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Abstract

A Bayesian approach is often applied when updating a deterioration model using observations from inspections, structural health monitoring, or condition monitoring. The observations are stochastic variables with probability distributions that depend on the damage size. Consecutive observations are usually assumed to be independent of each other, but this assumption does not always hold, especially when using online monitoring systems. Frequent updating using dependent measurements can lead to an over-optimistic assessment of the value of information when the measurements are incorrectly modeled as being independent. This paper presents a Bayesian network modeling approach for the inclusion of temporal dependency between measurements through a dependency parameter and presents a generic monitoring model based on the exceedance of thresholds for a damage index. Additionally, the model is implemented in a computational framework for risk-based maintenance planning, developed for maintenance planning for wind turbines. The framework is applied for a numerical experiment, where the expected lifetime costs are found for strategies with monitoring with and without dependency between observations, and also for the case where dependency is present but is neglected when making decisions. The numerical experiment and associated parameter study show that neglecting dependency in the decision model when the observations are in fact dependent, can lead to much higher costs than expected and to the selection of non-optimal strategies. Much lower costs (down to one quarter) can be obtained when the dependency is properly modeled. In the case of temporally dependent observations, an advanced decision model using a Bayesian network as a simple digital twin is needed to make monitoring feasible compared to only using inspections.

Keywords

Value of information, risk-informed decision support, condition monitoring, structural health monitoring, maintenance planning, wind turbines

Introduction

Condition monitoring or structural health monitoring is increasingly being applied in many industries such as the offshore wind industry[1] and for bridges[2,3]. A shift from a simple time-based inspection and maintenance regime to predictive maintenance based on an updated belief of the component health can lower the expected maintenance costs, especially if a risk-based approach is used to balance the expected costs of failures, preventive repairs, inspections, and monitoring.[4] The theoretical background for this was established in the Bayesian pre-posterior decision theory[5] and was adapted to civil engineering by Benjamin and Cornell[6]. For risk-based inspection planning (RBI) for offshore structures, efficient generic methods have been developed.[7,8] Here, the outcomes of inspections are stochastic variables with probability distributions that depend on the crack size. The outcomes of consecutive inspections are assumed independent, and for inspections, this assumption seems fair as the time between inspections is typically several years.[9] However, when frequent inspections or online monitoring are applied, the assumption of independence should be challenged, as joint uncertainties could cause dependency between inspection or monitoring outcomes.

Monitoring is defined as follows in COST 345: “Monitoring can be defined as any periodic or continuous operation where the behavior of a structure, or of its components – such as foundations, is quantified in some way so that its serviceability and stability can be evaluated.”[10] The term condition monitoring (CM) is often used for mechanical components and structural health monitoring (SHM) is often used for structural components. Rytter[11] defined four levels for vibration-based inspection, which are widely used for CM and SHM: Detection, localization, assessment (quantification of size), and consequence (for safety). The second and third levels are related to diagnosis, and the last level is considered to also include the future performance of the structure and is therefore often called prognosis and is related to remaining useful life (RUL) estimation.[12] To include monitoring in a framework for predictive maintenance decisions, one must have information about the diagnosis and prognosis.

There are many published studies on the use of monitoring for detection, localization, diagnosis, and prognosis. Monitoring can also be applied to assess the consequence of extreme events such as earthquake[13] or vehicle impact on a bridge[14], or it can be used to decrease uncertainties on loading[15] or to estimate the health of the structure or component. For modern wind turbines, CM systems based on vibration measurements are widely used for mechanical components in the drivetrain such as bearings and gears. Commonly used methods for diagnosis are developed based on envelope analysis utilizing the high-frequency resonance technique[16]. Methods for prognosis are being developed, for example, a data-driven failure prognostics mixture of Gaussian hidden Markov models for bearings[17], a mixture of Gaussian Bayesian belief networks[18], and neural network approaches[19]. Even for wind turbines without dedicated CM systems, supervisory control and data acquisition (SCADA) systems are always installed, and the data can be used for CM, although large uncertainties and false alarms are present[20]. For wind turbine main bearings, a non-linear model based on temperature measurements was developed by Bach-Andersen et al.[21], and Mazidi et al.[22] developed an approach for stress monitoring using neural networks and the proportional hazard model. For wind turbine blades, there is a large potential for SHM.[23] Methods based on actuated vibrations[24], frequency response transmissibility analysis[25,26], and acoustic emission[27] have been proposed. Also for the wind turbine structure, vibration-based methods have been proposed.[28]

Monitoring can only affect the reliability and maintenance costs when observations are used to support decisions on actions. ISO2394[29] states that when results from inspections, monitoring, etc. are available, Bayesian statistical methods should be applied to update the reliability, and the updated reliability should be the basis for decision making with respect to maintenance and repair. Some studies apply Bayesian methods for prognosis based on vibration measurements[30–32], but make the prognosis for the vibration measurements instead of for the underlying deterioration process. To account for the uncertainty related to the monitoring signal, the damage size and the outcome of the monitoring system can be considered as two separate variables, where a probabilistic model relates the variables. Then, it is possible to evaluate the reliability based on the probabilistic models, and decisions can be made on this basis. The link between monitoring and costs has been the focus of the COST Action TU1402. In this relation, the importance of unbiased measurements was emphasized in Faber et al.[33], where the principles for a theoretical framework for estimation of the value of information (VoI) from SHM was presented following the principles set by the Joint Committee on Structural Safety (JCSS)[34] and in ISO 2394[29]. In order for the measurements to be unbiased, the model needs to account properly for any dependency between measurements. This is in line with the ISO2394 that states that any temporal or spatial correlation should be accounted for.

Many published papers can be found on the assessment of the value of monitoring. However, the focus is often either load monitoring or inspections. If online monitoring is considered, the outcomes are often modeled as independent, and the temporal dependencies are neglected. Thöns[35] and Thöns et al.[15] used load monitoring of hot spots for a jacket structure and updated the inspection plan according to the loading information obtained. The optimal inspection plans without and with monitoring are obtained using the generic approach for RBI presented by Straub[7] and Straub and Faber[36]. Qin et al.[37] assumed that it was possible to monitor the annual damage increment, and the independent monitoring outcomes were used to update the mean value of the distribution for the annual damage increment. Straub[38] described how to estimate VoI of fatigue monitoring based on structural reliability methods and did also consider monitoring outcomes to be independent. In many studies, online monitoring observations were assumed to be independent given the damage size[4,39–44]. Pozzi and Der Kiureghian[45] considered the assessment of VoI from monitoring and propose modeling the additive error terms as jointly normally distributed random variables, possibly correlated with a given covariance matrix. However, the estimation of the covariance matrix or the implications for the results are not considered, and the example in the paper does not include the correlation. Straub and Faber[46] considered the correlation between inspection outcomes of different but similar hot spots and studied how this correlation influenced the updated failure probability of the system. They concluded that normally the influence of inspection dependency would be limited compared to other contributors of uncertainty. They identified the following contributions to the uncertainty of inspection outcomes:

- Random noise (aleatoric)
- Statistical uncertainty due to limited data available for estimation of the probability of detection (PoD) model
- Model uncertainty due to the use of a parametric model
- Model uncertainty due to factors not included in the inspection model, e.g. human factors, environment, defect orientation, geometry, and location.

The statistical uncertainties and some model uncertainties will be time-invariant, i.e. the stochastic variables modeling the uncertainties will have fixed (but unknown) values for a given defect. This would be the case for model uncertainties that depend on the inspector or the location/orientation of the defect. However, not all model uncertainties are time-invariant; they could also change with time if the influencing factor changes, e.g. if the inspector is different for each inspection or the environmental conditions change over the year. Time-invariant uncertainties introduce a dependency between consecutive observations of the same defect; for example, if a defect is in a location that makes it harder than usual to detect, it will decrease the probability of detection for all inspections of that defect. Most studies assume that these dependencies can be neglected, or even if they state that modeling of the dependency is important, they still model the observations as independent and give no guidance on how to model the temporal dependency. The temporal dependency can become important when frequent inspections or online monitoring is applied for sequential Bayesian updating of a deterioration model. For example, if a PoD curve was used to model the monitoring reliability, dependency could be introduced through time-invariant uncertainty on a parameter in the PoD model, e.g. the expected size of detectable defects. When the observations are assumed independent, the probability of detection stays the same for each consecutive observation (with fixed damage size), and repeated observations with no indication of damage lead to higher confidence in the structure being healthy. If instead the observations were fully correlated, additional observations after the initial observation would not give new information and would not influence the decision makers' belief of the health of the structure. The reality would most likely be something in between these two boundaries. The aim of this paper is to investigate the importance of acknowledging the dependency between temporally distributed monitoring observations of the same defect when the Bayesian decision theory is applied. First, section "Modeling temporally dependent monitoring observations" presents a generic monitoring model that includes temporal dependency, and in the section "Methodology for VoI assessment", the monitoring model is implemented in a Bayesian risk-based decision framework using Bayesian networks. Section "Numerical experiment" investigates the potential importance of acknowledging the temporal dependency between monitoring observations through an example and parameter study, and the conclusions are drawn in section "Conclusions".

Modeling temporally dependent monitoring observations

This section considers monitoring methods for which the observation is continuous and is an indicator of the damage size or health state. For most monitoring systems, e.g. vibration-based CM or SHM, the direct measurements will be high-frequency signals. To detect damage, various methods can be applied to derive a single variable, which is related to the component health, often referred to as the damage index. For CM of the drivetrain of a wind turbine, a short time series is usually recorded e.g. once a day when the turbine is operating within specified conditions. Methods such as envelope analysis are used to derive a single variable, which is related to the component health, e.g. the crest factor or a root mean square (RMS) value. The alarm threshold is set as the mean plus a factor times the standard deviation of the signal. For vibration-based SHM, several acceleration signals from spatially distributed sensors are often used. Tcherniak and Mølgaard[47] used the elements of the covariance matrix between the signals to form a statistical model of the healthy state, and the Mahalanobis distance from the healthy state to the current state was used as the damage index. Thresholds for the damage index are often set based on the allowed false alarm rate.

Generally, the damage index will have a lower frequency than the signal, for example, a measurement per day. If a probabilistic relationship between the damage state and damage index is known, the deterioration model can be updated using Bayesian methods each time an observation is received. However, for a Bayesian decision model, the computation time will be large if decisions are included for time steps with a duration of one day. A more appropriate time step for decisions is weeks or months, and therefore all damage indices received in each time step can be summarized into one variable, e.g. a mean or maximum value, as illustrated in Figure 1.

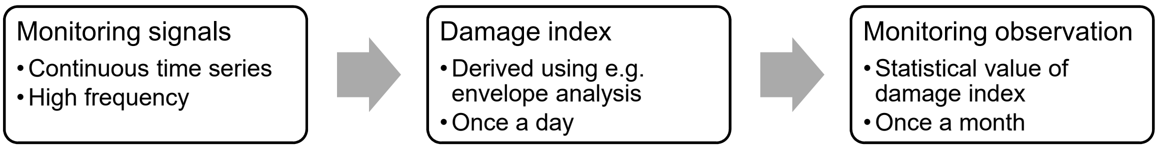


Figure 1: Principle for obtaining the monitoring observation used for updating the model.

The aim of this section is to establish a probabilistic monitoring model allowing for Bayesian updating of a deterioration model using outcomes of the damage index, where the temporal dependencies in the model are included. Thus, a monitoring model is here understood as a probabilistic model relating the outcome of the monitoring system to the health of the considered component.

It is assumed that the uncertainty on the mapping from damage index X to damage size D can be divided into two contributions: random noise and model uncertainty. The random noise is assumed normally distributed with mean zero and standard deviation σ, and realizations are independent. The model uncertainty is modeled using the time-invariant model parameter L. In the case of independent observations, the expected value of the damage index X will only be conditioned on damage size D, and $X(D)$ will follow a normal distribution around this value.

$$f_{X|D}(x|D) = N(E[X|D], \sigma) \tag{1}$$

When outcomes are dependent, the expected value of the damage index X will depend on both damage size D and model parameter L:

$$f_{X|D,L}(x|D,L) = N(E[X|D,L], \sigma) \tag{2}$$

The distribution function of X given D and L is then:

$$F_{X|D,L}(x|D,L) = \Phi\left(\frac{x - E[X|D,L]}{\sigma}\right) \tag{3}$$

This distribution can in principle be used for Bayesian updating each time a monitoring observation is received. However, as the time scale for decision making is longer than the time scale for receiving monitoring outcomes, it is more convenient to update based on a statistical quantity (typically the sample mean) of all monitoring outcomes received in a period. The distribution function for the mean value, $\bar{X}$, for each time step is:

$$F_{\bar{x}|D,L}(\bar{x}|D,L) = \Phi\left(\frac{\bar{x} - E[X|D,L]}{\frac{\sigma}{\sqrt{n}}}\right) \tag{4}$$

where n is the number of measurements used to compute the mean $\bar{X}$. This is valid if D and L do not change significantly during the averaging period, as the outcomes of the random error are assumed independent and normally distributed with a known standard deviation σ. The averaging period should therefore be chosen based on the deterioration model.

If the distribution for the monitoring observation I_M is discretized into k intervals with upper bounds $\bar{x}_k$, the conditional probability of obtaining an outcome in interval k is found by:

$$P\left(I_{M,k}|D,L\right) = F(\bar{x}_k|D,L) - F(\bar{x}_{k-1}|D,L) \tag{5}$$

The expected value of the monitoring outcome depends on damage size D and parameter L. For example, a linear dependency between the expected value of the monitoring outcome and the product DL can be written as:

$$E[X|D,L] = \mu_0 + kDL \tag{6}$$

where μ_0 and k are constants. The constant μ_0 is the mean value of the damage index for a healthy component, and the constant k is the increase of the damage index per unit increase in damage size for a defect where the parameter L is equal to one. The type of functional relationship would depend on the specific problem.

Estimation of model based on knowledge and data

To use the monitoring model described above, knowledge of the function $E[X|D,L]$, the standard deviation σ of the damage index, and the prior distribution of L are needed. The model assumes that the standard deviation of the damage index is independent of the damage size and dependency parameter. If this is the case, the standard deviation can be estimated from data after a run-in period with a healthy component. If this is not the case, this dependence should be included in the model and should be found based on experience. The functional relation between the expected value of the monitoring outcome and D and L could be estimated based on experience, experiments, or models.

Methodology for VoI assessment

To investigate the importance of including temporal dependencies on the value of SHM, the monitoring model presented in the previous section was implemented in a framework for risk-based operation and maintenance planning that was originally published by Nielsen and Sørensen[4]. The framework uses a discrete Bayesian network formulation for the probabilistic modeling, and in the original version, monitoring observations were assumed temporally independent. In this section, the main features of the computational framework are summarized, and the implementation of the monitoring model with temporal dependencies is presented.

Bayesian network model

Bayesian networks provide an efficient way to model deterioration and to perform Bayesian updating using measurements[48]. In the general case, where various types of distributions are applied, inference can be performed using sampling-based methods[49] or efficient exact inference methods can be used if all variables are discrete[50]. The latter approach can also be used for models with continuous variables if they are discretized, and thus an approximation is made. Bayesian networks consist of nodes representing stochastic variables and links representing causal relationships. The dependencies are quantified through the conditional probability distributions specified for each node, conditioned on the parent nodes. An elaborate introduction can be found in Jensen and Nielsen[51].

Generally, deterioration can be modeled using dynamic Bayesian networks, which consist of identical time slices, each only connected to the following and previous time slice. Thereby a Markov chain is made, and if all variables in a present slice are observed, knowledge of previous time slices does not change the belief of the future. However, the deterioration process does not need to be Markovian to be modeled in this way; time-invariant model parameters can be included in each time step, causing the future damage size to be dependent on the past given the present. Figure 2 shows a Bayesian network for a deterioration model with damage size *D* and time-invariant model parameter *M*. Additionally, a node for the monitoring outcome I_M is shown for the case where observations are independent, as in Nielsen and Sørensen[4]. This is modeled by a link pointing from the damage size to the monitoring observation, indicating that the monitoring outcome only depends on the damage size, and the monitoring models are specified as the conditional probability distribution $P(I_{M,i}|D_i)$, where index i denotes the time step.

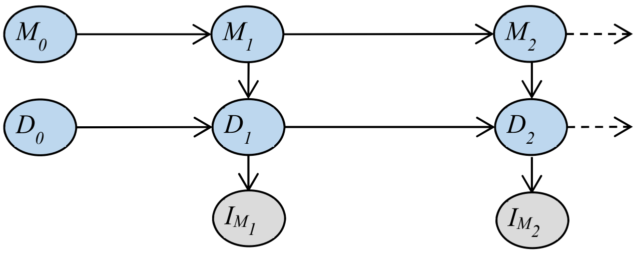


Figure 2: Bayesian network for damage size *D*, model parameter *M*, and monitoring outcome I_M, when monitoring outcomes are not temporally dependent.

To include temporal dependency between observations as described in the section "Modeling temporally dependent monitoring observations", the monitoring model parameter *L*, is added, as shown in Figure 3, Here, the conditional probability distribution for the monitoring observation is specified by $P(I_{M,i}|D_i, L_i)$, as in Eq. (5). This means that the monitoring observation is a stochastic variable that follows a distribution that depends on both *D* and *L*. In this model, there is no dependency between the model parameter *M* for the deterioration and the model parameter *L* for the monitoring observation. If both are affected by a common parameter, e.g. the location, it could be relevant to introduce an additional node that is a parent of both, but this is not included in the present study.

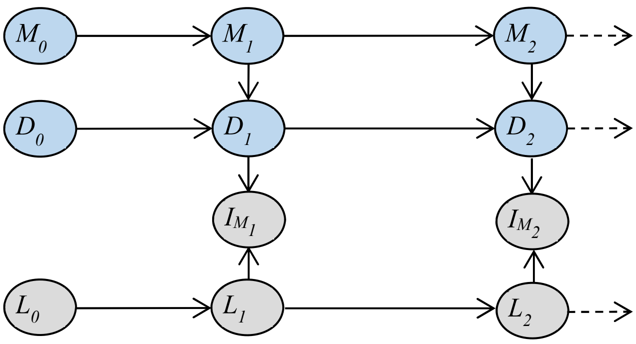


Figure 3: Bayesian network for damage size *D*, model parameter *M*, monitoring outcome I_M, and monitoring model parameter *L*, when monitoring outcomes are dependent.

For the Bayesian network shown in Figure 3, exact inference can be performed efficiently if all variables are discretized. The algorithms presented below are inspired by Straub[48] and Murphy[50] and make use of conditional independencies between variables.

The network is defined in terms of the prior distributions $P(M_0)$, $P(D_0)$ and $P(L_0)$ for the deterioration model parameter, initial damage size, and monitoring model parameter, and the conditional probability distributions $P(M_i|M_{i-1})$, $P(L_i|L_{i-1})$, $P(D_i|D_{i-1}, M_i)$, and $P(I_{M,i}|D_i, L_i)$.

Prediction of future deterioration is performed sequentially using the following expression, where elementwise multiplication is performed for multidimensional distributions:

$$P(D_i, M_i, L_i) = \sum_{L_{i-1}} P(L_i|L_{i-1}) \sum_{D_{i-1}} P(D_i|D_{i-1}, M_i) \sum_{M_{i-1}} P(M_i|M_{i-1}) P(D_{i-1}, M_{i-1}, L_{i-1}) \quad (7)$$

Bayesian updating using monitoring observations is performed using Bayes rule, which is expressed as:

$$P(D_i, M_i, L_i | I_{M_i} = i_{M,i}) \propto P(D_i, M_i, L_i, I_{M,i} = i_{M,i}) = P(D_i, M_i, L_i) P(I_{M,i} = i_{M,i} | D_i, L_i) \quad (8)$$

When monitoring observations are received in all time steps, Eqs. (7) and (8) are used alternating with increasing i, and the joint distributions $P(D_i, M_i, L_i)$ are conditioned on all observations from all past time steps, although for simplicity this is not indicated in the notation applied.

Strategies and decision rules

The computational framework can be applied to find the optimal heuristic decision rules for timing of inspections and repairs, when monitoring is used, and when it is not used, and thereby it allows for computation of the VoI of SHM. For inspections, the implemented decision rules include equidistant inspections, inspection when a threshold for the monitoring observation is exceeded, and inspection when the probability of failure is exceeded. Repairs can also be equidistant, based on inspection outcome, or based on an estimate of the probability of failure. A strategy consists of a decision rule for when to inspect and one for when to repair. In this paper three types of strategies are used, where the decision rules for inspections are given by:

1) Inspection interval for equidistant inspections
2) Threshold for monitoring observation to initialize inspections
3) Threshold for the probability of failure to initialize inspections

For all three strategies, preventive repairs are made when a threshold for the inspection outcome is exceeded.

To estimate the expected lifetime costs for a given strategy and selected decision rules, the probability of inspection, repair, and failure for each time step during the planned lifetime is found using decision models 1 and 2 as described below.

Decision model 1: Bayesian network

For the simple strategies (1 and 2), the decisions are made based on a directly observable value, e.g. the latest monitoring or inspection outcome. These decision rules are formulated as discrete conditional probability distributions, where all probabilities are either zero or one. In this way, the decisions on inspections and repairs are included directly in the Bayesian network model in the nodes for the decisions. In Figure 4, a Bayesian network is shown for strategy 2: 'inspect when the monitoring outcome exceeds the threshold' and 'repair when the inspection outcome exceeds the threshold'. Forward computations as in Eq. (7) are used, and the probability distribution is estimated for each node. The probability of inspection, repair, and failure in each time step is found from the nodes $I_{D,i}$. R_i and D_i. For strategy 1, the nodes $I_{M,i}$ and L are omitted, and the distributions for the nodes $I_{D,i}$ are directly set to a probability of inspection equal to one when inspections are to be made according to the inspection interval, and zero when they should not be made.

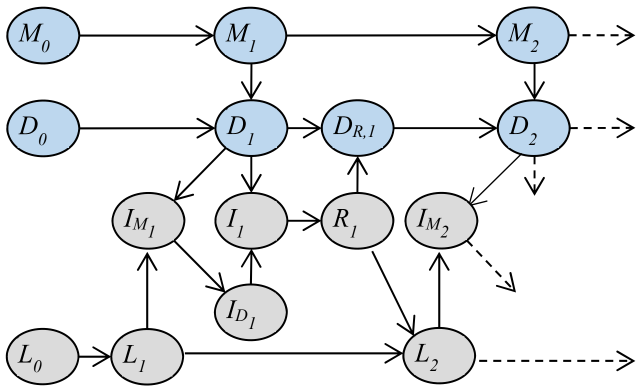


Figure 4: Bayesian network for decision model 1 with damage size *D*, damage size after potential repair D_R, model parameter *M*, monitoring outcome I_M, monitoring model parameter *L*, inspection outcome *I*, inspection decision I_D, and repair decision *R*.

Decision model 2: Monte Carlo simulations and Bayesian network

For advanced strategies, where a threshold for the probability of failure is used, the decision rule cannot be included directly in the Bayesian networks model. Instead, Monte Carlo simulations are used to estimate the probability of inspection, repair, and failure in each timestep. Lifetimes of outcomes of the stochastic variables are simulated from the discrete conditional probability distributions also used in the Bayesian network formulation. Within the simulations, the Bayesian network shown in Figure 5 is used to update the distributions using the same principles as in Eqs. (7) and (8) each time a monitoring or inspection outcome is simulated. Whenever a decision is to be made, the probability of failure within a reference period (e.g. one time step) is estimated based on the updated deterioration and monitoring model, and the decision is made based on this estimate. To use this strategy in practice, the decision-maker will need to have a system where the probabilistic Bayesian network model is regularly updated using observations so that it can recommend decisions based on decided strategies. This system can be seen as a simple digital twin.

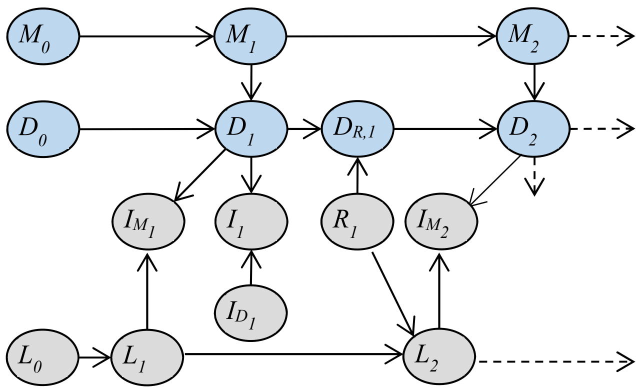


Figure 5: Bayesian network for decision model 2 with damage size *D*, damage size after potential repair D_R, model parameter *M*, monitoring outcome I_M, monitoring model parameter *L*, inspection outcome *I*, inspection decision I_D, and repair decision *R*.

Estimation of total expected costs and VoI

The outcomes of the decision models described in the previous subsections are the probability of inspection, repair, and failure, for each time step t, dependent on decision rules $\boldsymbol{d}$. In the following, these are denoted by $P_I(t,\boldsymbol{d})$, $P_R(t,\boldsymbol{d})$, and $P_F(t,\boldsymbol{d})$ respectively. For the strategy with equidistant inspections, the probability of inspection will be either zero or one for all time steps, as the decision parameters fully define the inspection times. For the other strategies, the inspection times will depend on the monitoring outcomes and the times of future inspections will therefore be uncertain.

The expected lifetime costs to inspections, repairs, and failures, $E[C(\boldsymbol{d})]$, can be estimated by the following summation over the number of time steps T:

$$E[C(\boldsymbol{d})] = \sum_{t=1}^{T} \left(c_I(t) P_I(t, \boldsymbol{d}) + c_R(t) P_R(t, \boldsymbol{d}) + c_F(t) P_F(t, \boldsymbol{d}) \right) \tag{9}$$

where $c_I(t)$, $c_R(t)$, and $c_F(t)$ are the specific cost of an inspection, a repair, and a failure at time t. Normally, a discount factor is included in these terms, which makes them dependent on the time t. However, with time, stationarity will set in for structures that are regularly maintained according to a fixed strategy. When all costs are distributed approximately uniformly in time, the discount factor will not affect the optimal strategy, as all cost contributions are affected equally.

For each strategy, ranges of possible values for each decision rule parameter (intervals and thresholds) are defined. The expected lifetime costs are estimated for each combination using the decision models and Eq. (9). For each strategy, the optimal combination of decision rules is where the lowest expected lifetime costs are obtained. The VoI of monitoring is estimated as the difference in expected lifetime costs for strategy 1 and strategy 2 or 3 when the optimal combinations of decision rules are used for each strategy. If the use of monitoring leads to lower costs, the VoI will be positive. The costs of a monitoring system are not included in the estimated costs, and the VoI is therefore a measure of the maximum price that is economically justifiable to spend on purchasing, installing, operating, and maintaining a monitoring system.

Numerical experiment

The aim of this numerical experiment is to investigate the effect of dependency/correlation between monitoring outcomes on the VoI. Obviously, the best results will always be obtained by the model that represents the reality most accurately. However, the decision-maker generally does not have perfect knowledge of reality, and models will always be simplifications of the reality. Often dependency is omitted due to the difficulties in including it, and the presumption that it is a fair assumption to neglect it.

In this numerical experiment, it is assumed that monitoring outcomes are temporally dependent due to a time-invariant model parameter in the monitoring model. The monitoring system is able to detect defects that are similar, but in slightly different locations, and the specific location of an initiated defect affects the monitoring model parameter. The overall variation of the model parameter is known from test campaigns. The decision-maker wrongly assumes that all the detected variation is random, and he makes decisions and estimates VoI with support from a model built on these assumptions. The aim is to estimate: i) the VoI he expects to get, ii) the VoI he could obtain if he had included dependency correctly, and iii) the VoI he would actually get when using the wrong model.

First, the models and methodology are presented. Then the results for the base case are presented, which is followed by a parameter study in order to derive more general conclusions on when the dependency will have the most influence on the VoI.

Probabilistic models

The intention of this example is to construct a flexible model, where parameters can be adjusted to reflect various deteriorations models, degree of dependencies, etc. The example is inspired by the case of SHM of wind turbine blades, where defects are often categorized in discrete states depending on their severity [42,52,53]. The example follows the assumptions on deterioration and inspection model used in the example in Nielsen and Sørensen[4], except for the monitoring model, and the main assumptions are repeated here.

The time step used in the model is one month, and the planned lifetime is 20 years. The deterioration model is defined by the distributions $P(D_0)$, $P(M_0)$, $P\left(D_i|D_{R,i-1}, M_i\right)$, and $P(M_i|M_{i-1})$. The variable for the damage size, D, has seven states, where the last state is 'fault', and initially, it is in the first state. For the base case, the transition probability is the same for each state of *D*, and the expected value of the transition probability is found such that the mean time to failure is 20 years. Uncertainty on the transition probability (and thereby defect growth rate) is modeled by multiplying the expected value of the transition probability by the time-invariant parameter, *M*. The parameter *M* can take values 0.7, 1.0, 1.3, and the prior distribution is uniform. The inspection model is described by the distribution $P(I_i|D_i, I_{D,i})$. For inspections, the probability of detection for the damage states are respectively 0, 0.4, 0.8, 0.9, 0.95, 0.98, and 1, and if a defect is detected, it is quantified correctly in state 1 to 7. No dependency is assumed between inspections. For further explanation of the models, see Nielsen and Sørensen[4].

Monitoring model

The monitoring model used in the example is based on the model presented in section "Modeling temporally dependent monitoring observations". The expected value of the damage index is assumed to be proportional to the damage size *D*, and to the time-invariant monitoring model parameter *L*: $E[X|D, L]$. The time-invariant monitoring parameter *L* can take values from zero to one. It is zero if the defect does not influence the expected value of the monitoring outcome, and it is one if it has the maximum possible influence. Numerical values are assigned to the discrete damage states by assuming that the last state 'fault' is entered at a damage size of one, the lower bound for the first state is zero, and the six non-faulty states are of equal size. The random noise part of the uncertainty of has a standard deviation of 0.2, and the number of samples in each month is assumed to 30.

The monitoring model is defined by the probability distributions:

- $P(L_0)$: prior probability distribution of time-invariant monitoring model parameter L_0
- $P(L_i|L_{i-1}, R_{i-1})$: conditional probability distribution for parameter *L* in time step i given the value of parameter *L* and the repair decision *R* in the previous time step
- $P(I_{M,i}|D_i, L_i)$: conditional probability distribution for monitoring outcome I_M given damage size *D* and parameter *L*

In the base case, *L* is assumed to follow a uniform distribution over the values 0.0, 0.2, 0.4, 0.6, 0.8, 1.0. As the parameter is assumed time-invariant between repairs, the conditional probability distribution for the decision 'no repair', $P(L_i|L_{i-1}, R_{i-1} = 0)$, is equal to the identity matrix. In case of repair, the distribution for L_i is equal to the prior distribution, $P(L_0)$, regardless of L_{i-1}, because the parameter is assumed to depend on the specifics of the initiated defect.

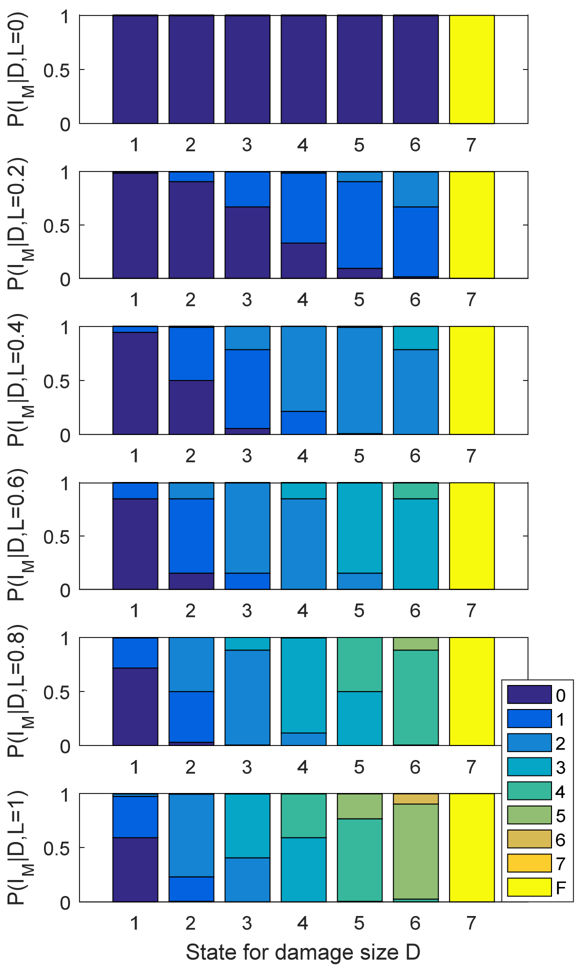
The updating is based on the mean of the outcomes received in a time step (a month), and the distribution $P(I_{M,i}|D_i, L_i)$ is evaluated using Eqs. (4) and (5). With these assumptions and the interval boundaries in Table 1, the monitoring model for dependent observations is found. The model is given by the conditional probability distribution $P(I_{M,i}|D_i, L_i)$, which is illustrated in Figure 6(a). The colors indicate the probability of each monitoring observation, given damage size and parameter *L*. They are influenced by the distance from the product *DL* to each of the monitoring thresholds (given in Table 1), the standard deviation of the sample, and the number of samples. The dependency introduces correlation between consecutive monitoring outcomes, but not full correlation, as there is also a variation due to the random noise. For the case where all variation is random, the observations are uncorrelated. Here, the same overall variation of monitoring outcomes is assumed as for the model with temporal dependency, and the distribution $P(I_{M,i}|D_i)$ is obtained by:

$$P(I_{M,i}|D_i) = \sum_{L_i} P(I_{M_i}|D_i, L_i)P(L_i) \tag{10}$$

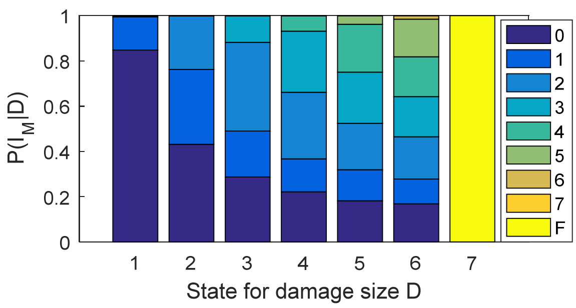
where $P(L_i) = P(L_0)$. The distribution is illustrated in Figure 6(b).

Table 1: Monitoring outcome, I_M, and the associated lower threshold for $\bar{x}$.

I_M	0	1	2	3	4	5	6	7	F
$\bar{x}_{k-1}$	-	0.1	0.2	0.4	0.6	0.8	1.0	1.2	-



(a)



(b)

Figure 6. Monitoring models for correlated (a) and uncorrelated (b) observations. Conditional probability of each monitoring outcome I_M given the state for the damage size *D* and for (a) monitoring model parameter *L*.

Cost model

The specific costs are normalized with respect to the inspection costs, such that the inspection costs are equal to 1. For the base case, the costs of a preventive repair are set to 37.5, and the costs of a corrective repair are 500. These relative specific costs correspond to the costs used in Nielsen and Sørensen[4]. All costs shown in the following are therefore relative costs. The costs of purchasing, operating, and maintaining the monitoring system are not included but should be added to the costs obtained for strategies that use monitoring.

Methodology

The influence of dependency between monitoring observations on the VoI will depend on how they are used for decision making. Three strategies for inspection planning are considered:

1) Equidistant inspections
2) Inspection upon exceedance of threshold for the monitoring outcome
3) Inspection upon exceedance of threshold for the probability of failure

Strategy 1 is included to estimate the expected lifetime costs without monitoring, as this is needed for the assessment of the VoI of monitoring. Strategy 2 and 3 represent the use of a simple and an advanced monitoring-based inspection strategy respectively. For all strategies, preventive repairs are made when a threshold for the inspection outcome is exceeded. As the damage size is quantified correctly in the case of detection, this is also a threshold for the state for the damage size. Therefore, for each strategy, there are two decision parameters: one for decisions on inspections (inspection interval, monitoring threshold, or probability of failure threshold), and one for repairs (damage state threshold).

The VoI will be estimated both when measurements are independent/uncorrelated (un), and when they are dependent/correlated (co). Additionally, the VoI will be estimated when measurements are in fact dependent but are wrongly assumed to be independent (co*). The expected lifetime costs are estimated for the following seven combinations of strategy and assumptions on the correlation between monitoring observations:

- 1: no monitoring
- 2-un: uncorrelated/independent observations
- 2-co: correlated/dependent observations
- 2-co*: correlated observations, assumed uncorrelated when making decisions
- 3-un: uncorrelated/independent observations
- 3-co: correlated/dependent observations
- 3-co*: correlated observations, assumed uncorrelated when making decisions

For the case of independent observations (un), the original framework without the time-invariant monitoring model parameter L is used for identifying the optimal decision rules and associated expected costs. For the case with dependent/correlated observations (co), the extended framework with the parameter L included is used for identifying the optimal decision rules and associated expected costs. For the third case (co*), where monitoring observations are in fact dependent, but decisions are made assuming that they are independent, the optimal decision rules identified in the independent case are used. For decision model 1, the expected costs are simply found by using the Bayesian network model (Figure 4) from the extended framework with the decision rules found using the original model. For decision model 2, Monte Carlo simulations are made by drawing samples from the extended model with dependency parameter L. But the Bayesian network used as a simple digital twin for decision making within simulations is the one from the original model, and the decision rules used are the optimal ones identified using the original framework.

Results of the base case

First, the expected lifetime costs are estimated for strategy 1, where equidistant inspections are made. The expected lifetime costs are estimated for 45 combinations of inspection interval and threshold for repairs as shown in Figure 7. The costs are found directly using Bayesian networks using exact inference algorithms, and the computed expected values are therefore exact given the input. The lowest costs are obtained when inspections are performed every 12 months, and repairs are made when a defect in state 5 or above is detected. The costs are 64.39 times the cost of an inspection.

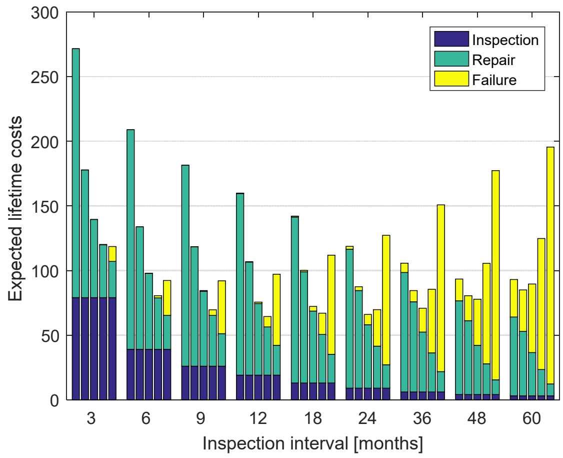


Figure 7. Expected lifetime costs for strategy 1 for inspection intervals from 3 to 60 months. For each inspection interval, five bars are shown for damage state thresholds for repairs 2, 3, 4, 5, and 6.

For strategy 2, decisions on inspections are made based on the state of the monitoring outcome. As for strategy 1, the exact expected costs are found using Bayesian networks. Figure 8 shows the relative expected lifetime costs for 30 combinations of thresholds for inspections and repairs for the cases when monitoring outcomes are uncorrelated and correlated.

For uncorrelated observations, the lowest costs (46.66) are obtained at the monitoring threshold 4, and damage state threshold 5. Here, there are almost no failures. However, if the monitoring observations are correlated, much more failures are generally seen, as low values of the parameter L will lead to defects not being detected. The lowest costs (154.12) are obtained when the monitoring threshold is 2 and the damage state threshold is 3. If the optimal strategy for uncorrelated observations is used, the costs are 181.73.

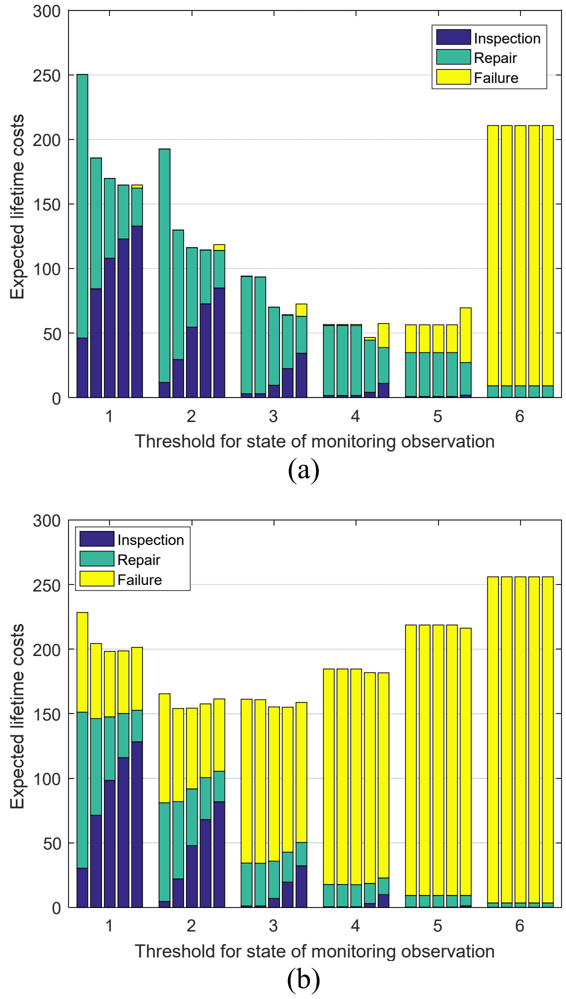
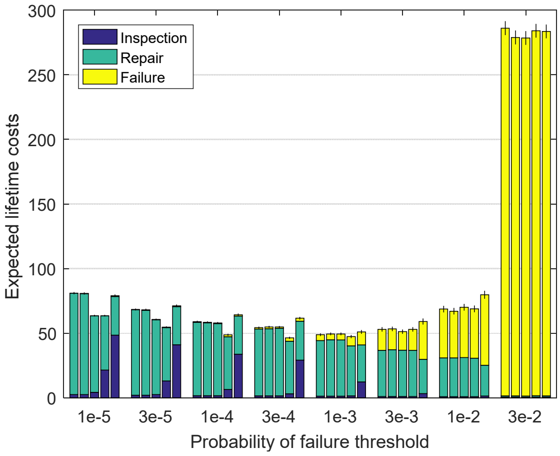


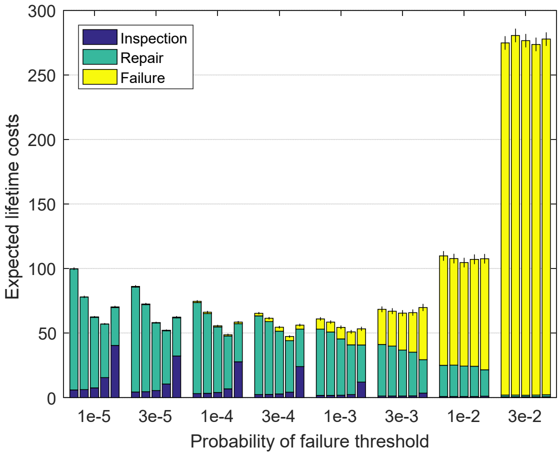
Figure 8. Expected lifetime costs for strategy 2 for (a) uncorrelated and (b) correlated. Costs are shown for thresholds for states of monitoring observations 1 to 6, and for each threshold, five bars are shown for damage state thresholds for repairs 2, 3, 4, 5, and 6.

For strategy 3, decisions on inspections are made based on the probability of failure within a time step (one month). Using 10 000 simulations, the relative expected lifetime costs shown in Figure 9 were obtained. The costs are shown for 40 combinations of the threshold for the probability of failure and threshold for repairs for the cases, when monitoring observations are uncorrelated, correlated, and when they are correlated, but decisions are made assuming that they are uncorrelated.

For uncorrelated observations, the lowest costs are 46 and for correlated they are 47. For both observations, the optimal threshold for the probability of failure is $3 \cdot 10^{-4}$, and the optimal threshold for the damage state for repairs is 5. If the monitoring observations are correlated but are assumed uncorrelated when decisions are made, the expected costs are 184. Although much higher than the costs obtained in the optimal preventive strategy, it is still less than the costs obtained when using only corrective maintenance, which is 285.



(a)



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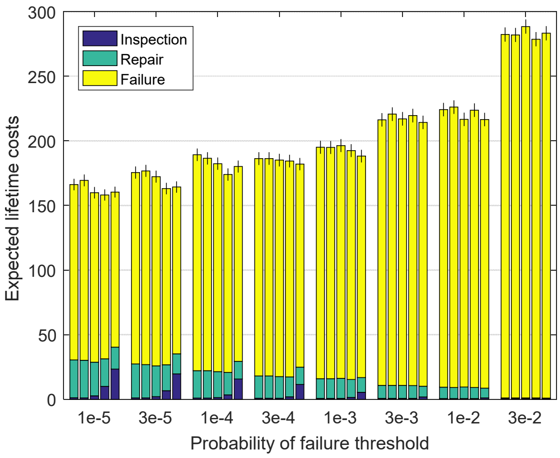
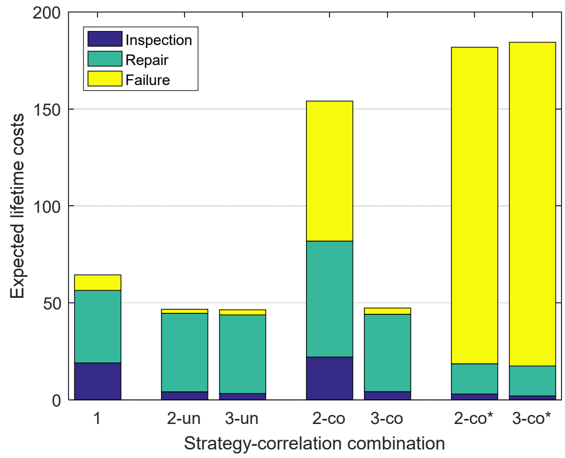


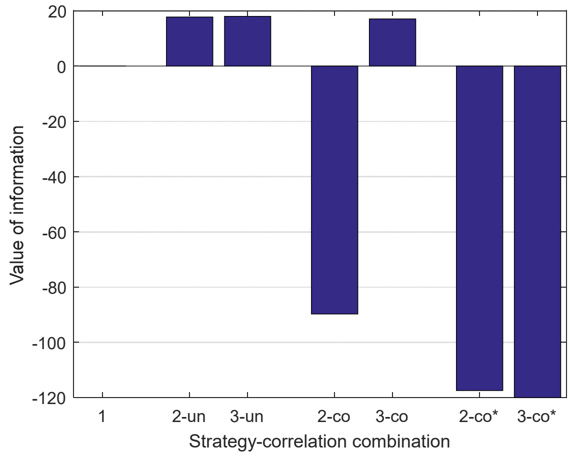
(c)

Figure 9. Expected lifetime costs for strategy 3 for (a) uncorrelated, (b) correlated, and (c) correlated, but assumed uncorrelated. Costs are shown for probability of failure thresholds for inspections $1 \cdot 10^{-5}$ to $3 \cdot 10^{-2}$. For each probability of failure threshold, five bars are shown for damage state thresholds for repairs 2, 3, 4, 5, and 6. The vertical black bars show 95% confidence intervals for the expected costs.

Figure 10(a) summarizes the expected costs for optimal decision parameters for strategies 1, 2, and 3, for uncorrelated and correlated monitoring outcomes, and for the case with correlated monitoring observations that are assumed uncorrelated when making decisions. Figure 10(b) shows the corresponding VoI found as the difference between the costs for strategy 1, and the costs for each of the other strategies. As the costs of the monitoring system are not included, these are also the maximum total lifetime costs of a monitoring system that would be feasible to install. Negative VoI implies that it is better not to use monitoring at all than to use that strategy.



(a)



(b)

Figure 10. Expected costs (a) and VoI (b) for strategy 1 and for strategies 2 and 3 for monitoring observations that are uncorrelated (un), correlated (co), and correlated but assumed uncorrelated (co*).

For uncorrelated observations, both strategies 2 and 3 give a decrease in costs and VoI around 18. For correlated observations, strategy 3 still performs very well, and a VoI of around 17 is obtained. However, using strategy 2 with correlated observations causes a substantial increase in the costs, and thereby a negative VoI of around -90. The reason that strategy 3 performs so well is that the probability distribution for the parameter L is also updated, each time observations are received, thus the distribution is learned. As such the decision model acknowledges the probability of defects, even if the monitoring system shows no increase in measurements. When the observations are assumed uncorrelated but are in fact correlated, the VoI is around -120 for both strategies 2 and 3. This clearly indicates that it can be very important to include the dependency in the model; neglecting it can cause monitoring to increase costs instead of decreasing costs, and the estimated VoI will be incorrect.

Parameter study

To investigate the generality of the tendencies observed in the base case, a parameter study is performed. Variables are changed, one at a time, and the optimal strategies and expected costs are found for each combination of strategy and assumptions on correlation, in the same way as for the base case. To reduce computation time for strategy 3, only values of the probability of failure 10^{-8}, 10^{-7}, 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2} and values for the damage state thresholds 4, 5, and 6 are used.

Changes related to the following seven points are considered, where 1 to 4 are related to the monitoring model.

1) Relation between monitoring outcome and damage size
2) Standard deviation of damage index
3) Shape of prior distribution of parameter *L*
4) Minimum value of parameter *L*
5) Deterioration model shape
6) Mean time to failure
7) Specific costs

Relation between monitoring outcome and damage size

The base case assumed linear dependency between damage size and the expected value of monitoring signal: $E[X|D,L] = DL$. Instead, a non-linear relation could exist, where smaller defects are harder to detect. The following exponential model reflects this behavior:

$$E[X|D,L] = \frac{\exp(c_{exp}D) - 1}{\exp(c_{exp}) - 1} L \tag{11}$$

Where c_{exp} is a constant, determining the shape. Figure 11 shows how the constant affects the shape of the function $E[X|D,L]$. Is can be seen that the relationship is closer to linear for small values c_{exp}, and for c_{exp} =0.1 the relationship is practically linear.

Figure 12 shows the costs obtained for each strategy and assumption on the correlation for five values of c_{exp}. It is seen that an exponential relationship between damage size and monitoring observation increases the feasibility of the three infeasible strategy-correlation combinations, although the VoI is still negative (the costs are higher than for strategy 1 without monitoring). For the uncorrelated cases, the costs would also decrease slightly. Exponential behavior is beneficial because inspections are only carried out when there is a defect that should be repaired and still only a few failures occur. If preventive repair costs were assumed to increase with damage size, instead of being constant, it could be feasible to repair earlier, and exponential behavior could be less beneficial. In contrast to the other strategies, for correlated observations in strategy 3, the costs were found to increase slightly with behavior that is more exponential. This could be because the late increase (in terms of damage size) of monitoring observations makes it harder to update the dependency parameter, because an increase is not expected until quite late, leading to both slightly more inspections and slightly more failures.

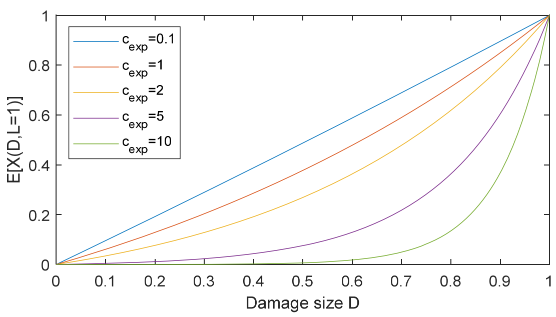


Figure 11. Expected value of monitoring signal $E[X|D,L]$ as a function of damage size *D* for *L*=1.

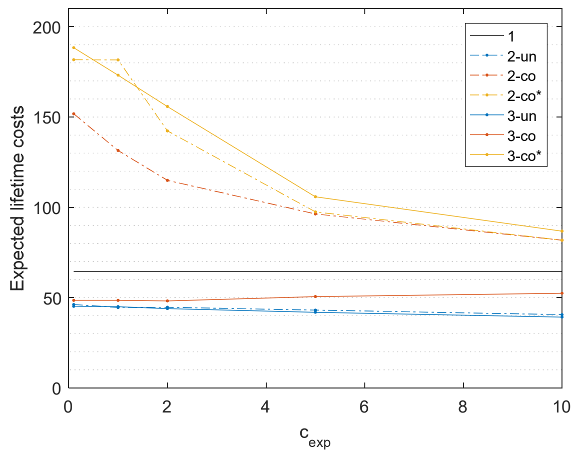


Figure 12. Expected lifetime costs as a function of c_{exp} for exponential dependency between expected monitoring outcome and damage size (base case value: ~0.1).

Standard deviation of damage index

The base case assumed a standard deviation of the damage index σ equal of 0.2, and the number n of samples per time step was 30. Multiplying the standard deviation by a factor x gives the same effect as reducing the number of samples by a factor of x^2, as the sample distribution for the mean of normally distributed signals has the standard deviation $\frac{\sigma}{\sqrt{n}}$. Figure 13 shows the influence of increasing or decreasing the standard deviation.

For the three feasible strategies, the costs are increased when the standard deviation is of the damage index is increased as expected. Surprisingly, for the infeasible strategy 2, for correlated measurements, increasing the standard deviation leads to a decrease in costs. Increasing the standard deviation leads to more inspections and preventive repairs, and fewer failures, and an optimal strategy with lower costs is obtained. This suggests that combining this strategy with inspections occurring almost randomly actually makes it better. In the case of correlated observations, an alternative to the advanced strategy using the probability of failure could be a strategy combining equidistant inspections with monitoring, such that some inspections are still made after a given period, even if the monitoring system does not indicate the presence of defects. This would reduce the number of defects with low values of the parameter L developing to failure.

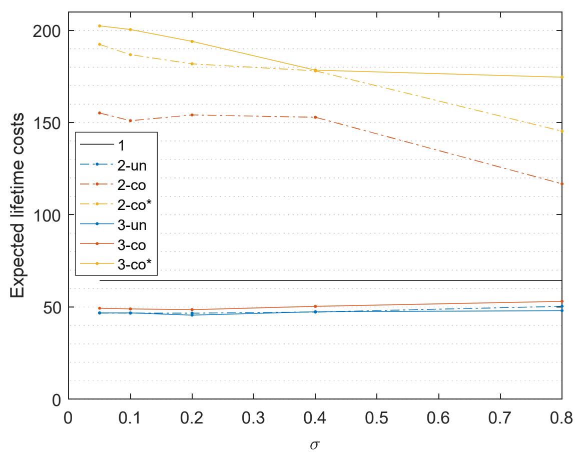


Figure 13. Relative expected lifetime costs as a function of the standard deviation of the signal σ (base case value: 0.2).

Shape of prior distribution of parameter L

For the base case, the dependency parameter *L* was assumed to have a uniform prior. If instead a triangular distribution is assumed, this would reduce or increase the probability of low or high values. Three cases, with an increasing expected value of *L*, are considered here:

- Linearly decreasing triangular distribution (zero probability of *L*=1)
- Uniform distribution (base case)
- Linearly increasing triangular distribution (zero probability of *L*=0)

Figure 14 shows the costs obtained in the three cases. The uncorrelated cases are also affected, as the monitoring model for uncorrelated observations is computed using Eq. (10).

For most strategies, the costs decrease when the expected value of *L* increase, and vice versa if it decreases. However, for strategy 3, when correlated observations are assumed to be uncorrelated, both triangular distributions give smaller costs than the uniform. This could be because the variance of the dependency parameter is smaller when a triangular distribution is used.

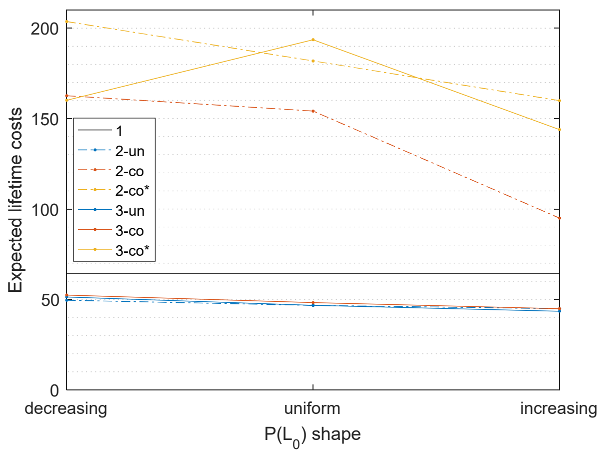


Figure 14. Expected lifetime costs as a function of the shape of the prior distribution of L (base case value: uniform).

Minimum value of parameter L

In the base case, the minimum value of the parameter *L* was assumed to be zero. If the minimum value is increased, and the prior is still assumed to be uniform, the costs are affected as shown in Figure 15. Intuitively, having a low probability of low values of the parameter *L* should lead to decreased costs, as defects will generally be easier to detect. As expected, the costs are seen to decrease when the minimum value of *L* is increased; although, there is a local increase at a minimum value of 0.6 for strategy 2 with correlated outcomes assumed to be uncorrelated. The reason for this is that here the optimal decision parameters for the uncorrelated case change from 4 to 5, which is unfavorable for the correlated case. When the minimum value of the dependency parameter is increased to 0.8, all strategies result in positive VoI. Strategy 3 with correlated monitoring observations – assumed uncorrelated – gives only slightly higher costs than the three best strategies and is better than using the simple strategy 2, considering the correlation. However, if the minimum value of the dependency parameter is 0.6, strategy 2 with correlated monitoring observations still gives positive VoI, unlike both of the strategies in which the correlation is present, but not accounted for.

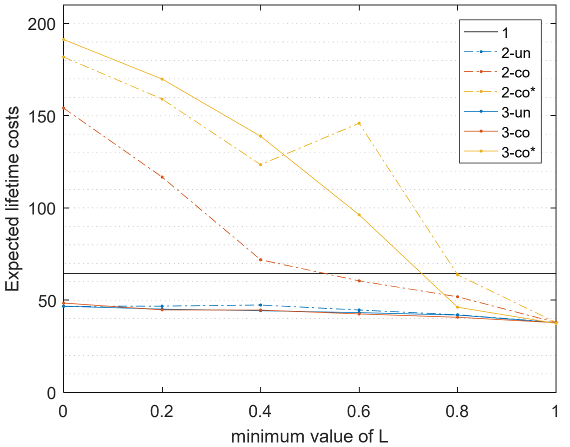


Figure 15. Expected lifetime costs as a function of the minimum value of L (base case value: 0).

Deterioration model shape

For the base case, the transition probability was assumed constant, corresponding to linear damage growth and constant mean sojourn time. For deterioration models with increasing transition probability, the sojourn time is decreasing, and vice versa. For this parameter study, the mean sojourn time is assumed to increase or decrease linearly with damage size. The mean time to failure is kept constant, and the transition probabilities are fully defined when the increase in sojourn time per state is defined. For convenience, this will be referred to as the deterioration growth parameter. Values above one give a convex damage model, and values below one give a concave model. As seen in Figure 16, the general tendency is that costs decrease when the deterioration growth parameter increase; although for some strategies, it begins increasing again. Increasing the deterioration growth parameter gives a similar effect as when having an exponential relationship between damage sizes and monitoring observations; a higher deterioration growth parameter gives lower costs. The reason is that it is then easier to repair defects as late as possible before failure, as thresholds based on damage size are used. When increasing the deterioration growth parameter, most strategies will generate less preventive repairs and inspections (for strategies 2 and 3) but more failures for each set of decision parameters.

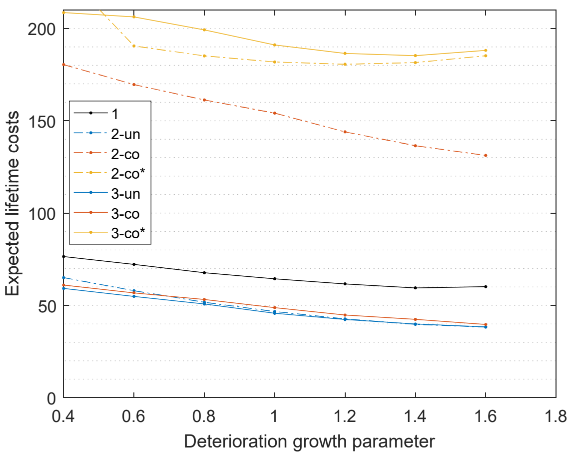


Figure 16. Expected lifetime costs as a function of deterioration growth parameter (base case value: 1).

Mean time to failure

For the base case, the mean time to failure was 20 years. Figure 17 shows the effect of increased mean time to failure. A logarithmic ordinate axis is used, as the costs for all strategies are generally decreased significantly, when the mean time to failure is increased. This is expected, as the probability of failure and consequently, the need for repairs are reduced. For higher mean time to failure, the strategy without monitoring performs worse than all strategies with monitoring, but apart from that, the ratio between the costs for the strategies remains approximately constant.

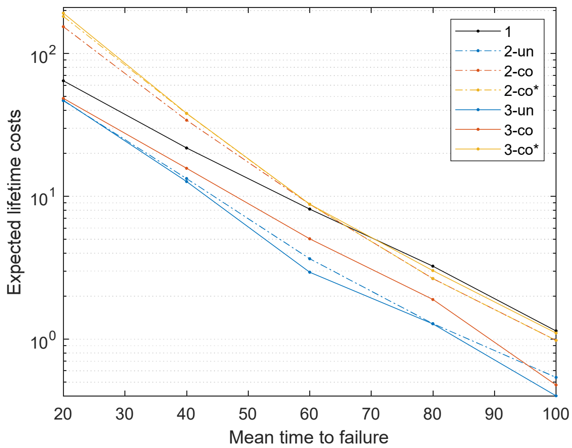


Figure 17. Expected lifetime costs as a function of mean time to failure in years (base case value: 20).

Specific costs

In the base case, the specific costs were defined relative to the costs of an inspection, such that the cost of a preventive repair was 37.5, and the cost of failure was 500. To assess the influence of changing the specific costs, each of the costs is in turn multiplied by a factor ranging from 0.1 to 5, and the optimal decision parameters are identified for each cost. Figure 17 shows the influence on total expected costs and VoI, of changing the specific costs. Naturally, increasing any of the specific costs generally leads to increased costs. However, changing the specific costs shows no difference in how the strategies perform in relation to each other. Smaller inspection costs make strategy 2 better for correlated observations, but it is still worse than equidistant inspections, thus monitoring is not feasible. When reducing the specific failure costs to 50 (0.1 of the base case value), only a third higher than the cost of preventive repairs, all strategies converge to the same costs. Here, a minimum preventive effort is optimal, and the costs are close to those obtained using corrective maintenance only, which are found to 28.5 for failure costs of 50.

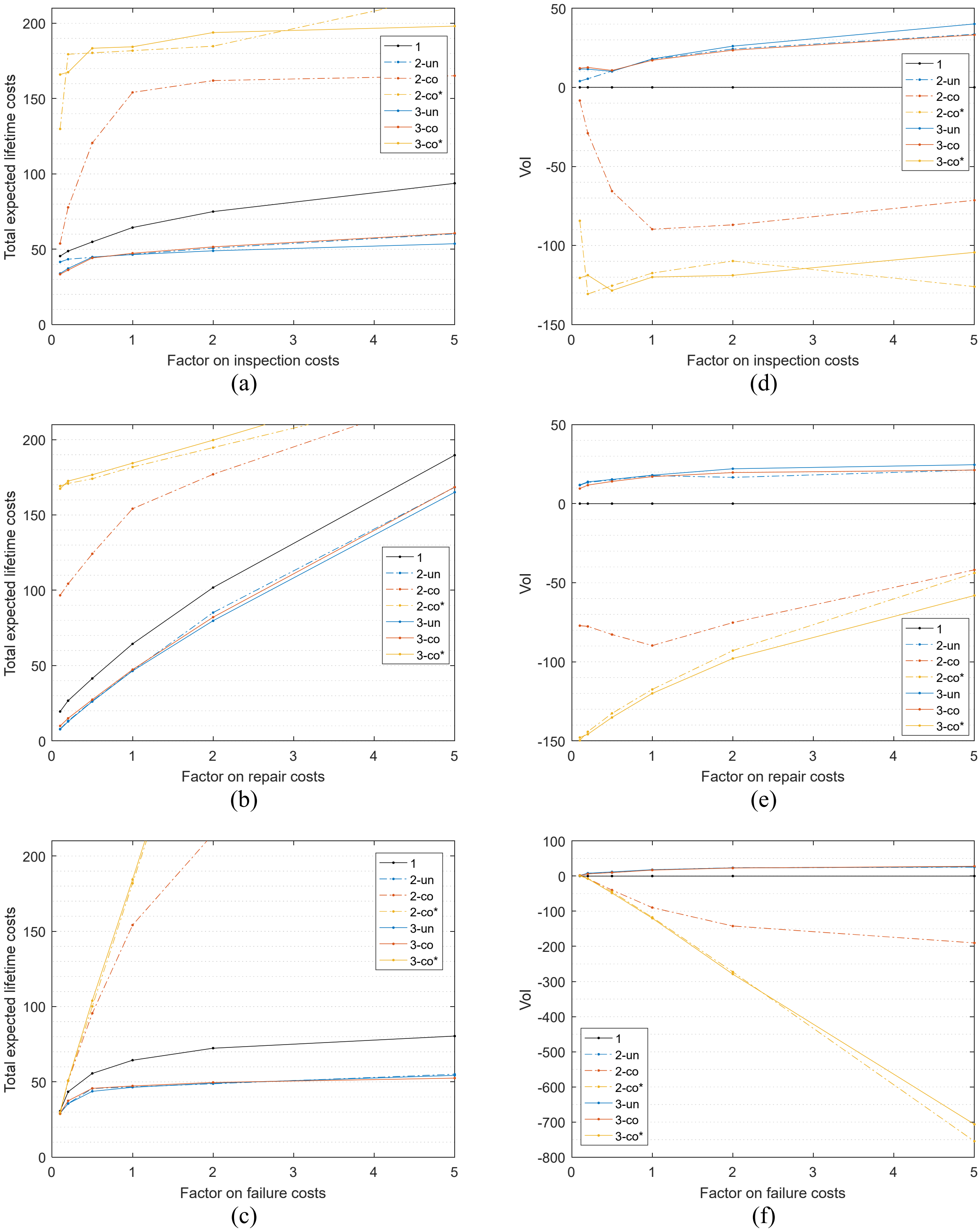


Figure 18. Relative expected lifetime costs (a)-(c) and VoI (d)-(f) as a function of the factor on specific costs of inspection, repair, and failure.

Conclusions

In this paper, the influence of temporal dependency between monitoring observations on the expected lifetime costs and the VoI is investigated. Dependency between measurements is introduced using a time-invariant model parameter modeling the uncertainty on the monitoring model.

Three strategies with heuristic decision rules are applied for the estimation of expected lifetime costs: Strategy 1 without monitoring but with equidistant inspections, strategy 2 where inspections are made when a threshold for the monitoring observation is exceeded, and the advanced strategy 3 where inspections are made when a threshold for the probability of failure is exceeded. For strategies 1 and 2, Bayesian networks are used directly to estimate the costs. For strategy 3, all past monitoring and inspection outcomes are used to update the probability of failure in each time step using Bayesian networks, and Monte Carlo simulations are used to estimate the costs.

The advanced strategy 3 generally performs very well for both uncorrelated and correlated observations. In fact, the presence of correlation generally only gives a minor increase in the expected lifetime costs, because the advanced model is able to learn the distribution of the time-invariant monitoring model parameter. The simpler strategy 2 performs similarly to strategy 3 for uncorrelated observations. However, in the case of highly correlated observations, it leads to much higher costs than when no monitoring was used at all, because many defects are not detected prior to failure, even if a small threshold is used. If decisions are made assuming uncorrelated measurements when they are in fact correlated, it can lead to much higher costs than when no monitoring is used at all for both strategies 2 and 3, as many failures will happen. The parameter study shows that if the uncertainty on the model parameter is small, strategy 2 can be used for correlated measurements with good results, and assuming uncorrelated measurements in case of correlated measurements will be less critical; it will still give positive VoI.

The main conclusion of this paper is that the presence of high dependency between monitoring observations due to high uncertainty on a time-invariant model parameter should not be neglected in a VoI analysis. Doing so can even lead to the realization of negative VoI. However, it is not straightforward to model accurately the dependency. If a sufficient amount of data is available, learning algorithms can be applied, and here it is important to consider the possibility of time-invariant model parameters. The Bayesian network model presented in this paper provides an efficient method for decision support which can include dependencies. As simulations are required for VoI assessment and for finding the optimal strategy, this is quite time-demanding. But the updating required for decision support throughout the lifetime is based on exact inference algorithms and can be made fast and efficiently.

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Declaration of Conflicting Interest

The Author declares that there is no conflict of interest.

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