Model Updating, Condition Assessment, and Maintenance of Multi-component Systems under Correlated Deterioration Processes

P.G. Morato & P. Rigo
Dept. of ArGEnCO,
University of Liege (Belgium)

C.P. Andriotis
Faculty of Architecture & the Built Environment,
TU Delft (The Netherlands)

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

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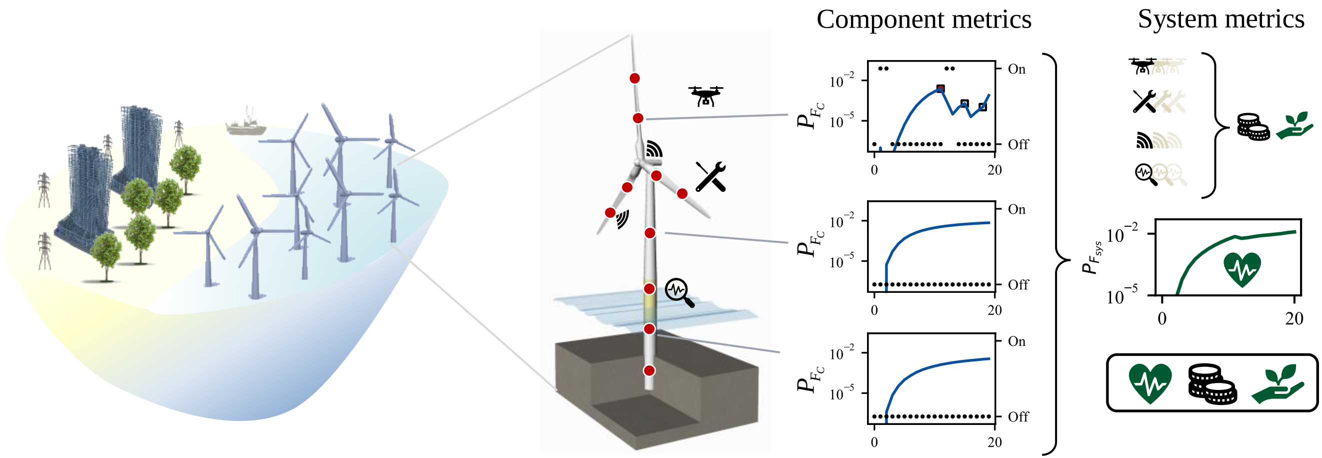
I&M optimization for deteriorating structural systems

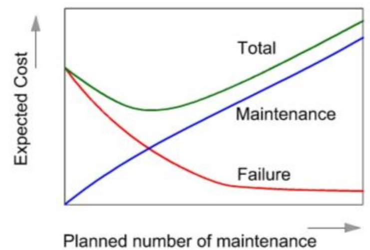


Sequential decision-making under uncertainty and imperfect information

- Stochastic environment
- Partially observable
- Sparse discounted rewards
- **System** of structural elements

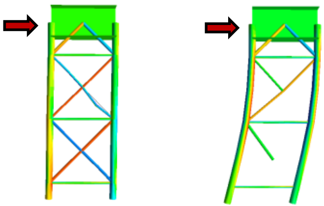
Stochastic optimization

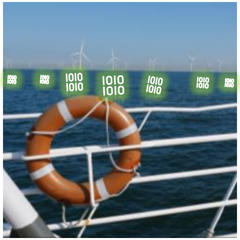
$$\arg\min_{\pi} \mathbb{E}[c_T] = \mathbb{E}[r_F] + \mathbb{E}[c_{ins}] + \mathbb{E}[c_{rep}]$$

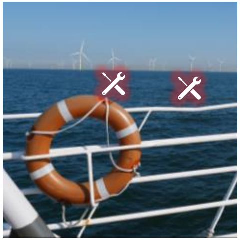


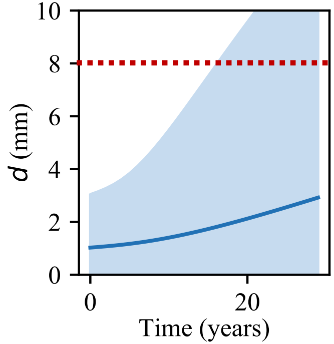
I&M optimization for deteriorating structural systems

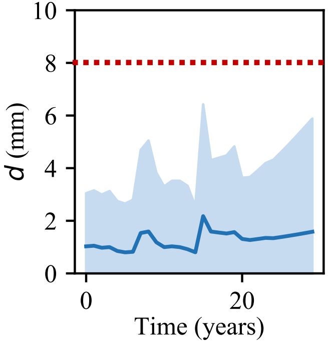
$$d_{t+1} = \left[\left(1 - \frac{m}{2} \right) C_{FM} S_R^m \pi^{m/2} n + d_t^{1-m/2} \right]^{2/(2-m)}$$

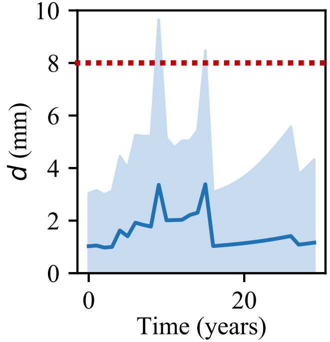












Deterioration (prior) model

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

Observations

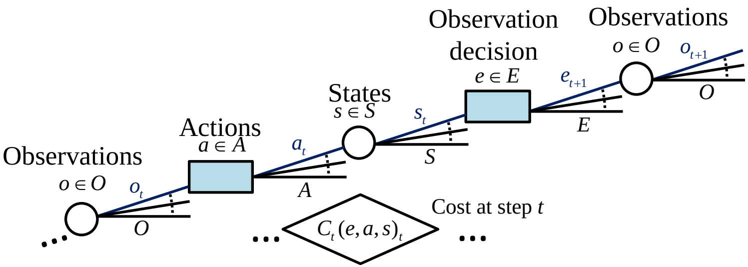
Actions for collecting information ($$)

Repairs/retrofits

Actions that influence the environment ($$$)

Challenges and available methods

(1) Curse of history

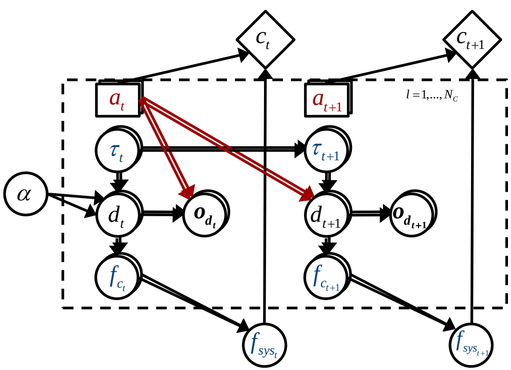


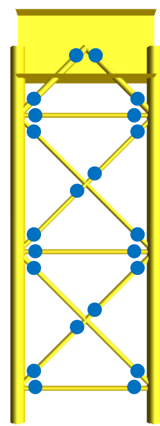
Policy space: $\left\{|\mathcal{A}|^{N_C}\right\}^{T_N}$

Methods:

- Heuristic decision rules
- Dynamic programming (POMDPs)

(2) Curse of dimensionality





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

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

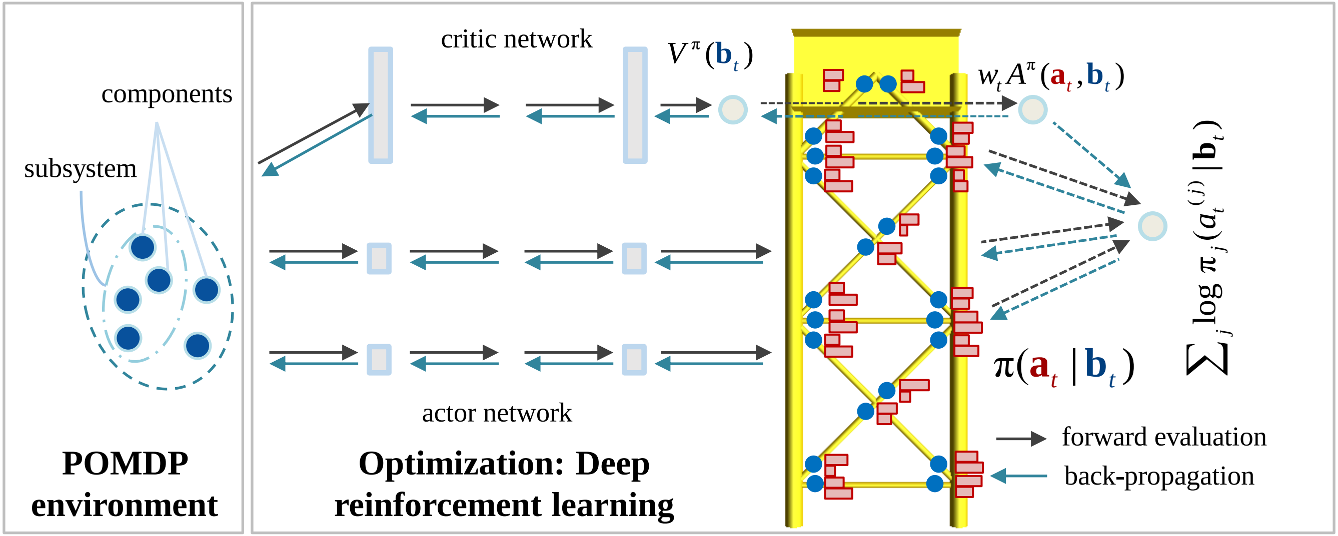
Methods:

- Component level policies
- Heuristic decision rules at the system level
- Deep reinforcement learning

Overarching algorithmic platform

$$\boxed{\arg\min_{\pi} \mathbb{E}[c_T] = \mathbb{E}[r_F] + \mathbb{E}[c_{ins}] + \mathbb{E}[c_{rep}]}$$

Belief state → Policy



Research objectives:

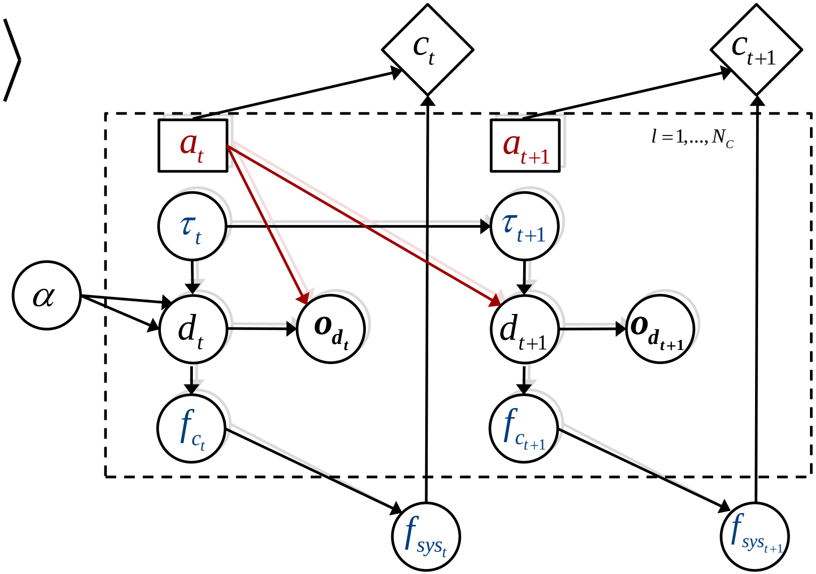
- "System-effects" on decision-making optimization.
- Optimal policies for environments characterized with large state, action, and observation spaces.

Decentralized POMDP environment

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

POMDP tuple:

- S: States
- A: Actions
- O: Observations
- T: Transition model
- Z: Observation model
- C: Cost model
- γ: Discount rate



Transition model

$p(\tau_{t+1} \mid \tau_t, a_t)$

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

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

Observation model

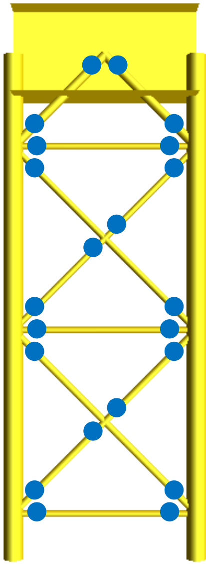
$p(o_{d_{t+1}} \mid d_{t+1}, a_{t+1})$

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

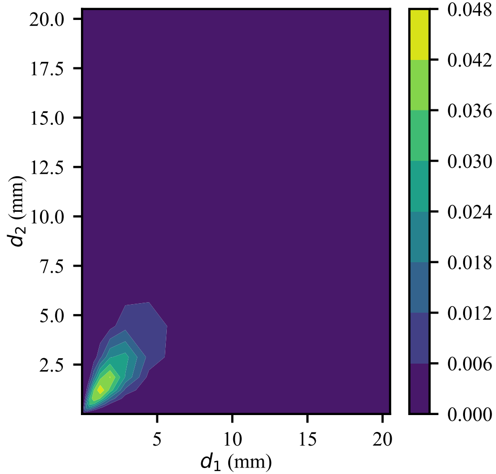
Cost model

$\gamma^t c_t(a_t, f_{sys_t})$

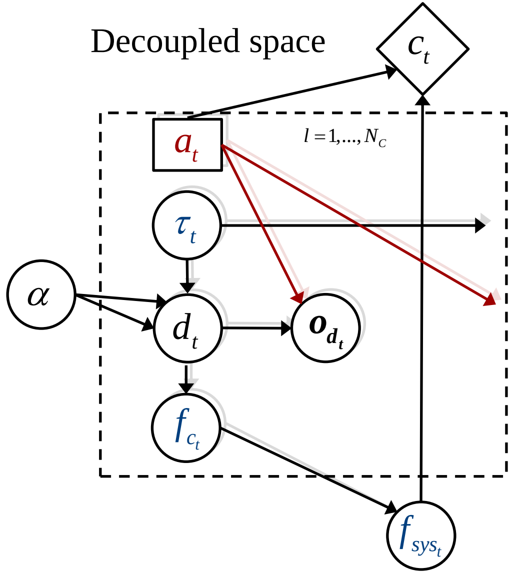
Deterioration correlation: Gaussian hierarchical structure

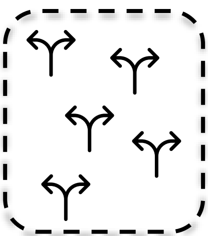


Joint space: $p(\mathbf{d}_t)$



Decoupled space





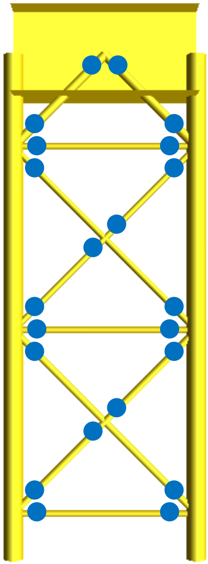
If d_{i} is stand. Gaussian:

$$F_{(d_i|\alpha)}(d_i) = \Phi\left[\frac{d_i - \lambda_i \alpha}{\sqrt{1-\lambda_i^{\,2}}}\right]$$

Otherwise:

$$F_{(d_i|\alpha)}(d_i) = \Phi\left[\frac{\Phi^{-1}\left[F_d(d_i)\right] - \lambda_i \alpha}{\sqrt{1-\lambda_i^{\,2}}}\right]$$

Deterioration correlation: Gaussian hyperparameters

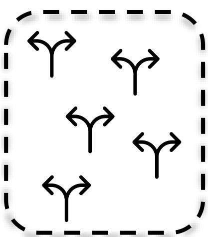


Hierarchical Gaussian formation: $Y_i = \sqrt{1-\lambda_i^{\,2}}\,Z_i + \lambda_i \alpha$

$$\mathrm{Cov}\left[d_i, d_j\right] = \mathrm{Cov}\left[\sqrt{1-\lambda_i^{\,2}}\,Z_i + \lambda_i \alpha, \sqrt{1-\lambda_j^{\,2}}\,Z_j + \lambda_j \alpha\right]$$

$$\mathrm{Cov}\left[d_i, d_j\right] = \left(1-\lambda_i^{\,2}\right)\overbrace{\mathrm{Cov}\left[Z_i, Z_j\right]}^{0} + \lambda_j \sqrt{1-\lambda_i^{\,2}}\,\overbrace{\mathrm{Cov}\left[Z_i, \alpha\right]}^{0}$$
$$+ \lambda_i \left(1-\lambda_j^{\,2}\right)\underbrace{\mathrm{Cov}\left[Z_j, \alpha\right]}_{0} + \lambda_i \lambda_j \underbrace{\mathrm{Cov}\left[\alpha, \alpha\right]}_{1}$$

$$\rho_{ij} = \frac{\mathrm{Cov}\left[d_i, d_j\right]}{\sigma_i \sigma_j} = \lambda_i \lambda_j \rightarrow \text{if } \lambda_i = \lambda_j : \lambda_i = \sqrt{\rho_{ij}}$$



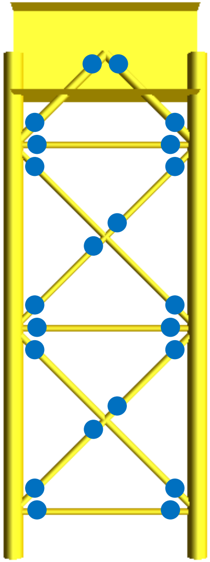
Equally correlated

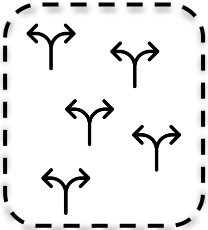
$$\mathrm{F}_{(d_i|\alpha)}(d_i) = \Phi\left[\frac{d_i - \sqrt{\rho_{ij}}\,\alpha}{\sqrt{1-\rho_{ij}}}\right]$$

Unequally correlated

$$\mathrm{F}_{(d_i|\alpha)}(d_i) = \Phi\left[\frac{d_i - \lambda_i \alpha}{\sqrt{1-\lambda_i^{\,2}}}\right]$$

Deterioration correlation: belief (model) updating





Update of conditional beliefs and hyperparameters:

for 1, N_c do:

$$b(s_{t+1} \mid \alpha) \propto b(s_t \mid \alpha)\, p(s_{t+1} \mid s_t, a_t)\, p(o_{t+1} \mid s_{t+1}, a_t)$$

$$b(o_{t+1} \mid \alpha) = \sum_{s \in S} \left[b(s_{t+1} \mid \alpha)\, p(o_{t+1} \mid s_{t+1}, a_t) \right]$$

$$b(\alpha) \propto b(\alpha)\, p(o_{t+1} \mid \alpha)$$

end for

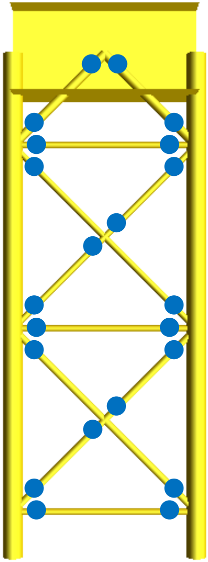
Computation of marginal beliefs:

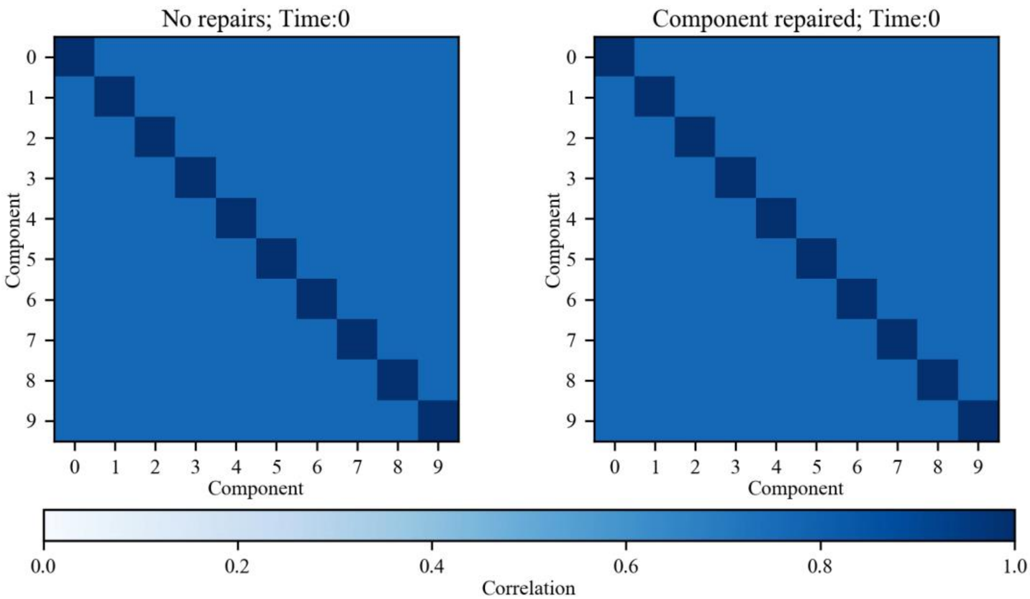
for 1, N_c do:

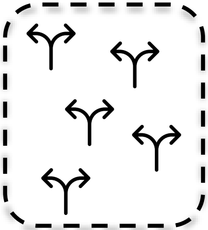
$$b(s_{t+1}) \leftarrow \sum_{\alpha \in \Gamma} \left[b(s_{t+1} \mid \alpha) b(\alpha) \right]$$

end for

Deterioration correlation: belief updating | actions





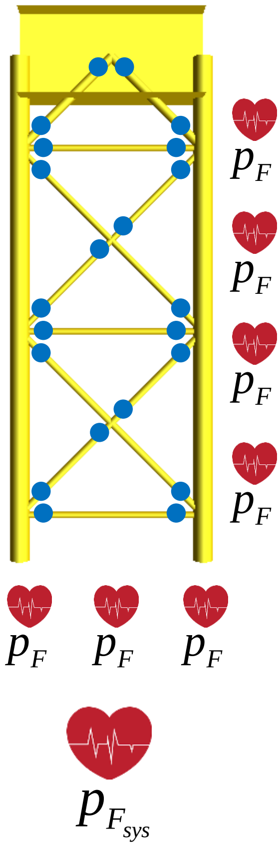


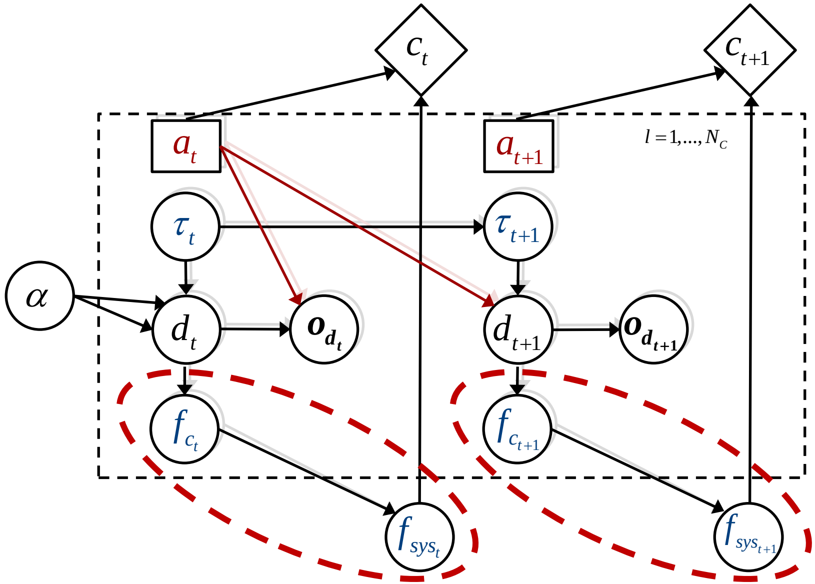
$$F_{(d_i|\alpha)}(d_i) = \Phi\left[\frac{d_i - \lambda_i \alpha}{\sqrt{1-\lambda_i^2}}\right]$$

* After a repair action:

$$F_{(d_i|\alpha)}(d_i) = \Phi\left[\frac{d_i - 0 \cdot \alpha}{\sqrt{1-0}}\right]$$

Structural dependencies

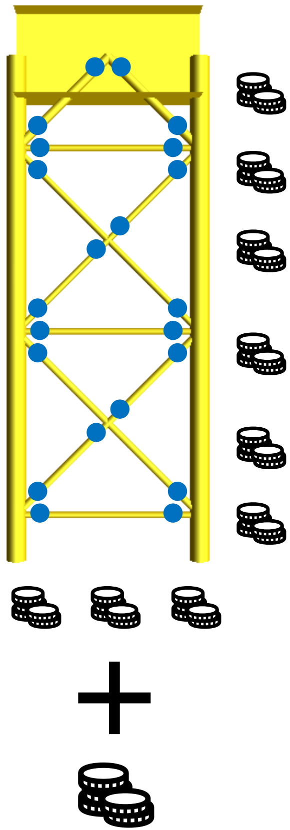


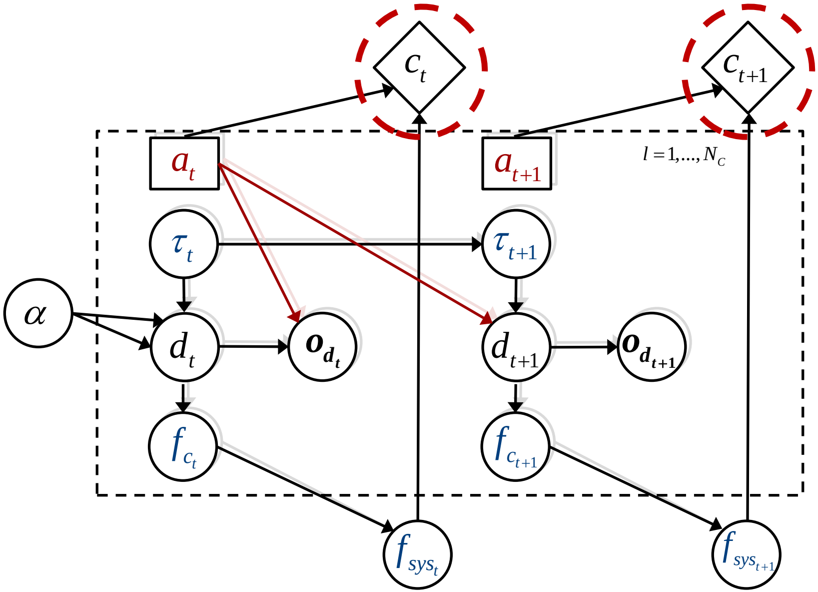


Failure probability of the structural system:

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

Cost dependencies



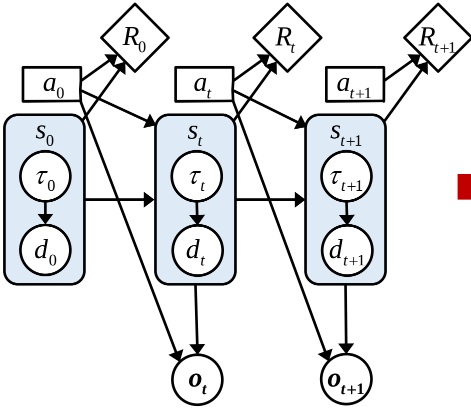


System level cost model (e.g. campaign cost):

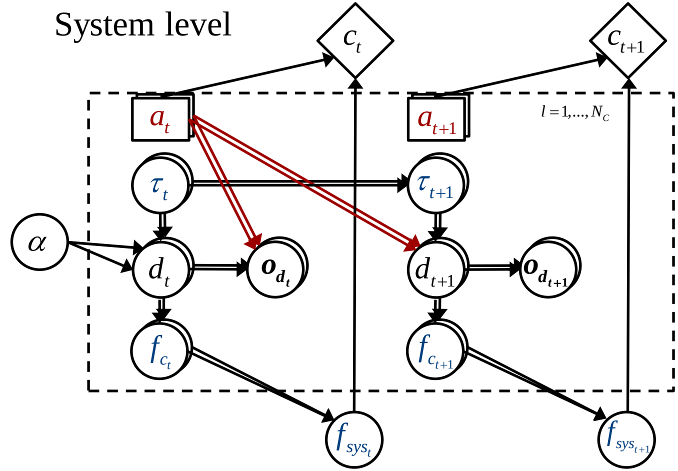
$$c_{T_{sys}} = c_{camp} + p_{F_{sys}} c_{F_{sys}} + \sum_i \left[c_{ins}{}^{(i)} + c_{rep}{}^{(i)} \right]$$

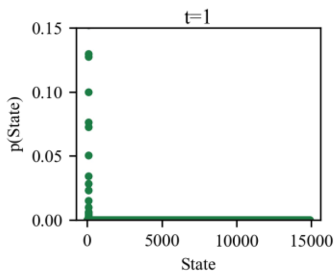
From POMDP point-based solvers to POMDP -DRL

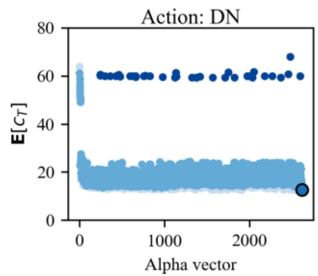
Component level



System level



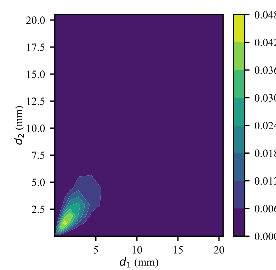




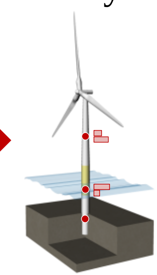
Morato, P. G., Papakonstantinou, K. G., Andriotis, C. P., Nielsen, J. S., & Rigo, P. (2022). Optimal inspection and maintenance planning for deteriorating structural components through dynamic Bayesian networks and Markov decision processes. *Structural Safety*, 94, 102140.

* Dynamic programming principles:

Belief

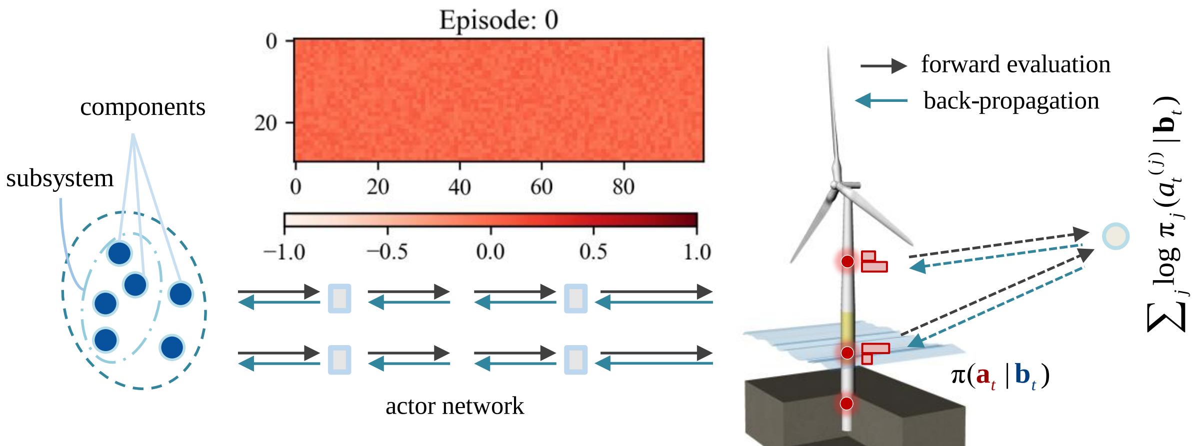


Policy



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

Training the actors through policy gradient:



Inputs: beliefs, time step

Output: stochastic policy

Experience replay ↔ on-batch "temporal difference" training

- Time step
- Deterioration beliefs
- Action
- Centralized reward
- Behavior policy

$$\boldsymbol{g}_{\boldsymbol{\theta}^\pi} = \mathbf{E}_{\boldsymbol{s}_t\sim\boldsymbol{\rho},\boldsymbol{a}_t\sim\boldsymbol{\mu}}\left[w_t A^\pi(\boldsymbol{s}_t, \boldsymbol{a}_t|\boldsymbol{\theta}^v)\left(\sum_{i=1}^{n_C} \nabla_{\boldsymbol{\theta}^\pi} \log \pi_i\left(a_t^{(i)}\middle|\boldsymbol{s}_t, \boldsymbol{\theta}^\pi\right)\right)\right]$$

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.

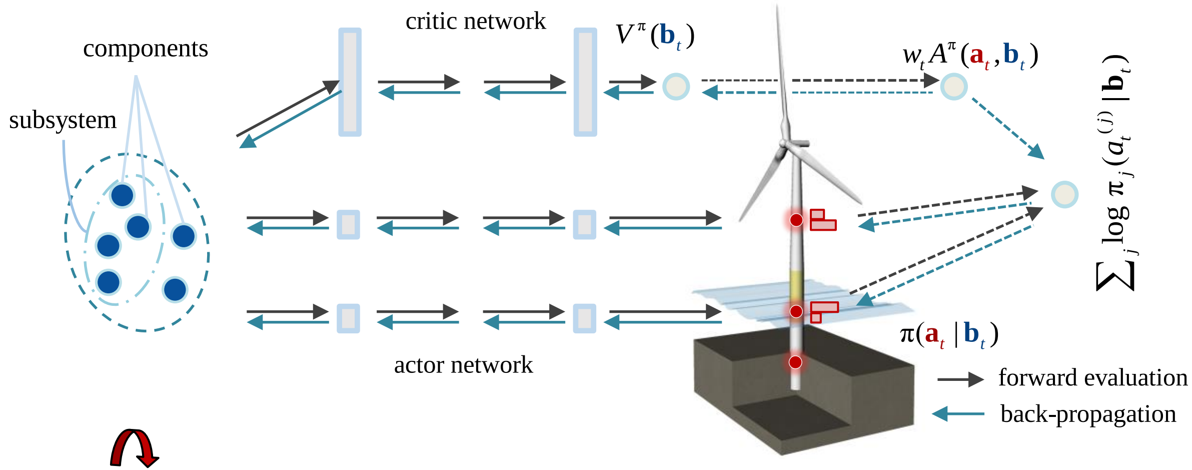
DDMAC: Deep decentralized actor-critic (based on A2C)

Critic provides a baseline:

$$A^{\pi}(\boldsymbol{s}_t, \boldsymbol{a}_t|\boldsymbol{\theta}^v) \approx r(\boldsymbol{s}_t, \boldsymbol{a}_t) + \gamma V^{\pi}(\boldsymbol{s}_{t+1}|\boldsymbol{\theta}^v) - V^{\pi}(\boldsymbol{s}_t|\boldsymbol{\theta}^v)$$

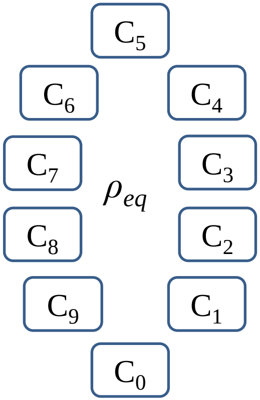
Training the critic:

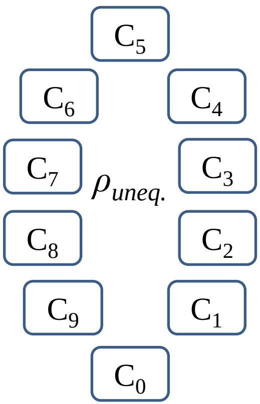
$$\boldsymbol{g}_{\boldsymbol{\theta}^V} = \mathbf{E}_{\boldsymbol{s}_t\sim\boldsymbol{\rho},\boldsymbol{a}_t\sim\boldsymbol{\mu}}[w_t A^{\pi}(\boldsymbol{s}_t, \boldsymbol{a}_t|\boldsymbol{\theta}^v)\nabla_{\boldsymbol{\theta}^V} V^{\pi}(\boldsymbol{s}_t|\boldsymbol{\theta}^v)]$$



Inputs: beliefs, time step → **Output:** stochastic policy

Case study “9-out-of-10” system: description





Fatigue deterioration

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

Cost model

$c_{camp} = 5$ $c_{ins} = 1$ // $c_{ins} = 0.2$

$c_{rep} = 20$ $c_{fail} = 10{,}000$ $\gamma = 0.95$

Neural networks:

TensorFlow

Keras

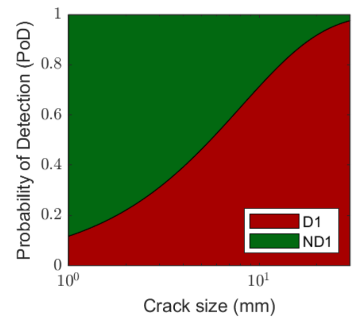
	Actors	Critic
	2x100	2x200
Learning rate	$10^{-4} - 10^{-5}$	$10^{-3} - 10^{-4}$

Do-nothing

Repair

Inspection

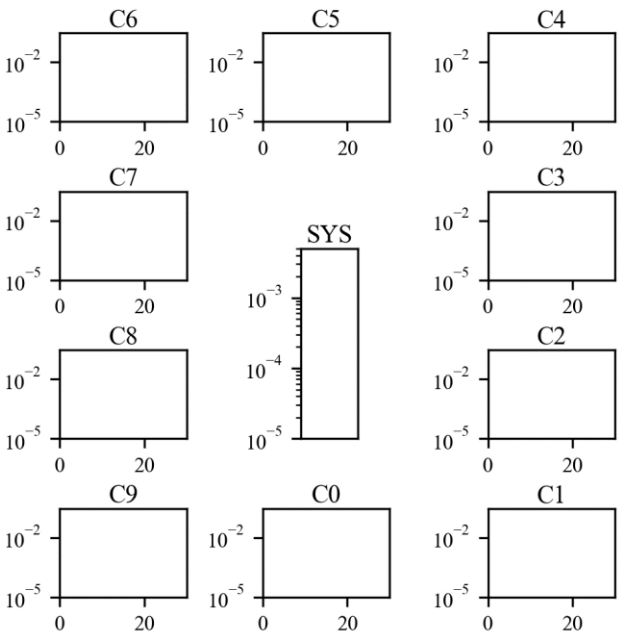
“NDE” inspections

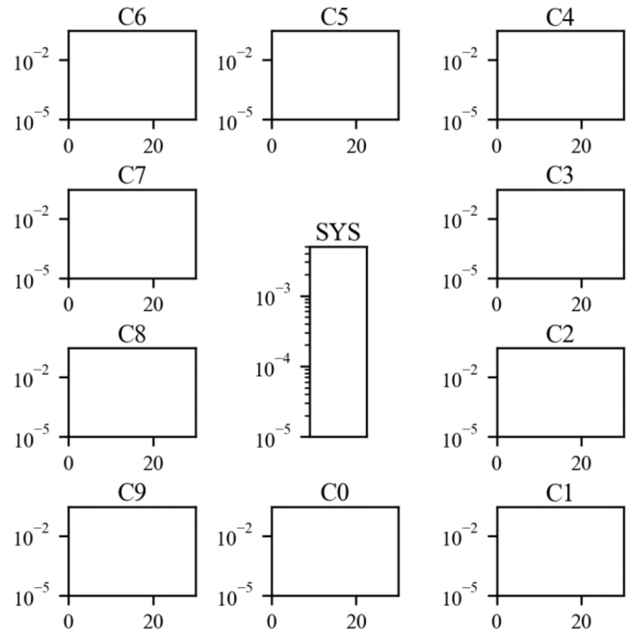


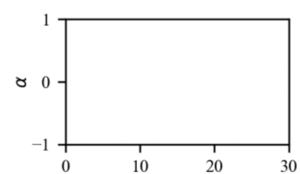
ε-greedy exploration: noise from 100% to 1% over 20,000 episodes

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.

Case study “9-out-of-10” system: uncorrelated vs correlated







Do-nothing

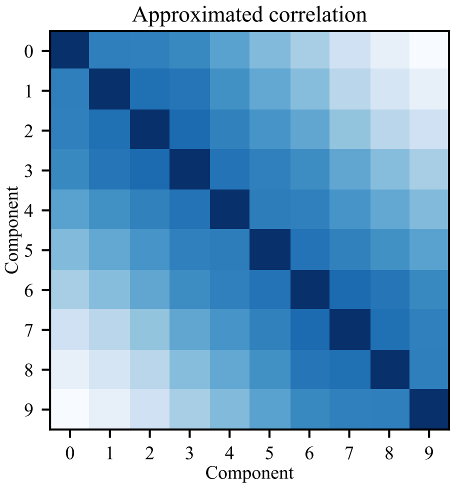
O Repair

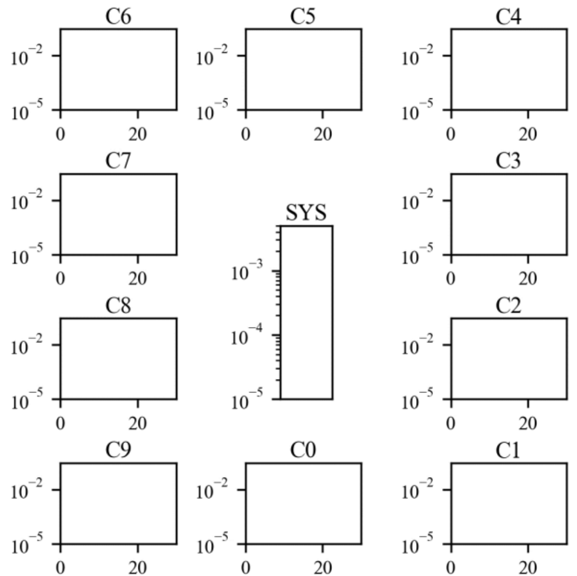
— Component failure prob.

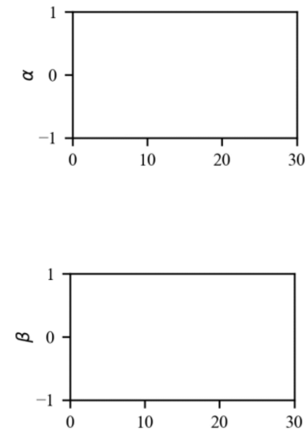
△ Inspection – detection

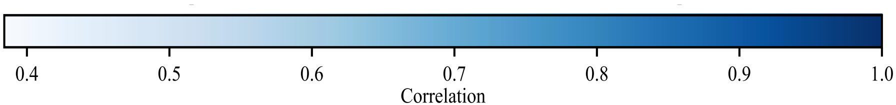
▽ Inspection – no detection

Case study “9-out-of-10” system: equally correl. vs unequal.









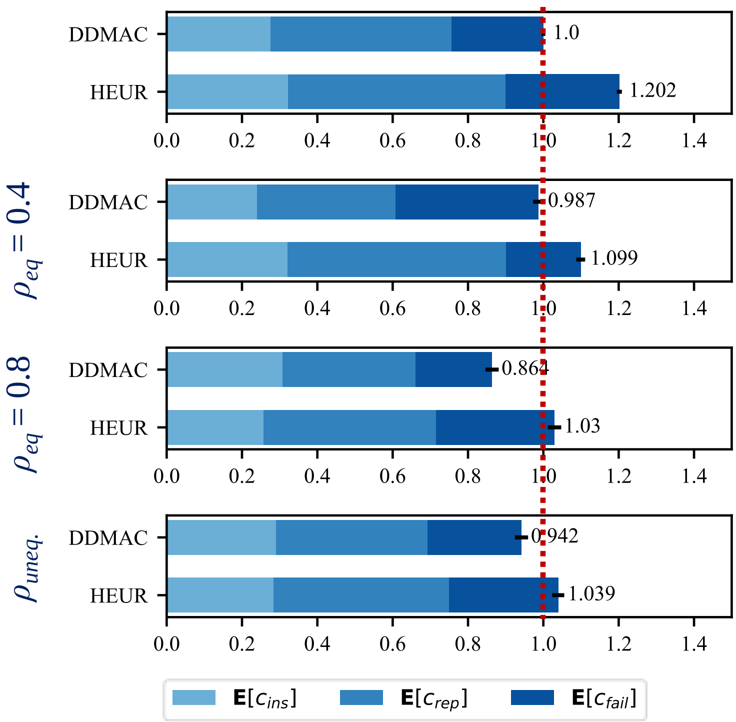
Do-nothing

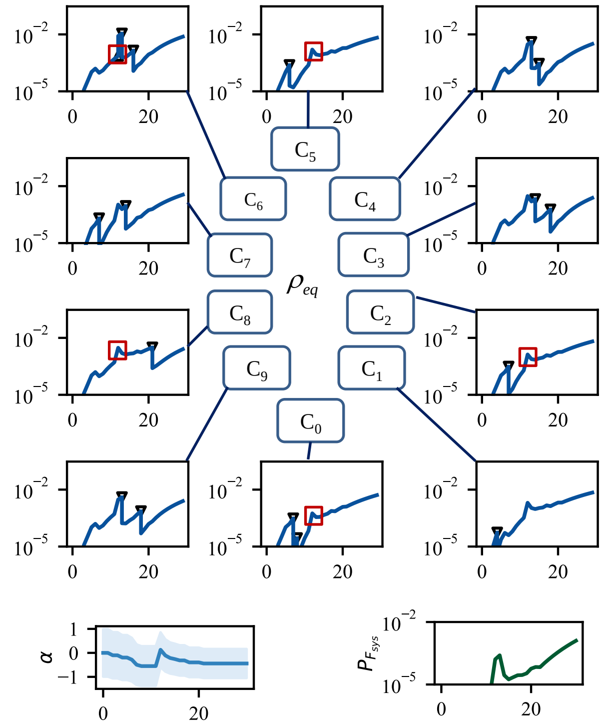
Repair

Inspection – detection

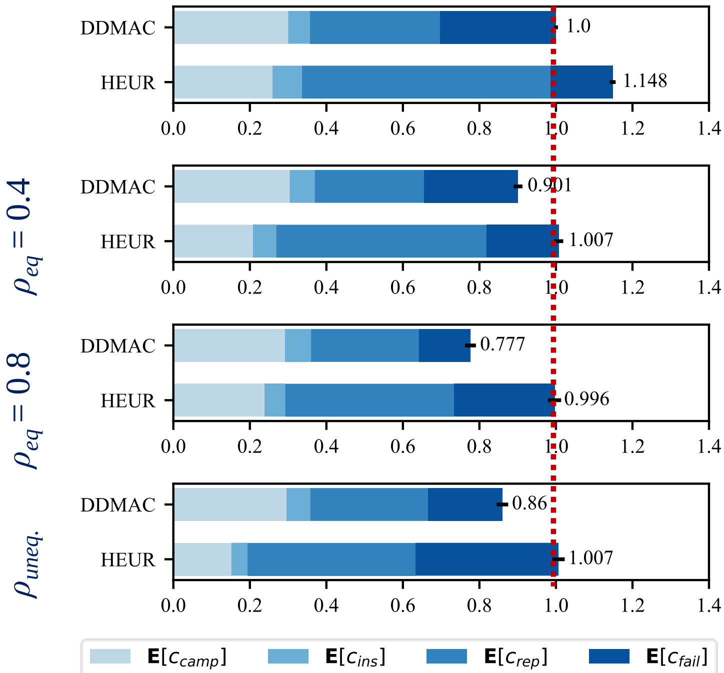
Inspection – no detection

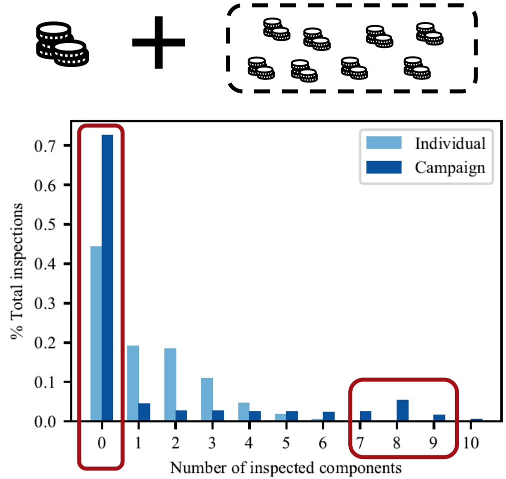
Case study “9-out-of-10” system: results



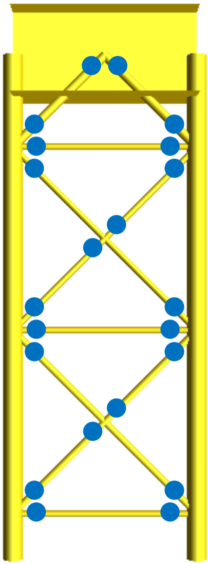


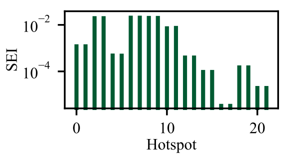
Case study "9-out-of-10" system: campaign cost





Case study “Zayas frame”: description





Fatigue deterioration

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

Cost model

$c_{ins} = 1$ $c_{fail} = 50{,}000$

$c_{rep} = 15$ $\gamma = 0.95$

Neural networks:

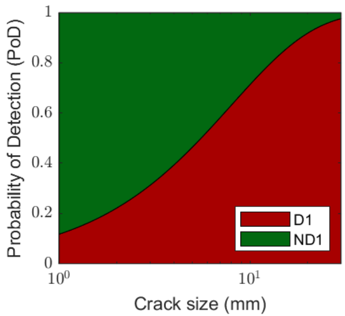
TensorFlow	Actors	Critic
Keras	2x150	2x300
Learning rate	$10^{-4} - 10^{-5}$	$10^{-3} - 10^{-4}$

Do-nothing

○ Repair

△ Inspection

“NDE” inspections



ε-greedy exploration: noise from 100% to 1% over 20,000 episodes

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.

Case study “Zayas frame”: correlated vs uncorrelated

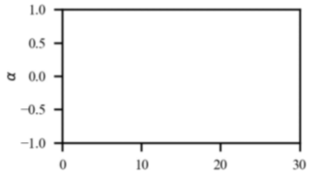
22 fatigue hotspots

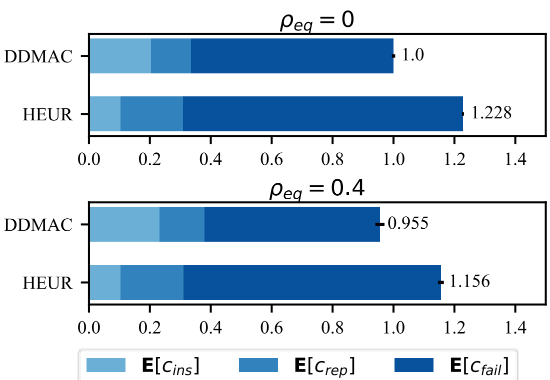
Do-nothing

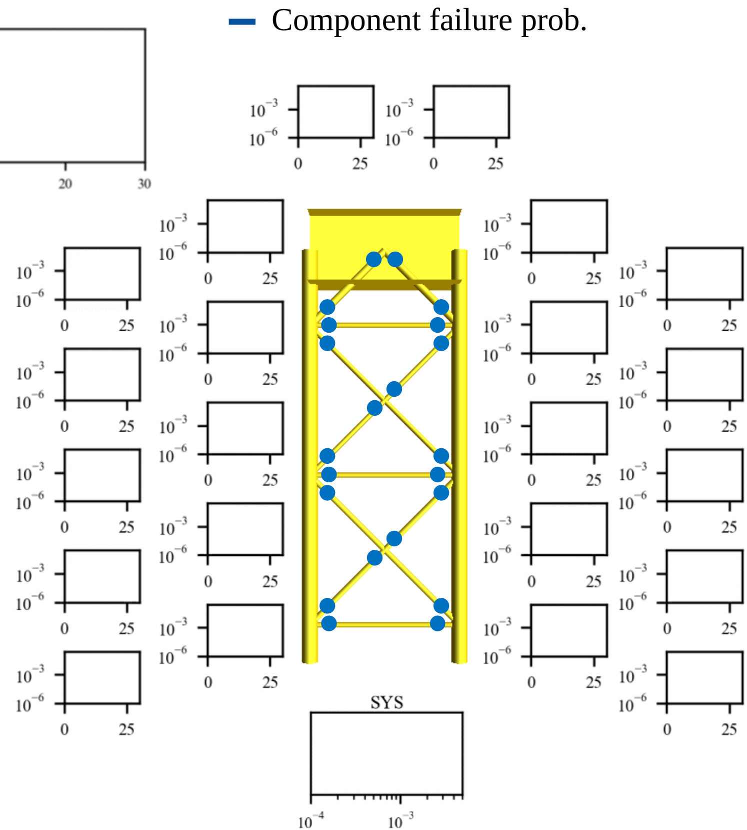
○ Repair

△ Inspection – detection

▽ Inspection – no detection

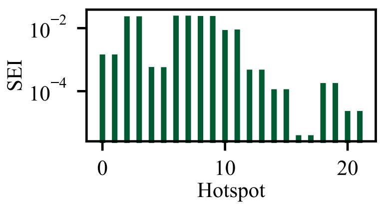


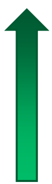


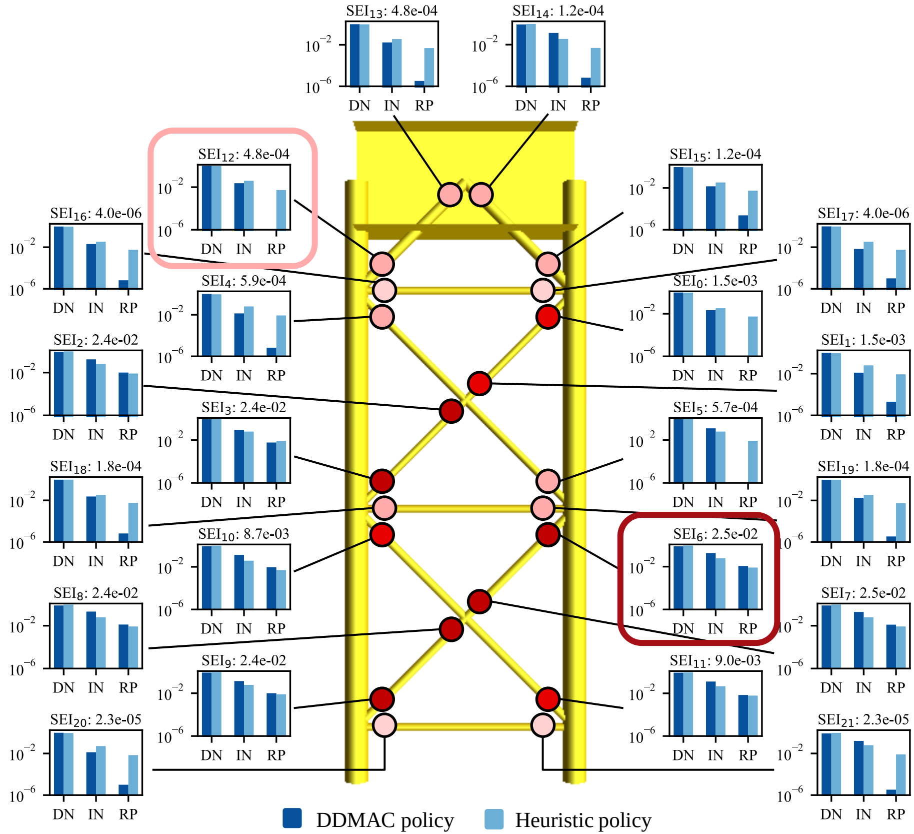


Case study “Zayas frame”: SEI

$$SEI_h = p_{F\,sys}^{(\sim h)} - p_{F\,sys}$$



SEI  Element importance



SEI: Single element importance

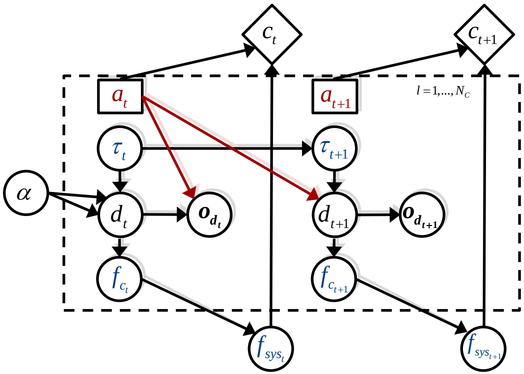
DN: Do-nothing action

IN: Do-nothing + inspection action

RP: Perfect repair action

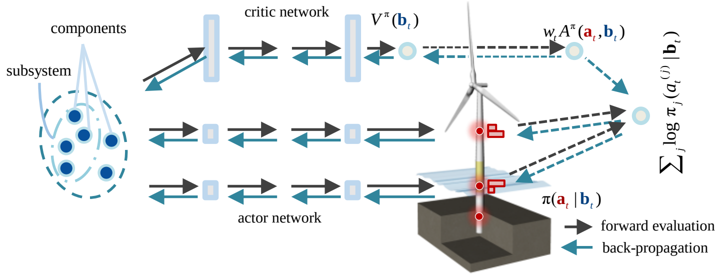
Conclusions

- "System-effects" on decision-making optimization.



✓ Deterioration dependencies
✓ Structural reliability dependencies
✓ Cost dependencies
✓ Decoupled factored POMDP

- Optimal policies for environments characterized with large state, action, and observation spaces.



✓ Multi-component structural systems
✓ Dynamic programming principles
✓ Optimal stochastic policies
✓ Intrinsically includes system effects

Model Updating, Condition Assessment, and Maintenance of Multi-component Systems under Correlated Deterioration Processes

Additional comments, questions ...

P.G. Morato

pgmorato@uliege.be

https://www.linkedin.com/in/pablomorato/

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