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Risk-based optimal inspection strategies for structural systems using dynamic Bayesian networks

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ABSTRACT

In most structural systems, it is neither possible nor optimal to inspect all system components regularly. An optimal inspection-repair strategy controls deterioration in structural systems efficiently with limited cost and acceptable reliability. At present, an integral risk-based optimization procedure for entire structural systems is not available; existing risk-based inspection methods are limited to optimizing inspections component by component. The challenges to an integral approach lie in the large number of optimization parameters in the inspection-repair process of a structural system, and the need to perform probabilistic inference for the entire system at once to address interdependencies among all components. In this paper, we outline a methodology for an integral risk-based optimization of inspections in structural systems, which utilizes a heuristic approach to formulating the optimization problem. It takes basis in a recently developed dynamic Bayesian network (DBN) framework for rapid computation of the system reliability conditional on inspection results. The optimization problem is solved by nesting the DBN inside a Monte-Carlo simulation for computing the expected cost associated with a system-wide inspection strategy. The proposed methodology is applied to a structural system subject to fatigue deterioration and it is demonstrated that it enables an integral risk-based inspection planning for structural systems.

1. Introduction

Deterioration processes in engineering structures lead to a reduction of service life and can affect the safety of the structures. Accurate modeling of deterioration remains a challenge today, due to the complexity of the processes and their inherent uncertainties. To address explicitly the prediction uncertainties, probabilistic approaches are suitable for deterioration modeling in an engineering context ([21,7,31,45,32,72]).

To reduce the uncertainty in deterioration processes, regular inspections are common practice for most engineering structures. An optimal inspection strategy balances the cost of inspections with the achieved risk reduction. An inspection strategy defines [8]: (a) what to inspect for (e.g., thickness diminution due to corrosion or erosion, fatigue cracks), (b) how to inspect (the inspection technique), (c) when to inspect, and (d) where to inspect (which components). Each combination of these factors defines an inspection strategy, among which the optimal one is sought.

Methods for risk-based optimization of inspections on structural systems have been developed during the past 40 years [68,69,63,27,52,57,58,38]. The scientific literature also documents industrial applications of inspection planning on offshore structures, aircrafts, bridges or ships [51,43,10,22,11,35,6]. The theory and the applications have focused almost exclusively on the optimization at the component level, with a simplified treatment of the system [57]. Only limited research efforts have been directed towards optimization procedures for entire systems, accounting for the statistical dependence among the deterioration states of individual structural details [56,57,54,42,33].

Risk-based optimization of inspection-repair strategies for large engineering systems is challenging in practice. Firstly, the interdependence among stochastic deterioration processes for all the system components must be modeled. The two common approaches to such an integral probabilistic deterioration modeling are random fields [16,66,53,70,18] and hierarchical models [28,29,44,2,23]. Secondly, Bayesian updating is required for computing the probability of failure of all components and the system conditional on a potentially large number of inspection results. This is a computationally challenging problem in itself [49]. In the context of inspection planning, these computations must be performed multiple times for the optimization of

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the inspection strategies. Thirdly, the inspection optimization must consider system-wide strategies, which – in the general case – leads to a number of optimization parameters that is exponentially increasing with the number of components [57].

Bayesian methods enable incorporating information from inspections into probabilistic deterioration models to quantify the reduction in uncertainty and to update the reliability estimate [61,26,36,60]. Bayesian Networks (BNs) can facilitate such analyses. BNs have been applied to engineering risk analysis problems during the last two decades [64,13,30,9,15,36,12,67,3]. Conditional independence among model parameters encoded in the graphical structure of the BN can facilitate the Bayesian updating. In addition, if a process can be represented by discrete random variables (e.g. by discretizing all continuous random variables), exact inference algorithms can provide fast and robust solutions to the Bayesian updating. These properties have been exploited in Straub [54] and Luque and Straub [25], where dynamic Bayesian networks (DBNs) are utilized to evaluate deterioration at the component and system level. Bespoke exact inference algorithms ensure rapid computation of the conditional probability of system failure given all inspection results, which is essential for solving the optimal inspection problem.

In this paper, we propose a heuristic approach to finding the optimal inspection strategy in structural systems. In contrast to existing methods, the approach can simultaneously account for system effects arising from (a) the dependence among the deterioration at different components, (b) the joint effect of deterioration at multiple components on the system reliability, and (c) the interaction among inspection costs, i.e. the reduction in the marginal cost of an inspection if these are grouped in larger inspection campaigns. This is achieved with the proposed heuristic approach to the optimization, which enables the definition of a system-wide inspection plan with just a few parameters. The optimization criterion is the total expected life-cycle cost, whose computation is made feasible by a novel two-level approach, in which the system DBN algorithm of Luque and Straub [25] is nested within a Monte-Carlo simulation that addresses the uncertainty on the inspection outcomes. The DBN algorithm allows to compute the conditional probability of system failure given inspection outcomes.

The proposed methodology is demonstrated and investigated by application to a Daniels system, an idealized redundant structural system, whose components are subject to fatigue deterioration.

2. Methodology

2.1. The inspection optimization problem

An inspection strategy for a structural system defines when, where, what and how to inspect. In general, static inspection regimes are not optimal; instead, one should account for results from previous inspections and maintenance activities when deciding upon new inspections. For this reason, the optimal inspection-planning problem belongs to the class of sequential decision problems [1,19].

The sequential inspection planning problem is visualized in the decision tree of Fig. 1. Branches following a circular node represent random outcomes (e.g. the deterioration state of the system, or the inspection outcomes) and branches after a square node represent possible decision alternatives (e.g. if and where to inspect or repair). This decision tree is equally applicable to single components or entire systems. When considering systems, the outcome space of the random variables and the number of decision alternatives increase exponentially with the number of components. This is one of the main reasons why previous work on risk-based inspection planning has focused mainly on individual components.

Solutions to sequential decision problems can be found through the definition of policies. Here, a policy for a decision at time t defines where, what and how to inspect and repair, taking into account the full history of the structure up to t, i.e. past inspection outcomes and repair actions. The set of policies at all times t is the strategy $\mathcal{S}$. If the policies are the same for all t, the strategy is stationary [17].

For a structural system with N components subject to deterioration, the inspection optimization problem of Fig. 1 can be formalized as follows. The joint deterioration state $\mathbf{D}$ of all components is represented through a probabilistic system deterioration model with random parameters $\mathbf{X}_D$. Each component can be inspected and/or repaired at discrete times t from 0 to the end of service life T. The strategy $\mathcal{S}$ defines for each component at each time step if and how that component is inspected and repaired, based on all previous inspection outcomes $\mathbf{Z}$ and the repair history of the structure.

Inspections, repairs and system failure are associated with consequences. These are quantified by the present value of total life-cycle cost C_T in function of the strategy $\mathcal{S}$ and the inspection outcomes $\mathbf{Z}$. It is defined as the sum of the life-time inspection cost C_I, repair cost C_R, and failure risk R_F:

$$C_T(\mathcal{S},\mathbf{Z}) = C_I(\mathcal{S},\mathbf{Z}) + C_R(\mathcal{S},\mathbf{Z}) + R_F(\mathcal{S},\mathbf{Z}) \tag{1}$$

For a given strategy $\mathcal{S}$ and inspection outcomes $\mathbf{Z}$, the inspection and repair actions are fixed. Hence, $C_I(\mathcal{S},\mathbf{Z})$ and $C_R(\mathcal{S},\mathbf{Z})$ can be directly evaluated in function of the cost of individual inspections and repairs, and the relevant discount rate.

The failure risk R_F is defined as:

$$\begin{aligned} R_F(S,\mathbf{Z}) &= \sum_{t=1}^{T} c_F\cdot\gamma(t)\cdot\Pr(F_t\ |\mathbf{Z}_{0:t-1}) \\ &= c_F\cdot\sum_{t=1}^{T}\gamma(t)\cdot[\Pr(E_{S,t}=Fail\ |\mathbf{Z}_{0:t-1}) - \Pr(E_{S,t-1}=Fail\ |\mathbf{Z}_{0:t-1})] \end{aligned} \tag{2}$$

where c_F is the undiscounted cost of a system failure event, $\gamma(t)$ is a discount factor, F_t is the event of a system failure during time step t, and $E_{S,t}$ is the system condition at time step t.

The conditional probability $\Pr(E_{S,t}{=}Fail|\mathbf{Z}_{0:t-1})$ is the probability of a system failure up to time t for given inspection outcomes $\mathbf{Z}_{0:t-1}$. Its computation is a structural reliability problem, which can be formulated as an integral over all random variables $\mathbf{X}$ of the problem (which include the deterioration parameters $\mathbf{X}_D$, but also load parameters):

$$\Pr(E_{S,t}=Fail\ |Z_{0:t-1}) = \int_{\Omega_x}[g_{S,t}(x)\leqslant 0]\cdot f_{x|Z_{0:t-1}}(x)\mathrm{d}x \tag{3}$$

$g_{S,t}(\mathbf{x})\leq 0$ is the limit state function describing system failure up to t, $I[\bullet]$ is the indicator function and $f_{\mathbf{X}|\mathbf{Z}_{0:t-1}}$ is the conditional probability density function of $\mathbf{X}$ given inspection outcomes $\mathbf{Z}_{0:t-1}$.

The solution of Eq. (3) is non-trivial, in particular if the system size and the number of observations are large. First Order Reliability Method-(FORM) and sampling-based solutions to this problem are available [55,60,49]. In inspection planning, the conditional probability must be evaluated many times, and an efficient and robust solution of Eq. (3) is thus required. For this reason, we apply DBNs to solve Eq. (3) following Luque and Straub [25].

Because the inspection outcomes $\mathbf{Z}$ are random variables themselves and are not known in advance, the total cost is also a random variable. If $f_{\mathbf{Z}}$ is the probability distribution of the vector of inspection outcomes, whose support $\Omega_{\mathbf{Z}(\mathcal{S})}$ depends on the strategy $\mathcal{S}$, then the expected total life-cycle cost associated with the strategy $\mathcal{S}$ is obtained as

$$\mathrm{E}_{\mathbf{Z}}[C_T(S,\mathbf{Z})] = \int_{\Omega_{\mathbf{Z}(S)}} C_T(S,\mathbf{z})f_{\mathbf{Z}}(\mathbf{z})\mathrm{d}\mathbf{z} \tag{4}$$

The optimal strategy $\mathcal{S}^*$ is defined as the one that minimizes the expected total cost:

$$\mathcal{S}^* = \underset{\mathcal{S}}{\mathrm{argmin}}\,\mathrm{E}_{\mathbf{Z}}[C_T(\mathcal{S},\mathbf{Z})] \tag{5}$$

This optimization is commonly subject to constraints on the