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BAYESIAN NETWORKS AS A DECISION TOOL FOR O&M OF OFFSHORE WIND TURBINES

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ABSTRACT

Costs to operation and maintenance (O&M) of offshore wind turbines are large. This paper presents how influence diagrams can be used to assist in rational decision making for O&M. An influence diagram is a graphical representation of a decision tree based on Bayesian Networks. Bayesian Networks offer efficient Bayesian updating of a damage model when imperfect information from inspections/monitoring is available. The extension to an influence diagram offers the calculation of expected utilities for decision alternatives, and can be used to find the optimal strategy among different alternatives. The method is demonstrated through application examples.

NOMENCLATURE

O&M: Operation and maintenance
LIMID: Limited memory influence diagram
SPU: Single policy updating
MTBF: Mean time between failures

1. INTRODUCTION

Optimal planning of operation and maintenance (O&M) has the potential of reducing the cost of energy from offshore wind turbines. The costs to O&M are large, up to 25-30% of the cost of energy, because a large number of failures of different components lead to costs to corrective maintenance and lost production. Some component failures can be avoided by using preventive maintenance strategies. Presently much focus is on condition based maintenance, where decisions on repairs are made based on the actual health of the system, see e.g. [1], [2], and [3]. Information on the condition of the components can be gained using inspections and online condition monitoring systems. Many monitoring methods are available, and these are subject to different levels of reliability. The large uncertainties connected to these methods introduce a risk of making non-optimal decisions, if the uncertainties are not dealt with.

Rational planning of O&M could be based on risk-based pre-posterior decision theory, where the decisions with minimal expected costs are made, see the wind turbine framework [4] and the basic theory in [5]. The optimal decisions can be found using a decision tree, if relevant utilities and probabilities are available. Application of risk-based methods requires a probabilistic damage model, and the inspection/monitoring results can be used for Bayesian updating of the model. This can efficiently be done using Bayesian networks, see the framework for deterioration modelling in [6]. Bayesian networks can be extended with utility and decision nodes to form an influence diagram which is a graphical model of a decision tree. Such an approach has been used by [7] for inspection planning for fatigue cracks in offshore jacket structures. This paper focus on the application of influence diagrams for risk-based decision making in the context of repair of deteriorating wind turbine components.

3. BAYESIAN NETWORKS

This section gives a short introduction to Bayesian networks. Elaboration can be found in e.g. [8] and [9]. Bayesian networks were developed in computer science for modelling of artificial intelligence. This requires the ability of a computer to reason under uncertainty and to make rational decisions, while including new information in a consistent way. The name Bayesian network refers to Bayes rule for calculation of a posterior estimate $P(A|B)$:

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

where $P(A)$ is the prior estimate, $P(B|A)$ is the likelihood of A given B, and $P(B)$ is the marginal probability of B.

A Bayesian network is a graphical model that consists of nodes, representing variables, and directed links between them representing causal relationships. The relationships between variables are described using familiar terms, so if X causes Y, X is a parent of Y, and Y is a child of X. The probabilities are given as conditional probability distributions for each node, conditioned on the parents. The joint probability distribution of a network with n nodes can be found using the chain rule:

$$P(V) = \prod_{i=1}^{n} P(A_i | pa(A_i)) \qquad (2)$$

where A_i is the i'th variable and $pa(A_i)$ means the parents of A_i. A node in a Bayesian network is independent of all other nodes, if the parents, children and parents of children are given. This set is called the Markov blanket.

When evidence is received for a node, the joint distribution can be updated using Bayes rule, and posterior marginal distributions can be found. This task is called inference, and for a network where all nodes are discrete exact inference can be performed. Different efficient algorithms are developed, e.g. the junction tree algorithm. For nodes with continuous distributions it is in general not possible to perform exact inference, and approximate methods must be used, e.g. Markov chain Monte Carlo methods.

2.1 DETERIORATION MODEL

For modelling of deterioration it is necessary that the Bayesian network allows development of the damage size over time. For a Markovian process the state of a variable is independent of the past given the state at the previous time step. In general deterioration is not a Markovian process, but if time independent variables are introduced, the Markovian assumption holds for the damage size given these variables, see [6].

This gives the possibility of modelling a deterioration process using a dynamic Bayesian network consisting of equal time slices that each are connected only to the neighbouring time slices. The network then has the property that a time slice is independent of all earlier time slices given the previous slice. The Bayesian network is fully defined when the conditional probability distribution is given for each node conditioned on the parents. Each node has a finite number of mutually exclusive states, and the states are equal for the same node in different time slices.

The Bayesian network modelling framework is usable for damages models, where the damage size at one time step can be calculated based on the damage size at the previous time step and some time-invariant and/or time-variant parameters, as shown in Figure 1. This is the case for e.g. damage models based on fracture mechanics and SN-curves. In is only necessary to include variables that should be modelled stochastic as nodes. Deterministic parameters can be included when calculating the conditional probability distributions.

When no observations are included, the model can be used to find a prior estimate on the damage size at any time step, based on the prior distributions. When observations results are available they can be inserted as evidence, and a posterior estimate is found for parameters and damage size. For a perfect observation procedure the evidence can be inserted directly in the damage node. But for imperfect observations based on e.g. inspection and monitoring an observation node can with advantage be included. This is described in the section with application examples.
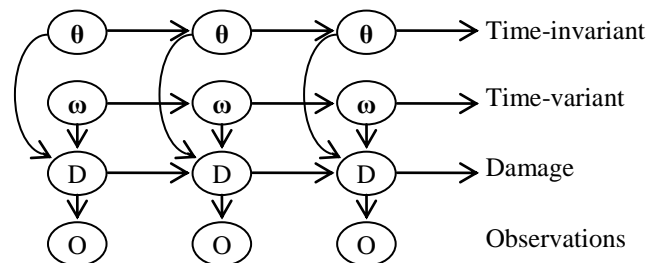

Figure 1. Section of Bayesian network for deterioration modelling. After [6].

3. O&M PLANNING

A life cycle decision problem for O&M of offshore wind turbines includes decisions on the

initial design, inspections/monitoring, and repairs. Inspection/monitoring results give indication of the state of the components, and provide a better basis for making decisions on repairs. Rational planning implies making decisions that maximize the expected utility over the life time, including all available information at the time of decision.

The utilities relevant for the analysis is the cost of initial design, cost of inspection/monitoring, and cost of repairs, both corrective and preventive. The utility of corrective repairs can alternatively be named the utility of component failure. In most structural analyses the probability of failure is very small, and the consequences are very high. But for wind turbines there are many component failures with limited consequences, and the components are repaired or replaced after failure. In addition component failures lead to costs due to lost production, which can be included in the costs to corrective repairs.

The decision problem can be illustrated with the decision tree shown in Figure 2. But the size grows exponentially with the number of time steps, and the probabilities are hard to assess, see e.g. [10].

3.1 INFLUENCE DIAGRAM
An influence diagram is a Bayesian network extended with utility and decision nodes shown as diamonds and rectangular boxes, respectively. Like the Bayesian network it provides efficient updating of a deterioration model, when indirect information is available, and in addition it includes the possibility to find expected utilities for
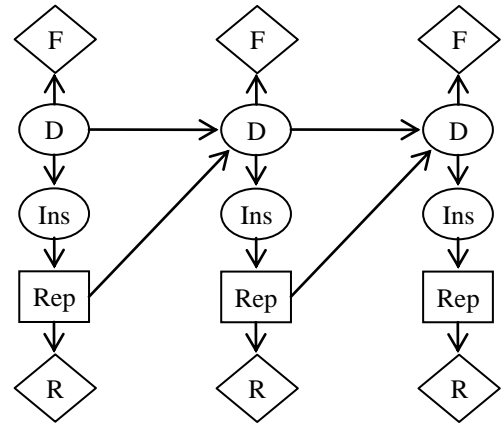

Figure 3. Section of simplified influence diagram for O&M planning with nodes: F: utility of failure, D: damage size, Ins: inspection result, Rep: decision on repair, R: utility of preventive repair.

decision alternatives. A simplified influence diagram for O&M planning is shown in Figure 3.

In general decisions on actions can only change the state of variables in the direction of the links in the network, whereas evidence can propagate both ways, see [9]. A decision on an inspection does not change anything apart from the cost used for it, but the inspection result can change the belief about the state of the unobserved variables. A decision on repair will change the state of the component in the future, but the action will not change the past.

For a diagram as the one shown in Figure 3 there are many decisions. In a traditional influence diagram there is an assumption of no-forgetting, meaning that the entire past is known at the time of the decision. When solving an influence
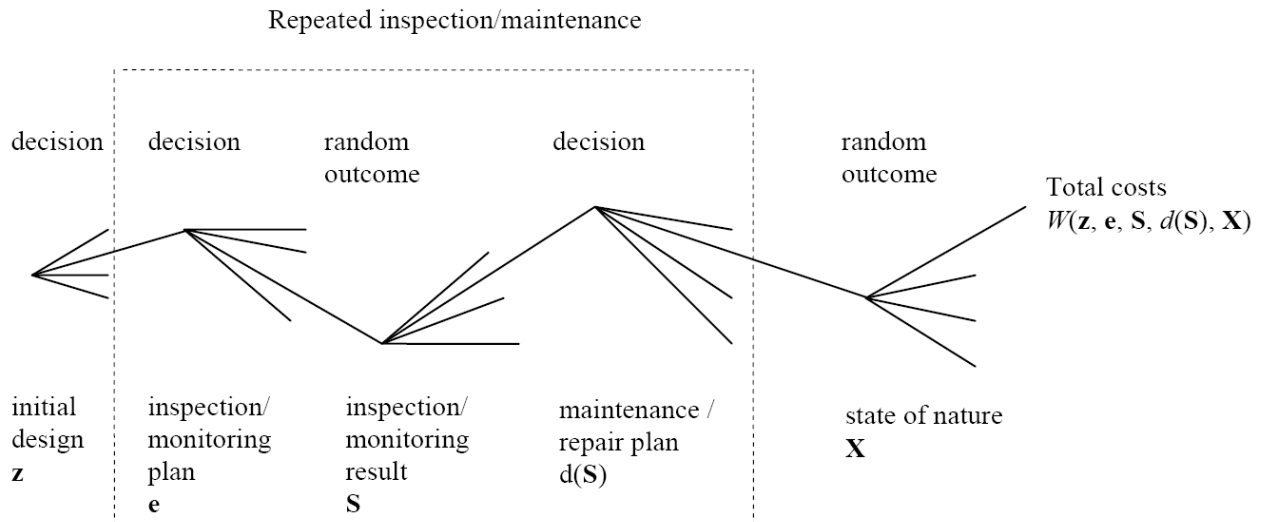
Repeated inspection/maintenance

Figure 2. Decision tree for O&M planning [4].

diagram the optimal decision policy is found for each decision node, dependent on all earlier nodes, both decision and probability nodes. For an influence diagram with only one decision there is no problem, because all previous information is available at the time of the decision. For a network with multiple decisions the same is the case, when the last decision is made. But when the other decisions are made is it necessary to know the policies for future decisions, in order to calculate the expected utilities used for finding optimal policies for the current decision. Thus the domain of a decision node increases exponentially with the number of previous nodes, and for a large network the problem becomes intractable, and it is necessary to use an approximation [11].

3.2 LIMITED MEMORY

Approximations can be utilized in different ways. A no-forgetting influence diagram can be constructed in such a way that the present is blocked from the past, and only the previous time step has influence on the decision. But for a decision problem as shown in Figure 3, which can be seen as a special case of a partially observed Markov decision process, this requires that the calculation of the damage size is not based on the previous damage size, and this is clearly not preferable.

An alternative is to use a limited information influence diagram (LIMID) that was first presented in [12]. The LIMID relaxes the assumption of no-forgetting, and it is necessary to specify exactly what is known at the time of decision. This means that the optimal decision policy is calculated dependent on the parents, so the decision maker knows what decision to make for each possible outcome of the parents. However, it is still possible to enter evidence into the Bayesian network, when it becomes available, and this is taken into account in the calculations. But for future decisions it is assumed that the decision maker only has the evidence from the parents as basis, even though there will be more information available. For a decision on making an inspection, it is not taken into account, that the inspection will give valuable information for a later repair decision, unless the repair node has the given inspection node as parent.

After defining the LIMID and all conditional probability distributions it is compiled into a junction tree. After this procedure evidence can be inserted, and the optimal strategy can be found using the single policy updating (SPU) algorithm, see [12]. The SPU algorithm finds a local maximum, by updating one decision at a time. When convergence is reached a decision with higher expected utility cannot be found by changing only one decision. However, there is no guarantee that the found strategy is also a global maximum. It might be possible to find a better strategy if two or more decisions are changed simultaneously.

4. APPLICATION EXAMPLE

This example shows how an influence diagram can be used for planning of preventive repairs for components exposed to deterioration processes. The model is generic and other damage and inspections models than the chosen ones can easily be adopted. It is assumed that inspections are performed every year in connection with service visits. Based on the inspection results a decision is made on whether a repair should be performed.

4.1 DAMAGE MODEL

The component is assumed to have a mean time between failures (MTBF) of 8 years, and the damage size, D, is measured on a relative scale, where a damage size larger than 1 is in the failure domain. An exponential damage model based on Paris' law for crack propagation is used, where the increase in damage size per stress cycle *dD/dN* is found using:

$$\frac{dD}{dN} = C \, \Delta K^m \qquad (3)$$

where *C* and *m* are model parameters and ΔK is the stress intensity factor range. The stress ranges are assumed to follow a Weibull distribution with scale and shape parameters *A* and *B*, and the differential equation can be solved to give the following, see [7]:

$$D_i = \left(D_{i-1}^{\frac{2-m}{2}} + \Delta K \, M_U A_t^m \right)^{\frac{2}{2-m}} \qquad (4)$$

where M_U is models the time invariant uncertainties, and the stress intensity factor range is found using:

$$\Delta K = C \, N \, \Gamma \left(1 + \frac{m}{B}\right) Y^m \pi^{\frac{m}{2}} \left(1 - \frac{m}{2}\right) \qquad (5)$$

where N is the number of stress cycles per year, and Y is a geometry constant. The model is calibrated using Crude Monte Carlo simulations to give a MTBF of 8 years, when a time step of one year is used. The values and distributions for the parameters are given in Table 1. It is assumed that the damage growth follows the above model from the beginning, where the initial damage size is D_0, i.e. a damage initiation time is not considered.

Table 1. Damage parameters and distributions.

Variable	Distribution	Mean	CoV
m	Deterministic	3	-
C	Deterministic	6E-12	-
B	Deterministic	0.66	-
Y	Deterministic	1	-
N	Deterministic	1E6/year	-
D_0	Exponential	0.02	100%
A_i	Normal	5.35 MPa	18%
M_U	Normal	1	18%

4.2 INSPECTION MODEL

It is important that the inspections are modelled as realistic as possible, and takes the present uncertainties into account. In this example two types of uncertainty are considered; the probability of detection of a damage and the measurement accuracy.

The probability of detection (PoD) is dependent on the inspection procedure, as a more expensive and throughout inspection gives a higher probability that a present damage is found. For a chosen inspection procedure it is in general more probable to detect a large damage than a small, and the PoD is given as function of the damage size (D). For this example an exponential PoD model is chosen, with parameters $P_0 = 1$ and $\lambda = 0.4$:

$$PoD(D) = P_0(1 - \exp(-D/\lambda)) \qquad (6)$$

The accuracy of the measurement of the damage size is modelled by an additive model, where the correct damage size equals the measured damage
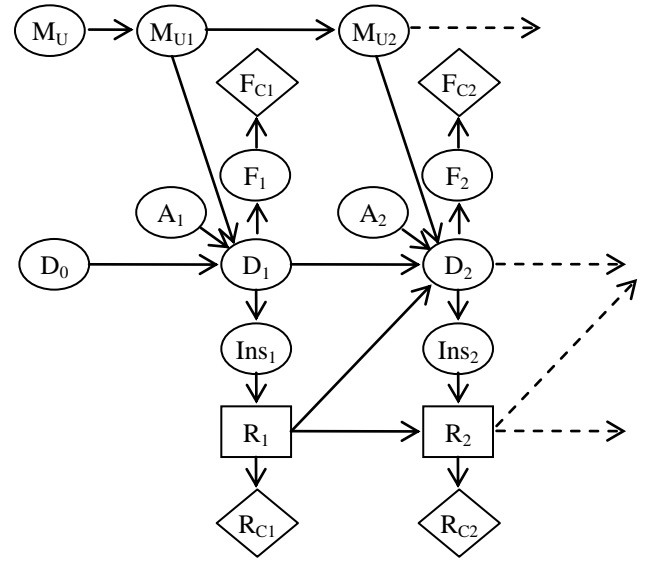

Figure 4. Section of LIMID for calculating optimal repair decisions. F: failure, R: repair, Ins: inspection.

size, D_m, plus a normal distributed error term, ε, with mean zero and standard deviation 0.05:

$$D = D_m + \varepsilon \qquad (7)$$

4.3 LIMID FOR DETERIORAITON

The LIMID for making optimal repair decisions for deteriorating components are shown in Figure 4, and is described in the following.

The LIMID is modelled in the program Hugin [13], and all nodes have to be discrete. Thus the continuous variables M_{Ui}, A_i, and D_i have to be discretized. Different discretization schemes have been tried out and compared to the results obtained by Crude Monte Carlo simulation. In the final scheme the nodes A_i and M_{Ui} have 10 states each, and D_i has 30 states.

Both A_i and M_{Ui} are discretized with intervals of equal sizes, except for the end intervals that are lumped. The interval boundaries are given as

$$-\infty, -3\sigma: \frac{6\sigma}{8}: 3\sigma, \infty \qquad (8)$$

where σ is the standard deviation.
For the damage size, D_i, an exponential increasing interval size is used, because the damage model is exponential, as proposed in [6]. The interval boundaries between 0 and infinity are given as the following, and are shown in Figure 5:

$$\exp\left(\ln(10^{-4}) : \frac{\ln(1) - \ln(10^{-4})}{28} : \ln(1)\right) \quad (9)$$
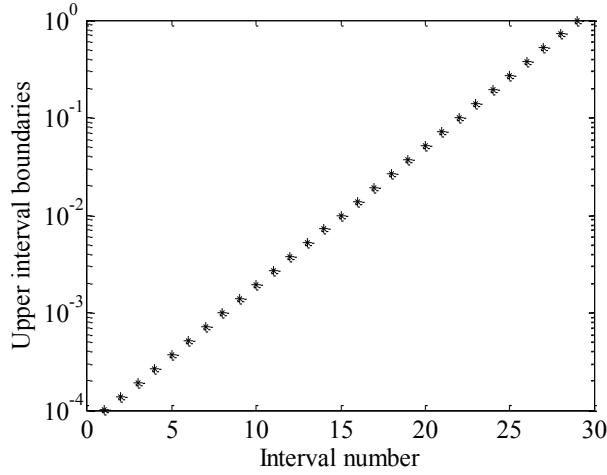

Figure 5. Upper interval boundaries for the node D_i.

The last interval of D_i corresponds to failure, but a binary node, F_i, with states 0 and 1 meaning no failure and failure respectively are also included. This node is necessary for entering the evidence that failure has not occurred as hard evidence. A utility node, F_{ci}, is connected to failure node, and the utility of failure corresponds to the cost of a corrective repair and the associated downtime. The utility of failure is set to -50 k€.

Inspections are modelled by a node, Ins_i, with the same states as D_i plus the state no detection. Based on the inspection results it is decided whether a repair should be carried out. The cost is modelled by the utility node, R_{Ci}, and the utility of a preventive repair is set to -10 k€. A decision node on repair has, besides the current inspection result, also the previous repair decision as parents. This has been done to avoid that the SPU algorithm is stuck at a local maximum, where a higher utility can be found by moving a repair one time step backwards or forwards.

Both corrective and preventive repairs at time step i-1 affect the damage size at time step i, and has to be taken into account when the conditional probability distribution for D_i is calculated. If a repair of either type is performed, D_i is calculated using (4) with the distribution of D_0 instead of D_{i-1}.

The discrete probability tables for the nodes without parents, M_U, A_i, and D_0, are found exact by truncation of the continuous distributions. M_U

is a time invariant variable, and therefore M_{Ui} is the identity matrix. The conditional probability tables for D_i and Ins_i are found using Monte Carlo simulation.

4.5 RESULTS

In order to demonstrate the capabilities of the LIMID, three different cases are examined. Case A is a simple case, where all inspections result in no detection. Cases B and C are more realistic cases, as the inspection results are chosen as realizations from the prior distributions. The observations for nine years are shown for all cases in Table 2.

Table 2. Observations for three cases, N means no detection, F means failure, and a number refers to the interval number.

Year	1	2	3	4	5	6	7	8	9
Case A	N	N	N	N	N	N	N	N	N
Case B	N	N	N	19	21	24	27	F	F
Case C	N	18	21	23	N	26	28	28	F

Evidence is entered in the LIMID for one year at a time, and the expected utility of each decision is found. Both the inspection result and the fact that no failure has occurred yet are entered as evidence. The LIMID in Figure 4 is extended to i=20, corresponding to a design life of 20 years. It is necessary to include the entire life time in the model, in order to get the correct expected utilities.

Figure 6 shows the probability of failure for each time step, calculated based on the information available in the previous time step, and Figure 7 shows the expected utility for decisions on repair.

In case A all inspections results in no detection. This implies that the failure probability is almost constant after the 6th year, because it is unlikely to have a large damage, when none of the inspections indicate so. The utility of repairing remains lower that the utility of not repairing, so no repair should be performed.

In case B the first three inspections also results in no detection, and the curves here are equal to the ones in case A. But a damage is detected in the 4th year, and this gives a drop in the failure probability because the damage size it is now known with less uncertainty that before the

detection. After the inspection in year 7, the probability of failure in year 8 is around 50%, and thus the utility of repair exceeds the utility of no repair – implying that a repair should be performed.

In case C the damage is detected in year 2, and the probability of failure drops as in case B. The inspections year 3 and 4 results in detection of a larger damage, so the probability of failure increases. In year 5 the damage is not detected, but even so it is known from the earlier inspections that damage is present, and the updated probability of failure in year 6 is around 12%. This gives a risk of failure of $0.12 \cdot 50 = 6$ k€, which is actually smaller than the repair cost of 10 k€. But because the repair cannot be avoided but only postponed a year or two, the expected utility of repair here exceeds the utility of no repair.

6. CONCLUSIONS

The paper presents how LIMIDs can be used for risk-based planning of O&M for offshore wind turbines. Bayesian graphical models are well suited for the job because they allow efficient Bayesian updating of the damage model, when information becomes available. Traditional no-forgetting influence diagrams are in general not possible to solve in practical applications because of computational difficulties, but a LIMID where the no-forgetting assumption is relaxed can be used instead. However, this results in an approximate model, and it is necessary to check that the model does in fact find the optimal solution.

An application example illustrated how a LIMID can be used for risk based planning of repairs. It can be used for real time decision making, as the optimal decision is updated, when new information is entered. Specific damage and inspection models were chosen, but the model is in principle generic and can easily be changed to model another case.
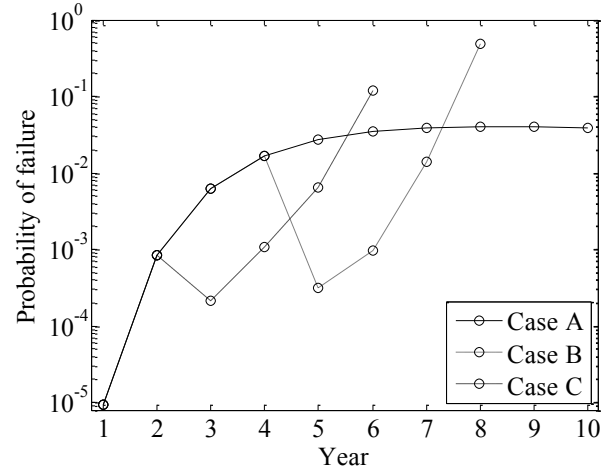

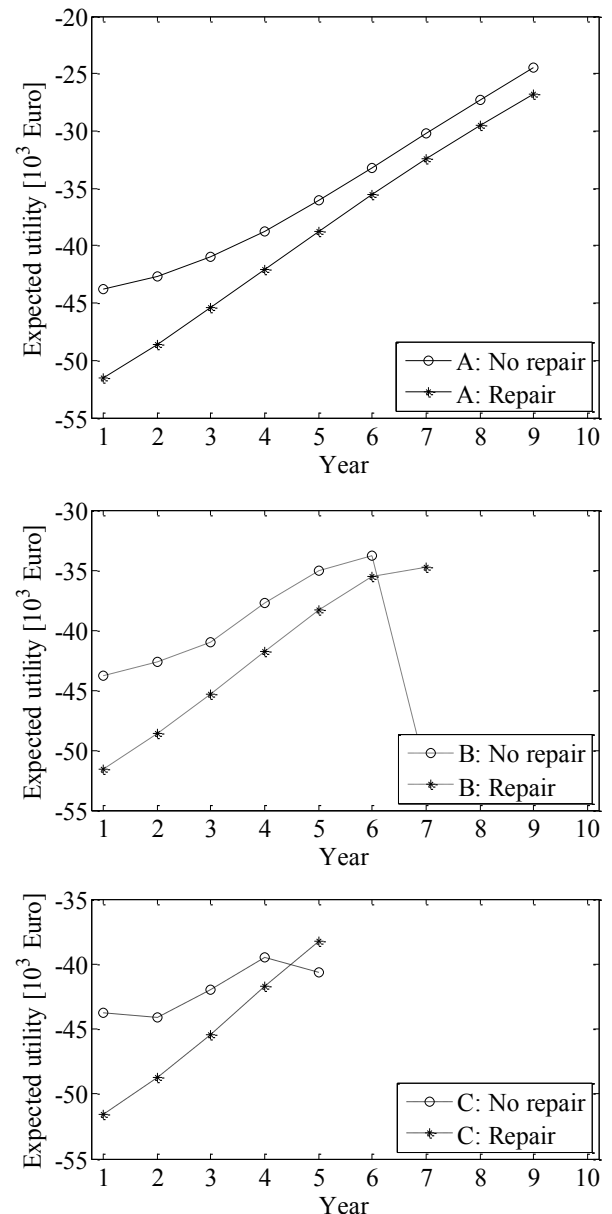Figure 6. Probability of failure based on evidence until the previous time step for case A, B, and C.

Figure 7. Expected utilities for decisions on repairs for each time step for the three cases.

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