



HAL
open science

Maintenance planning under imperfect monitoring: two POMDP approaches to quantify the value of information

Matthieu Roux, Anne Barros, Yiping Fang

► To cite this version:

Matthieu Roux, Anne Barros, Yiping Fang. Maintenance planning under imperfect monitoring: two POMDP approaches to quantify the value of information. 23ème congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision, INSA Lyon, Feb 2022, Villeurbanne - Lyon, France. hal-03595322

HAL Id: hal-03595322

<https://hal.science/hal-03595322>

Submitted on 3 Mar 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Maintenance planning under imperfect monitoring: two POMDP approaches to quantify the value of information

Matthieu Roux, Anne Barros, Yi-Ping Fang

Univ. Paris-Saclay, CentraleSupélec, LGI EA 2606

Chair Risk and Resilience of Complex Systems

{matthieu.roux, anne.barros, yiping.fang}@centralesupelec.fr

Keywords : *complex industrial system, Partially Observable Markov Decision Process, maintenance optimization, imperfect monitoring, value of information*

1 Context

In this work, we model a single-item system, composed a unique unit degrading over time. This constitutes a preliminary work, which will later lead to a more detailed study extended to multi-items systems. In the context of *condition-based maintenance* (CBM), our system is remotely monitored, providing a valuable additional information to the decision-maker in order to finely adapt the maintenance policy.

However, most of the studies in CBM tackling this maintenance optimization program, usually divided between models with continuous-time or discrete-time [1] processes, make the assumption of perfect sensors. The monitoring performance is an aspect that has not been extensively studied. Nevertheless, in a large variety of applications, such assumption is too strong, either for technical reasons or because of the prohibitive cost of high-performance sensors. Strongly confirmed by our industrial partners involved in the chair Risks and Resilience of Complex Systems, industrial systems will in general be monitored by imperfect sensors, capable of capturing only partially the exact degradation state of the system.

2 Modeling

As we chose to address the problem with discrete-time processes, we naturally adopt a *Partially Observable Markov Decision Process* (POMDP) model. This framework generalizes MDPs when the monitoring is imperfect, relying on the notion of *belief vector* $b \in \mathcal{B}$ [2]. We modeled different monitoring systems M_i , for which the performance is characterized by the probability $p_i(o|s)$ that the sensor outputs the signal $o \in \mathcal{O}$ given that the true degradation state is $s \in \mathcal{S}$ (with \mathcal{O} and \mathcal{S} finite sets). The resulting optimization program consists in minimizing the sum of all discounted maintenance cost c over an infinite time horizon. At each time step t , and based on their imperfect knowledge of the system state b_t , the decision-maker should take one decision a_t among: **NA** (no action), **PM** (preventive maintenance) and **OB** (perfect inspection that reveals the true degradation state of the system). The action **CM** (corrective maintenance) must be conducted as soon as possible after an unexpected failure. We then use dynamic programming to compute the optimal policy π^* , where γ is a discount factor:

$$\min_{\pi \in \Pi} \mathbb{E} \left[\sum_{t=0}^{+\infty} \gamma^t \cdot c(s_t, a_t) \right], \quad \text{where } a_t = \pi(b_t) \quad (1)$$

In order to prepare the ground for a future generalisation of the problem to a multi-items system, or a fleet of units, we introduce in the model the following elements. 1) For operational reasons, it is often required that the maintenance planning of a fleet is re-optimized every K

time steps (instead of a each one), called the *execution period*. Here, even if we only model a single-item system, we consider that a new (imperfect) observation on the degradation state is captured via the monitoring system every K time steps. 2) Because when maintaining a whole fleet, the decision-maker will have to manage and balance the use of maintenance resource, we decided to model the *limited maintenance resource* by imposing that at most one intervention (OB, PM or CM) can be conducted per execution period.

3 Numerical results

As for the choice of a POMDP solving technique, we compare two approaches:

- (A) an approximate modeling based on the concept of sample paths [3], which happens to be exact in the particular case of *no monitoring*; an exact solution can then be computed.
- (B) an exact POMDP modeling, but which can only be approximately solved because of its complexity; in that case, we chose to use *point-based value iteration*.

Result 1. Thanks to the good progress of current POMDP solving algorithms, approach (B) shows a better performance when tested on various scenarios (cost of maintenance actions; parameter K). Indeed, by computing bounds, it is possible to show that despite an approximate solving, this method outputs the optimal value with a satisfying precision.

Result 2. The described methodology computes the expected sum of discounted maintenance cost when the optimal policy is applied. By comparing the value obtained with the optimal value from the *no monitoring* case, we get the *value of information* brought by the considered imperfect monitoring system.

	no monitoring	imperfect monitoring				perfect monitoring
		M_1	M_2	M_3	M_4	
average maintenance cost (€)	486.10	457.59	438.63	428.48	410.88	361.89
value of information (€)	/	28.51	47.47	57.62	75.22	124.21

TAB. 1: Value of information brought by monitoring systems with different features

4 Perspectives

To carry on with this work, we are planning to extend the study to distributed systems, composed of a lot of independently degrading units, like in a fleet of trains or an offshore wind farm. A major difficulty that we expect to face will be to obtain a maintenance policy taking into account economic dependencies between units. Of course, the *curse of dimensionality*, here appearing with the exponential growth of the POMDP state space size as the number of units increases, will force us to explore heuristic modelings and/or solving techniques.

References

- [1] Elwany, A. H., Gebraeel, N. Z., & Maillart, L. M. (2011). Structured replacement policies for components with complex degradation processes and dedicated sensors. *Operations research*, 59(3), 684-695.
- [2] Papakonstantinou, K. G., & Shinozuka, M. (2014). Planning structural inspection and maintenance policies via dynamic programming and Markov processes. Part I: Theory. *Reliability Engineering & System Safety*, 130, 202-213.
- [3] Byon, E., & Ding, Y. (2010). Season-dependent condition-based maintenance for a wind turbine using a partially observed Markov decision process. *IEEE Transactions on Power Systems*, 25(4), 1823-1834.