# 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

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## 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 detailled 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 $\pi^*$, where $\gamma$ is a discount factor:

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

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


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