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Optimal predictive maintenance policy for multi-component systems

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Maintenance optimization problem

Equipments

- ▶ with several components,
- ▶ required for missions,
- ▶ subject to random degradation and failures.

Find a maintenance policy ..

- ▶ what action : mission / workshop (**repair** or **change**) ?
- ▶ when ?

.. in order to optimize some criterion

- ▶ **minimize** maintenance costs,
 - ▶ **maximize** availability.
- } **non-trivial compromise**

Industrial context (1)

Missions

- ▶ System required for fixed frequencies and durations missions,
- ▶ Over a finite time horizon,
- ▶ When the system is not functioning, it can not degrade or fail.

Equipments with 3 components

- ▶ Dynamics of the components 1, 2 and 3 :

stable $\xrightarrow{\text{Weibull}}$ degraded $\xrightarrow{\text{Exponential}}$ failed.

Global equipment state

- ▶ **stable** if all its components are in a **stable** state,
- ▶ **failed** if at least one of its component is in **failed** state,
- ▶ and **degraded** otherwise.

Industrial context (2)

Possible maintenance operations

- ▶ do nothing : in **stable**, **degraded** and **failed** states,
- ▶ **change** : in **stable**, **degraded** and **failed** states,
- ▶ **repair** : in **stable** and **degraded** states.

Workshop

- ▶ Immobilize the entire system,
- ▶ As good as new (**stable** state, functioning times reset to 0).

Costs

- ▶ Maintenances : **repair**, **change**,
- ▶ Penalties in **failed** state : failed missions, unavailability,
- ▶ **repair** < **change** < unavailability < **failure**.

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Our approach

- ▶ Propose a *mathematical model* for the evolution of the multi-component system by using the formalism of a Markov Decision Processes (MDP).
 1. System degradation modeling,
 2. Explicit the cost function.
- ▶ *Simulate* the process under different reference *maintenance policies* (corrective or preventive) and compare their *costs*.

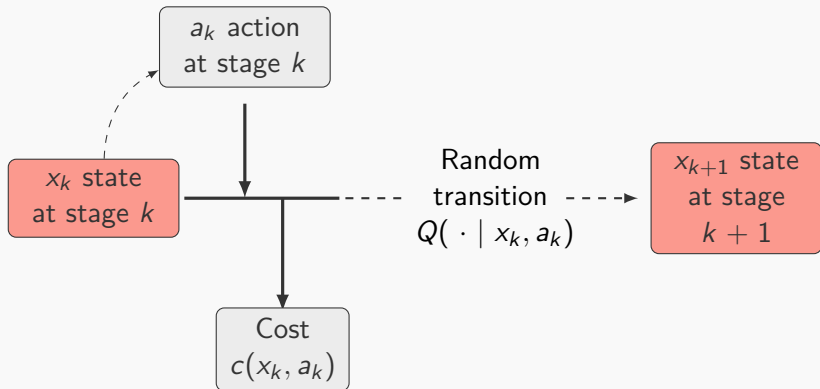
Markov Decision Processes (MDP)

A MDP is defined by the following parameters :

$$(\mathbb{X}; \mathbb{A}; \{\mathbb{A}(x) \mid x \in \mathbb{X}\}; Q; c)$$

- ▶ A state space \mathbb{X}
 $\mathbb{X} = \{x = (e_i, r_i), i \in \{1,2,3\}, e_i \in \{\text{stable, degraded, failed}\}, r_i \in \mathbb{R}^+\}$.
- ▶ An action space \mathbb{A} ,
 $\mathbb{A} = \{a = (a_1, a_2, a_3), a_i \in \{\text{nothing, repair, change}\}\}$.
- ▶ A set $\mathbb{A}(x)$ of admissible actions when the system is in state x ; is such that a failed component cannot be repaired.
- ▶ A transition kernel $Q(\cdot \mid x, a)$ which provides the distribution of the next state of the system, when the current state is $x \in \mathbb{X}$ and the action $a \in \mathbb{A}(x)$.
- ▶ A cost function $c : \mathbb{X} \times \mathbb{A}(x) \rightarrow \mathbb{R}$ depending on state-action.

Construction of controlled trajectories



Optimization problem

The total **cost** until the finite horizon N , with initial state $x \in \mathbb{X}$ and under the *policy* π :

$$V_N(\pi, x) = \mathbb{E}_x^\pi \left[\sum_{n=0}^N c(x_n, a_n) \right].$$

The optimal control problem associated to a MDP is to *minimize*, over all *admissible policies* Π , the function $\pi \rightarrow V_N(\pi, x)$.

The optimum is called the *value function* and is given by

$$V(x) = \inf_{\pi \in \Pi} V_N(\pi; x).$$

A strategy $\pi^* \in \Pi$ is called *optimal* if it satisfies

$$V_N(\pi^*, x) = V(x).$$

Reference policies

π_1 - Policy without any intervention

Do nothing (no change, no repair) during the studied period.

π_2 - Corrective maintenance policy

Send back the equipment to the workshop, 1 day after the **failure**,

- ▶ **repair** each **degraded** component,
- ▶ **change** each **failed** one.

π_3 - Preventive maintenance policy

After 1 day spent in a **degraded** or **failed** state, send back the equipment to the workshop,

- ▶ **repair** each **degraded** components,
- ▶ **change** each **failed** one.

Policy Comparisons

We compare the performances of these reference policies.
Their *cost* was evaluated through 10^5 Monte Carlo simulations.

Policy	cost	95% CI
π_1	22892	[22884, 22900]
π_2	18134	[18121, 18147]
π_3	15435	[15423, 15447]

Table – *Costs of the reference policies*

As expected, a *preventive* maintenance policy π_3 effectively *reduces maintenance costs* by intervening on the system before the failure.

This yields a *relative gain* with respect to the uncontrolled policy π_1 of 33% and 15% with respect to the *corrective* policy π_2 .

Non standard optimization problem

State space

- ▶ Discrete variables and *continuous variables* (functioning times of the components) : the state space is *not finite*.

Transition kernel $Q(dy|x, a)$

- ▶ Not analytically explicit, it can be simulated.

↪ Standard optimization technique for MDPs *do not apply*.

↪ The *next step* toward solving the global optimization problem will be to *discretize the state space*.

Discretization of the state space

State space

$$\mathbb{X} = \{(e_i, r_i); i \in \{1, 2, 3\}, e_i \in \{\text{stable, degraded, failed}\}, r_i \in \mathbb{R}^+\}$$

Discretize the state space, as a trade-off between :

- ▶ precision of the approximation
 - ▶ numerical complexity
- } **Non-trivial compromise**

Reference policy costs will be used to assess the impact of discretization on costs.

Problems :

- No "universal method",
- No theoretical result.

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Conclusions

- ▶ Propose a *mathematical model* for the evolution of the system by using the formalism of a Markov Decision Processes (MDP).
 - ▶ System degradation modeling,
 - ▶ Explicit the cost functions.
- ▶ *Simulate* the process under different reference *maintenance policies* (corrective or preventive) and compare their *costs*.

Work in progress

- ▶ Discretize the state space, as a compromise between numerical complexity and precision of the approximation.
- ▶ Use *simulation-based* optimisation algorithm to compute an approximation of the optimal *cost* and *policy*, over the whole space Π of admissible policies.

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Thank you for your attention !

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