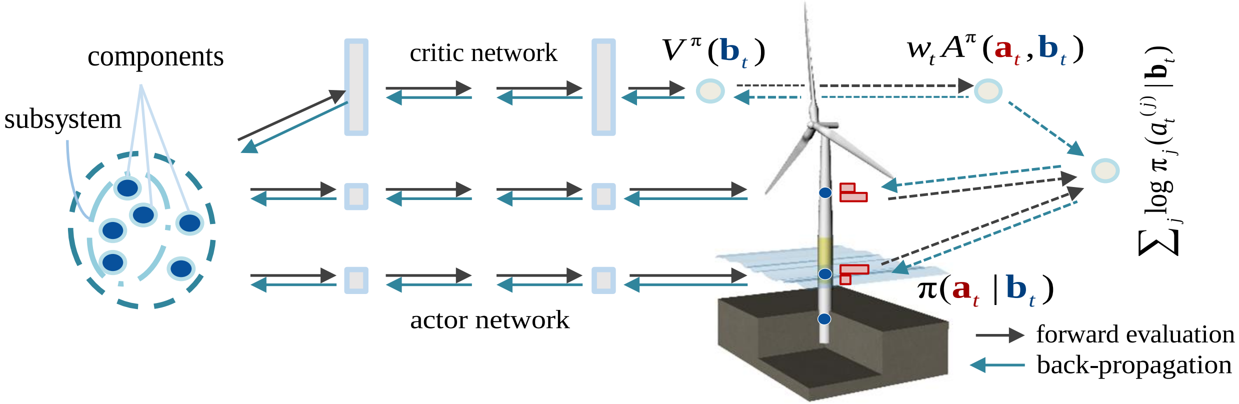
Optimal Management of Offshore Wind Structural Systems via Deep Reinforcement Learning

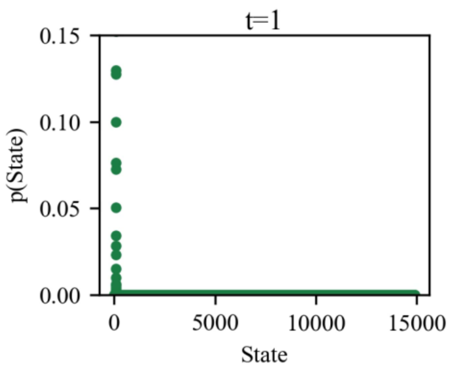


Seminar - ETSIN

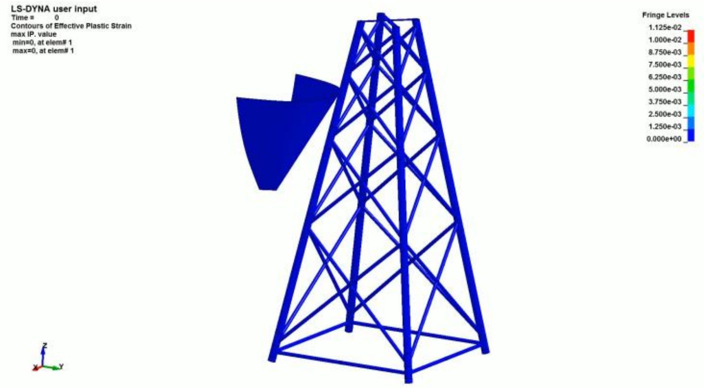
Pablo G. Morato

LIÈGE université
Urban & Environmental Engineering

Research at ANAST (ULiege)



Decision-making under uncertainty



Crashworthiness analysis

Decision-making under uncertainty

In collaboration with…

K.G. Papakonstantinou

Dept. of Civil & Environmental Engineering, The Pennsylvania State University (USA)

C.P. Andriotis

Dept. of AI in Structural Design & Mechanics, TU Delft (Netherlands)

N. Hlaing

Dept. of Naval and Offshore Engineering, ULiege (Belgium)

Engineering systems

https://www.researchgate.net/publication/323826793_Environmental_Risks_and_Uncertainty_with_Respect_to_the_Utilization_of_Recycled_Rolling_Stocks

https://www.enidnews.com/news/ag_energy/wind-turbine-collapses-outside-hunter-cause-under-investigation/article_b719d312-7cb9-11e9-9121-5b999361d68f.html

Healthy condition

↓

Economic and societal growth

Engineering systems


https://www.researchgate.net/publication/323826793_Environmental_Risks_and_Uncertainty_with_Respect_to_the_Utilization_of_Recycled_Rolling_Stocks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Healthy condition

Economic and societal growth

? Failure statistics



https://www.windfarmbop.com/gearbox-in-wind-turbines/

Structures

Mechanical components

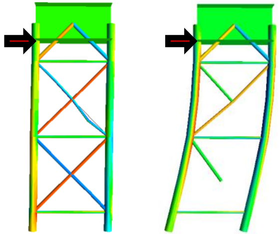
Engineering systems

Specific design

Low failure rate

Analytical models and/or numerical simulations

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



? Failure statistics

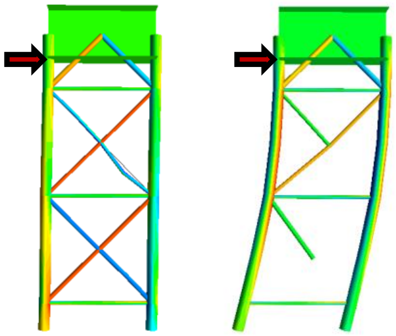
Structures

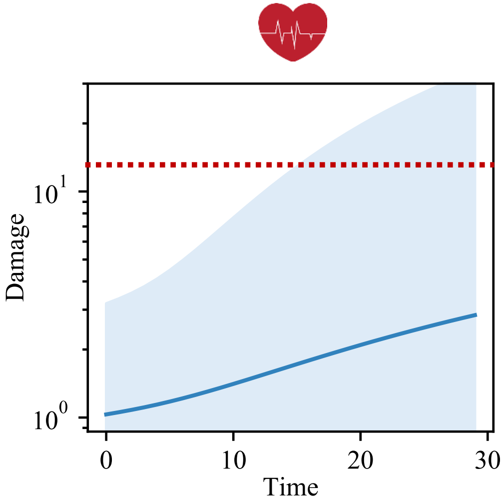
https://www.windfarmbop.com/gearbox-in-wind-turbines/

Mechanical components

Modeling deterioration... uncertainties

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



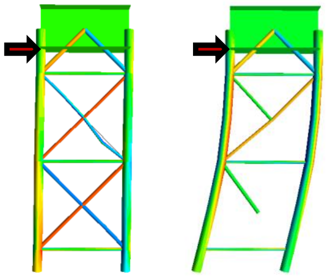


- Aleatory uncertainties
- Model uncertainties
- Statistical uncertainties

Maintenance actions?

Physics-based and data-driven models

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



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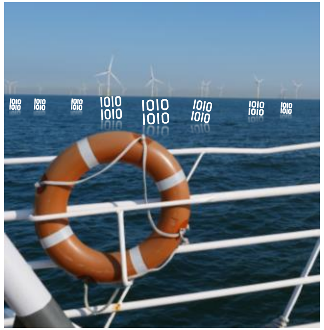
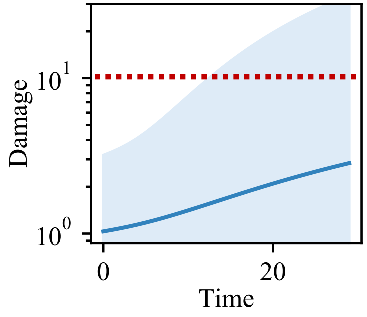
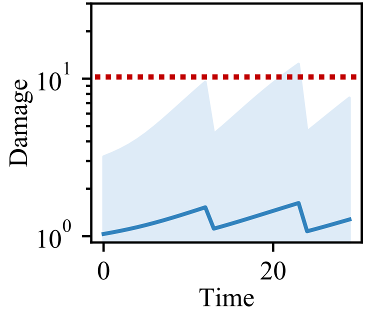






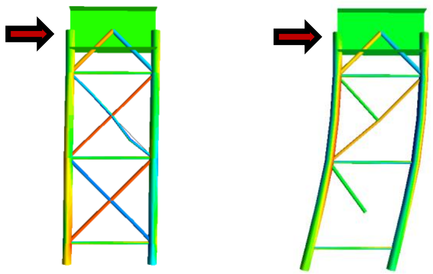
KNOWLEDGE KNOWLEDGE KNOWLEDGE

Design | Production | Operation | Decommissioning

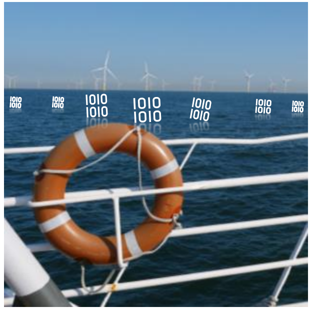
Inspection and maintenance planning

Deterioration model

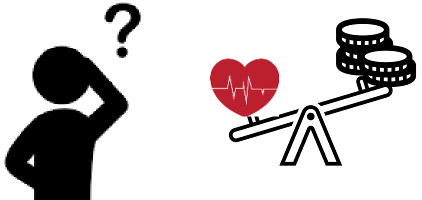
$$d_{t+1} = \left[\left(1 - \frac{m}{2}\right) C_{FM} S_R^m \pi^{m/2} n + d_t^{1-m/2} \right]^{2/(2-m)}$$



Actions



Decision-making

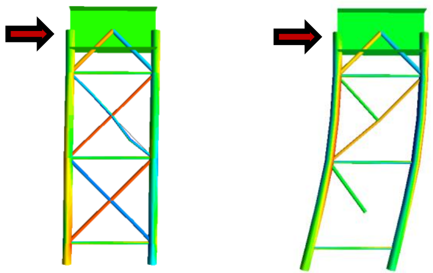


$$\mathbf{E}[c_t]$$

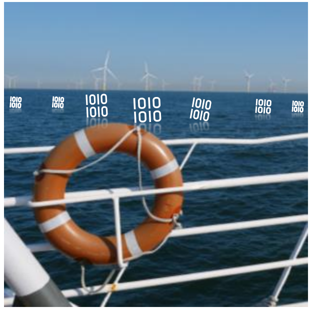
Inspection and maintenance planning

Deterioration model

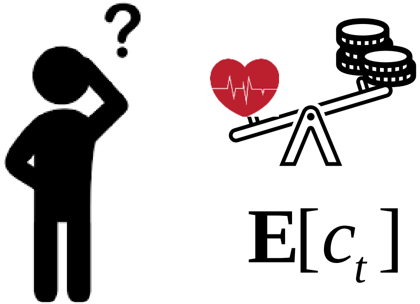
$$d_{t+1} = \left[\left(1 - \frac{m}{2}\right) C_{FM} S_R^m \pi^{m/2} n + d_t^{1-m/2} \right]^{2/(2-m)}$$



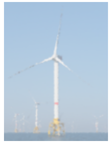
Actions



Decision-making



$$\mathbf{E}[c_t]$$



KNOWLEDGE

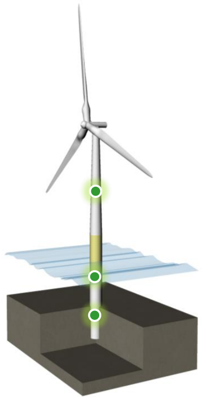
KNOWLEDGE

Information

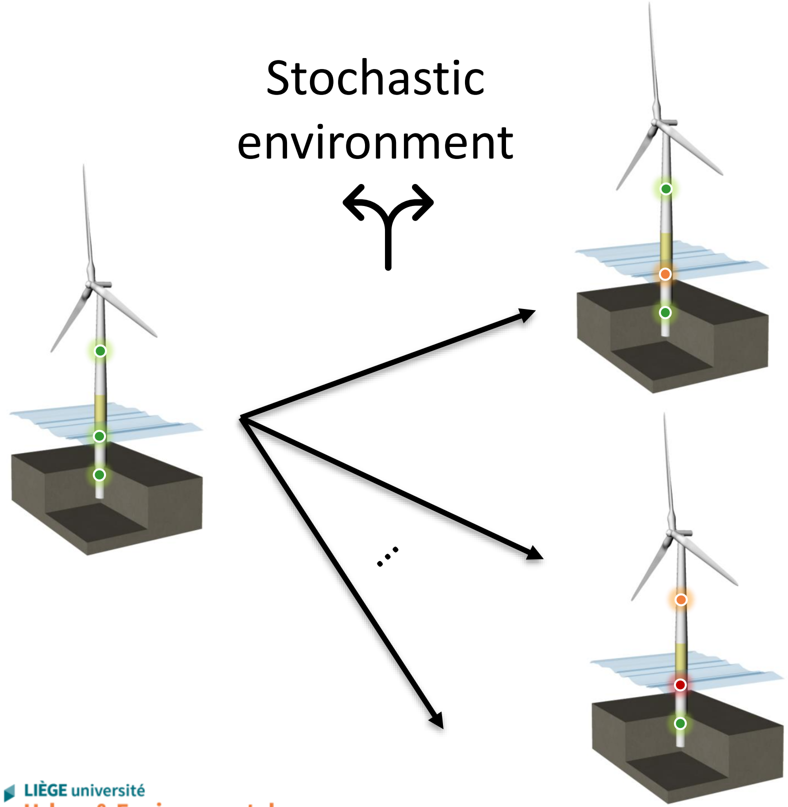
KNOWLEDGE

Design | Production | Operation | Decommissioning

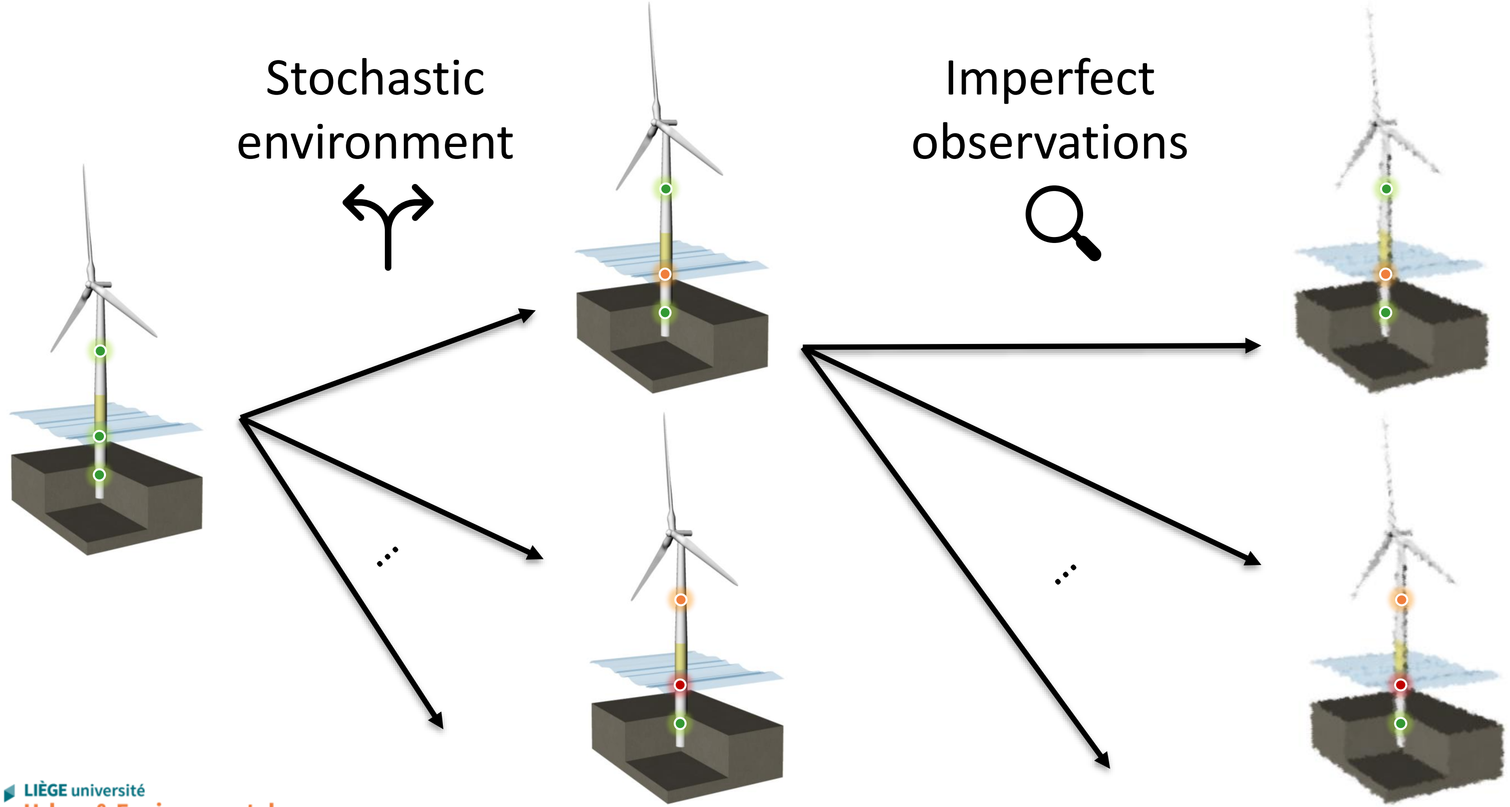
Decision-making problem



Decision-making problem

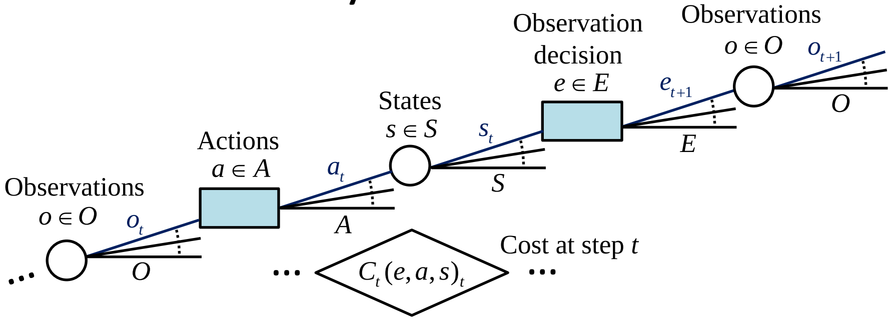


Decision-making problem



Decision-making problem

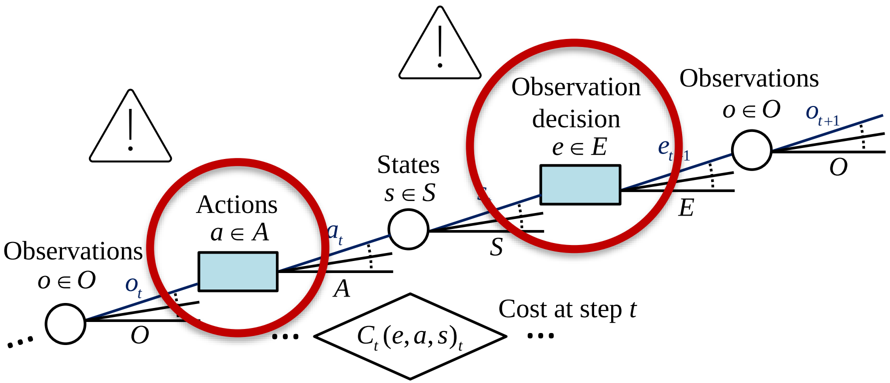
(1) Curse of history



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

Policy optimization - heuristic decision rules

... alleviates computational complexity



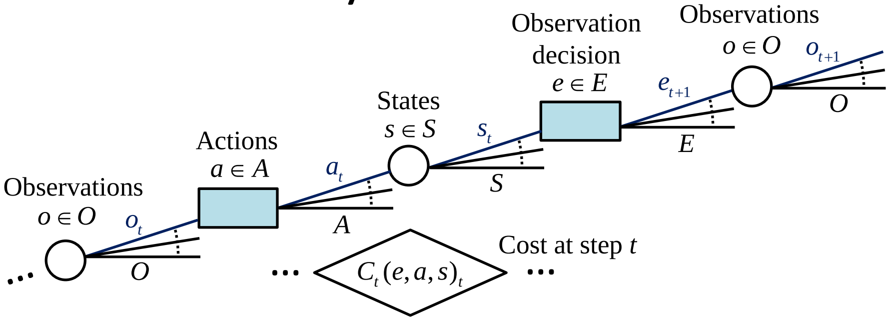
... optimality?

Set of heuristic rules

- Equidistant inspections
- Inspection after reaching a specified threshold
- Repair after detection indication

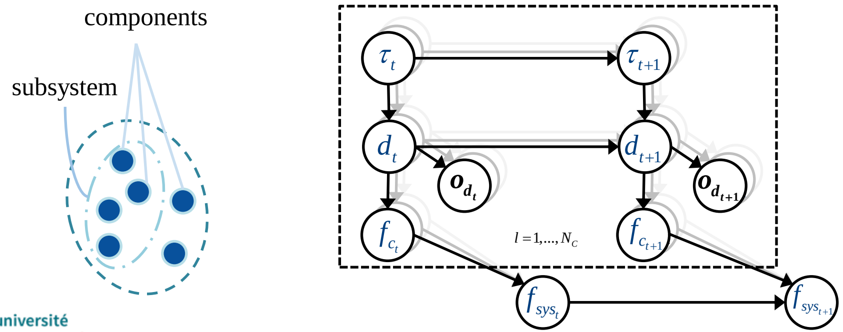
Decision-making problem

(1) Curse of history



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

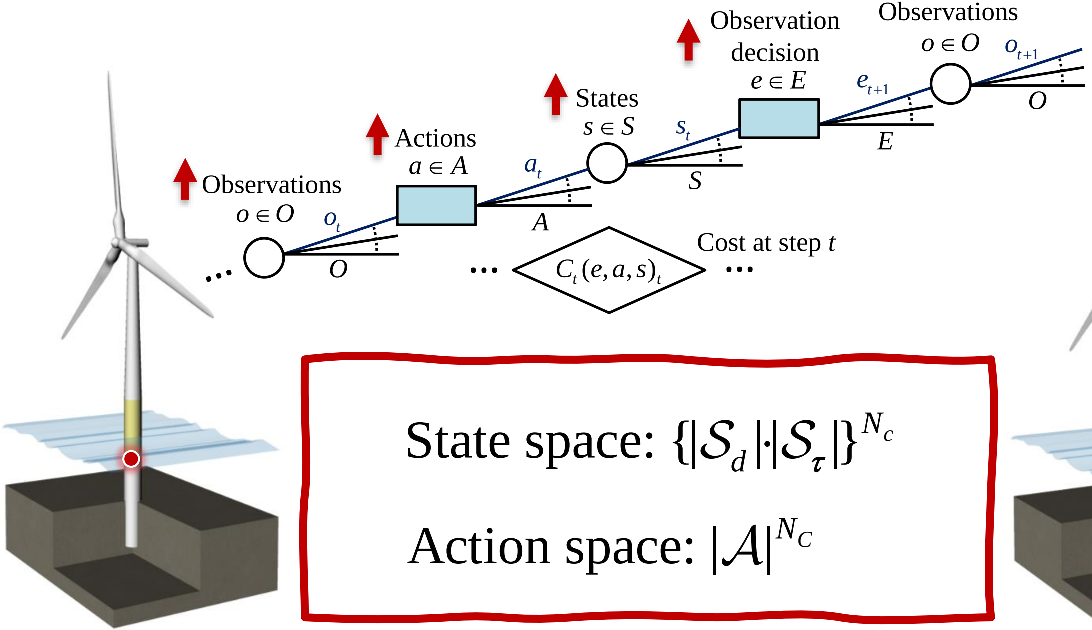
(2) Curse of dimensionality



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

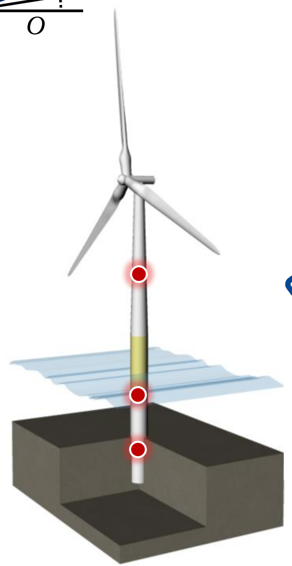
Action space: $|\mathcal{A}|^{N_C}$

Modeling approach – component level

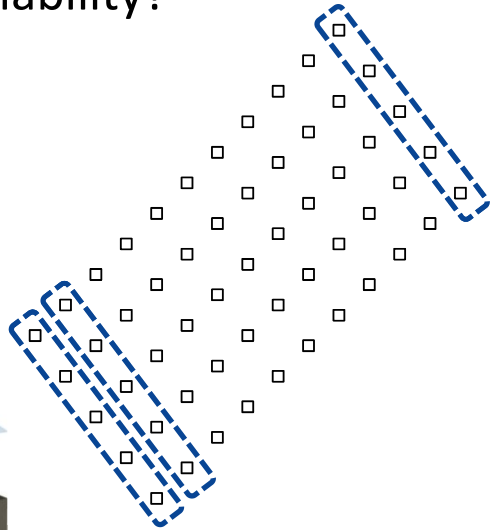


State space: $\{|\mathcal{S}_d| \cdot |\mathcal{S}_\tau|\}^{N_c}$

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



... scalability?

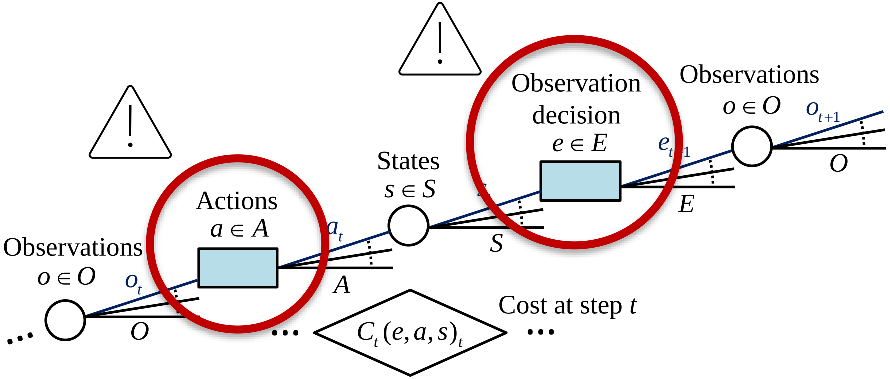


Component level

System level

Policy optimization ...

... alleviates computational complexity



Set of heuristic rules

- Equidistant inspections
- Inspection after reaching a specified threshold
- Repair after detection indication

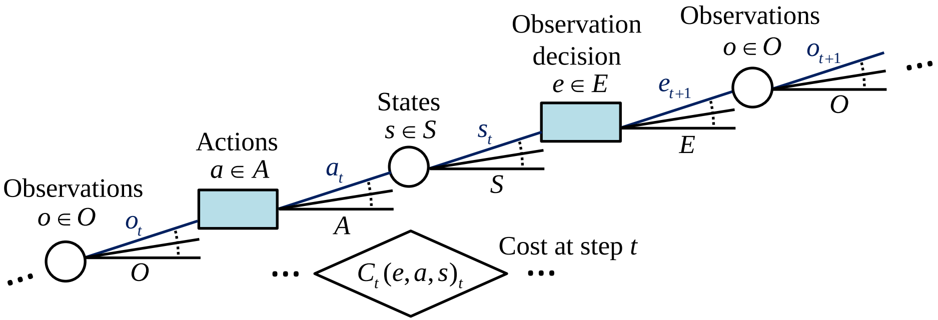
... **optimality**?

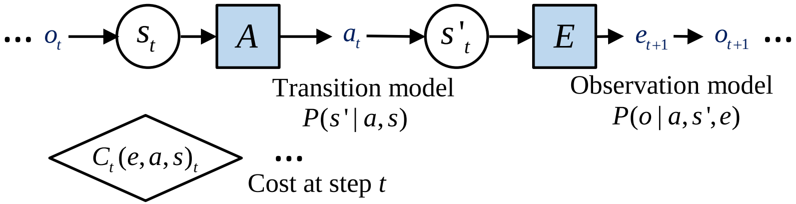
Policy optimization ...

... Partially Observable Markov Decision Processes **(POMDPs)**

Principled mathematical framework (Bellman's equation)

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

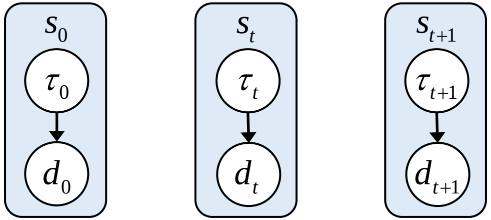




... specification ... scalability ...

Dynamic Bayesian networks – POMDP integration

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

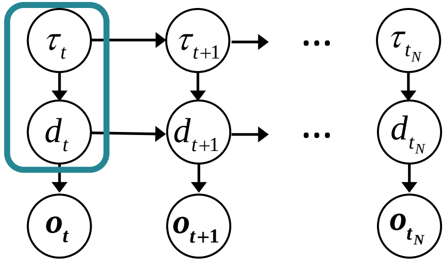


States

- Damage / deterioration rate
- Damage / parameters

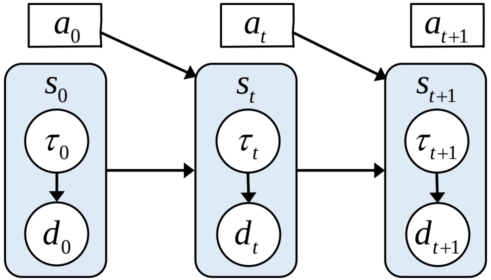
State augmentation

$$S_t = S_{d_t} \times S_{\tau_t} \text{ or } S_t = S_{d_t} \times S_{\boldsymbol{\theta}_t}$$



Dynamic Bayesian networks – POMDP integration

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



States

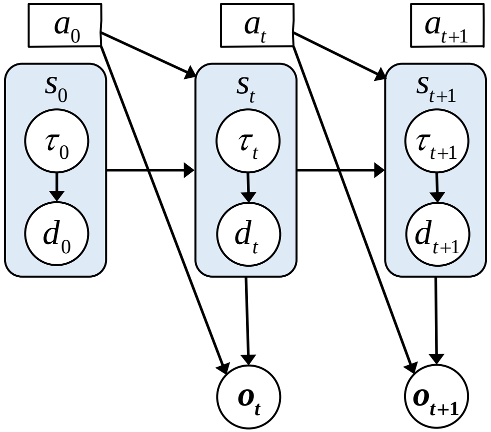
- Damage / deterioration rate
- Damage / parameters

Actions

- Do-nothing & no-inspection
- Do-nothing & inspection
- Perfect repair & no-inspection

Dynamic Bayesian networks – POMDP integration

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



States

- Damage / deterioration rate
- Damage / parameters

Actions

- Do-nothing & no-inspection
- Do-nothing & inspection
- Perfect repair & no-inspection

Observations

- Inspections (detection / no detection)
- Discrete observations (crack measurement)

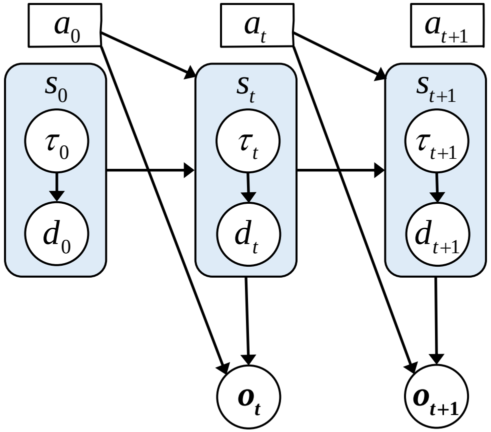
Dynamic Bayesian networks – POMDP integration

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

Transition model

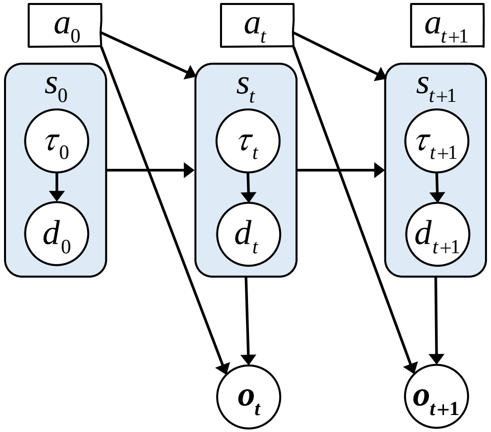
$$p(s_{t+1} \mid s_t) = p(s_{d_{t+1}}, s_{\tau_{t+1}} \mid s_{d_t}, s_{\tau_t}, a_t)$$

$$p(s_{t+1} \mid s_t) = p(s_{d_{t+1}}, s_{\boldsymbol{\theta}_{t+1}} \mid s_{d_t}, s_{\boldsymbol{\theta}_t}, a_t)$$



Dynamic Bayesian networks – POMDP integration

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



Transition model

$$p(s_{t+1} \mid s_t) = p(s_{d_{t+1}}, s_{\tau_{t+1}} \mid s_{d_t}, s_{\tau_t}, a_t)$$

$$p(s_{t+1} \mid s_t) = p(s_{d_{t+1}}, s_{\boldsymbol{\theta}_{t+1}} \mid s_{d_t}, s_{\boldsymbol{\theta}_t}, a_t)$$

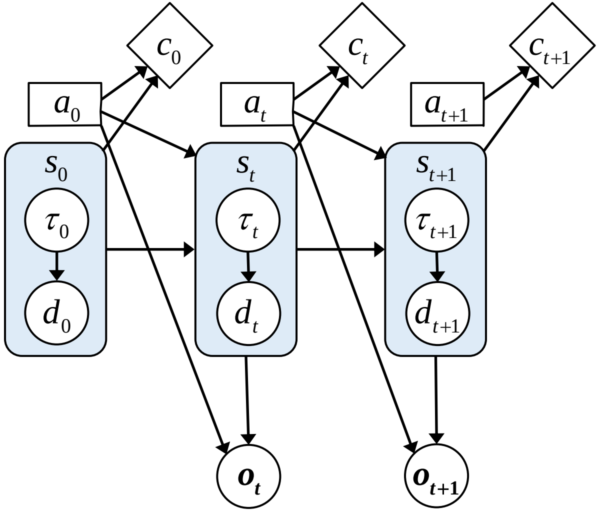
Observation model

$$p(\boldsymbol{o}_{t+1} \mid s_{t+1}) = p(\boldsymbol{o}_{t+1} \mid s_{t+1}, a_t)$$

$$p(\boldsymbol{o}_{t+1} \mid s_{t+1}) = p(\boldsymbol{o}_{t+1} \mid s_{t+1}, a_t)$$

I&M decision problem specified as a POMDP

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



Transition model

$$p(s_{t+1} \mid s_t) = p(s_{d_{t+1}}, s_{\tau_{t+1}} \mid s_{d_t}, s_{\tau_t}, a_t)$$

$$p(s_{t+1} \mid s_t) = p(s_{d_{t+1}}, s_{\boldsymbol{\theta}_{t+1}} \mid s_{d_t}, s_{\boldsymbol{\theta}_t}, a_t)$$

Observation model

$$p(\boldsymbol{o}_{t+1} \mid s_{t+1}) = p(\boldsymbol{o}_{t+1} \mid s_{t+1}, a_t)$$

$$p(\boldsymbol{o}_{t+1} \mid s_{t+1}) = p(\boldsymbol{o}_{t+1} \mid s_{t+1}, a_t)$$

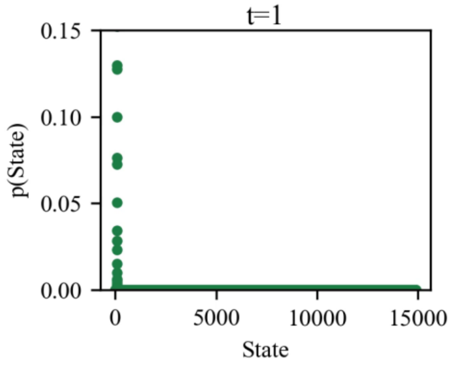
Cost model

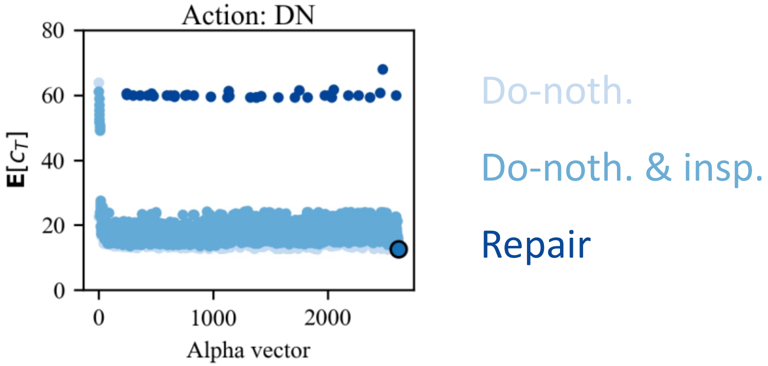
$$\gamma^t c_t(a_t, s_t)$$

$$\mathbf{E}[c_t] = \mathbf{E}[c_{ins}] + \mathbf{E}[c_{rep}] + \mathbf{E}[c_{fail}]$$

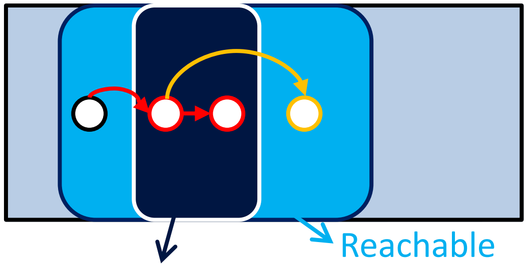
Solving POMDPs – point-based solvers

Policy is a mapping from the **belief state** to the **optimal action**

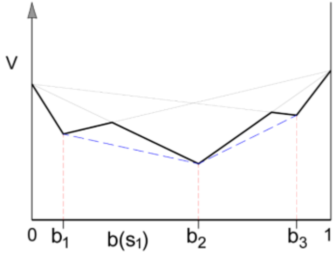


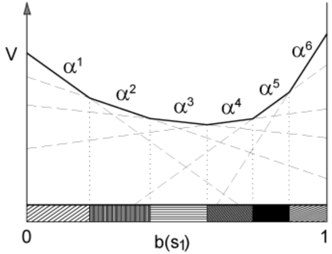


Sampling belief states



Value function is piece-wise linear and convex





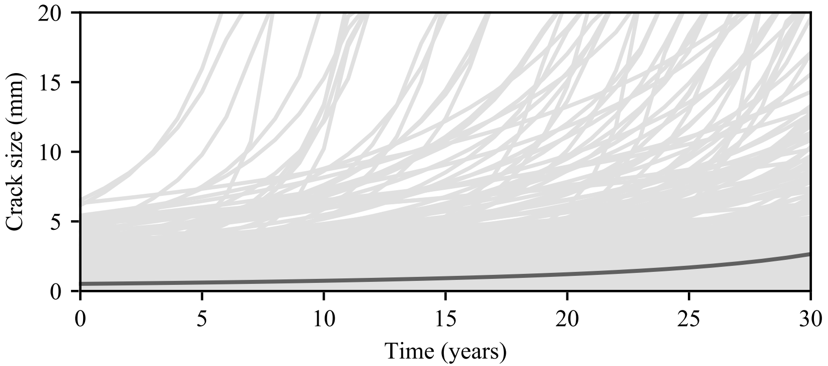
$$V(\mathbf{b}_t) = \max_{a_t \in A} \left\{ \sum_{s_t \in S} b(s_t) r(s_t, a_t) + \gamma \sum_{o_{t+1} \in \Omega} p(o_{t+1} | \mathbf{b}_t, a_t) V(\mathbf{b}_{t+1}) \right\}$$

I&M planning: Traditional setting

Deteriorating structure

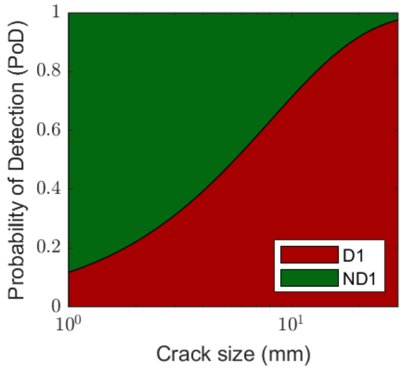
Component subjected to fatigue

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



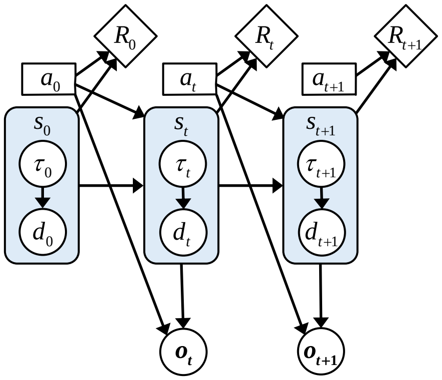
I&M decision-making problem

- Actions: Do-nothing, perfect repair
- Observation decision: No-inspection, inspection
- Observation outcomes: detected, no detected
- Decision horizon of 30 years

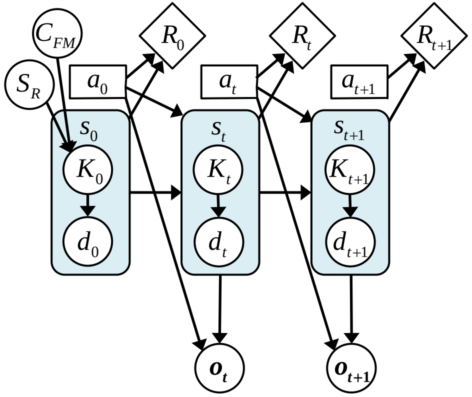


I&M planning: Traditional setting

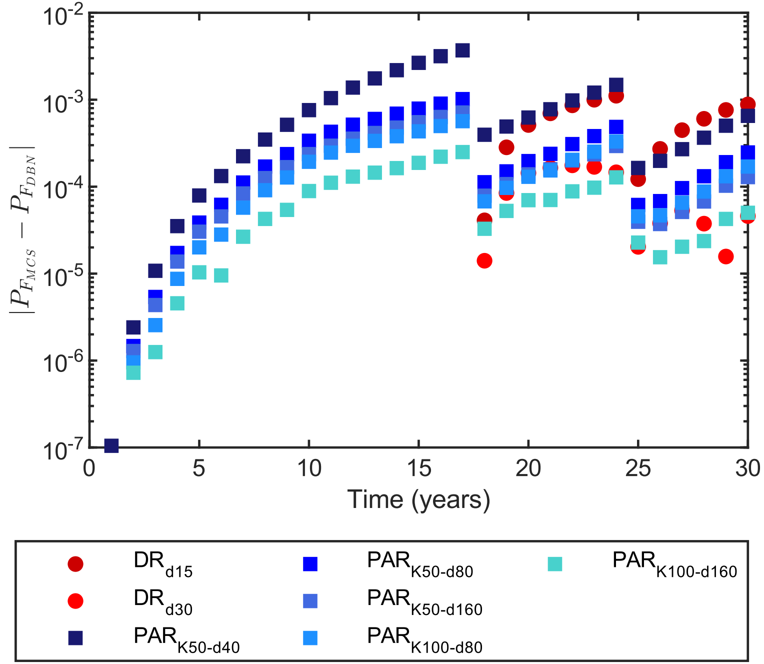
Discretization analysis – state space



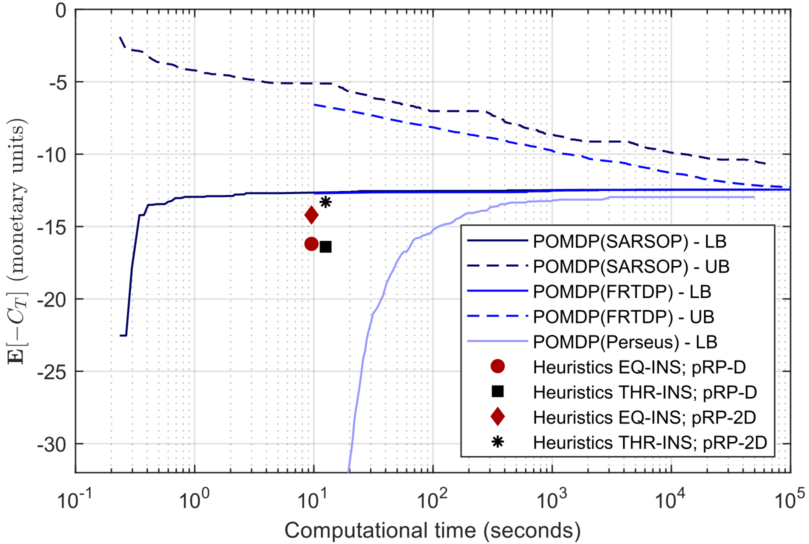
Deterioration rate (DR) model



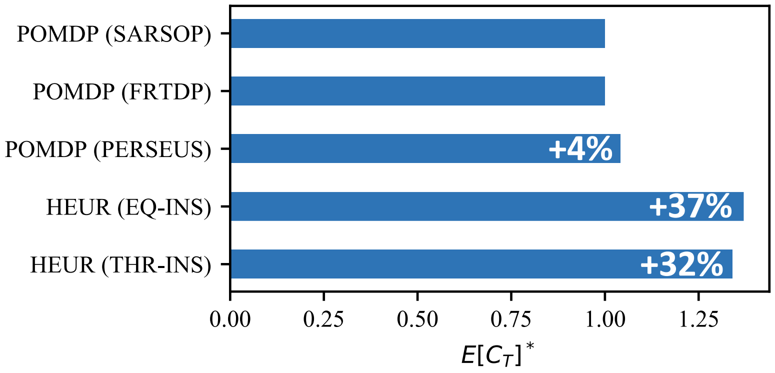
Parametric (PAR) model

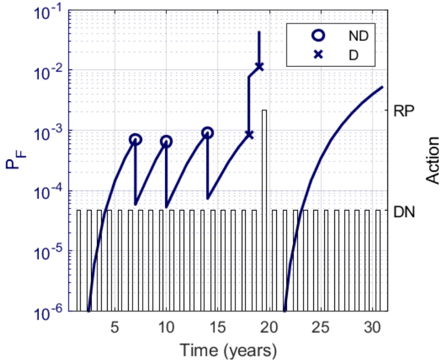


I&M planning: Traditional setting

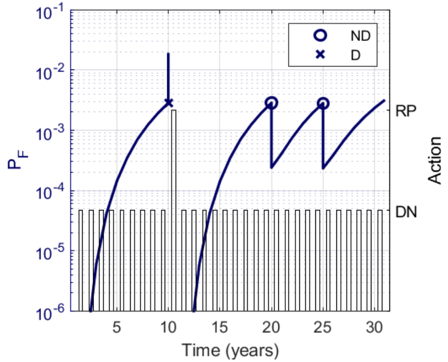


Optimality bounds





POMDP policy realization



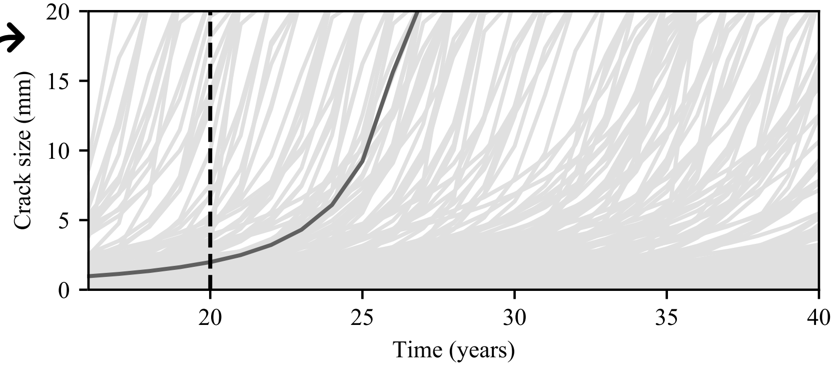
“Heuristics” policy realization

Lifetime extension planning

Deteriorating structure

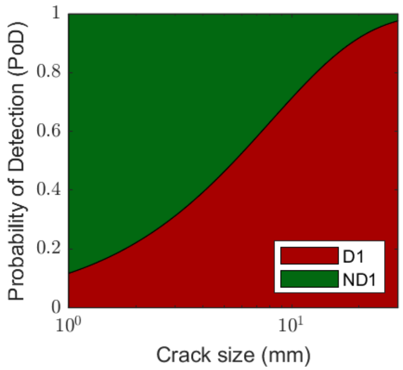
Offshore wind component subject to fatigue

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

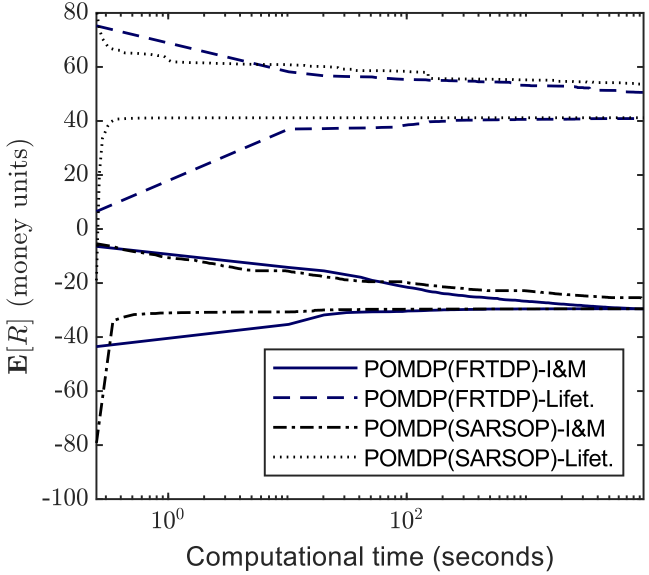


Lifetime extension decision-making problem

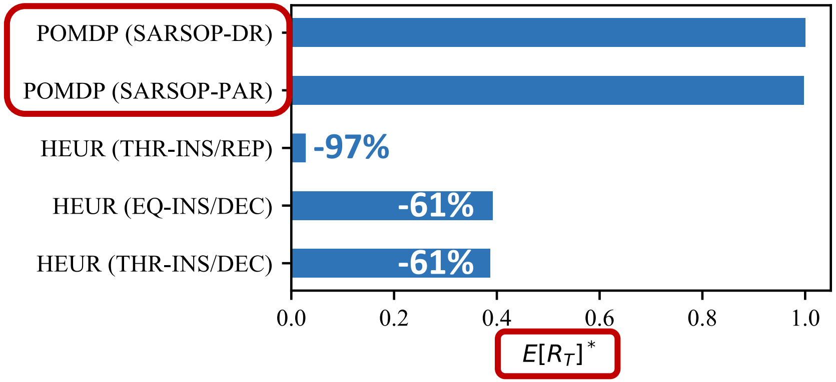
- Actions: Do-nothing, replace, decommissioning
- Observation decision: No-inspection, inspection
- Observation outcomes: detected, no-detected
- Horizon starts at year (infinite horizon)

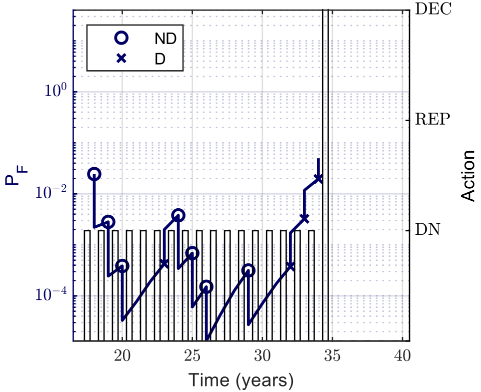


Lifetime extension planning

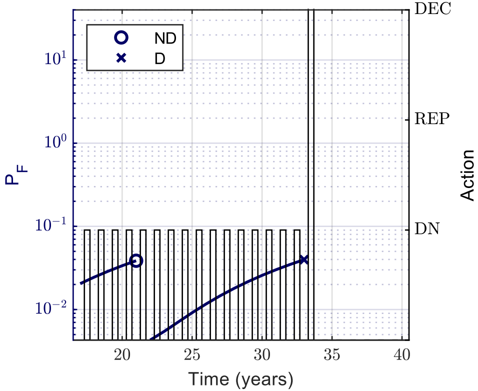


Optimality bounds



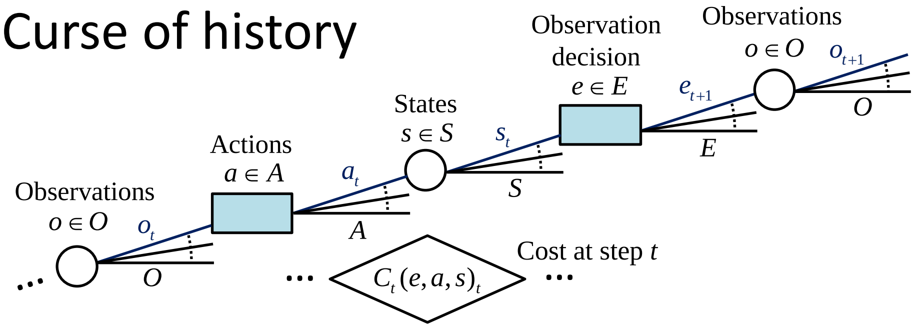


POMDP policy realization

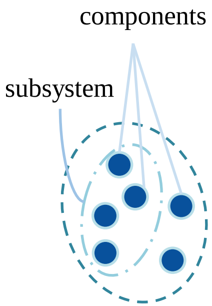


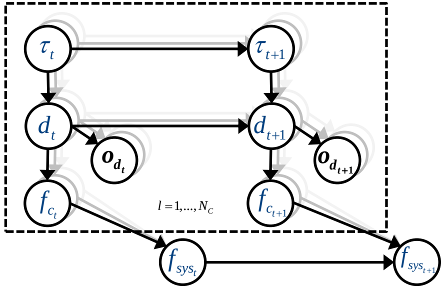
“Heuristics” policy realization

(1) Curse of history



(2) Curse of dimensionality





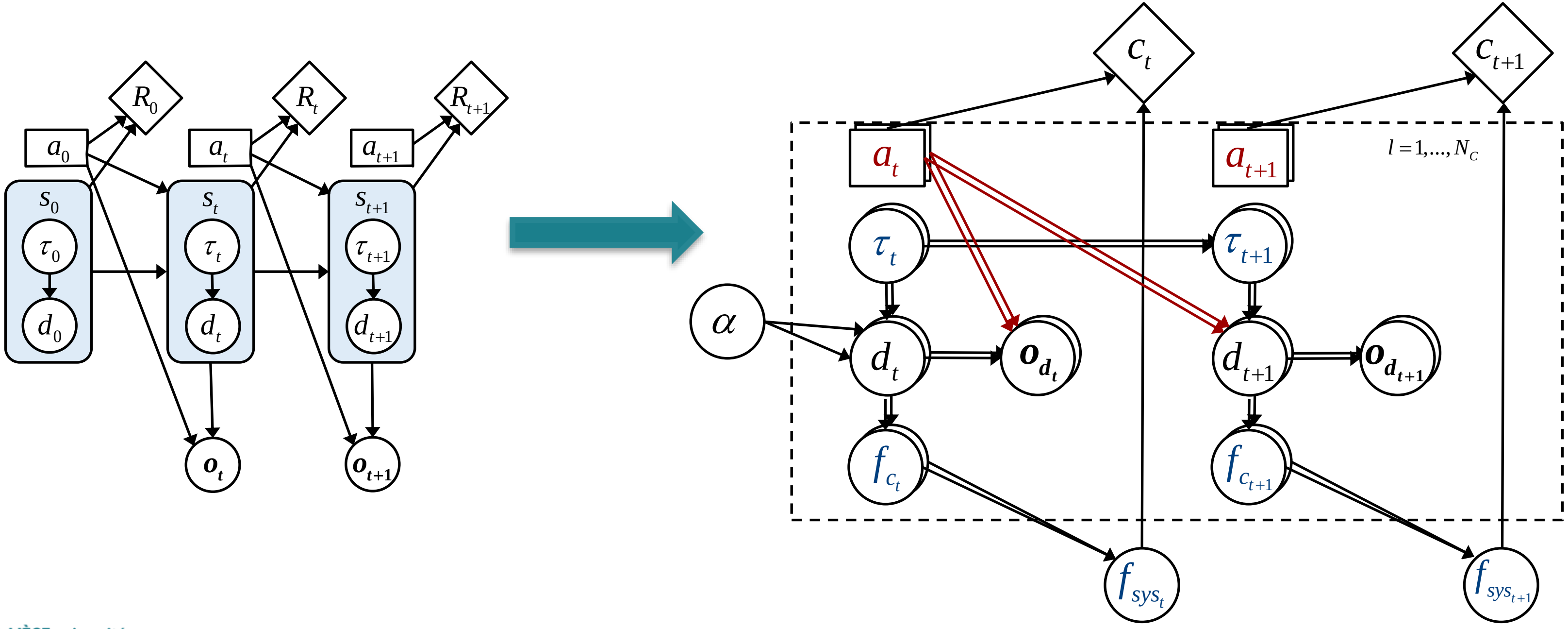
Partially Observable Markov Decision Process (POMDP)

Deep reinforcement learning

System level - graphical representation

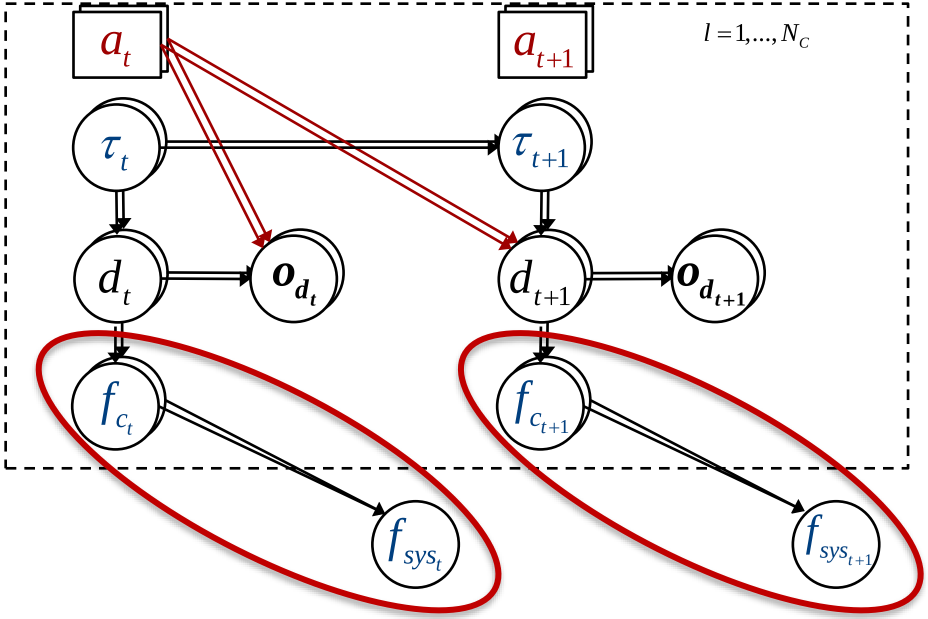
Component level

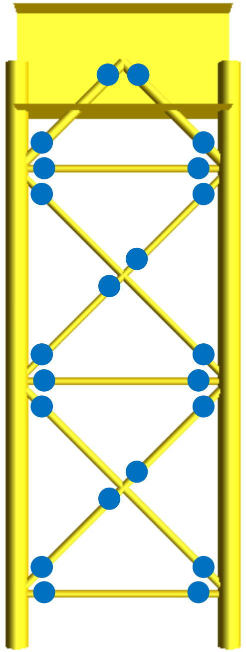
System level

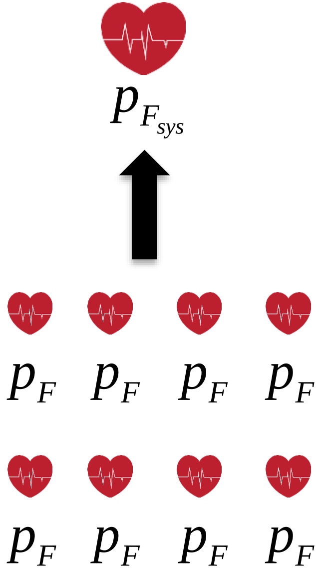


System level... structural reliability

$$p_{F_{sys}} = p(F_{sys} \mid \mathbf{F}_i)\, p_{\mathbf{F}_i}$$

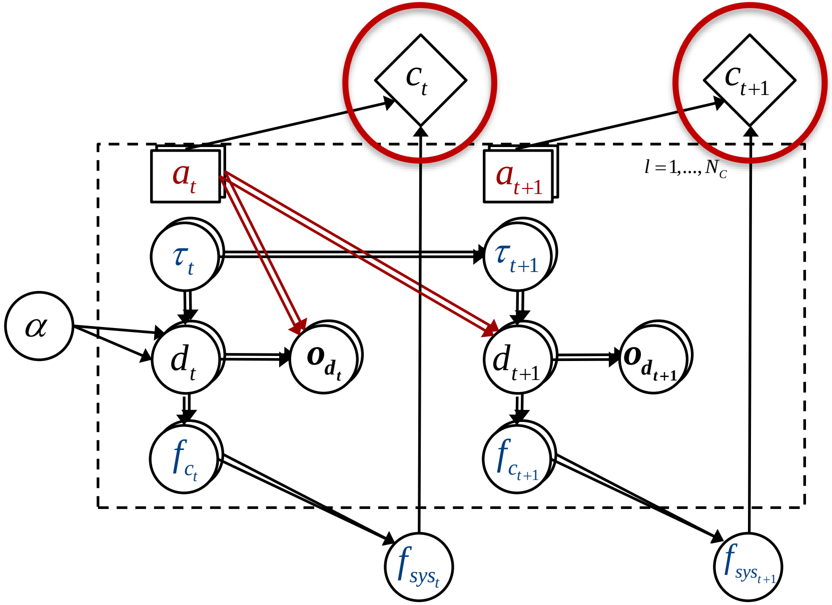


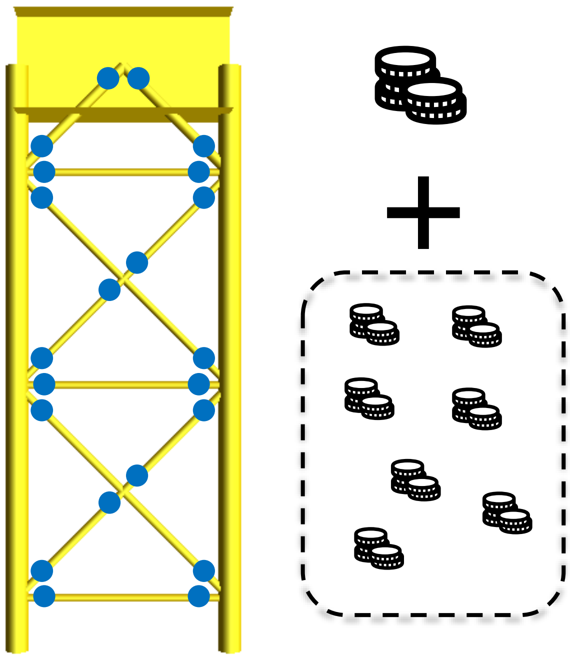




System level... cost dependence

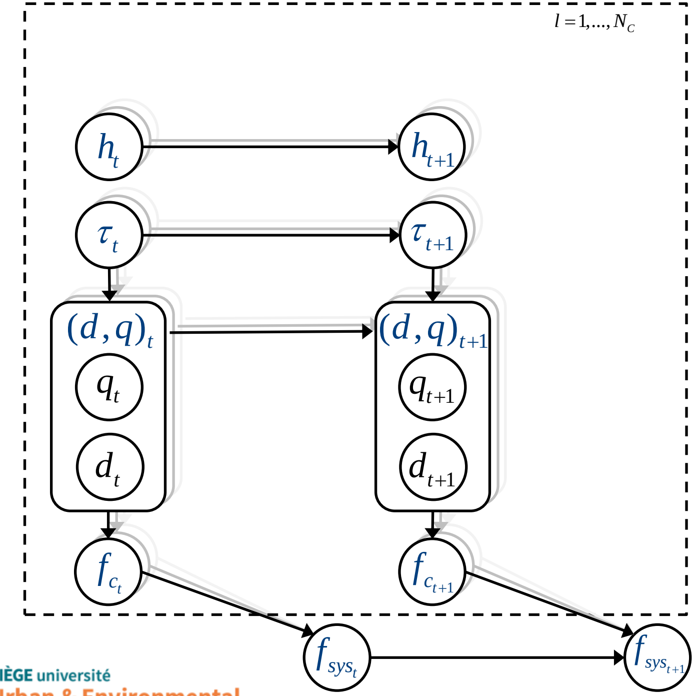
$$c_{camp} + \sum_{i}\left(c_{ins} + c_{rep}\right) + c_{fail}$$





POMDP formulation

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

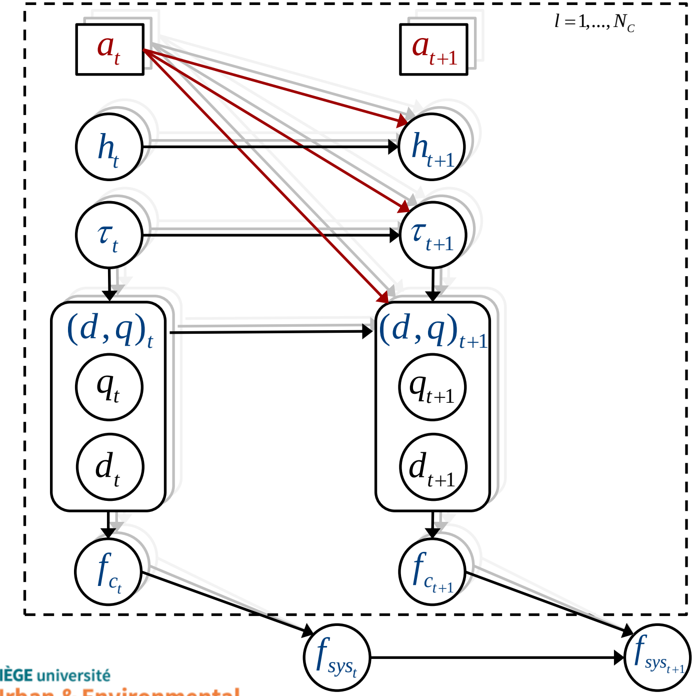


States

- Damage / deterioration rate
- Sensor health
- Component / system failure

POMDP formulation

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



States

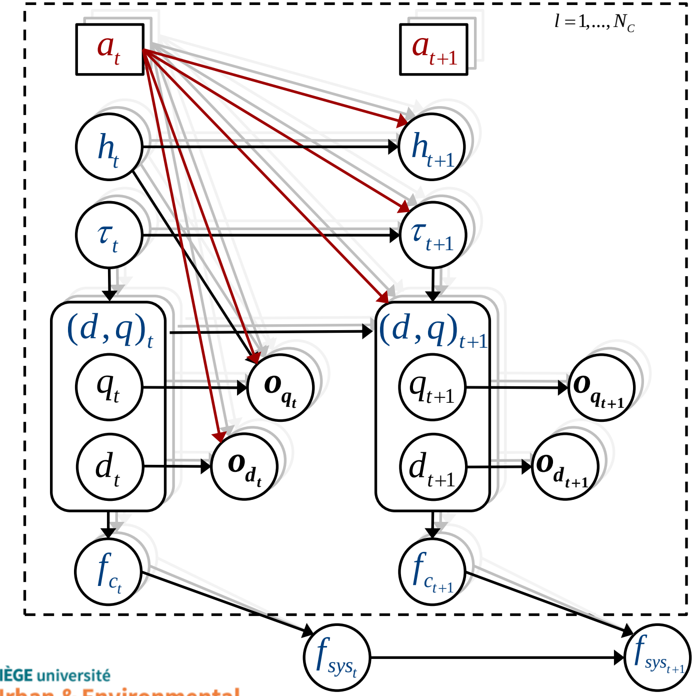
- Damage / deterioration rate
- Sensor health
- Component / system failure

Actions

- Do-noth. & no-insp. / Do-noth. & insp.
- Sensor & no-insp. / Sensor & insp.
- Repair & no-sensor / Repair & sensor
- Replacement

POMDP formulation

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



States

- Damage / deterioration rate
- Sensor health
- Component / system failure

Actions

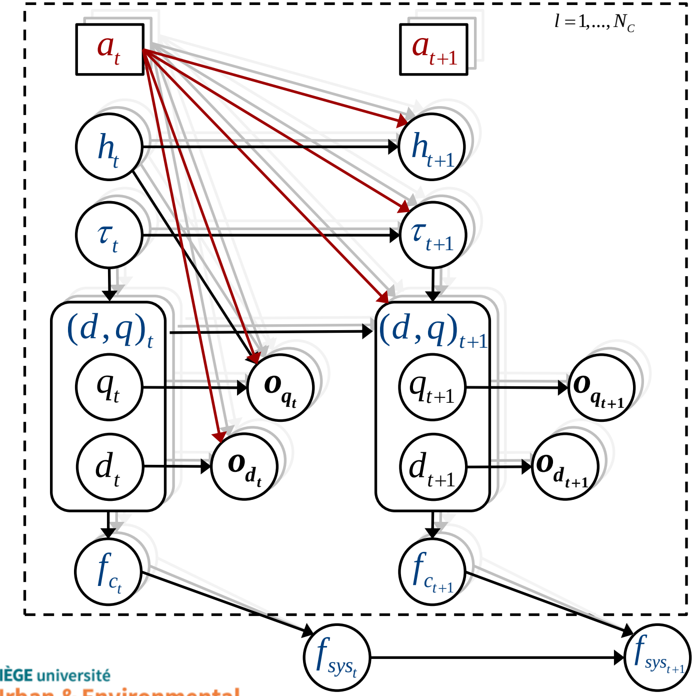
- Do-noth. & no-insp. / Do-noth. & insp.
- Sensor & no-insp. / Sensor & insp.
- Repair & no-sensor / Repair & sensor
- Replacement

Observations

- Inspections
- Monitoring
- System failure state

POMDP formulation

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

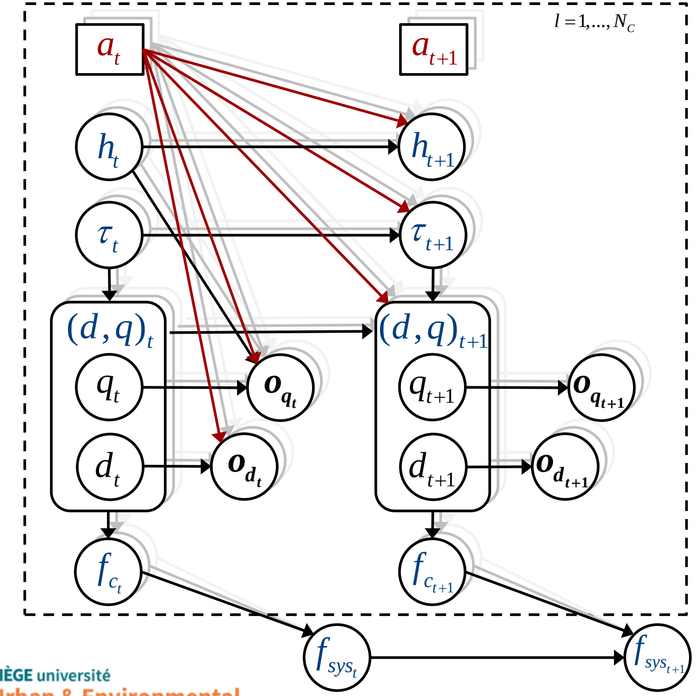


Transition model

- 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: $p(f_{sys_{t+1}} \mid \mathbf{f_{c,t+1}}, f_{sys_t})$

POMDP formulation

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



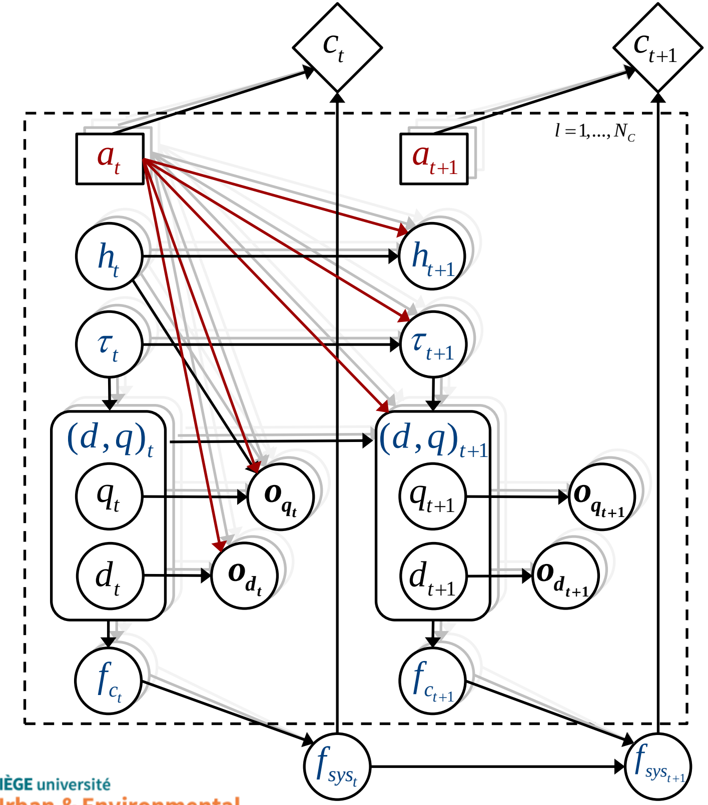
Transition model

- 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: $p(f_{sys_{t+1}} \mid \mathbf{f_{c,t+1}}, f_{sys_t})$

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: $f_{sys_{t+1}} \sim p(f_{sys_{t+1}})$

POMDP formulation



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: $p(f_{sys_{t+1}} \mid \mathbf{f_{c,t+1}}, f_{sys_t})$

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: $f_{sys_{t+1}} \sim p(f_{sys_{t+1}})$

Cost model

- System cost: $\gamma^t c_t(a_t, f_{sys_t})$

$$\mathbf{E}[c_t] = \mathbf{E}[c_{ins}] + \mathbf{E}[c_{sens}] + \mathbf{E}[c_{rep}] + \mathbf{E}[c_{fail}] + \mathbf{E}[c_{replac}]$$

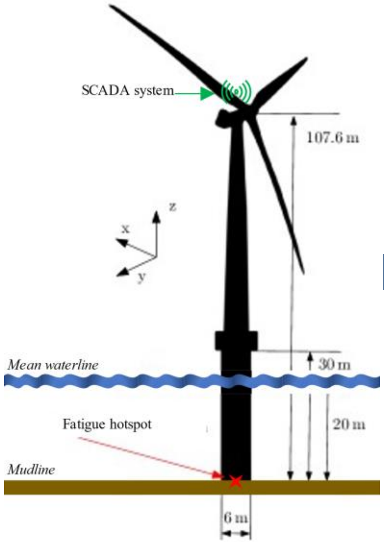
Observation model

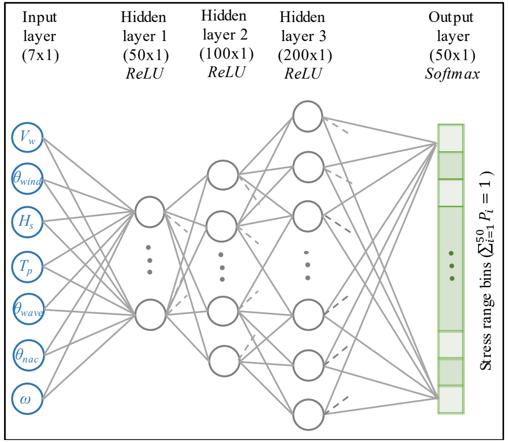
Monitoring: $p(o_{q_{t+1}} \mid q_{t+1}, h_{t+1}, a_{t+1})$

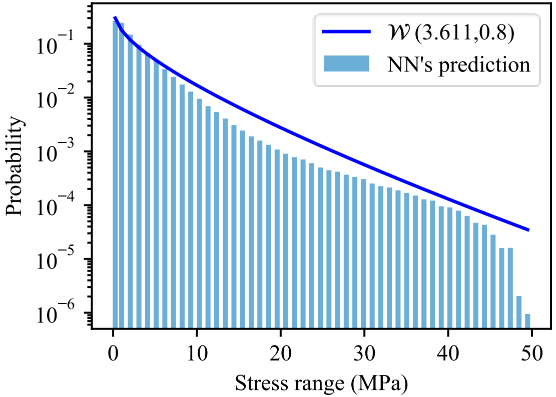
SCADA system
(Environmental and operational variables)

Neural network →

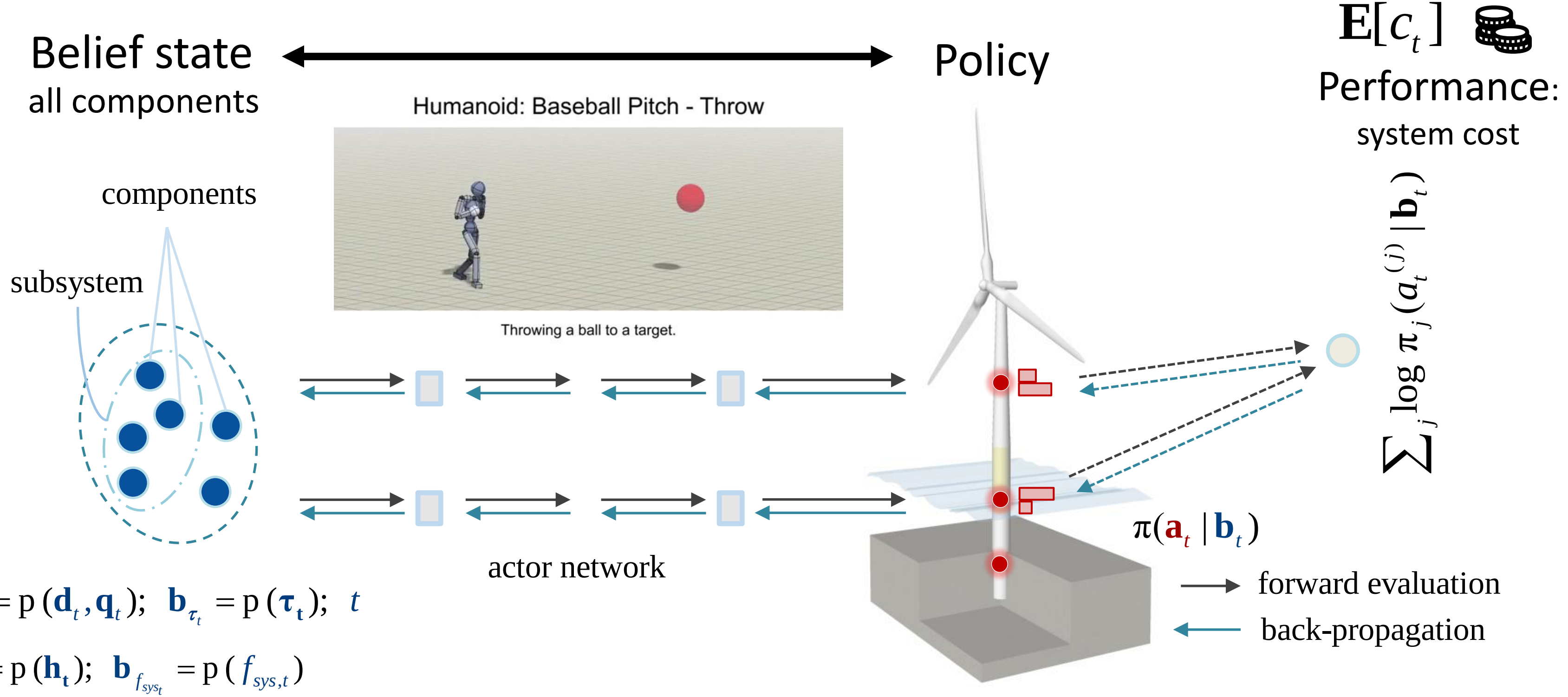
Strain gauge
(Load effect distribution)







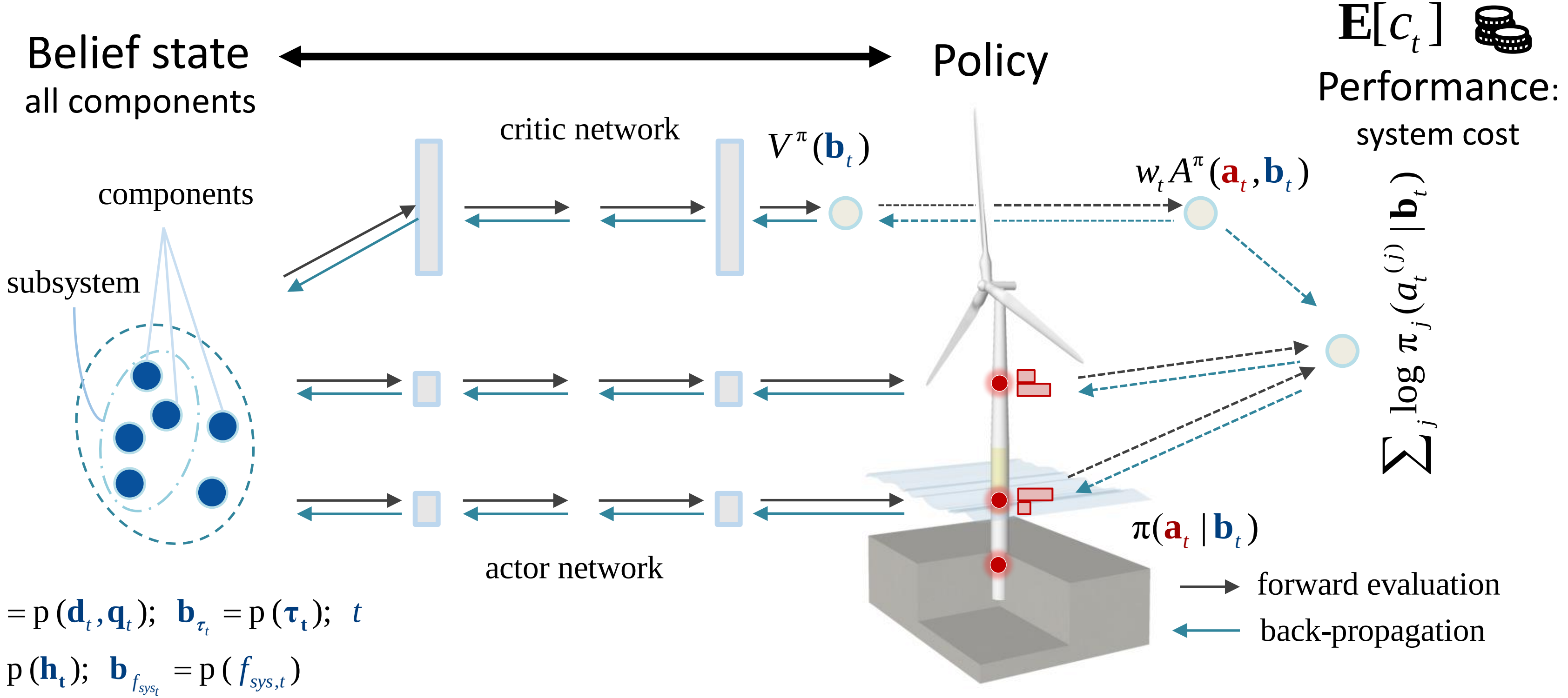
Decentralized Decoupled Multi-Actor Critic (DDMAC)



$$\mathbf{b}_{d_t, q_t} = \mathrm{p}(\mathbf{d}_t, \mathbf{q}_t); \quad \mathbf{b}_{\tau_t} = \mathrm{p}(\boldsymbol{\tau}_t); \quad t$$

$$\mathbf{b}_{h_t} = \mathrm{p}(\mathbf{h}_t); \quad \mathbf{b}_{f_{sys_t}} = \mathrm{p}(f_{sys,t})$$

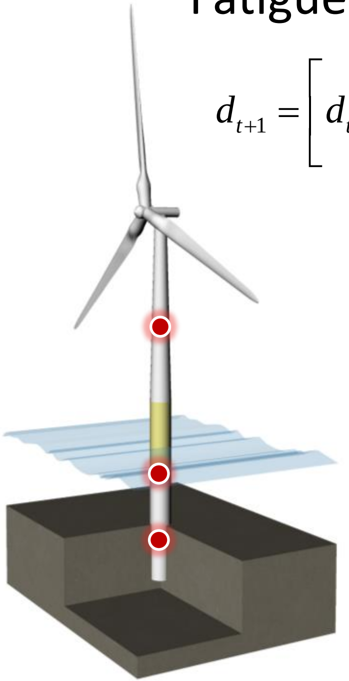
Decentralized Decoupled Multi-Actor Critic (DDMAC)



$\mathbf{b}_{d_t,q_t} = \mathrm{p}(\mathbf{d}_t, \mathbf{q}_t)$; $\mathbf{b}_{\tau_t} = \mathrm{p}(\boldsymbol{\tau}_t)$; t

$\mathbf{b}_{h_t} = \mathrm{p}(\mathbf{h}_t)$; $\mathbf{b}_{f_{sys_t}} = \mathrm{p}(f_{sys,t})$

Optimal management of OW substructures



$c_{ins} = 1$
$c_{rep} = 10$
$c_{sen} = 2$

$c_{ins} = 4$
$c_{rep} = 30$
$c_{sen} = 6$

$c_{fail} = 600$ // $c_{replac} = 350$

Fatigue deterioration

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

"NDE" inspections

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

Load monitoring

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

Neural networks

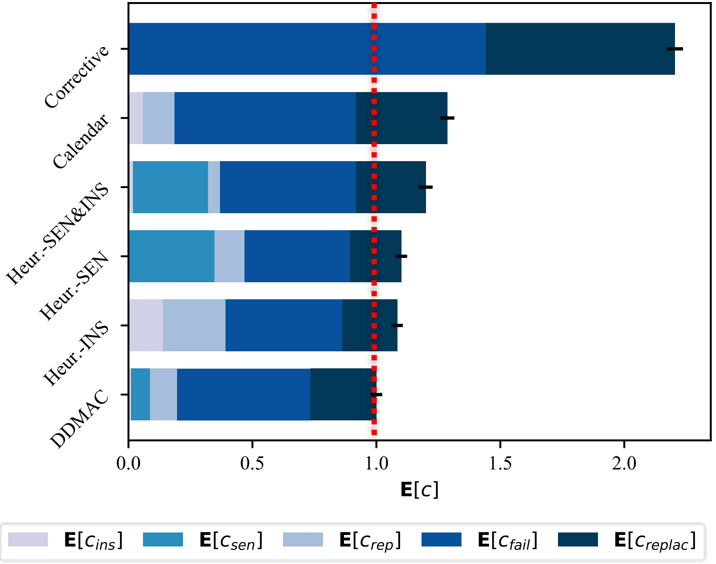
TensorFlow

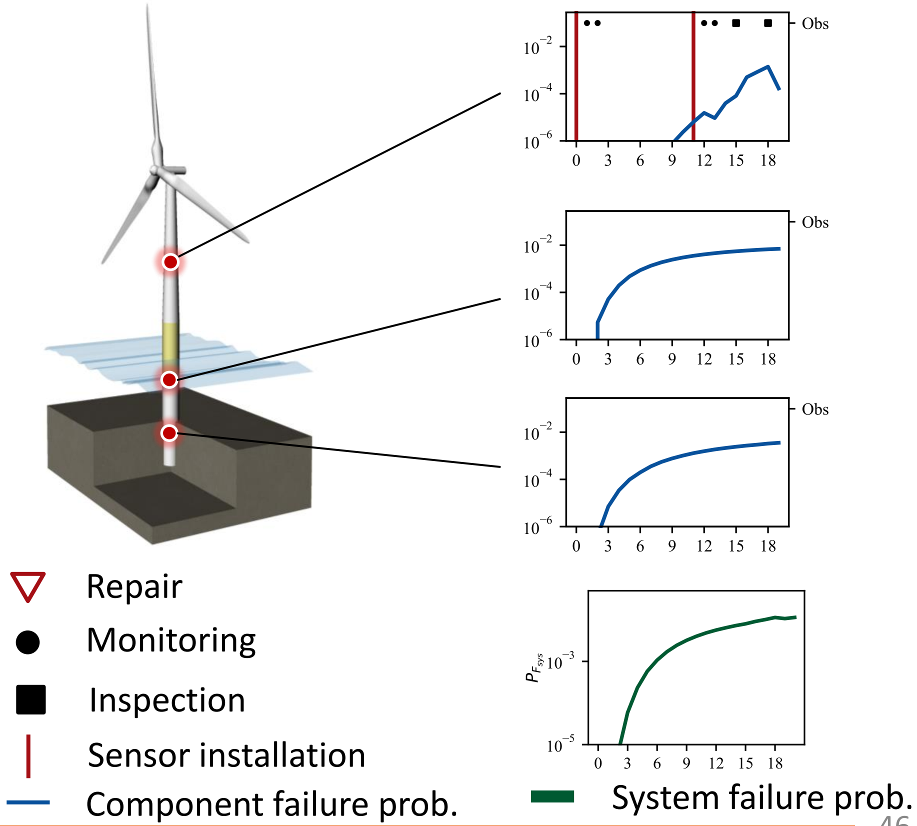
Keras

	Actors	Critic
	2x100	2x300
Learning rate	$10^{-4} - 10^{-5}$	$10^{-3} - 10^{-4}$

Exploration:
noise 100% to 1%
in 20,000 episodes

Optimal management of OW substructures



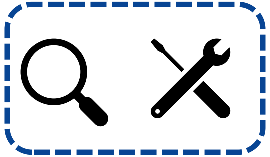


- Corrective maintenance (CORR) **+124%**
- Calendar-based (CAL) **+31%**
- Heuristic decision rules (HEUR) **+10%**
- **DDMAC DRL**

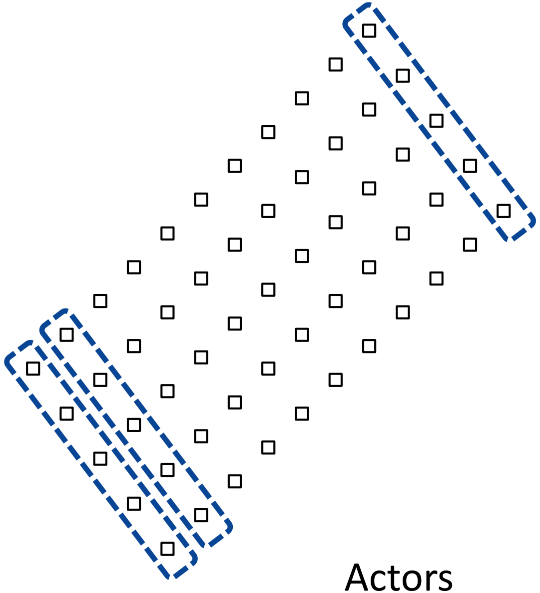
Optimal management of OW substructures

Belgianoffshoreplatform

5 OWTs



Campaign cost



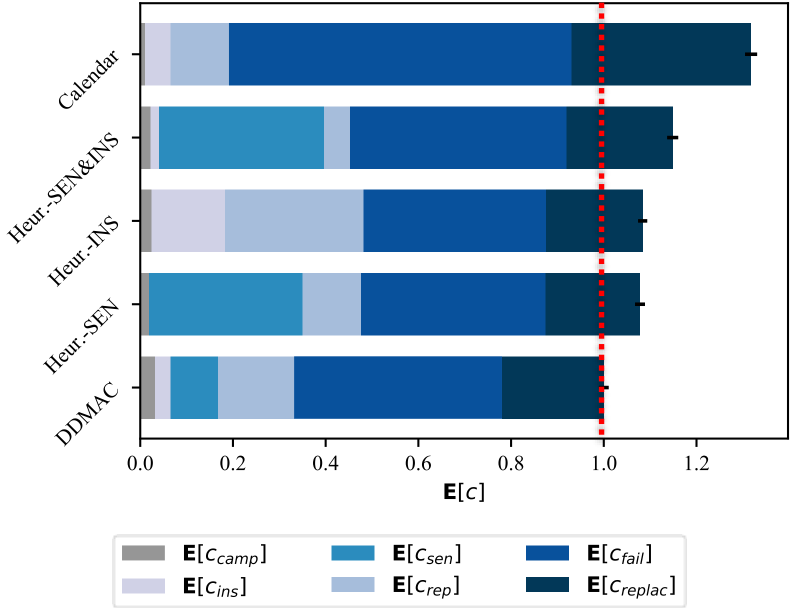
1 monetary unit ≈ 15 k€

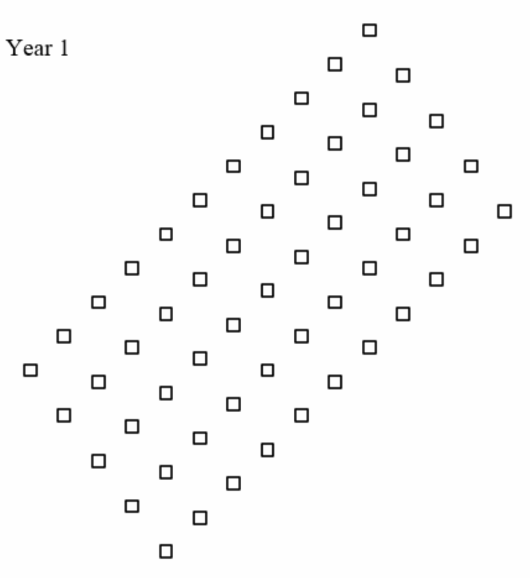
Cost dependence: $c_{camp} + \sum_i \left(c_{ins} + c_{rep} \right)$

$$\mathbf{E}[c_t] = \mathbf{E}[c_{camp}] + \mathbf{E}[c_{ins}] + \mathbf{E}[c_{sens}] + \mathbf{E}[c_{rep}] + \mathbf{E}[c_{fail}] + \mathbf{E}[c_{replac}]$$

Actors	Critic
2x100	2x400

Optimal management of OW substructures



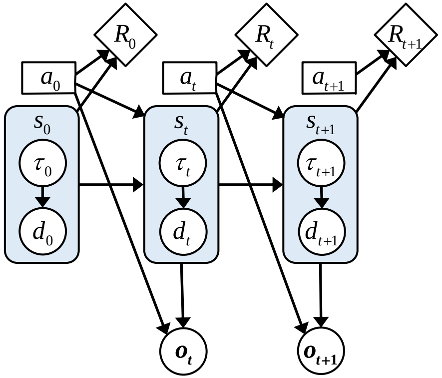


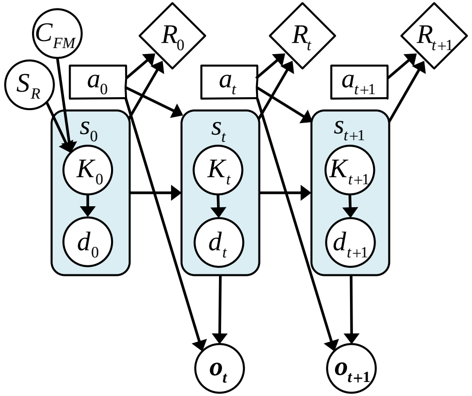
- Calendar-based: **+32%** +13.9M€
- Heuristic rules: **+9%** +3.8M€
- **DDMAC DRL**

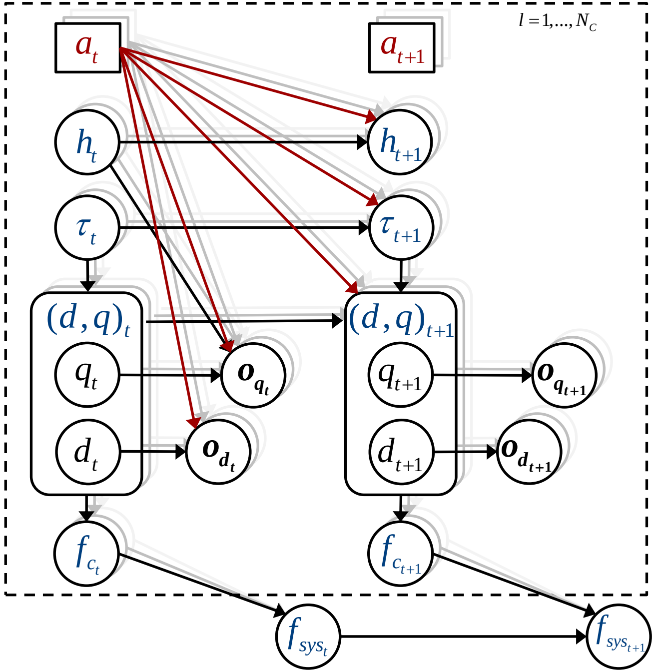
Do-nothing
Do-noth. & inspection
Sensor installation
Sensor inst. & inspection
Repair
Repair & sensor installation

Concluding remarks

- Dynamic Bayesian networks and POMDPs can be combined to provide an efficient algorithmic platform for decision-making under uncertainty.

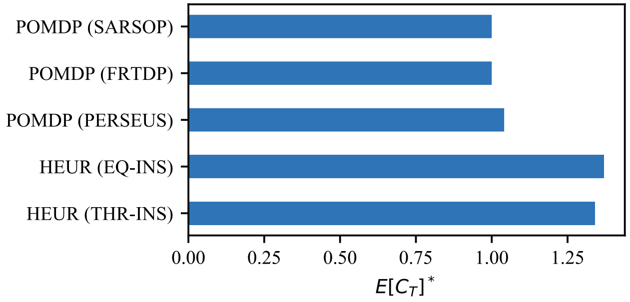


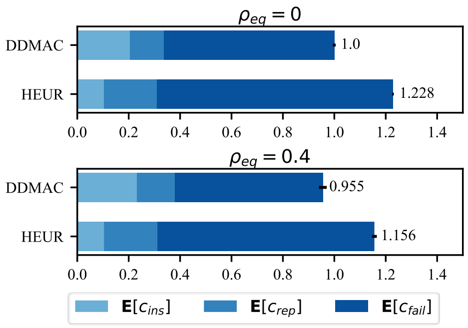


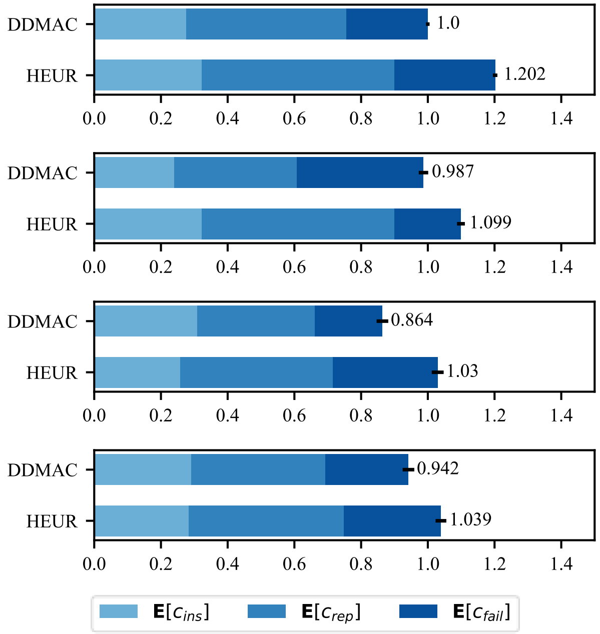


Concluding remarks

- POMDP-based policies outperform conventional and state-of-the-art inspection and maintenance planning methods.

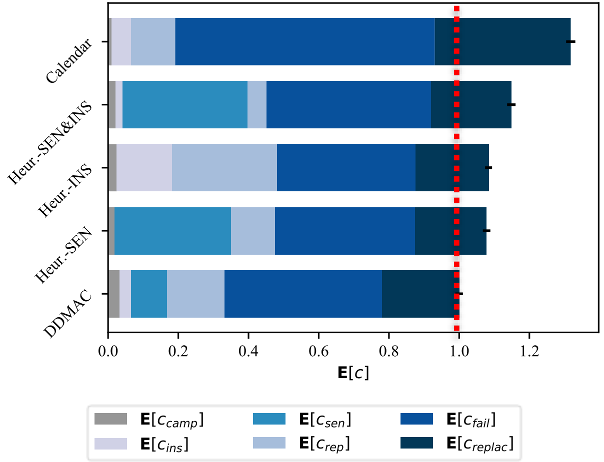


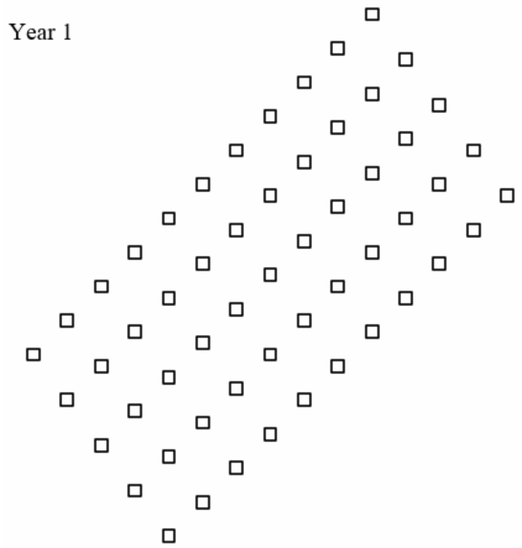




Concluding remarks

- POMDP-DDMAC provides substantial benefits for the management of offshore wind substructures.



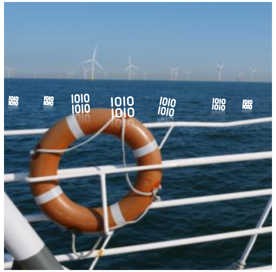


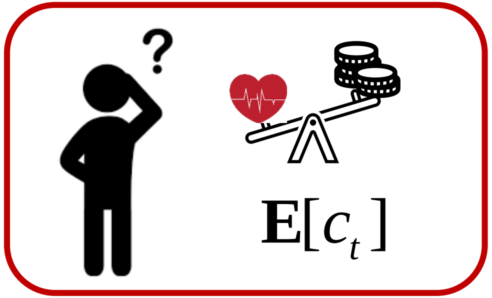
- Calendar-based: **+32%** +13.9M€
- Heuristic rules: **+9%** +3.8M€
- **DDMAC DRL**

Future work

? Actions ? Information

Decision-making problem





- Life-cycle management strategies including the design stage
- Post-event resilience response
- Multi-objective and constrained optimization problems

Optimal Management of Offshore Wind Structural Systems via Deep Reinforcement Learning

Additional comments, questions ...

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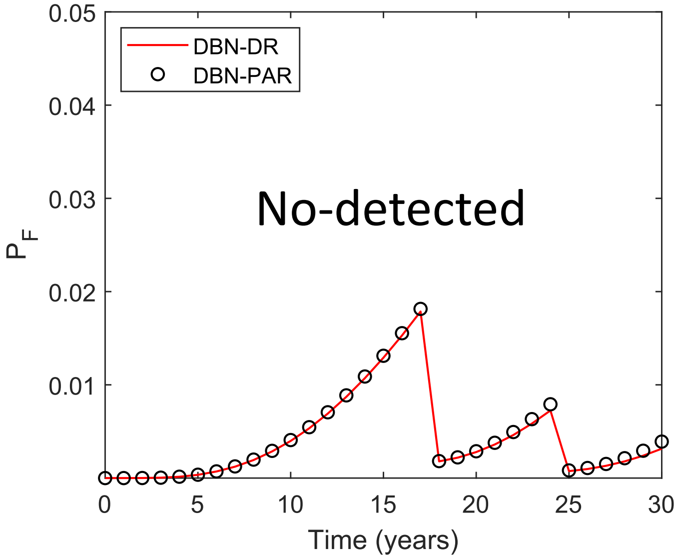
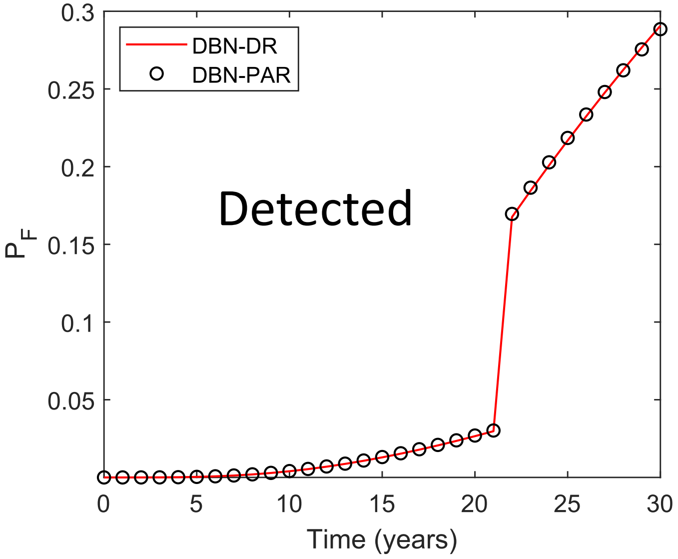
Deterioration rate vs parametric DBNs





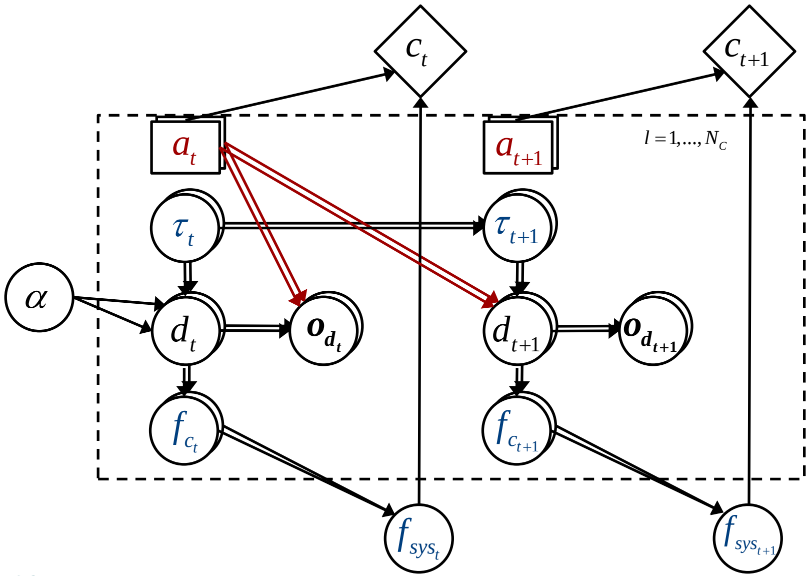
- Morato, P. G., Papakonstantinou, K. G., Andriotis, C. P., Nielsen, J. S. and Rigo P. (2021). Optimal Inspection and Maintenance Planning for Deteriorating Structural Components through Dynamic Bayesian Networks and Markov Decision Processes. *Structural Safety*, accepted for publication.

Practical implications

- Demonstrating cost savings ✓
- Incorporating safety constraints ✓
- Educating and/or disseminating
- Sharing code (software)
- Start-up company

Gaussian hyperparameters

Influence of maintenance actions (repairs)



$$p(a_0|\alpha) = \Phi\left(\frac{Y_i - \lambda_i \alpha}{\sqrt{1-\lambda_i^2}}\right)$$

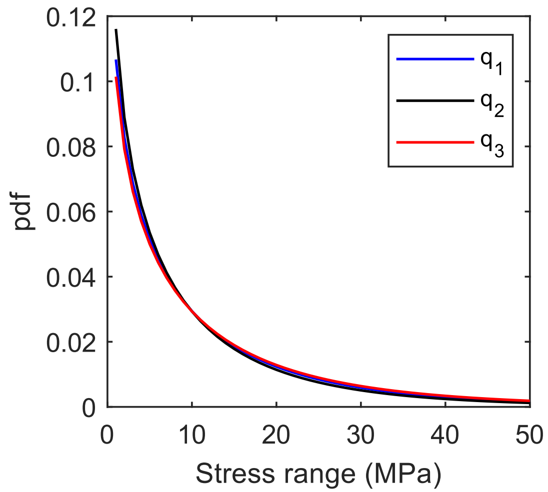
"Perfect repair"

$$p(a_0|\alpha) = \Phi\left(\frac{Y_i - \lambda_i \alpha}{\sqrt{1-\lambda_i^2}}\right)$$

$\alpha \rightarrow 0$

Stress range: scale parameter

Long-term stress range (Weibull distribution)



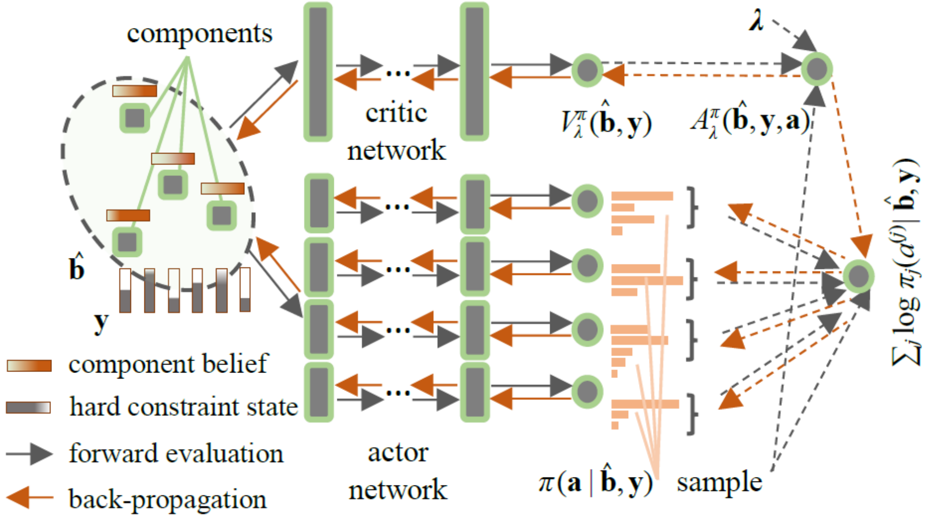
Expected stress range

$$E[\Delta S] = q\Gamma\left(1 + \frac{1}{h}\right)$$

Strain monitoring (1 year interval)

- Rainflow counting => stress range
- Retrieve scale parameter "q"
- Consider measurement noise
- Update "q"

Safety constraints



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