for calculating damages and to determine probabilities, the number of samples per bin would precisely match the bin probability which means that in fact the 0d-approach is applied. Since all approaches using data-based probabilities convergence to similar lifetimes within about one year and the design-based approaches converge to different values, again, it can be concluded that data-based bin probabilities are favourable. Here, the results of H05 (Figure 6(a)) are more meaningful and clearer, as more and higher quality stress data is available. The use of the design data basis can introduce a significant bias. In this case, the bias is conservative, as site conditions were calmer than those assumed in design. It has to be mentioned that if too small data sets (less than one year) are used for the probability determination or site conditions are changing in the long-term, the data-based version might become inaccurate as well.

4.3. Bin type

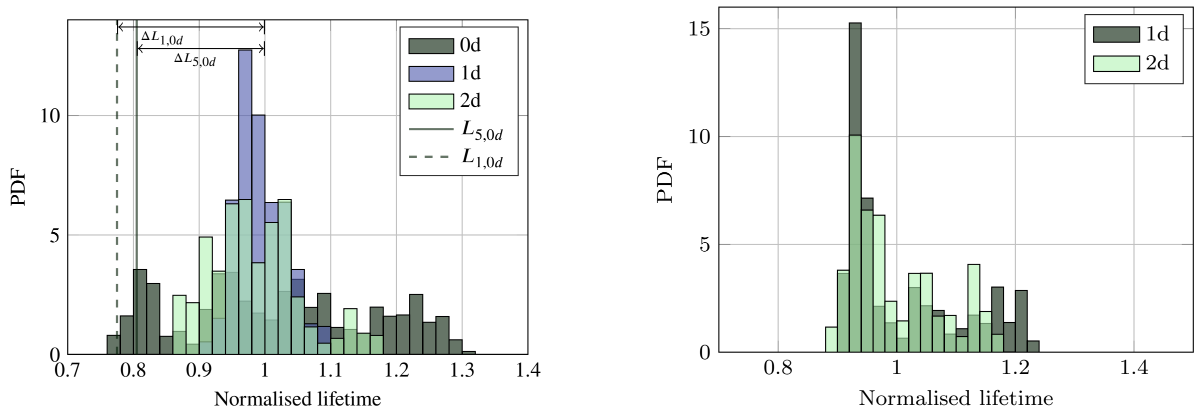
To finish up the analysis of the damage extrapolation in Figure 3, only the assessment of the bin type (1) is forthcoming (different empty bin filling algorithms (2) are not investigated). From Figure 6, it is clear that the mean lifetime is similar for different bin dimensions. Only for small time periods, there are differences that will be discussed later on. However, besides the mean, the uncertainty of the lifetime estimation is an important factor. It is varying for different bin dimensions. Hence, the lifetime distribution for different bin types and various measurement lengths is calculated using a time-based bootstrapping. Figure 7 illustrates two exemplary, normalised lifetime PDFs for a time period of 8 months. The use of no bins leads to higher scattering of the lifetimes. Lower and higher damages are possible, as the weight on either storm events or calm periods can be too high. For the 1d and 2d-approach, the differences are less pronounced. Uncertainties are a little higher for 2d-bins (see Figure 7(a)), and the mean value is slightly lower (see Figure 7(b)). The empty bin filling for the 2d-approach can



(a) H05 (3 years of data)

(b) D06 (2 years of data)

Figure 6. Convergence of mean lifetimes with increasing measurement times for different methods.



(a) Normalised lifetime PDFs of H05.

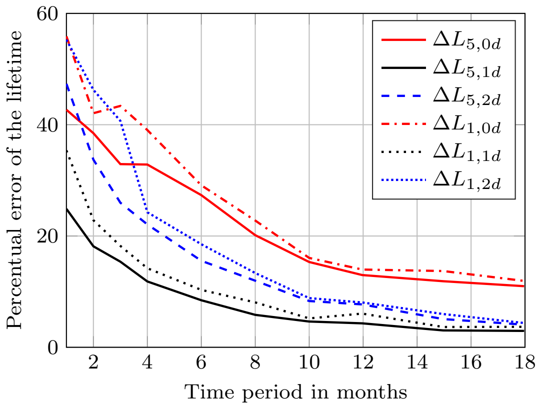
(b) Normalised lifetime PDFs of D06.

Figure 7. Normalised lifetime PDFs (normalised with 1d mean values) for both turbines and different bin types (data-based bin probabilities and 8 months measurement length).

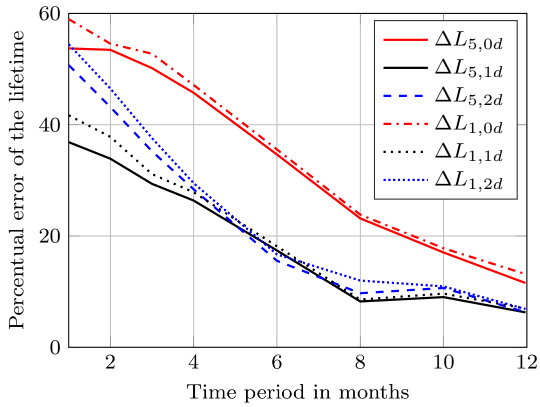
increase the uncertainty, as high outliers are spread to empty bins which increases their effect. Additionally, the mean value can be influenced by the bin filling algorithm. As empty bins are filled up with the highest available value of the same wind speed, in most cases, bins are filled up conservatively leading to reduced lifetimes. This can be clearly identified in Figure 6(a) and time periods up to 6 months. However, the use of the highest value of the same wind speed to fill up empty bins does not always lead to conservative results. It is not intuitive that filling up empty bins with the highest available damages can lead to too small damages. However, if the highest damages do not occur for the main wind direction (for high wind speeds), it happens with a high probability that empty bins are filled up with relatively small damages of the main wind direction. Hence, it is certainly true that filling up bins adds artificial damage data. This can either lead to an underestimation or an overestimation of the damages in filled up bins. The type of the bias (underestimation or overestimation) of the 2d-bins depends on the site conditions and the available data and is not known in advance.

While Figure 7 is illustrative, it does not provide any information for different time periods. That is why Figure 8 shows the convergence of the errors at the 1st and 5th percentile of the lifetime distribution (ΔL_5 and ΔL_1) for increasing time periods for different bin types. For

0d-bins, illustrations of ΔL_5 and ΔL_1 are given in Figure 7(a). Figure 8 makes clear that for increasing measurement periods, the uncertainty of the lifetime extrapolation decreases. If no bins are applied (0d), the resulting errors are significantly higher, since there is no averaging effect of bin probabilities. This means, for example, a calm period is much more influential. For a calm period, the mean damage decreases. Additionally, the inherent probability of low wind speeds (i.e. the proportion of low wind speed measurements) increases. For the 1d and 2d-approach, the probability remains constant. For long measurement periods, 1d and 2d-bins lead to fairly similar uncertainties, while for small time periods, for the 2d-approach, many bins remain empty adding additional uncertainty.



(a) Lifetime errors of H05.



(b) Lifetime errors of D06.

Figure 8. Convergence of extrapolations errors with increasing measurement times for both turbines and different bin types and data-based bin probabilities.

After all, disregarding the measurement lengths, the use of 1-bins is recommended. It leads to unbiased extrapolations with small uncertainties, and there is no need of filling up empty bin. Still, the use of 2d-bins or even higher dimensional bins might be beneficial in some situations. The use of additional wind direction bins enables a correlation between inflow conditions (undisturbed and wake conditions) and damages. Therefore, if only some turbines are equipped with strain gauges, more information on the lifetime of all turbines in a wind farm is available. Hence, the use of 2d-bins can be combined with approaches like the fleet leader concept [9].

4.4. Measurement length

Finally, the minimum measurement length that is required for reliable lifetime estimations is determined. Therefore, the mean value should be unbiased (converged), and uncertainties should have reached an acceptable level. Using Figures 6 and 8, it becomes clear that, for using 1d or 2d-bins, about 9-10 months of measurement data are needed to achieve unbiased mean values. ΔL_5 and ΔL_1 reach values below 10 %. For longer measurement times, the uncertainty is only slowly decreasing. Hence, at least 9-10 months of strain data should be used for lifetime extrapolations. In practice, 9-10 months after the installation of the sensors, "traditional" sample-based bootstrapping using all available data can be conducted to determine the present uncertainty. If it is higher than desired one, measurements have to be continued. Still, after this time period, a relatively representative and unbiased data set is already guaranteed and sample-based bootstrapping is meaningful.
After all, there is nearly no gain of measuring more than one year, if no significant changes of the

turbine or the ECs are expected over the lifetime. This means that it is not necessary to replace sensors that fail after, for example, 2 years. Much more beneficial is a second measurement campaign after several years to take long-term effects like soil hardening/softening or corrosion into account.

It has to be clarified that the determined measurement length and the benefit of continuing measurements for more than 1 year only apply to strain measurements. The data period of the ECs (e.g. SCADA data) to determine bin probabilities should be at least 1 year and long-term measurements are definitively beneficial, although, in this work, this was not investigated in detail.

5. Conclusion and outlook

Since the lifetime estimation based on measurement data becomes an important topic for ageing OWT substructures, firstly, this work assesses various damage extrapolation techniques. The use of plain wind speed bins is recommended for most applications, although higher dimensional bins might be useful, if a more wind farm orientated lifetime estimation is conducted. However, higher dimensional bins lead frequently to empty bins that have to be filled up. This bin filling can introduce a bias, whereby it does not have to be conservative. The occurrence probabilities of the bins should be based on measurement data, if a sufficient amount of data - being representative for the full lifetime of the OWT - is available. Several years are advisable. Finally, in each bin, mean damages should be used. It is not recommended to utilise high percentile values, as these are very conservative. Although the current work already analyses two turbines with deviating wind conditions (e.g. different wind directions lead to wake conditions), the generality of these recommendations should be tested by future investigations using other wind farms. Furthermore, different types of bins (e.g. turbulence intensity bins, 3d-bins, etc.) might be interesting as well. For wave dominated structures, possibly, wave height bins are more relevant than wind speed bins. However, for wave conditions, there is the challenge of available data for each OWT. Future work could also differentiate data based on operational states of the OWT (e.g. normal and abnormal behaviour). This can be useful especially if operating and idling/faulty conditions lead to significantly different damages. Whether abnormal behaviour leads to lower, similar, or significantly higher damages than normal behaviour depends on the structure itself (e.g. frequently, large monopiles exhibit increased loading while idling). In this work, the discretisation of the bins is not varied. However, this could be investigated in future research, since the optimal bins size depends on the amount of available data (smaller bins for more data).

The second focus of this contribution is the determination of a minimum measurement length to guarantee representative measurement data, and therefore, reliable lifetime values. Using time-based bootstrapping, a minimum time period of 9 months was determined to achieve unbiased mean values and errors - occurring with a probability of 1 % - below 10 %. Higher time periods reduce the occurring errors only slightly. Forthcoming work should address the question whether it is possible to reduce measurement times or uncertainties, if, for example, a minimum number of measurements in each bin is demanded.

Acknowledgments

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