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Probabilistic sensitivity analysis of optimised preventive maintenance strategies for deteriorating infrastructure assets

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ABSTRACT

Efficient life-cycle management of civil infrastructure systems under continuous deterioration can be improved by studying the sensitivity of optimised preventive maintenance decisions with respect to changes in model parameters. Sensitivity analysis in maintenance optimisation problems is important because if the calculation of the cost of preventive maintenance strategies is not sufficiently robust, the use of the maintenance model can generate optimised maintenances strategies that are not cost-effective. Probabilistic sensitivity analysis methods (particularly variance based ones), only partially respond to this issue and their use is limited to evaluating the extent to which uncertainty in each input contributes to the overall output's variance. These methods do not take account of the decision-making problem in a straightforward manner. To address this issue, we use the concept of the Expected Value of Perfect Information (EVPI) to perform decision-informed sensitivity analysis: to identify the key parameters of the problem and quantify the value of learning about certain aspects of the life-cycle management of civil infrastructure system. This approach allows us to quantify the benefits of the maintenance strategies in terms of expected costs and in the light of accumulated information about the model parameters and aspects of the system, such as the ageing process. We use a Gamma process model to represent the uncertainty associated with asset deterioration, illustrating the use of EVPI to perform sensitivity analysis on the optimisation problem for age-based and condition-based preventive maintenance strategies. The evaluation of EVPI indices is computationally demanding and Markov Chain Monte Carlo techniques would not be helpful. To overcome this computational difficulty, we approximate the EVPI indices using Gaussian process emulators. The implications of the worked numerical examples discussed in the context of analytical efficiency and organisational learning.

1. Introduction

The cost effective life-cycle management of civil infrastructure systems is highly dependent on the determination of optimal maintenance and rehabilitation strategies. The determination of optimal maintenance decisions is widely recommended [6] as an effective way of minimising system downtime and corresponding maintenance costs. For instance, Dobbs et al. [1] report that maintenance costs for infrastructure systems such as water energy, rail, etc. are rapidly rising and current estimates suggest that optimised maintenance strategies could save $100 bn p.a. on global infrastructure costs. Infrastructure maintenance practices have traditionally been premised on one of two strategies; Corrective Maintenance (CM) which involves repairing failed components and systems, or Preventative Maintenance (PM) which involves the systematic inspection and correction of incipient failures before they develop into major defects. Recent years have seen increasing dominance of PM approaches with overall costs demonstrated to (perhaps counter-intuitively) be lower than for a CM strategy. PM is widely used to mitigate asset deterioration and reduce the risk of unexpected failure and as a strategy can be sub-classified into two approaches; time-based maintenance (TBM), where maintenance activities take place at predetermined time intervals, and condition-based maintenance (CBM) where interventions are prompted by information collected through condition sensing and monitoring processes (either manual or automated). Ahmad and Kamaruddin [6] provide an extensive review comparing TBM against CBM (see also [2–5]).

Preventive maintenance strategies (both time and condition based) are widely used for infrastructure life-cycle management decision making. These strategies can be planned and scheduled and their costs

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are typically lower than those for CM strategies. However, early preventive maintenance intervention adds little to the reliability of the system and can lead to unnecessary costs, hence maintenance strategies often comprise a combination of preventative and corrective approaches. The challenge is then to identify the optimal PM decision that achieves the best balance between these types of maintenance and minimise overall maintenance costs, controlled over an appropriate time period. The central challenge for those who wish to make informed PM decisions is that determining the time to first inspection, maintenance intervention, or replacement is confounded by model parameter uncertainties associated with the adopted failure, deterioration, repair, or maintenance model. Consequently, SA of the model output (to identify an optimal maintenance strategy) with respect to the changes in the model parameters is of great interest. In this paper we investigate the issue of SA for maintenance optimisation models. To achieve this, we consider time based and condition based preventive maintenance strategies for infrastructure systems under continuous deterioration. Both strategies are discussed in detail in [6,11] and references therein. Under TBM, a component is replaced (or perfectly repaired) either at failure (CM) or when it has reached age T - whichever occurs first. The central objective of a TBM decision problem is to determine the replacement time which minimizes expected total cost. The CBM strategy involves the periodic inspection of a component/structure at a fixed time interval T_i and cost C_i. At the *specti* inspection, one of the following actions might be taken: (i) the system is operating satisfactorily and no action is required to be taken; (ii) immediate preventative maintenance is required to avoid component or system failure; (iii) a failure is identified and corrective maintenance (or a perfect repair) is required to restore the system's functionality (see Section 5.2 and [11] for further details). The optimal maintenance decision under the CBM strategy is taken as the inspection time and the PM ratio which are similarly determined by minimising the cost function of interest. The decision under a CBM policy for a deteriorating component constitutes a two-dimensional optimisation problem, whilst for the TBM case the aim is to find the critical age as a single variable. It has been argued that the types of PM strategy discussed above is more useful in practice (particularly for larger and more complex systems) since it removes the need to record component ages [6,7].

As inferred above, the preventive maintenance policy cost function is influenced by both the deterioration model and repair model's parameters. Thus, the calculation of a mean cost rate for a particular preventive maintenance policy is not sufficiently robust because of the uncertainty around parameter values, and the corresponding maintenance model can generate inefficient outcomes. In other words, the identification of an optimal maintenance intervention becomes sensitive to the model parameters creating uncertainty as to the optimal strategy. Variance based approaches [14] offer a partial answer to this problem and can be used to assess the degree to which uncertainty in each variable contributes to the overall variance in model output. However, these approaches do not take account of the decision-making context properly. In order to address this issue, we make use of the concept of the Expected Value of Partially Perfect Information (EVPPI). The EVPPI provides a decision-informed SA framework which enables researchers to determine the key parameters of the problem and quantify the value of learning about certain aspects of the system [8,7]. In maintenance studies [9,10], this information can play an important role, particularly where we are interested in not only identifying an optimal maintenance decision but in also gathering additional information about the system characteristics including the deterioration process to improve the robustness of decisions.

The determination of EVPPI involves the calculation of multi-dimensional integrals that are often computationally demanding, making conventional numerical integration or Monte Carlo simulation techniques infeasible in practice. To partially overcome this computational difficulty, we follow the work of [7,8], and execute SA through the use of Gaussian process emulators. The following section presents a well-known probabilistic model of deterioration; the Gamma process model, and discusses how this relates to TBM and CBM maintenance optimisation problems. We go on to describe how Gaussian Process (GP) emulators can be used to compute EVPPIs within the context of decision-theoretic SA. Robust optimised maintenance decisions are then derived for two forms of PM policy using several illustrative settings of varying complexity. We conclude by discussing the implications of our approach and identify opportunities for future work.

2. Deterioration models

Infrastructure asset deterioration processes are uncertain and can best be regarded as stochastic. Two previous studies have demonstrated the values of using Gamma process models to analysis the deterioration of physical assets. Pandey et al. [11] compared the use of random variable and gamma process models in the life-cycle management of infrastructure systems. They demonstrated that the random variable model cannot capture the temporal variability associated with the evolution of asset degradation. As a consequence, this model tends to underestimate the life-cycle cost due to the lack of consideration of temporal uncertainty. Van Noortwijk [12] extensively reviewed the application of stochastic deterioration processes, and particularly the use of the Gamma process model in maintenance. He concluded that gamma processes are well suited for modelling the temporal variability of deterioration, and of particular value when determining optimal inspection and maintenance decisions.

We now briefly introduce the *Gamma process* for deterioration modelling of an ageing asset. In mathematical terms, a gamma process is a stochastic process with independent non-negative increments having a gamma distribution [11,12]. The Gamma process with a shape function $\nu(t) > 0$ and scale parameter $\xi > 0$ is a continuous-time stochastic process $\{X(t),\ t \geq 0\}$ with the following properties:

1. $Pr(X(0) = 0) = 1$
2. $X(\iota) - X(t) \sim Ga(\nu(\iota) - \nu(t),\ \xi),\ \forall\ \iota > t \geq 0$
3. $X(t)$ has independent increments

and where $\nu(t)$ is a non-decreasing, right-continuous, real-valued function of $t \geq 0$ with $\nu(0) \equiv 0$.

Let $X(t)$ denote the deterioration at time $t \geq 0$, and let $X(t)$ follows a gamma process with the shape function $\nu(t) > 0$ and scale parameter $\xi > 0$, then the probability density function of $X(t)$ is given by

$$f_{X(t)}(x) = Ga\left(x \middle| \nu(t),\ \xi\right) = \frac{(x/\xi)^{\nu(t)-1}}{\xi \Gamma(\nu(t))} \exp\{-x/\xi\}, \quad \text{for } x \geq 0 \tag{1}$$

The structural failure for a deteriorating structure or component is defined as an event when its deteriorating resistance, denoted by $R(t) = r_0 - X(t)$, falls short of the applied stress s. The initial resistance r_0 and s are assumed to be fixed and known. We denote $\rho = (r_0 - s) > 0$ as the available design margin or a failure threshold. We let the time at which failure occurs be denoted by the lifetime T (also called the first hitting time of level ρ). Since the deterioration of a component at time t is given by Eq. (1), the cumulative lifetime distribution of this is then given by

$$F_T^G(t) = Pr(T \leq t) = Pr(X(t) \geq \rho) = 1 - \mathcal{G}(\rho;\ \nu(t)t,\ \xi) \tag{2}$$

where $\mathcal{G}(\rho;\ \nu(t)t,\ \xi)$ denote the cumulative distribution function of the deterioration model at ρ.

Expression (2) features outstanding duality between a component's deterioration and its lifetime that makes the Gamma process model tractable for cycle-life management analysis. It should be noted that the lifetime probability density function, denoted by $f_T^G = \frac{\partial}{\partial t} F_T^G(t)$, has no closed form expression, and the corresponding maintenance optimisation problem requires a computationally fast and powerful numerical