Load extrapolations based on measurements from an offshore wind turbine at alpha ventus

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Abstract. Statistical extrapolations of loads can be used to estimate the extreme loads that are supposed to occur on average once in a given return period. Load extrapolations of extreme loads recorded for a period of three years at different measurement positions of an offshore wind turbine at the alpha ventus offshore test field have been performed. The difficulties that arise when using measured instead of simulated extreme loads in order to determine 50-year return loads will be discussed in detail. The main challenge are outliers in the databases that have a significant influence on the extrapolated extreme loads. Results of the short- and long-term extreme load extrapolations, comprising different methods for the extreme load extraction, the choice of the statistical distribution function as well as the fitting method are presented. Generally, load extrapolation with measurement data is possible, but care should be taken in terms of the selection of the database and the choice of the distribution function and fitting method.

1. Introduction
Probabilistic methods allow the prediction of long-term loading of wind turbines with a limited amount of either simulation or experimental data. The current version of the IEC standard 61400-3 [1] for offshore wind turbines requires statistical extrapolation of loads in order to estimate the 1-year and 50-year extreme loads, without providing a precise extrapolation procedure. Therefore, the estimated loads depend on the implementation method of the individual designer. The presented work shall contribute to the validation of common methods for load extrapolation based on the experience gained from the extrapolation of load measurement data from a 5 MW offshore wind turbine located in the offshore test field alpha ventus. For onshore turbines, several studies on load extrapolations using measurement data have been performed, see for example [2] and [3]. Thereby measurement data from turbines with 2.5 MW respectively 1.5 MW rated power, that are no longer state-of-the-art, has been used.

Three years of high resolution 50 Hz data for sensors at different locations of the investigated wind turbine are available within the framework of the RAVE (Research at Alpha VEntus) initiative. In the presented study the tower base and blade root bending moments are evaluated. The preprocessing of the measurement data is described and the causes of outliers in the databases are analysed. In a first analysis the most suitable statistical distribution function as well as the fitting method for each analysed measurement position can be found. Goodness of fit tests and quantile-quantile plots are used in order to judge the quality of the short- and long-term extrapolations. For long-term extrapolations the results of the approaches ”fitting before aggregation” and ”aggregation before fitting” are compared. Finally, the differences of
short- and long-term 50-year extreme loads using the method of global maxima and the peak over threshold method are analysed.

2. The database

2.1. Description of the investigated turbine
The results presented in this paper are based on load data recorded at a AD5-116 wind turbine from Adwen located in the offshore test field alpha ventus. The bottom fixed wind turbine, mounted on a tripod substructure, has a rated power of 5 MW at a wind speed of 12.5 m/s, a rotor diameter of 116 m and a hub height of 90 m with reference to the lowest astronomical tide, see Figure 2. The wind farm layout and the position of the investigated turbine AV7, which is extensively equipped with measurement devices, are shown in Figure 1. More than three years of high resolution 50 Hz data for sensors at different locations of the wind turbine (for example the blade root bending moments, tower base bending moments etc.) and the tripod substructure have been recorded. Additionally, environmental data is available from the nearby research platform FINO1 [6].

![Figure 1. Wind farm layout of alpha ventus [4]. The investigated turbine is circled.](image1)

![Figure 2. AD5-116 wind turbine [5].](image2)

2.2. Preprocessing of the measurement data
Unlike simulated loads, measured loads need to be elaborately processed before performing load extrapolations. The procedure includes, among others, calibration and plausibility checks of the data. This is necessary in order to avoid the use of incorrect measurement data for the extrapolation. Furthermore, the measurement data is restricted to specific operating conditions, such as power production without faults and free flow conditions. Within the chosen sector from 207° to 270° the wind turbine AV7 as well as FINO1 are in undisturbed flow condition and the anemometers of FINO1 are not in the wake of the met mast itself, see [7]. Tower base bending moments in fore-aft and side-side direction as well as blade root bending moments in flapwise and edgewise direction are chosen to illustrate the extrapolation process.
For short-term extrapolations, extreme loads dependent on the undisturbed wind speed in front of the turbine are required. In order to assign the extreme loads to a mean wind speed, two wind speed measurements can be used: the wind speed measured by the nacelle anemometer of the turbine and the wind speed measured by the anemometer at FINO1 at approximately hub height. Both measurements do not reflect the wind speed in front of the rotor nor the spatial variation of the wind speed, which can induce extreme loads. Therefore a rotor effective wind speed is assessed based on a torque-balance-estimator using the turbines rotor speed, pitch angle and aerodynamic moment, see [8]. In the following sections the rotor effective wind speed is used for the binning of the extreme loads. A wind bin size of 2 m/s is applied.

2.3. Analysis of outliers

As outliers in the database may have a significant influence on the extrapolation result, they need to be analysed in detail before performing the load extrapolation. The maxima of the fore-aft tower base bending moment using the method of global maxima (see section 3.1) are shown in Figure 3 on the left hand side. They are normalised to the highest value and the amount of data for each wind bin is given in the legend. At first glance there are quite a few maxima that do not belong to the wind speed where they have been allocated. By checking the high resolution 50 Hz data of each 10 minute load time series with an outlier and the corresponding environmental conditions, one can examine and determine the possible cause of the outliers.

![Figure 3. Databases of the fore-aft tower base bending moment with outliers (left) and after elimination of outliers (right).](image-url)

Unlike time series of load simulations based on independently generated wind fields, successive measured load time series might be dependent on each other, see Figure 4. In that figure the 50 Hz high resolution data of the fore-aft tower base bending moment and the rotor effective wind speed are plotted over time for a period of 30 minutes. The 10 minute time series in the middle contains a maximum that corresponds to the highest outlier in the wind bin 18 m/s, see Figure 3. The increase of the wind speed at the transition between the first and the second 10 minute time series is responsible for the extreme loads in both time series (see green circles). These maxima are caused by the same event and they are therefore dependent on each other. For this reason the maximum of the second time series (number 2) is discarded and the second highest bending moment is investigated (number 4). It occurs at the end of the time series when a sharp decrease of the wind speed towards the rated wind speed can be observed. The analysis of
the following 10 minute time series shows that the extreme loads number 4 and 5 (see magenta circles) are not independent of each other as they are caused by the same event. Therefore maximum number 4 is also discarded. Finally the orange marked extreme load (number 3) is identified as the representative extreme load. As this extreme load lies within the normal range of extreme loads for the corresponding wind bin it has basically no impact on the extrapolation and is deleted from the database.

Figure 4. Analysis of high resolution data regarding dependencies of 10 minute load time series.

The 10 minute load time series related to the second highest outlier in the wind bin 18 m/s is shown in Figure 5. In this case there is no dependency on the previous or following time series. The extreme load occurs when the wind speed decreases to slightly below rated wind speed and the operating condition of the wind turbine changes for a short period of time. The cause of the extreme load is not related to the comparatively high mean wind speed of the 10 minute time series but to the way the controller deals with wind speed changes around rated wind speed. In general, the steepness of a wind speed change has a larger impact on the loads than the amplitude, especially when the controller has to switch between different operating conditions. Unlike the assumption used for simulations, the measured wind speed within ten minutes does not always follow a normal distribution. The skewness and kurtosis of the high resolution wind speed data of the time series with outliers are further analysed. Whereas the skewness is mostly close to zero, the kurtosis differs significantly from the value of three assumed by the normal distribution. It has values between 1.2 and 2.1. In cases like the shown example the maxima need to be assigned to a physically meaningful wind speed that causes the outlier. The extreme loads are either deleted if they lie within the range of extreme loads within the wind bin which represents the wind speed at the time the extreme load occurs or they are shifted to the corresponding wind bin if they are outside the usual range.

The detailed investigation of all outliers of the fore-aft tower base bending moment leads to a revised database, see Figure 3 right hand side, which can be used for load extrapolation. The databases of all sensors are analysed in the same way as described above. For the blade root bending moments not all outliers can be eliminated, see database of the flapwise blade root bending moment in Figure 6. Although an extensive examination of the load time series with outliers and the corresponding high resolution data of environmental and turbine parameters (e.g. shear, turbulence intensity, pitch angle, rotor speed etc.) is performed, the outliers can not
be explained. The only particularity that can be observed, is that all outliers occur within three stormy days of the measurement period and correlate with a high power output of the turbine. As there is no reason to omit these outliers, they remain in the database although this affects the extrapolation results.

3. Performance of load extrapolation

3.1. Extraction of extreme loads

For the extraction of the extreme loads from the recorded measurement data two different methods are used - the method of global maxima (GMM) and the peak over threshold method (POT). GMM uses only the maximum value from every 10 minute load time series whereas POT uses all values greater than a defined threshold as maximum values.

Extreme load extrapolation is based on the assumption of statistical independence of the maxima. For GMM independence of the extreme loads is not checked in general except for outliers. For POT Freudenreich [9] suggests to ensure independence of maxima by for example defining a certain number of rotor revolutions between successive peaks. The amendment of the IEC 61400-1 [10] proposes a minimum time separation between individual response extremes of three response cycles. In order to increase the likelihood of statistical independence of extreme loads, a minimum time separation of five rotor revolutions between peaks over the selected threshold is implemented for the POT method.

When using the POT method an appropriate threshold value for each sensor and wind bin needs to be defined. Based on standard values ([11], [12], [13]) threshold levels of mean value ($\mu$) plus 1.4, 2 and 2.5 times the standard deviation ($\sigma$) of the load time series are investigated. A high threshold level increases the probability of statistical independence of the extreme loads but on the other hand the number of local maxima decreases.
3.2. Exceedance probability
The probability of exceeding a certain load \(l\) conditional on the wind bin \(v\) and the observation period \(T\) can be calculated with Equation 1.

\[
P(L > l | v, T) = 1 - [F_{\text{local}}(l | v)]^{n(v, T)}
\]  

(1)

\(F_{\text{local}}(l | v)\) is the cumulative distribution function of the local maxima and \(n(v, T)\) is the average expected number of local maxima within the observation period (= mean crossing rate). An observation period of \(T = 10\) min is chosen, so that Equation 1 can be simplified to

\[
P(L > l | v) = 1 - [F_{\text{local}}(l | v)]^{n(v)} = 1 - F_{\text{short}}(l | v). 
\]  

(2)

After computing the short-term distributions \(F_{\text{short}}\) for all wind conditions, the long-term exceedance probability can be calculated by integrating the conditional short-term distributions with the probability density function of the mean wind speeds \(p(v)\)

\[
P(L > l) = \int_{v} P(L > l | v) \cdot p(v) \, dv. 
\]  

(3)

In this case only extreme loads during operation will be considered. This can be approximated by a sum from the cut-in wind speed \(v_{\text{in}}\) to cut-out wind speed \(v_{\text{out}}\) for the method of global maxima

\[
P(L > l) \approx \sum_{v_{\text{in}}}^{v_{\text{out}}} (1 - F_{\text{short}}(l | v)) \cdot \frac{p(v)}{\sum_{v_{\text{in}}}^{v_{\text{out}}} p(v)}
\]  

(4)

and the peak over threshold method

\[
P(L > l) \approx \sum_{v_{\text{in}}}^{v_{\text{out}}} (1 - [F_{\text{local}}(l | v)]^{n(v)}) \cdot \frac{p(v)}{\sum_{v_{\text{in}}}^{v_{\text{out}}} p(v)}
\]  

(5)

whereby the probability of the wind speeds is normalised. For the estimation of the probability density function of the wind speeds \(p(v)\) a 2-parameter Weibull distribution based on the measured wind speeds at FINO1 is used.

The described procedure is referred to as the ”fitting before aggregation” approach. Another option to determine the long-term distribution is ”aggregation before fitting”, where all extreme loads, independent of the corresponding wind speed, are collected and approximated by a distribution function. A detailed description of this approach can be found in [14].

In order to estimate the empirical exceedance probability, the extreme loads \(l\) in the wind speed bin \(v\) are ranked in descending order \((l_{1,v} > ... > l_{i,v} > ... > l_{N_v,v})\), where \(N_v\) is the total number of extreme values in the wind speed bin. The highest value \(l_{1,v}\) receives a rank of \(r(l_{1,v}) = 1\). The probability that any load \(L\) will exceed the load level \(l\) can be determined using the Weibull plotting position

\[
P(L > l | v) = \frac{r(l)}{N_v + 1} \quad r = 1, 2, ..., N_v 
\]  

(6)

On the assumption that the global 10 minute maxima are independent, the probability of exceeding the 50-year load in any given ten minute period is

\[
P(L > l_{50}) = \frac{1}{50 \cdot 365 \cdot 24 \cdot 6} = 3.8 \cdot 10^{-7}
\]  

(7)
4. Results
For the extreme loads measured at different turbine components, short- and long-term extrapolations can be performed. For GMM and POT different distribution functions have been applied. For GMM the Gumbel, 2-parameter Weibull (Weibull2), 3-parameter Weibull (Weibull3), Generalized Extreme Value (GEV), Lognormal and Gamma distribution are used, whereas the Generalized Pareto (GPD) and 3-parameter Weibull distribution are considered as suitable for POT. Three different fitting methods - method of moments, maximum likelihood, least squares - are used for the evaluation. In the following sections various results of the extensive evaluations of extreme loads are presented.

4.1. Goodness of fit criteria
Before evaluating the results, an objective criterion to judge the quality of the short- and long-term extrapolations needs to be defined. In order to find the most suitable distribution function for each measurement position and wind bin a visual inspection of the extrapolation curves is necessary but not sufficient. For the evaluation of the goodness of fit, Kolmogorov-Smirnov and Chi-squared tests are performed and quantile-quantile plots (qq-plots) are created. Through a visual inspection of the qq-plots, the investigated distribution functions can be assessed. Both, goodness of fit tests and qq-plots, are analysed in order to determine the best distribution function for each measurement position and wind bin.

4.2. Short-term extrapolation
First of all, the short-term extrapolations are analysed. GMM is used to extract the extreme loads and the results for different combinations of distribution functions and fitting methods are compared. The short-term extrapolations of the fore-aft tower base bending moment for the wind bin 10 m/s are shown in Figure 7. The exceedance probability is plotted over the extreme loads, which are normalised to the absolute maximum value of the wind bin. The horizontal black line represents the exceedance probability corresponding to a 50-year return period. Depending on the choice of the distribution function and the fitting method, the extrapolated 50-year extreme load for the shown example can vary between 1 and 1.9 times the maximum load, measured during the evaluated three years. For the evaluation it is assumed that the mean wind speed is 10 m/s for a period of 50 years.

Choice of distribution function
To judge the suitability of the different distribution functions, the goodness of fit is evaluated for each wind bin using goodness of fit tests and qq-plots, see section 4.1. This allows a general recommendation for the distribution function for each measurement position. The fact that the distribution function can model the most relevant wind bins (i.e. the wind bins with the highest loads) correctly is taken into account. Applying the criteria mentioned above, the GEV distribution is most suitable for the fore-aft tower base bending moment. However, the fitted distribution function has an upper boundary for some wind bins, so that an extrapolation to 50 years is not possible, see Figure 7. Therefore the second best distribution function, the 3-parameter Weibull distribution, should be used.

The results from the goodness of fit evaluation of all wind bins are combined to one overall recommendation for each evaluated measurement position, which is listed in Table 1.

Choice of fitting method
After the selection of the most appropriate distribution function for each sensor, an assessment of the fitting method can be carried out. Using the chosen distribution function short-term extrapolations with three different fitting methods - method of moments, maximum likelihood and least squares - are performed. The best fitting method is determined by the combination of a visual inspection how well the distribution function matches the measurement data and the evaluation of qq-plots, where the deviation of the fitted distribution function from the
Figure 7. Short-term extrapolations of the fore-aft tower base bending moment for the wind bin 10 m/s using different distribution functions and fitting methods.

Table 1. Choice of distribution function for the different sensors.

| sensor                        | distribution function                  |
|-------------------------------|---------------------------------------|
| fore-aft tower base bending moment | 3-parameter Weibull distribution       |
| side-side tower base bending moment | Gamma distribution                   |
| flapwise blade root bending moment  | 3-parameter Weibull distribution |
| edgewise blade root bending moment  | 3-parameter Weibull distribution |

theoretical quantiles is assessed. Overall, the maximum likelihood method is recommended for the best approximation to the measurement data.

4.3. Long-term extrapolation

For the long-term extrapolation the best combination of distribution function and fitting method, discussed in the previous section, is used. The long-term extrapolation can be performed by either using the "fitting before aggregation" (fba) or the "aggregation before fitting" (abf) approach, see section 3.2. The long-term extrapolations of the fore-aft tower base bending moment, using the 3-parameter Weibull distribution and the maximum likelihood fitting method, are shown in Figure 8. For the abf approach, the colors of the displayed extreme loads link to the wind speed bin and the fitting is only performed for the largest 20% of the extreme values to obtain a better match with the measurement data.

The extrapolated 50-year extreme loads differs slightly between the two approaches. For the tower base bending moments in fore-aft and side-side direction, the deviation is less than 5%,
Figure 8. Long-term extrapolations of the fore-aft tower base bending moment using both the "fitting before aggregation" and the "aggregation before fitting" approach.

when using only the largest 20% of the extreme values in the abf approach. For the blade root bending moments no long-term extrapolation with the fba approach using GMM can be performed because the amount of extreme loads for the wind bin 24 m/s is too little in order to carry out a short-term extrapolation.

4.4. Comparison of GMM and POT

In this section the differences between the method of global maxima and the peak over threshold method are analysed. The evaluation of the short-term extrapolations is performed for the fore-aft tower base bending moment and the flapwise blade root bending moment. For both sensors a threshold value of $\mu + 2\sigma$ is chosen for the POT method. A lower threshold of $\mu + 1.4\sigma$ leads to a worse goodness of fit whereas a higher threshold of $\mu + 2.5\sigma$ results in a reduced amount of data with mean crossing rates below one. To get comparable results, the 3-parameter Weibull distribution is used for GMM as well as for POT. The extrapolations are performed for a return period of 50 years using the maximum likelihood method for the parameter fitting. For both evaluated sensors the total amount of extreme load values is approximately five times larger when using POT instead of GMM. Exemplary short-term extrapolations of the fore-aft tower base bending moments for the wind bin 12 m/s are shown in Figure 9.

For the fore-aft tower base bending moment the scatter of the extreme loads within the different wind bins is much smaller for POT than for GMM, especially for the wind bins below rated wind speed. The short-term extrapolations based on POT give higher 50-year extreme loads for almost all wind bins. The differences between GMM and POT are up to 18%. The overall goodness of fit for all wind bins using goodness of fit tests is the same for GMM and POT. The evaluation of the qq-plots shows a better agreement for the POT results, particularly for the wind bins with the highest loads (10 m/s and 12 m/s). To sum up, the POT method seems to be a better choice for the extrapolations of the fore-aft tower base bending moment.

There is less measurement data for the flapwise blade root bending moment than for the fore-aft tower base bending moment. When using GMM, only three extreme loads for the wind bin 24 m/s are available, which is insufficient to perform a meaningful fitting of a distribution
Figure 9. Comparison of GMM and POT short-term extrapolations for the fore-aft tower base bending moment for the wind bin 12 m/s.

function. The results of the short-term extrapolations of the wind bins 4 m/s to 22 m/s tend to be higher for POT than for GMM (largest deviation: 19%). The evaluation of the goodness of fit tests and qq-plots does not give a clear statement about which of the methods is a better choice. In general the quality of fit is rather unsatisfactory because of the several outliers, see Figure 6. In order to be able to perform long-term extrapolations, the POT method should be chosen.

For the tower base bending moments, the long-term extrapolated 50-year extreme loads for GMM and POT can be compared as well. Similar to the short-term extrapolations, the POT method gives a higher estimate of the long-term 50-year extreme loads. They are increased by approximately 9% for the fore-aft direction and approximately 7% for the side-side direction. Due to the little amount of data for the blade root bending moments in the wind bin 24 m/s no comparison of the long-term 50-year extreme loads can be made for this sensor.

5. Summary and conclusion
Statistical extrapolations of loads can be used to estimate the extreme loads that occur on average once in a given return period. For the extrapolations, extreme loads recorded at an offshore wind turbine in the alpha ventus offshore test field are used. A considerable preprocessing and quality control of the measurement data is necessary. One main aspect of the presented work is the analysis of outliers in the databases. A meaningful extrapolation of extreme loads can only be performed with a reliable database. For each analysed measurement position the most suitable distribution function can be found by using both goodness of fit tests and quantile-quantile plots. For the fore-aft tower base and the blade root bending moments the 3-parameter Weibull distribution seems to provide a reasonable estimate of the extreme loads. For the side-side tower base bending moment, the Gamma distribution is found to be the suitable distribution function. The maximum likelihood fitting method is recommended for all investigated sensors, partly because it is least sensitive for outliers. For the long-term extrapolations of the tower base bending moments only marginal differences between the two applied approaches - “fitting before aggregation” and ”aggregation before fitting” - can be
observed. The short- and long-term extrapolation results are substantially different using the method of global maxima or the peak over threshold method for the extraction of extreme loads. The peak over threshold method generally results in higher 50-year extreme loads. It is a better choice compared to the method of global maxima, especially for sensors with very little measurement data for certain wind bins.

Overall this study shows that using measurement data to perform statistical extrapolations of extreme loads is subject to many uncertainties, which include the choice of the method for the extraction of extreme loads from the recorded measurement data, the choice of the distribution function and to a lesser extent also the choice of the fitting method. Particular caution is recommended for the selection of the databases, especially when extreme loads are triggered by the switching of the controller between different operating conditions.

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