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Optimization of inspection and monitoring of structures in case of spatial fields of deterioration/properties

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1 INTRODUCTION

In the general context of structural reliability of existing structures, the question of random variable updating has been widely addressed during the two last decades. Random variable updating is very useful when data from inspections or monitoring are collected for condition assessment and reliability updating (Straub et al., 2003; Schoefs et al., 2010a). Basically, the Bayes theorem and its derivative tools (Bayesian Networks) offer the theoretical context to deal with this issue. The so called Risk Based Inspection (RBI) generalizes these approaches in the case of non-perfect inspections by linking inspection and decisions (Faber, 2002; Sorensen et al., 2002; Schoefs et al., 2010b).

RBI methods are powerful once (i) there is no stochastic field involved into the problem, or (ii) the location of the most critical defect, from a reliability point of view, is known. In those cases, it can be assumed that the spatial distribution of defects in the neighboring zone does not affect the reliability assessment. Nevertheless, it has been showed that reality is more complex and that spatial randomness should be considered in several problems. For instance, in condition assessment, Schoefs (2009) has found that inspections should also account for stochastic fields of measured parameters.

The stochastic field could take several forms more or less complicated. The most simple is the stationary stochastic field that can be used, for instance, to model chloride distribution or other concrete properties (Bazant, 1991; 2000a; 2000b). A more sophisticated stochastic field is the piecewise stationary process that can integrate, for example, the variability of concreting materials by steps or the corrosion of structures located in contiguous environments with different characteristics.

During inspection, there are many factors that influence the quality of measurements—e.g, environmental conditions, error in the protocol, error due to material variability, and error induced by

the operator (Bonnet et al., 2009). These factors could lead, for a given inspection, under or overestimations of the measured parameter. If the parameter is underestimated and the owner could decide “do nothing” when repair is required. On the contrary, an overestimation generates a “wrong decision” where the early repair generates overcharges (Rouhan and Schoefs, 2003). On the whole, the stochastic nature of material properties and deterioration processes as well as the factors that reduce the quality of the inspections that can be used to quantify them, transform the management of deteriorating systems in a major challenge for owners and operators.

Within this context, the main objective of this work is to study influence of the noise of measurements on the reliability assessment. This paper focuses only on the inspection of stationary stochastic fields. Its description is outlined in section 2. Section 3 introduces the Karhunen-Loève decomposition for modeling the spatial variability and introduces the modeling of imperfect inspections. Section 4 describes the problem of measurement quality in the case of inspection of random fields and when only the objective of inspection is to determine a marginal probability distribution for reliability computation. Section 5 presents an illustrative example where we illustrate the effect of imperfect inspections on the reliability assessment.

2 MODELLING A STOCHASTIC FIELD WITH NON PERFECT INSPECTION

In terms of stochastic modeling, several approaches can be used to represent a stochastic field $X(x, \theta)$: Karhunen-Loève expansion, approximation by Fourier series, and approximation EOLE (Li and Der Kiureghian, 1993). In this paper, we used a Karhunen-Loève expansion to represent the stochastic field of resistance of a structure $R(x, \theta)$. This expansion represents a random field as a

combination of orthogonal functions on a bounded interval $[-a, a]$:

$$R(x, \theta) = \mu_R + \sigma_R \cdot \sum_{i=1}^n \sqrt{\lambda_i} \cdot \xi_i(\theta) \cdot f_i(x) \quad (1)$$

where, μ_R is the mean of the field R , σ_R is the standard deviation of the field R , n is number of terms in the expansion, ξ_i is a set of centered Gaussian random variables and λ_i and f_i are, respectively, the eigenvalues and eigenfunctions of the covariance function $C_{HH}(x_1, x_2)$. It is possible to analytically determine the eigenvalues λ_i and eigenfunctions f_i for some covariance functions (Ghanem and Spanos, 2003). For example, it can be determined if we assume that the field is second order stationary and we use an exponential covariance function:

$$C_{HH}(\Delta x = x_1 - x_2) = \exp\left(-\frac{|\Delta x|}{b}\right); 0 < b \quad (2)$$

where b is the correlation length and $\Delta x \in [-a, a]$.

As stated in Schoefs et al. (2010a) a non-biased inspection can be modeled with a centered noise η around the exact value. In this paper, it is assumed that the noise is normally distributed $N(0, \sigma_\eta)$ without loss of generality.

This work considers that inspections will be used to determine the marginal probability distribution of a variable of interest that has the properties of a random field. If inspections are carried out on the same structural element, the distance between two consecutive measurements, L_c , should ensure independency between two results. In that case, we could build a statistically independent sample from equidistant inspections on a random field. This sample will be used to determine the marginal probability distribution.

3 PROBABILISTIC MODELLING AND RELIABILITY ASSESSMENT FROM INSPECTION

Assuming that the loading S is deterministic and that R_I is normally distributed, the probability of failure, P_f , is obtained as:

$$P_f = P(R \leq S) = \Phi\left(\frac{S - \mu_{R_I}}{\sigma_{R_I}}\right) \quad (3)$$

where μ_{R_I} and σ_{R_I} are, respectively, the mean and the standard deviation determined taking into account the considerations described in previous section. Equation (3) is also used to compute the

probability of failure P_f obtained with “perfect” inspection (without noise) that will be used here to study the influence of the noise of the measurement.

In the following results, we will compare the probability of failure computed from measurements with noise, $P_{f,I}$, with the probability of failure computed without noise, P_f , in terms of a confidence interval $[c, d]$. The lower and upper limits of this interval are defined according to the following conditions in the case without noise:

$$P(P_f < c) = 5\% ; P(P_f < d) = 95\% \quad (4)$$

Figure 1 shows the zone corresponding to this confidence interval for the case without noise (grey zone) that is used to determine the limits of the interval. Once these limits are defined, it is possible to determine the probability that $P_{f,I}$ (determined from noised inspections) belongs to the interval $[c, d]$, i.e., $P(c < P_{f,I} < d)$ (Figure 1) as:

$$P(c < P_{f,I} < d) = P(P_{f,I} < d) - P(P_{f,I} < c) \quad (5)$$

The hatched zone in Figure 1 presents the probability $P(c < P_{f,I} < d)$. The standard deviation of R_I is higher than σ_R because of the noise. Therefore, the area of $P_{f,I}$ between the interval $[c, d]$ is lower than the area computed without noise. The effect of noise on the assessment of the probability $P(c < P_{f,I} < d)$ will be more discussed in next section.

Discussion: From an application illustrated in the paper, it shown that the estimate of the quality of condition assessment i.e. $P(P_{f,I} \in [c, d])$ decreases strongly and regularly for a $\sigma_n > 5$.

It leads to conclude that for a given structure of the underlying stochastic field, an inspections

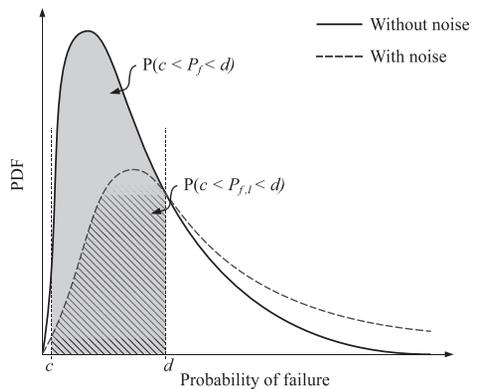


Figure 1. Determination of the limits of the confidence interval from the distribution of P_f .

quality can be required based on a acceptance criteria: $P(P_{f,t} \in [c,d]) > p$.

REFERENCES

- Bazant, Z.P. & Xi, Y. 1991. Statistical Size Effect in Quasi-brittle Structures: II. Nonlocal Theory. *ASCE J. of Engrg. Mech.* Vol. 117, No. 11, 2623–2640.
- Faber, M.H. 2002. Risk Based Inspection: The Framework. *Structural Engineering International (SEI)*, 12(3), August 2002, pp. 186–194.
- Schoefs, F., Clément, A., Boéro, J. & Capra, B. 2010a. The $\alpha\delta$ method for modeling expert Judgment and combination of NDT tools in RBI context: application to Marine Structures. *NSIE*, Jan. 2010, doi: 10.1080/15732479.2010.505374.
- Sørensen, J.D. & Faber, M.H. 2002. Codified Risk-Based Inspection Planning. *Structural Engineering International (SEI)*, 12(3), August 2002, pp. 195–199.
- Straub, D. & Faber, M.H. 2003. Modelling dependency in inspection performance, *Proc. ICASP 2003* pp. 1123–1130.