Risk-based planning of O&M for wind turbines using physics of failure models

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ABSTRACT

Wind turbines are in some countries contributing significantly the production of electricity. For offshore wind turbines reliability is a key issue since costs to operation and maintenance may be significant contributors to the Levelized Cost Of Energy and OM costs are highly dependent on the reliability of the components implying that it is important to focus on increasing the reliability as much as is economically reasonable. This paper describes aspects for reliability analysis of wind turbines with special focus on structural components, especially the wind turbine blades. In many wind turbine components deterioration processes such as fatigue, wear and corrosion may result in failures, for example in welded details, blades, bearings and gearboxes. In many cases it may be possible to detect the damages before actual failure, and thereby perform preventive maintenance instead of corrective, expensive repair/ maintenance. This requires some type of condition monitoring to give information on the condition of the components. It can either be online monitoring or manual inspections. The use of preventive maintenance can possibly reduce the costs, as repairs can be cheaper to perform before actual failure, and because the downtime will be shorter compared to corrective maintenance. On the other hand, preventive maintenance leads to more repairs in total, and optimally the maintenance effort should be adjusted to minimize the total expected costs. In this paper it is described how risk-based methods can be used to optimally plan operation & maintenance using Bayesian decision theory adapted to offshore wind. An illustrative example is presented considering wind turbine blades and using the reference wind farm in the NORCOWE research project.

1. INTRODUCTION

With the rapid growth of the offshore wind industry over the past two decades, and the implicit growth in the size of wind turbines, Operation & Maintenance (OM) has become a major focus point in the attempt to lower cost of wind energy to market competitive prices. It is in general estimated that OM operations account for around 25-30 [%] of the levelised cost of energy (Engels, Obdam & Savenje, 2009).

Current practices in the industry rely heavily on a combination of reactive/corrective maintenance and time-based inspections. This leads to many breakdowns in the turbines, which require expensive replacement/repair operations, significantly impacting the price of energy. In a number of situations, degradation of a component can be detected either with online condition monitoring or offline inspections and failure prevented by using an early, much cheaper repair. The result is a reduction in both cost and downtime.

However, the amount of effort put into preventing failures also needs to be limited, since a high number of preventive repairs and inspections leads to unnecessarily large expenses and downtime. Time-based inspections are commonly used, where inspections are carried out at regular time intervals, and repair decisions are made only depending on the size of the observed damage. This paper proposes an alternative strategy for preventive maintenance, namely by risk based inspections. This approach implies making decisions based on the reliability of a given component and is commonly used in e.g. the offshore oil and gas, aerospace, railway and many other industries.

In the first part of the paper, a risk based model is set up for maintenance of wind turbine blades, where a degradation model is used with a dynamic Bayesian network for optimal planning of inspections. In the second part, the model is used to perform a case study on the NORCOWE wind farm [2] and the results are compared to results from a more traditional time-based strategy, underlining the difference in levelized cost of energy.

2. DEGRADATION AND RELIABILITY MODEL

Preventive maintenance can be applied in cases in which condition monitoring is able to detect damage within a reasonable time interval before failure occurs, i.e. the estimated remaining useful life (RUL) is sufficiently long. In other words, degradation needs to be gradual and needs to have a clear indicator (crack length, delamination, erosion etc.).

In this paper, cracking on the trailing edge of blades is considered for the model, due to the fact that this type of degradation can be successfully detected and quantified at inspections, and it is responsible for a large number of failures in offshore wind turbine blades, as illustrated in figure 1 (Nissim, 2013).

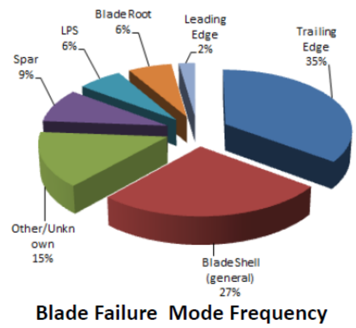

Figure 1. Causes for blade failures

From the point of view of the failure rate, it has been observed that a component goes through three distinct stages during its lifetime represented by the three typical stages in the bathtub failure rate model, see figure 2. (Sørensen, 2013).

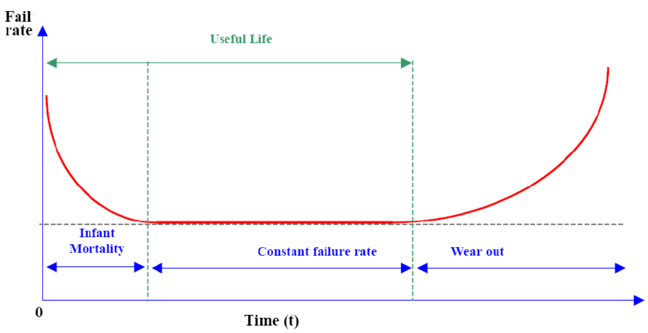

Figure 2. Failure rate 'bathtub' curve

The blade starts in the infant mortality stage, where the risk of failure is high, and is dependent on the quality and control of the manufacturing and installation process and possible series errors, having no correlation to weather conditions and other load inducing phenomena. It is not possible to predict using physical models. This is decreasing rapidly, meaning that if the blade is operating well after a starting period, the risk of infant mortality is over.

After this, the blade continues into its useful life with a lower, more constant failure rate. In this stage, the failure risk is only slightly degradation related, and is mostly dependent on randomly occurring phenomena, such as lightning strikes, icing, control mechanism failures etc.

Finally, degradation is becoming important, and the failure rates begin to increase when the blade enters the wear-out/ageing stage. At this point, fatigue, corrosion, erosion and other deterioration related damages increasingly add to the failure risk if maintenance activities are not conducted.

Since the focus of this study is on failures that can be prevented using inspection methods, only the wear out stage is considered for modelling.

Age related degradation can be described using a fracture mechanics based damage model, see e.g. (Florian & Sørensen, 2015). The model assumes that a failure results from crack development on the trailing edge of the blade and uses hub height wind measurements to compute the growth of a set of initial randomly generated cracks in the bond material. The model contains three stages, which are described in the following:

- defect initiation at the start of the blades life
- damage propagation during the blades lifetime
- failure and time-to-failure distribution

2.1. Crack initiation

The size and positions of the cracks at the beginning of the blades life-time is unknown. This being the case, a random damage state is generated using a lognormal distribution, defined by an initial crack size a_{in}.

2.2. Crack growth

The crack growth is determined by the load cycles applied on the blade and the crack length at a given time. The crack growth *da* will be assessed for a time period *dt* following Paris law, as shown in Eq. (1), (Sørensen, Frandsen & Tarp-Johansen, 2008).

$$\frac{da}{dt} = \frac{A(\Delta K)^m}{(1-R)^{m(1-\lambda_w)}} \tag{1}$$

The material parameters A, m and λ_w are dependent on the type of bond in the blade, while R represents the mean cycle range for the loading cycles. The stress intensity factor ΔK is determined as a function of the wind speed u, the crack size a, the turbulence intensity I and the distribution of load cycles Δs corresponding to Δt. This is shown in Eq. (2), (Sørensen et al., 2008), with the numerical values of all the input parameters used in the model given in section 2.3 in Table 1.

$$\Delta K(u, I) = \int_0^\infty \Delta s \; f(\Delta s|u, I) \; \sqrt{\pi \, a} \; d\Delta s \tag{2}$$

The statistical distribution function of the cycle ranges Δs is dependent on the turbulence intensity I for a given site and the mean wind speed u. To determine the distribution of the load cycles as function of the environment, a series of 10 minute simulations is made using the aero-elastic simulator FAST (Jonkman & Buhl, 2005). Data is collected for the flap-wise blade bending moment for 1 m/s wind bins from cut-in to cut-out wind speed. To avoid large statistical uncertainties, 15 are used for each wind bin.

The following step is to determine the load range distribution for each wind bin as a function of the wind speed. This is done by using rainflow counting after which the results are fitted to a 2-parameter Weibull distribution. The cycle count for a 10 m/s wind bin, along with the fit, is illustrated in figure 3.

By integrating according to Eq. (2), the stress intensity factor for a 10 minute interval, given the wind speed, the turbulence intensity and the crack size at the beginning of the time interval is determined and shown in figure 4, for a crack size of 10 mm.

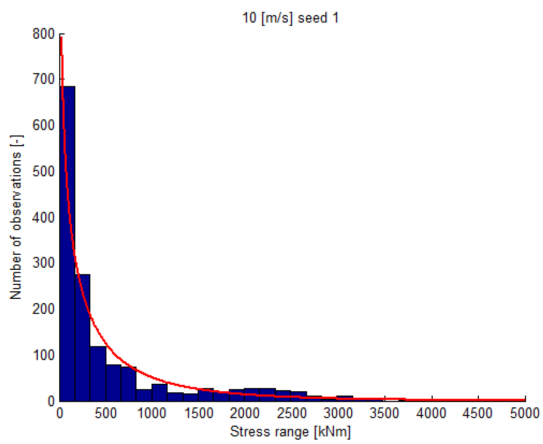

Figure 3. Cycle stress ranges for 10 m/s wind bin [5]

The figure illustrates the influence of the blades pitching mechanism, reducing the loads after rated wind speed of 11.4 m/s. Because the stress intensity factor is highly dependent on the crack size, its value is updated after every 10 minute interval, according to Eq. (2), considering the new crack size, determined by integration of Eq. (1).

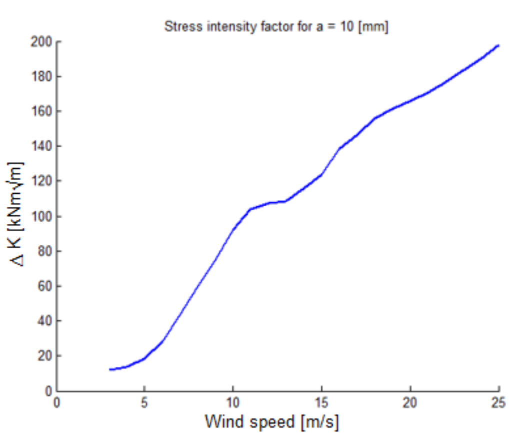

Figure 4. Stress intensity factor 10 m/s wind bin [5]

2.3. Failure and reliability estimate

Finally, it is assumed that when a crack reaches a threshold value a_{fail}, the blade collapses. This time-to-failure is dependent on the input parameters, out of which the initial crack size a_{in} and the material parameter A are considered stochastic. The time-to-failure (TTF) distribution is obtained by using Monte Carlo simulations, and integrating over time, as shown in figure 5. This distribution notes the initial reliability estimate of the component.

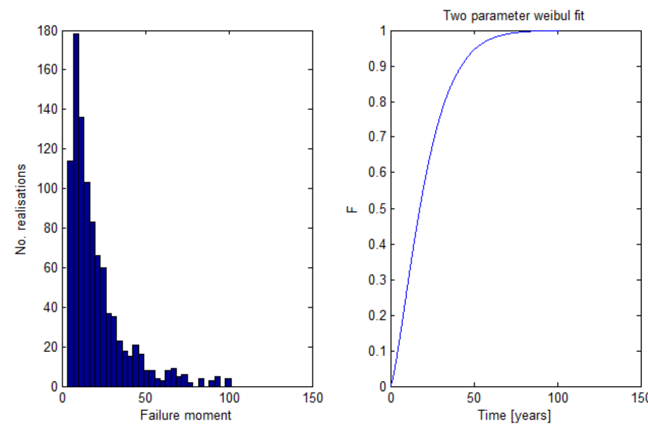

Figure 5. TTF distribution for blade

The TTF distribution shown above was determined using the numerical input in Table 1, with the stochastic parameters a_{in} and A, and their uncertain mean values q and v following lognormal distributions. The crack size a and its unknown mean q are determined by integrating the damage model up to a point of interest in time.

Table 1. Damage model parameter input

Par.	Description	Unit	Mean	COV
a_{in}	Intitial crack size	[m]	q_{in}	0.9
q_{in}	Mean of initial crack size	[m]	0.005	0.5
a	Crack size	[m]	q	logical
q	Mean crack size	[m]	logical	logical
A	Material parameter	$\left[\frac{1}{\text{kN s m}^{1/2}}\right]$	v	0.6
v	Mean value of material parameter A	$\left[\frac{1}{\text{kN s m}^{1/2}}\right]$	11^{-10}	0.3
m	Material parameter	[-]	1.45	-
λ_w	Material parameter	[-]	0.5	-
I	Turbulence intensity	[%]	10	-

3. MODEL UPDATING

During the life of a blade, condition monitoring is performed in the form of inspections. The results are used in a Bayesian network (Jensen & Nielsen, 2007) to update the reliability estimate, which is then used to plan for the next inspection or repair. The network is shown in figure 6. The nodes in the network represent the input parameters where, for simplicity, only the stochastic nodes are shown. The arrows indicate the conditional relations between each parameter i.e. the failure distribution F is conditional on the distribution of crack size a, which is in turn conditioned by the initial crack size a_{in} and the material parameter A.

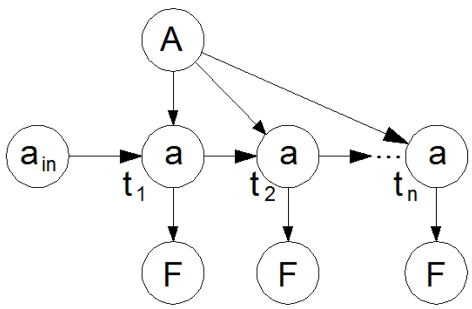

Figure 6. Dynamic Bayesian network model

The parameters a and A are uncertain with unknown mean values q and v, defined by a prior distribution. When an inspection is performed at time t_n, the result is used to calculate a posterior distribution by using Bayes update rule (Jensen & Nielsen, 2007). Since inference is being made on two parameters, Bayes update formula is used in the form shown in Eq. (3).

$$f_{(q,v|a_m)}'' = \frac{f(a_m|q,v) f_q'(q|v) f_v'(v)}{\int\int f(a_m|q,v) f_q'(q|v) f_v'(v)\, dq dv} \qquad (3)$$

The notations f' and f'' represent the prior and the posterior distributions respectively, and a_m notes the measured crack length determined at inspection. The prior joint distribution f' at time t_n is determined by integrating the damage model up to that moment in time, while the posterior joint distribution f'' is determined using Eq. (3).

An example is shown in the following, where an inspection was made after 1 year, and the inspection result was a_m = 0.007 m. The prior and posterior distributions are illustrated in figures 7 and 8 (with crack lengths in [m]).

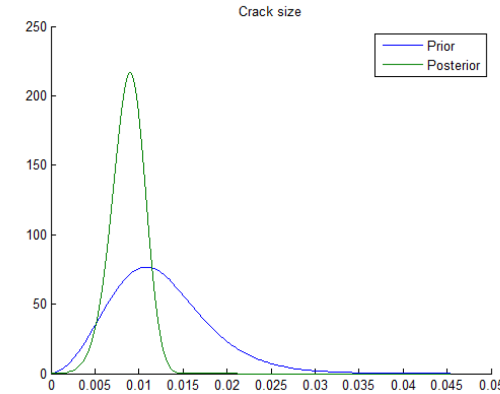

Figure 7. Prior and posterior distribution of crack size a

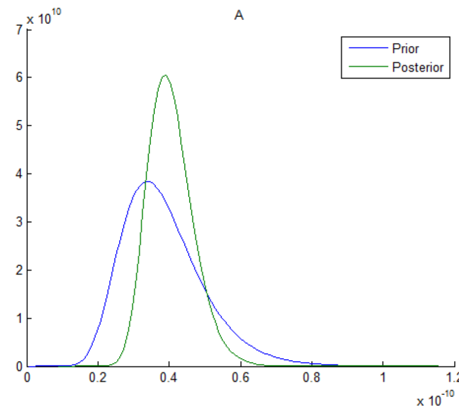

Figure 8. Prior and posterior distribution of material parameter A

It is seen that both posterior distributions are narrowed, which in turn leads to a more precise failure estimate. An example, showing how the failure distribution is updated on an annual basis is shown in figure 9.

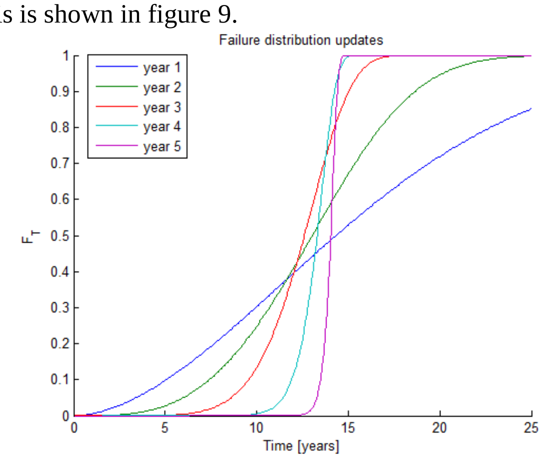

Figure 9. Failure distribution updated with regular inspections

It is seen that the distribution narrows down after every inspection. After the inspection in year five, it becomes clear that failure will occur somewhere in year 13. The information from this reliability estimate is used for optimal planning of maintenance operations.

4. DECISION MODEL

As mention in section 1, optimal planning of inspections and repairs can be made based on the reliability estimate for the blade. A practical way to do so, is shown in the following.

- a first inspection is performed after a certain time interval after the wind turbine operation starts, and the failure distribution is computed
- a fixed limit threshold is considered and the following inspection is performed in the year that threshold is reached. The failure distribution is then updated with the new results from the inspection
- if it is estimated that the failure threshold is reached within the same year as the last inspection, a repair activity is carried out right after the inspection

An example showing how the inspections are scheduled is shown in Table 2, where the first inspection was performed after the first year, and a failure threshold of 5 % was considered.

Table 2. Example inspection schedule

Inspection No.	Time
1	1
2	6
3	10
4	12
5	14

It is seen that inspections become more frequent when approaching the end of the blades lifetime, and a repair is performed after the inspection at year 14.

5. EXAMPLE CASE STUDY

The maintenance model is used on the NORCOWE reference wind farm (https://rwf.computing.uni.no/), to illustrate the potential in optimising preventive maintenance effort. The model covers only blade maintenance, hence all turbines in the farm are for simplicity modelled by a single (critical) blade.

5.1. Maintenance model

Table 3 shows the activities used in the model, along with the required resources in terms of cost and time.

Table 3. Cost and duration for maintenance

Activity	Cost [€]	Duration [h]
Inspection	1000	6
Repair	10000	24
Replacement	400000	80

In terms of work force, inspection and repair activities require a number of 3 technicians and a crew transfer vessel (CTV), while replacement operations require 6 technicians and a heavy lift vessel (HLV). Specifications on the vessels are shown in table 4.

Table 4. Vessel characteristics

	CTV	HLV
Number	4	1
Wave limit [m]	1.5	2
Wind limit [m/s]	-	20
Mobilisation time [days]	-	30
Mobilisation cost [€]	-	250000
Speed [knots]	20	11
Day rate [€]	1000	100000

In case there are not sufficient vessels to carry out all necessary actions at the same time, a priority system is used, so that downtime is minimized. Hence, replacement activities are carried out first, followed by repairs and finally inspections.

All activities are carried out from an onshore base 50 km from the farm, and spare parts are always available in stock. A number of 24 technicians is hired, working one 12 hour shift a day. An exception is made for replacement activities, where 2 twelve hour shifts are used in order to finish repairs as fast as possible.

5.2. Decision model

Two different strategies for preventive maintenance are considered. A traditional time/condition based model, where inspections are performed at regular intervals and repairs are made depending on the size of the cracks is used as a reference case.

The second model is the reliability based model described in section 4.

Both models are optimized with respect to their individual decision criteria, namely inspection interval and maximum damage size for time/condition based maintenance and failure threshold for reliability based maintenance. The results from the optimized strategies are then compared and discussed in section 6. Note that optimization is made strictly with respect to the total lifetime cost of maintenance, while the downtime of the models is not included in the decision. The reason for this is that downtime is very low, due to the fact that only maintenance of blades is modeled.

5.3. Lifetime simulation

A simulation based approach is used where lifetime (25 years) simulations are performed for the NORCOWE reference wind farm with the layout shown in figure 10; using the maintenance models presented in the previous sub section. This is done using a discrete event simulator model.

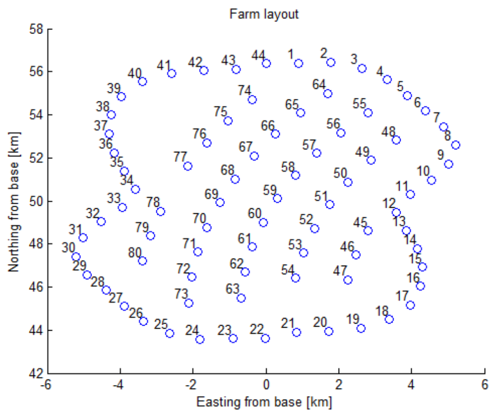

Figure 10. NORCOWE farm layout

Each turbine is modelled by a single turbine, using the damage model described in section 2 and a time step of one month. The input used for the damage model is shown in table 4.

When an activity is called for, considering that sufficient vessels are available, the time required for a repair activity is calculated with respect to the position of the turbine with respect to base, and the weather conditions. Weather conditions are given as 11 year wind and wave time series at the wind farm location. Based on this, 25 year time series are obtained by bootstrapping on a yearly basis, thus introducing a degree of weather variation between different simulations.

After the work force and weather conditions have been assessed, the repair activities are carried out. In this situation, a time step of 3 hours is used for increased accuracy.

Depending on the progress of repairs and the cost model, all the expenses are computed. The time-based availability is also calculated, including both effective time for repairs, and time in which turbines are non-operational due to failure of a blade.

6. RESULTS

6.1. Time/condition based maintenance

For this strategy, a fixed interval of inspections is set at the start of a simulation. The inspections are considered perfect, meaning that the probability for successfully detecting a crack is 100 % and there is no measurement error. If a detected crack is higher than a predefined threshold, a preventive repair is scheduled and carried out as soon as the weather conditions permit, and sufficient work force is available. For every turbine, the first inspection is fixed after 4 years of operation. This interval has been chosen as it is a common time period for warranty offered by turbine manufacturers.

For optimising the maintenance plan, a number of simulations is carried out for a range of inspection intervals and damage (crack size [m]) thresholds. The average outcome for these is shown in figure 11.

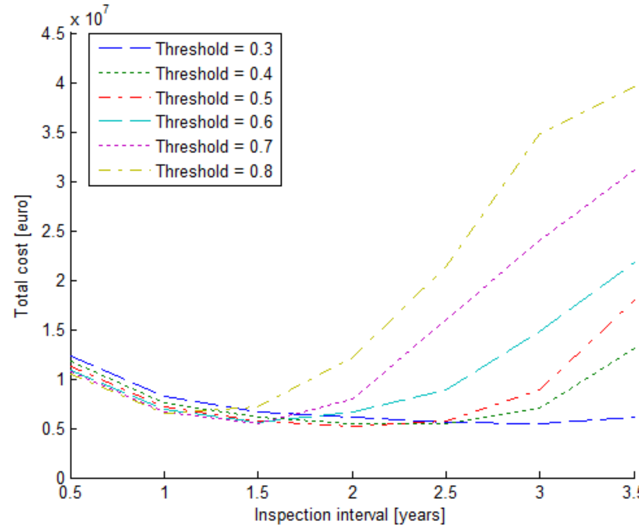

Figure 11. Mean cost output

It is seen that for all combinations of inspection interval and damage threshold used, the cost is increased at the extremities of the graph. If the inspection interval is too large, inspections are too far apart to succesfully prevent failure, which result in a large increase of the maintenance cost due to the expensive replacements and heavy lift vessels. On the other side, if the interval is to small, there is an unnecesarry large number of inspections and repairs. Although similar output can be obtained by various combinations of the two parameters, the optimal decision for the given cost model is estimated at a 2 year inspection interval and a damage threshold of 0.5 m.

The main output for the optimal plan is shown in table 5.

Table 5. Cost and downtime output

Total cost [€]	**Downtime [%]**
$5.25\ 10^6$	0.37

6.2. Risk and reliability based maintenance

In this case, the decision model described in section 4 is used. As in the condition based maintenance model, the first inspection is fixed in year 4, when it is expected that warranty expires. The remaining decision parameter is the failure threshold, and the optimal value is determined by running simulations covering a range of values. The results are shown in figure 11.

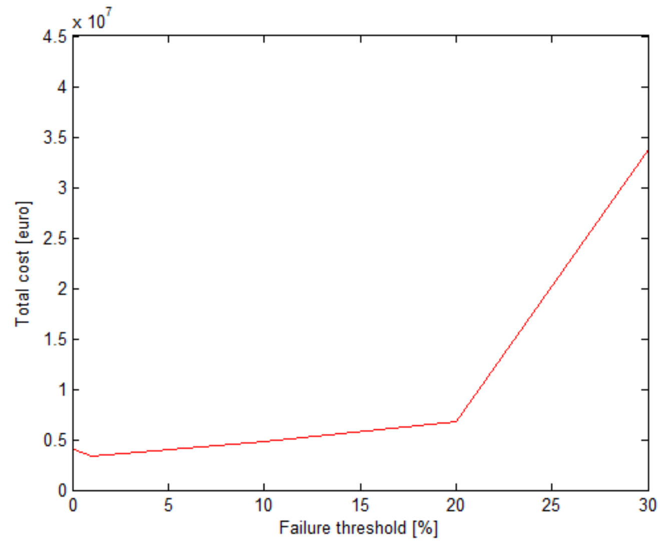

Figure 11. Mean cost output

It is seen that when the threshold is too high, the cost is greatly increased, due to the increased frequency of failures, as was is the case for condition based planning. However, when the threshold is kept below 10 % there is little variation in the results. This is due to the fact the number of inspections is not increased significantly, as was in the previous case. The optimal threshold is estimated at 1 %, and the corresponding results are shown in table 6.

Table 6. Cost and downtime output

Total cost [€]	Downtime [%]
4.55 10^6	0.27

A reduction of 14 % can be seen in the total average cost compared to the results from the condition based strategy. This is a result of the fact that the number of inspections and repairs is reduced, while keeping failure ratios low. The optimal risk based strategy has resulted in an average number of 1.9 repairs and 7.2 inspections per turbine, while the condition based strategy has resulted in 2.3 repairs and 11 inspections per turbine.

7. CONCLUSION

In this paper, two strategies for planning of preventive operation and maintenance were set up and optimised, with the goal of underlining the potential positive impact of implementing risk based inspections for offshore wind farm maintenance.

A fracture mechanics based degradation model was used in combination with a dynamic Bayesian network, and offline inspections to estimate the reliability of blade turbines. Using this model, inspection and repair planning has been optimised in a case study on the NORCOWE wind farm. The results have been compared to results from a more traditional condition based strategy, which has also been optimised.

It was shown that for the risk based maintenance, the number of inspections and repairs are reduced, while at the same time avoiding failures in the blades. This led to a reduction of 14 % of the total cost of blade maintenance has been obtained for the given cost model, showing that preventive maintenance effort is more efficiently dosed using risk based inspection planning.

ACKNOWLEDGEMENT

This work has partly been funded by the Norwegian Center for Offshore Wind Energy (NORCOWE) under grant 193821/S60 from Research Council of Norway (RCN). NORCOWE is a consortium with partners from industry and science, hosted by Christian Michelsen Research. Further, the paper is partly funded by 'LEX - Torsional Stiffening of Wind Turbine Blades – Mitigating leading edge damages' supported by the Danish Energy Agency through the Energy Technology Development and Demonstration Program (EUDP), grant no. 64013-0115. The financial supports are greatly appreciated.

NOMENCLATURE

a	*crack size*
A	*material parameter*
a_{in}	*initial crack size*
a_m	*measured crack size*
ΔK	*stress intensity factor*
Δs	*stress cycle*
f'	*prior density function*
f''	*posterior density function*
F	*failure distribution*
I	*turbulence intensity*
λ_w	*material parameter*
m	*material parameter*
q	*mean of initial crack size distribution* a_{in}
R	*mean cycle range*
t	*time*
u	*mean wind speed*
v	*mean of material parameter A*

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