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Estimation of the value of prognostic information for condition-based and predictive maintenance

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For components subject to degradation, cost-efficient maintenance is necessary. Periodic or continuous collection of information, reducing uncertainty on the component's state of health, generally leads to a better-informed and, thus, more efficient maintenance. Processing condition monitoring data to estimate the current and future health states of the component, can prove valuable. In this paper, it is proposed to quantify the Value of Information (VoI) that may be obtained from state estimation and prediction procedures, with known precision, applied for condition-based and predictive maintenance. VoI is computed numerically using gamma process paths and on the basis of the optimization of the parameters of different maintenance strategies.

Keywords: Condition-Based Maintenance, Predictive Maintenance, Value of Information, Prognostics, Maintenance optimization, Remaining Useful Life.

1. Introduction

Proper maintenance is necessary to keep a component undergoing degradation in a functional state and, thus, limit the risk and costs associated to its failure. Maintenance operations, such as repairs, replacements or inspections, are carried out in view of optimizing life-cycle performance and minimizing costs in an uncertain environment. Collection of additional information on the component's State of Health (SoH), thereby reducing the associated uncertainty, allows performing better maintenance.

In this practical context of condition-informed decision-making for maintenance, it is worth considering seminal works on optimal decision-making under uncertainty proposed in the sixties by Raiffa (1961), DeGroot (1962), Howard (1966). The latter offer a framework wherein the value of a particular piece of information depends on its ability to 'guide our decision'. Formally, the metric of Value of Information (VoI) is defined as the difference in expected utility when a decision is made with and without the possession of additional information. For maintenance planning and optimization, such a metric may be used to 'evaluate the benefit of collecting additional information to reduce or eliminate uncertainty in a specific decision-making context', according to Pozzi and Der Kiureghian (2011).

Maintenance optimization approaches developed over the years along with probabilistic

models and methods, see e.g. early works of Barlow and Proschan (1967), Abdel-Hameed (1975). Exact resolution of the maintenance optimization problem is sometimes possible using renewal theory. Good reviews of the extensive literature are given by Dekker (1996), Wang (2002), Frangopol et al. (2004), van Noortwijk (2009). With the progress of computer power, maintenance optimization may also be carried out numerically, see e.g. Marseguerra et al. (2002). This is the approach used in this paper.

With the reduction in the cost of monitoring devices, an increasing amount of condition-monitoring (CM) data is available. The latter may not directly represent information on the component's state and may have to be processed using adapted methods for state estimation or prediction. In the field of Prognostics and Health Management (PHM), extracting information on a component's state for the purpose of improving maintenance decisions is a growing concern, see good reviews of Jardine et al. (2006), Heng et al. (2009), Si et al. (2011), or approaches of Bayesian filtering in Myotyrki et al. (2006), Zio and Peloni (2011).

In this paper it is proposed to investigate, with numerical simulation and using concepts from the VoI framework, the effect of state estimation and prognostics information obtained from condition monitoring data, on condition-based and predictive maintenance policies. Similar considerations

have been studied by Huynh et al. (2012), and the present paper will adopt the same approach, albeit using only numerical tools and a particular model for specifying the precision of state estimation and prognostics.

The paper is organized as follows. In section 2, a brief history of maintenance policies involving information collection are given. The different maintenance strategies that are considered and compared in this paper are, then, described in section 3. The proposed numerical experimentation and resolution of the maintenance planning problem with different strategies, for gamma degradation processes, is described in section 4. The effect of information in different decision settings is discussed in 5. Conclusions and future perspectives are detailed in section 6.

2. Review on maintenance strategies involving information collection

Early cases of inspection policies were considered by Thoft-Christensen and Sorensen (1987), Park (1988), Mori and Ellingwood (1994) and van Noortwijk and Klatter (1999). In these works, the objective is mostly to optimize the time interval between costly inspections, generally using renewal theory.

The formulation of the maintenance planning issue as a sequential decision problem, not involving resolution schemes based on renewal theory and using Markov Decision Process (MDP), was proposed by Madanat (1993) and latter extended by Ellis et al. (1995). In these works, inspections are not necessarily perfect and may be affected by measurement uncertainty.

Interest in so-called Condition-Based Maintenance (CBM) policies, and associated formalization and resolution approaches, started growing, as they generally lead to improved maintenance outcomes, see e.g. Christer and Wang (1995), Wang and Christer (2000), Grall et al. (2002) or Dieulle et al. (2003). In many cases, it is assumed that the current condition of the component is known perfectly through inspections or continuous monitoring. In particular, the choice of control-limit strategies, popular in CBM, is used in the present paper.

Considering limited resources and imperfect inspection outcomes, risk-based inspection planning was studied by Faber (2002), Straub and Faber (2005) and Kallen and van Noortwijk (2005).

The notion of Value of Information (VoI) has recently received increasing attention for inspection prioritization, sensor placement or complex policies for maintaining systems, especially in Structural Health Monitoring (SHM) where sensors or inspections can be expensive, see works of Pozzi and Der Kiureghian (2011), Straub (2014), Zonta et al. (2014), Konakli et al. (2015) and Memarzadeh and Pozzi (2016).

On the other hand, developments of numerical schemes for the resolution of sequential decision problems using MDP and Partially Observable Markov Decision Process (POMDP), support the progress of more advanced maintenance policies, e.g. with decision structures that may be more dynamic, see e.g. Papakonstantinou and Shinozuka (2014), Srinivasan and Parlikad (2013) and Memarzadeh and Pozzi (2016). For such policies, different information collection strategies can be compared on the basis of a VoI metric, notably for resource prioritization and sub-optimal and heuristic resolution schemes.

In this paper, it is proposed to consider VoI as a metric for evaluating the interest of processing CM data with state estimation and prognostics approaches, with different levels of precision. Said precision must be specified in advance.

3. Maintenance strategies and information processing

3.1. Maintenance policies

For a component undergoing continuous degradation, the elaboration of maintenance strategies generally consists in specifying a schedule or condition-based decision rules for repair, replacement or inspection actions. Preventive maintenance (PM) strategies only rely on time-based actions whereas condition-based maintenance (CBM) involves decisions rules dependent on the component's state, either known exactly or with uncertainty and periodically or non-periodically, see reviews e.g. in Dekker (1996), Wang (2002) and van Noortwijk (2009).

Here, three strategies are considered, namely:

- Block Replacement (BR)
- Periodic Inspection and Replacement (PIR)
- Predicted Quantile Replacement (PQR)

Block replacement policy (BR) is purely time-based. The component is preventively replaced at cost c_p at time T_{BR} or correctively replaced, at cost $c_c > c_p$, when failed, whichever occurs first. Failure of the component is observed without need of inspection and component is immediately replaced upon failure. These hypotheses may not represent all conceivable situations in practice, but the purpose here is not to compare all possible situations.

Periodic inspection and replacement policy (PIR) involves inspections with a given cost c_i . At each inspection date, with time-interval ΔT , the component is preventively replaced if its condition is above a specified threshold or control-limit M . The component is correctively replaced if it fails before the next inspection date.

A more detailed description of these policies can be found for example in Huynh et al. (2012). In this latter reference, more complex policies

with dynamic decision rules, e.g. inspection dates that are not fixed in advance, are proposed. Here it is proposed to focus on studying the effect of additional information from state estimation and prognostics.

The efficiency of the policy, in the sense of life-cycle cost, is quantified by the average cost per unit time C^∞ . The latter is estimated through the use of renewal theory, which states that it may be calculated as the ratio of the average renewal cycle cost over the average renewal cycle length.

$$C^\infty = \lim_{t \rightarrow \infty} \frac{C(t)}{t} = \frac{E[C(S)]}{E[S]} \quad (1)$$

where S is the length of a given renewal cycle, which brings the system back to an ‘as good as new’ condition and $C(S)$ is the cost associated to the cycle.

3.2. State-estimation-based and prognostics-based policy

Processing the data from inspections or continuous monitoring into an estimate of the current or future state of health (SoH) of the component may provide information allowing policy decisions that are better adapted to the component’s degradation path.

It is proposed to consider a policy where the decision to proceed to a preventive replacement is piloted via a control-limit level M and via a quantile value $\alpha \in [0, 1]$. The latter is associated to the uncertain distribution of the current or future SoH of the component, known from the processing of condition data collected and/or processed periodically at dates separated by a time interval ΔT . The policy is denoted as Predicted Quantile Replacement (PQR).

A prediction is made for the SoH of the component on the current interval $[t, t + \Delta T]$. If for a given quantile $\alpha \in [0, 1]$ of the predicted distribution of the SoH and for any date t_α in the time interval, the value is above the threshold M , a random value X_{t_α} is drawn from the former distribution and considered as a possible realization of the component’s SoH at time t_α . If X_{t_α} correspond to a failed state, the component is correctively replaced at cost c_c , otherwise it is preventively replaced at time t_α and cost c_p . Thus the parameter α of the decision rule, somehow controls the risk of having a prediction that underestimates the true state.

3.3. Model for precision evolution in time

It is assumed that the precision of the state estimation or prognostics approach that is used to process condition data has been previously evaluated, with techniques outside of the scope of the present paper. Estimation of such precision is

often known through the difference between the predictions \tilde{X}_i and the true values X_i , for a set of labeled examples and generally involving cross-validation. The Root Mean Square Error (RMSE) metric can be used as an estimate of the deviation between the predicted and true state:

$$\text{RMSE}(h) = \sqrt{\sum_i (\tilde{X}_{t+h,i} - X_{t+h,i})^2} \quad (2)$$

where \tilde{X}_{t+h} is the prediction of the state of the component at time $t + h$ that is made using the available information on $[0, t]$, $h \in [0, \Delta T]$ is the prediction horizon and X_{t+h} is the true state of the component at time $t + h$.

In this paper, a model for the evolution of the precision of the prediction approach with time is specified. While, the representativeness of this model may be debatable or hard to assess in practice, it is nonetheless interesting to study the influence of additional prediction information on the outcome of the maintenance policy based on such prediction information.

It is, then, assumed that the true state of the component on $[t, t + \Delta T]$ is distributed normally $X_h \sim \mathcal{N}(\tilde{X}_h, \delta(h)\tilde{X}_h)$, where $h \in [0, \Delta T]$, \tilde{X}_h is the prediction obtained from the processing of CM data and $\delta(h)$ is the coefficient of variation which controls the prediction precision and may be related to a RMSE evaluated outside the framework of this paper. Here, the following model is proposed and two parameters are used to control the estimation and prediction uncertainty, namely e_u and p_u . The coefficient of variation $\delta(h)$ is assumed to evolve linearly according to:

$$\delta(h) = e_u + p_u \frac{h}{\Delta T} \quad (3)$$

It is worth noting that when $h = 0$, this model, even if not strictly, can approximate a PIR policy with measurement uncertainty. Indeed, there is the possibility that high measurement uncertainty (here through e_u), with a significant chance (say α) of crossing the threshold M , will trigger preventive replacement.

Let us also note that a normal distribution of the prediction may create degradation paths that are not strictly non-decreasing. This is not a serious concern if high quantiles α of the distribution are considered and compared to preventive replacement and failure thresholds.

4. Comparison of maintenance policies

4.1. Simulation-based optimization and evaluation

As described in section 2, different approaches can be considered for the optimization of main-

tenance strategies. Here it is proposed to evaluate C^∞ numerically, using (1). The average length and costs of renewal cycles $E[S]$ and $E[C(S)]$ will be dependent on the design parameters of the selected maintenance strategies, namely:

- For BR: the time of replacement T_{BR}
- For PIR: the interval between inspections ΔT and the preventive replacement threshold M
- For PQR: the interval between collections/predictions ΔT , the preventive replacement threshold M and the quantile of the prediction uncertainty α

Multiple random realizations of renewal cycles are obtained through the generation of degradation paths, based on a gamma process model described hereinafter, and the application of maintenance strategies described in section 3. The estimated average cost per unit time C^∞ is the quantity to be minimized. The minimization problem is solved using the bounded and non-constrained stochastic optimization technique of simulated annealing, see Kirkpatrick et al. (1983).

4.2. Gamma degradation process

As continuous-time representations of degradation, Gamma processes are very often considered, see e.g. an extensive review in van Noortwijk (2009). They are quite amenable to mathematical treatment and the fact that they are non-decreasing makes them an appropriate representation for many monotonous degradation mechanisms. A gamma process $X(t)$ is a stochastic process with independent, non-negative, random increments, having the following distribution:

$$X(m) - X(n) \sim \text{Ga}(v(m) - v(n), u) \quad (4)$$

where $\text{Ga} : x \rightarrow \text{Ga}(x, v, u)$ is the gamma probability density function, v is the shape parameter and u is the scale parameter. At any time, the expectation and variance of the degradation can be derived according to:

$$E[X(t)] = v(t)/u \quad (5)$$

$$\text{Var}[X(t)] = v(t)/u^2 \quad (6)$$

The specification of the mean function may allow the description of different degradation trends. If $v(t) = vt, \forall t \in [0, \infty[$ the gamma process is said to be stationary. Power laws are also used $v(t) = vt^b$, where the exponent b may be quite different for different degradation mechanisms, e.g. mechanical, chemical, etc., see details in van Noortwijk (2009).

5. Results and discussion

5.1. Comparison of BR and PIR policies

First, let us insist on the fact that, the metric that will be denoted as VoI here, does not correspond to the formal definition of VoI but is in fact the ‘net gain of information’. Indeed, the cost of acquiring information is already included in the optimization of the policy. Thus, as opposed to the formal definition of VoI, see Raiffa (1961), the calculated metric can be negative here. A negative VoI indicates that it is not worth collecting information at cost per inspection c_i .

The comparison of the outcome of the optimization of the parameters of both the BR and PIR policies is given in Figure 1. The parameters used to describe what will be referred to as the decision context, namely, the degradation process and the cost and outcome of actions (here perfect) is given in Table 1. In this particular configuration of the decision context, the (net) VoI obtained from inspection is 0.07.

Table 1. Parameters of the considered decision context.. Degradation rate is fixed for failure on average at time $t = 200$ for simplicity of visualization and analysis

Parameter	Notation	Value
Failure threshold	y	100
Power law exponent	b	1
Degradation variability	u	8
Degradation rate	v	$y/(200^b u)$
Corrective replacement cost	c_c	300
Preventive replacement cost	c_p	50
Inspection cost	c_i	2

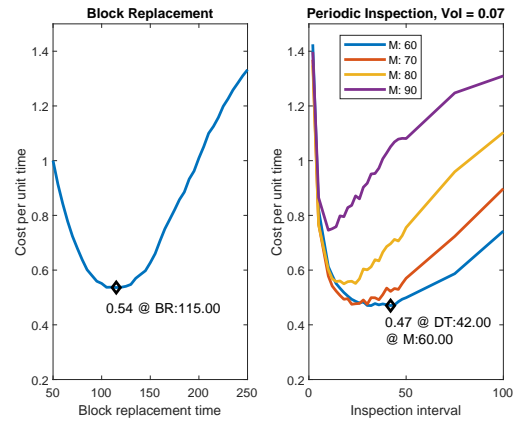


Fig. 1. Comparison of the outcome of maintenance strategies and visualization of the effect of maintenance parameters

5.2. Comparison with PQR policy

A visualization of the implementation of the PQR policy is displayed in Figure 2. On $[t, t + \Delta T]$, maintenance actions are taken based on a conditional decision rule which is linked to a quantile of the predicted distribution of the component's SoH.

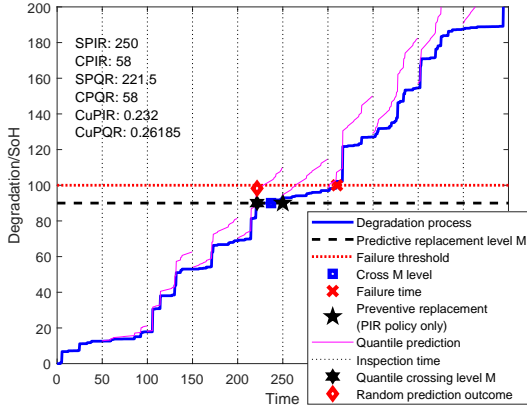


Fig. 2. Example of degradation path and practical implementation of PIR and PQR policies. Thin solid lines indicate predictions (α quantile) on the different intervals

For the specific example of Figure 2, both the PQR and PIR decision rules would provide quite similar outcomes. On the segment $[200, 250]$, the predicted quantile first crosses the preventive replacement level M , thus triggering a random generation of a value from the normal distribution $X_{t_\alpha} \sim \mathcal{N}(\tilde{X}_{t_\alpha}, \delta(h)\tilde{X}_{t_\alpha})$, which is in that case, below the failure level and the component is subsequently preventively replaced at time t_α .

Here, the prediction mean \tilde{X} is directly taken to be the degradation path, which is supposedly unknown. This is obviously a debatable choice, as the latter is not necessarily representative of the mean value of the degradation phenomenon but only of a given degradation path. Yet, the purpose here is not to develop a prediction tool and such a choice has been made for lack of a better, and nonetheless simple, alternative.

The result in terms of average outcome of policies, whose parameters are optimized numerically through simulated annealing, is given in Figure 3. It is seen that the use of prediction is valuable from the perspective of expected outcome. As could be expected, the advantage of a predictive policy does no longer hold when the prediction uncertainty p_u increases. Indeed, a high prediction uncertainty may have the effect of making the predicted quantile value (for fixed α) cross the threshold level M too early. Thus, the decision

rule, in a case of poor confidence in the prediction model, can be overly conservative.

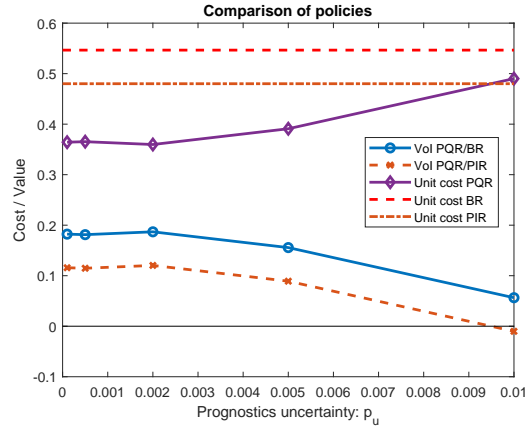


Fig. 3. Effect of prognostics information on policy output. Comparison of PQR versus BR and PIR

5.3. Influence of the decision context on the value of prognostic information

The interest of using prognostic information extracted from the collected CM data in order to improve maintenance outcomes is further studied by repeating the estimation of VoI with different values of the parameters of the decision context. The comparison between PQR policy and BR and PIR policies is displayed in Figures 4 and 5 for different decision contexts and varying prognostic uncertainty p_u . As can be expected, when the variability of the degradation process is more significant, it is more valuable to gather information on the condition of the component. With low variability, it may be enough to plan maintenance actions with a time-based schedule and, thus, inspections and predictions become less valuable.

The interest a prognostics-based policy is also evaluated for different values of inspection/monitoring cost in Figure 6. It is seen that with an increase in inspection cost, overall it becomes more advantageous to make the most out of the available information. When the cost of inspection/monitoring decreases, it may be more valuable to inspect more and to rely less on predictions that may be imperfect.

Let us point out again that, here the evaluated metric denoted as VoI, is in fact the net gain between two policies with specific structures, thus not necessarily optimal (in a very large action space), with one policy involving additional information in the form of processed condition data, i.e. prognostic information.

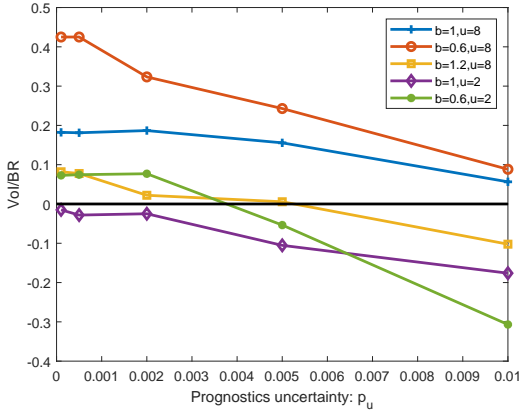


Fig. 4. Influence of the degradation process on the VoI obtained from a prognostic-based maintenance policy with different levels of precision and comparison with BR policy; b and u control the trend and variability of the degradation process

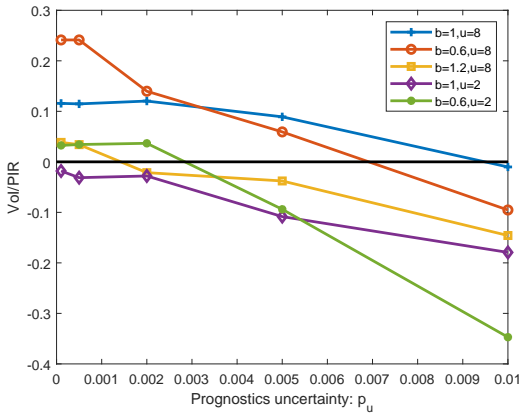


Fig. 5. Influence of the degradation process on the VoI obtained from a prognostic-based maintenance policy with different levels of precision and comparison with PIR policy; b and u control the trend and variability of the degradation process

6. Conclusions

In this paper, different maintenance strategies have been compared in terms of overall maintenance cost. They can be based on the combination of the available stochastic information on deterioration, the outcome of periodic inspections and on the information that can be obtained by processing condition-monitoring data through adapted state estimation and prognostics procedures, with known precision. The parameters of maintenance policies have been optimized to achieve minimal cost. All estimations have been carried out numerically, using a sample of simulated paths from a gamma degradation process.

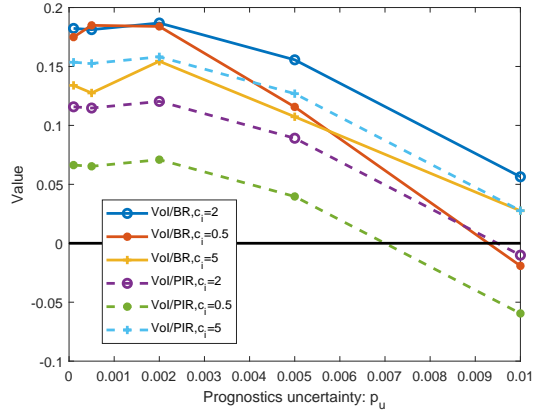


Fig. 6. Influence of the inspection/monitoring cost on the VoI obtained from a prognostic-based maintenance policy with different levels of precision and comparison with BR and PIR policies

It is seen that the Value of Information (VoI) concept can provide a relevant metric to quantitatively assess if the processing of condition monitoring data into predictions of the current and future states of the component has a positive effect on the maintenance policy. The reasoning behind the present study is that such assessment may provide insights into the need and interest of further investing in the development of a more precise prediction tool, in a particular maintenance decision context.

For illustration purposes, rather simple settings, in terms of maintenance cost and consequences, have been considered in this paper but the same overall approach could be used for more complex settings. In the end, the interest of using additional information is always dependent on the considered decision context, namely the degradation process and the cost and outcomes of maintenance actions.

Perspectives of the present work include studies of predictive policies involving specific prediction tools from the Prognostics and Health Management domain, especially in a setting where the degradation process can evolve in time, thus requiring dynamic updating of models and decisions. Another interesting perspective is to look at a more strict application of the VoI concept, which involves a comparison between policies that are optimal, given a certain state of knowledge. This may not be the case with predefined specific policy structures, thus demanding that the complete sequential decision problem is formulated, e.g. using POMDP.

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