Modelling the Impact of the Environment on Offshore Wind Turbine Failure Rates

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Abstract: For offshore wind turbines to become an economical energy generation option it is vital that the impact of the offshore environment on reliability is understood. This paper aims to model the impact of the wind speed and the external humidity and temperature. This is achieved using reliability data comprising of two modern, large scale wind farm sites consisting of approximately 380 wind turbine years of data. Weather data comes from a nearby weather station and an onsite met mast. A model is developed, using the reliability data, which calculates weather dependant failure rates and downtimes which are used to populate a Markov Chain. Monte Carlo simulation is then exercised to simulate the lifetime of a large scale wind farm which is subjected to controlled weather conditions. The model then calculates wind farm availability and component seasonal failure rates. Results show that offshore, of the weather conditions wind speed will have the biggest impact on component reliability, increasing the wind turbine failure rate by approximately 61%. The components affected most by this are the control system and the drive train. The higher offshore wind speeds appear to cause a higher proportion of major failures than experienced onshore. Research from this paper will be of interest to operators and wind turbine manufacturers who are interested in maintenance costs.

1. Introduction

Despite the development of onshore wind turbines, offshore wind still remains an expensive option for investors. The cost of offshore wind is far greater than its competitors, as shown in **Table 1**[1]. Operation and maintenance (O&M) is a larger percentage of the cost of energy for offshore wind than any other technology, it is vital that this reduces to attract investors [1] [2] [3].

Table 1: Cost of energy and O&M for different generating technologies

Power Station Type	£ per MWh	O&M Cost (% of cost of electricity)
Nuclear	23	19.6 %
Gas (CCGT)	22	6.4 %
Coal (IGCC)	32	10 %
Onshore Wind	37*	13.2 %
Offshore Wind	55*	30.9 %

* Not taking standby generation into account

An important measure of wind asset performance is availability – which is the proportion of time that an asset is available to generate electricity. Typically onshore turbines lose little electricity to downtimes and achieve around 97 – 99% availability [3]. Offshore wind farms however only manage availabilities of 90 – 95% and require much higher costs per turbine to attain this [4]. The periods of unavailability generally consist of planned maintenance and corrective maintenance.

In order to achieve higher availabilities at lower costs, there must be attempts made to refine current O&M practices to reduce their direct costs [3]. Currently the most influential factor in the cost of O&M for a large offshore project is the distance of the wind farm from shore [4]. The reason for this is because the further the distance from shore the wind farm, the more inaccessible it is throughout the year [4]. Planned maintenance which is well scheduled in advance and takes place during the calmer summer months does not affect availability as much as the corrective maintenance which can take place anytime throughout the year and can cause long downtimes due to component lead-in time, vessel lead-in time, long transit times and poor accessibility [3] [4].

This paper aims to reduce the cost of O&M by helping make more efficient and informed decisions when planning scheduled maintenance to reduce the costs of unscheduled maintenance. This will be achieved by using weather conditions to calculate more accurate component failure rates which can be used in computer simulations to highlight components which are most at risk of failure so maintenance can be planned appropriately.

2. Literature Review

Research has been carried out previously to investigate the effects of the environment on wind turbine reliability. Using wind turbine reliability data from the German WMEP database, [5] showed that the failure rate of certain wind turbine components increased linearly as the average daily wind speed also increased. The components most badly affected by wind speed were electric components.

Further research from [6] was undertaken to investigate if their dataset - Windstats Denmark - showed any relationship between the wind energy index and wind turbine components. A time series of the wind speed was compared to wind turbine component availability time series to calculate their correlation. The availability time series of the generator, yaw system and mechanical control had the strongest correlation with wind speed.

This research was taken forward further by [7] who considered a wider, more detailed database which consisted of three sites in Germany which operated Enercon E30 and E33 wind turbines. As well as average wind speed, maximum wind speed, temperature and humidity were also analysed along with component availability time series. [7] found that the maximum wind speed time series correlated most closely with the wind turbine component availability time series, but overall there was a considerable cross-correlation between the weather data and the failure data for each site. However, the turbines used in their database were 300kW variable speed, hydraulic blade pitch controlled wind turbines which consisted of a synchronous rotor and a gearbox – not therefore representative of the type of wind turbine which would be deployed presently offshore.

[8] used a database of SCADA alarm logs from more than 23,000 wind turbines to evaluate the impact of the environment on wind turbine failure rates. It was found that, in general, as the average monthly temperature increased the downtime decreased. However for air temperatures between 18 - 21°C and wind speeds between 28 – 33m/s the failure rate and average downtime of the wind turbines increased [8]. This is to be expected however as wind turbine nacelles have limited access during period of high wind speeds and so would be inaccessible for maintenance if a component failed [9]. It then stands to reason those periods of low wind speeds would result in lower average downtimes and that these periods were more likely to occur in the summer when wind speeds were low and temperatures were high, as [8] found.

3. Methodology

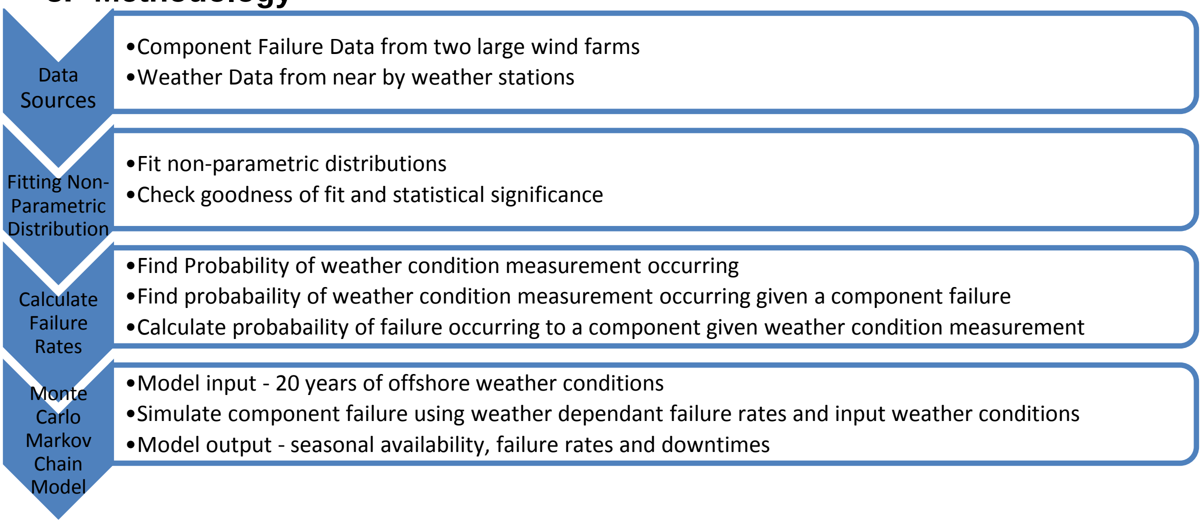

Figure 1: Methodology procedure

The methodology used in this research is outlined in Figure 1. The overall aim is to model any relationship that exists between component failure modes and the weather; these relationships will then be used to model the effect of the offshore environment on wind turbine component failure rates.

i. Data Sources

a. Wind turbine reliability data

Table 2: Summary of reliability data

Site	Installed Capacity (MW)	Number of Wind Turbines	Duration of Data (years)	Wind Turbine Years
A	322	140	2.01	281.5
B	119.6	52	1.91	99.4

Table 2 gives a brief summary of the wind turbine reliability data used. The data comes from a wind farm operator's work order system and comprised of two onshore sites which use turbines of the same model and relatively similar age. In total there was 380.9 turbine years of data.

Table 3: Wind turbine component failure rates

Wind Turbine Component	No Filter	12 Hour Filter	24 Hour Filter
Emergency System	0.021	-	-
Meteorological Instruments	0.060	0.008	0.002
Rotor	0.037	0.010	0.006
Blade Pitch System	0.054	0.021	0.014
Drive Train	0.124	0.070	0.023
Yaw System	0.120	0.035	0.019
Hydraulic System	0.062	0.027	0.012
Control System	0.414	0.176	0.062
Main Generator	0.025	0.008	0.004
Lifting System	0.008	-	-
Nacelle	0.012	-	-
Tower	0.048	-	-

Failures were defined by the operator as an event which caused the wind turbine to stop generating electricity and suffer downtime. The operator logged the failure component, downtime, date and time, turbine number and the type of maintenance undertaken (preventative or corrective). Incomplete entries were removed from the dataset along with all preventative failures as these would have been planned in advance and would have involved pre-emptive actions on components which would not have failed yet.

The wind turbine model consists of twelve sub-assemblies, shown with their respective failure rates in Table 3. The data can be filtered to remove failure events according to the length of their downtime. In some cases there was not enough data after filtering to calculate a reliable failure rate – these instances are represented in table 3 as blank rows.

b. Weather Data

Onshore weather data comes from weather stations located near to the two onshore wind farm sites and wind data from a met mast located on site A. The wind, temperature and humidity data for site B comes from weather station 2 (WS2), while the wind data for site A comes from the met mast and the temperature and humidity data comes from weather station 1 (WS1).

Offshore weather data comes from the FINO weather station and Janice oil rig weather station which are located in the North Sea [14]. The wind speed measurements from FINO and the temperature and humidity measurements from Janice are merged to create a single North Sea offshore weather dataset. This approach is a result of FINO only measuring wind speed and the height at which wind speeds are measured at Janice being uncertain; therefore a merged dataset is used for analysis. A histogram of offshore wind speeds measured at FINO is shown in Figure 2.

The resolution of the data was reduced from 1 hour to a day. Three weather conditions were considered – daily average wind speed, humidity and temperature.

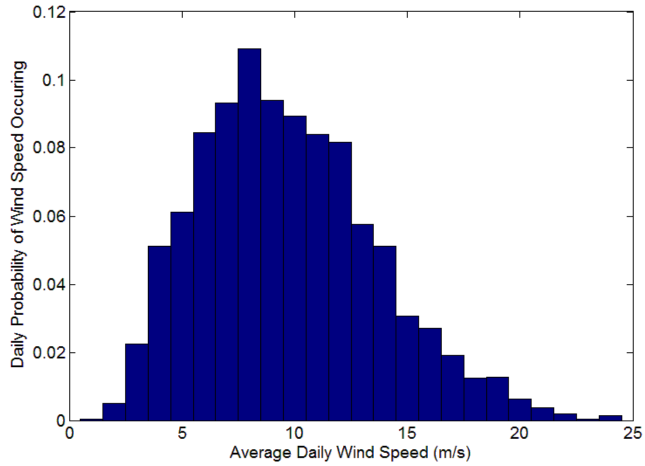

Figure 2: FINO Offshore wind speed histogram

ii. Fitting Curves and Non-Parametric Distributions

a. Reliability Data

The weather station data is paired up with the reliability data so that for every failure recorded, the average temperature, humidity and wind speed on the day of the failure occurring are also recorded.

The merged reliability and weather data is then split up into the twelve subcomponent categories with a corresponding daily average temperature, humidity and wind speed at the time of the recorded failure.

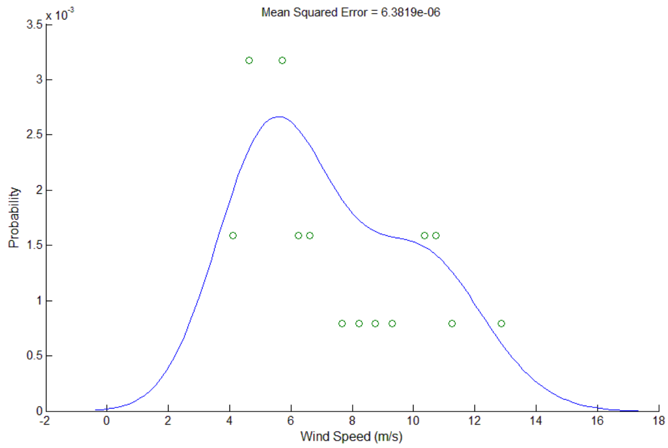

Figure 3: Example of kernel density estimate

Average wind speed distribution is commonly represented by a Weibull function. However it is not known how the average wind speed on days when a failure has occurred to a particular subcomponent will be distributed. This is also the case with humidity and temperature. For this reason non-parametric distributions are fitted to the data, using kernel density estimations, as illustrated in Figure 3.

b. Weather Station Data

Similarly a Kernel Density Estimate is calculated for the input weather data in order to calculate the probability of weather condition occurring on a given day regardless of a failure occurring. The weather data from the met mast and WS1 and 2 is merged proportionally according to the number of wind turbine years of data from each site.

c. Downtime

To investigate the effect of the weather conditions on wind turbine downtime, curves were fitted to describe how the downtime of wind turbine due to a component failure changes according to the weather conditions on the day the failure occurred. The downtime is therefore a function of the weather.

iii. Calculating the Weather Dependant Failure Rate

To calculate the probability of a component failure occurring at a specific weather measurement, Bayes Theorem is used; this is shown in equation 1.

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)} \tag{1}$$

The top term breaks down to P(A) which is the probability of a component failing (the failure rate) and P(B|A) is the probability of a weather condition measurement occurring, given a failure has occurred to the component. This top term is the component failure kernel density estimate discussed in section 3iia, the values of which change according the component which has failed A, and the weather condition measurement B. The bottom term P(B) is the probability of a weather condition measurement occurring on any given day. This is simply the second kernel density estimate, calculated in section 3iib using the weather data.

iv. Monte Carlo Markov Chain Model

A Markov Chain Monte Carlo model has been developed which, using the weather dependent failure rates calculated in section 3iii, determines the impact of wind speeds on the availability of the wind turbine and its components throughout its lifetime. This method has been used previously to model reliability by [11][12][13][14]. Seasonal component failure trends and predicted site availabilities are calculated using historical wind speed data as a model input.

Figure 4 summarises the simulation method where *t* represents time in days since the start of the simulation, *a* denotes the availability of the wind turbine, which is either available (*a* = 1) or unavailable (*a* = 0). The downtime and failure rate are, respectively, *d* and *λ*. Both *d* and *λ* are functions of the weather condition, *w* which is a function of time, *t.* The simulation runs for 100000 wind turbine years separately for each input weather condition. Downtime filters can be used to investigate different severities of failure.

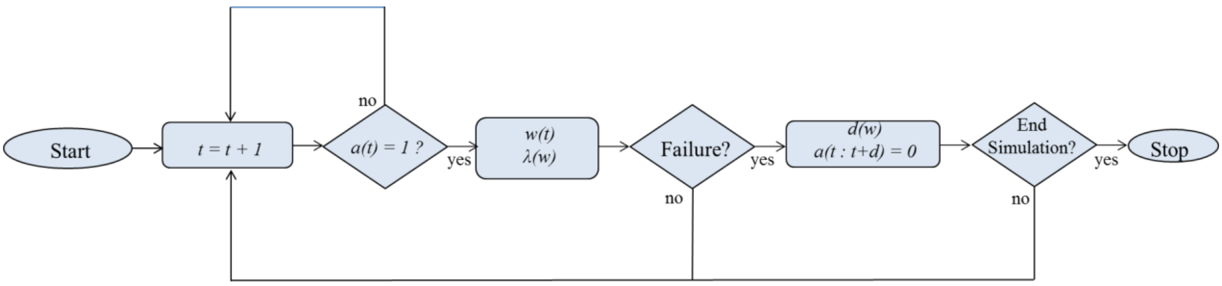

Figure 4: Simulation flow chart

4. Results

Table 4 shows the output which comes from using 20 years of offshore weather data from the Janice offshore weather station and the FINO met mast in the model. The failure rates of the components which come from the original reliability database are shown in the first column. The model output when offshore average daily temperature and humidity are inputted is very similar to the failure rates in the original dataset. The model simulates a slight difference of approximately 2% and -6% when average daily temperature and average daily humidity are inputted respectively. However average daily wind speed and maximum daily wind speed inputs calculate the overall failure rate to increase significantly by 61% and 40% respectively.

Table 4: Model output of wind turbine components failure rates

Component	Onshore Original Data	Average Temperature	Average Humidity	Average Wind Speed
Emergency System	0.021	0.021	0.021	0.015
Meteorological Instruments	0.060	0.064	0.061	0.057
Rotor	0.037	0.040	0.037	0.054
Blade Pitch System	0.054	0.054	0.051	0.062
Drive Train	0.124	0.128	0.118	0.178
Yaw System	0.120	0.128	0.117	0.214
Hydraulic System	0.062	0.060	0.055	0.096
Control System	0.414	0.416	0.376	0.762
Main Generator	0.025	0.022	0.022	0.032
Lifting System	0.008	0.008	0.009	0.009
Nacelle	0.012	0.012	0.012	0.025
Tower	0.048	0.048	0.045	0.079
Total	0.984	1.002	0.923	1.586

This suggests that offshore the most significant environmental factor is the wind speed. Figure 5 shows the humidity and average temperature monthly trends for onshore weather stations WS1, WS2 and the offshore data from Janice.

The ambient air temperatures offshore do not vary significantly offshore when compared to the two onshore stations as illustrated in Figure 5. This is reflected in the calculated offshore temperature dependant failure rates.

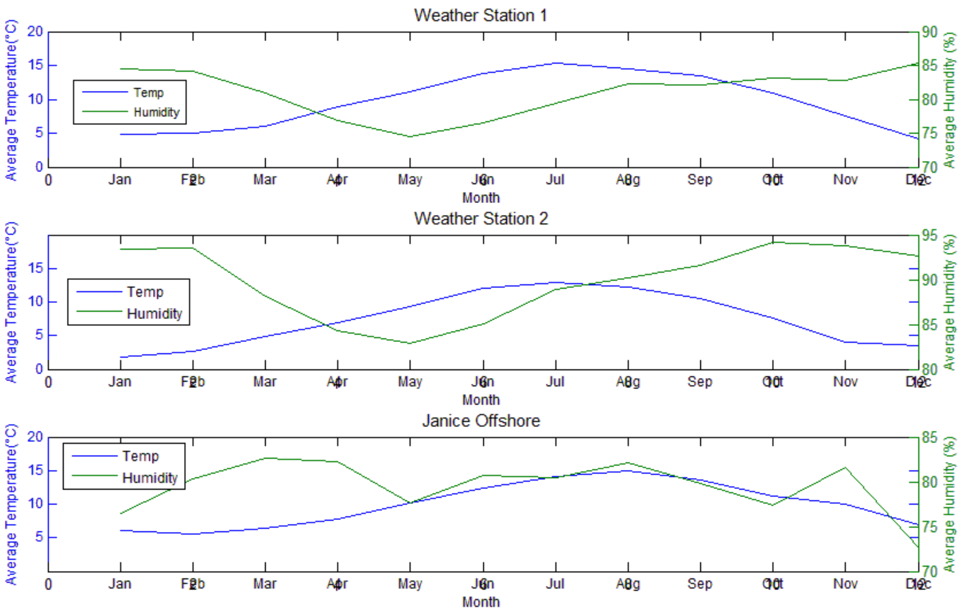

Figure 5: Weather station plots of monthly average humidity and temperatures

The humidity varies less seasonally and is lower on average offshore compared to onshore as shown in Figure 5. The effect this has on the control system, as simulated in the model, is shown in Figure 6. The range of seasonal humidity shown for the onshore stations in Figure 5 is between roughly 80% - 95%. This range includes the section of the weather dependant failure rate, shown in Figure 6, where the failure rate increases almost exponentially between 85% - 95%. The offshore conditions on Janice tend to vary between 70% - 85%, which as shown in Figure 6 is an area where the failure rate is at a low level. This has the effect of actually reducing the failure rate to the controller as shown in Table 4.

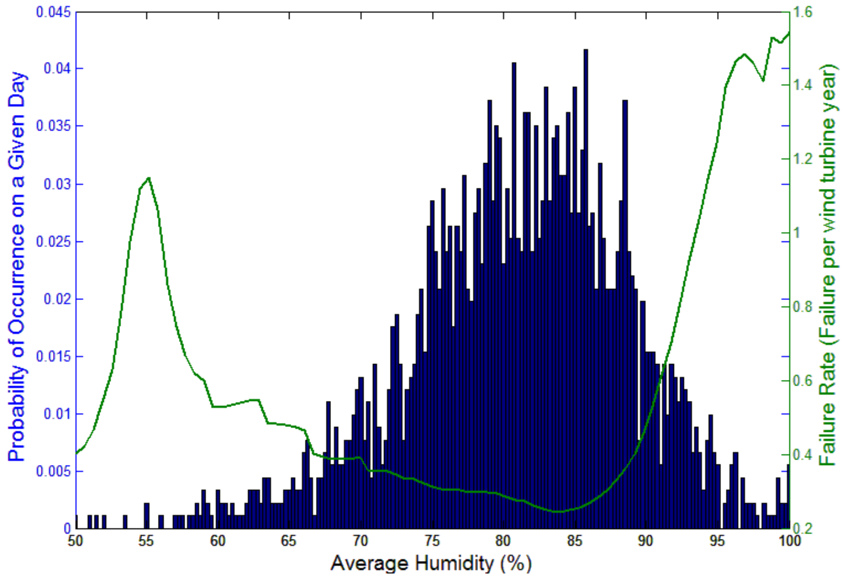

Figure 6: Histogram of offshore humidity and control system humidity dependent failure rate

The difference between the average daily wind speed offshore and onshore is shown in the histograms in Figure 7. The average wind speed of the two onshore weather stations is 6.46 m/s at hub height, while the average wind speed offshore is 9.68 m/s.

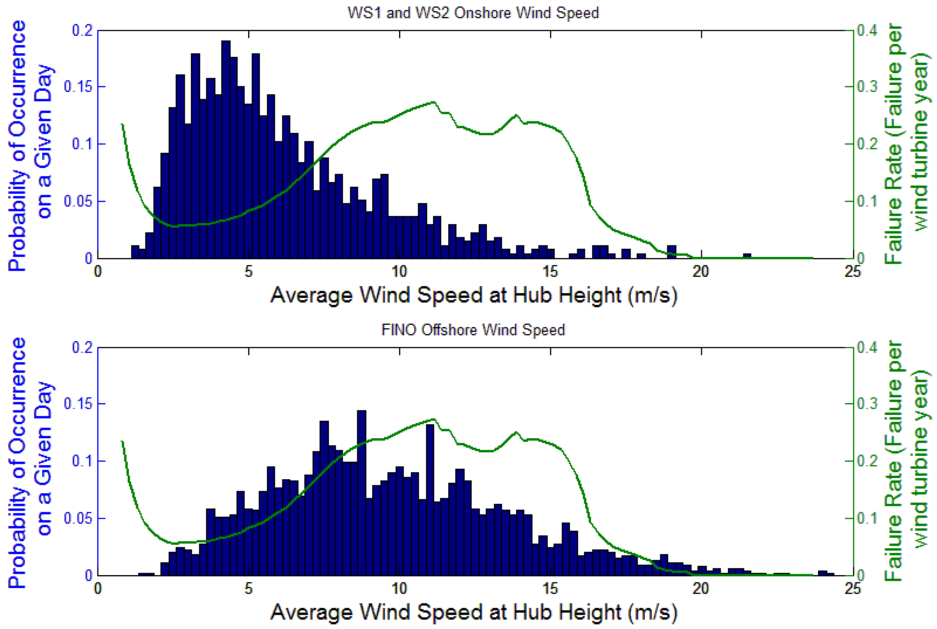

Figure 7: Comparison between failure conditions for drive train offshore and onshore

The effect of this increase in wind power on the failure rate of the overall wind turbine system can be observed in Figure 7, which shows the average daily wind speed dependant failure rate for the drive train overlaying the onshore and offshore wind speed for each site. Clearly the wind speeds which have caused most failures in the onshore data (between 7 m/s – 16 m/s) are much more prevalent offshore and this is reflected in the increased offshore drive train failure rate shown in Table 4.

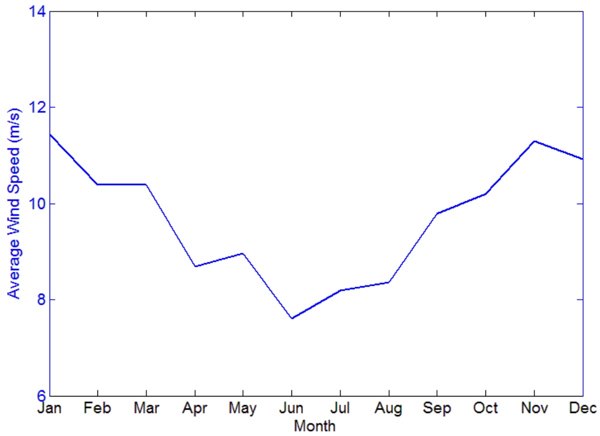

Figure 8: Average monthly offshore wind speed

Figure 8 shows the seasonal changes in average daily wind speed for the offshore data. The wind speed is greater in the winter months than in the summer months, therefore the failure rate of the wind turbine components should also be affected seasonally. The model can be used to plot the failure rate for all the wind turbine components throughout a year based on the input weather data. Figure 9 shows the seasonal change in failure rate for the control system, the drive train, the yaw system and the hydraulics due to changes in average wind speed.

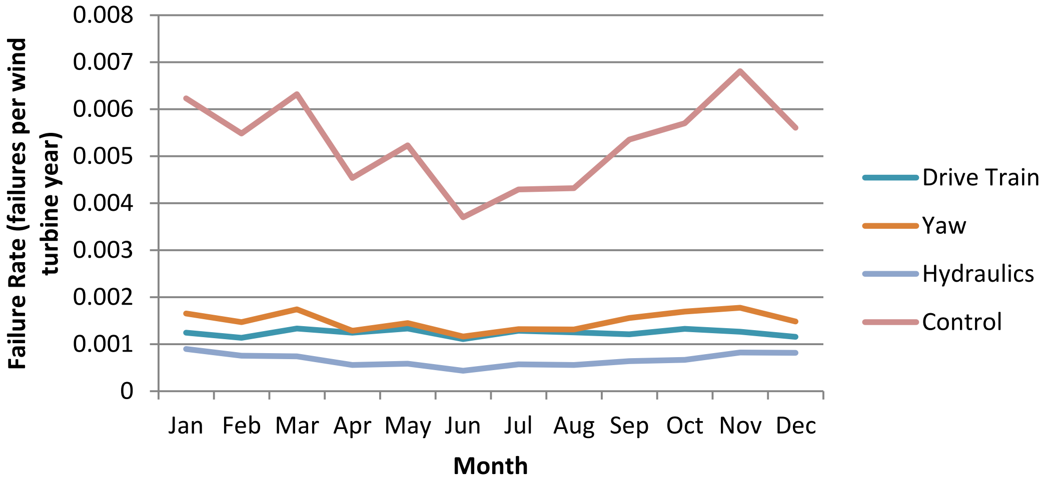

Figure 9: Seasonal failure rates of drive train, yaw, hydraulics and control system

The control system, hydraulics and yaw system all show strong season trends. The implication of higher failure rates in the winter months would be exacerbated by the decrease in offshore accessibility at this time of the year. This means that even a small increase in failure rate during the winter months can result in excessive downtimes and reduced availability.

Figure 10 shows the seasonal variations for major failures to the yaw system, hydraulics, drive train and control system. Major failures have been classified as failures which have caused downtimes greater than 24 hours which has been considered to be severe enough that if experienced offshore they would require a jack-up barge. As Figure 10 shows, major failures can still occur to components in the summer months, however they are far more likely to occur from October to March. Having a vessel ready to use in those months could increase availability and minimise lost energy.

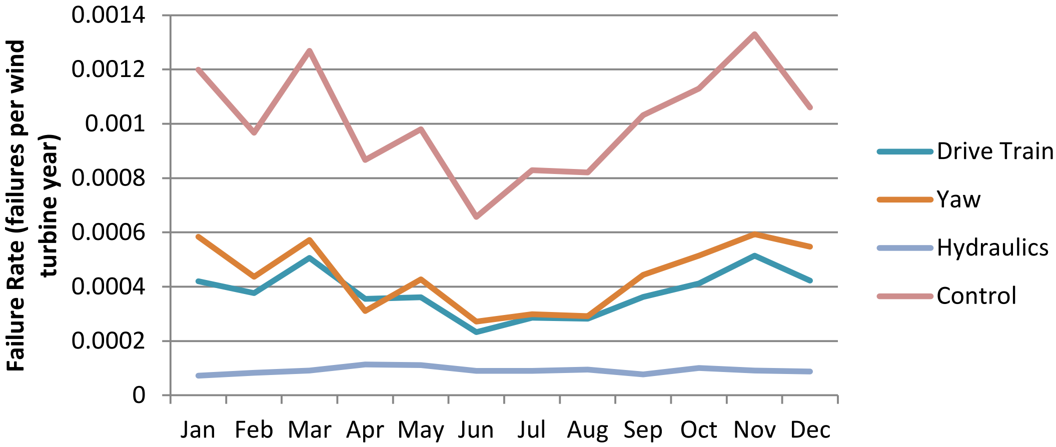

Figure 10: Seasonal failure rates of wind turbine components with 24 hour filter applied

The difference in seasonality in the drive train failure rate can be observed from Figure 9 to Figure 10. This is partly due to the severity of the failures increasing at higher wind speeds. Figure 11 shows how the average wind speed dependent failure rate changes as the model filters out failures which cause downtimes of less than 0 hours, 12 hours and 24 hours.

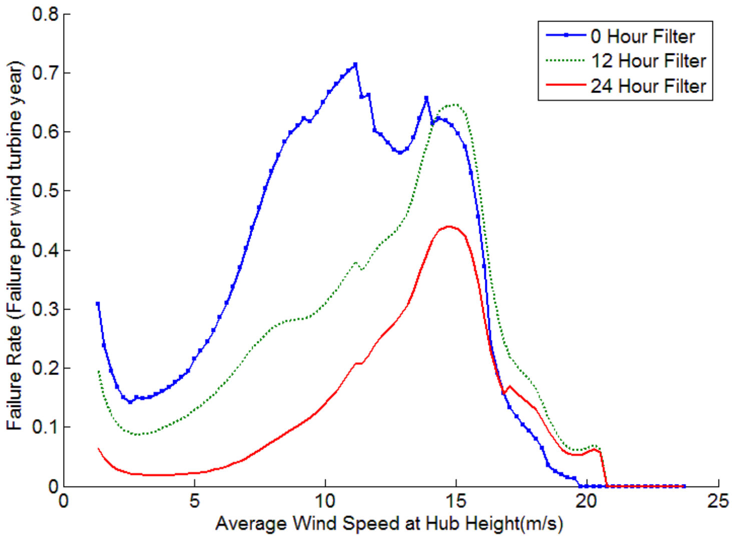

Figure 11: Average Wind Speed dependent failure rate of the drive train with downtime filters applied

5. Conclusion and Discussion

This paper has demonstrated a methodology for calculating failure rates which are dependent on weather conditions. These failure rates have then been used in estimating the effect of the offshore environment on wind turbine failure rates. Results have suggested that the impact of temperature and humidity will do little to effect present reliability as the conditions offshore are less extreme. However the wind speed will have a significant impact as it differs greatly offshore. It has been calculated that the failure rate of the whole wind turbine system will rise by roughly 61% due to the wind speed. However this is an optimistic figure as it relies upon data gathered from onshore wind turbines which do not operate in as harsh an environment.

As a result of using only this data, many wind speed dependent failure rates lose their accuracy beyond wind speeds which rarely occur onshore. For example Figure 11 shows the failure rate of the drive train at 15 m/s is less than the failure rate at 20 m/s, this is counter intuitive as it would be expected that the higher the wind speed the more likely the component is to fail. The effect of this inaccuracy makes the model optimistic, but not completely inaccurate as the wind speed only reaches the point where the curve falls away at 15.5 m/s 8.5% of the time. However at such high wind speeds the failures are likely to cause more major failures than the model allows them to and would therefore make a significant impact to availability.

The model will be improved upon in future by including more data from different wind farms which experience different weather conditions. Met mast data from site B will be used in future analysis as it is more representative of what occurred on site than readings from WS2. Accuracy would improve greatly if offshore reliability data could be included. If offshore data cannot be sourced it is possible to extrapolate the failure rate curves from areas of the graph where there are lots of data points and the gradients calculated are reliable. This will be investigated in future research.

Lastly economic assessments will be made of the model to investigate whether the knowledge gained from using it could be sensibly used in planning maintenance scheduling. This will be achieved by building an offshore availability program, which will look at the environmental effects with vessel availability, transit time and offshore accessibility taken into account.

6. References

[1] The Royal Academy of Engineering, *The Cost of Generating*. London: The Royal Academy of Engineering, 2004

[2] Mott MacDonald, “UK Electricity Generation Costs Update,” 2010.

[3] G. J. W. Van Bussel and a R. Henderson, “State of the Art and Technology Trends for Offshore Wind Energy : Operation and Maintenance Issues,” *Offshore Conroe TX*, pp. 10–12, 2001.

[4] J. Phillips, P. Reynolds, L. Gosden, G. Hemmingsen, I. Mcdonald, G. Mackay, W. Hines, P. O. Repower, J. Brown, and J. Beresford, “A Guide to UK Offshore Wind Operations and Maintenance.”

[5] B. Hahn, “‘ Zeitlicher Zusammenhang von Schadenshäufigkeit und Windgeschwindigkeit ’,” in *FGW-Workshop Einflub der Witterung auf Windenergieanlagen,*, 1997.

[6] P. Tavner, C. Edwards, A. Brinkman, and F. Spinato, “Influence of Wind Speed on Wind Turbine Reliability,” pp. 55–72, 2006.

[7] P. J. Tavner, D. M. Greenwood, M. W. G. Whittle, R. Gindele, S. Faulstich, and B. Hahn, “Study of weather and location effects on wind turbine,” no. May 2012, pp. 175–187, 2013.

[8] M. Wilkinson, G. L. G. Hassan, S. Vincent, S. Lane, B. Bs, T. Van Delft, and K. Harman, “The Effect of Environmental Parameters on Wind Turbine Reliability,” in *EWEA 2012*, 2012, no. April.

[9] D. McMillan and G. W. Ault, “Condition monitoring benefit for onshore wind turbines : sensitivity to operational parameters,” *IET Renew. Power Gener.*, vol. 2, no. 1, pp. 60 – 72, 2008.

[10] FINO, Deutsches Windenergie Institut, German Wind Energy Institute

[11] F. Besnard, K. Fischer and L. Bertling, “Reliability-Centred Asset Maintenance – A step towards enhanced reliability , availability , and profitability of wind power plants,” pp. 1–8, 2009.

[12] R. Billington and R. N. Allan, *Reliability Evaluation of engineering Systems: Concepts and Techniques*, 1st ed. New York: Plenum Press, 1983.

[13] F. Castro Sayas and R. N. Allan, “Generation availability assessment of wind farms,” *IEE Proc. Gener. Transm. Distrib.*, vol. 143, no. 5, p. 507, 1996.

[14] D. McMillan and G. W. Ault, “Quantification of Condition Monitoring Benefit for offshore wind turbines,” *Wind Eng.*, vol. 31, no. 4, 2007.