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Published in:
Proceedings IFIP WG7.5 Conference on Reliability and Optimization of Structural Systems

Publication date:
2009

Document Version
Publisher's PDF, also known as Version of record

Link to publication from Aalborg University

Citation for published version (APA):
Sørensen, J. D. (2009). Risk-based Operation and Maintenance of Offshore Wind Turbines. In *Proceedings IFIP WG7.5 Conference on Reliability and Optimization of Structural Systems* The IFIP International Conference on Research and Practical Issues of Enterprise Information Systems.

RISK-BASED OPERATION AND MAINTENANCE OF OFFSHORE WIND TURBINES

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ABSTRACT

For offshore wind turbines costs to operation and maintenance are substantial. This paper describes a risk-based life-cycle approach for optimal planning of operation and maintenance. The approach is based on pre-posterior Bayesian decision theory. Deterioration mechanisms such as fatigue, corrosion, wear and erosion are associated with significant uncertainty. Observations of the degree of damage can increase the reliability of predictions, especially in connection with condition-based maintenance. The approach can be used for gearboxes, generators, cracks, corrosion, etc. The paper also describes how probabilistic indicators can be used to quantify indirect information about the damage state for critical components, e.g. gear-boxes.

Keywords: wind turbines, operation & maintenance, risk

1. INTRODUCTION

For offshore wind turbines costs to operation and maintenance are substantial, and can be expected to increase when wind farms are placed at deeper water depths and in more harsh environments. This paper describes a risk-based life-cycle approach for optimal planning and design of offshore wind turbines. For oil & gas offshore installations cost-effective procedures for risk-based inspection planning have been developed during the last 10-15 years and are used at several locations world wide, see e.g. (Moan 2005), (Faber et al. 2000) and (Sørensen et al. 2001). These procedures are based on pre-posterior Bayesian decision theory. This paper describes how these procedures can be applied for offshore wind farms, especially:
how risk-based methods can be used to optimal planning of
  • future inspections / monitoring / service (time / type)
  • decisions on maintenance/repair on basis of (unknown) observations from future inspections / monitoring
taking into account uncertainty and costs.

Deterioration mechanisms such as fatigue, corrosion, wear and erosion are associated with significant uncertainty. Observations of the degree of damage can increase the reliability of predictions. Maintenance activities can be divided in corrective and preventive (timetabled or conditioned) maintenance. Condition-based maintenance using observations from e.g. condition monitoring should optimally be based on pre-posterior Bayesian decision theory. This approach can be used for operation and maintenance planning related to failure & error types such as: Gearbox, Generator, Rotor blades, Blade pitch mechanism, Yaw mechanism, Main shaft, Tower / support structure (jacket): cracks, corrosion, … Another important aspect for decisions related operation and maintenance is the time scale which can be short (minutes), medium (days) for e.g. deciding if an offshore maintenance / repair action should be initiated depending on the weather forecast or long (months / years) for e.g. preventive maintenance and inspection / monitoring planning for gear boxes.

An important aspect is collection and probabilistic modelling of information. Information can come from Condition Monitoring System (CMS), direct inspections or indirect indicators. Indicators contain indirect information on failure rates and statistical models can be formulated and updated based on Bayesian statistics. The use of indicators is illustrated for typical wind turbine components.

2. OPTIMAL PLANNING OF MAINTENENCE

Figure 2.1 shows a decision tree related to the life cycle of an engineering structure such as a wind turbine or wind farm. The decisions taken by the decision maker (designer / owner / …) and observations of uncertain parameters (unknown at the time of the decision) are:

- At the design stage a decision on the optimal design parameters $\mathbf{z} = (z_1,...,z_N)$ is made which in principle should maximize the total expected benefits minus costs during the whole lifetime such that safety requirements are fulfilled at any time. In practice requirements from standards and actual costs of materials are used to determine the optimal design.
- During the lifetime continuous monitoring of the wind turbines and inspections of critical components / details are performed. These are indicated in the box 'repeated inspection/maintenance' in figure 2.1. Each box consists of:
  - o a decision on times and types of inspection / monitoring for the rest of the lifetime
  - o observations from inspection / monitoring
  - o decision on eventual maintenance / repair based on the inspection / monitoring results
- Realisation of uncertain parameters such as wind and wave climate, strengths, degradation, model uncertainties will take place during the lifetime. It is noted that these uncertainties can be divided in aleatory and epistemic uncertainties. Aleatory uncertainty is inherent variation associated with the physical system or the environment – it can be characterized as irreducible uncertainty or random uncertainty. Epistemic uncertainty is uncertainty due to lack of knowledge of the system or the environment – it can be characterized as subjective uncertainty, reducible uncertainty.
- The total cost is the sum of all costs in the remaining part of the lifetime after the decision time.
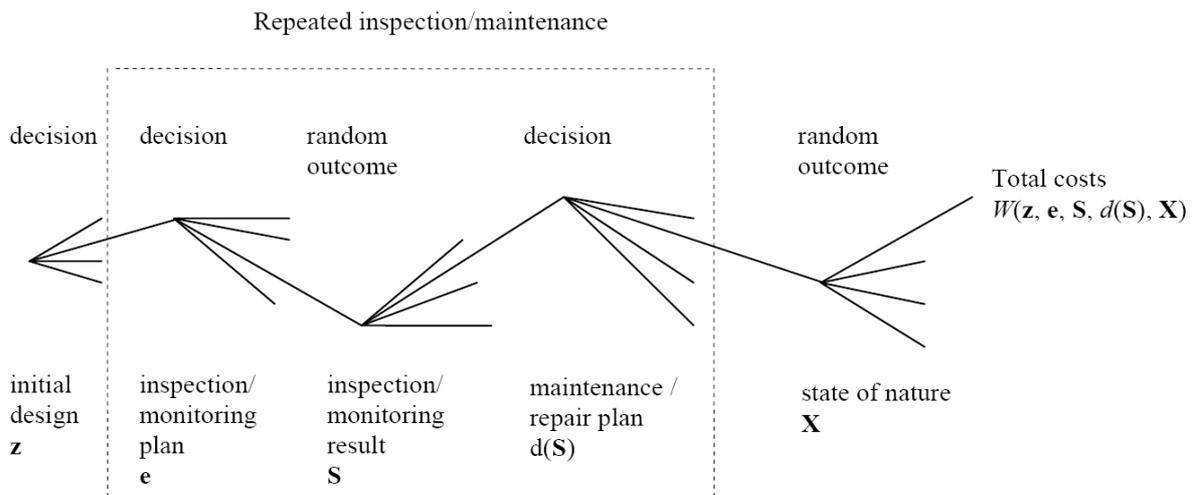

Figure 2.1 Decision tree for optimal maintenance planning.

The approach can be used for operation and maintenance planning related to different failure & error types in Gearbox, Generator, Rotor blades, Blade pitch mechanism, Yaw mechanism, Main shaft, Tower / support structure (fatigue cracks, corrosion), …

Further, decisions related to operation and maintenance are related to different time scales:

- short (minutes) for decision related to e.g. parking the wind turbine,
- medium (days) for e.g. decisions on when to start offshore maintenance / repair actions depending on e.g. weather forecasts, or
- long (months / years) for e.g. preventive maintenance and inspection / monitoring planning for gear boxes.

An important step in risk-based inspection & maintenance planning is collection of data / information and probabilistic modelling of this information. Information can come from Condition Monitoring Systems (CMS), inspections or indicators. Indicators that contain indirect information on e.g. failure rates can be formulated and updated based on Bayesian statistics, see (Faber & Sørensen 2002).
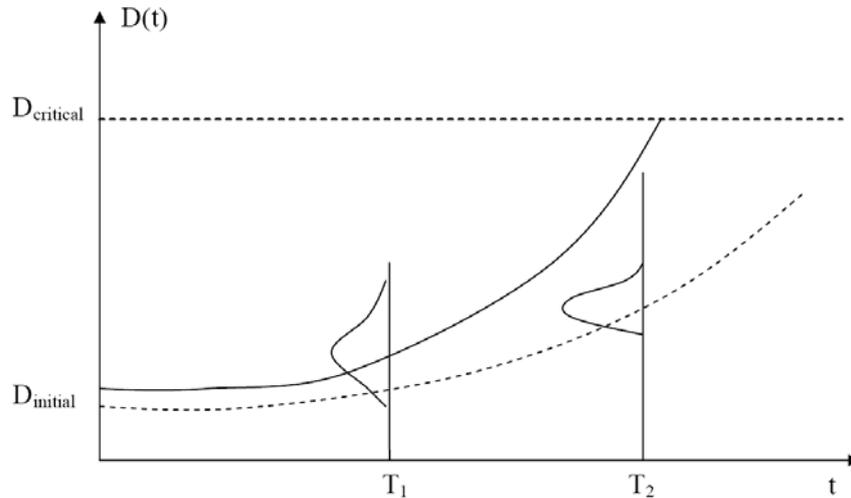
Figure 2.2 Damage model with inspection / repair at time T_1.

Deterioration mechanisms such as fatigue, corrosion, wear and erosion are associated with significant uncertainty. Observations of the degree of damage $D(t)$ can increase the reliability of predictions using Bayesian statistical techniques as illustrated in figure 2.2. Generally an inspection at time T_1 and associated maintenance/repair will decrease the uncertainty and the expected mean damage level at time T_2 will be smaller since most realizations with large damage level at time T_1 can be expected to be maintained / repaired.

The performance of wind turbines is subject to a number of uncertainties. These include operational conditions, material characteristics and environmental exposure. The uncertainties are due to inherent physical randomness and uncertainties associated with the models used to assess the performance of the systems. If, furthermore, the statistical basis for the assessment of the uncertainties is limited then also statistical uncertainties may be important.

When inspection / maintenance planning for wind turbines is considered, it is important to take all these uncertainties into consideration, as they will strongly influence the future performance of the systems. It is also important to realize that the degree of control of the engineering systems achieved by the inspections is strongly influenced by the reliability of the inspections, i.e. their ability to detect and size degradation. The reliability of inspections themselves may be subject to significant uncertainty and this must be taken into account in the planning of inspections.

The decision problem of identifying the cost optimal inspection plan may be solved within the framework of pre-posterior analysis from the classical decision theory see e.g. (Raiffa and Schlaifer 1961) and (Benjamin and Cornell 1970). Here a short summary is given, see e.g. (Sørensen et al. 1991), (Madsen & Sørensen 19900), (Faber et al. 2000) and (Sørensen et al. 2001). A similar formulation has with large success been applied for planning of inspection and repair of offshore oil & gas installations.

In the general case the parameters defining a inspection plan are the possible repair / maintenance actions which are modeled by the decision rule d, the number of inspections N in the service life T_L, the time intervals between inspections and possible repair/maintenance $\mathbf{t} = (t_1, t_2, ..., t_N)$ and the inspection qualities $\mathbf{q} = (q_1, q_2, ..., q_N)$.

These inspection/maintenance parameters are written as $\mathbf{e} = (N, \mathbf{t}, \mathbf{q})$. The outcome of inspections (typically a damage level, e.g. a crack size, the extent of corrosion or wear) is modeled by a random variable S since it is unknown at the time of decision making. A decision rule $d(S)$ is then applied to the outcome of the inspection to decide whether or not repair / maintenance should be performed. The different uncertain parameters (stochastic variables) modeling the state of nature such as load variables and material characteristics are collected in $\mathbf{X} = (X_1, X_2, ..., X_n)$.

If the total expected costs are divided into fabrication, inspection, repair, maintenance, strengthening and failure costs and a constraint related to a maximum annual (or accumulated) failure probability $\Delta P_F^{\max}$ is added then the optimization problem can be written

$$\max_{\mathbf{z},\mathbf{e},d} \quad W(\mathbf{z},\mathbf{e},d) = B(\mathbf{z},\mathbf{e},d) - C_1(\mathbf{z},\mathbf{e},d) - C_{IN}(\mathbf{z},\mathbf{e},d) - C_{REP}(\mathbf{z},\mathbf{e},d) - C_F(\mathbf{z},\mathbf{e},d)$$

$$\text{s.t.} \quad z_i^1 \le z_i \le z_i^u \qquad\qquad , i = 1,...,N \tag{2.1}$$

$$\Delta P_t(t,\mathbf{z},\mathbf{e},d) \le \Delta P_F^{\max} \qquad , t = 1,2,...,T_L$$

$W(z,\mathbf{e},d)$ is the total expected benefits minus costs in the service life time T_L, B is the expected benefits, C_1 is the initial costs, C_{IN} is the expected inspection costs, C_{REP} is the expected costs of repair and C_F is the expected failure costs. The annual probability of failure in year t is $\Delta P_{F,t}$. The N inspections are assumed performed at times $0 \le T_1 \le T_2 \le ... \le T_N \le T_L$.

The total capitalized benefits are written

$$B(\mathbf{z},\mathbf{e},d) = \sum_{i=1}^{N} B_i \left(1 - P_F(T_i)\right) \frac{1}{(1+r)^{T_i}} \tag{2.2}$$

where the i th term represents the capitalized benefits in year i given that failure has not occurred earlier, B_i is the benefits in year i, $P_F(T_i)$ is the probability of failure in the time interval $[0,T_i]$ and r is the real rate of interest.

The total capitalized expected inspection costs are

$$C_{IN}(\mathbf{e},d) = \sum_{i=1}^{N} C_{IN,i}(\mathbf{q}) \left(1 - P_F(T_i)\right) \frac{1}{(1+r)^{T_i}} \tag{2.3}$$

where the i th term represents the capitalized inspection costs at the i th inspection when failure has not occurred earlier, $C_{IN,i}(q_i)$ is the inspection cost of the i th inspection.

The total capitalized expected repair costs are

$$C_{REP}(\mathbf{e},d) = \sum_{i=1}^{N} C_{R,i} P_{R_i} \frac{1}{(1+r)^{T_i}} \tag{2.4}$$

where $C_{R,i}$ is the cost of a repair at the i th inspection and P_{R_i} is the probability that a repair is performed after the i th inspection when failure has not occurred earlier.

The total capitalized expected costs due to failure are estimated from

$$C_F(\mathbf{e},d) = \sum_{t=1}^{T_L} C_F(t) \Delta P_{F,t} P_{COL|FAT} \frac{1}{(1+r)^t} \tag{2.5}$$

where $C_F(t)$ is the cost of failure at the time t. $P_{COL|FAT}$ is the conditional probability of collapse of the wind turbine given fatigue failure of the considered component and models the importance / consequence of fatigue failure. The probabilities of failure at year t and the probability of repair can be determined as described in e.g. Madsen et al. (1990).

The above model is in principle related to a single wind turbine and a single component. For wind turbine placed in a wind farm with many critical components the same basic formulation can be used, but the initial costs, inspection, repair and failure costs should be formulated as a basic cost plus marginal costs for each extra wind turbine in the park.
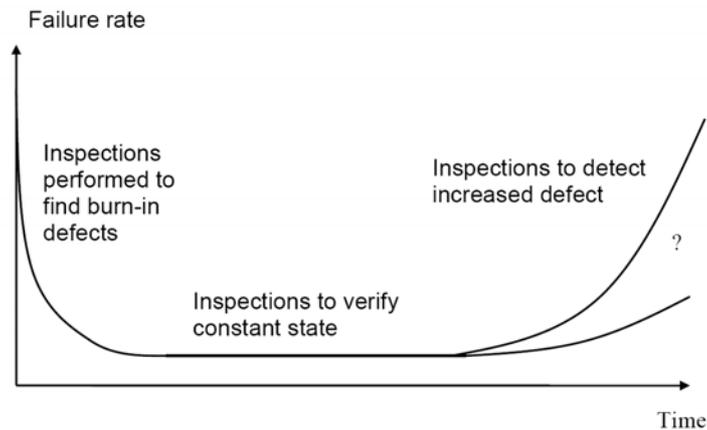
Figure 2.3 Bath-tub model for lifetime failure rate.

For many components – also wind turbine components - subject to degradation / damage accumulation the model in figure 2.3 can be used to illustrate the development of the failure rate during the lifetime. Initially a high failure rate can be expected due to fabrication / burn-in defects. Next, a period with a 'normal' constant failure / defect rate will take place. Corrective maintenance is performed in this period. At the end of the lifetime of the component the failure / defect rate can be expected to increase. If the failure rate increases strongly (time to failure is „known") then preventive maintenance should be performed. If the failure rate is moderately increasing deterioration / damage can be observed before failure, and condition control / condition & risk based maintenance should be performed and planned using the principles described above for risk-based inspection & maintenance/repair planning.

The risk-based methods described abobe can thus be used to optimal planning of decisions on
- future inspections / condition monitoring (time and type), and
- maintenance / repair actions based on (unknown) observations from future inspections / monitoring taking into account uncertainty and costs.

The next section illustrates how this can be used for typical components in wind turbines.
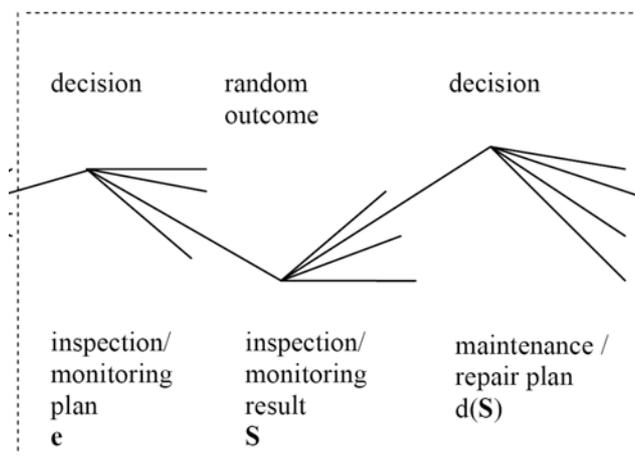

3.   EXAMPLES

Figure 3.1 Repeated inspection/maintenance.

Table 3.1 Indicators for inspection of gear-boxes.

Inspection type	Description
Visual inspection Visual inspection	though inspection covers: indication of extent of wear
Oil analysis	with time intervals a sample is taken indicating extent of wear
Magnet	with time intervals a representative sample is taken indicating extent of wear material
Investigation of oil filters	with time intervals a representative sample is taken indicating extent of wear material
Particle counting online	continuously representative samples are taken indicating extent of wear material
Condition monitoring	continuously the vibration response is monitored and used to indicate mechanical changes

The models described in section 2 can e.g. be used for gearboxes in wind turbines when planning inspection and maintenance / repair. Only the process of planning repeated inspection / service and maintenance / repair is considered, see figure 3.1. Examples of inspection methods and inspection results for gearboxes are shown in table 3.1. All the assessment methods shown give indirect information on the damage/deterioration state of the gearbox, since the damage/deterioration state is not measured directly. The indicators will have different reliabilities with respect to information about the real damage state and they will have different costs. These aspects can be modelled using the risk-based inspection & maintenance planning approach described in section 2. In order to use the pre-posterior Bayesian decision models optimal, risk-based inspection & maintenance planning it is further necessary to formulate decision rules for maintenance / repair actions given inspection/monitoring results, i.e. it is beforehand decided which future maintenance / repair to perform when future inspection results become available.

The models to be established are:

- A maintenance model for the decision parameters describing the future maintenance, service and inspection plan and methods, see below
- A deterministic model for damage / deterioration accumulation – as function of time: $D(t)$, see below
- A stochastic model for uncertain parameters in the damage accumulation model such that a probabilistic model for the damage accumulation can be obtained, i.e. the probability of certain damage levels can be calculated
- A stochastic model for the uncertainty / reliability of each inspection type
- A decision model $d(S)$ for repair / maintenance (action) given future result of inspection / condition monitoring. The decision model can also include decisions depending on uncertain weather forecast
- A model for costs related to inspections, maintenance, repair and possible failure (including loss of income), see below

It is noted that information from continuous quality control and monitoring systems can be used to establish the stochastic models. The model can easily be extended with information from other inspection methods, and inspection / monitoring from other (correlated) components (gear-boxes).

A typical model for damage accumulation for various mechanical/electrical components can be written:

$$D(t) = \sum_i \Delta D(\Delta t_i) \tag{3.1}$$

where the damage accumulation increments over time intervals Δt_i depend on the operational mode, e.g.

$$\Delta D(\Delta t) = \begin{cases} \Delta t \cdot d_2 & \text{if } V = 0 \text{ (standstill)} \\ \Delta t (d_0 + d_1 \cdot V) & \text{if } V > 0 \end{cases} \tag{3.2}$$

V is the mean wind speed and d_0, d_1, d_2 are constants modelling the damage accumulation. The model in Eqn. 3.2 implies that the damage accumulation depends on the operational mode (standstill or production of electricity) and also on the mean wind speed. The constants d_0, d_1, d_2 can be modelled by stochastic variables which are updated continuously when new information / measurements of actual damages become available.

For various mechanical/electrical components a typical maintenance/service strategy is as follows:

- Time-tabled maintenance: service is performed with regular time intervals of 6 (or 12) months where the components are inspected / maintained and in many cases exchanged. Service is only made when access to the wind turbines can be made by cheap boat transport
- Corrective maintenance: failed components (implying stop of the wind turbine) are repaired as soon as possible, i.e. by boat if 'low mean wind speed' (low cost) or by helicopter if 'high mean wind speed' (high cost)

This maintenance strategy can be extended by using risk- and condition-based maintenance planning:

- At repeated time intervals (e.g. month 3, 6, 9, 12,…) a decision is made where the alternatives are:
  o service now, or after 3, 6, 9, 12 months
  using information from e.g. measured mean wind speed to estimate the damage accumulation.

The optimal decision is the one which minimize the total expected costs in the rest of the lifetime of the wind turbine. The decisions can be extended to include methods for repair/maintenance.

The cost model should include:

- Cost of inspection / service
- Cost of repair / maintenance
  – Transport: (weather dependent)
    • Boat / helicopter
    • Waiting time
  – Spare parts etc.
- Loss of revenue in case of failure
- Discounting rate r

4. CONCLUSION

A risk-based life-cycle approach for optimal planning of operation and maintenance is described. The approach is theoretically based on pre-posterior Bayesian decision theory and can be used when deterioration mechanisms such as fatigue, corrosion, wear and erosion are present and can be observed by inspection and/or monitoring before failure of the component considered. The risk based approach can rationally take into account the uncertainty related to the deterioration and the future costs related to inspection/monitoring, maintenance, repair and failure (loss of income).

Observations of the degree of deterioration damage can increase the reliability of predictions, especially in connection with condition-based maintenance using Bayesian updating. The approach can be used for gearboxes, generators, cracks, corrosion, etc. Further, it is described how probabilistic indicators can be used to quantify indirect information about the damage state for critical components. The approach is illustrated for application to gear-boxes in situations where deterioration can be observed before failure.

5. ACKNOWLEDGEMENTS

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