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Robustness of maintenance decisions: Uncertainty modelling and value of information

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ABSTRACT

In this paper we show how sensitivity analysis for a maintenance optimisation problem can be undertaken by using the concept of expected value of perfect information (EVPI). This concept is important in a decision-theoretic context such as the maintenance problem, as it allows us to explore the effect of parameter uncertainty on the cost and the resulting recommendations. To reduce the computational effort required for the calculation of EVPIs, we have used Gaussian process (GP) emulators to approximate the cost rate model. Results from the analysis allow us to identify the most important parameters in terms of the benefit of 'learning' by focussing on the partial expected value of perfect information for a parameter. The analysis determines the optimal solution and the expected related cost when the parameters are unknown and partially known. This type of analysis can be used to ensure that both maintenance calculations and resulting recommendations are sufficiently robust.
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1. Introduction

Unexpected failure has adverse effects not only in terms of system efficiency, but also in terms of maintenance costs. Preventive maintenance (PM) is employed as a means to control the decreasing with time reliability of deteriorating systems, reduce the risk of unexpected failure and offset the cost of corrective maintenance (CM), which is typically high. PM can be further divided into time-based (TM) maintenance, where maintenance activities take place at predetermined time intervals, and condition-based maintenance (CBM), where activities occur in reaction to the system state. An example of CBM is the delay time model [1,2], which takes into account observed warning signs to assess the risk of incipient failures. Within the literature one can find extensive reviews on preventive maintenance [3–5].

The effect of maintenance on the system condition can be described broadly as perfect or imperfect repair. Perfect repair brings the system to a new condition and is often described as As Good As New (AGAN) [6]. Minimal or As Bad As Old (ABAO) repair, when maintenance restores the system to the condition it was just before failure [7], is a limiting case of imperfect maintenance. Within the literature one can find a number of other models that describe cases not as extreme as perfect or minimal maintenance, such as the Brown–Proschan model [8], where the effect of maintenance is AGAN with some probability p and ABAO with the remaining probability $1-p$, and the virtual age models [9]. Nakagawa in [10] proposes a model where the failure rate increases at PM by some proportion.

PM is anticipated and scheduled, and its cost is usually lower than that of corrective maintenance, which is unexpected. However, early preventive maintenance adds little to the reliability of the equipment and can lead to unnecessary costs. Typically, maintenance strategies often comprise of a combination of types of maintenance, both PM and CM. The challenge is to identify the strategies that achieve the best balance between these types of maintenance and minimise overall maintenance costs, judged over an appropriate time period.

In this type of maintenance problems, as in other modelling problems, studying the sensitivity of the model output (optimal strategy) with respect to the changes in the model parameters (e.g. reliability parameters) is of great interest. In this paper we will investigate the issue of sensitivity analysis for maintenance optimisation models. To achieve this we will consider two of the most commonly discussed time-based maintenance policies: the age-replacement policy (ARP) and the block-replacement policy (BRP). Both policies are discussed in [7]. Under the ARP, a component is replaced (AGAN repair) either at failure or when it has reached age T—whichever occurs first. Under the BRP, one or more components are replaced periodically (AGAN repair) at times kT ($k=1,2,\ldots$), regardless of their failure history, whereas individual components are replaced when failed. Since one does not have to record the

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Table 1
Methods of sensitivity analysis.

Method	Approach	Value and validity
Brute-force approach	Explore the effect of changes in the parameters on the corresponding output, by varying one or more parameters directly	Simple and straightforward approach for simple and computationally cheap models, but impractical for large or computationally expensive models. Computational burden increases considerably for second-order sensitivity analysis. Local measure, parameters are varied around some assigned point values
Partial derivatives	Explore the effect of infinitesimal changes (around some baseline scenario) in the parameters on the corresponding output	First order local sensitivity measures, information provided relates to single value (assigned point value)
Regression coefficients	Fit a regression model on the training data set and use the regression coefficients as measures of importance. Explore the effect of varying a parameter round its expected value on the output, while the rest of the parameters are fixed at their expected values	Like emulators, this is a metamodel; however, it is used only for interpolation purposes. Parameters are assigned distributions rather than point values
Variance-based measures	Explore the effect of learning the true value of an input parameter on the *output variability*	Measures the first order effect of a parameter on the model output. It is a meaningful measure when the objective is to reduce output uncertainty. Global measure, parameters are assigned distributions rather than point values
Expected value of perfect information	Explore the effect of learning the true value of an input parameter on the *utility*	Considers optimal decision, appropriate for decision-making problems. It is a meaningful measure when the objective is to maximise the utility associated to a decision. Global measure, parameters are assigned distributions rather than point values

individual ages of the components comprising the system, this type of policy can be more practical for larger, more complex systems. Both maintenance policies depend on a single strategy variable—usually considered fixed: for ARP this is the critical age, and for BRP it is the periodic interval. A commonly used cost criterion in such settings is the expected cost per unit of time [11]. In such a setting the objective function is expressed in terms of a cost/time fraction and depends on the strategy variable T. Therefore, the problem of identifying the optimal maintenance strategy is equivalent to finding the value of T that minimises the objective function. The ARP and BRP models are used here as illustrations, though more complex models including different types of repair effects can be considered in the same way. This is discussed in more detail later on in the paper.

Sensitivity analysis in maintenance optimisation problems is important because if the cost-calculations are not sufficiently robust, the use of the maintenance model can lead to optimisation recommendations that are themselves not robust. Variance based methods [12] give 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, variance-based methods do not take account of the decision-making context properly. 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 system. This information is of great importance within a maintenance context, where decisions may not only relate to replacement timings, but also to accumulation of information about aspects of the system, like the ageing process. However, decision-theoretic sensitivity analysis within a maintenance optimisation context is demanding: the computation of expected utility requires the use of numerical integration or Monte-Carlo simulation techniques. To partially overcome this computational difficulty, we follow the work of Oakley in [13] and perform sensitivity analysis by using Gaussian process emulators.

This paper is structured as follows: Section 2 presents the maintenance optimisation problem, discusses decision-theoretic sensitivity analysis and explains the use of Gaussian process (GP) emulators within this context. In Section 3 the suggested methodology is illustrated by using two settings of different complexities: the first setting is a simple one with an analytic cost expression that we use to illustrate and validate the method, whereas in the second setting the additional complexity of system and maintenance policy requires us to use Monte-Carlo simulation to compute costs. Finally, we conclude with a discussion in Section 4.

2. Optimum replacement policy

In a maintenance optimisation model the objective is to find a minimal cost solution amongst the alternative maintenance choices. When the problem is defined over a finite horizon $[0,t]$, the objective function one seeks to minimise represents costs over the interval $[0,t]$. For infinite horizon models, an appropriate objective function is the long-term average costs, or the expected cost per unit of time (cost rate) in this policy [7,11,14]. If we define a life cycle to be the period between two consecutive replacements, then the expected cost per unit of time under decision T (e.g. critical age or periodic interval) is equal to

$$g(T) = \frac{C(T)}{L(T)} \tag{1}$$

where $C(T)$ is the *expected cycle cost* and $L(T)$ is the *expected cycle length*.

The objective is to identify the optimal strategy T^* that corresponds to the minimum cost rate (cost per unit of time), that is

$$T^* = \arg\min_{T>0}\{g(T)\}. \tag{2}$$

2.1. Sensitivity analysis

The cost induced by a specific strategy (chosen value for T) is influenced by aspects like the failure behaviour of individual components and the characteristics of the replacement task. These aspects are part of a real-world system, and, thus, subject to uncertainty. Therefore, it is of key importance to perform sensitivity analysis on the maintenance model. For a mathematical model in general, the purpose of sensitivity analysis is twofold: it serves as a means to understand the ‘robustness’ of the inferences

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