Estimating Maintenance Cost of Offshore Electrical Substations

ROADEF 2026

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24/02/26

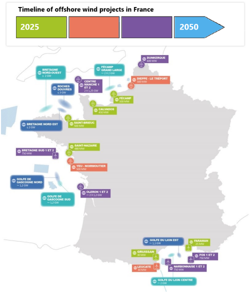
Le réseau de transport d'électricité

CERMICS
École nationale des ponts et chaussées

Contents

Context

Offshore wind is growing.



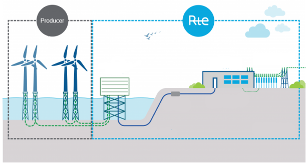
Source: RTE - 2024

France wants to promote offshore wind farms.

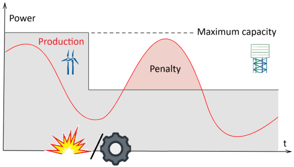
- Attractive conditions for producers.

From the TSO perspective:

- Penalties apply to curtailed energy exceeding the allowed maintenance days quota.



Source: RTE



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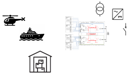
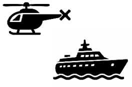
Estimating maintenance cost to make informed strategic choices.

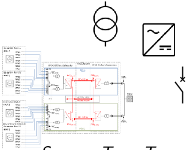


Estimating maintenance cost to make informed strategic choices.

transport



storage



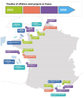
Source: TenneT

substation design

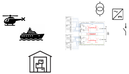
- Strategic choices must account for 40-year maintenance costs.

Context

Offshore wind is growing.



Estimating maintenance cost to make informed strategic choices.



Estimating maintenance cost is challenging.

Estimating maintenance cost is challenging.

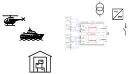
Source: RTE - PSEM Calvados

- Substations are 50/100 miles offshore.
- Workers may or may not sleep at location.
- 2 hours of effective work per day vs. 7 hours on land.

Context

Offshore wind is growing.

Estimating maintenance cost to make informed strategic choices.



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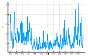
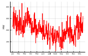
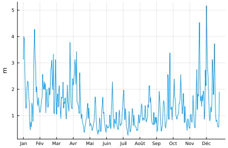




Estimating maintenance cost is challenging.

Two weather-related uncertainties:

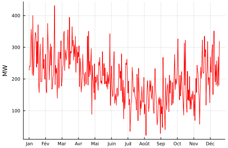
Accessibility



Source: Copernicus

Daily average **wave height**
(Baie de Saint-Brieuc - 2023)

Production



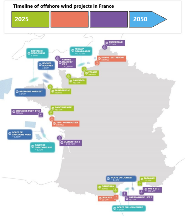
Source: RTE

Daily average offshore wind farm **production**
(Baie de Saint-Brieuc - 2023)

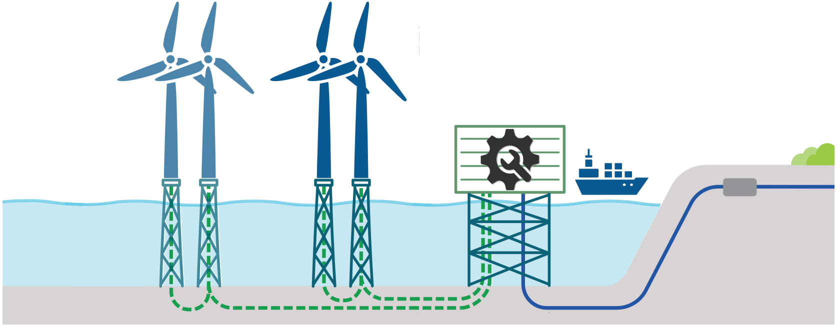
- If waves are too high, access to the substation is impossible.
- Penalties are proportional to curtailed energy.

Contents

Modeling the maintenance of a single substation as a Markov Decision Process (MDP)



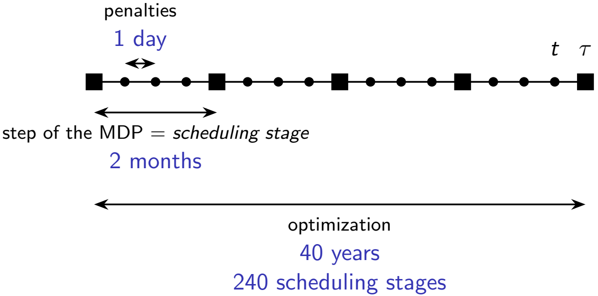
- In practice, there are interactions between the substations.
- In this presentation, we focus on the maintenance of a single substation.



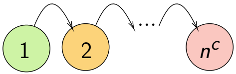
Temporal structure

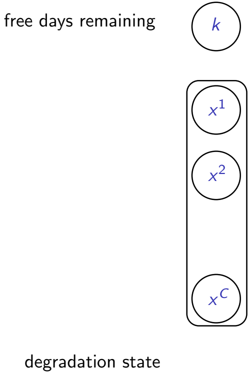
Assumptions:

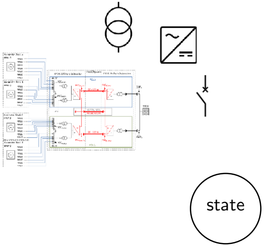
- To benefit from free maintenance days in a two-month period, the TSO must declare them at the start of that given period.
- Maintenance operations are scheduled at the beginning of a period and cannot be canceled during the period.



MDP: state





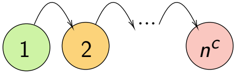


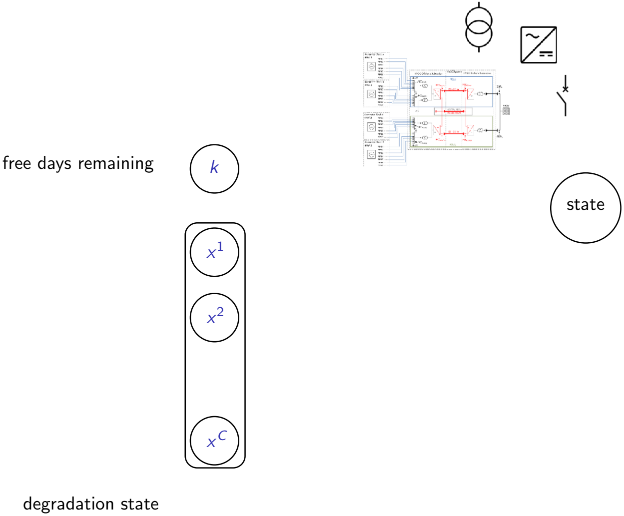
The station consists of C components.

- *Joint degradation state*

$$x = (x^c)_{c\in[1:C]} \in \bigotimes_{c\in[1:C]} [1 : n^c].$$

MDP: state





The station consists of C components.

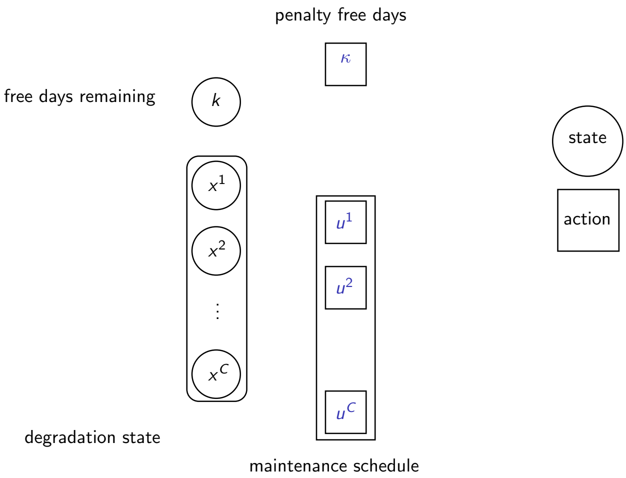
- *Joint degradation state*

$$x = (x^c)_{c\in[1:C]} \in \bigotimes_{c\in[1:C]} [1 : n^c].$$

$\bar{k}$ penalty free maintenance days are available per year.

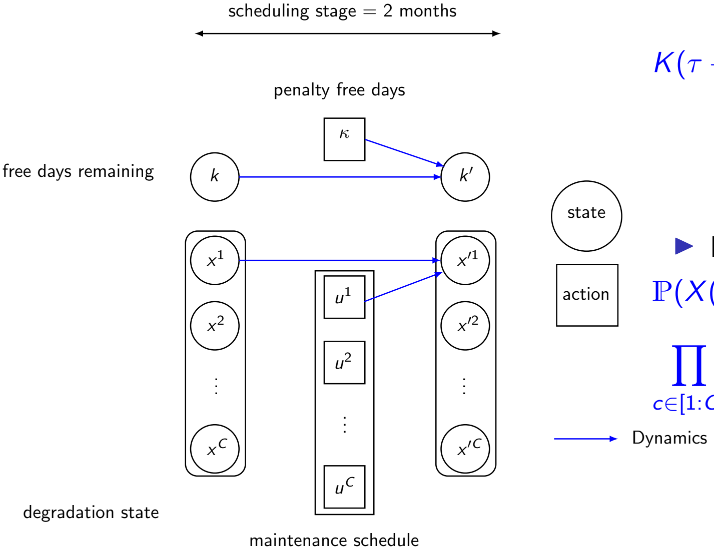
- *Penalty free days remaining* $k \in [0 : \bar{k}]$.

MDP: actions



- *Penalty free days for the scheduling stage* κ (Applicable to all components).
- *Maintenance schedule* $u = (u^c)_{c \in [1:C]}$.

MDP: transitions



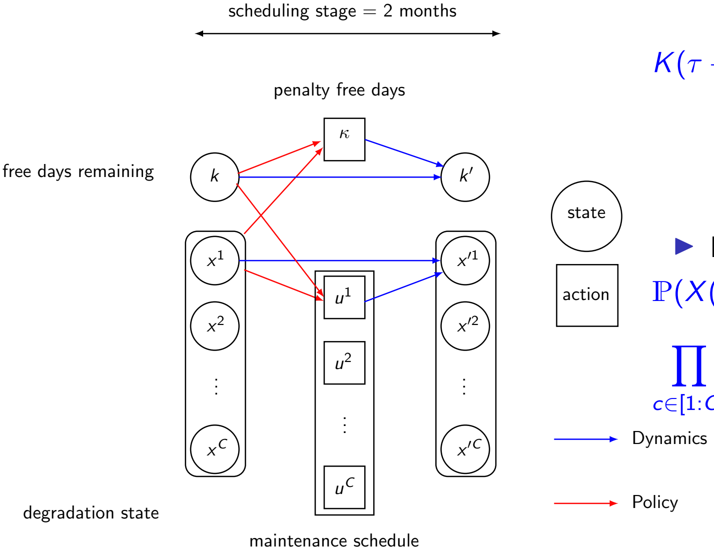
- Quota dynamics

$$K(\tau+1) = \phi_\tau(\mathcal{K}(\tau), K(\tau)) = \begin{cases} \bar{k} \text{ if } \tau \equiv 0 \pmod 6; \\ K(\tau) - |\mathcal{K}(\tau)| \text{ otherwise.} \end{cases}$$

- Independent degradations

$$\mathbb{P}(X(\tau+1) = x' | X(\tau) = x, U(\tau) = u) = \prod_{c \in [1:C]} p^c(x'^c | x^c, u^c).$$

MDP: transitions



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$$\mathbb{P}(X(\tau+1) = x' | X(\tau) = x, U(\tau) = u) = \prod_{c \in [1:C]} p^c(x'^c | x^c, u^c).$$

MDP: cost

$$\text{Stage cost} = \overbrace{\sum_t \mathbb{1}_{t \notin \kappa}(\text{Production}_t - \text{Capacity}_t)^+}^{\text{Penalty}} + \underbrace{\gamma^m(u)}_{\text{Maintenance cost}} .$$

MDP: cost

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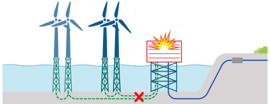
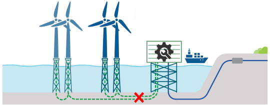
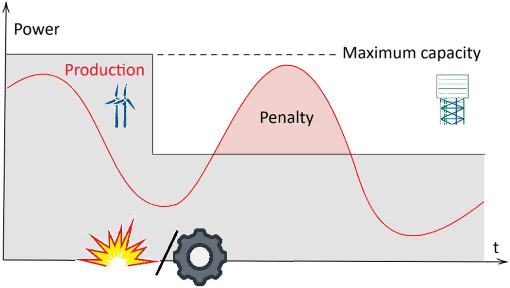
Capacity reduction in case of:

- failure;

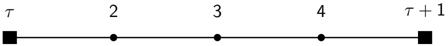


- or maintenance.



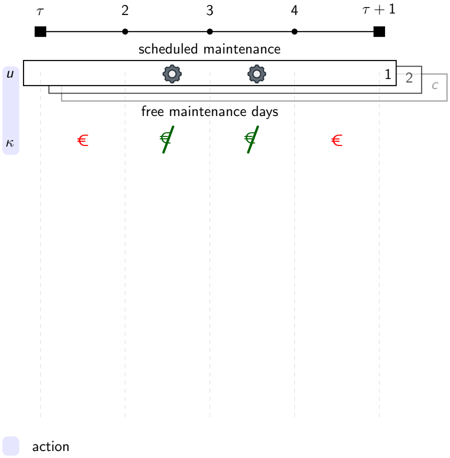


Dynamics over a scheduling stage (= 2 months)



A *scheduling stage* τ is divided into daily time steps $t \in [1 : \bar{t}]$.

Dynamics over a scheduling stage (= 2 months)



- Scheduled maintenance

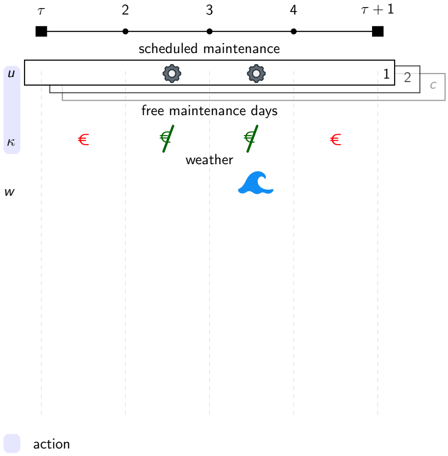
$$u = (u_t^c)_{t \in [1:\bar{t}], c \in [1:C]} \in \mathbb{U} \subset \{0,1\}^{[1:\bar{t}] \times [1:C]}.$$

- Subset of free maintenance days

$$\kappa \in \mathbb{K} \subset \mathcal{P}([1:\bar{t}]).$$

example: $\kappa = \{\text{day } 2, \text{day } 3\}$

Dynamics over a scheduling stage (= 2 months)



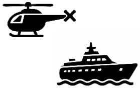
- *Weather scenario* $w \in \mathbb{W}_\tau$.

$$w = (\pi_t, a_t)_{t \in [1:\bar{t}]}$$

production $\in \mathbb{R}^+$

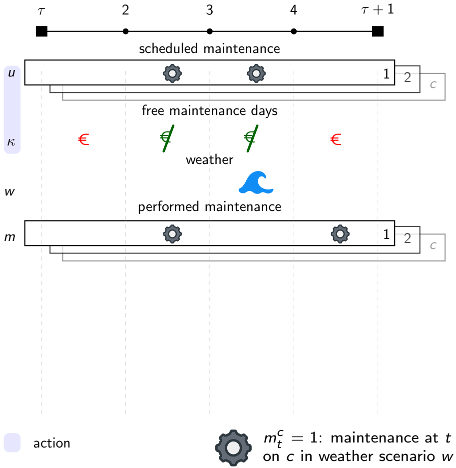
accessibility $\in \{0; 1\}$

$a_t = 0$



inaccessible

Dynamics over a scheduling stage (= 2 months)



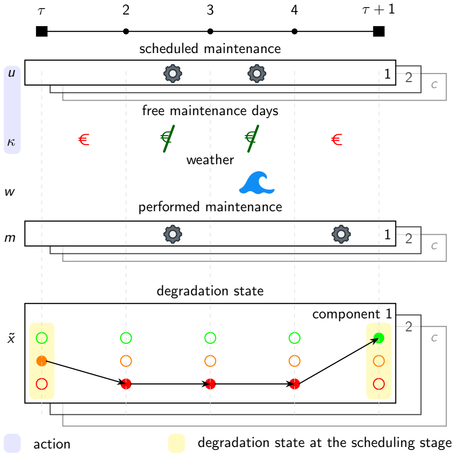
- *Performed maintenance*

$$m = (m_t^c)_{t \in [1:\bar{t}], c \in [1:C]} \in \{0,1\}^{[1:\bar{t}] \times [1:C]}.$$

- From u and w we determine $m = \psi(u, w)$.

example: ψ: "Maintain at the earliest opportunity from the desired start date."

Dynamics over a scheduling stage (= 2 months)



- *Failure scenario* $\xi \in \mathcal{X}^{[1:\bar{t}]\times[1:C]}$.
- The daily dynamics of component c can be written as:

$$\tilde{x}^c_{t+1} = f^c(\tilde{x}^c_t, \xi^c_t, m_t).$$

Penalty over a scheduling stage

The penalty over the scheduling stage is:

$$\gamma^P(x,u,\kappa,w,\xi) = \sum_{t\in[1:\bar{t}]} \mathbb{1}_{\{t\notin\kappa\}}\big(\underbrace{\pi_t}_{\text{production}} - \boxed{\text{Capacity}(\tilde{x}_t, m_t)}\big)^+$$

joint degradation state (↔ $\tilde{x}_t$), performed maintenance (↔ m_t)

$$\begin{aligned} m &= \psi(u,w) \\ \tilde{x}_1 &= x \\ \tilde{x}^c_{t+1} &= f^c(\tilde{x}^c_t, \xi^c_t, m_t) \quad \forall t \in [1:\bar{t}-1]. \end{aligned}$$

- Sum of daily penalties over the scheduling stage;
- Weather dependent;
- Does not decompose.

Cost over a scheduling stage

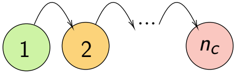
The stage cost is as follows:

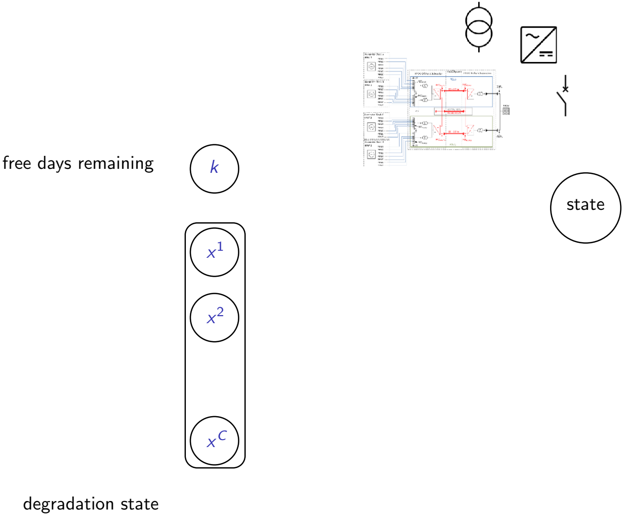
$$\gamma(x, u, \kappa, w, \xi) = \overbrace{\gamma^P(x, u, \kappa, w, \xi)}^{\text{Penalty}} + \underbrace{\gamma^M(u)}_{\text{Maintenance cost}} .$$

We can eliminate the dependence on both random variables by taking expectations over all scenarios:

$$\tilde{\gamma}_\tau(x, u, \kappa) = \frac{1}{\mathbb{W}_\tau} \sum_{w \in \mathbb{W}_\tau} \mathbb{E}_\Xi[c(x, u, \kappa, w, \Xi)].$$

Curse of dimensionality





The station consists of C components.

- *Joint degradation state*

$$x = (x^c)_{c \in [1:C]} \in \bigotimes_{c \in [1:C]} [1 : n^c].$$

$\prod_{[1:C]} n^c$ possible degradation states.

Contents

Conventional techniques are not directly applicable to solve the MDP

- The MDP cannot be solved directly by dynamic programming.

Conventional techniques are not directly applicable to solve the MDP

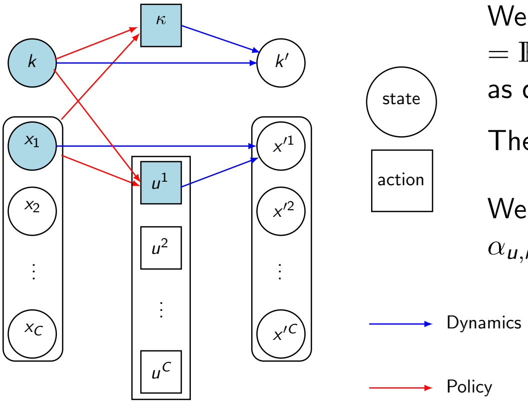
- The MDP cannot be solved directly by dynamic programming.
- Every MDP can be written as a Linear Program (LP) with the moments $\mu_{xku\kappa}(\tau)$ as decision variables:

$$\mu_{xku\kappa}(\tau), \quad x \in \prod_{[1:C]} n^c, k \in [0 : \bar{k}], u \in \mathbb{U}, \kappa \in \mathbb{K} |\ |\kappa| \leq k, \tau \in [1 : 240].$$

$$\begin{aligned} \underset{\mu \geq 0}{\text{minimize}} \quad & \sum_{\tau=1}^{240} \sum_{x,k,u,\kappa} \tilde{\gamma}_\tau(x, u, \kappa)\mu_{xku\kappa}(\tau) \\ \text{subject to} \quad & \sum_{u,\kappa} \mu_{x'k'u\kappa}(\tau) = \sum_{x,k,u,\kappa} \mathbb{1}_{\{\phi(k,\kappa)=k'\}} p(x'|x, u)\mu_{xku\kappa}(\tau - 1) \\ & \forall x' \in \prod_{[1:C]} n^c, k' \in [0 : \bar{k}], \tau \in [2 : 240]. \end{aligned}$$

However, this LP is intractable in our setting.

First approximation leveraging the structure of the MDP [1]



We consider a new LP with *local moments* $\mu^c_{x^c k u \kappa}(\tau)$ $= \mathbb{P}(X^c(\tau) = x^c, K(\tau) = k, U(\tau) = u, \mathcal{K}(\tau) = \kappa)$ as decision variables.

The number of variables scales as $\sum_{[1:C]} n^c$.

We also introduce $\alpha_{u,\kappa}(\tau) = \mathbb{P}(U(\tau) = u, \mathcal{K}(\tau) = \kappa)$.

[1] D. Bertsimas and M. Mišić, *Decomposable Markov Decision Processes: A Fluid Optimization Approach*, Operations Research, vol. 64, no. 6, pp. 1537-1555, Oct 2016.

Constraints

To every policy we can associate local moments that satisfy:

- The *Flow constraints:* $\forall c \in [1:C], x'^c \in [1:n^c], k' \in [0:\bar{k}], \tau \in [2:240]$

$$\sum_{u,\kappa} \mu^c_{x'^c k' u \kappa}(\tau) = \sum_{x^c,k,u,\kappa} \mathbb{1}_{\{\phi(k,\kappa)=k'\}} p^c(x'^c|x^c,u) \mu^c_{x^c k u \kappa}(\tau-1);$$

- The *Consistency constraints:* $\forall u \in \mathbb{U}, \kappa \in \mathbb{K}$

$$\sum_{x,k} \mu^c_{x^c k u \kappa}(\tau) = \alpha_{u,\kappa}(\tau).$$

These are the constraints of the new LP. It is a relaxation of the original LP: any μ and α satisfying them are not necessarily associated with a policy for $\tau \in [2:240]$.

Second approximation: linear cost function

We approximate the stage cost by an additive cost:

$$\sum_{c=1}^{C} \ell_\tau^c(x^c, u, \kappa).$$

This is an upper bound of the true cost. The marginals associated to a policy are solution to:

$$\begin{aligned} \underset{\mu,\alpha\geq 0}{\text{minimize}} \quad & \sum_{T=1}^{240} \sum_{c=1}^{C} \sum_{x^c,k,u,\kappa} \ell_\tau^c(x^c, u, \kappa)\mu_{x^c k u \kappa}^c(\tau) \\ \text{subject to} \quad & \textit{Flow constraints}; \\ & \textit{Consistency constraints}; \\ & \sum_{u,\kappa} \mu_{x^c k u \kappa}^c(1) = \mathbb{1}_{\{x^c=1 \wedge k=K\}}. \end{aligned}$$

Rolling-horizon heuristic

Input: scheduling stage h, state $(\mathbf{x}, \mathbf{k})$.
Output: action (u^*, κ^*).

- Solve the LP with initial state $\mathbf{x}, \mathbf{k}$ over horizon $\bar{h}$ (typically 6 stages for 1 year).
- Return action with the highest marginal probability $u^*, \kappa^* = \arg\max_{u,\kappa} \alpha_{u,\kappa}(h)$.

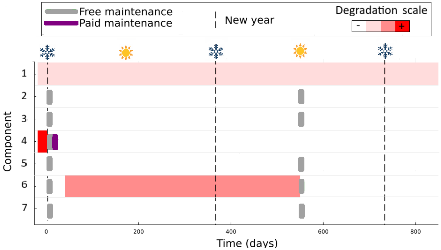
$$\begin{aligned}
\underset{\mu,\alpha\geq 0}{\text{minimize}} \quad & \sum_{\tau=h}^{h+\bar{h}} \sum_{c=1}^{C} \sum_{x^c,k,u,\kappa} \ell_\tau^c(x^c, u, \kappa)\mu_{x^c k u \kappa}^c(\tau) \\
\text{subject to} \quad & \textit{Flow constraints}; \\
& \textit{Consistency constraints}; \\
& \sum_{u,\kappa} \mu_{x^c k u \kappa}^c(h) = \mathbb{1}_{\{x=\mathbf{x}^c \wedge k=\mathbf{k}\}}.
\end{aligned}$$

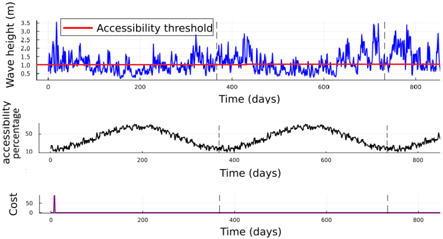
Case study

- **7** key High-Voltage Direct Current (HVDC) components.
- Weather scenarios corresponding to the upcoming **Centre Manche 1** project location, built using Copernicus data.
- Benchmark against an **operational rule** (among others).

Table: Simulated cost over 40 years

Policy	Mean	$VaR_{0.05}$
Fluid	**126**	257
Operational	249	1671





Contents

Conclusion

Outline of the talk:

- Strategic choices translate into the parameters of the MDP. We evaluate the associated maintenance cost.
- Main difficulty: solving a decomposable MDP.

Our next focus:

- Distributionally Robust Optimization for decomposable MDPs;
- Interactions between substations.

Thank you for listening!