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Design Loads for an Offshore Wind Turbine using Statistical Extrapolation from Limited Field Data

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ABSTRACT

When interest is in establishing design loads for wind turbines, it is common to either carry out extensive simulation studies or undertake a field measurement campaign. At the Blyth offshore wind farm in the United Kingdom, a 2MW wind turbine was instrumented, and environment and load data were obtained in a pervious study. Here, we discuss how such data, even though very limited, may be used along with parametric models to establish design loads associated with return periods on the order of 20-50 years. The environmental characteristics at the Blyth site are such that wind and waves are of primary importance. Distributions for the extreme mudline bending moment at the tower base are established using parametric models. Long-term design loads are derived for different wind regimes possible at the site and the results are compared. Using bootstrap techniques, the effect of variability in the parameters for load distribution is investigated.

KEY WORDS: Offshore wind turbines; statistical load extrapolation; design loads; bootstrap techniques.

INTRODUCTION

Our objective here is to estimate design loads for an offshore wind turbine for which the environmental and load data are available from field measurements. Using a probabilistic approach, we will estimate design loads associated with a target failure probability or, equivalently, a prescribed service life for the turbine. In the probabilistic approach, variables describing the wind and wave environment as well as the turbine response are modeled as random variables whose probabilistic distributions need to be established. In general, the required data may be obtained either from simulations with a turbine model or from the field measurements on the turbine. While data obtained from the simulations can ensure inclusion of a wide range of environmental input variables and resulting response statistics, simulation models are limited by how closely they can represent the wind turbine. Data obtained from full-scale field measurements, on the other hand, provide a true representation of the turbine response subjected to observed environmental conditions. Field data, however, can be 'limited' in the sense that they are often recorded only for a finite duration of time, and may not cover all possible environmental conditions expected to occur over the life of the turbine. Therefore, when using limited field data, statistical parametric or non-parametric techniques are often used to extrapolate the loads from observed events to loads associated with prescribed safety levels. Statistical extrapolation techniques have been used to predict both extreme and fatigue design loads for wind turbines. Examples of such studies include those by Moriarty et al (2004) and Fitzwater and Winterstein (2001).

In the present study, we employ statistical load extrapolation procedures to estimate design loads using limited field data recorded at an offshore wind turbine. We focus our attention on the bending moment at the base of the turbine tower (the mudline bending moment) as the load variable of interest. The turbine under consideration is an instrumented 2MW wind turbine at the Blyth wind farm, which is located about one kilometer off the northeast coast of England, and for which data were recorded for about sixteen months. Key features of the site pertinent to the present study include contrasting characteristics of the environment and response characteristics associated with winds blowing from the shore to the sea versus those associated with winds blowing from the sea to the shore. In addition, the turbine located in shallow water is likely subjected to breaking waves. We will discuss the possible importance of these features in estimation of design loads using the statistical extrapolation procedure.

STATISTICAL LOAD EXTRAPOLATION

In reliability-based design of wind turbines, one is required to estimate design loads associated with a prescribed level of safety – e.g., a required service life. The appropriate design load, l_T, corresponding to a service life of T years (T would ordinarily be on the order of 20 years for an offshore wind turbine) needs to be determined by consideration of the probabilistic distribution for all important environmental random variables, as well as for the turbine load conditional on the environment. We assume here that the environment for the turbine under consideration is defined by the ten-minute mean wind speed at the turbine nacelle, denoted by the random variable V, and the significant wave height, denoted by H_s. The variables, H_s and V, are modeled as jointly distributed random variables. The turbine load of interest, L, depends on V and H_s, and is thus an implicit function of the environmental random variables. For the target failure probability, P_T, associated with the service life, T, we are interested in estimating l_T such that:

$$P_T = P[L > l_T] = \iint_{H_s,V} P[L > l_T \mid (V,H_s)] f_{V,H_s}(v,h)\, dv\, dh \tag{1}$$

where $f_{V,H_s}(v,h)$ is the joint probability density function of the environmental random variables. Equation (1) makes it possible to estimate the long-term probability of exceedance of any specified load by integrating short-term load distributions conditional on V and H_s with the relative likelihood of all (V,H_s) pairs. As such, the form of Eq. (1) enables one to directly compute the probability of exceedance, or the failure probability for a given load level. Our purpose, however, is to estimate the design load associated with a given exceedance probability. To this end, we will construct the probability of load exceedance curve for various assumed load levels; then, using this exceedance probability curve that represents the long-term distribution of loads, we can simply read off the design load associated with the prescribed level of safety or the target exceedance probability.

In order to be able to use Eq. (1), one needs to establish the joint distribution for wind speed and wave height as well as the conditional distribution of the load given V and H_s. We will use parametric probability distributions to describe all the random variables. To estimate the parameters of these distributions, we will use the field data recorded at the Blyth site. Since the field data are limited, the parametric distributions may not accurately represent true conditions at the site. We will address details regarding statistical uncertainty in design load estimation due to limited field data by making use of bootstrap techniques (Efron and Tibshirani, 1993). Next, we briefly discuss the Blyth site and the recorded data, and then present the distributions of the random variables of interest in this study.

BLYTH SITE

The Blyth project is an experimental wind farm consisting of two 2MW Vestas V66 wind turbines. The Blyth site is located on the northeast coast of England, off the Northumberland shore. The wind turbines are located approximately 1 km from the shoreline. The mean water depth at the instrumented turbine varies between a Lowest Astronomical Tide (LAT) level of 6 m and a Mean High Water Springs (MHWS) level of 11 m. The average water depth at the turbine location is approximately 9 m. One of the two turbines at Blyth was instrumented as part of a research project funded by the European Commission; it has a hub height of 62 meters above the LAT level and a blade diameter of 66 m. The turbines are located on a sharply sloping submerged rock, known as the 'North Spit,' in rock-socket type foundations. This local bathymetry results in rather large breaking waves at the turbine.

Field measurements were collected for sixteen months between October 2001 and January 2003, thus covering more than one full winter season. Measured data included wind speed and direction at the nacelle, sea surface elevation, and bending moments at several vertical stations along the tower and the pile. One of these stations – the mudline bending moment – is our load variable of interest here. The nacelle wind speed data were calibrated such that the mean wind speed measured at the nacelle was approximately equal to the mean free wind speed measured at a similar elevation at a nearby shore location. The wave climate data were measured using a wave radar system located at the entrance platform of the turbine, 11.7 m above the LAT line. Additional details regarding the data and measurement system may be found in Camp et. al. (2003).

Time series data in ten-minute segments were sampled at 40 Hz, and the minimum, maximum, mean, and standard deviation for each channel were recorded as part of the statistics comprising the 'summary' data sets. From these summary data sets, we focus our attention on the mean wind speed, V, at the nacelle, and the significant wave height, H_s, obtained from the sea surface elevation, as the environment variables of interest. For the load variable, we consider the absolute maximum (larger of the maximum positive and negative values) of the mudline bending moment, M, in one of two available orthogonal components.

DESCRIPTION OF ENVIRONMENT AND RESPONSE

Of central importance in the evaluation of the exceedance probability, using Eq. (1), is the estimation of distributions of the random variables defining the environment and the response conditional on the environment. We discuss next our procedure for deriving these distributions from the available field data at the Blyth site.

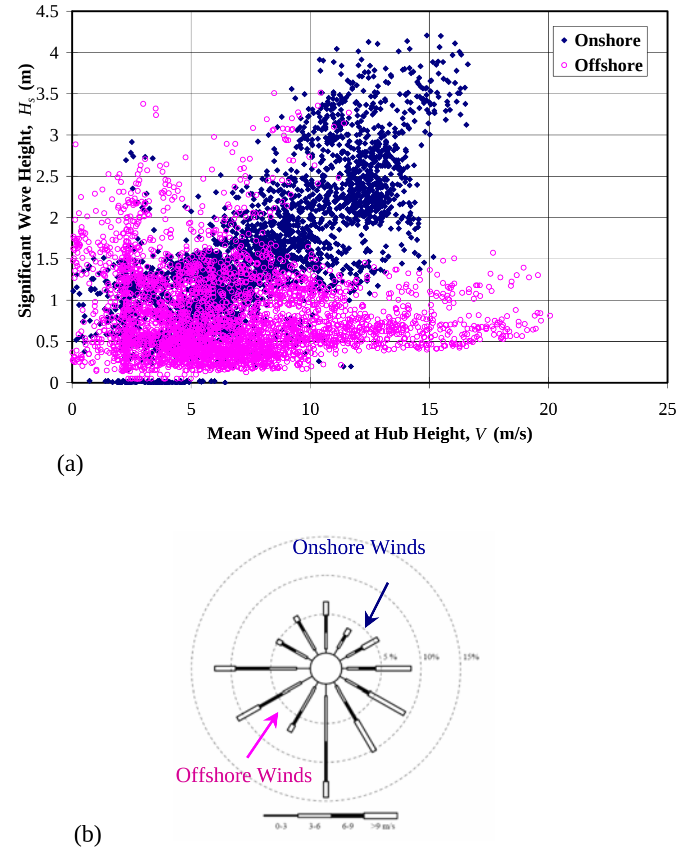


Figure 1: (a) Wind-wave scatter diagram, (b) Wind rose (from Camp et al, 2003).

Environment Random Variables

We assume that the environment at the Blyth site is adequately described by the mean wind speed, V, and the significant wave height, H_s. Before we present the distributions for these variables, we believe it is instructive to study the wind and wave data that we use to establish the respective distributions. A scatter diagram of the mean wind speed and significant wave height data is shown in Fig. 1a. It is useful to study separately the data associated with "onshore" and "offshore" wind directions. Here, onshore winds will refer to winds that blow towards the shore from the sea, while offshore winds will refer to winds that blow towards the sea from the shore. Thus, all ten-minute data for which the mean direction is between 0° and 140° are treated as onshore winds, while data for which the mean wind direction is between 180° and 325° are treated as offshore winds (Camp et al, 2003). A third control set, consisting of all of the available data, regardless of associated wind direction, is treated as the "the all-direction" winds in this study. It may be seen from Fig. 1a that there is significant scatter in the data, with onshore and offshore winds following markedly different trends. The onshore winds suggest greater correlation between wind speed and wave heights, which is possibly due to the longer fetch associated with onshore winds. Another feature of interest is the presence of some fairly high wave heights associated with relatively low wind speeds, a feature more prominent in the offshore wind data since this would not be expected in open seas where larger wave heights are generally associated with higher wind speeds. The distribution of wind speeds and directions, as presented in the wind rose in Fig. 1b, suggests that onshore winds are associated with a greater relative frequency of higher wind speeds than lower wind speeds. This is in contrast with the offshore wind data where lower wind speeds are more common. This is reflected in the respective mean wind speeds for each data set separately. The mean wind speeds are 9.57 m/s, 6.25 m/s, and 7.70 m/s, respectively, for the onshore, offshore, and all-direction winds.

We assume that the mean wind speed, V, follows a Rayleigh distribution. We are interested here in studying loads that arise while the turbine is operating. Accordingly, the Rayleigh distribution is truncated both below a cut-in wind speed, V_{in}, of 4 m/s, and above a cut-out wind speed, V_{out}, of 25 m/s. The expression for the truncated cumulative distribution function (CDF), $F_V(v)$, of V is thus:

$$F_V(v) = \frac{G(V_{in}) - G(v)}{G(V_{in}) - G(V_{out})}; \qquad G(v) = \exp\left[-\left(\frac{v}{\alpha}\right)^2\right] \tag{2}$$

where α is a single parameter of the Rayleigh distribution that can be estimated from the average value of V.

To represent the variability in the wave climate and account for the dependence of wave heights on wind speed, we assume that the random variable, H_s, the significant wave height, conditional on the mean wind speed, V, follows a Weibull distribution. The expression for the CDF of H_s conditional on V, namely $F_{Hs|V}(h)$, is given by:

$$F_{H_s|V}(h) = 1 - \exp\left[-\left(\frac{h}{\eta(v)}\right)^{k(v)}\right] \tag{3}$$

Both the shape parameter, k, and the scale parameter, η, of the Weibull distribution depend on the mean wind speed. They are estimated on the basis of the available summary data, and quadratic polynomials in mean wind speed were found to yield good estimates for k and η as functions of the mean wind speed.

Turbine Load

For the turbine load (or response) random variable, we focus our attention on the absolute ten-minute maximum (larger of the maximum positive and negative values) of the mudline bending moment in one of two available orthogonal components. Hereinafter, we refer to this load variable simply as the mudline bending moment and denote it by M. We choose to represent the random variable, M, by a two-parameter Gumbel distribution, conditional on the environmental variables, V and H_s. The cumulative distribution function for M is given by:

$$F_{M|V,H_s}(m) = \exp\left[-\exp\left[-\left(\frac{m - u(v,h)}{\beta(v,h)}\right)\right]\right] \tag{4}$$

The Gumbel parameters, u (modal value) and β (measure of dispersion), are dependent on V and H_s, and are evaluated from the available (V, H_s, M) data. To this end, the data are binned into (V, H_s) cells and the parameters, u and β, are estimated for each cell. A cell size of 2 m/s in the V direction and 0.5 m in the H_s direction is used. The parameters, u and β, are estimated using the method of moments, with distribution fits adjusted sometimes in order to obtain a better representation of tail fits because of our interest in extreme loads which require extrapolation to higher load levels than were recorded.

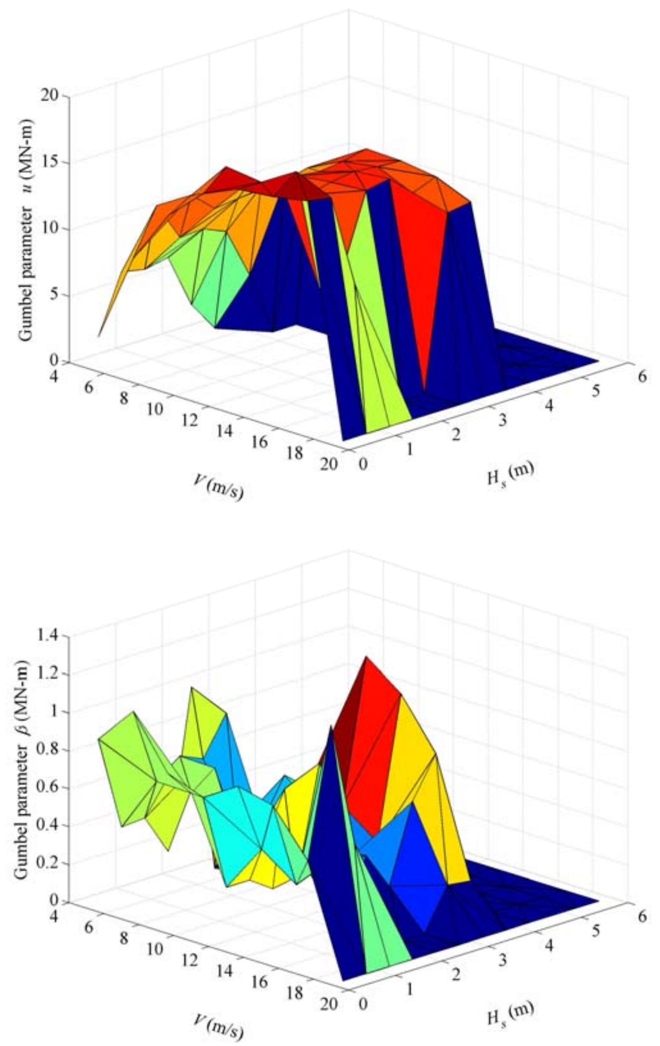


Figure 2: Variation of Gumbel parameters, u and β, with mean wind speed, V, and significant wave height, H_s, for all-direction winds. Estimates at the centers of the (V, H_s) cells are shown.

The parameters, u and β, thus obtained are presented in Fig. 2, for the all-direction winds only. It is observed from Fig. 2 that both parameters exhibit very high variability with respect to the environmental variables. This precludes development of a smooth surface fit over all the values of V and H_s of interest, which would have yielded a simple closed-form conditional distribution of the random variable M (given V and H_s). Figure 2 also highlights the limitations of using recorded data, which was alluded to earlier. It is observed that data are not available for many cells (shown by zero values of the parameters) – most notably at large (V, H_s) values. We estimate Gumbel parameters for these "empty" cells by using a weighted average of estimated parameters from all the cells that included some data, with larger weights assigned to cells closer to the empty cell. The Gumbel parameters for the offshore and onshore wind cases not shown in Fig. 2 are based on data that are subsets of the all-direction wind data, and they follow similar non-smooth trends with V and H_s.

APPLICATION AND RESULTS

Once the distributions for the environmental and load random variables are obtained, we can establish the probabilistic distribution of long-term loads and thus estimate design loads using Eq. (1). The integrand in Eq. (1) cannot be evaluated analytically, however, since not all the involved distribution functions there are available in closed form. Accordingly, we evaluate the integral using a finite summation that again involves dividing the V-H_s plane into cells of equal size. The contribution to the probability of exceedance of a given load level from each cell is computed by evaluating the load distribution at the center of the cell, under the assumption that the distribution remains fairly constant over each cell. The total probability is finally obtained by summing contributions from all the cells as expressed by the following double summation:

$$P_T \approx \sum_{i=1}^{N_V} \sum_{j=1}^{N_H} \left[1 - F_{L|V,H_s}(l_T) \,|\, v_i, h_j\right] f_{V,H_s}(v_i, h_j)\, \Delta V\, \Delta H_s \qquad (5)$$

where N_V and N_H denote the number of cells along the V and H_s directions, respectively. The width of the cells is denoted by ΔV and ΔH_s in each of the directions. Each cell (i, j) has central value, (v_i, h_j). We use the same cell widths as were used to estimate the turbine load distribution parameters – namely, 2 m/s in the V direction and 0.5 m in the H_s direction. This leads to a total of 96 cells when we evaluate the summation for wind speeds between 4 and 20 m/s, and for significant wave heights up to 6 m. The upper bounds for V and H_s were verified to be satisfactory for the purposes of these computations, primarily due to the low probability associated with higher wind speed and significant wave height levels.

The long-term load exceedance probability (i.e., the probability of exceeding specified levels of M in ten minutes), computed using Eq. (5), is shown in Fig. 3 with the thicker lines, for all three wind direction cases – namely, the all-direction, onshore, and offshore winds. It is observed that at higher load levels associated with longer return periods, the exceedance probability in offshore winds is generally higher than for all-direction winds, while this probability for onshore winds is significantly lower (by two to three orders of magnitude). The exceedance probability curve for the all-direction winds lies between the probability curves for the onshore and offshore winds as might be expected since the all-direction winds include the onshore and offshore winds as subsets. The design load for a specified target probability (or return period) may be estimated from the exceedance probability curves in Fig. 3. Results for 20- and 50-year return periods are summarized in Table 1 – for example, the design load for a 20-year return period is found to be 28.3 MN-m, 32.9 MN-m, and 19.7 MN-m, respectively, for the all-direction, offshore, and onshore winds. Small increases in these loads are seen at the higher 50-year return period level.

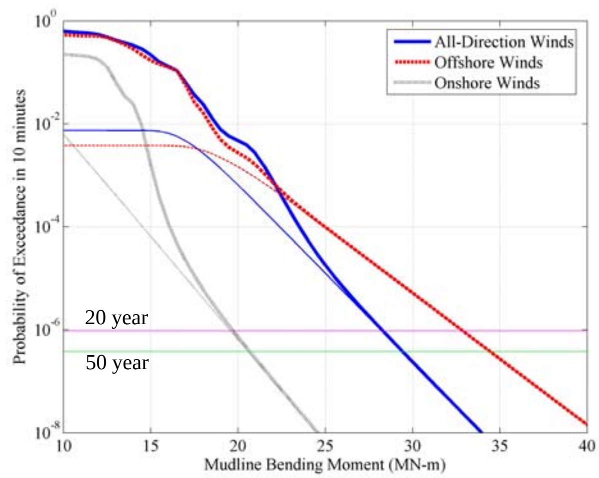
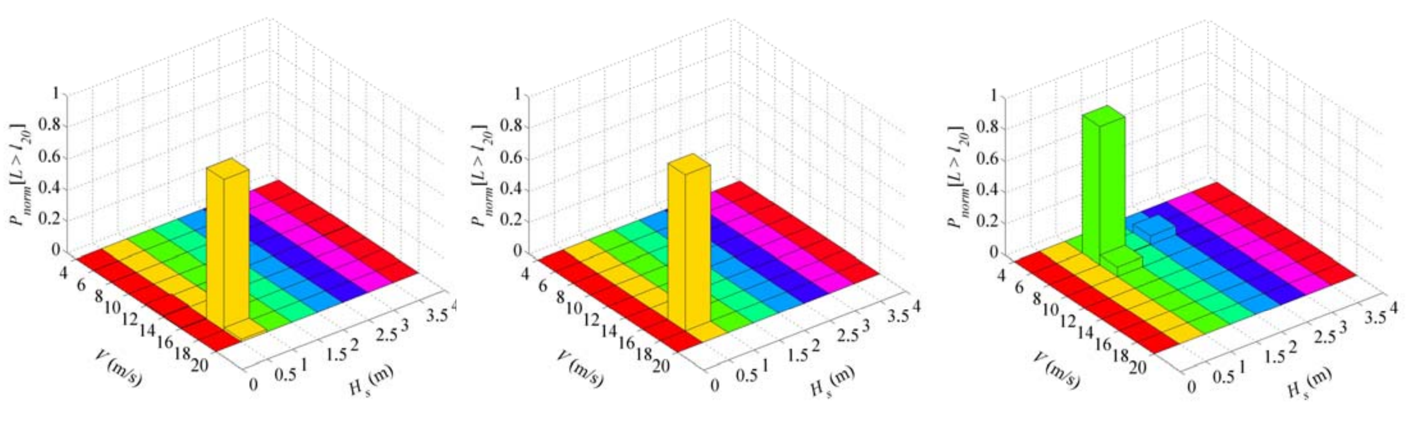


Figure 3: Probability of load exceedance curves for the three wind direction cases. The thick lines represent the total probability, while the thin lines represent contributions only from significant cells identified in Fig. 4.



(a) (b) (c)

Figure 4: Fractional contributions of individual (V, H_s) cells to the normalized probability, P_{norm}, representing the cell probability divided by the total probability of exceeding the 20-year design load for (a) all-direction winds, (b) offshore winds and (c) onshore winds. Significant cells are the cells with the largest contributions.

Table 1: Design loads for different wind directions.

Return Period (years)	Design Load (MN-m)		
	All-direction	Offshore	Onshore
20	28.3	32.9	19.7
50	29.4	34.4	20.7

We now study the relative contribution of different (V, H_s) cells to the total probability of exceedance of a given load level. This enables one to determine the most significant environmental conditions that govern the overall risk. Figure 4 shows the fractional contribution of each cell to the exceedance probability associated with a 10-year return period load. It is observed that, for all three wind direction cases, a single cell alone makes almost the entire contribution to the overall exceedance probability; we refer to these cells as significant cells in the following. The exceedance probability curves for these significant cells are plotted in Fig. 3 using thin lines. It may be seen that these cells contribute almost all of the probability at high loads, which include the design loads presented earlier for the 20- and 50-year return periods. To understand why only a few individual cells identified in Fig. 4 contribute significantly to the total exceedance probability, we note that the long-term load exceedance probability is obtained by summing, from each cell, the product of the short-term distribution of loads (given the environment) and the environment distribution itself, as described by Eq. (5). In this study, it is found that, for all three cases, contributions from the significant cells are large due mainly to the large short-term load exceedance conditional probability. This, in turn, is due to large estimates of Gumbel parameters, u and β, for the significant cells compared with those for other cells in the three wind direction cases. It should be pointed out that the results presented and conclusions regarding significant cells are directly dependent on the available data, which, are extremely limited in some cells.

Because estimates of the parameters for the distributions of the load variable, M, greatly influence the results, it is important to investigate the effect of variability or uncertainty in these parameters on predicted design loads. This variability stems from the relative scarcity of data in some cells as well as from the uncertainty associated with statistical estimation of the parameters using the data that are available. We discuss the effect of variability in parameters in the following.

Variability in Parameters for Load Distribution

We study the effect of uncertainty in the parameters, u and β, for the short-term load distribution, M, conditional on environmental variables, V and H_s, and the resulting variability in the predicted design loads. In order to quantify this variability, we employ non-parametric bootstrap techniques (Efron and Tibshirani, 1993) that rely on randomly resampling data, say N_r times, and then estimating parameters, u and β, for each resampling, using the same approach followed for the mean (no-variability) parameter predictions that were presented before (in Fig. 2). Using the set of N_r estimates for the two parameters, it is possible to obtain appropriate statistics such as the mean value and standard deviation of each parameter, which helps to quantify the variability in that parameter. We study the effect of variability in these parameters on the long-term load exceedance distribution by computing exceedance probability curves for each of the resamplings, and then computing 5- and 95-percentile levels of probability for a specified load level. These can then be used to provide confidence bounds on our mean value (no variability) estimates of design loads for specified return periods.

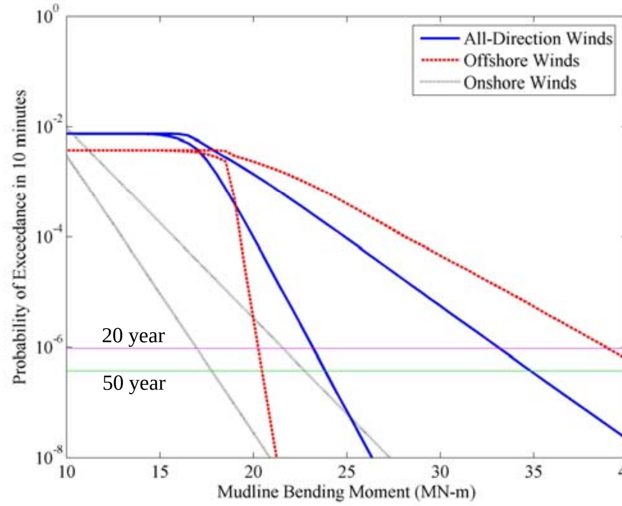


Figure 5: Probability of load exceedance curves at the 5- and 95%-confidence levels based on bootstrapping of recorded loads data. Results shown are for significant cells only.

The effect of the variability in parameters of the short-term load distribution is presented in Fig. 5, which shows the 5- and 95-percentile values of the exceedance probability, for a given load level. The curves shown are only for the significant cells (i.e., the cells contributing most to total probability, as indicated in Fig. 4). It is evident from these curves that, for any given planned service life or return period, the range of predicted design loads can be very large, which is a direct result of the limited data available. For example, for the all-direction winds, the 5- and 95-percentile design loads for a 20-year service life are about 23 MN-m and 33 MN-m, respectively. This range represents greater than 30% of the mean design load prediction (see Table 1). The effect of variability is most prominent for offshore winds and least so for onshore winds. Onshore wind loads exhibit the lowest uncertainty because the significant cell for this case had a larger amount of data (58 records) than was the case for the offshore and all-direction winds. Moreover, the Gumbel parameters estimated in this case led to a very good distribution fit to the data; hence, bootstrap resamplings did not introduce large variability in the parameter values and thus in the design loads. The significant cell in the offshore winds, on the other hand, had much less data (only 32 records) and these data exhibited relatively large scatter leading to worse fits from parameter uncertainty out of the bootstrap resamplings. This, in turn, led to significant uncertainty in design load predictions for the offshore case. The variability in design loads for the all-direction case was not as large as in the onshore case but not as small as in the offshore case.

Discussion

In order to interpret the various results presented from a physical point of view, a question of particular interest relates to why the design loads are governed by offshore winds, even though the mean wind speed for the offshore winds case is smaller (6.25 m/s) than that for the onshore winds (9.57 m/s) and the water depth is fairly small which might suggest relatively low importance of hydrodynamic loads. Possible reasons include (i) the complex wave kinematics at the site due to the shallow water and the steeply sloping sea bed; and (ii) wind-wave misalignment. Camp et al (2003) showed that the wind and wave directions for the offshore winds at the Blyth site are generally misaligned, in contrast to onshore wind conditions where wind and wave directions are generally aligned, due to the larger fetch associated with onshore winds. Because the wind turbine response variable (a component of the mudline moment) studied here has a fixed orientation in space, the misalignment of the wave load relative to the wind load can act to reduce the net bending moment at the point under consideration. If this occurs, it is then possible that higher waves might lead to lower bending moments, and vice versa, for offshore wind conditions. This might, in part, also explain why the significant cells (see Fig. 4) for offshore winds are associated with low values of significant wave height. In addition to wind-wave misalignment, several other factors specific to the Blyth site might influence turbine loads. One such factor is that the turbine is located in shallow water (about 9 m), on a very sharply sloping sea bed, where changes in the mean water level can lead to significant changes in the wave kinematics and in hydrodynamic loads. It was, in fact, found from the data that the low wave heights causing the larger loads are generally associated with relatively higher mean water levels. Furthermore, this turbine location experiences breaking waves that cause impact loads on the tower. Due to all of these factors, the resulting lateral hydrodynamic loads on the tower are rather complex in nature (Henderson et al, 2003). If one were to model these various effects, additional random variables (such as the inclusion of wave period, wave spreading/directionality parameters, etc.) that define such more complex environmental conditions would need to be considered.

Finally, the nature and quantity of the recorded data place severe limitations on the analysis based on such data. While the ten-minute environmental and turbine load statistics were recorded at the Blyth site for a period of sixteen months, the amount of good usable data (for which meaningful measurements for all the relevant channels are available) makes up only about ten percent of the overall data. These data are thus limited in the sense that they may not represent all the likely environmental conditions at this site. If more data were available, confidence bounds on estimates of the parameters used for distributions, and on subsequent quantitative results such as on predicted design loads, would be improved. Recognizing that there are limitations in making definitive inferences, the presented analyses here suggest that design loads for mudline bending moment, obtained using the statistical load extrapolation procedure are governed by offshore winds.

CONCLUSIONS

We have used a statistical load extrapolation procedure to estimate design loads for an offshore wind turbine using limited field data. The mean wind speed at the nacelle and the significant wave height were used to describe the environment, while the mudline bending moment was used to describe the turbine load of interest. Short-term distributions for the turbine load conditional on the environmental variables were modeled using parametric distributions. Parameters for these distributions as well as for the environmental random variables were estimated from the available data, which were extremely limited. Design loads, associated with return periods of 20 and 50 years, were obtained.

It was observed that the environmental and response characteristics associated with onshore winds (winds blowing from the sea to the shore) and offshore winds (winds blowing from the shore to the sea) are significantly different. The design loads were thus calculated separately for these different wind regimes and it was found that the offshore winds governed the design loads even though the average wind speeds are lower for these wind conditions, compared with those for onshore winds. “All-direction” winds were also studied for the sake of comparison. It was found that, for each wind regime, only a small subset of mean wind speed and significant wave height combinations made dominant contributions to the exceedance probability of a given load level. This was mainly due to the relatively large values of the distribution parameters (modal value and measure of dispersion for the Gumbel model used) for the short-term load conditional on the environmental random variables that were found over a small range of wind speeds and wave heights. It was noted that the estimation of these parameters has limitations as the field data available for such estimation are very limited. The variability in the estimation of the parameters for the short-term load distributions was studied using bootstrap techniques, and it was found that the range of predicted design loads for a given return period was very large – a clear manifestation of the lack of sufficient data.

In summary, it was concluded that, within the limitations related to the quantity of field data, offshore winds govern the design loads for mudline bending moment for the turbine at the Blyth site. It was identified that features particular to the site such as the wind-wave misalignment for offshore winds as well as the complex wave kinematics and hydrodynamics at the site due to the presence of nonlinear, breaking waves may partly explain why offshore winds govern the design. Further studies may be needed to quantify some of these effects.

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