A Bayesian network based approach for integration of condition-based maintenance in strategic offshore wind farm O&M simulation models

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ABSTRACT: In the overall decision problem regarding optimization of operation and maintenance (O&M) for offshore wind farms, there are many approaches for solving parts of the overall decision problem. Simulation-based strategy models accurately capture system effects related to logistics, but model condition-based maintenance (CBM) in a simplified manner. The influence of the CBM strategy on the failure rate can be directly considered using a risk-based approach, but here logistics is modelled in a simplified manner. This paper presents an efficient approach for accurate integration of CBM in simulation-based strategy models. Using Bayesian networks, the probability distribution for the time of failure and the conditional probability distribution for the time of CBM given the time of failure is estimated accounting for the CBM strategy, and are used by the simulation-based strategy model to generate failures and CBM tasks. An example considering CBM for wind turbine blades demonstrates the feasibility of the approach.

1 INTRODUCTION

Decision problems regarding operation and maintenance (O&M) of offshore wind farms are related to different time scales. Thus, methods and models that support decision making can be classified into the categories strategic, tactical and operational, e.g. as suggested by Shafiee (2015). Typical time-horizons for the decisions are one or a few days (operational), several weeks or months (tactical) and several years (strategic) (Welte *et al.* 2018). For operational maintenance decisions, such as the choice of the next inspection interval or the decision about which components to replace or repair, decision rules are often used. Different decision rules comprise different maintenance strategies. For example, replacement of components after a fixed time interval results in a strategy with predetermined preventive (scheduled, or calendar-based) maintenance, and replacement based on the outcome of the last inspection results in a condition-based maintenance (CBM) strategy.

The identification and selection of the best maintenance strategy is a strategic decision problem, and strategic O&M simulation models may be used to estimate availability and costs for different strategies. Accurate evaluation of an O&M strategy requires a representation of operational aspects in the simulation model. This implies estimating the influence of decision variables for operational decision problems on other aspects of offshore wind farm O&M, such as logistics and turbine access. Therefore, the integration of operational aspects in strategic models is of interest in wind farm O&M modelling and optimization. Typical decision variables are time of next inspection or maintenance task, and maintenance intervention level (i.e. technical condition or level of degradation that triggers a maintenance task or replacement of the component).

Generally, aspects of the wind farm O&M decision problem are modelled with different accuracy by different models. Furthermore, different model aspects might interact. Simulation-based strategy models, which are typically used for optimizing maintenance logistics strategies, accurately capture system effects related to logistics, e.g. concerning sharing of vessels for several maintenance tasks or splitting of maintenance tasks over multiple weather windows. However, most such models do not represent aspects of CBM of deteriorating components accurately, and they usually do not consider directly the influence of inspection, condition monitoring, and repair strategy on the failure rate. These effects are instead considered indirectly through different choices of high-level input data such as annual failure and maintenance rates, see e.g. (Welte *et al.* 2017). A challenging problem is to find good estimates for the high-level inputs as a function of different strategies. Integration of different models can provide in many cases a good solution for this problem.

The influence of a CBM strategy can be directly considered using a risk-based approach based on Bayesian pre-posterior decision analysis. An efficient approach to solve the decision problem is to apply decision rules and discrete Bayesian networks for modelling of deterioration and effect of inspection and repair strategies (Nielsen and Sørensen 2017a). These approaches usually include only simple representations of the influence of weather, vessels and system effects related to vessel utilization through the specific costs. However, by integration of the risk-based approach with a strategic O&M model, more advanced representations of these interactions can be included.

In this paper, an efficient approach developed within the EU FP7 LEANWIND project (www.leanwind.eu) is presented for accurate integration of CBM in strategic simulation models. In section 2, approaches for strategic maintenance planning are discussed with focus on simulation-based strategy models and risk-based models. In section 3, general approaches for integration of models are discussed, and a novel integration approach based on Bayesian networks is presented. In section 4, the approach is illustrated by an example considering CBM for wind turbine blades. Section 5 summarizes the findings of the paper.

2 STRATEGIC MAINTENANCE PLANNING

Methods and models for strategic maintenance planning typically aim for minimization of total expected O&M costs including lost revenue. An overview of models can be found in the review by Hofmann (2011) and in (Welte *et al.* 2018). Several of the models consider the whole wind farm, and some include the full life cycle, but many focus just on selected aspects and parts of the wind farm. Some of the models are optimization models that use mathematical optimization approaches. However, most models are simulation models.

For timing of inspection and maintenance, a review can be found in (Shafiee and Sørensen 2017). It is essential to model the influence of the maintenance strategy on the failure rate, which is generally the focus of risk-based maintenance models (Nielsen and Sørensen 2014, 2017a). To do this, probabilistic models for deterioration, inspection, condition monitoring (CM), and repair are needed. The basis for the risk-based approach is the Bayesian pre-posterior decision analysis and the risk-based inspection (RBI) approach developed for oil and gas structures (Faber 2002).

2.1 *Simulation-based strategy models*

Offshore wind farm O&M simulation models are used to analyse and provide decision support for different aspects of offshore wind farm operation. Examples of decision problems such models are used for are wind farm investment decisions (calculate expected availability and O&M costs for planned wind farm to assess profitability), O&M vessel selection (which vessel types and how many vessels of each type), logistic strategies (e.g. shore-based or investing in an offshore O&M base), and O&M investment decisions (e.g. buying or developing an improved CM system); see (Welte *et al.* 2018) for further details.

Most strategic simulation models include the following features: weather model, failure model, corrective and (pre-determined) preventive maintenance tasks, offshore logistics (vessels and technicians), accessibility limits, and lead/mobilization times for spare parts/vessels. Other features that are less common are the effect of corrective and preventive maintenance on component reliability and condition, or the representation of CBM, to mention some examples.

In this paper, the NOWIcob model developed by SINTEF Energy Research has been used for simulating wind farm O&M. NOWIcob uses a time-sequential (discrete-event) Monte Carlo simulation technique. Descriptions of the model and the simulation methodology can be found in (Hofmann and Sperstad 2013) and (Sperstad *et al.* 2017). Maintenance operations and related logistics are simulated by the model with an hourly resolution over a specified number of years. Wind farm performance parameters such as wind turbine availability and O&M costs are estimated by the model. Typical input and output parameters of the model are illustrated in Figure 1.

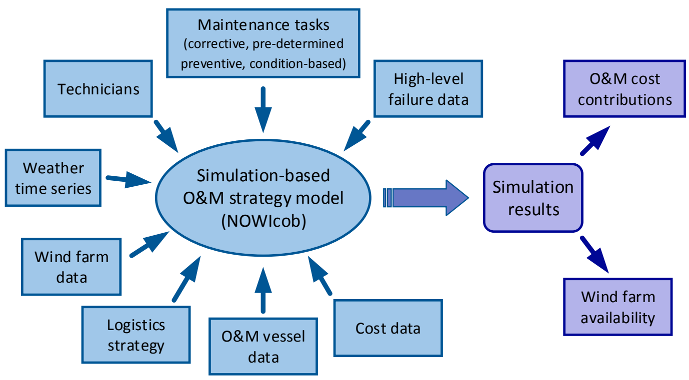

Figure 1. Typical input and output parameters of simulation-based strategy model (NOWIcob).

2.2 *Risk-based O&M models*

Risk-based O&M models are used for timing and selection of methods for CM, inspections, and maintenance, and for the assessment of value of information (VoI) of CM. Nielsen and Sørensen (2017a) presented a framework for optimal timing of inspections and preventive maintenance, both containing classic simple inspection strategies, but also advanced strategies utilizing all available CM data and observations from inspections. Simple strategies implemented in this framework include equidistant inspections, and inspections when a CM threshold is exceeded. Implemented advanced strategies include inspections when a threshold for the probability of failure (or expected damage size) is exceeded.

For the probabilistic modelling, discrete Bayesian networks were applied. For simple strategies, Bayesian networks were used directly for computation of the expected number of inspections, preventive repairs, and corrective repairs in each month of the planned lifetime. For advanced strategies, Monte Carlo simulations were run using the same discrete probability distributions as used for the simple model, and Bayesian networks were used within simulations for updating of the probability of failure for decision making.

For both simple and advanced decision rules, the total expected lifetime O&M costs are found by multiplication of probabilities for inspections, preventive repairs and corrective repairs by specific costs for these maintenance operations. The specific costs should include all relevant contributions such as spare parts, vessel, equipment, salary, fuel, and lost revenue. These contributions are not modelled explicitly in the risk-based O&M model, and the influence of the vessel types, fleet size, jack-up vessel strategy etc. is only considered through the specific costs. For instance, effects related to sharing of vessels for multiple repairs cannot be considered directly.

3 INTEGRATION OF MODELS

To model accurately decision problems for CBM where system effects in relation to logistics are important for the estimation of maintenance costs, neither of the models presented above have a sufficiently detailed representation of all relevant aspects.

To combine the advantages of two models in solving a decision problem, one can broadly speaking distinguish between the following approaches to integration of the models: Full integration and data interfacing. For full integration, a time-consuming simulation-based model needs to be run to optimize decision variables for inspections and repairs. Especially for advanced strategies, this seems inefficient. Furthermore, the design of a flexible input format for CBM in the simulation-based strategy model (e.g. including different deterioration processes) is not straightforward. For data interfacing, output from one model is used as input for the other.

One approach for data interfacing is the loose integration approach presented in (Welte *et al.* 2017). Here, CBM was modelled through the failure rate, overall probability of detection before failure, p_{det}, and pre-warning time, T_{det} (i.e. time from detection/repair decision, t_R, to time of potential failure, t_F). A disadvantage of this approach is that events are not distributed correctly in time, although the mean value is correct. This could lead to wrong predictions of the utilization of vessels, benefit of sharing of vessels, and to a wrong estimate of the probability of failure in the period after detection while waiting for a preventive repair to be performed.

3.1 *Integration approach using Bayesian networks*

In this section, a new approach is presented for model integration using data interfacing between the risk-based O&M model and NOWIcob, which could also be implemented for other strategic O&M simulation models. Compared to the loose integration approach presented by Welte et al. (2017), the new approach is more accurate because it models the distribution of failures, inspections, and maintenance events more accurately in time. In the proposed new integration approach, input to NOWIcob is generated using an extension of the framework for risk-based planning presented in (Nielsen and Sørensen 2017a), and therefore risk-based strategies can easily be integrated in NOWIcob with the new approach, as illustrated in Figure 2.

First, the optimal strategies are found using the risk-based O&M model, using a cost model that considers each maintenance task separately. Then, for the optimal strategy, the input to NOWIcob is generated. Using Bayesian networks, the probability distribution

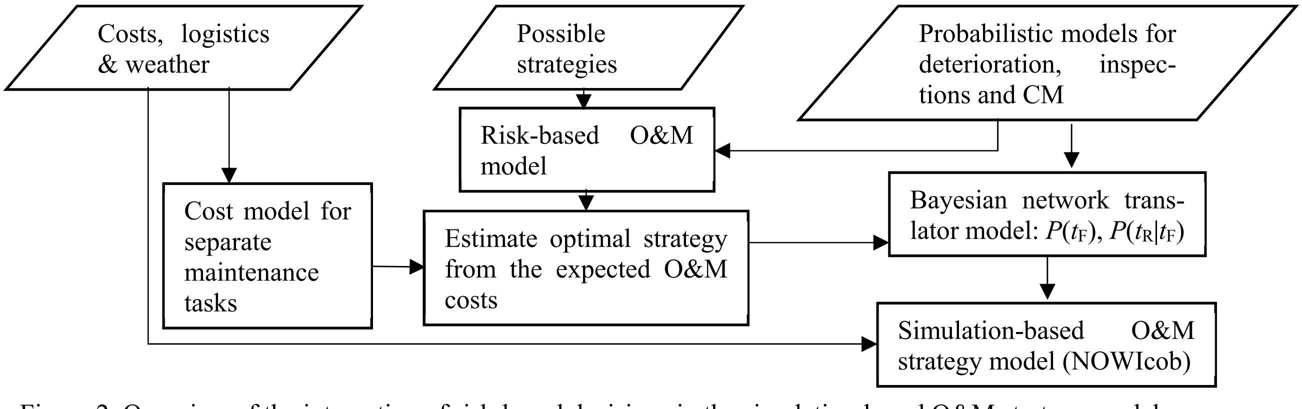

Figure 2. Overview of the integration of risk-based decisions in the simulation-based O&M strategy model.

$P(t_F)$ for the time of failure given no CBM is first estimated. Then, the conditional probability distribution $P(t_R|t_F)$ for the time of detection (i.e. time of the decision to make a preventive repair) given the time of failure is estimated, which accounts for the CBM strategy. The following simulation procedure is then applied in NOWIcob for each component:

1. Draw time of potential failure from distribution $P(t_F)$
2. Draw time of detection (or no detection) from $P(t_R|t_F)$
3. At 'time of detection', schedule CBM task (preventive repair).
4. If not repaired before time of failure, schedule corrective repair. After repair, draw new time of failure and time of detection.

The costs obtained by simulations in NOWIcob are then compared to the costs found by the risk-based model, to assess the influence of the more detailed logistics model capable of considering system effects. If large deviations are found, the optimal strategy found by the risk-based model could in fact be sub-optimal, and an iterative process could be applied to find the true optimal strategies.

3.2 *Estimation of distributions*

To use the approach, the distributions $P(t_F)$ and $P(t_R|t_F)$ must be found. The distribution $P(t_F)$ only depends on the deterioration model, and can be found directly from a Bayesian network using a forward algorithm similar to those used in (Nielsen and Sørensen 2017a).

For simple decision rules, the conditional distribution $P(t_R|t_F)$ can also be found using Bayesian networks. Here the evidence of failure in time step *j,* and evidence of no failure in all preceding time steps is entered in the network shown in Figure 3, and smoothing is performed using a forward-backward algorithm inspired by (Straub 2009), to estimate the probability of making the decision to repair (detection above threshold for repairs) in all preceding time steps. The network is defined by conditional probability distributions: the distributions for M (deterioration model parameter) and D (damage size) represent

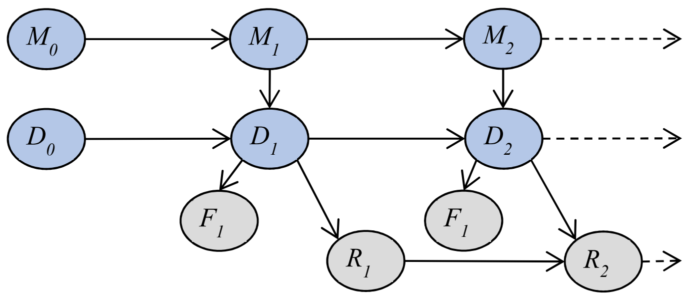

Figure 3. Bayesian network for estimation of the distribution for time of repair given time of failure $P(t_R|t_F)$. M: deterioration model parameter, D: damage size, R: repair decision (yes/no), F: event of failure (yes/no).

the deterioration model, and the distribution for R (repair decision) is estimated based on strategies for CM, inspections and repairs; for details see (Nielsen and Sørensen 2017a). The node F (event of failure), is in the fault state, when D is in the fault state, and is included to allow hard evidence to be entered on the event 'no failure'.

For advanced decision rules, simulations are run using the deterioration model, CM model, inspection model, and strategy for inspections and CBM. The time of detection t_R is stored, but the repair is not executed. Instead, the simulations continue without CM and inspections until failure, to find the time of failure t_F. A parameterized distribution $P(t_R|t_F)$ can then be fitted based on the pairs of t_R and t_F values. An approach for this will be presented in section 4.4.

3.3 *Inspections*

To estimate the costs of inspections, the implication for logistics and inspection tasks should be included in NOWIcob, although the influence of inspections on CBM is already included by using the $P(t_R|t_F)$ distribution. Correct stochastic distribution of inspections for individual turbines, resembling realistic sequences of events preceding CBM tasks, is only possible to capture in the simulation-based strategy model through a full integration approach. Instead, we could aim to get the correct expected number of inspections for the wind farm in each month by modelling inspections as random events with a rate equal to the rate estimated in the risk-based O&M model.

Since inspections cannot be modelled with a time-varying inspection rate in NOWIcob's module for predetermined preventive maintenance tasks, inspections are instead represented as a corrective maintenance tasks with a time-varying 'failure' rate. For the ease of implementation, the rate for this maintenance task is assumed constant for each year, but NOWIcob could be extended to allow for rates changing within the year, to place inspections in the correct months. The turbine is only required to shut down in the duration of this maintenance task.

4 EXAMPLE

This example considers risk-based O&M for wind turbine blades with and without CM. First, the optimal decision rules for inspections and repairs are found using the risk-based model (Nielsen and Sørensen 2017a) based on simple estimations of the specific costs. Second, input is generated for the strategic O&M simulation model, which is then run to give a more accurate estimation of the costs for that strategy, and the costs are compared to the costs found by the risk-based model. The planned lifetime of the wind farm is set to 20 years.

The following four strategies for inspections are considered, see (Nielsen and Sørensen 2017a) for details:

a) Equidistant inspections (constant inspection interval)
b) Dynamic inspection scheduling based on the probability of failure (estimated based on the outcome of the inspections, without considering CM)
c) Inspections when CM outcome exceeds a threshold
d) Dynamic inspection scheduling based on the probability of failure (estimated based on the outcome of the inspections and CM)

For all strategies, the decision to repair is based on the outcome of the inspection. Strategy a) and c) are simple strategies, where the distributions can be found directly using Bayesian networks, and strategy b) and d) are advanced strategies, where the distribution $P(t_R|t_F)$ is fitted based on simulations.

4.1 *Costs*

The example is based on the LEANWIND reference wind farm with 125 wind turbines, 8 MW each, located at West Gabbard; this case was also used in (Welte *et al.* 2017). Only maintenance tasks related to blade maintenance are included: inspections, CBM and corrective maintenance, and the main assumptions for these tasks are shown in Table 1. The direct costs include spare part costs and technician costs. For corrective maintenance, a jack-up vessel is required. Here, a 30 days mobilization time, a day rate of € 140 000, and mobilization costs of € 840 000 are assumed. Inspections and CBM tasks are always completed within one weather window, thus perfect weather forecast is assumed for the duration of the tasks. Corrective maintenance tasks can be split up over several weather windows.

For strategies b), c), and d), all three blades of a turbine are not necessarily inspected at the same time when one of the blades is inspected. The number of inspections of 3, 2, and 1 blades in each time step is estimated based on the probability p that the optimal decision would be to inspect a given blade. When looking at a wind turbine in a large wind farm, the number of inspected blades in a random wind turbine in one time step will follow a binomial distribution thus yielding the probabilities of each type of inspections: $P(3\text{ blades})=p^3$, $P(2\text{ blades})=3p^2(1\text{-}p)$, and $P(1\text{ blade})=3p(1\text{-}p)^2$.

In NOWIcob, a logistics time of 0.2 hours is included for inspections and CBM, and a technician transfer time and a vessel approach time is included for the crew transfer vessel (CTV). Costs for the CTVs and fuel costs are also included. Details on vessel operational phases, weather limits, and estimation of lost revenue are given in (Welte *et al.* 2017) and the associated supplementary material.

Table 1. Main assumptions for inspection and maintenance tasks.

Task	Duration [hours]	Direct costs [€]	No. technicians / vessel type
Inspection 1 blade	2	1600	2 / CTV
Inspection 2 blades	3	2400	2 / CTV
Inspection 3 blades	4	3200	2 / CTV
CBM	6	6000	3 / CTV
Corrective maintenance	6+24+4	400000	- / jack-up vessel

4.2 *Input to risk-based model*

In this example, deterioration for a wind turbine blade is modelled using a Markov model for the size of the largest crack in the blade. Based on inspection data, a model was fitted in (Nielsen and Sørensen 2017b), and this model is used here. The deterioration state can take discrete values from 0 to 6, and the transition probabilities per month were found using a maximum likelihood approach.

Both preventive and corrective repairs are assumed to be perfect, thus taking the blade to as good as new conditions. Preventive repairs can be performed for damages of state 1 to 4, whereas corrective maintenance is needed for damages of state 5 and 6. The reliability of inspections is described by the probability of detection, which increase with damage size. If a damage is detected, the measurement of the damage size is assumed to be correct.

For CM, four outcomes are possible, 'No detection', 'Low alarm', 'High alarm', and 'Failure'. The probability of alarm increases with damage size, and the probability of high alarm, given there is an alarm, increase with damage size. For both inspections and CM, the models presented in (Nielsen and Sørensen 2017b) are used.

For the risk-based model, the specific costs of inspections, CBM and corrective maintenance are needed. For the estimation of these, a cost model for separate maintenance tasks is used. For inspections and CBM, inspection/repair costs and lost revenue are included. For corrective repairs, repair costs, jack-up vessel charter costs, and lost revenue are included. The lost revenue and number of jack-up vessel day rates are estimated based on access limits and time series of significant wave height and mean wind speed.

The specific costs for CBM are estimated to € 7340, and for corrective maintenance they are € 2 740 000. The costs associated with an inspection of three blades are estimated to € 3790. For inspection of two blades, ¾ of these costs are assumed, and for one blade, ½ of these costs. Using the binomial distribution with parameter p equal to the probability of inspection in each time step, and €3790/3 as base, the inspection costs were corrected to account for higher costs per blade, when less than three blades were inspected.

4.3 *Optimal risk-based strategies*

Using the input presented in the previous section, the optimal decision rules were found using the risk-based O&M model (Nielsen and Sørensen 2017a) for each of the four strategies. For strategy a) and c) the expected lifetime costs are found directly using Bayesian networks, and for strategy b) and d) they are found using 100 000 simulations. The probability/simulated frequency (i.e. the estimated probability) of inspection and CBM for each time step is shown in Figure 4 for all strategies, where the simulation-based results show fluctuations due to the limited number of simulations.

For strategy a), inspections have predefined intervals, and the probability of inspection is either zero or one. For strategy b), where a threshold for the probability of failure (P_f) is used, the probability of inspection is in the beginning close to either zero or one, but the probability becomes more constant as more and more CBM tasks have been performed. For the strategies with CM, c) shows similar behaviour to d), but d) generally has slightly more inspections and CBM tasks than c). The total expected lifetime costs are shown in Figure 5, and the optimal decision rules for inspections are: a) 12 months interval, b) threshold for annual P_f: 10^{-5}, c) threshold for CM: 'Low alarm', and d) threshold for P_f: $3 \cdot 10^{-7}$. The optimal decision rule for CBM was to repair whenever a damage was detected. Without CM, the optimal strategy is a). It

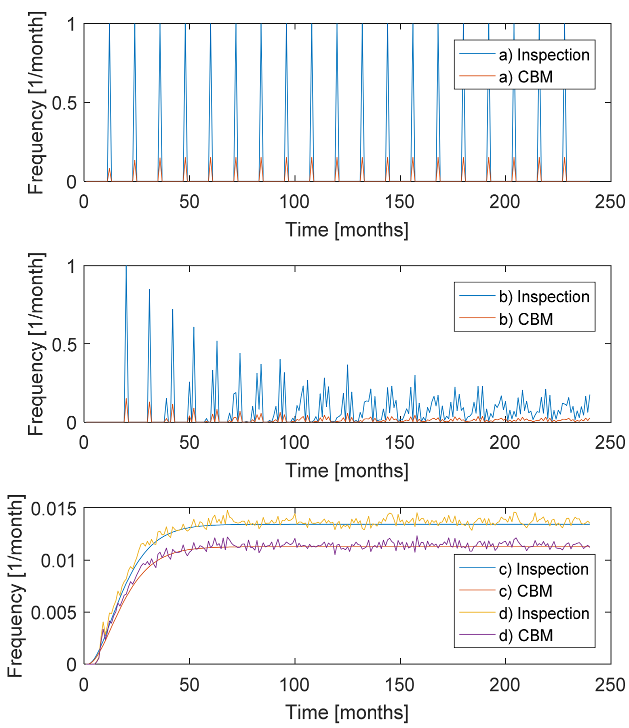

Figure 4. Frequency of inspection and CBM for each time step per blade.

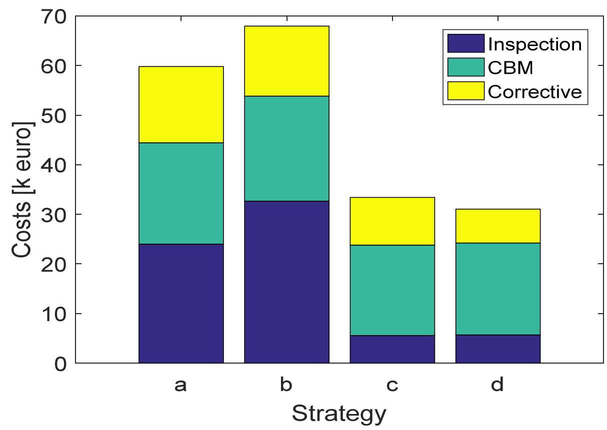

Figure 5. Total expected lifetime costs per blade for each strategy for the risk-based model.

performs better than the more advanced strategy b) because of increased inspection costs for b), as not all three blades are inspected together. However, when CM is included, the advanced strategy d) performs better than c), as the information from CM is better exploited. The value of information (VoI) of CM is the difference between the best strategy with and without CM and is here found to € 27 700 per blade.

4.4 *Input to simulation-based strategy model*

The distribution for time to failure, given no preventive maintenance, only depends on the deterioration model, and can be found using a Bayesian network. As it should be possible to generate failures happening after the planned lifetime, because they could generate CBM within the lifetime, the distribution is computed for 50 years (600 timesteps). The probability of failure later than 50 years is found to be 0.15%, and this number is added to the last time step to make the distribution a valid probability mass function. The distribution is shown in Figure 6.

For the simple strategies a) and c), the conditional probability distribution for time of detection given time of failure can be estimated directly using Bayesian networks, as described in section 3.2. The conditional distributions for time of failure in years 5, 10, 15, and 20 are shown in Figure 7. For the advanced strategies b) and d), a distribution can be fitted to the outcome of simulations (time of detection and time of failure). Examination of histograms of t_R values for small ranges of t_F values revealed that a beta distribution would fit the ratio t_R/t_F well for a given t_F, and that the distribution parameters would vary with t_F. Therefore, the two parameters α and β in the beta distribution were each represented by a 2nd order polynomial of t_F. Thereby, the conditional distribution $P(t_R|t_F)$ is determined by six parameters. These parameters were found using the Maximum likelihood method. A nonlinear solver for constrained optimization was used under the constraints $\alpha > 0$ and $\beta > 0$ for all t. The conditional distributions for time of failure in years 5, 10, 15, and 20 are shown in Figure 8.

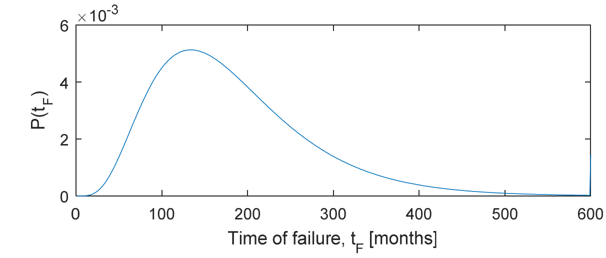

Figure 6. Probability density function for time to failure.

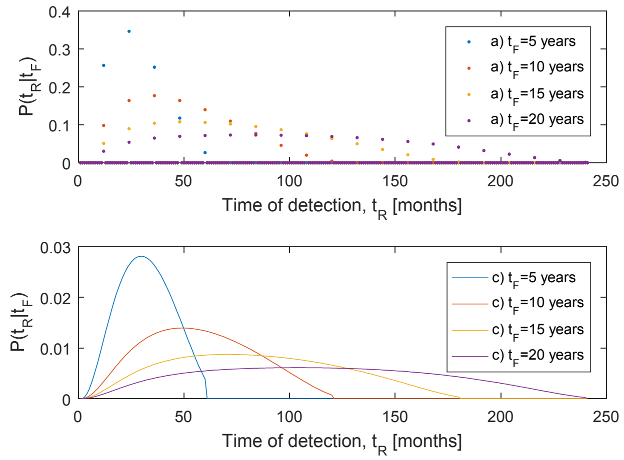

Figure 7. Conditional probability distributions for time of detection given time of failure for strategies a) and c) for time to failure t_F equal to 5, 10, 15 and 20 years.

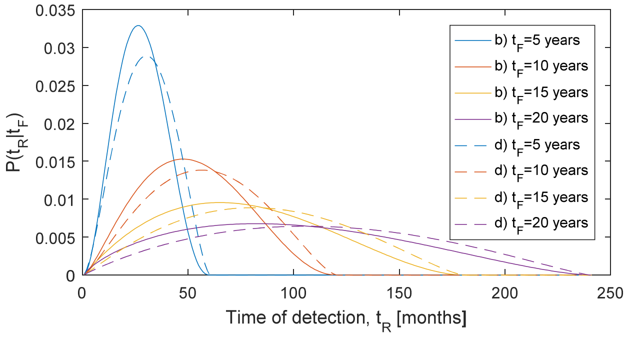

Figure 8. Conditional probability distribution for time of detection given time of failure for strategies b) and d) for time to failure t_F equal to 5, 10, 15 and 20 years.

The distributions are multiplied by the overall probability of detection p_{det}, and the probability of no-detection is then 1-p_{det}.

The overall probability of detection is estimated as the ratio between the number of simulations with detection before failure, and the total number of simulations with failure within the time horizon used in the simulations. If p_{det} had been found to depend on the time of failure, this could have been considered in the distribution $P(t_R|t_F)$. For verification of the distributions, p_{det} was estimated by simulating from the distributions, and was compared to the values found using the risk-based O&M model. Agreement was found on the values: a) 99.79%, b) 99.82%, c) 99.86, d) 99.88%, which means that almost all defects are detected prior to failure.

4.5 *Results from simulation-based strategy model*

The NOWIcob model was run for each of the four strategies using the input presented in the previous sections for a lifetime of 20 years. Only inspection and maintenance tasks related to blade maintenance were included. The total expected lifetime O&M costs for the wind farm is shown in Figure 9 for each strategy together with results from the risk-based model, which have been split up into the same contributions as for the NOWIcob model.

Generally, good agreement is observed between the costs of inspections and CBM. The direct costs of corrective repairs, cost of jack-up vessel charter, and downtime show larger variations, but the overall ranking of strategies remains the same. Variations in jack-up charter costs and lost revenue were expected, as the NOWIcob model has a more detailed model of the execution of maintenance tasks, thus these costs are affected by the simulated duration of the tasks. However, direct costs of corrective maintenance only depend on the number of corrective tasks, not the duration, and better agreement between models was expected, as it would mainly be influenced by the time to failure and overall probability of detection p_{det}, which was verified to be unchanged in the input distributions used in the NOWIcob model. However, some of these discrepancies could be explained by some CBM tasks ending up being executed as corrective maintenance tasks according to the simulations in NOWIcob, if there was not enough time from detection to the potential failure to execute the CBM task.

For the presented example, the p_{det} values are generally very high due to very proactive strategies used (due to very large failure costs compared to CBM costs). Thus, the resulting probability of failure, considering the maintenance strategy, is very low. Therefore, rare events such as failures happening in the period between the decision to repair and the execution of the repair, will cause noticeable changes to the overall costs of corrective maintenance. In such cases, it is therefore important to model the tail of the distri-

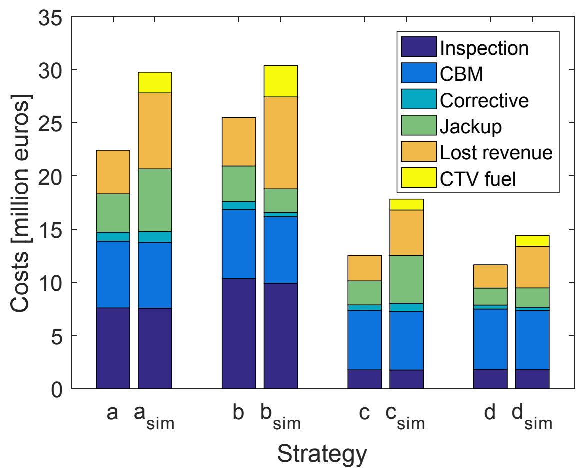

Figure 9. Comparison of total expected lifetime O&M costs for the wind farm for the risk-based model and the NOWIcob simulation-based strategy model (sim) for each strategy.

bution for time of repair given time of detection accurately. Also, the way events in discrete time steps are converted to continuous time can be important for correct estimation of the amount of CBM tasks being converted to corrective.

Figure 10 shows the frequency of inspection and CBM tasks as function of time for the risk-based model and the NOWIcob simulation-based strategy model for strategy c). The models show similar results, however the frequency of inspections increases stepwise for the simulation model results, as the mean rate is used for each year.

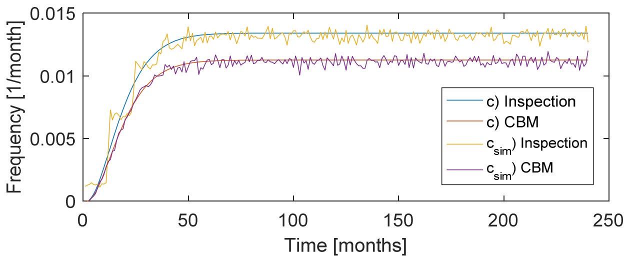

Figure 10. Comparison of distribution of inspections and CBM tasks in time for the risk-based model and the NOWIcob simulation-based strategy model (sim) for strategy c).

5 CONCLUSIONS

This paper presented a novel method for integration of CBM of deteriorating components in simulation-based O&M strategy models for offshore wind farms. Various types of risk-based CBM strategies could be implemented, and CBM and corrective maintenance tasks were distributed correctly over the lifetime. For simple strategies, Bayesian networks were used to generate input to a simulation-based strategy model, and this gave correct overall distribution of repairs and correct distribution over the year. For advanced strategies, simulations were used, and a distribution was fitted to the simulation results. This approximated the overall distribution well but did not capture variations within the year.

The example confirmed that additional effects influencing the costs were seen in the simulation-based strategy model, where logistics was modelled more accurately compared to the risk-based model. Care should be taken to ensure that these effects are realistic and not a result of approximations made in the strategy model and how its integration with the risk-based model was implemented. For example, when fitting the distribution to the simulation results, the modelling of the tail has importance for the occurrence of failures while waiting for CBM to be completed. On the other hand, the correct mean value of the time of repair given time of failure is of importance to get the correct total expected number of CBM tasks, and thus the correct estimation of the costs. The presented approach will allow a decision maker to combine detailed CBM modelling with detailed logistics modelling, to get a more accurate estimation of expected costs for a given strategy, and therefore a better basis for identifying the optimal strategy.

6 ACKNOWLEGEMENTS

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