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Published in:
Reliability, Risk and Safety : back to the future

Publication date:
2010

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

Link to publication from Aalborg University

Citation for published version (APA):
Nielsen, J. J., & Sørensen, J. D. (2010). Planning of O&M for Offfshore Wind Turbines using Bayesian Graphical Models. In J. M. Ale, I. A. Papazoglou, & E. Zio (Eds.), Reliability, Risk and Safety : back to the future: ESREL 2010 : annual conference, 5-9 September 2010, Rhodes, Greece Leiden: CRC Press.

Planning of O&M for offshore wind turbines using Bayesian graphical models

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ABSTRACT: The costs to operation and maintenance (O&M) for offshore wind turbines are large, and risk-based planning of O&M has the potential of reducing these costs. This paper presents how Bayesian graphical models can be used to establish a probabilistic damage model and include data from imperfect inspections and monitoring. The method offers efficient updating of the failure probability, which is necessary for risk-based decision making. An application example is presented to demonstrate the capabilities of the method.

1 INTRODUCTION

The costs to operation and maintenance (O&M) of offshore wind turbines are large contributors to the cost of energy. These costs can be reduced if better maintenance strategies are used. Presently component failures cause large costs to corrective maintenance. Failure of even a minor component might cause escalated damage, and the wind turbine stops producing power until a repair or replacement is utilized. Because repairs of offshore wind turbines require good weather conditions, the harsh environment often delays the repair, and the production of energy is reduced. The costs to lost production and repairs can be reduced if preventive maintenance strategies are used, so damages are repaired before failure occurs.

Condition based maintenance is a preventive maintenance strategy where decisions on repairs are made based on the actual condition of the components. This knowledge is obtained using condition monitoring. There exist a large number of condition monitoring methods that in general can be divided into offline inspections and online monitoring, see (Walford 2006). A review of condition monitoring methods for wind turbines is given in (Hameed et al. 2009). The benefit of condition monitoring has been quantified in (McMillan and Ault 2007), and the benefit was found to be highly dependent on the reliability of the condition monitoring, which was not modeled explicitly. In the project CONMOW it was concluded that the monitoring methods still need development in order to detect failures reliably (Wiggelinkhuizen et al. 2008).

Optimal planning of O&M should be based on risk-based methods, where all information from past experience and condition monitoring is taken into account, and the uncertainties are modeled as realistic as possible, see the framework for risk-based O&M for wind turbines in (Sørensen 2009). Rational decisions can be made based on a pre-posterior decision analysis where the expected costs through the lifetime of the wind turbines are minimized, see theory in (Raiffa and Schlaifer 1961).

For components exposed to deterioration processes damage models can be used to describe the development in damage size with uncertain parameters described by stochastic models. Damage models are in general associated with large uncertainties, and information from (imperfect) inspections/online monitoring should be included to make a more reliable posterior estimate on the damage size. The Bayesian updating can efficiently be done using Bayesian graphical models, and has earlier been used for deterioration modeling, see (Friis-Hansen 2000) and the framework in (Straub 2009). This paper presents how Bayesian graphical models can be used to assist in decision problems for O&M of offshore wind turbines, and discusses how to include data from inspections and monitoring properly.

2 DECISION MODEL

Decisions on inspections and repairs should be made such that the expected costs through the lifetime are minimized. For different inspection plans/methods and different decision rules for repairs the expected costs can be calculated based on a decision tree. For wind turbine components it is relevant to consider both corrective repairs that are required if failure occurs, and preventive repairs, which can be made based on the inspection/monitoring results. If it is assumed that a repaired component behaves like a new component, the simplified decision tree in figure 1 can be used.

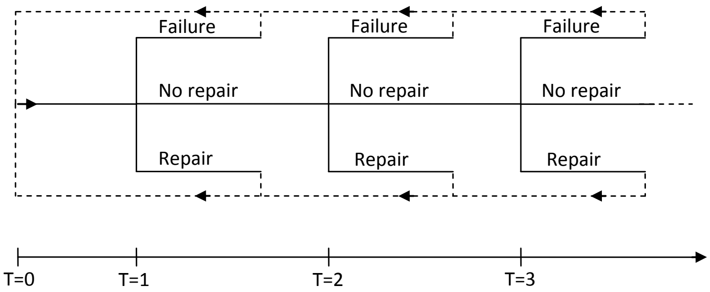

Figure 1: Simplified decision tree.

The decision tree should be expanded to correspond to the design life of the wind turbine. If either repair type is performed, continuation should be made from the beginning of the tree, but now the length of the tree should be the remaining life time. Based on the decision tree with the associated utilities and probabilities, the optimal inspection plan and decision rule can be found among a finite set of alternatives, see e.g. (Straub 2004).

3 DETERIORATION MODELING

The primary focus should be on components that are large risk contributors. In general offshore wind turbine operators do not make failure data public available, and third parties have to be content with the limited available material. For onshore wind turbines public databases with failure data are available, e.g. from the scientific measurement and evaluation programme (WMEP), see (Faulstich et al. 2009). For a generic offshore project the distribution of risk from different contributors, divided by component and failure type, was shown in (Skjærbæk et al. 2009), and data from different sources were collected in (McMillan and Ault 2007).

In general most failures are caused by electric components, control system, sensors and hydraulic system. These failures are critical for offshore wind turbines because of the limited accessability. Failures from large components, i.e. gearbox, generator, main shaft/bearing, and rotor, are rare, but the risk is high because they cause long downtime, require large vessels, and the spare parts are expensive.

3.1 *Damage models*

In order to use risk-based planning of O&M it is necessary to establish a probabilistic damage model, which allows for the calculation of the failure probability. Appropriate damage models requires knowledge of the relevant failure types, what the cause (load) is, and how they progress. The data for the prior damage model can be obtained from theoretical models, experiments, and measured data for similar components.

Components exposed to fatigue are typically designed using SN-curves combined with the Palmgren-Minor damage accumulation law. This model cannot be used directly for risk-based inspection planning, because it does not include a measurable damage size. Therefore a fracture mechanical (FM) approach is necessary, e.g. Paris law for crack propagation:

$$\frac{da}{dN} = C \cdot \Delta K^m \tag{1}$$

This model gives the increase in damage per stress cycle, da/dN, as function of the stress intensity factor range, ΔK, and parameters C and m.

The FM curve can be calibrated to the SN-model so the probability of failure or reliability index is equivalent for the two models, see e.g. (Straub 2004). This approach have been used in the context of risk-based inspection planning of offshore steel jacket structures. For wind turbine components exposed to other deterioration processes a similar calibration to a crack propagation law can be utilized.

The failure limit state could for a specific component be chosen to the damage size that causes the wind turbine to stop production. Another important limit state is the damage level where it is not possible to repair a damage, and instead requires a component exchange because of escalated damage.

3.2 *Condition monitoring*

Condition monitoring is essential for updating of the damage model in accordance with the actual state of the component. Modern wind turbines are equipped with a supervisory control and data acquisition (SCADA) system that monitors production, start and stops, occurrences of alarms, and measurements of e.g. temperature, tower vibrations, and fluid levels. More advanced equipment are increasingly used, i.e. vibration monitoring of bearings and gearbox, and monitoring of fluid contamination, and other possible techniques are strain measurement using optic fibers, crack detection using acoustic emission sensors, see (Walford 2006) and (Hameed et al. 2009). In addition a number of offline monitoring methods are available, e.g. analysis of oil samples, thermography of electric components, and visual inspections.

In general the measurements obtained using condition monitoring are indicators of the health of different components, or indicators of the load. Particles in the gearbox oil indicates the extend of wear, vibration measurements can indicate damages in the drive train, and power production and tower vibration measurements gives indications of the loads from wind and waves. All this data can in principle be used to update the damage model, but as the measurements are not direct nor perfect measurement of the damage size, the uncertainties should be taken into account in the model.

For methods that gives an indication on whether a damage is present or not, the probability of detecting a damage can be modeled by a PoD-curve that gives the probability of detection as function of the damage size. An example is an exponential model with parameters P_0 and λ, see e.g. (Straub 2004):

$$PoD(a) = P_0(1 - \exp(-a/\lambda)) \tag{2}$$

For methods where a damage size or extend of damage can be measured, the model should take the measurement accuracy into account. This can be done by either a additive or a multiplicative model. A simple additive model assumes that the correct damage size, a, equals the measured size, a_m, plus an error term given as a normal distributed random variable with mean zero, ε:

$$a = a_m + \varepsilon \tag{3}$$

The indirect load measurements can be included in a similar way with a measurement error on e.g. the stress intensity factor range, ΔK, in equation 1.

4 BAYESIAN NETWORKS

A Bayesian Network is a graphical modeling tool that originated in computer science for modeling of artificial intelligence, introductions can be found in e.g. (Murphy 2001) and (Jensen and Nielsen 2007). The name Bayesian refers to the well known Bayes rule for calculation of a the probability of event A, given event B:

$$P(A|B) = \frac{1}{P(B)} P(B|A)P(A) \tag{4}$$

In the context of Bayesian updating, $P(A|B)$ is the posterior distribution of A given B, $P(A)$ is the prior distribution of A, and $P(B|A)$ is the likelihood of A given B.

A Bayesian network consist of a set of variables, graphicly shown as nodes, and their causal relationships, shown using directed links. Together the nodes and links form a directed acyclic graph (DAG). If a variable A causes B, A is a parent of B, which is a child of A. Figure 2 shows a simple Bayesian network with three nodes, where A is a parent of B and C. If evidence is received about node A, it will change the belief about node B and C. If instead information about B is found, it will give indirect information about A, therefore also change the belief about C.

The probability distributions are given as a conditional distribution for each variable given the parents. The joint distribution for a network with n nodes,

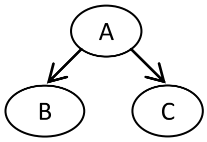

Figure 2: Simple Bayesian network.

$P(V)$, can be found using the chain rule for Bayesian networks:

$$P(V) = \prod_{i=1}^{n} P(A_i|pa(A_i)) \tag{5}$$

where A_i is the i'th variable in the network, and $pa(A_i)$ is the parents of A_i. When knowledge about the value/state of a variable becomes available, it can be entered in the network, and the marginal posterior distribution of each node can be found using Bayes rule. The calculation on posterior probabilities in Bayesian networks is called inference.

In order to model deterioration the network should allow the damage size to increase with time. This can be done using a dynamic Bayesian network, that consist of equal time slices, one for each time step. Each time slice is connected only to the neighboring slices, and will thus be independent of all other past slices given the previous slice. This equals the property of a Markovian process, but is general deterioration processes are not Markovian. However (Straub 2009) used a dynamic Bayesian network with time independent parameters equal for each slice to make the Markovian assumption hold.

4.1 *Inference*

The variables used for modeling of deterioration are generally continuous. In general exact inference is not possible for a network with continuous nodes, as opposed to networks with discrete nodes, where efficient algorithms exist, see (Murphy 2002). Therefore the variables have been discretized in previous applications where deterioration processes have been modeled using Bayesian networks, see (Friis-Hansen 2000) and (Straub 2009). But even though the inference can be performed exact, the discretization introduces an approximation for the probability distributions. The nodes without parents, e.g. damage variables, can be truncated without approximation. But in general discretization of conditional distributions introduces an error. The damage size at one time step is in the model in section 3.1 assumed to be a deterministic function of the parents. For a discrete model a conditional probability distribution has to be found, which performs an operation corresponding to the deterministic function. For each combination of states of the node representing the damage size at time $t-1$ and the nodes representing parameters in the damage model, the probability that the damage size at time step t is in each state should be calculated, and this can be done using sampling. The accuracy of this conditional distribution highly affects the final result when inference is performed.

An alternative to the discrete models is to use continuous model, where approximate inference methods are needed. Markov Chain Monte Carlo (MCMC) methods can be used to handle continuous distributions, e.g. the Gibbs sampling algorithm, see (Gelfand and Smith 1990). The method was earlier considered not to be usable for deterioration modeling partly because it does not allow deterministic/logic relations among variables according to (Hrycej 1990). This problem has been overcome in the program WinBugs (Lunn et al. 2000), where it is possible to include logic nodes, that are deterministic functions of other nodes. These nodes are not considered as being variables, and are not allowed to receive evidence. In the Gibs sampling iteration scheme values are not drawn from the logic nodes, but the logic relationship are used to calculate the variables needed for the calculations.

The evaluation is performed via simulation from a Markov chain that has the property that the stationary distribution is the posterior. In Gibbs sampling, sampling is performed from the full conditional distributions. In a Bayesian network a node is independent of all other nodes given the Markov blanket (parents, children, and parents of children). Thus the full conditionals only contain these nodes, and can be evaluated as (Lunn et al. 2000):

$$P(v|V\backslash v) \propto P(v|pa(v)) \times \prod_{w \in ch(v)} P(w|pa(w)) \quad (6)$$

where $ch(.)$ means the children of. Since all distributions in a Bayesian network is given conditional on the parents, the distributions used for calculating the full conditionals are known. Gibbs sampling is performed by first choosing an initial value for all variables. In a loop over all variables a new value is sampled for each variable, given the value of all other variables, so that the variables are updated in turn. For three variables X, Y, Z the updating can be performed in the following scheme, where $\sim$ means "drawn from":

$$\begin{array}{lll} X_i & \sim & P(X|Y_{i-1}, Z_{i-1}) \\ Y_i & \sim & P(Y|X_i, Z_{i-1}) \\ Z_i & \sim & P(Z|X_i, Y_i) \end{array} \quad (7)$$

In the first rounds of the loop the samples are influenced by the initial values, X_0, Y_0, Z_0, but after a burn in period the set of values sampled using Gibbs sampling can be shown to be a sample from the true posterior distribution (Gelfand and Smith 1990).

5 APPLICATION EXAMPLE

This example demonstrates how Bayesian networks can be used to update damage size and failure probability, when new information becomes available, and be used for risk-based repair planning. A specific case relevant for wind turbine O&M is considered, but the model is in principle generic, and can easily be changed to model other cases.

The considered failure mechanism is fatigue crack growth in a main bearing with a mean time between failures (MTBF) of 10 years. The crack growth is considered to be governed by the wind load on the wind turbine, which is monitored in the SCADA system. Further visual offline inspections are performed once a year. Failure is defined as the crack size, that makes the system shut down, and stops power production. Thus it is detected if failure occurs. Failure is assumed to occur at a crack size of 20 mm.

5.1 *Damage model*

The damage model considered is based on Paris' law, equation 1. In this example the formulation used in (Friis-Hansen 2000) is used. Here the stress ranges are assumed to follow a Weibull distribution and the differential equation is solved to yield the following expression for the crack size at the i'th time step, a_i, given the crack size at previous time step, a_{i-1}:

$$a_i = \left(a_{i-1}^{\frac{2-m}{2}} + \Delta K M_U A_t^m \right)^{\frac{2}{2-m}} \quad (8)$$

where the stress intensity factor range, ΔK, is found using:

$$\Delta K = CN\Gamma\left(1 + \frac{m}{B}\right) Y^m \pi^{\frac{m}{2}} \left(1 - \frac{m}{2}\right) \quad (9)$$

C and m are damage parameters, A and B is scale and shape parameter for the Weibull distribution, Y is a geometry constant, N is the number of load cycles in each time step, and M_U models the time independent model uncertainty. The effect of the control system of the wind turbine is assumed to be included in the load model.

The values and distributions for the parameters are given in table 1. Most of the variables are taken as given in (Friis-Hansen 2000), but C is calibrated using Crude Monte Carlo simulations with a time step of 3 months to give the assumed MTBF of 10 years.

5.2 *Bayesian network*

The Bayesian network is modeled in the program WinBugs. The model consist of stochastic nodes, logic nodes and constants, but only the stochastic and logic nodes are shown in the graphical model. In addition to the continuous variables necessary for the damage model, a discrete logic failure node is made

Variable	Distribution	Mean	CoV
m	Deterministic	3	-
C	Deterministic	$6 \cdot 10^{-12}$	-
B	Deterministic	0.66	-
Y	Deterministic	1	-
N	Deterministic	10^6 /year	-
a_0	Exponential	1 mm	100 %
A_i	Normal	5.35 MPa	18 %
M_U	Normal	1	18 %

Table 1: Distributions for damage parameters.

for each time step with the two states, 0 and 1, corresponding to no failure and failure respectively. The mean of the failure node is thus the failure probability.

The indicators available in this example are:

- An inspection every year: uncertain measurement of a_i (additive measurement error)
- Continuous load measurement: uncertain measurement of A_i (additive measurement error)
- If no failure has occurred, it is known

In order to take a measurement accuracy into account, a stochastic node has to be included for a_i and A_i with the names $a_{m,i}$ and $A_{m,i}$ respectively. They are both considered to be normal distributed with the true value as mean, and standard deviations $\sigma_a = 0.5$ mm and $\sigma_A = 0.25$ MPa. This correspond to an additive measurement error, and is a more convenient notation in WinBugs.

The failure node, F_i, cannot directly receive the evidence that failure has not occurred, because a logic node cannot receive evidence. Therefore a stochastic node also has to be made for the observation of the failure node, and it is called $F_{m,i}$. This node follows a Bernoulli distribution, where the probability of an observation that is failure, is equal to the state of the failure node. If the state of the failure node is 1, the probability that $F_{m,i}$ is 1, is 1. If the state of the failure node is 0, the probability that $F_{m,i}$ is 1, is 0.

The nodes M_U, a_0, and A_i have no parents, and their prior distributions are already given in table 1. The distribution types of the other nodes are summarized in table 2, and the Bayesian network is shown in figure 3.

The time step is chosen to be 3 months. The Bayesian network is made for 10 years, and thus consist of 40 time slices. This gives a relatively low computation time and the time step is short enough to make use of information from monitoring between the annual inspections.

A burn in period of 5000 samples and additional 25000 samples for the calculation of posterior distributions, have been found appropriate to give a sufficient good approximation of the failure probability.

Variable	Distribution	Parameters
a_i	Logic	Eqn. 8
F_i	Logic	1 if $a_i > 20$ mm
$a_{m,i}$	Normal	$\mu = a_i$, $\sigma = 0.5$ mm
$A_{m,i}$	Normal	$\mu = A_i$, $\sigma = 0.25$ MPa
$F_{m,i}$	Bernoulli	$p = F_i$

Table 2: Distributions for nodes with parents.

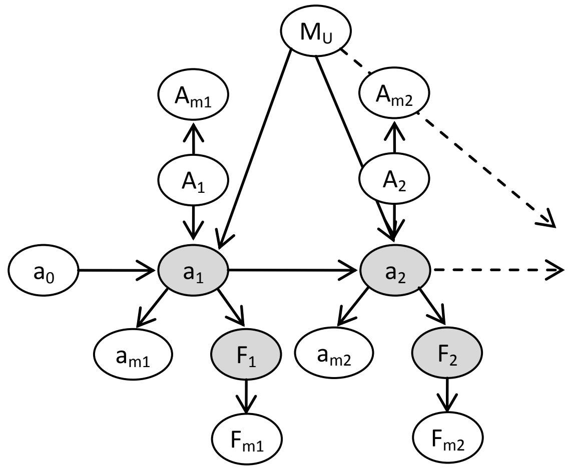

Figure 3: First two time slices of the Bayesian network. Grey nodes are logic nodes, white nodes are stochastic.

5.3 *Decision rule*

In principle the decisions on repairs should be made based on a life cycle analysis with a decision tree as explained in section 2, where it is possible to take the limited life time into account. For simplicity a more simple decision rule is chosen for this example. This decision rule is set as a limit value of the probability of failure until next inspection. The limit value is set such that the expected total costs for repairs and failure per year is equal for the case where a repair is performed at time t, and the case where the repair is postponed a year to time $t + \Delta t$. The expected annual costs for a repair performed at time t is:

$$E[C_t] = \frac{C_R}{t} \tag{10}$$

where C_R is the cost of a preventive repair. If the repair instead is postponed to time $t + \Delta t$, there is a probability of failure, P_F, and the annual expected costs are:

$$E[C_{t+\Delta t}] = \frac{C_F \cdot P_F + C_R(1 - P_F)}{t + \Delta t} \tag{11}$$

where C_F is the cost of failure. As the cost of failure is larger than the cost of a preventive repair, the numerator of the second expression is always larger than for the first. But it is divided with a longer period, because the repair is postponed one year. For each value of t the 'optimal' limit failure probability, P_{FL}, can be found by setting $E[C_t] = E[C_{t+\Delta t}]$, which yields:

$$P_{FL}(t) = \frac{\Delta t}{t(\frac{C_F}{C_R} - 1)} \tag{12}$$

In the example the ratio C_F/C_R is set to 5.

5.4 *Results*

Application of the above decision rule requires the evaluation of the failure probability. In a situation where no inspections and no load monitoring is available, the cumulative distribution of the failure time is shown in figure 4, updated in year 1 to 4 with the information that no failure has yet occurred. The thick black line shows the cumulative distribution reset for each year, and can be compared with the limit value for repairs, which is shown with the dashed line. As the two lines intersect before four years, the decision after observation in year three should be to repair.

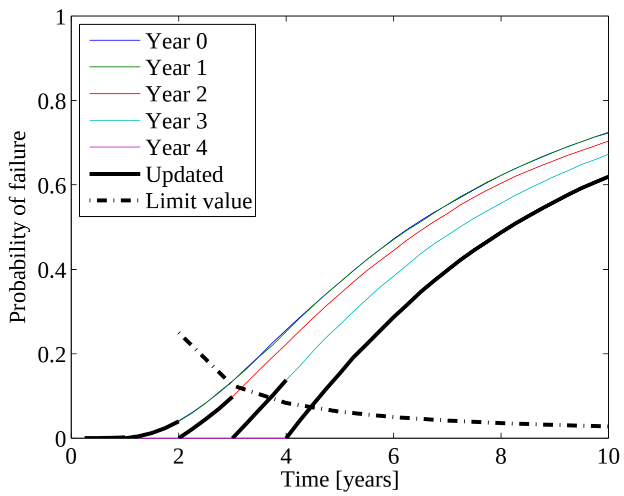

Figure 4: Cumulative distribution function of failure time for case without inspections.

In order to illustrate a situation where inspections are available for updating of the damage model, a realization from the population has been chosen as case study. The damage size and the uncertain observation for each year until failure occurs are shown in table 3 for the specific realization. These observations and the observation that no failure has occurred yet are entered for one year at a time as evidence in the model. The resulting failure probabilities are shown in figure 5, where the model is updated with new evidence in year one to four. The thick black line again shows the cumulative distribution reset for each year. In the case without observations the probability of failure in the third, fourth, and fifth year were each year in the range 0.10–0.15. In the case where observations are used to update the model, the annual probability of failure is very low until the fifth year, and the updated probability of failure in the fifth year is more than 0.9. Even

Year	1	2	3	4	5
a [mm]	1.10	1.75	3.56	10.10	fail.
a_m [mm]	0.7	1.8	3.6	9.3	fail.

Table 3: Realizations of the damage size (a) and the observations from annual inspections (a_m).

without the decision rule it would be clear that the decision in year four should be to repair rather than waiting until year five.

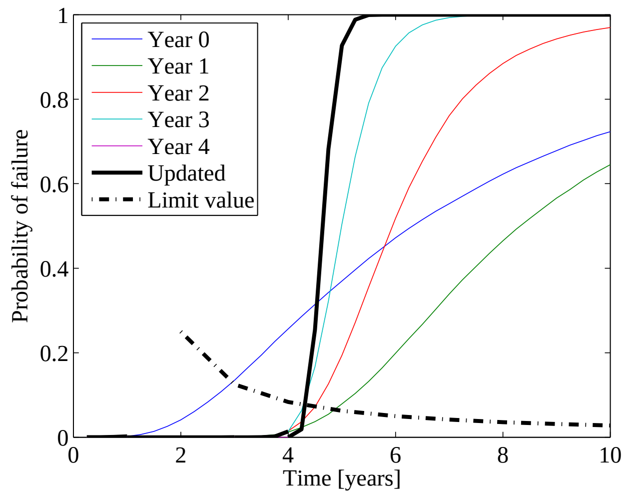

Figure 5: Cumulative distribution function of failure time in case with inspections.

Next the realizations of the uncertain measurements are inserted as evidence in addition to the inspections. Figure 6 shows a box plot of the posterior distribution of the damage size in each time step. For each time step the present and all previous observations are used for the estimate. The actual damage size for the realizations and the uncertain observations of it are also shown.

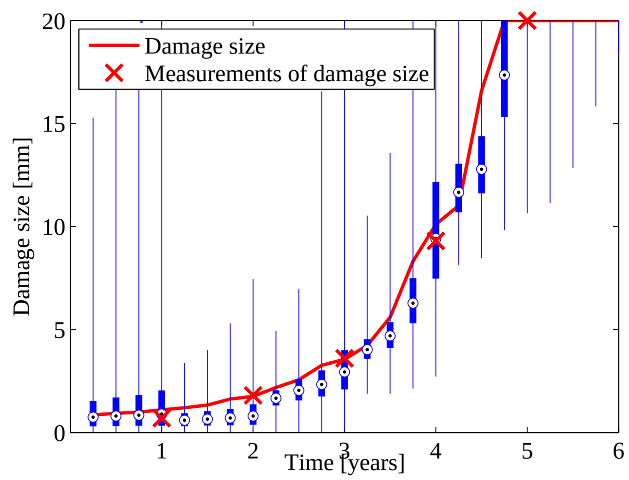

Figure 6: Box plot of damage size with inspections and monitoring. The bullets shows the medians, the filled bar is the range between the 25-75% quantiles.

The observations at year one and four are both significantly lower than the correct damage size, caused by the randomness of the uncertain inspections. Thus the Bayesian network also expects the damage to be smaller than it actually is after year four, but the probability of it being larger is acknowledged. If the observations were trusted 100%, failure would be predicted to occur later than it actually does. With a Bayesian network the uncertainties are taken into account, and the probability of failure can be used for risk-based decision making.

In figure 7 the probability of failure is shown after year four, updated for each three months. It is shown both with and without inclusion of monitoring results. It shows that the inclusion of monitoring results gives better confidence in when failure will happen, and shows that it in this case will be possible to postpone the repair half a year with only low additional risk. According to the decision rule the repair should be performed after three month, but the failure probability is still close to the limit value after half a year.

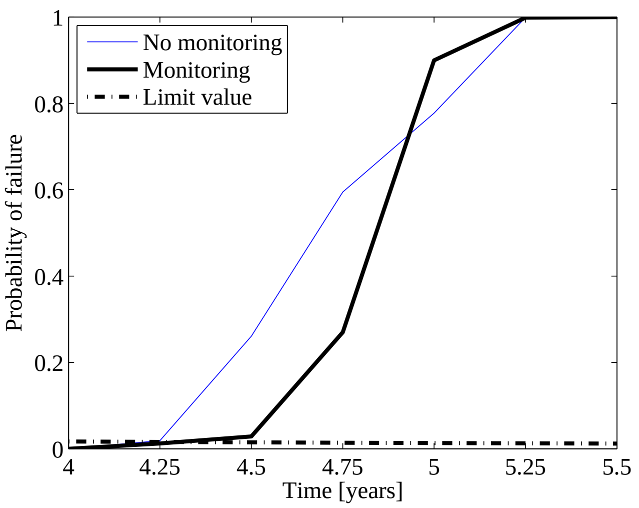

Figure 7: Probability of failure between previous and current monitoring result, based on previous monitoring result. Or in the case without monitoring only updated with the information that failure has not yet occurred.

6 CONCLUSIONS

This paper presents how Bayesian graphical models can be used to assist in decision problems for risk-based planning of O&M for offshore wind turbines. It is possible to use continuous nodes in the network, when Gibs sampling is used to perform approximate inference. In this paper it has been shown that it is possible to model deterioration processes with such a network, when e.g. WinBugs is used, where it is possible to make logic nodes as well as stochastic nodes.

An application example was used to show how a Bayesian network can be used for inclusion of inspection results and load monitoring for updating of the damage model. This gave a better estimate on the probability of failure, and could be compared to a decision rule given as a limit value of the failure probability. The model is generic and can easily be changed to include other damage and inspection models, e.g. condition monitoring results could be included. The model can also be extended to include more components, this can e.g. be relevant if one indicator is common for more components.

REFERENCES

Faulstich, S., P. Hahn, P. Lyding, and P. Tavner (2009). Reliability of offshore turbines - identifying risks by onshore experience. In *European Offshore Wind 2009 Conference proceedings*.

Friis-Hansen, A. (2000). *Bayesian networks as a decision support tool in marine application*. Ph. D. thesis, Technical University of Denmark.

Gelfand, A. E. and A. F. M. Smith (1990). Sampling-based approaches to calculating marginal densities. *Journal of the American Statistical Association 85*(410), 398–409.

Hameed, Z., Y. S. Hong, Y. M. Cho, S. H. Ahn, and C. K. Song (2009). Condition monitoring and fault detection of wind turbines and related algorithms: A review. *Renewable and Sustainable Energy Reviews 13*(1), 1–39.

Hrycej, T. (1990). Gibbs sampling in bayesian networks. *Artificial Intelligence 46*(3), 351–363.

Jensen, F. V. and T. D. Nielsen (2007). *Bayesian Networks and Decision Graphs*. Information Science and Statistics, Springer.

Lunn, D. J., A. Thomas, N. Best, and D. Spiegelhalter (2000). Winbugs - a bayesian modelling framework: Concepts, structure, and extensibility. *Statistics and Computing 10*(4), 325–337.

McMillan, D. and G. W. Ault (2007). Quantification of condition monitoring benefit for wind turbine generators. *Wind Engineering 31*(4), 267–285.

Murphy, K. (2001). *An introduction to graphical models*.

Murphy, K. (2002). *Dynamic Bayesian networks: Representation, inference and learning*. Ph. D. thesis, University of California, Berkeley.

Raiffa, H. and R. Schlaifer (1961). *Applied statistical decision theory*. Harvard University.

Skjærbæk, P., T. Mousten, and H. Stiesdal (2009). Reliability assessment and improvement through arm modeling. In *European Offshore Wind 2009 Conference proceedings*.

Sørensen, J. D. (2009). Framework for risk-based planning of operation and maintenance for offshore wind turbines. *Wind Energy 12*(5), 493–506.

Straub, D. (2004). *Generic approaches to risk based inspection planning for steel structures*. Ph. D. thesis, Swiss Federal Institute of Technology, ETH Zurich.

Straub, D. (2009). Stochastic modeling of deterioration processes through dynamic bayesian networks. *Journal of Engineering Mechanics 135*(10), 1089–1099.

Walford, C. A. (2006). Wind turbine reliability: Understanding and minimizing wind turbine operation and maintenance costs. Technical Report SAND2006-1100.

Wiggelinkhuizen, E., T. Verbruggen, H. Braam, L. Rademakers, J. Xiang, and S. Watson (2008). Assessment of condition monitoring techniques for offshore wind farms. *Journal of Solar Energy Engineering, Transactions of the ASME 130*(3), 0310041–0310049.