From partial and limited structural health data to optimal management of engineering systems

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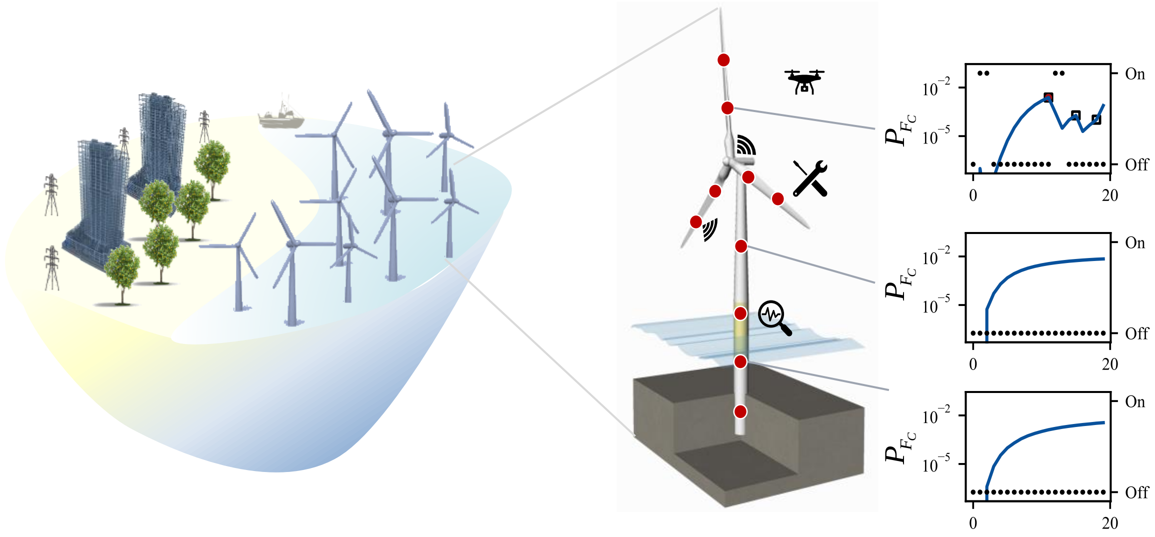
Motivation: management of engineering systems

- **Deteriorating structural systems**
  Fatigue, corrosion, erosion, ...
- **Uncertainties**
  Loads, model, measurements, ...
- **Structural failure risk**
  Environmental and economic consequences
- **Maintenance decisions under uncertainty**
  Uncertainties hinder effective decision-making



Information available: Bayesian inference

- Physics-based engineering simulators

  (Prior)

- Available data: Inspections, SHM

  (Likelihood)

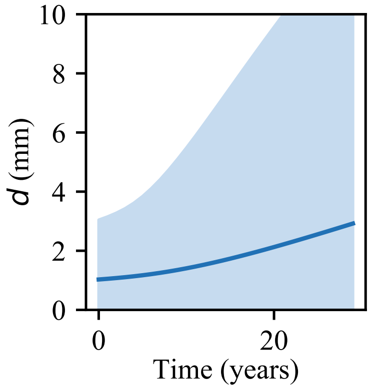
- Inference via Bayesian networks (Posterior)

  Dynamics Bayesian networks are models particularly suited for inference tasks in probabilistic environments.

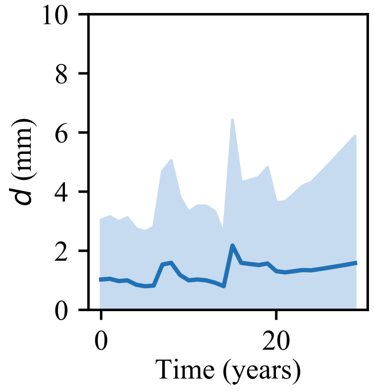
  *Assumptions:

  (i) Discrete state space

  (ii) Markovian



(Prior)
Deterioration model



(Posterior)
Inspections/SHM

- Maintenance decisions under uncertainty

  More effective decisions

Information available: Bayesian inference

- Transition step

$p(d_{t+1}, q_{t+1} \mid d_t, q_t, \tau_t)$ damage

$p(\tau_{t+1} \mid \tau_t)$ deterioration rate

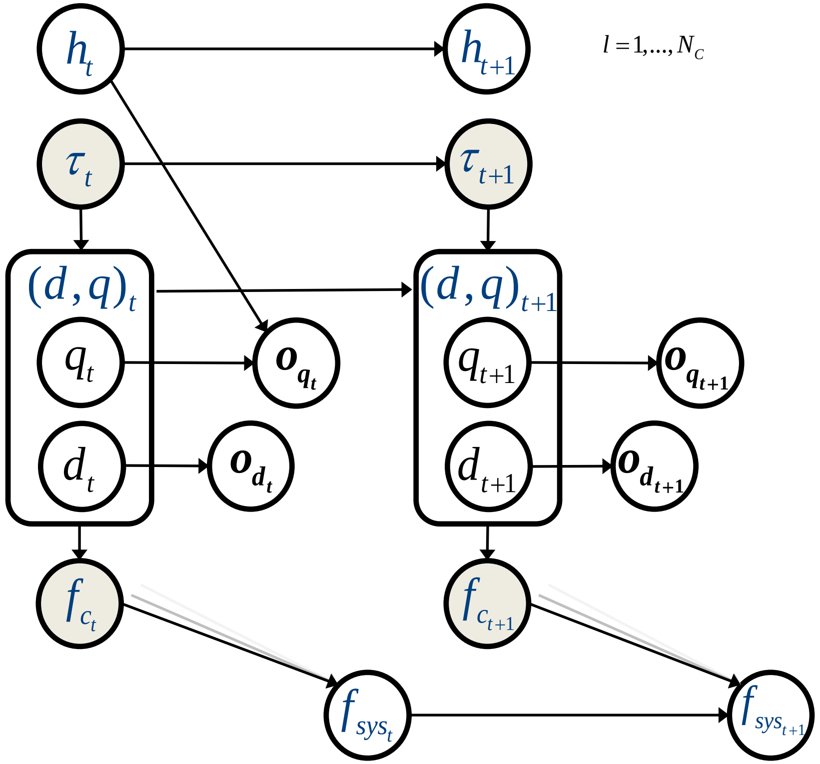
$p(h_{t+1} \mid h_t)$ sensor condition

- Estimation step (Bayesian updating)

$$p(d_{t+1}, q_{t+1} \mid \boldsymbol{o_0}, \ldots, \boldsymbol{o_{t+1}}) \propto p(\boldsymbol{o_{t+1}} \mid d_{t+1}, q_{t+1})\, p(d_{t+1}, \boldsymbol{\theta}_{t+1} \mid \boldsymbol{o_0}, \ldots, \boldsymbol{o_t})$$

inspections $p(o_{d_{t+1}} \mid d_{t+1})$

load effect $p(o_{q_{t+1}} \mid q_{t+1}, h_{t+1})$



Morato, P. G., Papakonstantinou, K. G., Andriotis, C. P., Nielsen, J. S., & Rigo, P. (2022). Optimal inspection and maintenance planning for deteriorating structural components through dynamic Bayesian networks and Markov decision processes. *Structural Safety*, 94, 102140.

Planning under limited and imperfect information

- **Recurrent costs**

  Inspections, sensor installation, ...

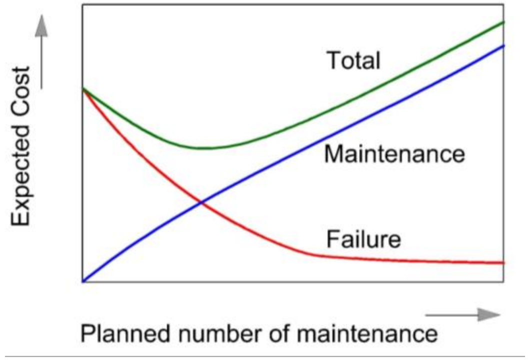
- **Measurement uncertainty**

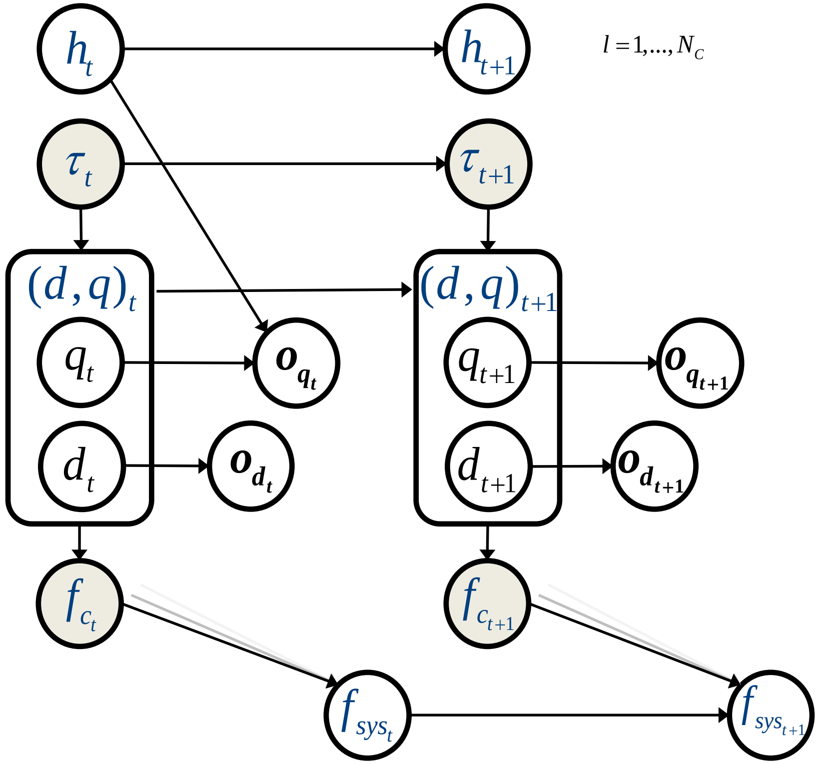
  Sensors and inspections accuracy

- **Stochastic optimization objective:**

  Sum of expected discounted costs

$$\min \mathbf{E}[c_0] = \mathbf{E}\left[\sum_{t=0}^{T-1} \gamma^t \left\{c_{t,ins} + c_{t,sens} + c_{t,rep} + r_{t,fail} + c_{t,replac}\right\}\right]$$





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Challenges and context

▶ Course of history

Partially observable Markov Decision processes (POMDPs)

Policy space: $\left\{ |\mathcal{A}|^{N_C} \right\}^{T_N}$

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.

Morato, P. G., Papakonstantinou, K. G., Andriotis, C. P., Nielsen, J. S., & Rigo, P. (2022). Optimal inspection and maintenance planning for deteriorating structural components through dynamic Bayesian networks and Markov decision processes. *Structural Safety, 94*, 102140.

▶ Course of dimensionality

Deep reinforcement learning

State space: $\{|\mathcal{S}_d|\cdot|\mathcal{S}_\tau|\cdot|\mathcal{S}_q|\}^{N_c}$

Action space: $|\mathcal{A}|^{N_C}$

$N_c = 15;\ |\mathcal{A}| = 6;\ T_N = 20$

$|\pi| = 6^{300}$

Andriotis, C. P., & Papakonstantinou, K. G. (2019). Managing engineering systems with large state and action spaces through deep reinforcement learning. *Reliability Engineering & System Safety, 191*, 106483.

Morato, P. G., Andriotis, C. P., Papakonstantinou, K. G., & Rigo, P. (2023). Inference and dynamic decision-making for deteriorating systems with probabilistic dependencies through Bayesian networks and deep reinforcement learning. *Reliability Engineering & System Safety, 235*, 109144.

Context: POMDPs

A POMDP is a 6-tuple

< *S*, *A*, *Ω*, **P**, **O**, **R** >

$s_t \in S$

$a_t \in A$

$o_t \in \Omega$

$p(s_{t+1} \mid s_t, a_t)$

$p(o_t \mid s_t, a_t)$

$r(s_t, a_t)$

Value function

Sum of expected discounted rewards

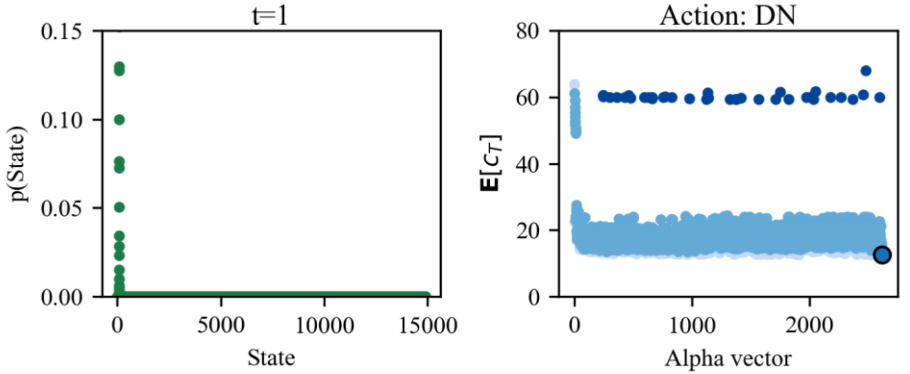
$$V(\mathbf{b}_t) = \max_{a_t \in A} \left\{ \sum_{s_t \in S} b(s_t) r(s_t, a_t) + \gamma \sum_{o_{t+1} \in \Omega} p(o_{t+1} \mid \mathbf{b}_t, a_t) V(\mathbf{b}_{t+1}) \right\}$$

Belief state

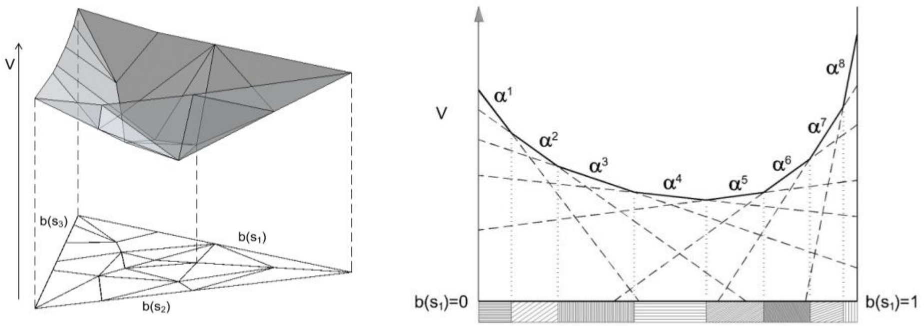
Sufficient statistic

$$b(s_{t+1}) = p(s_{t+1} \mid o_{t+1}, a_t, b_t) = \mathbf{b}_t^{a,o} = \frac{p(o_{t+1} \mid s_{t+1}, a_t)}{p(o_{t+1} \mid \mathbf{b}_t, a_t)} \sum_{s_t \in S} p(s_{t+1} \mid s_t, a_t) b(s_t)$$

Dynamic policies



Point-based solvers



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Research objective and outline

- Planning sequential SHM decisions
  - Bayesian inference
  - SHM costs
  - Sensors condition

- Outline
  - Definition of the decision problem as a POMDP
  - Integration with multi-agent reinforcement learning
  - Case study: management of an offshore wind farm

POMDP definition: states, observations, and actions

States

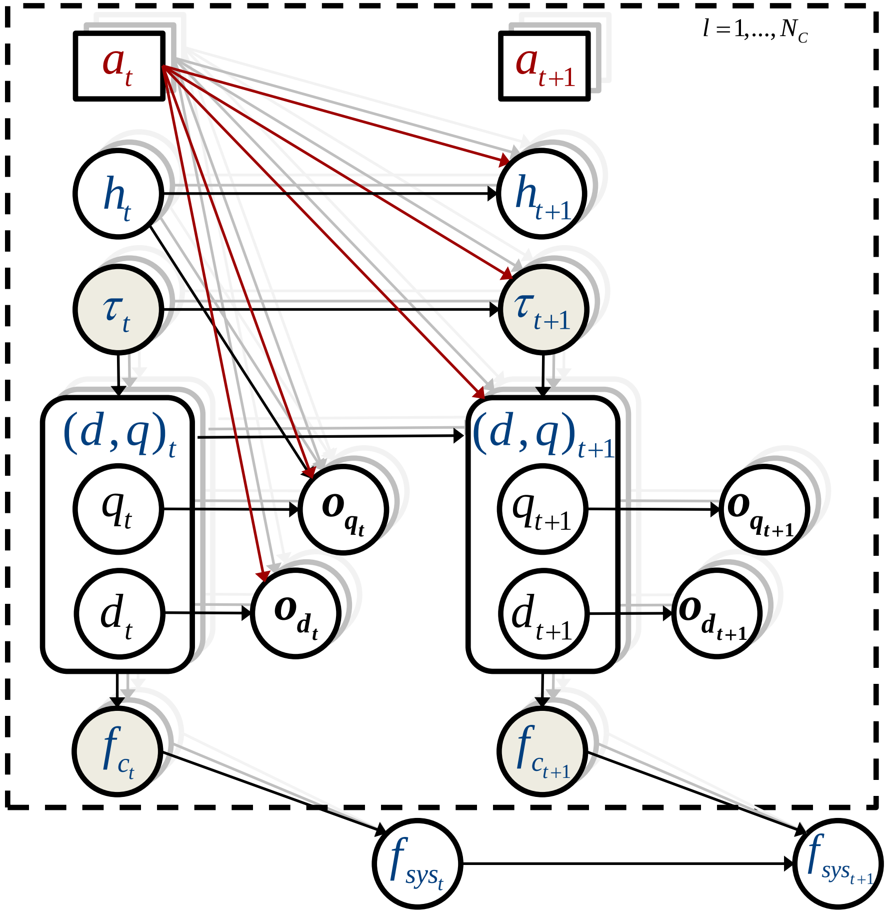
- Damage / deterioration rate d_t, τ_t
- Sensor health h_t
- Component / system failure f_{c_t}, f_{sys_t}

Actions

- Do-nothing / Inspect
- Install sensor / Install sensor & inspection
- Repair & no-sensor / Repair & sensor
- Replacement

Observations

- Inspections $\boldsymbol{o}_{d_t}$
- Monitoring $\boldsymbol{o}_{q_t}$
- System failure state f_{sys_t}



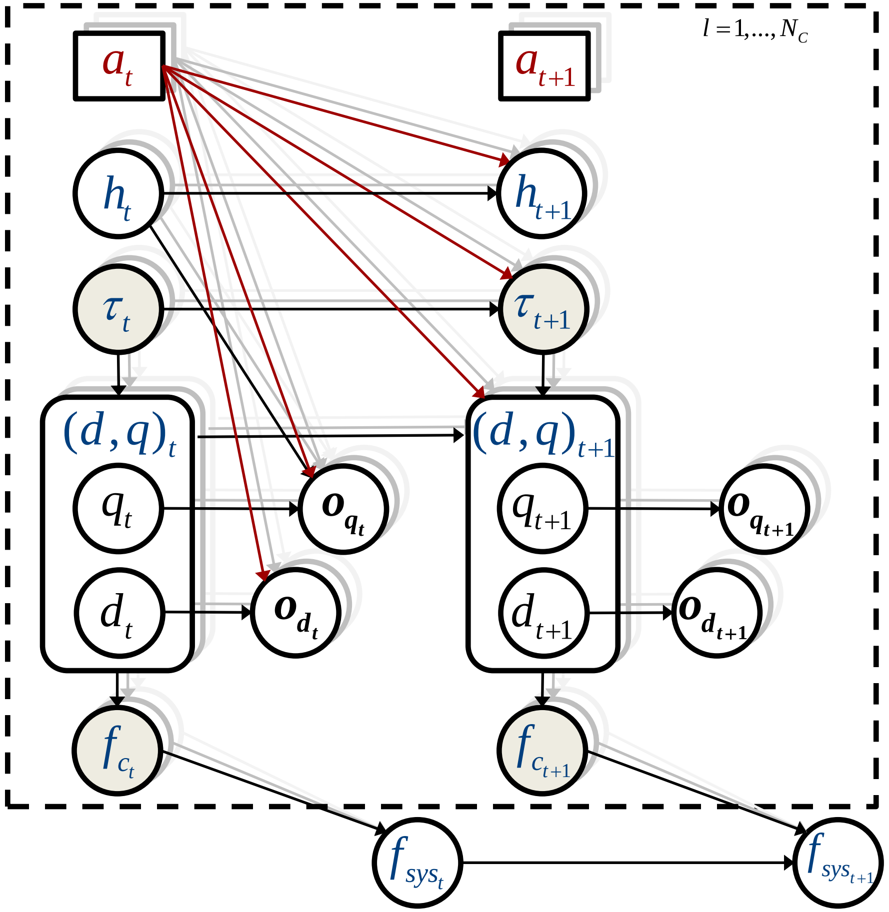
POMDP definition: transition and observation models

Transition model

- Damage: $p(d_{t+1}, q_{t+1} \mid d_t, q_t, \tau_t, a_t)$
- Deterioration rate: $p(\tau_{t+1} \mid \tau_t, a_t)$
- Sensor health: $p(h_{t+1} \mid h_t, a_t)$
- System failure: $p(f_{sys_{t+1}} \mid \mathbf{f}_{\mathbf{c,t+1}}, f_{sys_t})$

Observation model

- Inspections: $p(o_{d_{t+1}} \mid d_{t+1}, a_{t+1})$
- Monitoring: $p(o_{q_{t+1}} \mid q_{t+1}, h_{t+1}, a_{t+1})$
- System failure: $\mathrm{f}_{sys_{t+1}} \sim \mathrm{p}(f_{sys_{t+1}})$



POMDP definition: cost model and objective

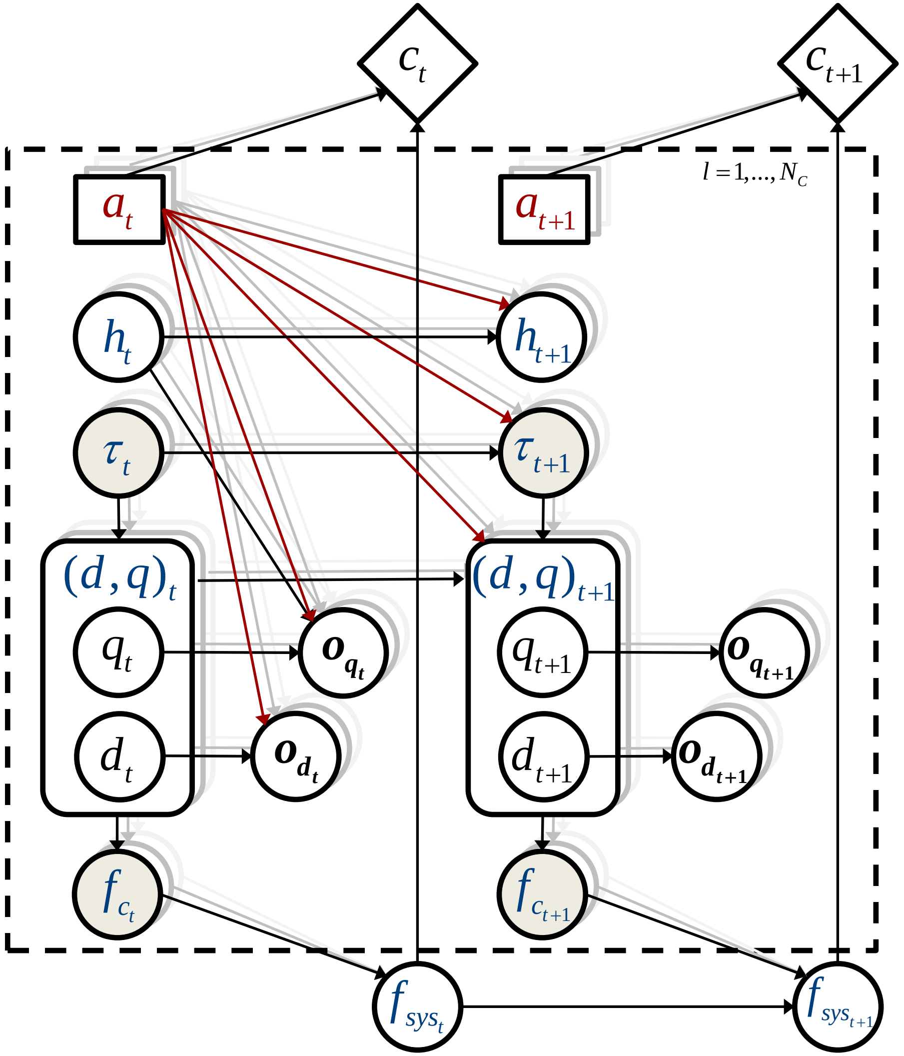
Cost model

- Inspection cost: c_{ins}
- Sensor installation cost: c_{sens}
- Repair cost: c_{res}
- Failure risk r_{fail}
- Replacement cost c_{replac}

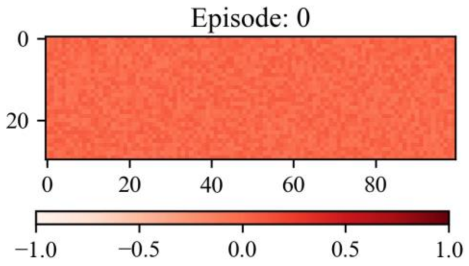
Failure risk: $r_{fail} = f_c \cdot c_{fail}$

Objective function

$$\min \mathbf{E}[c_0] = \mathbf{E}\left[\sum_{t=0}^{T-1} \gamma^t \left\{c_{t,ins} + c_{t,sens} + c_{t,rep} + r_{t,fail} + c_{t,replac}\right\}\right]$$



DDMAC: Deep decentralized actor-critic (based on A2C)



Actor weights adjusted according to the gradient:

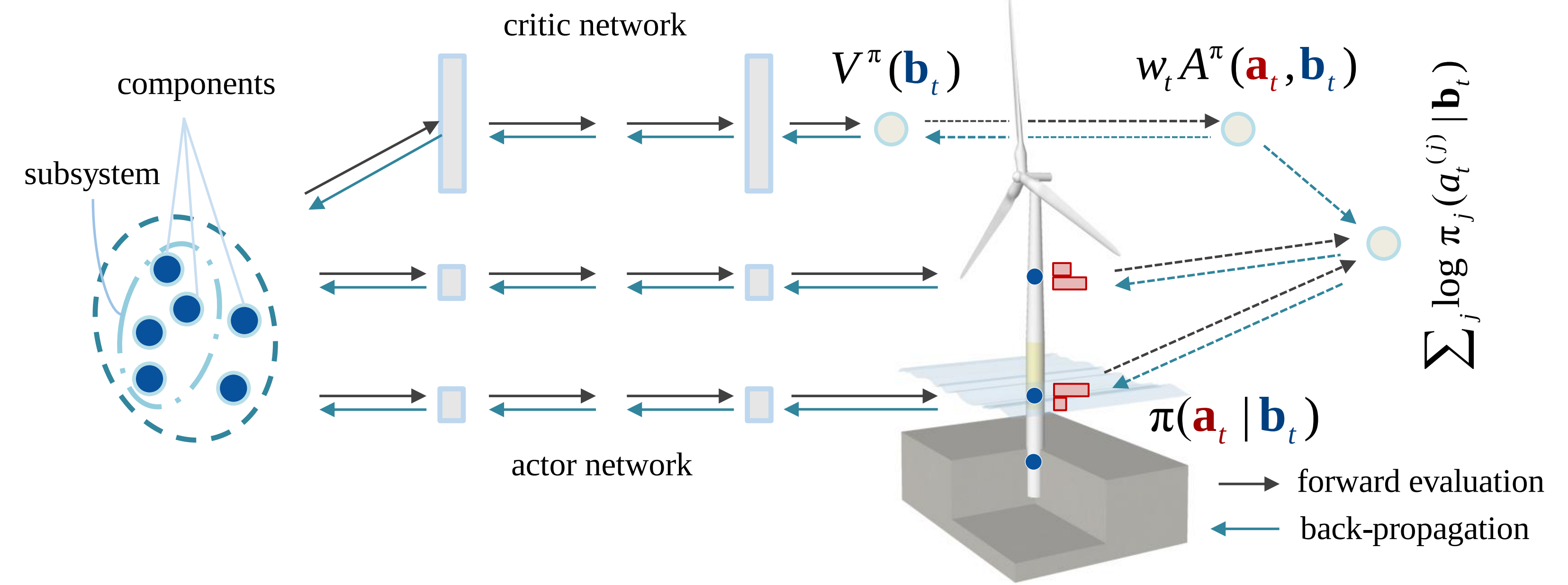
$$g_{\theta^\pi} = \mathbf{E}_{s_t\sim\rho, a_t\sim\mu}\left[w_t A^\pi(s_t, a_t|\theta^v)\left(\sum_{i=1}^{n_c}\nabla_{\theta^\pi}\log\pi_i\left(a_t^{(i)}\middle|s_t,\theta^\pi\right)\right)\right]$$

Advantage function:

$$A^\pi(s_t, a_t|\theta^v) \approx c(s_t, a_t) + V^\pi(s_{t+1}|\, \theta^v) - V^\pi(s_t|\, \theta^v)$$

Inputs: beliefs, time step

Output: stochastic policy



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Andriotis, C. P., & Papakonstantinou, K. G. (2021). Deep reinforcement learning driven inspection and maintenance planning under incomplete information and constraints. *Reliability Engineering & System Safety*, 212, 107551.

Case study: offshore wind farm management (I)

- **Objective function**

$$\min \mathbf{E}[c_0] = \mathbf{E}\left[\sum_{t=0}^{T-1} \gamma^t \left\{c_{t,ins} + c_{t,sens} + c_{t,rep} + r_{t,fail} + c_{t,replac}\right\}\right]$$

- **Actions available per component**

  Do-nothing, inspect, install sensor, inspect & install sensor, repair, repair & install sensor

- **Observations available per component**

  Crack detected, crack not detected, stress range scale parameter

- **Decision horizon**

  20 years

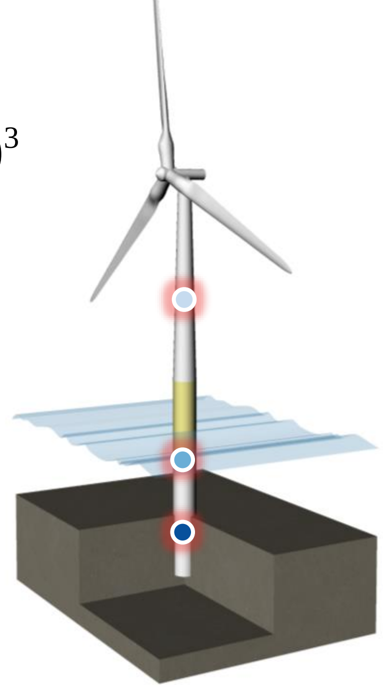
- **Baselines**

  Corrective, calendar-based, heuristic decision rules

$|\mathcal{S}| = 113,414$

$|\mathcal{A}_t| = 6^3$

$|\mathcal{O}_t| = 60^3$



TensorFlow

Keras

	Actors	Critic
	2x100	2x400
Learning rate	$10^{-4} - 10^{-5}$	$10^{-3} - 10^{-4}$

Case study: offshore wind farm management (I)

Fatigue deterioration

$$d_{t+1} = \left[d_t^{\frac{2-m}{2}} + \frac{2-m}{2} C_{FM} \{ Y \pi^{0.5} q \epsilon_q \Gamma(1+1/h) \}^m n \right]^{\frac{2}{2-m}}$$

d_0; d_{crit}

Limit state; series system

$$g(t) = d_c - d(t)$$

Inspections

$$p(o_{d_t} \mid d_t) \sim 1 - \frac{1}{1+(d_t/\chi)^b}$$

Load monitoring

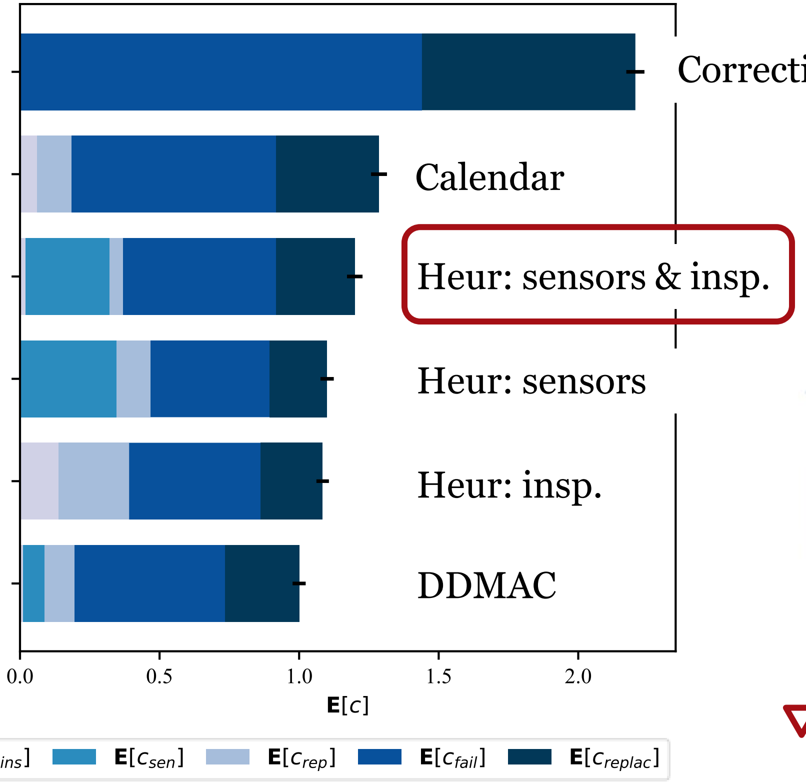
$$p\left(o_{q_t} \mid q_t\right) \sim q_t + \mathcal{N}\left[0, CoV = 15\%\right]$$

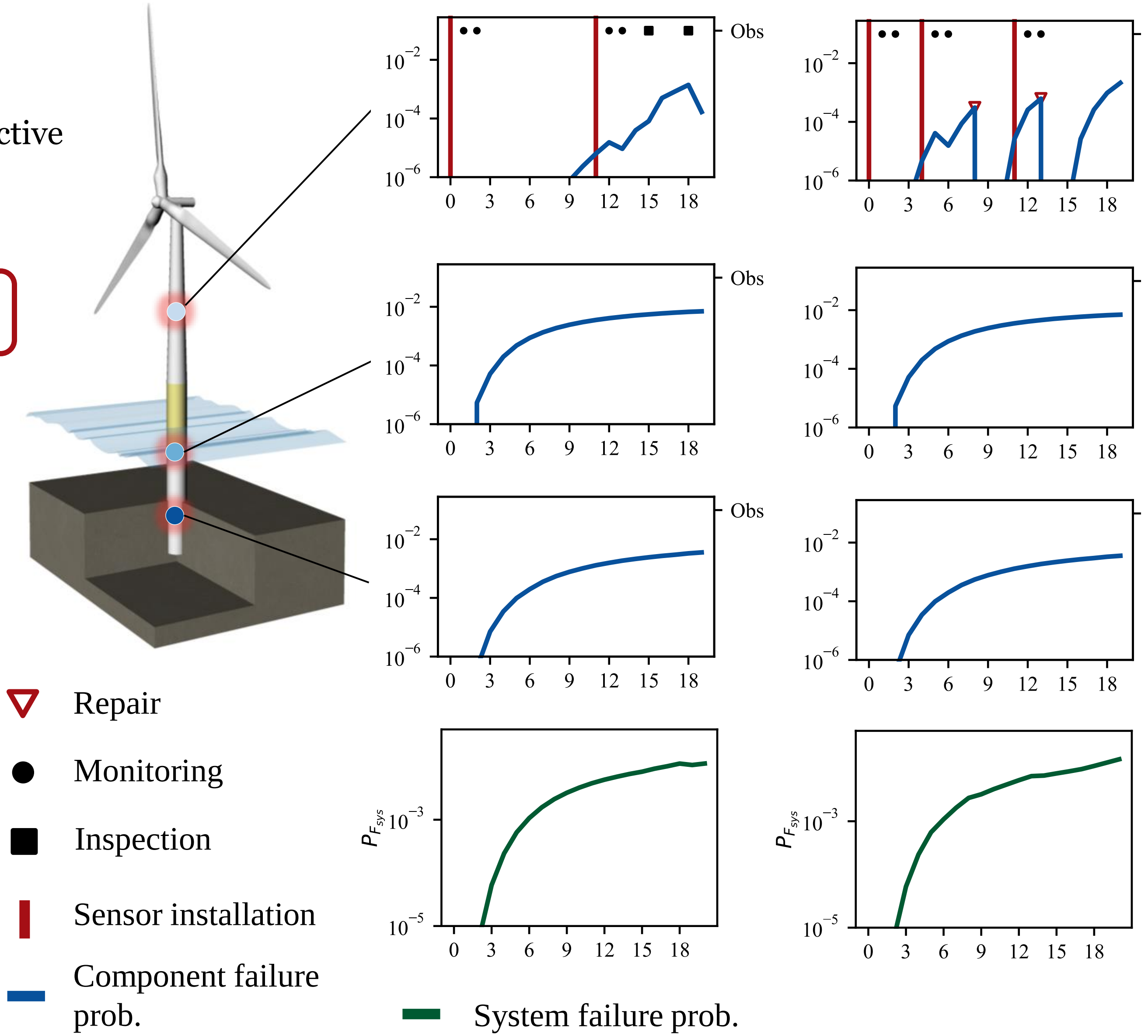
- Crack size d
- Paris' law parameters m, C_{FM}
- Geometric factor Y
- Annual stress cycles n
- Initial crack, critical crack size d_0, d_{crit}
- Expected long-term stress range:

  $$\mathbf{E}[\Delta S] = q\Gamma(1+1/h)$$ *Weibull distribution*

- Scale, shape parameters q, h
- Scale parameter noise ϵ_q
- Inspection PoD parameters χ, b

Results (I)





- Corrective maintenance
- Calendar-based
- Heuristic decision rules (Heur)
- Multi-agent reinforcement learning: **DDMAC**

Case study: offshore wind farm management (II)

Belgianoffshoreplatform

1 monetary unit ≈ 15 k€

TensorFlow

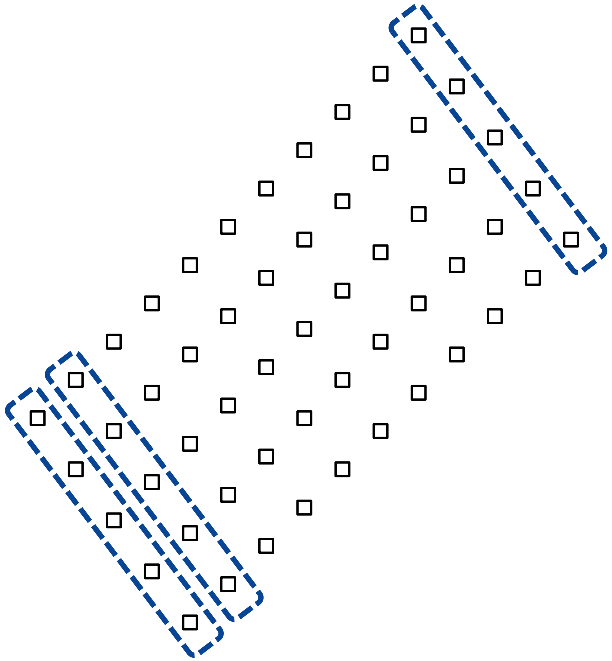
Keras

	Actors	Critic
	2x100	2x400
Learning rate	$10^{-4} - 10^{-5}$	$10^{-3} - 10^{-4}$

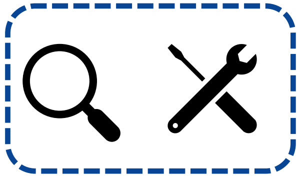
▶ Objective function

$$\min \mathbf{E}[c_0] = \mathbf{E}\left[\sum_{t=0}^{T-1} \gamma^t \left\{c_{t,camp} + c_{t,ins} + c_{t,sens} + c_{t,rep} + r_{t,fail} + c_{t,replac}\right\}\right]$$

cost dependency: $c_{camp} + \sum_{l}\left(c_{ins} + c_{rep}\right)$

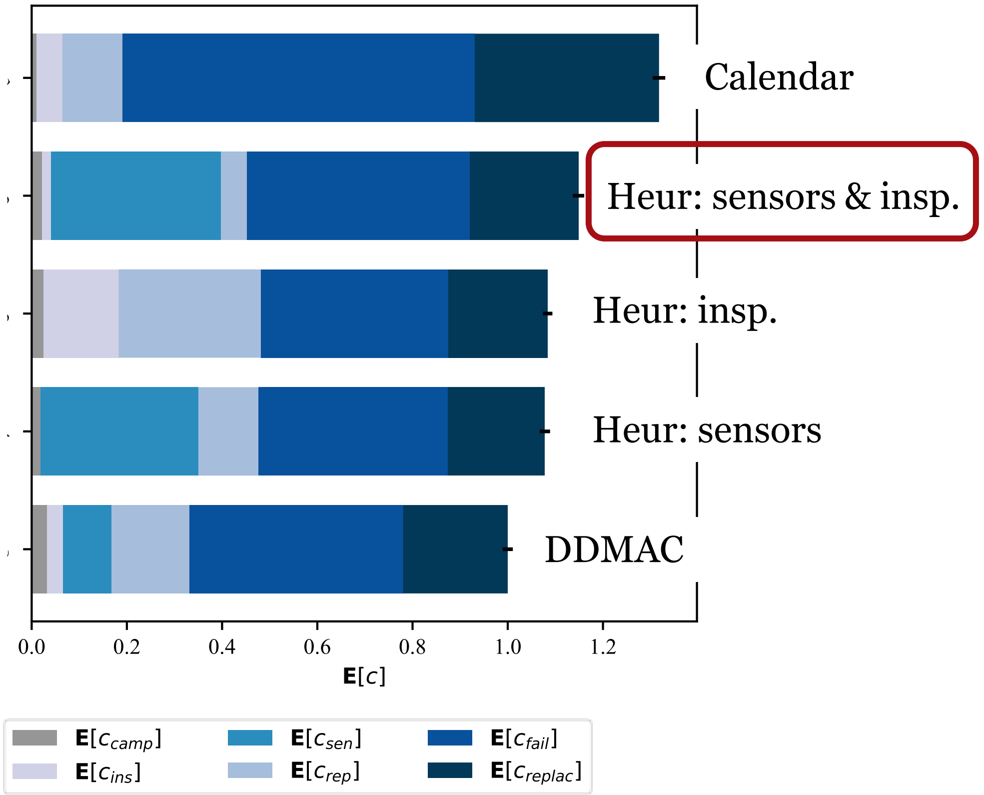


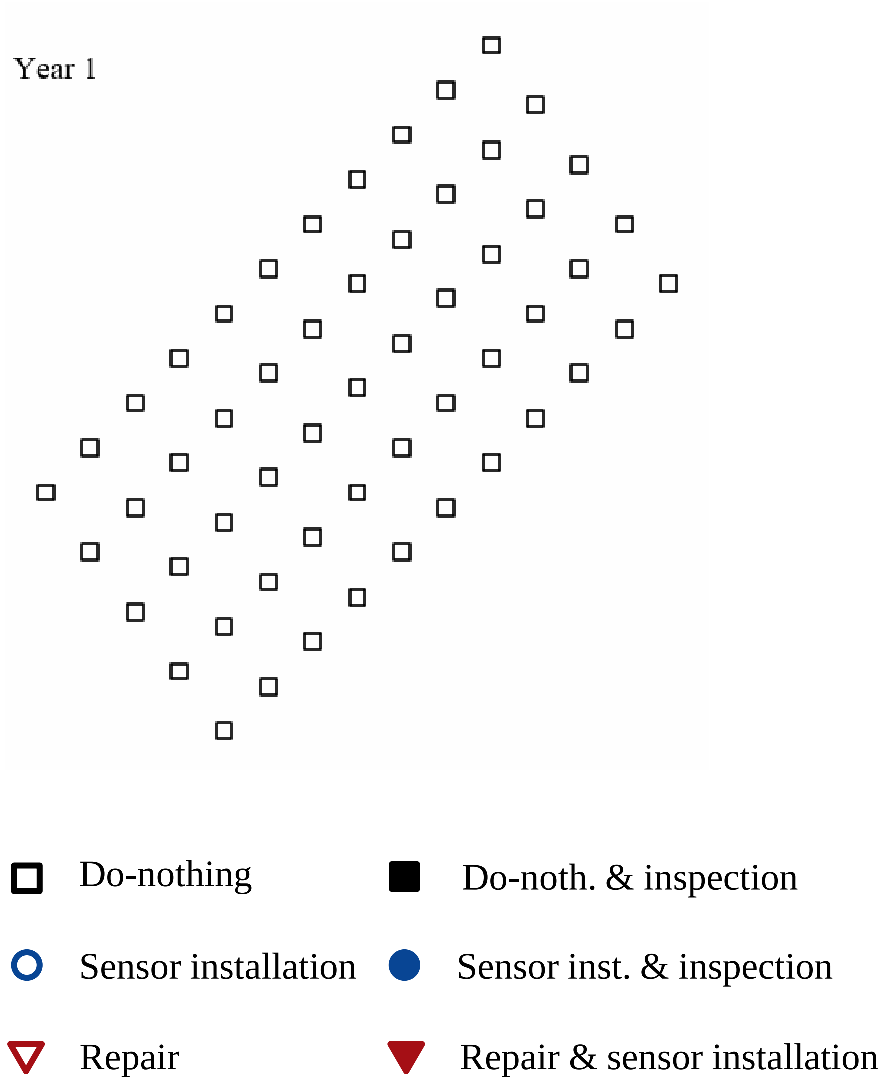
5 OWTs



Campaign cost

Results (II)





- Calendar-based: **+32%** +13.9M€
- Heuristic rules: **+9%** +3.8M€
- Multi-agent reinforcement learning: **DDMAC**

Conclusion an outlook

- Remarks

  SHM sequential decisions can be effectively planned

  The definition of expert knowledge decision rules becomes complex in multi-component engineering systems

  Multi-agent reinforcement learning (DDMAC) outperforms its counterparts

- Outlook

  Virtual sensing

  Scaling up: centralized training and decentralized execution approaches

  Development of cost models

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