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Title: Quantifying the value of vibration-based structural health monitoring considering environmental variability

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ABSTRACT

The value of structural health monitoring (SHM) can be quantified as the difference in expected total life-cycle costs between two different maintenance planning strategies, one representing the standard means to assessment, namely intermittent visual inspections, and the other based on availability of continuous SHM data. We show how to quantify the value of vibration-based SHM conditional on a damage history over the structural lifetime. We showcase the analysis through application on a numerical benchmark model of a two-span bridge system subjected to gradual deterioration and sudden damages in the middle elastic support over its life-cycle, simulating the case of scour. The effect of environmental variability is included in the analysis by means of a stochastic model for the dependence of the Young's modulus on temperature (E-T). The numerical investigations provide insights related to the effect of the temperature variability, as well as the visual inspections' quality, on the value of SHM.

INTRODUCTION

Deployment of continuous vibration-based structural health monitoring (SHM) systems on structures and infrastructures can support and facilitate infrastructure operation and maintenance (O&M). However, to date, such systems are not used extensively on real-world structures due to reasons relating mostly to acceptance and familiarization of infrastructure owners and operators with this technology. One of the biggest challenges lies in accounting for the fact that the damage sensitive features (typically the identified system's modal characteristics in the case of vibration-based SHM) are also sensitive to variations in environmental and operational conditions (e.g., ambient air temperature) [1, 2]. Neglecting to explicitly account for this dependence can result in false indications of damage in the structure, or in failure to identify damage that is present [3]. Another significant challenge relates to the fact that it is often difficult for owners and operators to grasp the potential benefits of installing SHM systems [4, 5].

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The authors are currently developing a framework for the quantification of the Value of SHM (VoSHM) for demonstrating the benefit of continuous vibration-based SHM-aided maintenance planning [6]. The current contribution briefly summarizes this framework, and applies it on a numerical benchmark model of a two-span bridge system subjected to combined gradual and shock deterioration, as well as to environmental variability, over its life-cycle. In the presented numerical investigations, emphasis is placed on the capability of the Bayesian framework to account for the stochastic dependence of the Young's modulus on temperature (E-T). It is shown that neglecting to account for this dependence can affect the damage identification results, and consequently the maintenance decisions triggered from the SHM system. Furthermore, the effect of the quality of the visual inspection measurements on the VoSHM is investigated.

VALUE OF STRUCTURAL HEALTH MONITORING

Preposterior Bayesian decision analysis [7] offers an appropriate formal mathematical framework to investigate the potential economic benefit of installing a specific SHM system for damage detection tasks prior to actual deployment.

The analysis starts from prior probabilistic information on the uncertain structural system state and on the parameters of deterioration models describing the system state evolution over time, summarized in a random vector $\boldsymbol{X}$. Additionally, a model of the investigated SHM system is required, which allows simulating extraction of noisy SHM data $\boldsymbol{Z}_{SHM}$, for given sampled realizations of the random vector $\boldsymbol{X}$. The SHM modal data sampling process is presented in the next section. Finally, a probabilistic inspection model is employed, which allows probabilistic predictions of visual inspection measurements $\boldsymbol{Z}_{insp}$ for a given $\boldsymbol{X}$; here $\boldsymbol{Z}_{insp}$ is assumed to follow the Gaussian distribution conditional on $\boldsymbol{X}$, with mean $\boldsymbol{X}$ and an assigned coefficient of variation cv_{insp}, whose chosen value reflects the quality of a visual inspection measurement.

The VoSHM can be quantified via Equation (1), and emerges from the solution of two different preposterior analyses, one for the case without SHM (only with visual inspections), and one for the case with continuous SHM (complemented by additional visual inspections). Equation (1) quantifies the difference in expected total life-cycle costs between the two different cases.

$$VoSHM = \mathrm{E}_{\boldsymbol{X},\boldsymbol{Z}_{insp}}\left[C_{tot}\left(\boldsymbol{X},\boldsymbol{Z}_{insp}\right)\right] - \mathrm{E}_{\boldsymbol{X},\boldsymbol{Z}_{insp},\boldsymbol{Z}_{SHM}}\left[C_{tot}\left(\boldsymbol{X},\boldsymbol{Z}_{insp},\boldsymbol{Z}_{SHM}\right)\right] \qquad (1)$$

The total life-cycle cost C_{tot} comprises the cost of the different inspections C_{insp}, repairs C_{rep}, and the risk (expected cost of failures) R_F. C_{tot} is a function of the different actions taken over the life-cycle. These actions are implemented following heuristic decision rules, which are prescribed for the solution of the sequential decision problem and the computation of the expected total life-cycle cost. It is assumed that at discrete time instances t, structural performance can be assessed via the updated estimate of the structural reliability [8]. The following two heuristic rules are employed.

1. p_{th}^{insp}: Perform an inspection at any time step before the updated structural reliability estimate exceeds p_{th}^{insp}.

2. p_{th}^{rep}: Perform a repair at any time step before the updated structural reliability estimate exceeds p_{th}^{rep}.

In the case without SHM, periodic inspections must additionally be performed every Δ_{t_I} years. It is considered that with SHM, one will put enough trust on the SHM system, and will not perform periodic inspections every Δ_{t_I} years.

NUMERICAL BENCHMARK CASE STUDY

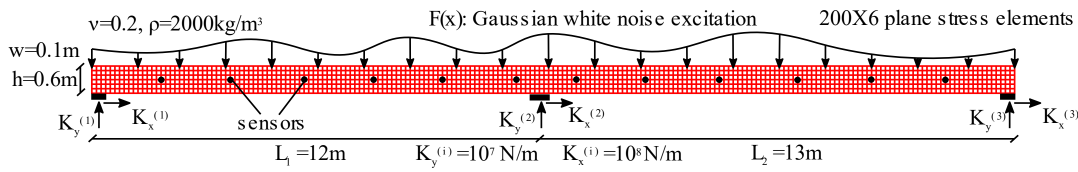

Figure 1: Bridge system subject to environmental variability and to damage due to deterioration (reduction of stiffness $K_y^{(2)}$) at the middle elastic support (pier).

Figure 1 shows the numerical benchmark model of a two-span bridge system, which is assumed to be subjected to environmental variability, and to damage (stiffness reduction) due to gradual and shock deterioration at the middle elastic support. This type of damage is typical in cases of scour in bridge structures [9].

Environmental Variability Model

A linear elastic material is assigned. The Young's modulus of the structure (i.e., the stiffness) is modeled to vary for changing temperatures according to equation (2). Parameter θ in equation (3) is a stochastic function of temperature, which contains five hyper-parameters. The prior probability distributions of these hyper-parameters are shown in Table I. E_0=29.11GPa for a reference temperature of 20°C. This environmental variability model has been used in [10].

$$E(T_t) = \theta(T_t) \cdot E_0 \tag{2}$$

$$\theta(T_t) = Q + S \cdot T_t + R \cdot \left(1 - erf\left(\frac{T_t - Y}{\tau}\right)\right) \tag{3}$$

TABLE I. PRIOR DISTRIBUTION OF ENVIRONMENTAL MODEL PARAMETERS

Parameter	Distribution	Mean	CV
Q	Normal	–0.005	10%
S	Normal	1.115	2.5%
R	Normal	0.165	10%
Y	Normal	–1.00	25%
τ	Normal	3.00	20%

Damage Model

It is assumed that the stiffness in the y-direction of the middle elastic support boundary, modeled by a spring with stiffness $K_y^{(2)}$, is subject to reduction over the structural life-cycle, as described by Equation (4). $X(t)$ is the deterioration model, describing the gradual and shock deterioration process over time, following equation (5). The first part of Equation (5) models the gradual deterioration. The second part models the shock deterioration, described by a homogeneous compound Poisson process (CPP) [11, 12], which is superposed to the gradual deterioration. $N(t)$ describes the number of shock occurrences, and is a Poisson process with rate λ, and D_i are the shock deterioration increments. The prior probability distributions for all the associated random variables of Equation (5) are given in Table II.

$$K_y^{(2)}(t) = \frac{K_{y,0}^{(2)}}{1 + X(t)} \tag{4}$$

$$X(t) = At^B \cdot e^{\omega} + \sum_{i=1}^{N(t)} D_i \tag{5}$$

TABLE II. PRIOR DISTRIBUTION OF DETERIORATION MODEL PARAMETERS

Parameter	Distribution	Mean	CV
A	Lognormal	$1.94{\cdot}10^{-4}$	40%
B	Normal	2.0	10%
ω	Normal	-0.005	10%
$N(t)$	Poisson	0.04	-
D_i	Lognormal	3.75	25%

SHM Modal Data Sampling

In simulating extraction of SHM data, the numerical model (Figure 1) is utilized as a forward simulator to sample dynamic responses (vertical accelerations at the 12 assumed sensor locations) and temperature measurements, based on a reference realization of the deterioration process and the E-T model, assumed as the ground truth system response. The noisy vertical acceleration measurements are subsequently processed by an output-only operational modal analysis (OMA) scheme [13], which identifies the system's m lower eigenfrequencies $\tilde{f}_m$.

Bayesian Filtering

The eigenfrequency data, sequentially identified at different time instances t and temperatures $\tilde{T}_t$, are fed into a Bayesian filtering framework, whose initial goal is to learn the E-T dependence, and whose subsequent goal is to estimate the filtering distributions of the deterioration state. This leads to a continuous updating of the time-dependent structural reliability estimate, which forms the basis on which inspection/repair decisions are made within the heuristic-based life-cycle cost optimization. The SHM likelihood function is formulated based on the discrepancy between the OMA-identified eigenvalues $\tilde{\lambda}_m = \left(2\pi\tilde{f}_m\right)^2$ and the forward finite element model $\mathcal{G}$-predicted eigenvalues λ_m. The likelihood function describing the SHM data obtained at a time instance t, for an unknown true deterioration state $X(t)$, is shown in Equation (6).

$$f_{\tilde{\lambda}_t|X(t)}\left(\tilde{\boldsymbol{\lambda}}_t \middle| X(t)\right) = \prod_{m=1}^{N_m} N\left(\tilde{\lambda}_{t_m} - \lambda_{t_m}\left(\mathcal{G}(X(t), E = \theta(\widetilde{T}_t)E_0)\right); 0, c_\lambda{}^2\tilde{\lambda}_{t_m}^2\right) \tag{6}$$

NUMERICAL INVESTIGATION RESULTS

Bayesian Learning of Environmental Variability Model

With the assumption that no damage will be present in the beginning of the operation of the instrumented structure, the SHM modal data of the first few months of operation, identified at different temperatures, can be used within a Bayesian analysis [14] to update the distributions of the environmental variability model hyper-parameters. Posterior samples of the hyper-parameters are then used to estimate the ground truth E-T model (blue curve in Figure 2). For subsequent sequential deterioration state estimation tasks, the learned posterior mean E-T model can be used.

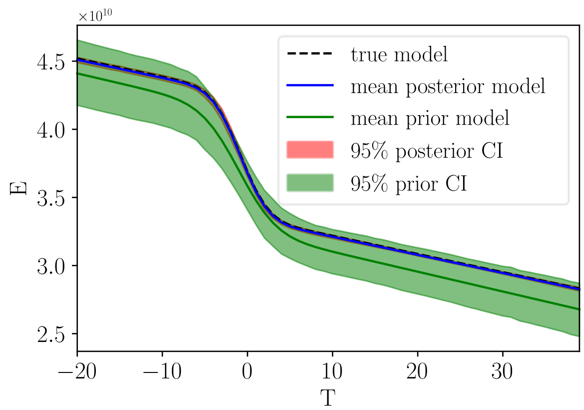

Figure 2: Learning the underlying "true" E-T model via Bayesian analysis

Bayesian Filtering of Deterioration and Sequential Decision Making

The structure's lifetime of $T = 50$ years is discretized in yearly intervals. The Bayesian filtering estimation and the heuristic-based decision making is performed in these yearly intervals. It is assumed that a CPP shock deterioration occurrence is the result of an observed extreme event, e.g., a flood occurrence. In this scenario, it is prescribed that a visual inspection should take place at the time right after the extreme event occurrence, both without and with SHM. For the visual inspection likelihood function, cv_{insp}=0.15 is assumed.

The following heuristic parameter values are prescribed: p_{th}^{insp}=$5{\cdot}10^{-4}$, p_{th}^{rep}=$1{\cdot}10^{-3}$ for both cases with and without SHM. For the case without SHM, scour-specific periodic inspections are additionally performed every Δ_{t_I}=5 years. The cost of an individual inspection is assigned a value $\tilde{c}_{insp}$= $2{\cdot}10^4$€, an individual repair costs $\tilde{c}_{rep}$= $6{\cdot}10^5$€, and the failure event cost is $\tilde{c}_f$= $5{\cdot}10^7$€.

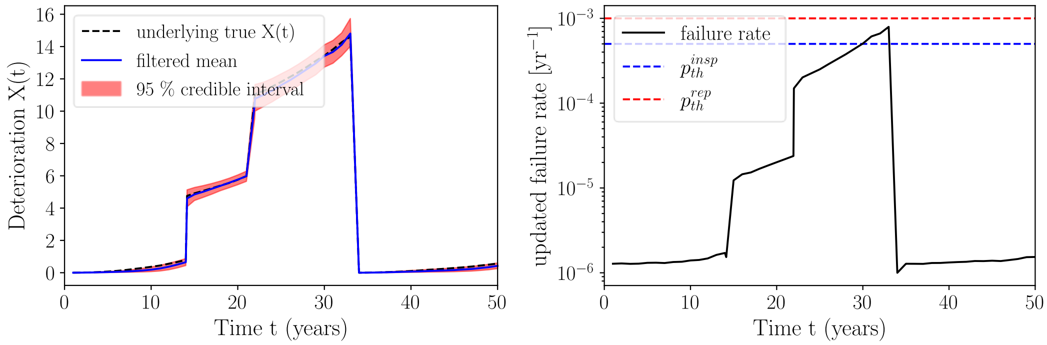

Figure 3: Bayesian filtering of the deterioration state and the reliability estimate with continuous SHM, complemented by visual inspection data, and the associated sequential decision making

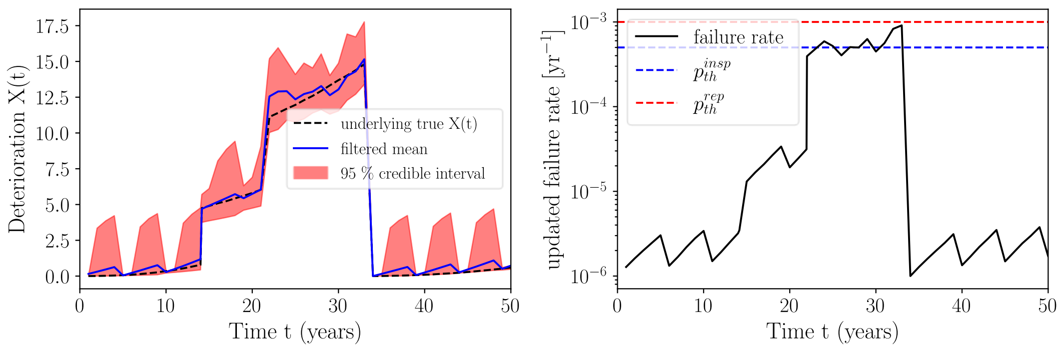

Figure 4: Bayesian filtering of the deterioration state and the reliability estimate with intermittent visual inspection data, and the associated sequential decision making

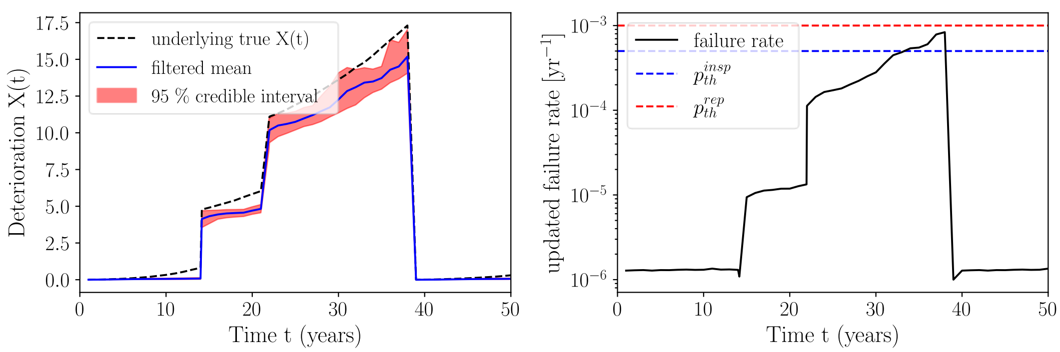

Figure 5: Bayesian filtering of the deterioration state and the reliability estimate with continuous SHM, without accounting for the environmental variability, and the associated sequential decision making

The black dashed line in the left panel of Figures 3-5 is the same reference realization of the deterioration process $X^{(i)}$, assumed as the ground truth system state evolution over time.

The left panel of Figure 3 plots the filtered estimate of the deterioration state, obtained using continuous OMA-identified modal data, while the right panel plots the continuously updated failure rate of the structure, conditional on survival up to the previous time instance. It is clear that, when continuous data from the SHM system is available, and when the temperature variability has been properly accounted for, the ground truth deterioration state is very well tracked over time. For Figure 3, the heuristic thresholds trigger inspections at t_{insp}= [14.2, 21.9, 31, 32, 33] and a repair at t_{rep}=33. For this single sample, $C_{tot}(X^{(i)}, \boldsymbol{Z}_{insp}, \boldsymbol{Z}_{SHM}, \boldsymbol{w})$= 520006€.

Figure 4 plots the same estimates as Figure 3, but for the case without SHM. In this case, many more inspections need to be performed, t_{insp}= [5, 10, 14.2, 19, 21.9, 24, 25, 27, 29, 31, 32, 33, 39, 44, 49], and the ground truth deterioration state is not estimated as well at all time steps. Also, a much larger uncertainty is present in the estimation. A repair decision is triggered at t_{rep}=33. The total life-cycle cost without SHM for this deterioration process sample is $C_{tot}(X^{(i)}, \boldsymbol{Z}_{insp}, \boldsymbol{w})$= 630006€, which is larger than the cost in the case with SHM.

Finally, Figure 5 demonstrates that, in the case with SHM, but without accounting for the environmental variability, the ground truth deterioration state is underestimated at all times. Obviously, this further affects the decisions. Inspections are performed at t_{insp}= [14.2, 21.9, 34, 35, 36, 37, 38], and a repair is triggered at t_{rep}=38, five years later than the repair triggered in Figure 3. $C_{tot}(X^{(i)}, \boldsymbol{Z}_{insp}, \boldsymbol{Z}_{SHM}, \boldsymbol{w})$= 652442€, which is larger than the total cost computed in both cases above. This result shows how detrimental it can be to not account properly for the environmental variability.

VoSHM Quantification

In the previous section, the total cost computation was shown for one single sample of the deterioration process. However, Equation (1) requires the evaluation of the expectation operator for quantifying the VoSHM, i.e., one needs multiple deterioration samples and the corresponding SHM and visual inspection data. With 1000 Monte Carlo samples, we obtain an expected $VoSHM$=110972€, which indicates that installation of this SHM system on the deteriorating bridge structure provides an economic benefit in the expected value sense.

The quality of the visual inspection, as defined by the assumed cv_{insp} value in the visual inspection likelihood function, can affect the VoSHM. To demonstrate the capability of the presented framework to account for this, the full VoSHM analysis was run for three different visual inspection likelihood functions (for the same $\tilde{c}_{insp}$ cost in all three cases), and the following results were obtained:

1. $VoSHM$=110972€ for cv_{insp}=0.15.
2. $VoSHM$=102104€ for cv_{insp}=0.05.
3. $VoSHM$=133454€ for cv_{insp}=0.30.

As expected, better visual inspections lead to a lower VoSHM, while a reduced visual inspection quality leads to a higher VoSHM.

CONCLUSIONS

This paper summarizes a recently developed framework for the quantification of the value of continuous vibration-based SHM, and demonstrates the application of this framework to a bridge system subjected to gradual and shock deterioration and environmental variability. The framework quantifies the expected gains that SHM-aided maintenance planning can provide compared to inspection-based maintenance planning. It is exemplified that not properly accounting for the environmental variability present in the SHM data can severely affect the maintenance decisions triggered by an SHM system. Furthermore, we show how the quality of visual inspections affects the value of the SHM.

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