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Nielsen, Jannie Sønderkær; Tcherniak, Dmitri; Ulriksen, Martin Dalgaard

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Quantifying the value of SHM for wind turbine blades

Jannie S. Nielsen[1], Dmitri Tcherniak[2], and Martin D. Ulriksen[1]
1 Department of Civil Engineering, Aalborg University, Denmark, jjn@civil.aau.dk
2 Brüel & Kjær Sound & Vibration Measurement A/S, Nærum, Denmark,
Dmitri.Tcherniak@bksv.com

Abstract

In this paper, the value of information (VoI) from structural health monitoring (SHM) is quantified in a case study for offshore wind turbines (OWTs). This is done by combining data from an operating turbine equipped with a blade SHM system with cost information from a service provider for OWTs in a Bayesian decision framework. The reliability of the blade SHM system is evaluated based on a monitoring campaign with a 225 kW Vestas V27 wind turbine, where one of the blades was introduced to an artificial trailing edge damage of increasing size. The blade was equipped with a prototype of an SHM system, which consists of an electro-magnetic actuator that periodically impacts the blade and an array of accelerometers mounted along the leading and trailing edges of the blade. Changes in the structural integrity can be detected using conventional outlier analysis, where the current state of the blade is compared to a statistical model from the healthy state using a metric that yields a damage index representing the structural integrity. As the damage was introduced artificially, it is possible to statistically estimate the confusion matrix corresponding to different threshold values, and here we opt to select thresholds to optimize the value of SHM. Based on SHM data from the V27 wind turbine, a probabilistic model is developed for the relation between the damage level and indicator, and this is assumed to be representable for the reliability of similar SHM systems installed on OWTs. A case study is developed to quantify the value of SHM for an 8 MW OWT using a decision framework based on Bayesian pre-posterior decision analysis. Deterioration is modelled as a Markov chain developed based on data, and the costs are obtained from a service provider for OWTs. Discrete Bayesian networks are used for deterioration modelling and Bayesian updating within the decision framework. First, the value of SHM is evaluated for different interference thresholds for the damage indicator. Then, strategies are applied using thresholds for the probability of failure, which is updated using Bayesian networks with damage indicators received from the SHM system. Three sensor configurations are tested, and for the least reliable configuration, the strategy using thresholds for the probability of failure results in much higher VoI than the strategy using a threshold for the damage indicator. For the most reliable configuration, they result in similar VoI.

1. Introduction

For offshore wind turbines, operation and maintenance (O&M) costs are high – around 25-30% of the cost of energy (1). To limit the amount of catastrophic failures, condition monitoring systems are often installed to detect incipient failures in the drivetrain, where many failures are seen. The blades also experience a large number of defects, and to avoid catastrophic failures, inspections are usually performed at regular intervals. Traditionally, inspections are performed using rope access, which is relatively expensive. Cheaper but less reliable alternatives are inspections from the ground using telephoto cameras or scanning systems and inspections from drones. Another promising technique is to use structural health monitoring (SHM) systems. These systems can detect incipient faults without need to access the turbines (2,3), and therefore have the potential to reduce maintenance costs; especially for offshore wind turbines in distant locations with harsh weather conditions causing low accessibility. However, the SHM systems come with a cost and they are not perfect, resulting in false alarms, defects not being detected, and, as such, the risk of increasing the costs instead of reducing them. Therefore, quantification of the value of monitoring prior to installation is crucial. To this end, the value of information (VoI) concept can be applied, as proposed in the COST Action TU1402 (4). The objective of this paper is to quantify the value of SHM for blades of an 8 MW offshore wind turbine.

2. Value of information

The concept of VoI originates from Bayesian decision analysis (5). In this application context, VoI is the difference in the total expected lifetime operation and maintenance costs for a wind turbine without SHM and with SHM. These costs will not only depend on the nature of the deterioration processes, the SHM system, and so forth; they will also depend on the decisions made based on the SHM observations, and the decisions made in the situation without SHM. The Bayesian decision analysis provides the basis for making these decisions in an optimal way, hence minimizing the expected lifetime costs.

2.1 Bayesian decision analysis

In the context of maintenance planning, the Bayesian pre-posterior decision analysis can be explained as follows. The decision maker knows that the blades are deteriorating, and that there is a probability of the event of catastrophic failure if no maintenance is performed. Maintenance, for example, a repair or exchange of a blade, will improve the condition of the blade and hereby decrease the probability of failure, but it comes with a cost. The amount of maintenance should be balanced against the reduced risk of failure. As the condition of the blade is uncertain, the decision maker can decide to gain more information on the condition by ordering an inspection. The inspection also comes with a cost, although it does not improve the condition of the blade, and therefore inspections alone do not reduce the failure rate. Inspections only reduce the amount of failures when a decision rule on an action on maintenance is coupled to the inspection outcome. The same is true for SHM; only when SHM observations eventually affect decisions on maintenance, they can be beneficial.

If the decision maker only was to make the decision on whether to inspect and whether to do maintenance once in the lifetime, the problem would be a standard pre-posterior decision problem that could be solved by constructing a decision tree (6) and evaluating the expected costs associated with each combination of decisions. However, inspections and maintenance can be performed at various points in time, and the number of branches in the decision tree would increase exponentially, thus making the problem computationally intractable. Approximative methods for solving the decision problem include the use of limited memory influence diagrams (LIMIDs), partially observable Markov decision process (POMDP), and stationary decision rules (7). In this paper, we apply a computational framework using Bayesian networks, which employ stationary decision rules. A short introduction to the framework is provided below, and for details we refer to (8).

2.2 Risk-based decision framework

The computational framework for risk-based planning of inspections, maintenance and monitoring can be applied to find the total expected lifetime O&M costs for various decision rules for inspections and preventive repairs. Simple and advanced decision rules are distinguished. Simple decision rules include equidistant inspections and decision rules depending on directly observed variables, for instance, the most recent SHM or inspection outcome. Advanced decision rules depend on a variable that summarizes all past acquired information, for instance, the probability of failure.

The cores of the computational framework are two decision models, which are used to evaluate the probability of each event (inspections, repairs and failures) for each time step during the planned lifetime. For both decision models, the modelling is based on discrete Bayesian networks. The first uses Bayesian networks directly for the evaluation of the probabilities of each event; the second uses Monte Carlo simulations for the estimation of probabilities of each event and use Bayesian networks within simulations to update the probability of failure for use of advanced decision rules. The first decision model is fast and exact but does not support advanced decision rules; the second decision model is more time consuming but supports both simple and advanced decision rules. For both decision models, the required input are strategies (sets of decision rules) and probabilistic models (conditional probability distributions for deterioration, inspections, SHM, and repairs). After running the decision models, the probabilities of each event in each time step are multiplied by the specific costs of each event and summarized over the lifetime to obtain the total expected lifetime O&M costs.

2.2.1 Bayesian networks

Discrete Bayesian networks are used within the risk-based decision framework to predict deterioration using a probabilistic deterioration model. The predictions can be efficiently updated when information from SHM and inspections becomes available based on models for the reliability of the monitoring methods, for example, probability of detection as function of damage size. Within the framework, Bayesian networks with different structures are used for the different strategies included in the framework. An example is the network shown in figure 1 that can be used to estimate the expected number of inspections, repairs, and failures in the case where inspections are made after damage detection by SHM, and decision to repair is made based on the inspection. The dashed arrows indicate that the network continues with more time steps equal to time step number one. Elaboration on how to use the network is provided in (8), and a general introduction to Bayesian networks can be found in (9).

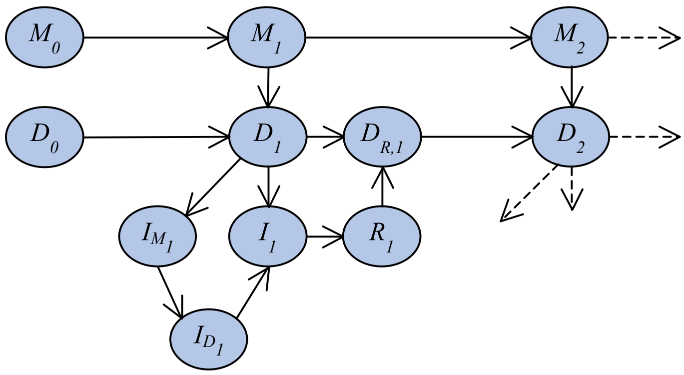

Figure 1. Bayesian network used for estimation of expected number of inspections, repairs, and failures when inspections are made after damage detection by SHM, and decision to repair is made based on the inspection. D_i: damage size, $D_{R,i}$: damage size after any repairs, M_i: model parameter, I_i: inspection outcome, $I_{M,i}$: SHM outcome, $I_{D,i}$: inspection decision, R_i: repair decision.

3. Reliability of SHM system

When estimating the value an SHM system can bring, one has to take into account that the system is not perfect: it can produce false alarms and can miss faults. These situations are known as Type I and Type II errors and can be characterized by the probability of such events. This probability is an important part of the SHM VoI model. Unfortunately, the very nature of SHM systems makes it difficult providing such probability numbers based on collected statistics. First of all, only few blade SHM systems have been installed. Secondly, the events the SHM systems are supposed to detect happen quite seldom. In principle, such statistics can be estimated from a proper simulation of operating wind turbine dynamics, including the effects of possible faults at different locations and including the SHM system into the model (so-called SHM virtual test environments). However, nowadays such test environments are in a very early stage of development (10). In this study, the estimations are based on the results of a test campaign, in which an active vibration-based SHM system was installed on one blade of an operating Vestas V27 wind turbine, and an artificial damage (a trailing edge opening) was introduced to the instrumented blade. In subsection 3.1, we provide a short overview of the SHM system and the test campaign, while a detailed description can be found in (3).

3.1 Measurement campaign

The test campaign started in November 2014 and lasted 104 days. One blade of a 225 kW Vestas V27 wind turbine was equipped with a prototype of an SHM system developed in the frame of a research project (11). The SHM system consists of an electromagnetic actuator (mounted near the blade root) and 16 accelerometers (mounted along the blade) as shown in figure 2. The actuator and accelerometers were connected to the data acquisition system located inside the spinner. The actuator was set up to impact the blade surface every five minutes; synchronously, data from the accelerometers, rotor azimuth, and blade pitch were recorded. The information regarding weather conditions (wind speed and direction, temperature, and so forth) and wind turbine-related information (for example, generated power) were collected as well.

From the data acquisition system in the spinner, the data was wirelessly transmitted to the nacelle and stored on a computer located inside the tower. No damage detection was performed in real-time; instead, the data was processed remotely and off-line.

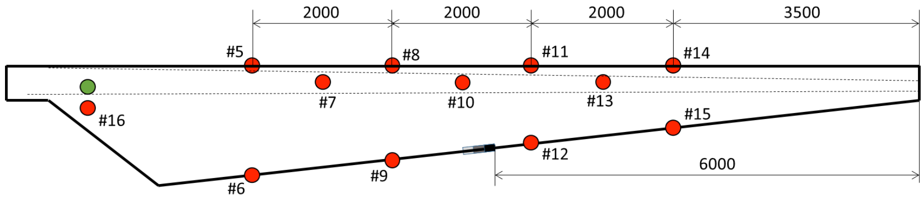

Figure 2. Contour of the blade where the red circles indicate the location of the accelerometers and the green circle is the actuator position (3).

After few weeks of collecting data characterizing the healthy blade, a defect, in the form of a trailing edge opening, was artificially introduced to the blade. This particular damage type was selected due to two reasons; (a) it is one of the typical defects for the blades manufactured using this technology and (b) a trailing edge opening is easy to implement and easy to repair. First, a 15 cm opening was introduced, and then, after few weeks of collecting enough data for characterizing this damage, the opening was extended to 30 cm and subsequently to 45 cm. After collecting the necessary amount of data, the damage was repaired, and data for this state was collected as well. Finally, after measuring in 104 days under different weather conditions and operating regimes, the SHM system was dismounted. A total of about 25,000 samples, covering the five states of the wind turbine, were collected and made available for damage detection analyses.

3.2 Damage detection methodology

In the study, we employ a standard SHM scheme, which has been used extensively for damage detection purposes, see, for example, (12). The specifics of the methodological steps are provided in (3), and below a brief overview is given. The first step of the scheme is the so-called feature extraction. From the measured acceleration signals, the algorithm extracts information, which is believed to be sensitive to damage. This step includes filtering and signal trimming and subsequent computation of a covariance matrix of the measured accelerations. Finally, dimensionality reduction based on principal component analysis is employed, hence resulting in a low-dimensional *feature vector*, which is shown to be sensitive to structural damage. The feature vector is computed for each actuator hit; further in the text, it is referred to as a *sample*. The next step is the training of the classification algorithm. A semi-supervised learning approach is employed, implying that a baseline/training model representing the healthy state is computed based on the data from this state. The discordance between a sample from the current, potentially damaged state and the baseline model is found as a Mahalanobis distance. The latter becomes a *damage indicator*; in the sense that a Mahalanobis distance exceeding some pre-defined threshold indicates that the dynamics of the structure have changed significantly, potentially due to damage. To find the threshold value, it is common to utilize the distribution of the samples in the healthy state. For example, one can allow some percentage of the outliers in the training set and select the threshold accordingly. In this way, thresholds are selected based on the allowed false alarm rate. In this paper, three sensor configurations are considered. For each sensor configuration, the thresholds for the damage indicator are identified for false alarm rates 0 % to 10 %, and the detection rates are estimated for the three damage lengths. The resulting detection rates are shown in figure 3.

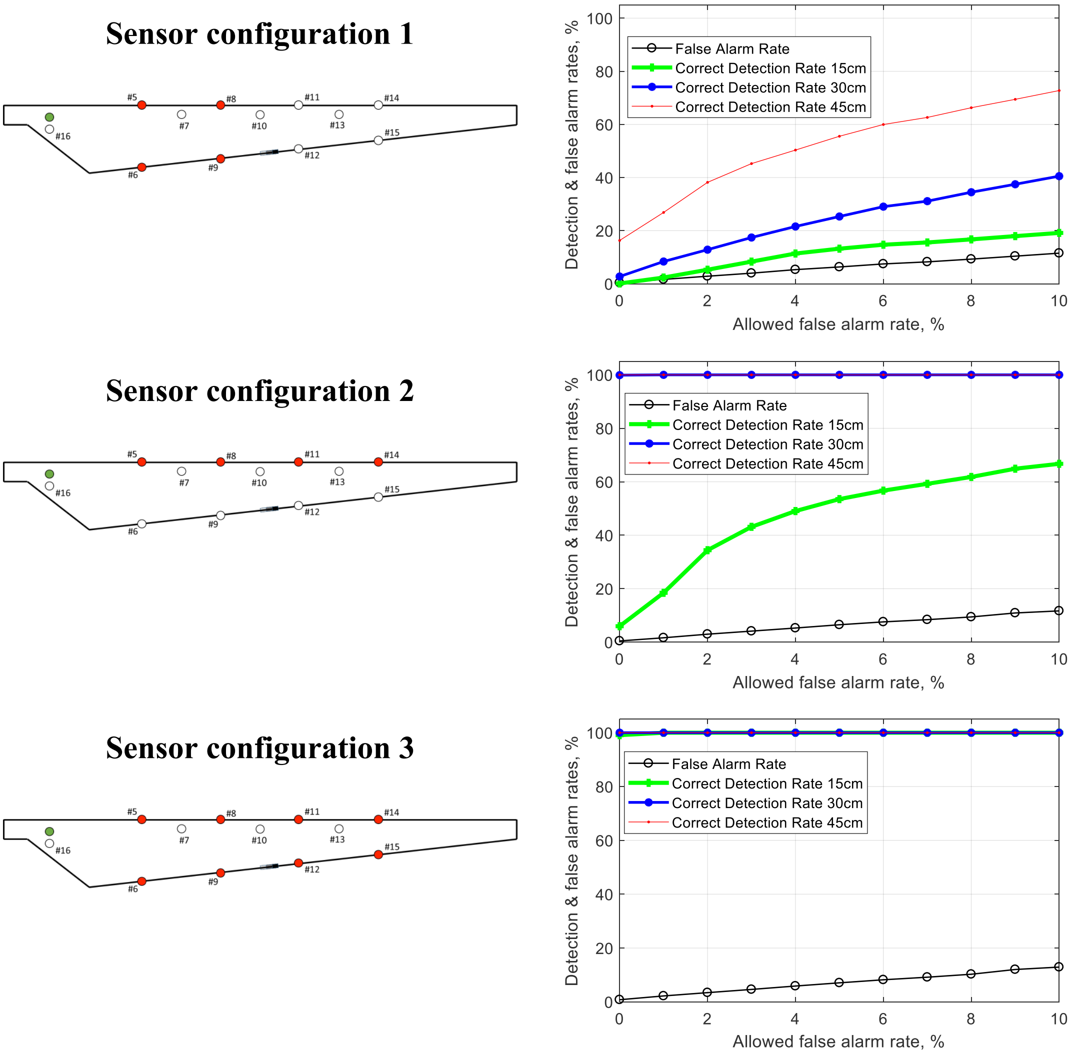

Figure 3. Test false alarm rate and correct detection rate as a function of allowed false alarm rate, for three sensor configurations. The corresponding sensor configurations, with the engaged accelerometers shown as filled circles, are shown next to the graph (3).

4. Case study

In this case study, the value of SHM of the blades is quantified for an 8 MW offshore wind turbine using the risk-based decision framework described in section 2. The SHM system is assumed to have the same performance as that used in the measurement campaign described in section 3. Decisions on repairs are assumed to be based on the outcome of inspections. Three strategies for inspections are considered:

- S1: Equidistant inspections (no SHM)
- S2: Simple SHM strategy (inspections are made when a threshold for the damage indicator is exceeded)

- .... S 3: Advanced SHM strategy (inspections are made when a threshold for the probability of failure is exceeded)

The VoI is quantified for three sensor configurations to assess the influence on costs. For each strategy and sensor configuration, the optimal interference threshold is found, and the VoI is estimated. Thereby, the computations can be used for decisions on sensor configuration, as it can be assessed if a more expensive and more reliable configuration is worth the increased costs.

4.1 Modelling

The input models for the risk-based decision framework described in section 2 are given as conditional probability distributions defining a Bayesian network; for details see (8).

4.1.1 Deterioration model

A wind turbine blade can experience many types of failures. Often, wind turbine operators group blade failures into categories, depending on their severity. Then the statistics and response actions are provided for each category; typically, five such categories are set up. The annual defect detection rates shown in table 1 are assumed representative for this case study. They are estimated based on Vestas' statistics for 2011 (14) and interviews with persons directly involved in wind turbine blade maintenance.

Table 1. Annual detection rates for defects of each category per wind turbine.

Defect category	Example of description	Annual turbine detection rate %
Category 1	Minor crack in trailing edge	20
Category 2	Crack in trailing edge panel	15
Category 3	Crack in trailing edge	10
Category 4	Major crack in trailing edge	8
Category 5	Trailing edge split	2
Catastrophic	New Blade	1

As proposed in (15), deterioration is modelled as a Markov chain, with the states 0 to 6. The first state represents a healthy one with no defects, while states 1 to 6 represent the defect categories given in table 1. It is assumed that each defect cannot increase more than one category per month, and only the presence of one defect per turbine is considered. The transition probabilities are estimated assuming perfect annual inspections and preventive repairs of failures of state 2 and above. The decision model described in section 2.2 is used to estimate the transition probabilities, such that the annual turbine failure rates given in table 1 are obtained. The result is given in table 2.

Table 2. Estimated monthly transition probabilities.

From state	0	1	2	3	4	5
Probability	0.0497	0.1404	0.1825	0.2190	0.1180	0.2146

4.1.2 Inspection and repair model

Inspections are assumed to be perfect, which implies that existing defects are always detected and categorized correctly. Both preventive and corrective repairs (exchanges) are assumed to be perfect, hence bringing the damage state to state zero.

4.1.3 SHM model

The SHM model is based on the estimated detection and false alarm rates found using the results from the measurement campaign described in section 3. For use in the computational framework, a conditional probability distribution for the SHM outcome as function of damage state is formulated. The measurement campaign included measurement for four states: no damage, 15 cm damage, 30 cm damage and 45 cm damage (the data from the repaired state was not used). We assume that the states with damage correspond to damage category 1, 2, and 3, respectively. The probability of false alarm and the probability of detection for each damage size were found for different allowed false alarm rates (figure 3); each allowed false alarm rate corresponds to a threshold for the damage indicator. The probability of detection for a given false alarm rate is therefore the probability of exceeding a given threshold for the damage indicator. The SHM model summarizes the probability of exceedance of each threshold for each damage category in a conditional probability distribution for the SHM observation given the damage state. For convenience, the SHM thresholds are referred to by numbers 1 to 11, and the relation between these numbers and the allowed false alarm rate is shown in table 3.

Table 3. Relation between SHM thresholds defined in the SHM model and the allowed false alarm rate used to set the threshold for the corresponding damage index.

SHM threshold	1	2	3	4	5	6	7	8	9	10	11
False alarm rate [%]	10	9	8	7	6	5	4	3	2	1	0

4.2 Costs

The cost model is built on the data that is publicly available or collected from interviews with persons directly involved in wind turbine blade maintenance. Unfortunately, there is a huge discrepancy between the numbers provided by different public sources (often web-based), thus the provided numbers should rather be considered as parameters to the model, which can be substituted by the numbers (often confidential) available from a particular wind energy operator bookkeeping system. The costs of an inspection (by rope access) is assumed to be 4800 euros. Loss due to damage may be split into several components, namely, the cost of repair (materials and working hours), the production lost (downtime) due to repair, and, finally, associated cost such as logistics, unplanned access, crane hire (if necessary), and so forth. The estimated costs of repair for different damage categories are presented in compact form in table 4.

Table 4. Assumed costs for repairs according to damage category (euros).

Damage category	Lost revenue	Mobilization cost	Repair cost	Total cost
Category 1	1,600	0	2,000	3600
Category 2	3,200	2000	4,000	9,200
Category 3	4,800	2000	6,000	12,800
Category 4	8,000	2000	8,000	18,000

Category 5	232,000	2000	15,000	249,000
Catastrophic	720,000	317,000	450,000	1,487,000

4.3 Results

This section presents the results: the total expected lifetime O&M costs, the optimal strategies, and the VoI for the three different sensor configurations shown in section 3.4.

4.3.1 Base case - equidistant inspections (S1)
In the base case (S1), no SHM is used for damage detection. Instead, inspections are assumed to be made at regular intervals, and preventive repairs are made when the inspection reveals defects with category above the threshold for repairs. Figure 4 shows the expected lifetime costs for combinations of inspection intervals and repair thresholds. The optimal values can be found as the combination leading to lowest costs. For strategy S1, it is optimal to inspect every 9 months and repair damages of category 1 and above.

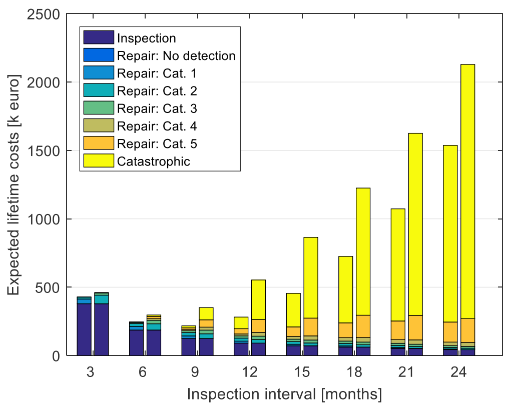

Figure 4. Expected lifetime costs for strategy S1 for inspection intervals 3 to 24 months. For each inspection interval, the costs are shown for two repair thresholds: damage category 1 and 2.

4.3.2 Simple SHM strategy (S2)
In strategy S2, inspections are made when a threshold for the SHM outcome is exceeded, and, as for S1, preventive repairs are made when inspection reveals defects with category above the threshold for repairs. To identify the optimal thresholds, the expected lifetime costs were found for different thresholds, as shown for sensor configuration 1 in figure 5. For the two other configurations, the optimal thresholds were found in the same way.

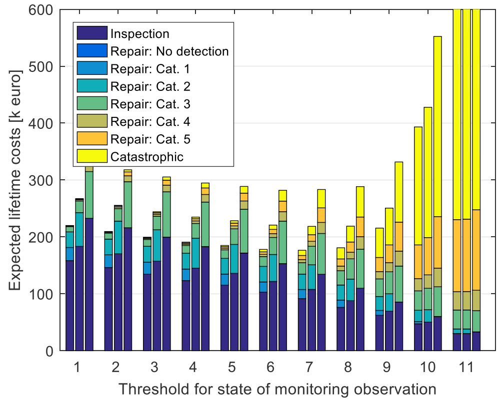

Figure 5. Expected lifetime costs for strategy S2 for sensor configuration 1 for thresholds for SHM observation 1 to 11. For each threshold, the costs are shown for three repair thresholds: damage category 1, 2, and 3.

For sensor configuration 1, it is optimal to inspect when the SHM threshold 7 (corresponding to a 4 % false alarm rate) is exceeded. For sensor configuration 2 and 3, the SHM threshold 11 (corresponding to 0 % false alarm rate) should be used. For all configurations, all detected damages (category 1 and above) should be repaired.

4.3.3 Advanced SHM strategy (S3)

In strategy S3, inspections are made when a threshold for the probability of failure within a year is exceeded. In this strategy, all past SHM observations are included when making the decision. Figure 3 shows the expected lifetime costs for sensor configuration 1 for different thresholds, and the optimal thresholds were found for configurations 2 and 3 using similar figures. For sensor configuration 1, the optimal threshold for the probability of failure within a year is 0.1, and for configurations 2 and 3 the optimal threshold is 0.2. As for the other strategies, all detected damages (category 1 and above) should be repaired.

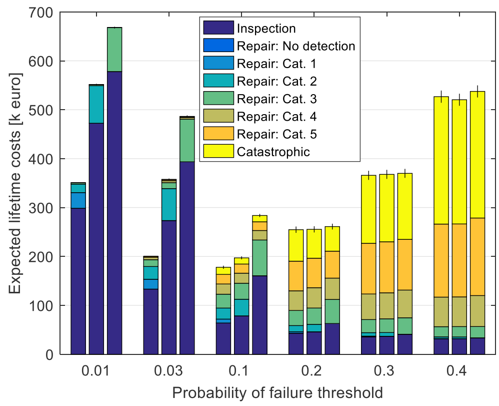

Figure 6. Expected lifetime costs for strategy S3 for sensor configuration 1 for thresholds for probability of failure 0.01 to 0.4. For each threshold, the costs are shown for three repair thresholds: damage category 1, 2, and 3.

4.3.4 Comparison of strategies and value of information

In figure 7, the expected lifetime costs are shown for all strategies (S1, S2, and S3) and for the three sensor configurations (1, 2, and 3) for the optimal thresholds. Additionally, the VoI is shown, which has been estimated as the difference between the strategy without SHM (S1) and each of the strategies with SHM.

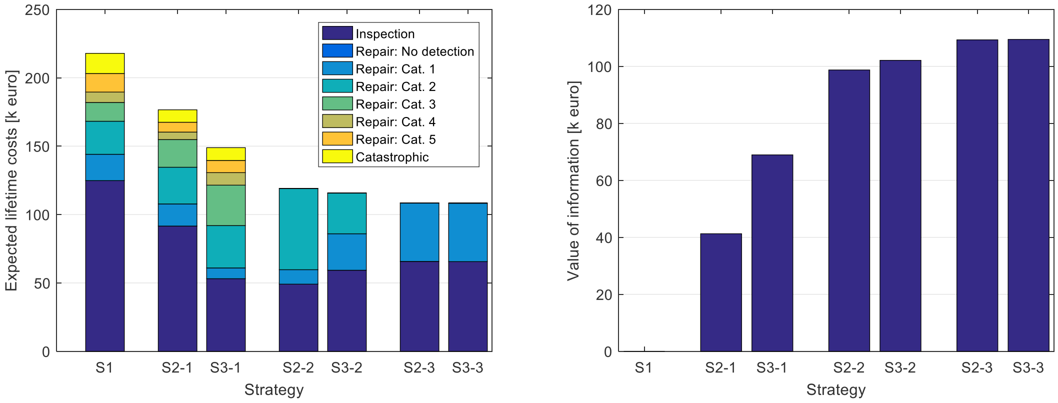

Figure 7. Expected lifetime costs and value of information for strategies S1 to S3 and sensor configurations 1 to 3.

4.4 Discussion

For the models used in the case study, early repair of failures is generally beneficial, as the repair costs increase dramatically with damage category. For the base case without SHM (S1), the found optimal inspection interval is quite low, as higher intervals will lead to large expected costs of catastrophic failures. For the simple SHM strategy (S2), the highest threshold for the damage indicator (corresponding to a false alarm rate of 0 %) should be used for sensor configurations 2 and 3, as defects would still be detected in time, and avoidance of false alarms reduced costs of inspections. For the less reliable sensor configuration 1, a lower threshold should be used, as the number of faults of higher categories would be too large; it would be better to allow for some false alarms. For the advanced SHM strategy (S3), the optimal threshold for probability of failure within a year is large; namely, 0.1 to 0.2. The reason is that even when the probability of failure within a year is, for example, 0.1, it is still very certain that the SHM system will detect the defect before failure and the preventive repair will almost certainly be made in time.

The results show that the potential for cost reductions using SHM is large. The sensor configuration will affect the VoI, as a more reliable SHM system will be more effective in eliminating the occurrence of repairs of defects of higher categories. For less reliable systems, the advanced strategy performs much better than the simple strategy, whereas for the most reliable system, their performance is similar. In the shown costs, the costs of the SHM system are not included. The costs of a system are expected to be in the order of 60,000 euros. Therefore, sensor configurations 2 and 3 could both be beneficial to install, and the difference in price of SHM system will determine which one is better.

Some of the assumptions behind the models can be questioned. It is, for instance, assumed that a defect can only transfer one state per time step (one month) and therefore needs to go through all states. Also, the deterioration model models the health state of the rotor as one and does not consider multiple defects in one rotor. This corresponds to the assumption that the largest defect drives the costs and the probability of detection, and that all smaller defects are also repaired when a repair is made (15).

The annual rates used when fitting the deterioration model might not accurately represent this. The SHM outcomes are assumed to be independent given the damage size. In case of correlations, for example, if the location affected the outcome, this should be included in the model (16).

3. Conclusions

The paper presents a method to assess VoI of SHM based on probabilistic models for deterioration, SHM, and inspections. As demonstrated in the case study, the model can be applied to assess the VoI for different sensor configurations, thereby providing support for decisions on where to install sensors and how many sensors to install. The VoI was estimated both for a simple and an advanced SHM strategy. For very reliable sensor configurations, the VoI was similar, but for less reliable sensor configurations, the advanced strategy provided higher VoI, as more than one SHM outcome was used when making decisions. The approach demonstrated in this paper can also be used to identify the optimal characteristics of an SHM system in order to specify design objectives for developers of SHM systems.

References

1. C Röckmann, S Lagerveld and J Stavenuiter, "Operation and maintenance costs of offshore wind farms and potential multi-use platforms in the Dutch North Sea", Aquaculture Perspective of Multi-Use Sites in the Open Ocean: The Untapped Potential for Marine Resources in the Anthropocene, pp 97-113, 2017.
2. MD Ulriksen, D Tcherniak, LM Hansen, RJ Johansen, L Damkilde and L Frøyd, "In-situ damage localization for a wind turbine blade through outlier analysis of stochastic dynamic damage location vector-induced stress resultants", Struct. Health Monit.16(6), pp 745-761, 2017.
3. D Tcherniak and LL Mølgaard, "Active vibration-based structural health monitoring system for wind turbine blade: Demonstration on an operating Vestas V27 wind turbine", Struct. Health Monit. 16(5), pp 536-550, 2017.
4. COST Action TU1402: Quantifying the Value of Structural Health Monitoring, http://www.cost-tu1402.eu
5. H Raiffa H and R Schlaifer, Applied statistical decision theory. Harvard University, 1961.
6. JJ Nielsen and JD Sørensen, "Risk-based operation and maintenance of offshore wind turbines using Bayesian networks", Proc. 11th Int. Conf. Appl. Stat. Probab. Civ. Eng., Zurich, Switzerland, pp 311–7, 2011.
7. JS Nielsen and JD Sørensen, "Methods for risk-based planning of O&M of wind turbines", Energies 7, pp 6645–64, 2014. doi:10.3390/en7106645.
8. JS Nielsen and JD Sørensen, "Computational framework for risk-based planning of inspections, maintenance and condition monitoring using discrete Bayesian networks." Struct. Infrastruct. E., 2017. doi: 10.1080/15732479.2017.1387155.
9. FV Jensen and TD Nielsen, Bayesian Networks and Decision Graphs. Information Science and Statistics, Springer, 2007.
10. D Garcia and D Tcherniak, "Virtual prototyping of an actuator-based structural health monitoring system of wind turbine blades", Proceedings of Int Conf on Noise and Vibrations (ISMA) 2018, to appear.

11. EUDP project final report, “Predictive health monitoring of wind turbine blades”, 2015. https://energiteknologi.dk/sites/energiteknologi.dk/files/slutrapporter/eudp_phm_final_report_v4_-_full_id_494016_id_494018.pdf
12. K Worden and G Manson, “The application of machine learning to structural health monitoring”, Philos T R Soc A 365, pp 515–537, 2007
13. D Molyneux, “Benefits of Proactive Inspection and Early Intervention
14. of Blades”, 2017. http://canwea.events/wp-content/uploads/2017/02/Benefits-of-Proactive-Inspection-and-Early-Intervention-of-Blades-Dan-Molyneux.pdf
15. JS Nielsen and JD Sørensen, “Bayesian Estimation of Remaining Useful Life for Wind Turbine Blades.” Energies 10(5), 664, 2017. doi:10.3390/en10050664
16. JS Nielsen, “Bayesian updating and decision making using correlated structural health monitoring observations”, Submitted to Reliab. Eng. Syst. Safe, 2018. Preprints: http://vbn.aau.dk/files/273328298/Nielsen_23032018_preprint.pdf