Managing offshore wind turbines through Markov decision processes and dynamic Bayesian networks

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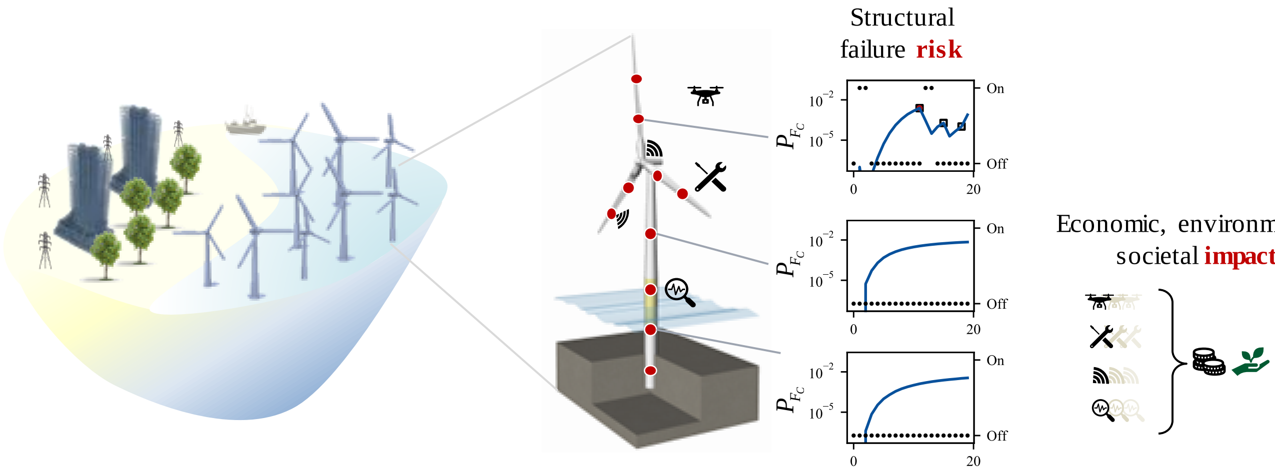
I&M optimization for deteriorating structures

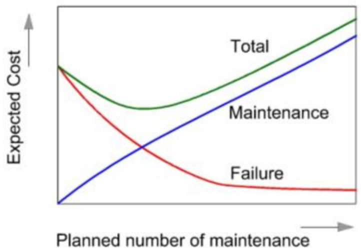


Sequential decision-making under uncertainty and imperfect information

- Stochastic environment
- Partially observable
- Discounted rewards

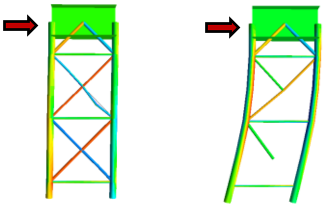
Stochastic optimization

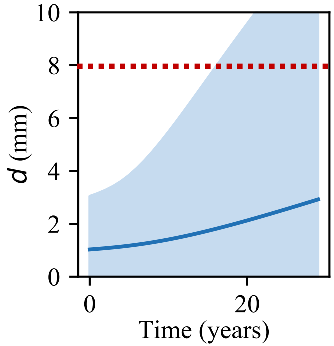
$$\arg\min_{\pi} \mathrm{E}[c_T] = \mathrm{E}[c_F] + \mathrm{E}[c_{ins}] + \mathrm{E}[c_{rep}]$$

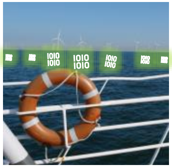


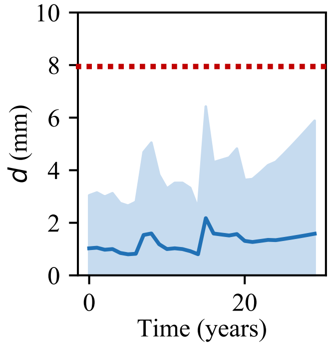
I&M optimization for deteriorating structures

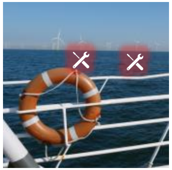
$$d_{t+1} = \left[\left(1-\frac{m}{2}\right) C_{FM} S_R^m \pi^{m/2} n + d_t^{1-m/2}\right]^{2/(2-m)}$$

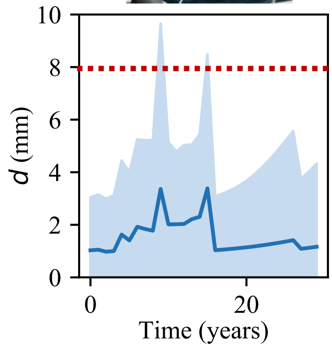












Deterioration (prior) model

Physics-based (analytical and/or numerical engineering models)

Observations

Actions for collecting information ($$)

Repairs/retrofits

Actions that influence the environment ($$$)

I&M optimization for deteriorating structures

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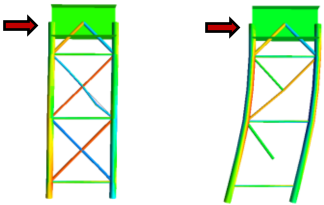
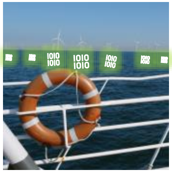
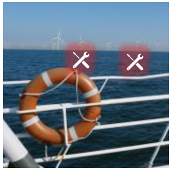
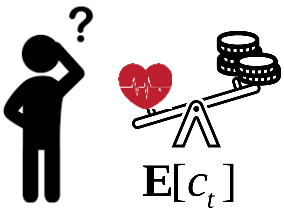
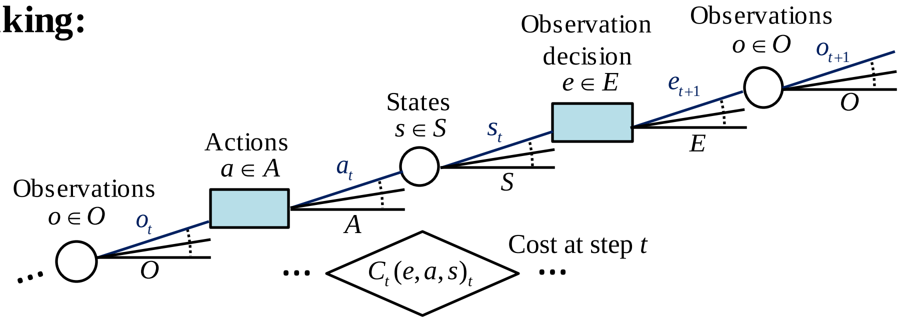






Sequential decision-making:





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I&M optimization for offshore wind turbines

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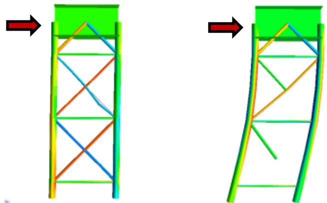
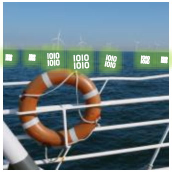
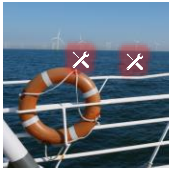
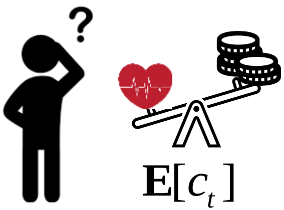
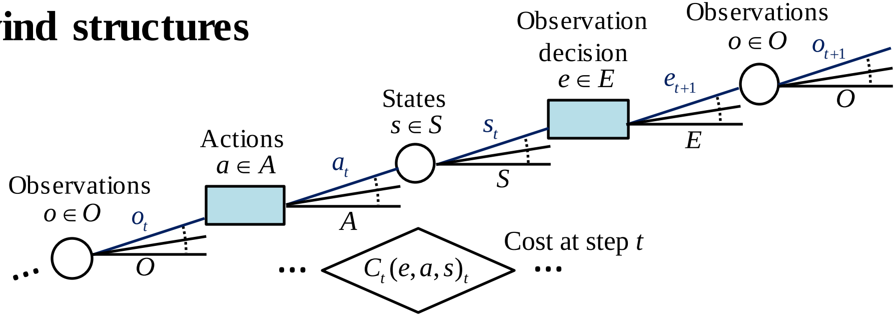






Offshore wind structures

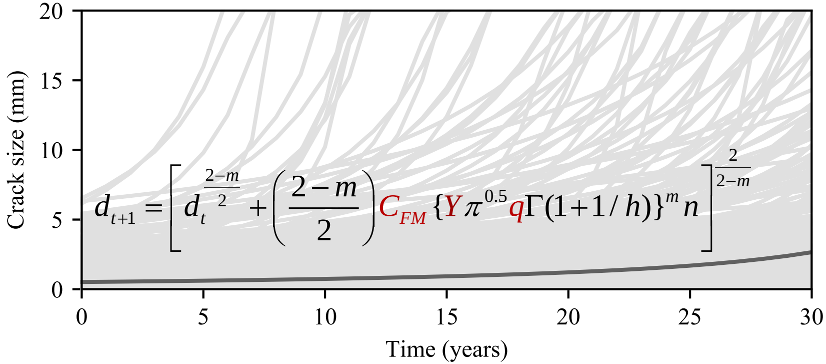




- **Deterioration:** dynamically sensitive structures (fatigue), marine environment.
- **Expensive inspections:** Far from shore, underwater.
- **Risk:** economic, environmental, societal.

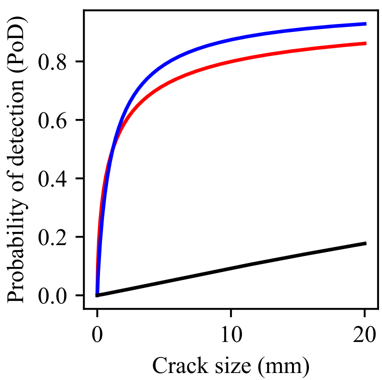
Fatigue deterioration environment

Offshore wind component subject to fatigue:



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

- d: crack size (mm).
- n: annual number of stress cycles.
- m, C_{FM}: crack growth parameters.
- Y: geometric factor.
- q, h: scale and shape corresponding to stress range Weibull's distribution.



Inspection model: $\mathrm{PoD}(d) = 1 - \frac{1}{1+(d/X_0)^b}$

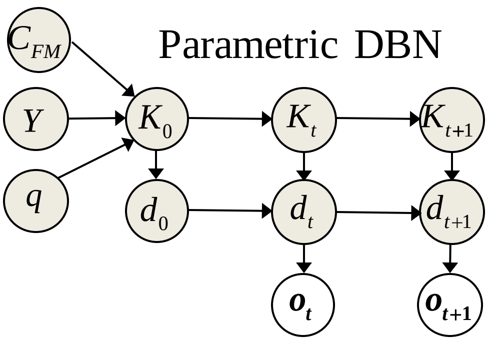
- Eddy current inspection: $X_0 = 1.16$; $b = 0.9$
- Ultrasonic testing: $X_0 = 1.16$; $b = 0.642$
- **Visual inspection**: $X_0 = 83.03$; $b = 1.079$

DNVGL-RP C203: Fatigue design of offshore steel structures.

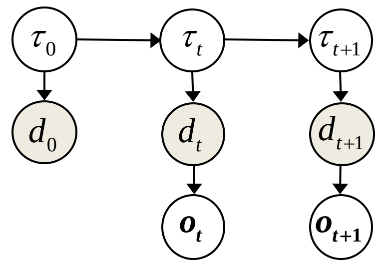
Inference: Dynamic Bayesian networks (DBNs)

$$d_{t+1} = \left[d_t^{\frac{2-m}{2}} + \left(\frac{2-m}{2}\right) C_{FM} \{ Y \pi^{0.5} q \Gamma(1+1/h)\}^m n \right]^{\frac{2}{2-m}} \quad \langle S, A, O, T, Z, C, \gamma \rangle$$

Parametric DBN



Deterioration rate DBN



- **Transition step:**

$$p(d_{t+1}, \boldsymbol{\theta}_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t}) = p(d_{t+1}, \boldsymbol{\theta}_{t+1} \mid d_t, \boldsymbol{\theta}_t)\, p(d_t, \boldsymbol{\theta}_t \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t})$$

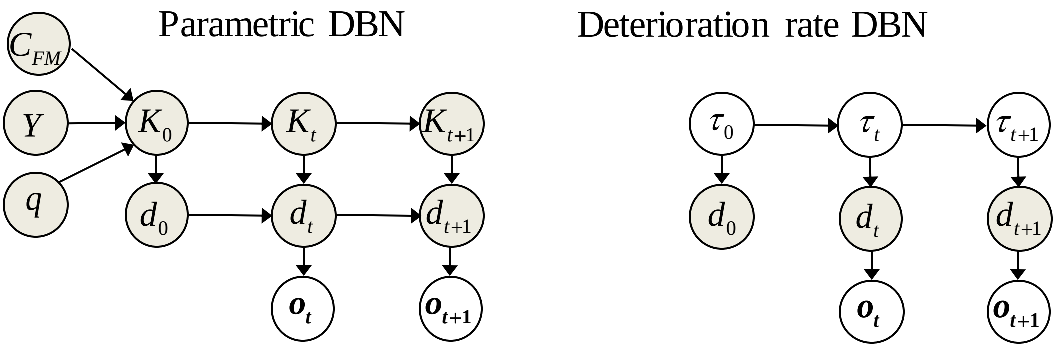
$$p(d_{t+1}, \tau_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t}) = p(d_{t+1}, \tau_{t+1} \mid d_t, \tau_t)\, p(d_t, \tau_t \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t})$$

- **Estimation step** (Bayesian update):

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

$$p(d_{t+1}, \tau_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_{t+1}}) \propto p(\boldsymbol{o_{t+1}} \mid d_{t+1}, \tau_{t+1})\, p(d_{t+1}, \tau_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t})$$

Dynamic Bayesian networks (DBNs)



Direct policy search. Evaluation of heuristic decision rules:

- Inspection planning: intervals, failure probability threshold.
- Repairs: once a detection is observed, condition threshold.

Heuristic decision rules (h): Simulation-based evaluation of the expected total cost

$$R_{T_i}^{(h)} = \sum_{t=t_0}^{t_N} \gamma^t \left[C_i(t) + C_r(t) + C_d(t) + \Delta P_F(t) C_f \right] \longrightarrow \mathrm{E}\left[R_T(h)\right] = \frac{\sum_{i=1}^{n_{ep}} \left[R_{T_i}(h) \right]}{n_{ep}}$$

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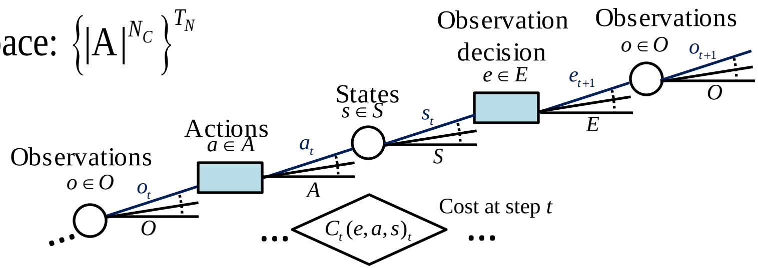
Challenges and available planning methods

Curse of history

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



Methods:

Heuristic decision rules

- Policy is constrained by the explored policy space
- Optimality is influenced by the ability of exploring the appropriate space of decision rules

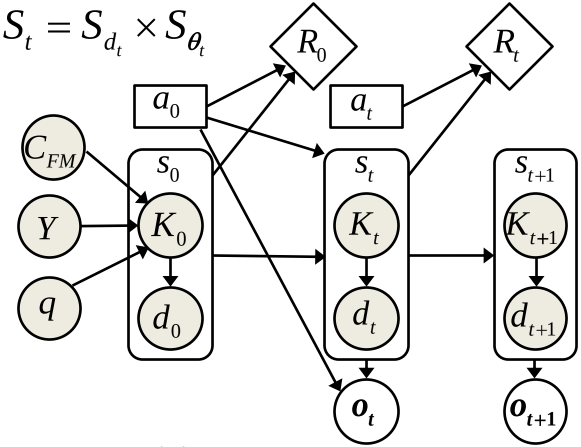
Dynamic programming (POMDPs)

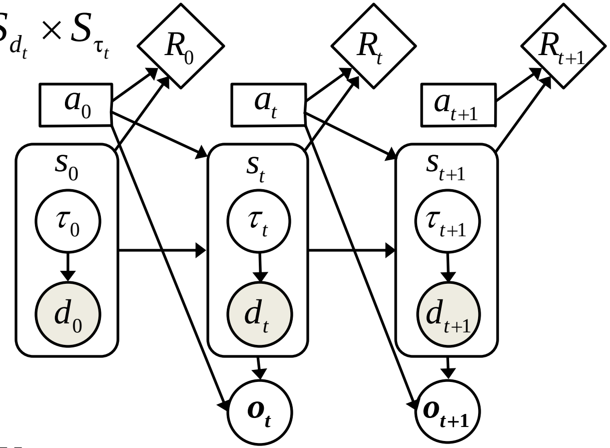
- Principled framework for decision-making under uncertainty
- Dynamic programming principles (Belman equation)
- Adaptive policy defined as a function of a sufficient statistic, i.e., belief state

Stochastic optimization: Partially Observable Markov Decision Processes (POMDPs)

$\langle S, A, O, T, Z, C, \gamma \rangle$

$S_t = S_{d_t} \times S_{\theta_t}$ $\quad$ $S_t = S_{d_t} \times S_{\tau_t}$





- **Transition step:**

$$p(d_{t+1}, \tau_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t}, a_{0:t}) = \overbrace{p(d_{t+1}, \tau_{t+1} \mid d_t, \tau_t, a_t)}^{\textbf{DBN}} p(d_t, \tau_t \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t}, a_{0:t})$$

- **Observation step** (Bayesian update):

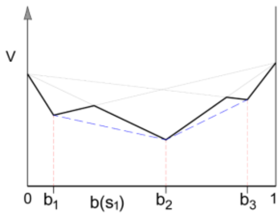
$$p(d_{t+1}, \tau_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_{t+1}}, a_{0:t}) \propto \overbrace{p(\boldsymbol{o_{t+1}} \mid d_{t+1}, \tau_{t+1}, a_t)}^{\textbf{DBN}} p(d_{t+1}, \tau_{t+1} \mid \boldsymbol{o_0}, ..., \boldsymbol{o_t}, a_{0:t})$$

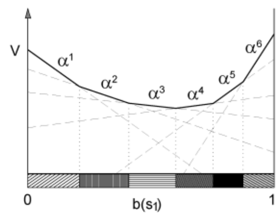
Adaptive I&M planning policies

POMDP policy is a mapping from the belief state to the optimal action

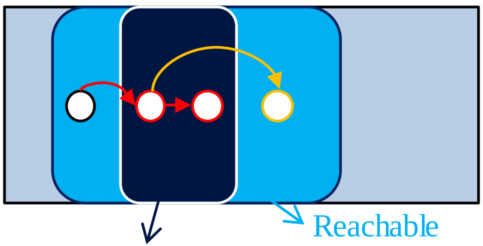
$$V(\mathbf{b}_t) = \max_{a_t \in A} \left\{ \sum_{s_t \in S} b(s_t) r(s_t, a_t) + \gamma \sum_{o_{t+1} \in \Omega} p(o_{t+1} \mid \mathbf{b}_t, a_t) V(\mathbf{b}_{t+1}) \right\}$$

Value function is piece-wise linear and convex

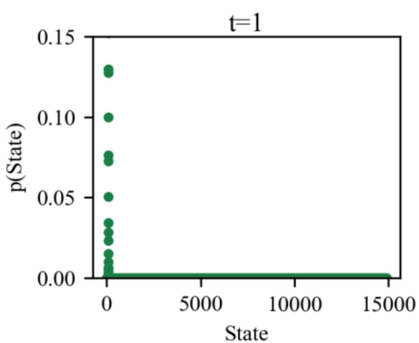


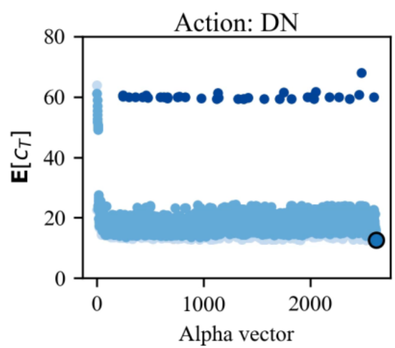


Sampling belief states



'Optimally' reachable beliefs





Do-noth.

Do-noth. & insp.

Repair

Point-based POMDP solvers

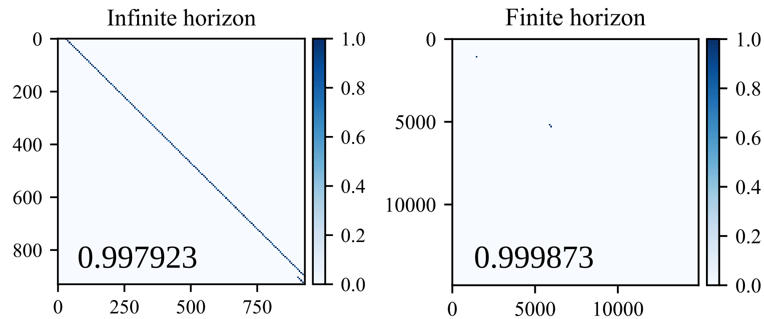
Infinite horizon vs **finite horizon:**
state augmentation

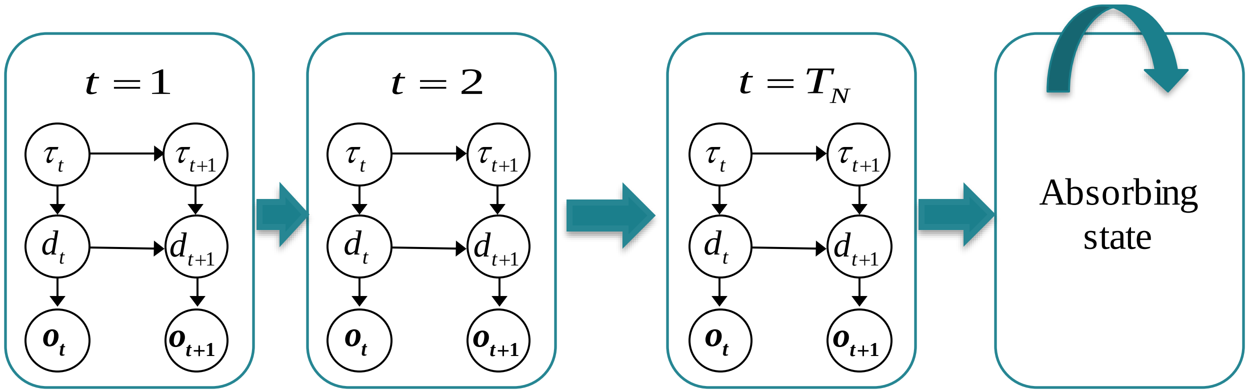
- Damage, deterioration rate and **time**
- Damage, parameters and **time**

$$S = S_d \times S_\tau \times S_t$$

$$S = S_d \times S_\theta \times S_t$$

Sparse matrices



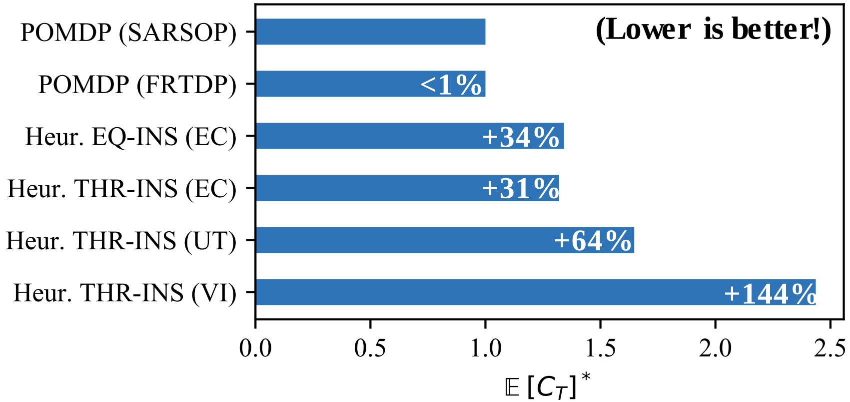


I&M planning setting definition

Offshore wind subject to fatigue deterioration

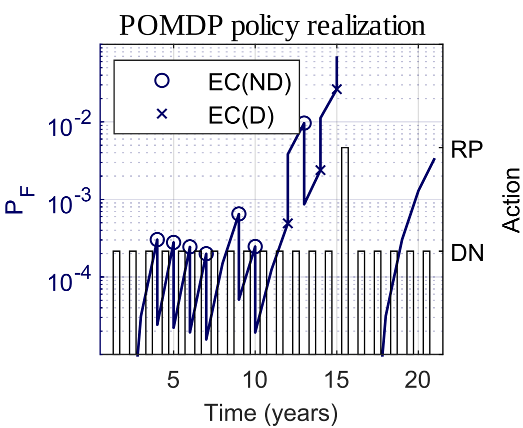
- **Actions**: Do-nothing, perfect repair.
- Observation decisions: Do-nothing, inspect.
- **Inspection** techniques available: eddy current, ultrasonic, visual.
- Observation outcomes: crack detected / crack not detected.
- **Decision horizon**: 20 years (finite horizon).
- **Policies compared**:
  - Finite horizon deterioration rate POMDPs (SARSOP, FRTDP).
  - Heuristic decision rules:
    - Equidistant inspections and repair if a crack is detected.
    - Inspections planned if a failure prob. threshold is reached and repair if a crack is detected.

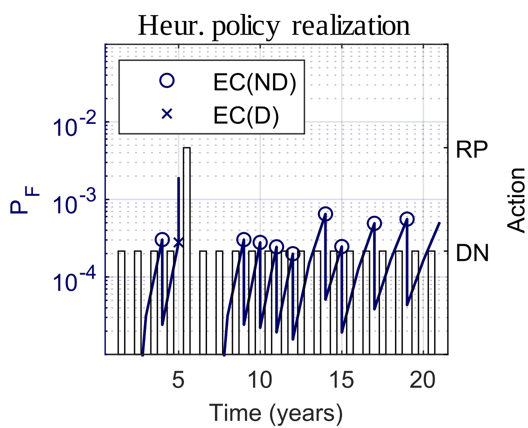
I&M planning setting results



Cost model

$c_{i_{EC}} = 1$
$c_{i_{US}} = 1.5$
$c_{vis} = 0.5$
$c_{rep} = 100$
$c_f = 1000$
$\gamma = 0.95$



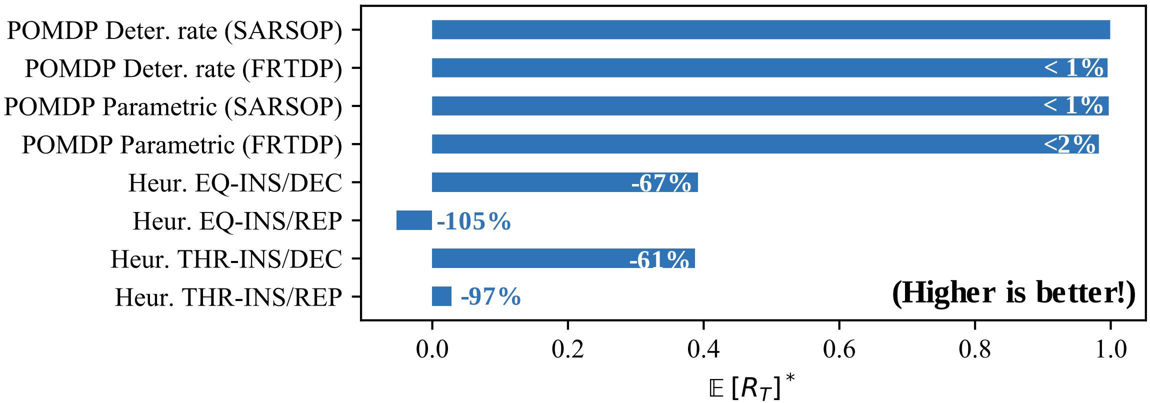


Lifetime extension planning setting definition

Offshore wind subject to fatigue deterioration

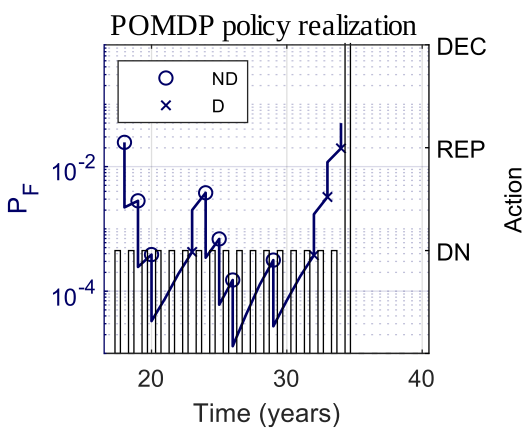
- **Actions**: Do-nothing, perfect repair, decommission.
- Observation decisions: Do-nothing, inspect.
- **Inspection** techniques available: eddy current.
- Observation outcomes: crack detected / crack not detected.
- **Decision horizon**: infinite horizon, starting at year 16.
- **Policies compared**:
  - Infinite horizon POMDPs (SARSOP, FRTDP).
  - Heuristic decision rules:
    - Equidistant inspections and repair (decommission) if a crack is detected.
    - Inspections planned if a failure prob. threshold is reached and repair (decommission) if a crack is detected.

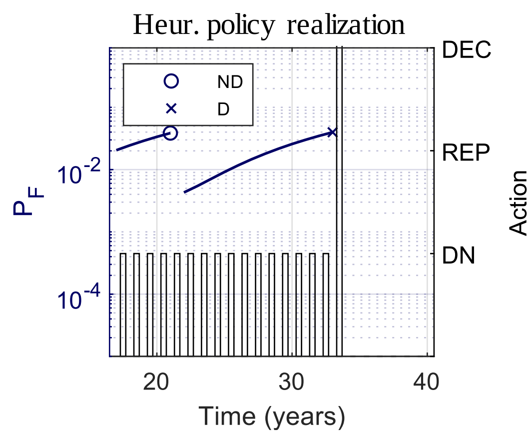
Lifetime extension planning setting results



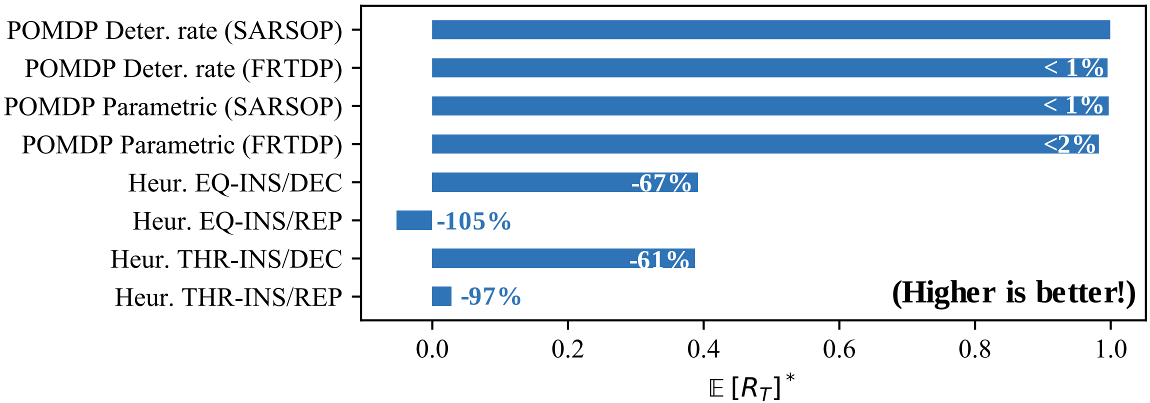
Reward model

$r_{ins} = -1,$
$r_{replac} = -100,$
$r_{dec} = -20,$
$r_{prod} = 5,$
$r_f = -1000,$
$\gamma = 0.95$





Lifetime extension planning setting results



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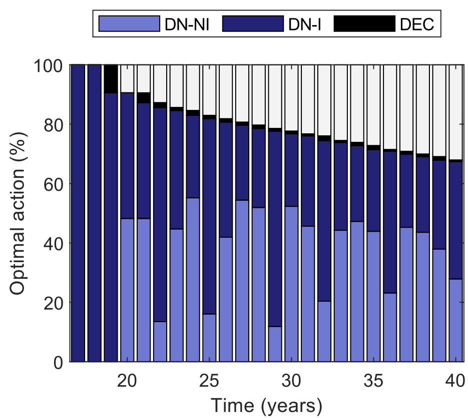
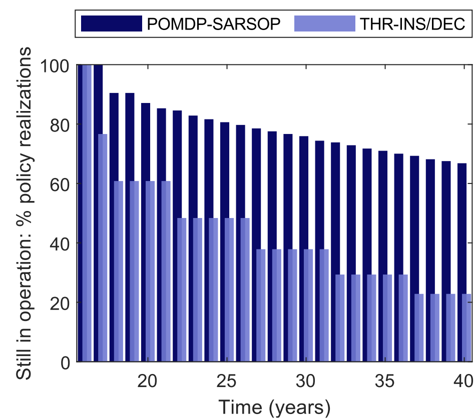
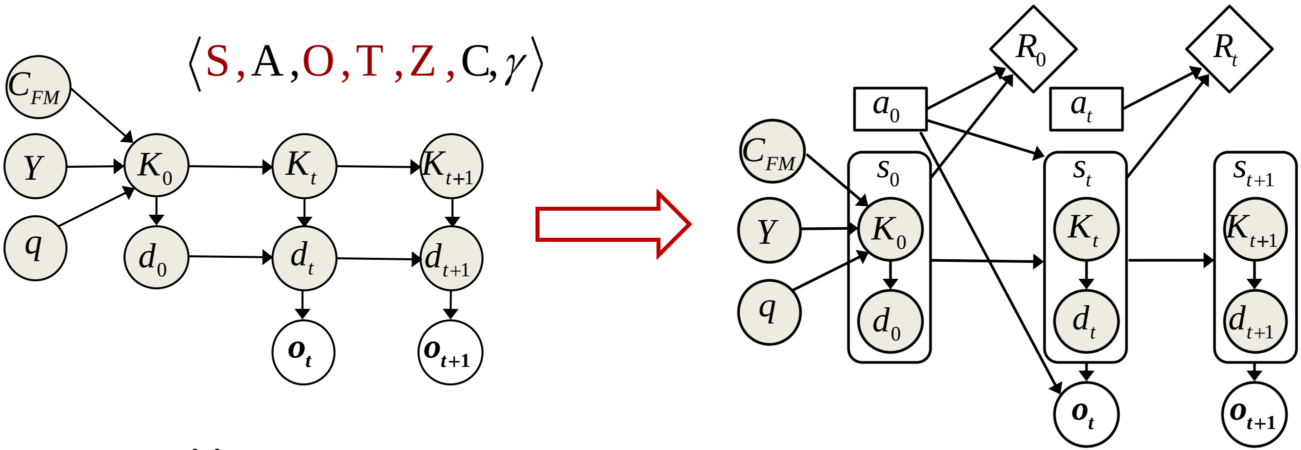




Concluding remarks

Integration of DBNs and POMDPs for decision-making optimization

$$\langle S, A, O, T, Z, C, \gamma \rangle$$



- **Transition step:**

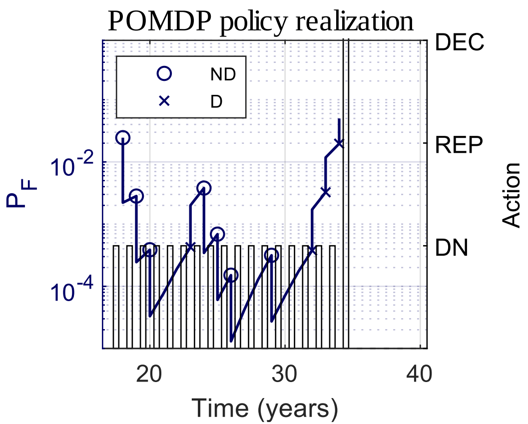
$$p(d_{t+1},\tau_{t+1} \mid \boldsymbol{o_0},\ldots,\boldsymbol{o_t},a_{0:t}) = \overbrace{p(d_{t+1},\tau_{t+1} \mid d_t,\tau_t,a_t)}^{\textbf{DBN}}\, p(d_t,\tau_t \mid \boldsymbol{o_0},\ldots,\boldsymbol{o_t},a_{0:t})$$

- **Observation step** (Bayesian update):

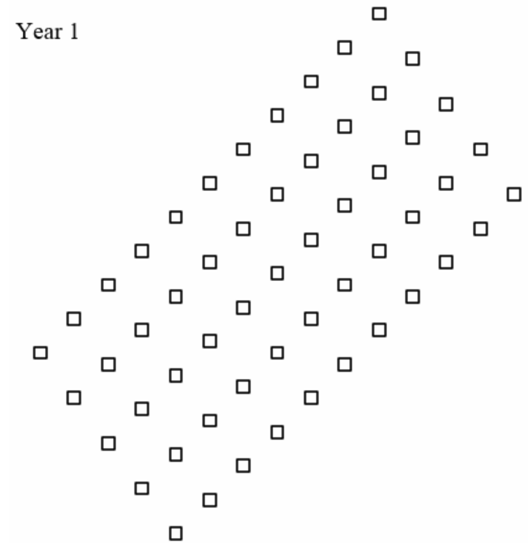
$$p(d_{t+1},\tau_{t+1} \mid \boldsymbol{o_0},\ldots,\boldsymbol{o_{t+1}},a_{0:t}) \propto \overbrace{p(\boldsymbol{o_{t+1}} \mid d_{t+1},\tau_{t+1},a_t)}^{\textbf{DBN}}\, p(d_{t+1},\tau_{t+1} \mid \boldsymbol{o_0},\ldots,\boldsymbol{o_t},a_{0:t})$$

Concluding remarks

** Sophisticated heuristic decision rules based on POMDP patterns



Complex decision patterns in high-dimensional action spaces



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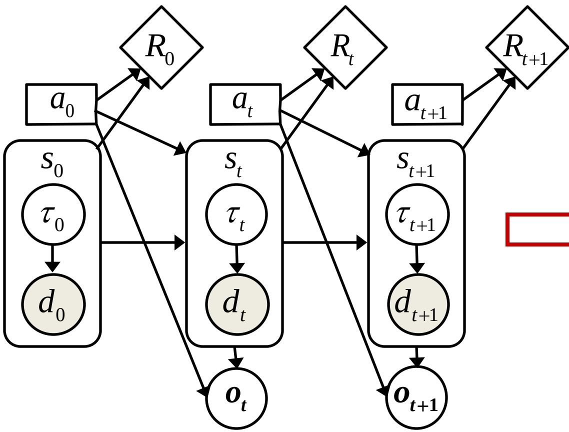
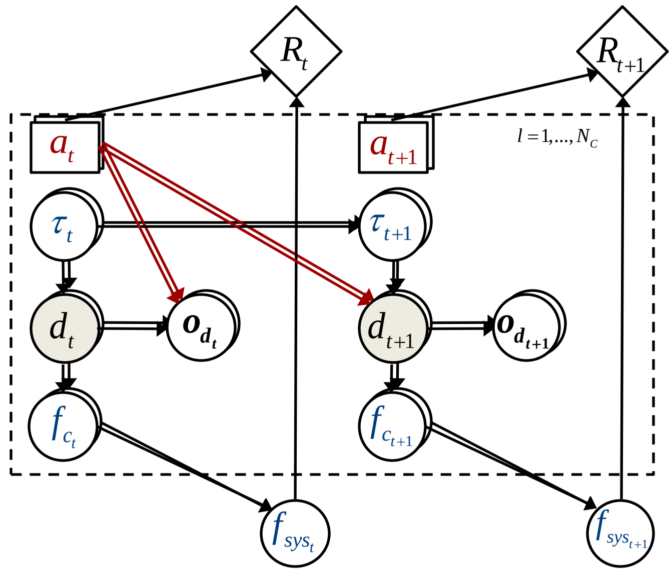
Future work

System level: Factored POMDPs based on DBN formations

Component level



System level



Morato, P. G., Andriotis, C. P., Papakonstantinou K. G., & Rigo, P. (2022). Inference and dynamic decision-making for deteriorating systems with probabilistic dependencies through Bayesian networks and deep reinforcement learning. *Reliability Engineering & System Safety*, Under review.

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Additional comments, questions ...

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