Planning of operation & maintenance using risk and reliability based methods

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Abstract

Operation and maintenance (OM) of offshore wind turbines contributes with a substantial part of the total levelized cost of energy (LCOE). The objective of this paper is to present an application of risk- and reliability-based methods for planning of OM. The theoretical basis is presented and illustrated by an example, namely for planning of inspections and maintenance of wind turbine blades. A life-cycle approach is used where the total expected cost in the remaining lifetime is minimized. This maintenance plan is continuously updated during the lifetime using information from previous inspections and from condition monitoring with time intervals between inspections and maintenance / repair options as the decision parameters.

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risk; reliability; offshore; life-cycle; maintenance; turbine; blade

1. Introduction

Operation and maintenance (OM) activities have been shown to contribute to around 25 - 30% of the total energy cost from offshore wind power, leading to an increased effort for optimizing maintenance plans, with current industry practices relying mostly on a corrective/run-to-failure approach, and for certain aspects on time based preventive maintenance.
This paper analyses the potential of implementing risk and reliability based approaches, with decision criteria formulated in terms of turbine failure probability. Although such methods have been successfully used in the offshore Oil & Gas industry, the risk acceptance criteria in this situation is unreasonably high for a direct implementation in the case of wind farms, where the financial and not the human life factor is design driver.

In the following, an application of risk and reliability planning is presented, concerning the optimum planning of inspections for blade maintenance using reliability as the decision parameter. The cost output for different reliability thresholds is determined using life-cycle simulator models and are compared with outputs from more traditional approaches such as corrective/time based maintenance.

**Nomenclature**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>Paris law material parameter</td>
</tr>
<tr>
<td>$a$</td>
<td>Crack length</td>
</tr>
<tr>
<td>$da$</td>
<td>Increase in crack length</td>
</tr>
<tr>
<td>$f(ds</td>
<td>\mu,I)$</td>
</tr>
<tr>
<td>$F$</td>
<td>Time-to-failure distribution</td>
</tr>
<tr>
<td>$\Delta K$</td>
<td>Stress intensity factor</td>
</tr>
<tr>
<td>$\Delta s$</td>
<td>Stress range</td>
</tr>
<tr>
<td>$\Delta t$</td>
<td>Time step</td>
</tr>
<tr>
<td>$\lambda_0$</td>
<td>Paris law material parameter</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Expected value of the smallest detectable crack size</td>
</tr>
<tr>
<td>$m$</td>
<td>Paris law material parameter</td>
</tr>
<tr>
<td>$R$</td>
<td>Stress ratio</td>
</tr>
<tr>
<td>$POD$</td>
<td>Probability of detection</td>
</tr>
</tbody>
</table>

### 2. Life cycle model

A framework for the basic life-cycle approach for planning of operation and maintenance has been described in [1] and is used as basis for the analysis in this paper.

In this section, a life-cycle simulator is described and used for analysing different maintenance strategies. The model is simplified in the sense that it simulates one NREL 5 MW offshore turbine, which is structurally described by a single component, namely a laminated carbon fiber blade, on which inspections and repairs can be performed using various decision parameters.

In the following, the various modules of the model are described.

#### 2.1. Weather condition

The weather is modelled using wind and wave time series measurements covering a period from 2004 to 2012 at the FINO1 location 45 km off the coast of Germany into the North Sea.

The measurements are used to assess the appropriate working conditions, energy production and health condition of the components.

#### 2.2. Damage and reliability model

The health state of the blade is described using a fracture mechanics based damage model that has been described in [2]. The model assumes 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
2.2.1. 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, defined by the distance between two neighboring cracks and the crack size. The distances are generated from a Poisson process with intensity $\lambda_p$ and the size $a_{in}$ of each crack is randomly generated using a lognormal distribution.

2.2.2. 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 will be assessed for 10 minute intervals following Paris law, as shown in equation 1,

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

(1)

The stress intensity factor $\Delta K$ for a time interval $\Delta t$ is determined as a function of the wind speed, the crack size and the load cycle distribution corresponding to $\Delta t$. The model is shown in equation 2.

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

(2)

The statistical distribution function of the cycle ranges is dependent on the turbulence intensity for a given site and the mean wind speed. 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 [3], covering all operational wind bins of the NREL 5MW turbine. Data is collected for the flap-wise blade bending moment for 1 m/s wind bins from cut-in to cut-out wind speed, using a reference turbulence intensity of 0.08, as determined for the weather data used from the platform location. To avoid large statistical uncertainties, a number of 15 seeds is used for each wind bin.

![Fig. 1. (a) Distribution of stress ranges in 10 minute simulation (b) Stress intensity factor](image)

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 a rainflow count 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 shown in figure 1(a). Along with the stress ranges, the mean value of the cycle midpoints is determined in order to estimate the cycle ratio $R$.

By integrating according to expression 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. This is shown in figure 1(b), for a crack size of 10 mm.

The figure illustrates the influence of the blades pitching mechanism, reducing the loads after rated wind speed. Because the stress intensity factor is highly dependent on the crack size, its value is updated after every 10 minute interval, according to equation 2, considering the new crack size, determined with equation 1.

### 2.2.3. Failure

Failure is finally assumed when the cracking reaches a threshold value $a_{\text{fail}}$. A run of the damage model is shown in figure 2(a). The various cracks increase at a different rate, depending on the initial size, with failure occurring once one of the defects reaches the failure threshold.

Using Monte Carlo simulations, the time-to-failure (TTF) density is obtained, which is then integrated, to obtain the TTF distribution, thus assessing the reliability of the component. This is shown in figure 2(b).

![Fig. 2(a). Simulation of crack growth on blade (b) Time-to-failure distribution](image)

### 2.3. Inspection modeling

The reliability of the inspection procedure is modeled using a probability of detection curve [4] as shown in expression 3,

$$POD(a) = 1 - \exp \left( -\frac{a}{\lambda} \right)$$

where $\lambda$ is the expected value of the smallest detectable crack size.

### 2.4. Reliability model updating

During the life cycle of the turbine, a number of inspections is performed in order to attain new information on the health of the blade.

The reliability estimate is then updated with the inspection results using Bayesian updating. Thus, the initially considered (prior) distributions for the variables are updated with new information, obtaining more accurate
posterior distributions. A detailed description of Bayes update theory can be found in [5] and similar applications can be found in [6]. An illustration can be seen in figure 3, with the nodes M and W representing input on material parameters, respectively weather conditions, the crack length a and the time-to-failure distribution F.

![Bayesian updating of failure distribution](image)

Fig. 3. Bayesian updating of failure distribution

Results from inspections are inserted into node a and the posterior distributions of F are determined using Bayes update rule.

3. Maintenance optimisation

In this section, two maintenance strategies are presented and optimised using different criteria.

3.1. Condition based maintenance

In the first case, a classic condition-based maintenance is presented, where inspections are performed at regular intervals, and a preventive repair is carried out if a crack that is larger than a certain limit is successfully detected. If inspections are not successful and the blade reaches failure, a corrective repair is carried out. The optimisation is made with respect to the intervention threshold and the annual cost of maintenance is calculated using the life-cycle model and the cost and downtime model presented in table 1.

<table>
<thead>
<tr>
<th>Activity</th>
<th>Cost [-]</th>
<th>Downtime [h]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inspection</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>Preventive repair</td>
<td>20</td>
<td>24</td>
</tr>
<tr>
<td>Corrective repair</td>
<td>100</td>
<td>72</td>
</tr>
<tr>
<td>Energy</td>
<td>0.1</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 1. Cost and downtime input

Figure 4 shows an example run of the life cycle model, using an inspection interval of 2 years, and a repair limit of 0.2 m. Every successfully detected crack that is higher than the threshold is repaired, while the ones that are not detected continue to grow and can eventually lead to failure. This can be seen in the figure between the inspections from year 10 and 12, when the failure limit is reached, resulting in the need for a more expensive corrective repair. It is noticed that both preventive and corrective repairs are imperfect, meaning that after the activity new crack is generated. This is done to account for crack initiation during the life of the blades, which is not accounted for by the damage model.

The cost of maintenance is calculated by counting the number of inspections and preventive/corrective repairs and adding the corresponding cost shown in table 1. The revenue loss is then added to the total maintenance cost.
by calculating the downtime from each activity and weighing it together with the power production and energy cost. The power curve for the NREL 5MW turbine can be found in [3].

![Example life time simulation](image.png)

Fig. 4. Example life time simulation

Using Monte Carlo simulations, a number of 100 simulations for a 20 year lifetime is generated for different values of the repair limit, and the expected value is calculated, as shown in figure 6(a). The time interval between inspections is kept fixed at 2 years.

It can be seen that a decision to intervene at low values of crack sizes leads to higher repair expenses, while high levels lead to high cost of corrective replacement due to an increased failure probability. An optimum limit is estimated at around 0.2 m leading to a normalised annual cost of around 14.3 for the given cost model.

3.2. Risk based maintenance

In this case, maintenance is planned using a reliability criteria. As for the condition based maintenance, decisions are made every 2 years as follows:

- a decision on whether or not to perform an inspection is made depending on the initially estimated failure probability
- if an inspection is performed, the failure probability estimate is updated with the new information
- if an inspection is not performed, the distribution is updated with the ‘no-failure’ observation
- if according to the updated distribution, the probability of failure up until the next decision exceeds the chosen threshold limit, a repair is performed
For illustration, figure 5 shows an example of the initial time-to-failure distribution at year 0 and an update after year 2. It is seen that based on the inspection result, the failure probability after around year 4 becomes considerably greater than initially estimated, and serves as basis for future decisions.

Monte Carlo simulations are made using the life cycle model, and an optimisation is made with respect to the failure probability threshold. The result are shown in figure 6(b).

It is seen the optimum threshold is estimated at around 30%, leading to an annual cost of 13.1, almost 10% lower than when using the condition based criteria. The cost difference is saved mostly through the fact that inspections are not performed at every 2 year interval, if the risk of failure is not considerable.

4. Summary

A life-cycle model was built to simulate operation and maintenance activities on the degrading blades of an offshore wind turbine, where maintenance activities, i.e. inspections and repairs, were scheduled using a conventional condition based strategy, with fixed inspections and preventive repairs motivated by inspection
results and a non-conventional reliability based approach, where both inspections and preventive repairs are motivated by an estimated failure probability for a future time.

An optimisation was made for both strategies in terms of lifetime expected cost of maintenance, and was concluded that a reliability based approach has a higher potential of reducing expenses. The main reason for this is that, unlike in the case of condition based maintenance, inspections are not carried out unless motivated by a high failure probability in the near future.

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References