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# ANALYSIS OF OFFSHORE WIND TURBINE OPERATION & MAINTENANCE USING A NOVEL TIME DOMAIN METEO-OCEAN MODELING APPROACH

**I. Dinwoodie*, F. Quail**
Doctoral Training Centre for Wind Energy Systems
Department of Electronic and Electrical Engineering
University of Strathclyde
G1 1XW Glasgow, Scotland, UK
Email: iain.dinwoodie@eee.strath.ac.uk

**D. McMillan**
Institute for Energy and Environment
Department of Electronic and Electrical Engineering
University of Strathclyde
G1 1XW Glasgow, Scotland, UK

## ABSTRACT

*This paper presents a novel approach to repair modeling using a time domain Auto-Regressive model to represent meteo-ocean site conditions. The short term hourly correlations, medium term access windows of periods up to days and the annual distribution of site data are captured. In addition, seasonality is included. Correlation observed between wind and wave site can be incorporated if simultaneous data exists. Using this approach a time series for both significant wave height and mean wind speed is described. This allows MTTR to be implemented within the reliability simulation as a variable process, dependent on significant wave height. This approach automatically captures site characteristics including seasonality and allows for complex analysis using time dependent constraints such as working patterns to be implemented. A simple cost model for lost revenue determined by the concurrent simulated wind speed is also presented. A preliminary investigation of the influence of component reliability and access thresholds at various existing sites on availability is presented demonstrating the ability of the modeling approach to offer new insights into offshore wind turbine operation and maintenance.*

## INTRODUCTION

Since the mid 1990s, there has been an exponential growth in the world wide installed capacity of wind turbines from around 6GW, concentrated in Northern Europe and the USA in 1996 to almost 200 GW spread across the world [1]. Onshore wind power is now considered the most mature renewable technology and operators have obtained significant experience in operation and maintenance (O&M) of wind farms. The most common approach for large onshore wind farms is a combination of scheduled maintenance, typically one to two visits per year and reactive maintenance, restoring components after failure. This approach has been deemed to be cost effective for operators and has allowed onshore availabilities of over 97% to be achieved [2].

In the last decade offshore wind energy has experienced exponential growth to a worldwide installed capacity of over 3GW focused in Northern European waters [3]. This expansion has coincided with the arrival of larger, multi MW machines suited to sites with higher mean wind speeds and has been driven by the decrease in available onshore sites and planning issues. This is particularly true in the UK where applications for large onshore wind farms have met with increasing planning difficulty and public resistance due to their visual impact. The shift towards offshore development has resulted in greater capacity currently being under development in the UK than onshore [4]. In addition, offshore projects currently at the scoping or development stage in Europe total exceed 100GW in capacity, [5]. It will only require a small proportion of these projects to be developed to create a significant market.

The large capital expenditure for an offshore wind farm has resulted in a significantly different market structure from onshore wind. The market currently only exists for large scale developers and is dominated by a few OEMs and this trend is expected to continue. Offshore, there has been a lack of diverse operator experience and a conspicuous lack of failure databases such as those available for onshore [6-8]. In addition, many of the larger offshore wind farms are still operated under warranty. The result is that significant uncertainty exists surrounding offshore failure characteristics and early offshore wind farms have tended to adopt conventional operational strategies. This has resulted in poor availabilities of around 80% and a wide variation between operating years and different sites [9, 10]. Similar uncertainty exists around the costs of O&M with estimates ranging from 20 – 33% of overall project cost [11, 12]. Even at lower estimates this represents a huge financial

 

investment with significant scope for savings. It is therefore necessary to identify which components have a critical influence on operations and to quantify the benefits of alternative operational strategies.

Due to the emphasis of getting turbines into the water and generating power, much of the current industry and research focus has been on adapting onshore turbines to the offshore environment and developing foundation design and installation techniques. Nevertheless, a useful body of work exploring longer term O&M of turbines and advanced Asset Management (AM) has recently begun to emerge. A recent review covering the broad range of work in the field is presented in [13, 14].

## METHODOLOGY

Various methodologies have been used to represent the failure and repair process of wind turbines. The problem is considered too complex to adequately capture using analytical expressions therefore simulation has been used to represent the process in the majority of cases. The methodology in this work is based on simulation of failures as a stochastic process based on available failure rates. Time to repair is determined by using a representative time series for wave height and waiting for an adequate repair window. A similar general approach has been considered for commercial applications [15] however, the use of an AR time series model to generate a wave height time series with a correlated wind speed time series is presented for the first time.

An alternative approach to understanding to failure modeling is to consider the statistical distribution of mean time to failures (MTTF), repair times and weather. This allows a more direct analysis of the influence of failure, repair and weather on offshore wind turbine O&M [16]. This approach allows for quicker analysis but does not allow for the level of complexity that a time series approach enables. For example modeling the influence of the number of turbines in a wind farm, vessel availability and spares provisions on O&M cannot be explored using statistical approaches as they are time constrained. In addition, statistical approaches to

A frequency domain approach is used to generate a representative wave series in [15] in order to examine some of these influences. As well as helping to reduce uncertainty by providing alternative methodology to the industry, the approach in this paper adds a correlated wind speed. This allows a more accurate assessment of losses associated with down time as well as advanced operating strategies involving the use of helicopter access in combination with vessels to be investigated.

### Monte Carlo Markov Chain Failure Model

The approach to simulating failure behavior in this work is described in [17]. The turbine is represented as a series of subsystems with known failure rate, λ defined in equation 1. Each subsystem may exist in one of a finite number of states and at each simulation time step will remain in that state or move to another state with a specified transfer probability. With sufficient knowledge of a system, deterioration can be represented using several system states as well as interdependencies between subsystems [18]. Currently, an adequate level of system knowledge is unavailable but the methodology presented in this study could be extended to incorporate this detail if it becomes available.

The simplest representation of an engineering system was adopted where each subsystem is statistically independent and is represented as a binary system either operating or failed. The transition probability of moving from an operating state to a failed state is governed by the failure distribution of the subsystem. The failure characteristics of onshore wind turbines have received some examination [8, 19] however no comparable work exists for offshore turbines. For this study it has therefore been assumed that failures have an exponentially distributed probability distribution, corresponding to random failures under normal operation. With this assumption, the probability of a failure occurring during any time step is described in Eq. (2).

$$\lambda(t) = \frac{f(t)}{N(t)} \tag{1}$$

$$U(t) = 1 - e^{-\lambda t} \tag{2}$$

To implement this in the simulation, a random number is generated in the range zero to one for each subsystem and compared to the corresponding probability obtained in Eq. (2). Where the random number exceeds the specified value, a failure occurs. A single simulation run covers 20 years, a typical expected lifetime of a turbine including warranty. A sufficient number of simulations are performed for the results to converge, the availabilities calculated at this point provide the desired results.

A turbine is deemed operational if all subsystems are operational. A solution of Eq. (2). for each subsystem at each time step is required and overall availability determined by looking at the ratio of time steps when all systems are operating versus those where at least one system is down. With sufficient knowledge of the system, advanced features such as redundancies or the ability to operate the overall system at reduced capacity under failure of individual subsystems could be investigated.

### AR Climate model

Auto-Regressive modeling approaches to describe time series data were first developed in [20], and have since been applied to a diverse range of applications. Of particular relevance to this work, AR models have been used to successfully describe significant wave height time histories [21], wind speeds for wind turbine power generation [22] and wind turbine maintenance [23]. The AR models, normalized by the mean of the data are described by Eq. (3).

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{p} \varphi_i (X_{t-i} - \mu) \qquad (3)$$

This equation is valid only for a process having a Normal (or Gaussian) distribution. Neither annual wind speed nor significant wave heights follow a normal distribution and must therefore be transformed before Eq. (3) is applied to the data sets.

It has been demonstrated that for mean wind speed removing a fit of monthly mean and diurnal variation from observed data results in the annual distribution approximating a Normal distribution. For significant wave heights it is necessary to remove a fit of monthly mean values and then apply a Box-Cox transformation on the data shown in Eq. (4) [21].

$$Y_t = T(Hs_t) = \ln(Hs_t) - \hat{\mu}_{\ln(Hs_t)} \qquad (4)$$

The required order of AR model in each case was determined using the auto-correlation function and partial autocorrelation function and determined as 2 and 20 for wind and wave models respectively. The determination of AR coefficients and model generation was performed using the MATLAB system identification toolbox. Figure 1 shows a sample original and transformed data set as well as a sample simulated time series of significant wave height. From Figure 1 it is evident that the simulated time series displays common characteristics with the original data. The simulation is deemed acceptable if it captures the short, medium and long term characteristics of the observed site, the ability of this modeling approach to meet these criteria is discussed in the climate modeling section of this report.

By using a common modeling approach for both wind and wave climate it is possible to introduce correlation between the two. This is introduced by using a common random noise component based on correlation observed in the data.Figure 2 shows how the relationship between wind and wave observed and simulated site at 3 hour resolution.

Analysis of available data in the North Sea [24] has observed that typical Pearson Correlation coefficient values between wind and wave data are of the order of 0.7-0.8. The correlation observed at both sites with coherent wind and wave data can be captured using this approach. Further sites with adequate data were not available for analysis but it is hoped that further analysis of several sites will determine the extent to which correlation between wind and wave data can be captured using this approach. The modeling approach may be unacceptable for sites where a very high correlation is observed. Countering this, it is likely that such a site would share similar seasonal trends in wind and wave data and the modeled values would have a higher correlation.

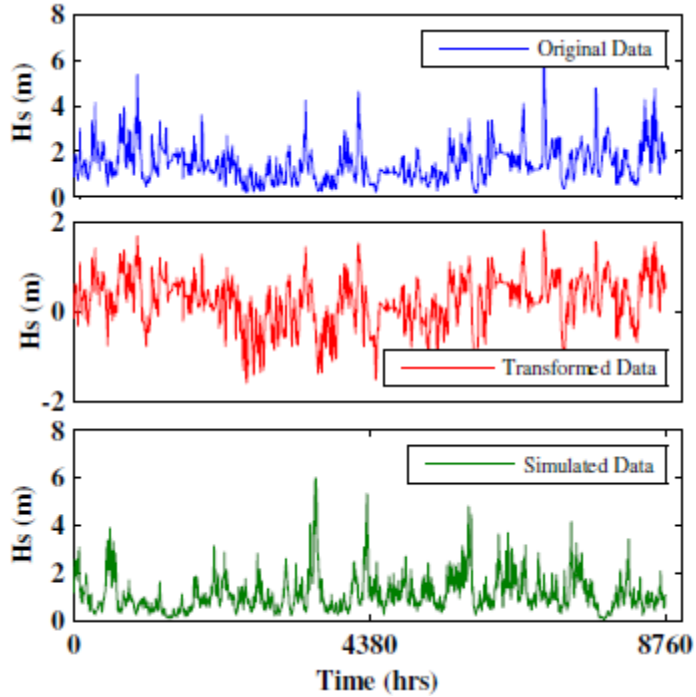


Figure 1. INPUT DATA, TRANSFORMED DATA AND SIMULATION OUTPUT OF MEAN SIGNIFICANT WAVE HEIGHTS

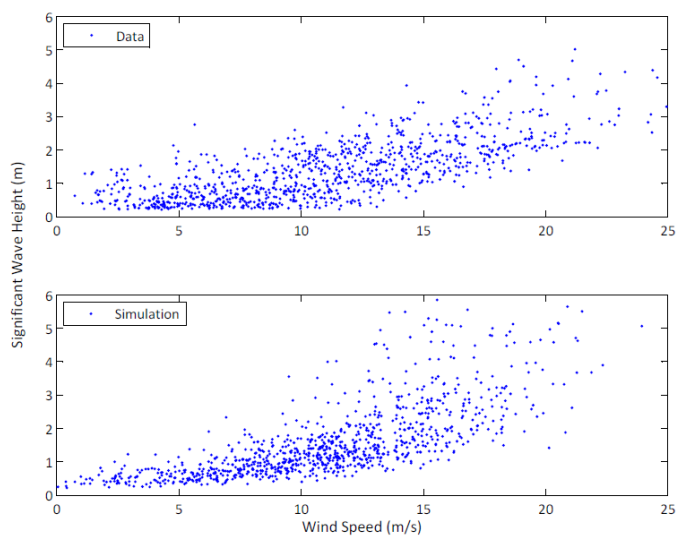


Figure 2. CORRELATION OF WIND AND WAVE DATA AND SIMULATION.

## Cost model

Due to the large size of offshore turbines, it is crucial to accurately capture the loss of earnings associated with turbine downtime. Basic analysis taking the rated power of a turbine and assuming a capacity factor and multiplying this by downtime does not take into account characteristics of individual sites such as seasonality and the fact access

limitations are more likely in above average site winds. By producing a time series of wind speed and determining lost revenue from a power curve a more representative loss of earning calculation is possible. This is particularly important when examining operational strategies as optimal strategies may vary between site and within a site depending on the season. A representative loss of earnings model is crucial to quantifying the benefit of different operational strategies as the optimum strategy is the one that minimizes the cost of energy, not simply the cost of O&M or maximizes availability. Mean simulated loss of earnings show good agreement with reported losses [9]. Each repair operation will also have an associated cost due to vessel and staff hire as well as component replacement. Although these costs are independent of the wind model, inclusion allows an investigation into the importance of climate dependent factors on overall costs.

## Sources of data

Various sources of wave and wind climate data are available. Weather data in the North Sea area is readily available although not always at the required locations or with adequate quality. Satisfactory time series of wave data in particular is difficult to obtain due to the harsh operating environment resulting in gaps in data and short measurement campaigns. The longest simultaneous wind speed and significant wave height time series data available was obtained from the FINO research platform database [25, 26] located off the coast of Germany close to the location of the Alpha Ventus research wind farm. Several years of high quality time series data was obtained through this resource and was primarily used for wave modeling verification. It was necessary to source alternative wind and wave data that were located close to the wind farms with published availability. As well as operation reports there is a large amount of climate data available at OWEZ [9] which has been extensively used in this work. For the UK Round 1 sites, wave data for access modeling was obtained from two separate databases; CEFAS Wavenet and BODC online data sets [27, 28]. It should be noted that the data extracted from these databases was not the data set located closest to the wind farms but rather the nearest with a sufficient duration and data quality.

Little offshore WT failure data exists in the public domain. The two principle sources of data are the UK round 1 wind farms that received government funding under the capital grants scheme and data from Egmond aan Zee wind farm in the Netherlands [9, 10]. The failure data set is for a single turbine type and is biased by a serial defect where a overhaul of the drive train on all machines was required. In addition, the reported data includes all recorded faults the majority of which were corrected with remote resets and therefore did not significantly contribute to down time and were independent of wave climate. The total numbers of transfers to turbines are reported and this was taken to correspond to the number of failures, requiring action. The overall faults reported were scaled to correspond to the number of failures requiring a site visit while maintaining the ratio of failures between subsystems. The original data and resulting adjusted failure rates are shown in Table 1.

Table 1: WT SUBSYSTEM FAILURE RATES AND DOWNTIME.

| ***Failures*** | | | |
|---|---|---|---|
| **Subsystem** | **Total Fails** | **Turbine/Yr** | **Adjusted λ** |
| **Ambient** | 1204 | 11.15 | 0.37 |
| **Blade** | 180 | 1.67 | 0.06 |
| **Brake** | 40 | 0.37 | 0.01 |
| **Control** | 8788 | 81.37 | 2.69 |
| **Converter** | 644 | 5.96 | 0.20 |
| **Electrical** | 615 | 5.69 | 0.19 |
| **Gearbox** | 1643 | 15.21 | 0.50 |
| **Generator** | 682 | 6.31 | 0.21 |
| **Pitch** | 2145 | 19.86 | 0.66 |
| **Scheduled** | 3522 | 32.61 | 1.08 |
| **Yaw** | 4810 | 44.54 | 1.47 |
| **Structure** | 173 | 1.60 | 0.05 |
| **Grid** | 68 | 0.63 | 0.02 |
| **Total** | **24514** | **226.98** | **7.5** |
| ***Downtime*** | | | |
| | **Down /failure** | **Total Down** | **Adjusted θ** |
| **Ambient** | 16.56 | 1788 | 44.94 |
| **Blade** | 29.88 | 3227 | 542.57 |
| **Brake** | 2.95 | 319 | 241.36 |
| **Control** | 165.84 | 17911 | 61.68 |
| **Converter** | 63.59 | 6868 | 322.76 |
| **Electrical** | 35.56 | 3840 | 188.97 |
| **Gearbox** | 966.35 | 104366 | 1922.43 |
| **Generator** | 262.34 | 28333 | 1257.30 |
| **Pitch** | 86.13 | 9302 | 131.24 |
| **Scheduled** | 83.47 | 9015 | 77.47 |
| **Yaw** | 15.22 | 1644 | 10.34 |
| **Structure** | 7.61 | 822 | 143.80 |
| **Grid** | 6.94 | 746 | 333.35 |
| **Total** | | **188184** | |

Applying onshore failure rates from previous studies to the offshore environment was considered as an alternative due to the greater availability of data. However, this approach was not adopted as these studies include a wide range of machines sizes and configurations, the majority of which are significantly different to large offshore turbines. Due to the small size of the data set, significant uncertainty is associated with failure rates and MTTR values. A simulation based approach allows this uncertainty to be quantified through sensitivity analysis of

failure rates for different subsystems against overall availability. The analysis presented is based on observed turbine and climate data as this was deemed preferable to an idealized example.

## RESULTS

The results presented highlight the ability of an AR climate model coupled with a MCMC failure model to represent observed climate and availability trends. In addition, an investigation into the effect the introduction of fault classes has on availability with different access constraints is presented.

### Climate model

A representative climate is required if the model is to be used to perform meaningful analysis. The climate model must capture the short and medium term duration characteristics that will determine waiting time after failures as well as the overall annual distribution observed at the site. In addition, any chosen methodology must be easily simulated and be generated from available data. Figure 3 shows a comparison of observed and simulated results at the Egmond aan Zee wind park (OWEZ); the ability of the AR methodology to successfully capture site characteristics is demonstrated.

Another important characteristic observed in the data is the annual variation between wave climate characteristics at a single site. Data from the FINO met mast was used in order to analyze this as it provides time series data over several years and is located in the North Sea.

The observed variability in annual wave distributions is shown in Figure 4, simulations of 10 years based on the site data and the variation in mean value in data and sample simulations are shown in Figure 4. The thick black line in both distribution pictures represents the mean annual distribution from the data and demonstrates good agreement with the observed data shown in Figure 3.

Good agreement is found between data and simulation although there is more scatter amongst the measured data. This result can be explained by examining the availability of data where large gaps exist in years 2004, 2006 and 2009. The magnitude of variation in mean value is also consistent between the simulation and observed data.

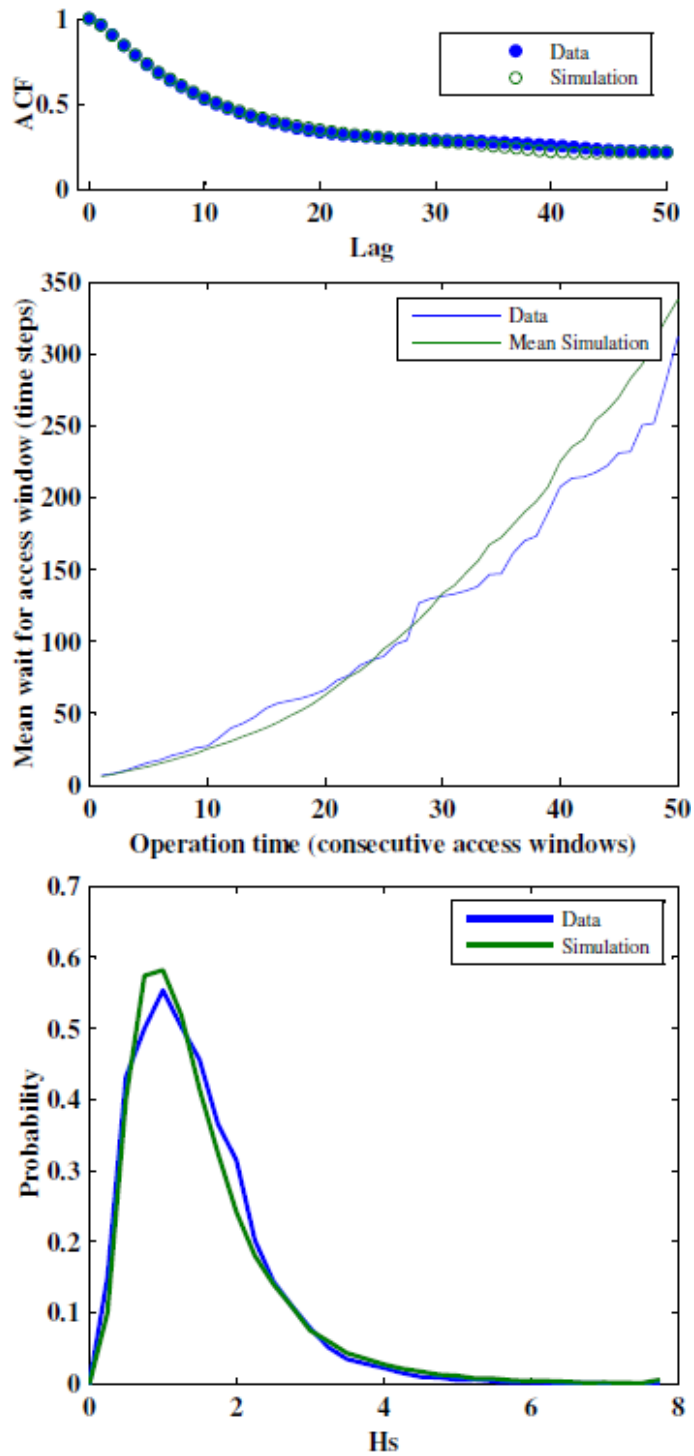


Figure 3. SIMULATION AND DATA SHORT AND MEDIUM TERM BEHAVIOUR AND OVERALL ANNUAL DISTRIBUTION

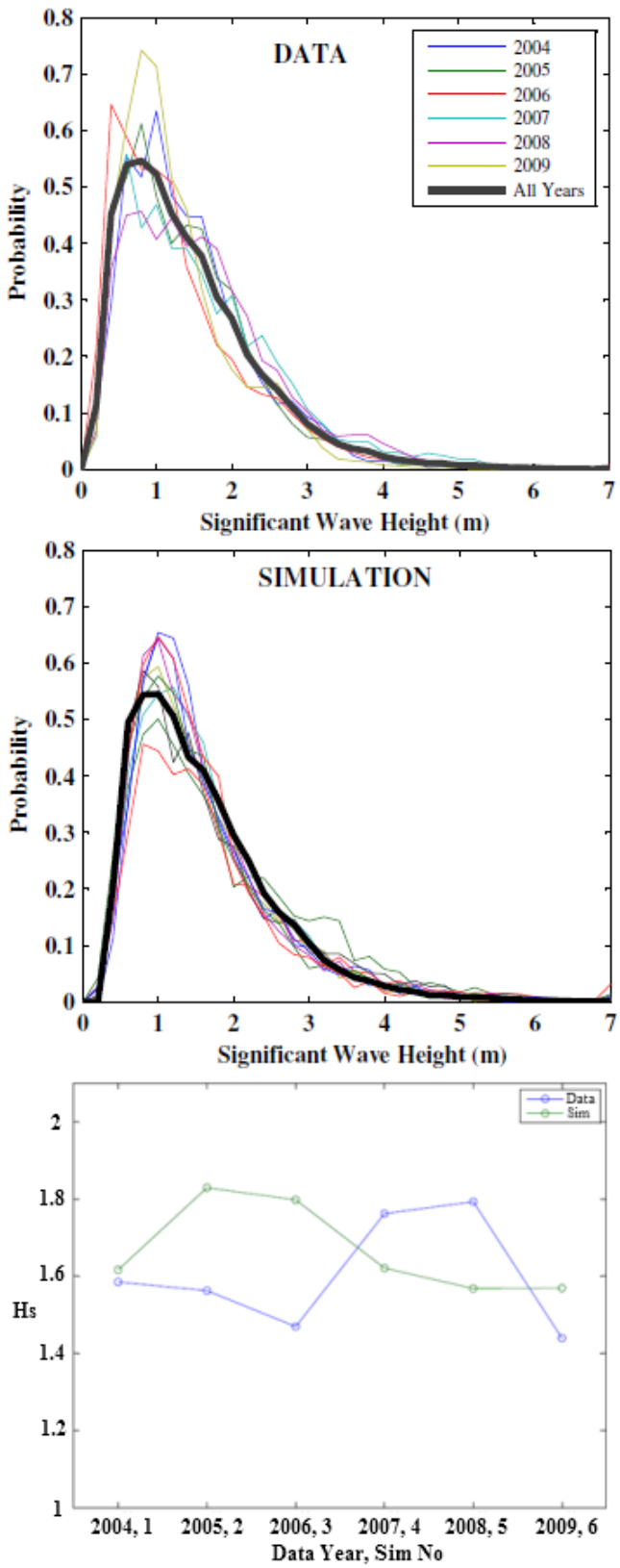


Figure 4. ANNUAL VARIABILITY IN DATA AND SIMULATION OUTPUT

## Availability model

Having established that the climate model captures key site characteristics, it was combined with the failure model to produce an availability simulation model. It is assumed that after a failure occurs to a subsystem it will remain in a down state until an adequate access window is present. The value of the access window required for each subsystem was determined from the reported MTTF values and time to repair vs access window plot shown in Figure 3. This approach does not take into account the fact that the repair process will have a weather independent aspect in operations planning and parts acquisition. Consequences of this are discussed in the Conclusion and Future work section.

An inherent advantage of this modeling approach is that the seasonal variations in availability are captured in a single simulation. This is shown in Figure 5 where the availability over 20 years shows a clear seasonal component. This is driven purely by the climate model as failures occur at random and at this stage of modeling are not assumed to be more likely to occur in higher than average winds, an assumption that could be varied in future work. There has been investigation into the correlation of failure rates for onshore wind turbines and wind speed [29] but no such work exists for offshore turbines at this time and so was not incorporated. Comparing the simulated availability to observed ability shows agreement although only 3 years of observed data are available leading to larger variation in the data than would be expected over the life time of the wind farm.

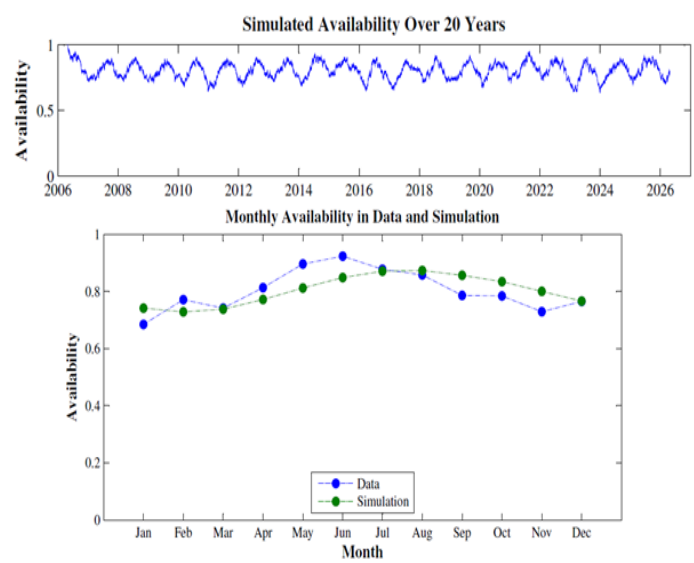


Figure 5. SIMULATED AVAILABILITY VARIATION OVER 20 YEARS AND MONTHLY AVAILABILITY OF SIMULATION AND DATA

## Inter site analysis

Using the OWEZ wind farm as the base case an investigation into the impact of wave climate on availability at other sites with published availibilites was performed. This analysis is simplified as it ignores key influences on overall availability such as distance from shore, spares provisions and operational strategy differences between sites. The round 1 sites are all near shore and use the same turbine model therefore the wave climate is the dominant difference between sites. The location of the sites as well as the wave buoys used for analysis is identified in Figure 6. Only the OWEZ site has wave buoy data at the same location as the wind farm and significant uncertainty therefore exists at the other sites. However, the study provides an insight into the degree to which wave climatology impacts availability.

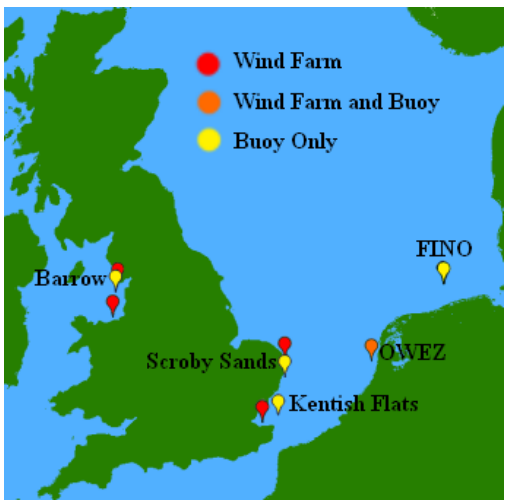


Figure 6. LOCATION OF WIND FARMS AND WAVE BUOYS

The results of the baseline simulation with an access constraint of 1.5m significant wave height and the observed values at the published sites are displayed in Table 2. The model highlights the higher availability at sites sheltered by the UK mainland although as previously identified the influence of wave climate on availability is overstated by not considering weather independent factors.

Table 2. OBSERVED AND SIMULATED AVAILABILITY [9, 10].

| *Wind Farm* | *Observed Availability* | *Modelled Availability* |
|---|---|---|
| **OWEZ** | 80.1 | 80.2 |
| **Barrow** | 72.5 | 79.1 |
| **Scroby Sands** | 81 | 88.8 |
| **Kentish Flats** | 83 | 89.9 |
| **Alpha Ventus*** | N/A | 71.0 |

## Influence of improved access and reduced λ

There has been wide spread recognition in the wind industry that improving the significant wave height that maintenance vehicles can operate in is necessary in order to improve availability of wind farms. Figure 7 shows a typical exceedance plot of significant wave height.

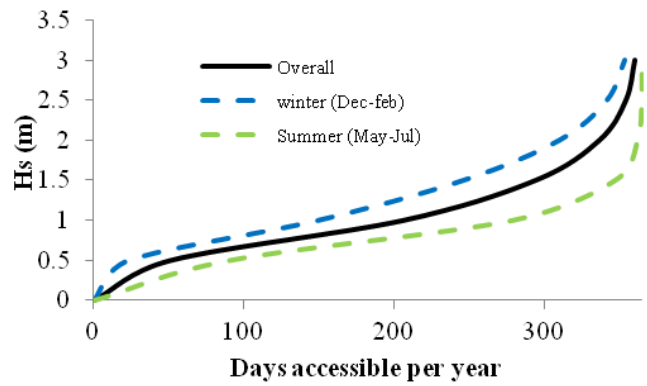


Figure 7. TYPICAL WAVE HEIGHT EXCEEDANCE PLOT.

Considering only the number of days accessible per year as a measure of availability ignores the influence of failure rates. The combined modelling approach presented in this work overcomes this simplification. Availability was calculated for various access thresholds across the different sites and is shown in Figure 8 as highlighting the current industry standard as well the onshore availability.

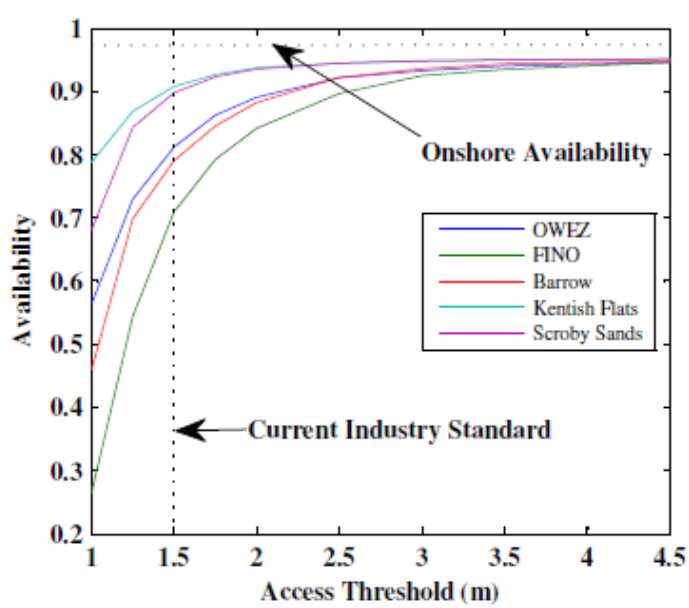


Figure 8. AVAILABILITY VS. ACCESS VEHICLE THRESHOLD FOR VARIOUS SITES.

From Figure 8 it is evident that increasing access vehicle threshold has significant benefits but does not achieve onshore levels of availability. The modelling approach identifies that there is greatest benefit at all sites from increasing the access threshold from 1.5 to 2.5 m but beyond this there is a drop off in improvement at near shore sites. A significant benefit identified is that improving the access vehicle reduces variation between sites and therefore operator uncertainty in revenue.

An alternative approach to improving availability is to reduce failure rates by improved turbine design or reduce the number of repair operations performed by the implementation of advanced asset management techniques. An initial analysis, of this approach examining failure rates is shown in Figure 9. It is identified that reducing failure rates to a sixth of the rate observed in early offshore sites, onshore availability levels are achieved without improving access vehicles. This failure rate equates to half the observed failure rate for onshore, a significant but feasible technical challenge for wind turbine manufacturers and operators.

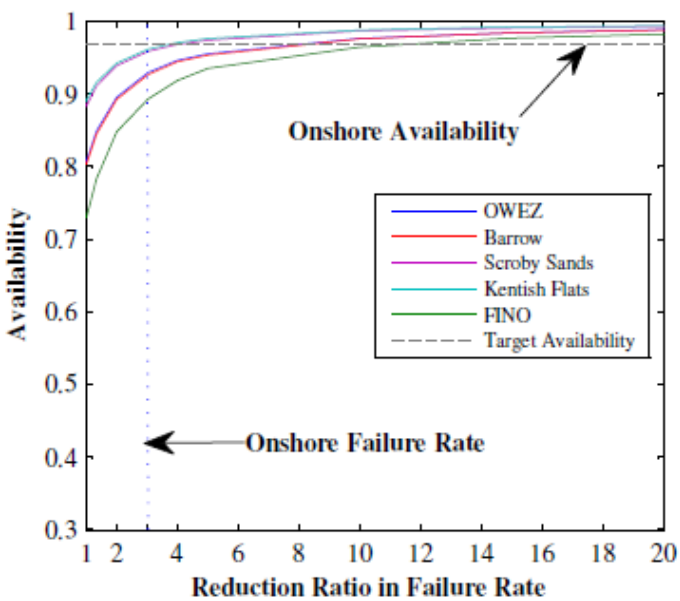


Figure 9. AVAILABILITY VS. OVERALL TURBINE FAILURE RATE AT VARIOUS SITES.

Reduction of failure rates through modification of design is expensive and may be impractical to implement on existing turbines. Therefore, reducing repair operations through condition monitoring and specifically developed O&M strategies merit further investigation.

### Major and minor faults investigation

Recent work has identified that offshore there is a need to distinguish between minor faults that can be repaired remotely or with a single maintenance engineer visiting the site and major faults that require heavy lifting equipment, suitable vessels and a team of engineers [30]. An investigation into the degree to which modeling major and minor faults has on availability has been performed and the results are shown in Figure 10. The ratio of major to minor failure rates is based on those observed onshore in [30]. Minor failures are considered to have fixed downtime of one working day, independent of climate. Major fault rates and associated down time were modified so that overall downtime for the base case is consistent with the single fault class case. The original and modified values are shown in Appendix 1.

From Figure 10 it is observed that the influence of significant wave height is exacerbated when considering failure class. This is explained by the increase in waiting time for major repair activities increasing sensitivity to access vehicle constraints. A further analysis considering several classes of failures is required to fully establish the importance of including failure classes in availability modeling.

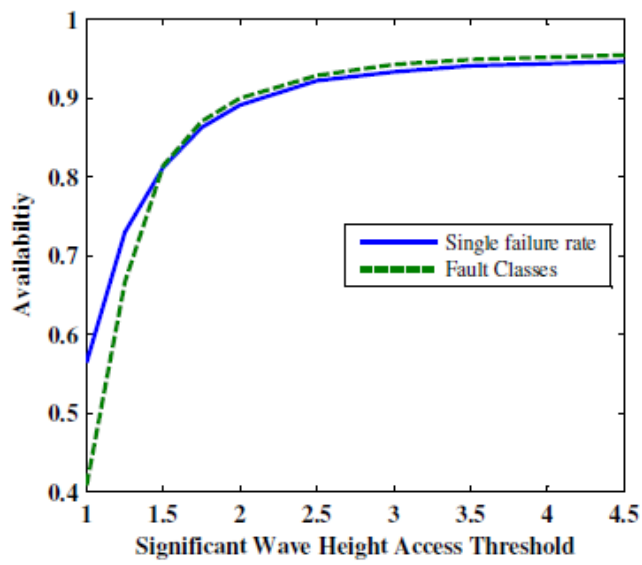


Figure 10. INFLUENCE OF FAILURE CLASSES ON AVAILABILITY CURVE.

## CONCLUSIONS AND FUTURE WORK

The paper presents an offshore wind turbine availability model based on a MCMC failure and an AR climate modeling approach. The abilities of the climate model to capture necessary site characteristics has been demonstrated for sites in the North Sea corresponding to current offshore wind farms. The capability of the combined model to represent observed failure behavior, including seasonality has been shown. An investigation into the impact of wave climatology, failure rates and failure classification on availability is also included.

The investigation identifies the benefit and limitation in influencing availability by increased access vehicle thresholds. The most significant gains at all sites are obtained by increasing vehicle operability from 1.5 to 2.5 m significant wave height, after which gains diminish and a limit is reached that is dependent on failure characteristics of the turbine. For the reported failure rates, the limit is approximately 92%,

significantly below the 97% availability achieved onshore. Reduction in overall turbine failure rate to levels observed onshore increases availability at the baseline site to over 92% but a reduction by a factor of 8 is required to achieve onshore availabilities. A full sensitivity study combining improved access and reduced failure rates will be performed in the future. The introduction of failure classes has been explored for the case of minor and major faults. The results show that the availability curve is more sensitive to wave climate due to the extended downtime associated with major failures. This agrees with previous research for other UK sites using different methodology [16]. Expansion to include several categories and further analysis on a variety of sites will also be carried out in later work.

It has been identified that the current delay model does not incorporate weather independent aspects of repair operations or variations in site logistic times; the model will be expanded to include these in future studies.

The results presented in this work have concentrated solely on availability of a wind farm. Although availability is an important metric to indicate how well a wind farm is performing the principal driver for operators is to minimize cost of energy. Investing in a more advanced maintenance vehicle, condition monitoring system or refurbishment program may outweigh the benefit of improved availability. To investigate this full cost model is required. The added benefit of the AR modeling approach in reflecting loss of earnings was highlighted and a description of how this will be calculated has been described in this work.

Future studies based on the analysis presented here will therefore include more complex failure and repair representation and will determine optimum solutions based on minimizing costs. In particular, a detailed sensitivity analysis to quantify the importance of failure rates and down time of all subsystems on availability and cost of energy will be possible using the described approach. In addition, the model can underpin investigations into unconventional maintenance approaches such as opportunistic or conditioned based maintenance to quantify their value to the operator.

## ACKNOWLEDGMENTS

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## NOMENCLATURE

| Symbol | Definition |
|---|---|
| f(t) | Observed Failure Rates |
| Hs | Significant wave height |
| N(t) | Observed Time Period |
| p | AR degree |
| U(t) | Failure likelihood function |
| Xt | Modeled time data |
| Yt | Transformed time series |
| εt | White noise disturbance |
| λ | Failure Rate |
| μ | mean |
| $\hat{\mu}_{\ln(Hs_t)}$ | Fourier Series fit of log means |
| φt | AR parameter |

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# APPENDIX 1

ORIGINAL AND MAJOR / MINOR CLASS FAILURE RATES AND DOWNTIMES

| | Original | | Modified | | | |
|---|---|---|---|---|---|---|
| | λ | | λ | | Downtime (hrs) | |
| | | Downtime (hrs) | minor | major | minor | major |
| **Ambient** | 0.37 | 44.94 | | 0.37 | | 44.94 |
| **Blade** | 0.06 | 542.57 | 0.04506 | 0.01001 | 24.00 | 2876.13 |
| **Brake** | 0.01 | 241.36 | 0.00962 | 0.00262 | 24.00 | 1038.41 |
| **Control** | 2.69 | 61.68 | 2.12263 | 0.56604 | 24.00 | 202.99 |
| **Converter** | 0.20 | 322.76 | 0.15555 | 0.04148 | 24.00 | 1443.09 |
| **Electrical** | 0.19 | 188.97 | 0.14855 | 0.03961 | 24.00 | 807.59 |
| **Gearbox** | 0.50 | 1922.43 | 0.33511 | 0.16756 | 24.00 | 5719.29 |
| **Generator** | 0.21 | 1257.30 | 0.13910 | 0.06955 | 24.00 | 3723.89 |
| **Pitch** | 0.66 | 131.24 | 0.51042 | 0.14584 | 24.00 | 506.60 |
| **Scheduled** | 1.08 | 77.47 | | 1.07755 | | 77.47 |
| **Yaw** | 1.47 | 10.34 | 1.05115 | 0.42046 | 6.00 | 21.20 |
| **Structure** | 0.05 | 143.80 | 0.04234 | 0.01059 | 24.00 | 622.99 |
| **Grid** | 0.02 | 333.35 | 0.01642 | 0.00438 | 24.00 | 1493.42 |

Where the MTTF was not related to failures, ambient and scheduled, no fault class was introduced. Where the expected down time was less than one day, the fixed downtime for a minor failure was reduced to 6 hours.