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INSPECTION AND MAINTENANCE PLANNING IN LARGE MONITORED STRUCTURES

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Structural health monitoring (SHM) systems have become a popular technology to collect information about the condition of structural assets. SHM is typically paired with traditional onsite inspection and maintenance (I&M). Incorporating SHM information in I&M planning is non-trivial, but is key to an improved prediction of the structural condition and to save costs on I&M. In this paper, we propose a framework to combine SHM information with visual inspections and repair actions. It utilizes a hierarchical dynamic Bayesian network (DBN) to probabilistically model the deterioration in the structural system, including all component interactions. The DBN calculates the evolution of the system probability of failure given the monitoring information and I&M actions. By attributing discounted costs to I&M actions and to the consequences of failure, we calculate the expected life cycle-cost for a given I&M strategy by simulating monitoring and inspection histories. The cost optimization of I&M strategies is then approached with a heuristic approach. Finally, the value of information of the SHM system is calculated by comparing the optimal strategies with and without monitoring system.

Keywords: Structural Health Monitoring, Reliability, Optimization, Value of Information.

1 The added value of Structural Health Monitoring

With the development of cheaper sensors and increased automated data storage and computing power, structural health monitoring (SHM) systems in civil engineering infrastructures have grown popular in the past decade. A major goal of SHM application is to reduce the high uncertainty surrounding the stochastic deterioration process that these structures are typically subject to. The financial impact of SHM systems on operational costs can be quantified as the potential gain from integrating the information collected by the monitoring system into the inspection and maintenance (I&M) planning. Several challenges arise when quantifying this gain. Firstly, the monitoring data needs to be processed and translated into the system model to propagate the collected information to the quantities of interest (e.g. identify component failure within a system based on data). Secondly, the monitoring data might also reflect the influence of parameters that are not identified by the model and can lead to erroneous conclusions (Ostachowicz and Güemes 2013). Finally, quantifying the value of information (VoI) of the data that will be collected compared to not having a monitoring system involves a sophisticated analysis based on Bayesian decision theory (Schlaifer and Raiffa 1961). For large systems, the solution becomes computationally expensive or intractable due to the high number of possible deterioration histories, actions and inspection and monitoring outcomes (Straub and Faber 2006). Within the framework of risk based inspection (RBI) planning (Straub and Faber 2005), several studies have investigated the VoI of SHM in simple deteriorating systems by comparing expected total life cycle costs with and without SHM (Pozzi and Der Kiureghian 2011, Zonta et al 2014).

In these studies, interdependence and interactions among components were ignored or the strategy optimization was carried out at a component level, not at a system level. It is not clear how these approaches can be extended to consider a system of interdependent components.

In this paper, we adopt a dynamic Bayesian network model described in (Straub 2009, Luque and Straub 2016, Bismut et al 2017) to integrate the SHM into the structural system model with interdependent components. The I&M strategy optimization is performed with a heuristic approach (Luque and Straub 2017, Bismut et al 2017), with and without SHM, to obtain the VoI of the SHM. The proposed methodology is summarized in section 2. In section 3, the methodology is applied to a single-component system with a damage detection monitoring system. In section 4, a large structural frame is considered and the effect of a SHM on the expected cost of one strategy is investigated.

2 Integrating SHM in the inspection and maintenance planning process

Because of the stochastic nature of deterioration processes in infrastructures, such as corrosion or fatigue, determining an optimal I&M plan is non-trivial. The sequential decision process associated with I&M actions and their effect on the total lifetime of the system can be represented by a simple decision tree (from Straub and Faber (2005)), where each decision path leads to the failure or the survival of the system. The decision process can be represented more concisely by an influence diagram (Fig. 1). The evolution of the system is here modelled as a Markov process; non-Markovian deterioration processes can be transformed to Markovian processes by state-space augmentation (Straub 2009).

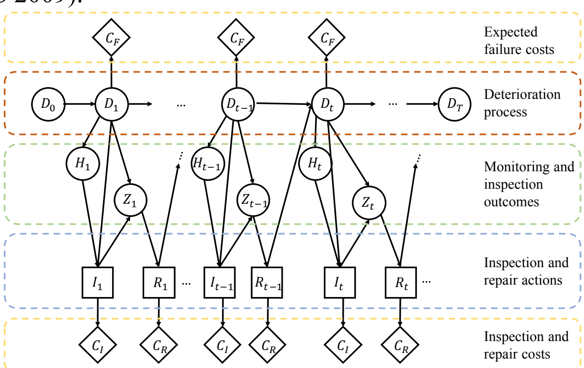

Figure 1. Influence diagram, assuming a discrete-time model. D_t is the deterioration state of the system at time step t, H_t the monitoring outcome and Z_t the inspection outcome.

Finding the optimal I&M strategy is equivalent to finding the strategy which minimizes the expected total life-cycle cost (Luque and Straub 2017, Bismut et al 2017). The system performance and evolution is modelled by a dynamic Bayesian network (DBN) model with discrete-state variables. The expected life-cycle cost of a strategy is estimated with a Monte Carlo simulation over deterioration histories of the system. The strategy optimization is performed with a heuristic approach, whereby the strategies are characterized by a small number of parameters. The approach is described in detail in Bismut et al (2017).

3 Numerical application to a single-component system

3.1 *Deterioration process*

For illustrative purposes, we first consider a very simple model. The system damage at time t is described by a random variable $D_t > 0$, and failure occurs when the damage exceeds 1. The initial damage D_0 is exponentially distributed with mean value 0.02. The deterioration process is modelled as a Markov process, where the state of the system D_{t+1} at time $t+1$ is dependent on D_t at time t through Eq. (1), where A is lognormal with moments $\mu_A = 0.02$ [yr^{-1}] and $\sigma_A = 0.04$ [yr^{-1}]:

$$D_{t+1} = D_t + \mathrm{A}. \tag{1}$$

The design life of the structure is $T = 40$yr.

3.2 *Inspection and repair*

The inspection is characterized by the probability of detection (PoD), which gives the probability that an inspection would identify a problem. It is defined in function of the damage d as $PoD(d) = 1 - \exp\left(-\frac{d}{500}\right)$. If the damage exceeds a threshold D_{rep}, the system is repaired, which corresponds to restoring it to the initial state, i.e. the probability distribution of the damage after a repair is the one of D_0.

3.3 *SHM*

The monitoring system provides information on the state of the system at every time step. The SHM variable H can take two states 'damaged' or 'safe', with the conditional probabilities: $\Pr[H = 'damaged' | D > 0.4] = 0.8$ and $\Pr[H = 'damaged' | D < 0.4] = 0.3$. The monitoring outcomes at multiple time steps are here assumed to be independent conditional on D.

3.4 *Strategy cost and SHM Value of Information*

The expected cost of a strategy is the discounted sum of the expected inspection and repair costs and the risk of failure for each year t. The probability of system failure up to time step t, conditioned on the previous monitoring and inspection outcomes, can be found with the DBN. The exact formulation of the expected strategy cost is given in Bismut et al (2017) and the parameters of the cost function are provided in Table 1.

The VoI of the SHM is the difference between the expected cost of the optimal strategy without SHM and the expected cost of the optimal strategy with SHM. We assume a risk-neutral decision-maker.

Table 1. Cost function parameters.

Inspection	Repair	Failure	Discount rate
1	10	$3 \cdot 10^3$	0.02

3.5 *Heuristics*

We investigate a heuristic characterized by three parameters, here listed with their possible values:

- Inspections are carried out at fixed inspection intervals $\Delta T = \{1,2,..10,15,20,25,30,35\}[\mathrm{yr}]$.
- When the annual probability of failure of the system exceeds the probability threshold p_{th}, an inspection is carried out. The investigated threshold values are $\{10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1\}$.
- The system is repaired if the deterioration exceeds a threshold value $D_{rep} = \{0, 0.2, 0.6, 1\}$.

3.6 *Strategy optimization results*

The expected cost of each strategy with and without SHM is approximated with a Monte Carlo simulation over 400 deterioration histories; it is plotted in Figs. 4 and 5. The optimal strategies without and with SHM are given by $\mathcal{S}_{\text{opt,no SHM}} = \{\Delta T = 5, p_{th} = 10^{-3}, D_{rep} = 0.2\}$ and $\mathcal{S}_{\text{opt,SHM}} = \{\Delta T = 10, p_{th} = 10^{-3}, D_{rep} = 0.2\}$. As shown in Fig. 5, for $\Delta T > 10$, the expected strategy cost with SHM is significantly lower than without SHM. This is due to a reduction in the risk of failure from the information regularly provided by the monitoring system.

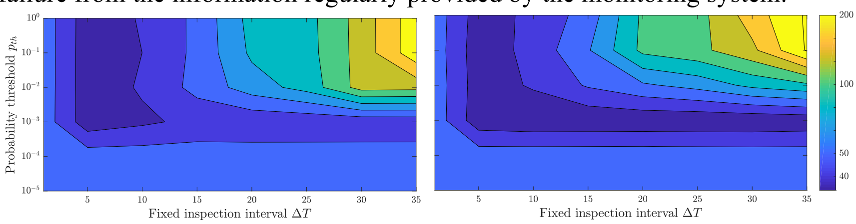

Figure 4. Contour plots of the expected strategy cost without (left) and with (right) SHM, for $D_{rep} = 0.2$.

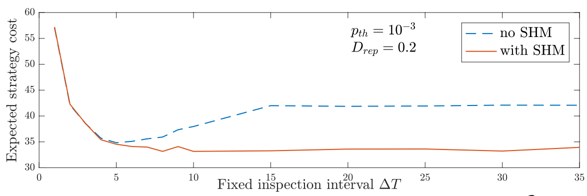

Figure 5. Evolution of the expected strategy cost for $p_{th} = 10^{-3}$ and $D_{rep} = 0.2$.

The expected cost of the optimal strategies are estimated to be $\mathbf{E}[C_T(\mathcal{S}_{\text{opt,no SHM}})] = 34.8$ and $\mathbf{E}[C_T(\mathcal{S}_{\text{opt,with SHM}})] = 33.2$. Hence the VoI of this monitoring system is $34.8 - 33.2 = 1.6$. This value can serve as a basis for the decision of the operator whether or not to implement the SHM system.

4 Numerical application to a large structural frame

4.1 *DBN model*

The Zayas frame example is taken from Bismut et al (2017). In this frame structure, 22 fatigue hotspots constitute the system components. The frame is loaded laterally with a time-varying load, and failure is determined by the deterioration state and the applied load. The DBN models the deterioration process at the component level and at the system level as per Fig. 6. The model parameters are according to Bismut et al (2017). The SHM model is taken as in section 3.3, and monitoring information is acquired every 5 time steps.

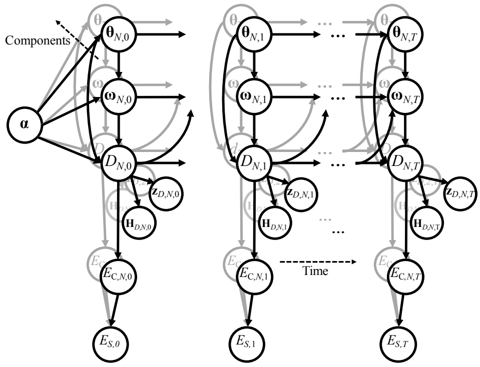

Figure 6. Hierarchical DBN model of the deterioration process of the Zayas frame. The components' interdependence is modelled through the hyper-parameters α (adapted from Luque and Straub (2016))

4.2 *Approximation of the annual risk of failure*

In this example, the event F_t='system failure between time steps 0 and t' is the union of the interval events F_t^*='system failure between time steps $t-1$ and t', which cannot be assumed to be disjoint or independent events due to the random load applied at every time step. However, it is reasonable to approximate $\Pr[F_t]$ with an upper bound based on the assumption of independent failure events as per Eq. (2). An equivalent formula is used for $\Pr\left[\mathrm{F_t}|(\boldsymbol{z},\boldsymbol{h})_{1:22,0:t}\right]$.

$$\Pr[F_t] \approx 1 - \prod_{0\leq i\leq t} 1 - \Pr[\mathrm{F_i^*}] \tag{2}$$

$\Pr[F_i^*]$ can be calculated from the DBN by discrete inference. The algorithm is described in Luque and Straub (2016), and is adapted to include monitoring results. The annual probability of failure is defined as:

$$\Pr\left[F_{annual,t}\right] = \Pr[F_t] - \Pr\,[F_{t-1}]. \tag{3}$$

4.3 *Heuristics*

The heuristic is defined by parameters ΔT, p_{th} and D_{rep} as in section 3.5, and additionally:

- The number $\mathrm{n_I}$ of components to be inspected at every inspection campaign.
- A component prioritization parameter η introduced in Bismut et al (2017).

For the purpose of this study, we compare the expected cost of one strategy $\mathcal{S}^*$ with and without monitoring system, defined by $\mathcal{S}^* = \{\Delta T = 20, p_{th} = 10^{-2}, D_{rep} = 0, n_I = 10, \eta = 1\}$.

4.4 *Effect of SHM on expected strategy cost*

The expected costs for strategy $\mathcal{S}^*$ are estimated from 100 sampled histories and are summarized in Fig. 7. The SHM lowers considerably the expected risk of failure. It should be noted that the cost difference $\mathbf{E}[C_T(\mathcal{S}^*)_{\text{no SHM}}] - \mathbf{E}[C_T(\mathcal{S}^*)_{\text{with SHM}}] = 86.9 - 59.6 = 27.3$ is not equal to the VoI of the SHM, for which the optimal strategies should be identified with and without SHM.

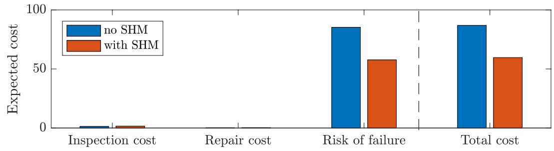

Figure 7. Breakdown of the expected cost of strategy $\mathcal{S}^*$ with and without SHM

5 Conclusion

In this study, the I&M planning optimization method developed in (Straub 2009, Luque and Straub 2016, Bismut et al 2017) is adapted to integrate SHM outcomes, and is applied to a single-component system and a large structural frame subject to deterioration. This method can efficiently quantify the effect of SHM on the risk of failure, estimate the Value of Information of a SHM system, and inform the decision whether or not to implement the SHM system.

Acknowledgments

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