Training Onshore Failure Rate to Offshore Cost Effectiveness Analysis in Condition Monitoring System

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Abstract
Offshore wind energy is a fast growing technology within the marine energy sector. In contrast to onshore, offshore wind farms require larger installation and incur higher O&M costs due to the challenges of the marine environment. In this context condition monitoring systems have an important role to play in reducing maintenance costs.

The high initial cost of condition monitoring systems motivates this analysis of the cost effectiveness of such technology O&M cost data are commercially sensitive and generally protected by the wind industry, especially for offshore operations. Component failure rates are essential for modelling wind turbine O&M costs but very little offshore failure rate data available in the public domain.

With cooperation of the operator of the largest onshore wind farm in the UK and that of a large Swedish offshore wind farm, three years of operational data records have been made available for this research. With wind and wave parameters extracted from the database and set as inputs to a cost model is has been possible to compare the O&M cost of reactive maintenance with condition based maintenance. The cost model available uses empirical failure rate based on onshore data and so will not fully represent the offshore situation as failure rates are expected to affected by offshore operational conditions. To overcome this limitation, a mathematical translation of failure rate from onshore to offshore is applied to the operational data. The way this translation is calculated is sensitive to the way the relevant probability distributions are represented and improved curve fitting approaches have been explored.

Keywords: Wind Energy, Offshore, Cost Effectiveness, Failure rate, Reliability

Introduction

Driven by the Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC), adopted in Kyoto, Japan on 11th December 1997 and entered into force on 16th February 2005, the European Union (EU) in 2005 assigned an 8% CO_2 reduction target for the year 2008 to 2012, and it is one of the few parties which have committed to further reductions for 2013-2020 with a 20% binding figure. (United Nations, 2014) The United Kingdom, as one of the member country in EU, has exceeded the initial target, ending up with 12.5% reduction for 2008-2012. The UK has also assigned further 19% reduction for the next 8 year run. Much of this success has been due to the rapid growth of wind energy, and in recent years much of this has been offshore. In 2014, 16.9GW of new power generating capacity was installed in the EU, with wind power having the largest share with 11.8GW, accounting for 43.7% of all energy installed, followed with Solar PV of 8GW accounting for 29.7%. These two renewable energy generation methods account for 73.4% of the entire annual installed power capacity, as shown in Figure 1. Since 2000, the annual renewable capacity additions have been 24.7-34.6GW, 8-10 times higher than what was in 2000. The net growth of European wind power since the year 2000 is 116.8GW (EWEA, 2015)

The high quality of the offshore wind resource together with a reduced sensitivity from a public planning perspective accounts for the present political support for offshore wind development. 2,488 turbines are now installed offshore and grid connected, making a cumulative total of 8,045.3MW in 74 wind farms in 11 European countries. A further 2.9GW of capacity will be added when 12 on-going projects complete. This will bring the cumulative capacity in Europe to 10.9GW. Nearly half of the final investment decisions in 2014 were billion-euro projects. The industry raised €3.14 billion of non-recourse debt in 2014, which was the highest level in its history. The UK has the largest amount of installed offshore wind capacity with 4.5GW, counting for 55.9% of European installations, as shown in Figure 2.

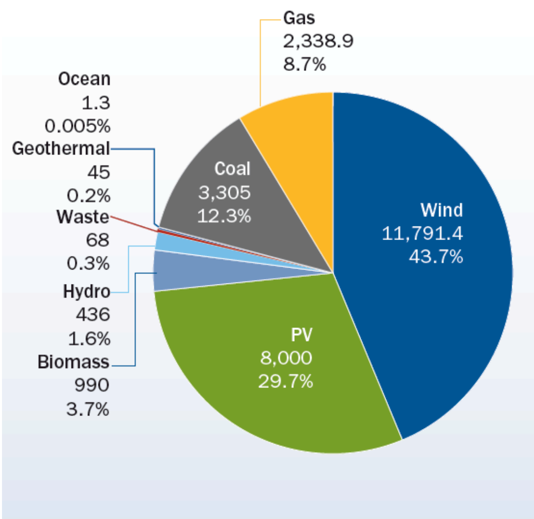

Figure 1: share of new power capacity installations in EU (MW), (EWEA, 2015)

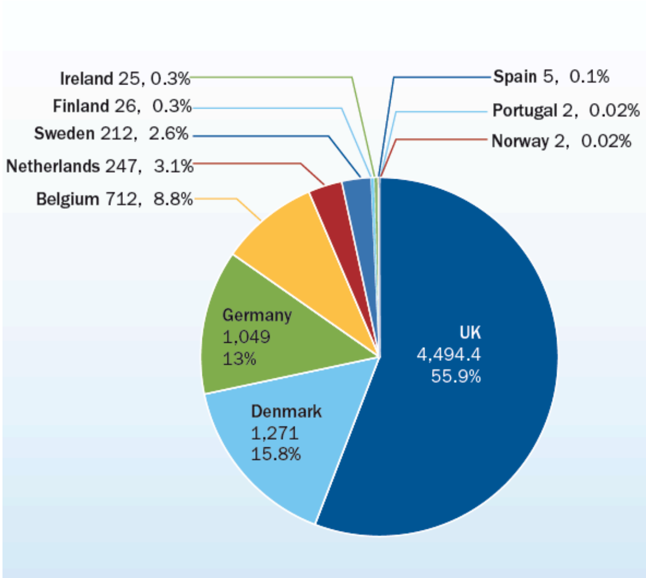

Figure 2: Installed Cumulative Capacity by country in the EU (MW), (EWEA, 2015)

Compared to onshore, offshore wind has the advantage of generally higher mean wind speed, less temporal variation and lower turbulence. In addition there is a reduced negative impact on the landscape and noise is a less critical issue. On the other hand, some of these advantages come at a cost. The low disturbence to human population is the result of a substantial distance between the offshore wind farm and shoreline where the port of operation and maintenance (O&M) centre is located. The marine conditions restricts access for maintenance which depend on the prevailing wind and wave conditions. This characteristic of offshore wind farm operations motivates the interest in condition monitoring.

Compared to reactive maintainence, condition based maintenance is based on data providing the real time condition of the certain turbine subsystems or components. The O&M team can arrange the maintainence considering both component condition and vessel access. In this way, major failures of the turbine can often be circumvented; at the same time, the cost of maintainece should reduce due to a more effective maintenance regime.

For quantifing the cost effectiveness of O&M, and condition monitoring in particular, failure rate is a key input. However, offshore component failure rate data is not publically available as it has been commercially protected by manufacturers and operators. This results in failure rate data in the public domain being very limited, especially for offshore. Three years of operational data records have been made available for this research through bi-lateral research agreements.The onshore data come from the largest British onshore wind farm, and the offshore data come from a large Swedish offshore wind farm. This enables the translation of componet failure rates from onshore to offshore. The translation considers the ambient conditions in terms of wind speed and temperature.

Failure rate translation

The failure rate translation allows calculation of offshore failure rates from onshore data. The core calculation is for the ratio of the expectation of the failure rate, offshore to onshore. The expectation of the failure rate is dependent on the prevailing environment. As described in the introduction, the most relevant environmental factors are the wind speed and the temperature. Therefore the wind speed and temperature time series data are taken from both on and offshore sites.

This is not to say that there are no other factors that influence failure rate, but if that data was available it could be included in a similar manner, e.g. for wind turbulence. For the results presented here, the relationships between failure rate and the selected environmental factors have been obtained based on analysis of data from the UK onshore wind farm covering 3 years of operation. The probability distributions of wind speed and temperature are derived from both on and offshore data. The ratio of expected failure rates on/offshore can be derived for wind speed and temperature, separately.

Failure rate probability

The wind turbine component failure rate probability is an important element in the expectation calculation. According to Bayes' rule (Laplace, 1814), the probability of failure rate dependent on weather condition, P(F|W), is calculated from the product of the probability of weather condition given failure rate, P(W|F), and the annual mean failure rate of the selected turbine component, P(F), divided by the weather parameter distribution, P(W).

$$P(F|W) = \frac{P(W|F) \cdot P(F)}{P(W)} \tag{1}$$

The probability of weather condition given failure rate is the information which can be directly obtained from failure record of the wind turbine operational data, where the failure type, location, date and the corresponding weather statistics are recorded. It is important to note that the value used for wind speed and ambient temperature is the daily mean value since it is accepted that the impact of the environment on failure will not be instantaneous. One day may well be insufficient and in future work, longer averaging periods will be investigated.

Fitting a suitable function to the failure probability distribution

The common approach to estimate curves for the probability density function (PDF) is by using a non-parametric estimate of the density function, such as the Kernel function (Epanechnikov, 1969). Although these fitted distributions look reasonable, as in Figure 3, the tails are not at all precise and this is a problem because for high and low values (in this case of wind speed), P(W|F) is determined by a ratio of the tails of two PDFs.

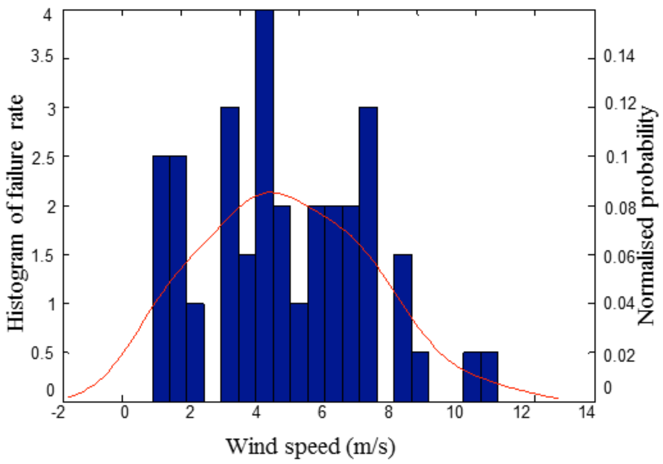

Figure 3. Failure rate histogram and normalized probability Kernel distribution of an onshore drive train system

Because of the limited size of the database, it is difficult to derive smooth and reliable probability distributions. Unexpected spikes occur in the distribution curves which only reflect the data limitations and are not generic. In order to obtain a smoother distribution curve, a procedure of finding a fit to the cumulative probability distribution (CPD) of P(W|F) and then differentiating the result to regain the desired probability distribution function has been applied in this research.

The first fitting function for the CPD in this example is a 2nd order polynomial function. The 2nd order polynomial function has suitable characteristics for of the ascending curve with a flexible tangent. It provides reasonable fitting to the data and is easy to differentiate. The disadvantage is that the curve extends (extrapolates) at the two ends with high-value tangents, which creates significant error in the fitting of the tails to the original curve. This error will have exaggerated impact when differentiation is applied.

An alternative fitting function is the exponential. The most observable nature of the CPD curve is the asymptotic ends towards 0 and 1. The exponential function can be derived to reflect this and this makes the fitting of the tails much more reliable. The disadvantage of exponential fitting is the complexity of the function itself, which increases the difficulty of parameter estimation. The accuracy of the exponential function to the target curve is also slightly lower than for the polynomial function.
Once obtained from the fitting function, the parameters allow algebraic differentiation of the CPD function to give the required PDF function.

Wind speed distribution fit

Figure 4 shows the staircase curve of the CPD dependent on wind speed (blue) with the fitting curves (red and green). The red line shows the exponential function fit, and green dashed line represents the 2nd order polynomial fit. In this figure, the two fitted functions show good agreement with the main body of the staircase CPD curve.

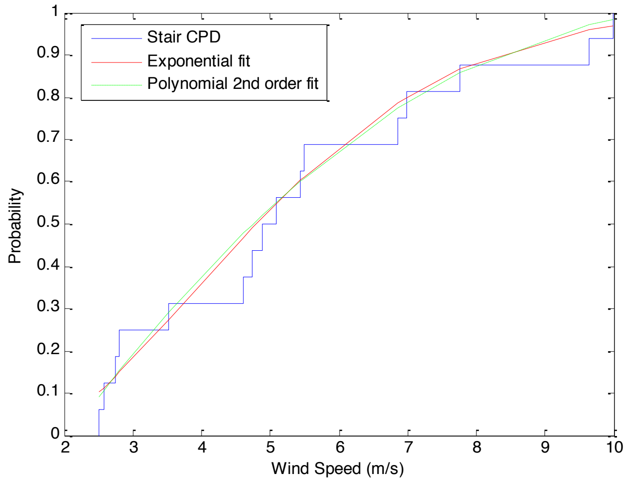

Figure 4: Staircase plot of CPD fitted by 2nd polynomial and exponential function of rotor system in an onshore wind turbine dependent on wind speed

The parameters obtained from the fitting function are substituted into the expression for P(W|F). The failure rate probability function P(F|W) is then calculated based on the Bayes' rule (equation 1). Figure 5 compares the curves from the fitting methods with the original directly obtained failure rate probability function curve. The upper plot presents the non-fitted curve, where a lump at the high wind speed is shown. This lump is likely the result of the limited data record and does not reflect an actual functional relationship. The middle plot shows the P(F|W) calculated from the exponential fitted P(W|F). It retains the basic shape of the long term distribution but avoids the fluctuations in short term. The lower plot presents the P(F|W) calculated from the 2^{nd} polynomial fitted P(W|F). Because of the issues concerned with any extrapolation using the 2^{nd} polynomial function, as stated above, the curve is only calculated within the two vertical bars, which reflect the low and high wind speed values in the original data. In the absence of any other indication, constant value extrapolation has been used outside these limits.

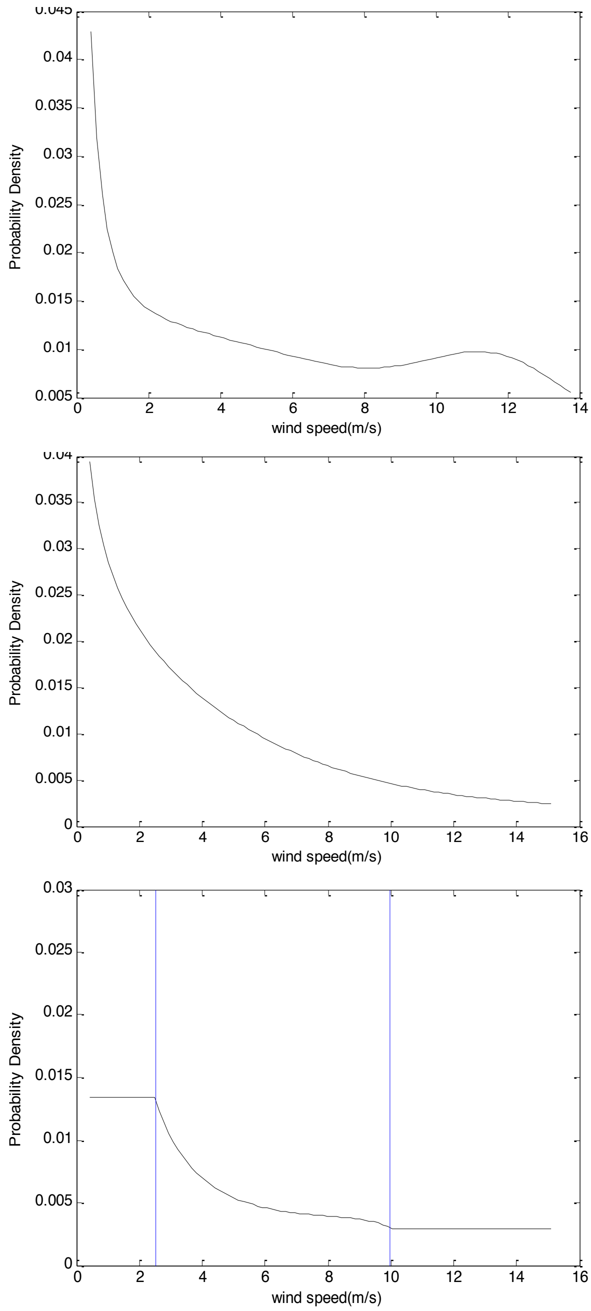

Figure 5: Failure rate PDF with an onshore rotor system non-fitted (upper), exponential fitting function (middle) and 2nd order polynomial fitting function (lower) dependent on wind speed

Temperature distribution fit

The situation for temperature is slightly different. Unlike wind speed, temperature can have a negative value. This is an obstacle to fitting an exponential function to the temperature distribution because of the non-negative-x-value nature of the exponential function. The curves are offset to the right-hand side of the y axis, fit with exponential functions, and shifted back. In this way, the parameters are obtained in the offset stage and put in the PDF calculation.

Figure 6 shows an example of the staircase curve of the CPD dependent on temperature (blue) with the fitting curves (red and green). In this figure, the 2nd order polynomial (green dashed) shows a high-value tangent at the high temperature values. This can be observed at the right hand side of the curve.

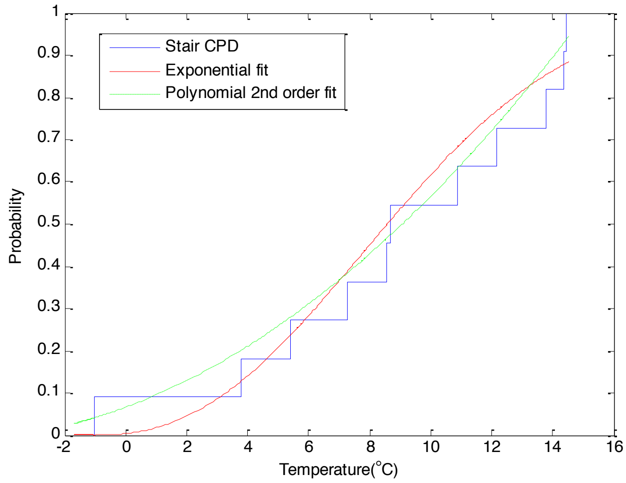

Figure 6: Staircase plot of CPD fitted by 2nd polynomial and exponential function for an onshore wind turbine blade system dependent on temperature

Figure 7 (left) shows the failure rate probability function P(F|W) based on the Bayes' rule. This figure clearly shows the high-tangent nature of the 2nd polynomial function (green dashed line). The high-temperature tail expands far above 1, which of course is not allowed for probability function plot. Ignoring the illogical tails and zooming in on the middle range of temperatures, as shown in the right hand figure, the three methods can be observed agreeing each other to a certain extent. The non-fitted method shows a peak in failure rate at around -4 degree, in some agreement with the 2nd order polynomial method but with a much higher fluctuation; whereas the exponential method shows a peak at around 5-10 degrees. It is not possible to confirm which method is closer to the reality due to a lack of data.

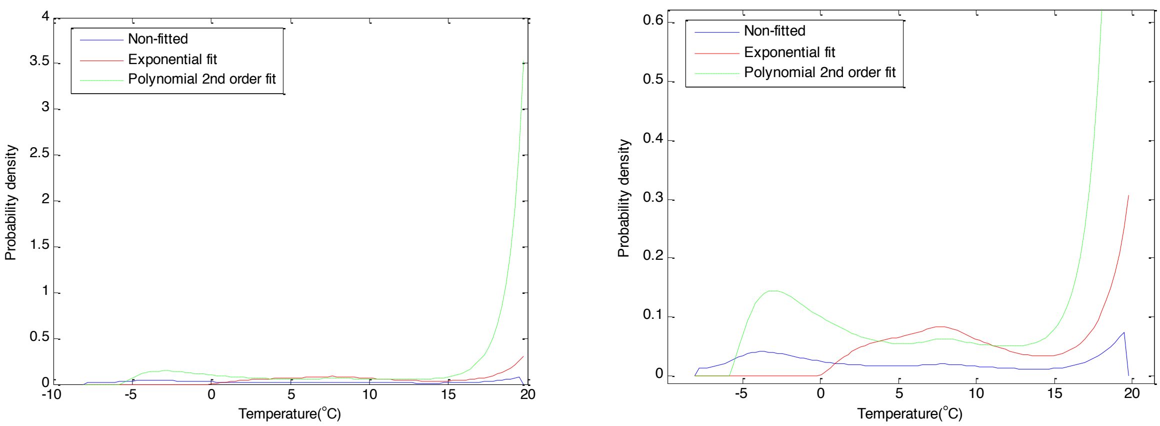

Figure 7: Failure rate PDF with an onshore rotor system non-fitted, exponential fitting function and 2nd order polynomial fitting function dependent on temperature (left) and zoomed-in figure (right)

Cost model

The cost model used in this research is based on statistical analysis of O&M (Feuchtwang & Infield, 2013) specifically for offshore wind. The purpose of the development of this cost model is to access offshore wind turbine maintenance by calculating access probabilities, expected delays and the associated costs using a probabilistic approach. Failure rate of each turbine subsystem is an important input of the cost model. The accuracy of the failure rate directly affects the accuracy of the cost estimation. The final output of the cost model is annual maintenance cost.

This cost model is compared with other four cost models: the ECUME model from EDF; the NOWIcob model from SINTEF Energy; the UiS model from the Univeristy of Stavanger; and the OPEX model from CDT, University of Strathclyde (Dinwoodie & Endrerud, 2015). The comparison uses the same input of a virtual offshore wind farm 45km off the coast of Germany with 8 years of wind and wave data. In this way, the results from the different methods can be compared.

Results

The subsystem failure rates translated from onshore to offshore are listed in Table 1 for the three different fitting methods. The failure rate results are substituted into the cost model. The results of the cost model are shown in Table 2, among which the annual O&M costs are compared with other cost models. Figure 8 shows the comparison in one chart. It shows that the exponential fitted failure rate provides the closest cost results to the other models. The non-fitted and 2nd-polynomial-fitted failure rate has a higher value for the O&M cost.

Table 1: failure rate translation from onshore to offshore for the selected subsystems

			RatioWindSpeed			RatioTemperature			offshore failure rate		
code	onshore failure rate	failure R%	Nonfitted	Poly2Fitted	ExpFitted	Nonfitted	Poly2Fitted	ExpFitted	Nonfitted	Poly2Fitted	Exp Fitted
Generator Assembly27	0.78	7.20%	0.92	0.74	0.63	1.69	0.74	0.52	1.208	0.424	0.255
Gearbox Assembly14	0.56	5.10%	1.00	1.33	0.94	1.04	1.84	1.40	0.579	1.367	0.734
Blades9	0.16	1.50%	1.00	1.01	0.82	1.22	1.06	0.78	0.193	0.170	0.102
Pitch System11	2.32	21.30%	0.87	0.79	0.69	1.26	1.53	0.89	2.551	2.813	1.425
Yaw System18	1.23	11.30%	1.27	0.92	1.04	1.04	2.34	0.88	1.616	2.648	1.135
Rotor Other8	0.01	0.10%	0.94	0.84	0.79	1.25	0.69	1.19	0.008	0.004	0.007
Control & Comms Other	0.05	0.50%	1.26	1.18	1.17	0.95	1.74	1.21	0.061	0.105	0.072
Mechanical Brake15	0.05	0.50%	0.96	0.60	0.74	0.77	3.50	1.18	0.037	0.108	0.045
High Speed Shaft transmi	0.05	0.40%	1.58	1.00	0.95	0.81	3.54	2.49	0.057	0.159	0.107
Main Shaft13	0.03	0.30%	0.90	0.70	0.69	1.26	0.77	1.44	0.036	0.017	0.032
Hydraulic System23	0.13	1.20%	1.09	0.84	0.87	1.46	0.93	0.59	0.206	0.102	0.067
Tower33	0.29	2.70%	1.10	1.28	0.96	0.82	1.34	0.89	0.262	0.499	0.249

Table 2: cost model output with comparison of different methods

WITH DOWNTIME based on		REACTIVE MAINTENANCE: NONFITTED	REACTIVE MAINTENANCE:2ND POLY FIT	REACTIVE MAINTENANCE: EXPONENTIAL FIT
downtime		31.8 days	33.5 days	23.4 days
availability		91.3%	90.8%	93.6%
capacity factor with downtime	Cfd	45.6%	45.3%	46.9%
energy lost	Estot	1273.4 MWh	1344.7 MWh	938.1 MWh
mean power generated over year with downtime	Pmd	1.37 MW	1.36 MW	1.41 MW
total annual energy generated with downtime	Ead	11976.8 MWh	11905.5 MWh	12312.2 MWh
annual revenue with downtime	Rad	1077.9 £k	1071.5 £k	1108.1 £k
revenue lost	srev	114.6 £k	121.0 £k	84.4 £k
annual maintenance cost	ftot	454.1 £k	505.2 £k	343.1 £k
entire wind farm annual maintenance cost		36.3 £m	40.4 £m	27.4 £m
vessel cost	per unit	£0.025 /kWh	£0.026 /kWh	£0.018 /kWh
wage cost	per unit	£0.0016 /kWh	£0.0018 /kWh	£0.0012 /kWh
component cost	per unit	£0.0109 /kWh	£0.0146 /kWh	£0.0089 /kWh
Total O&M cost (w/o revenue loss)	per unit	£0.0379 /kWh	£0.0424 /kWh	£0.0279 /kWh
revenue lost	per unit	£0.0096 /kWh	£0.0102 /kWh	£0.0069 /kWh
Total O&M cost (with revenue loss)	per unit	£0.0475 /kWh	£0.0526 /kWh	£0.0347 /kWh

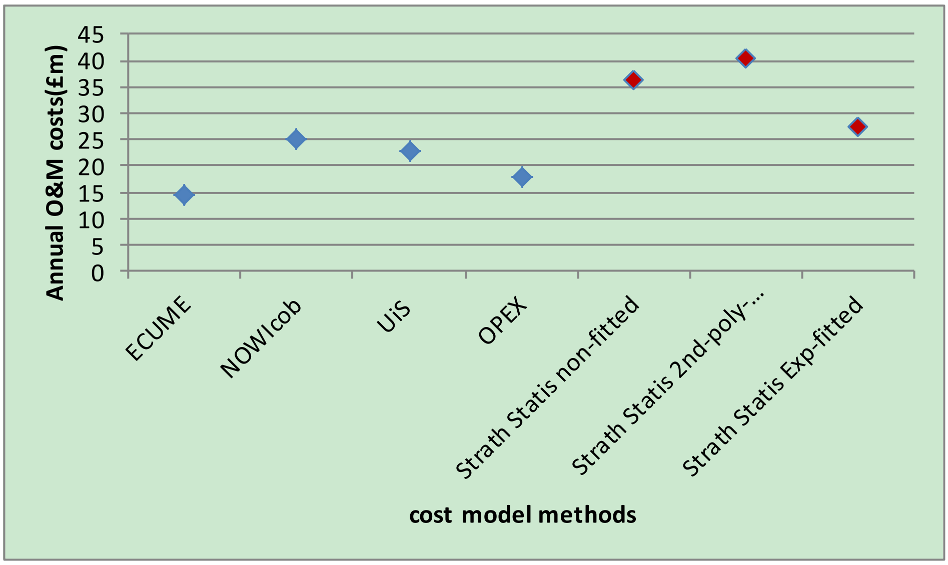

Figure 8: Annual O&M costs for the cost models with different methods

Conclusion

This paper presents an initial analysis that attempts to estimate failure rates for offshore wind turbines based on the onshore values. It applies correction factors dependent on wind speed and temperature to the failure occurrence in the cost model calculation. The correction factors are calculated by comparing the failure rate expectations from on and offshore wind farms. The failure rate probabilities obey Bayes' rule, and a range of fitting functions are applied in an attempt to obtain the probability density functions. The failure PDF is derived from the CPD in order to get a more realistic result. 2nd order polynomial and exponential function are proved to fit the failure rate function in order to give a smoother and more generic function. The fitting functions together with the non-fitted method are used to derive the final costs, and compared with other cost models in the research domain. The comparison of the final O&M costs suggests the exponential fitting method has the closest result with other cost models. However, no final evidence shows which method is the closest to the reality because of the lack of long term failure data in the operational domain.

In future work, the cost model will be applied to assess how the use of condition monitoring systems might reduce offshore wind O&M costs, and how these depend on the characteristics of the offshore sites.

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