Robust and scalable prescriptive analytics for the resilience of interdependent networks

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Chair on Risk and Resilience of Complex Systems

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Interdependent networks & risk landscape

How to make our systems (more) resilient?

extreme weather events

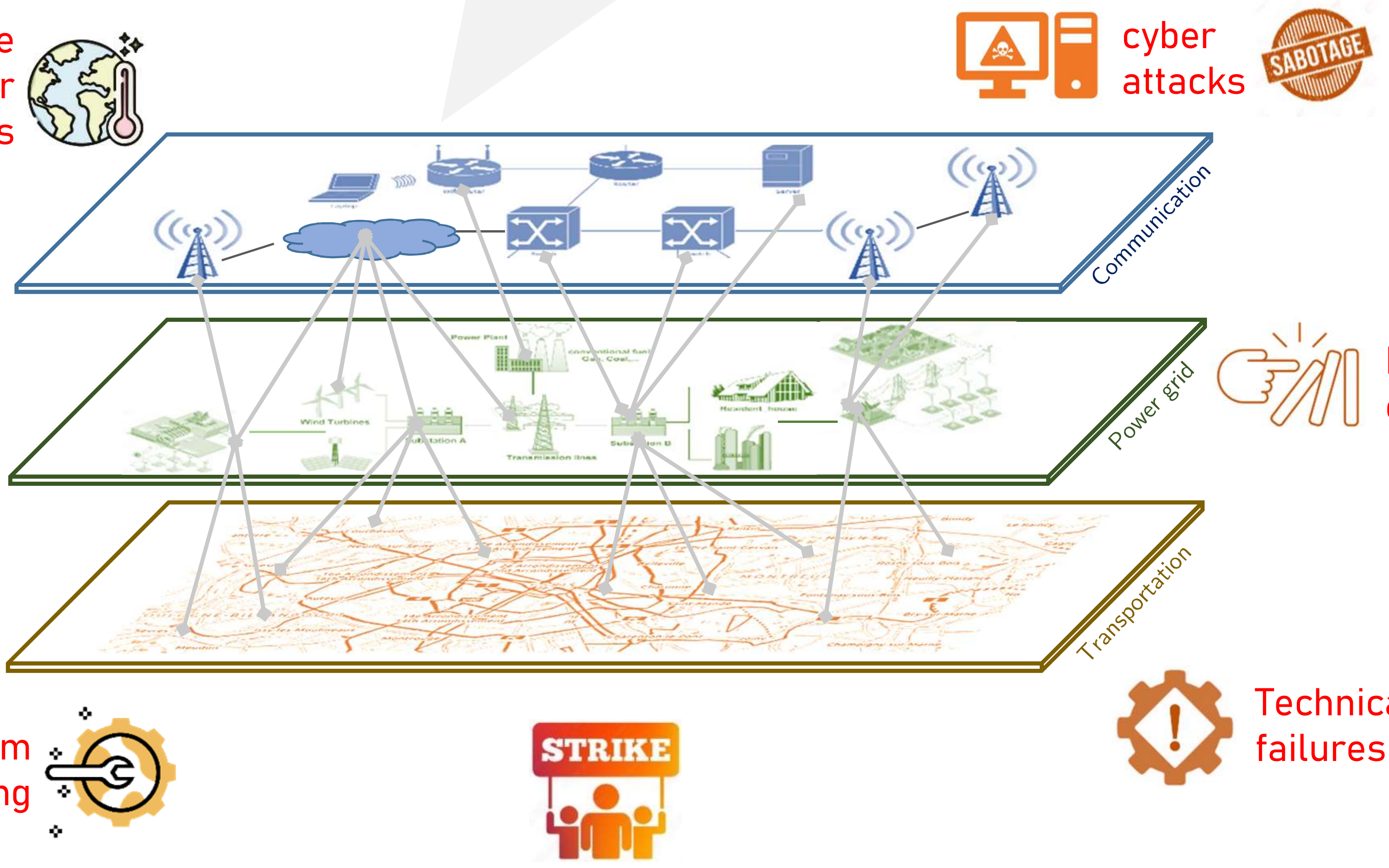
cyber attacks

natural disasters

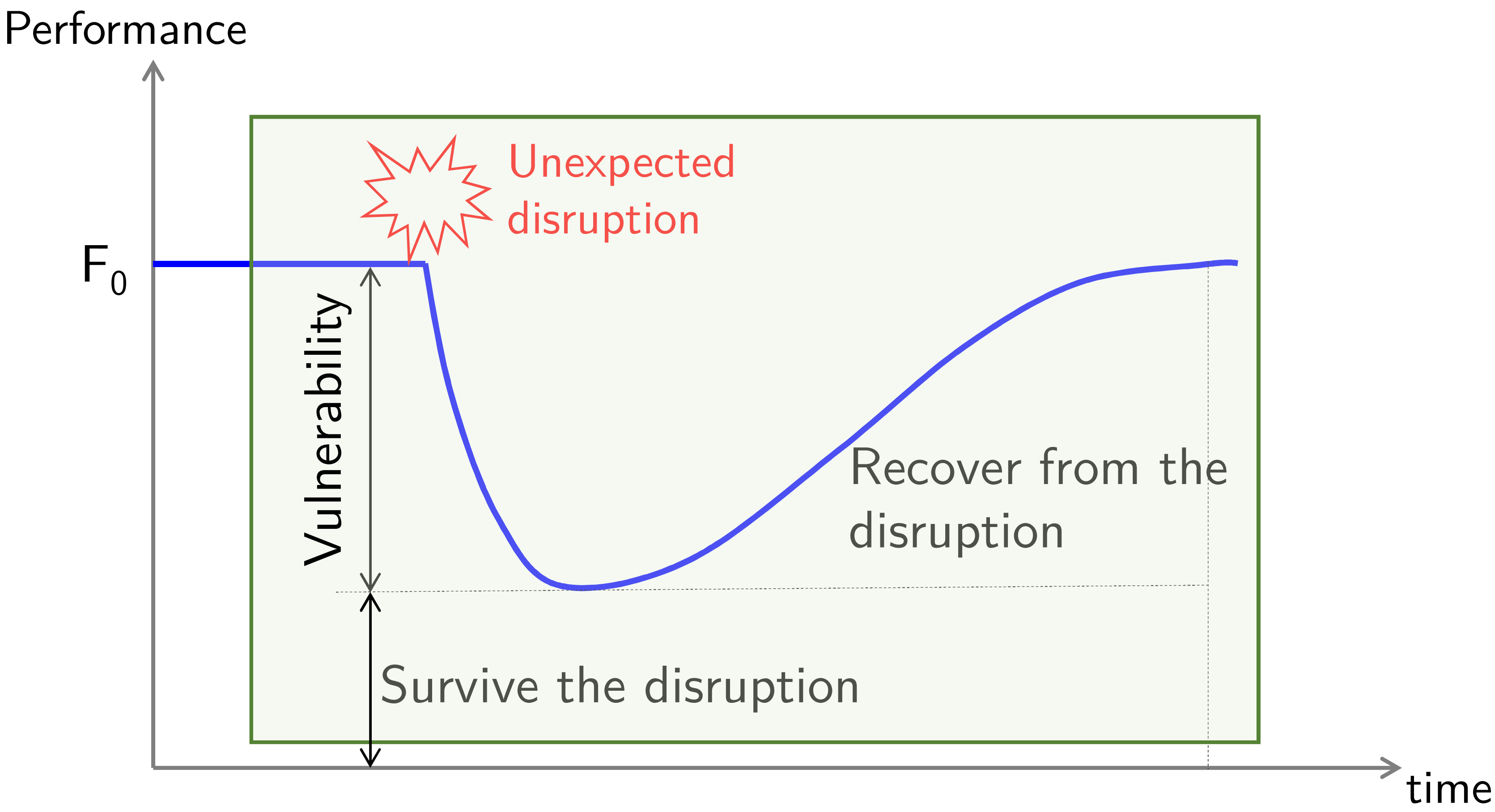
Failure cascade

System aging

Technical failures

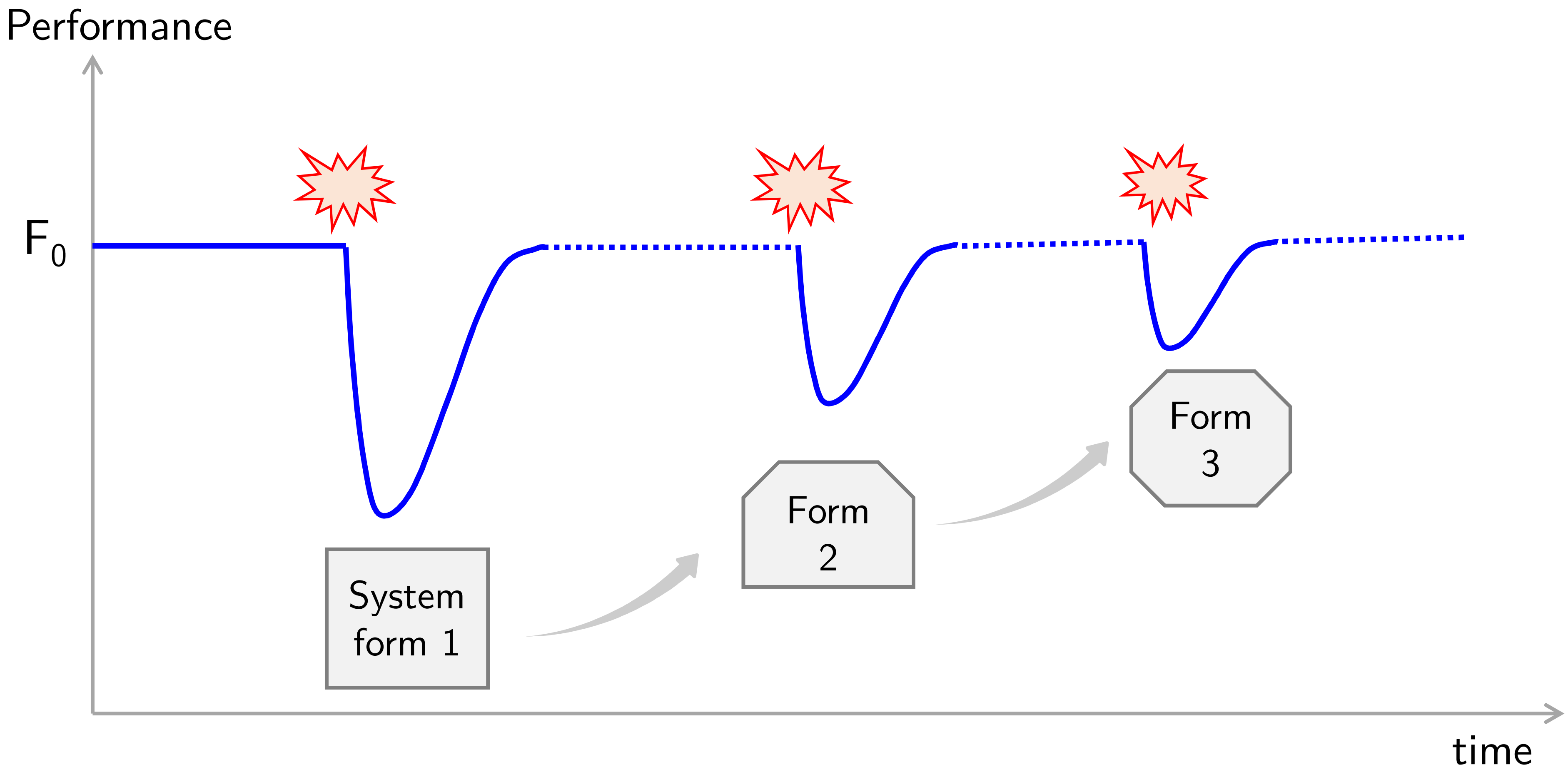


Resilience: symptom-wise



survivability + recoverability

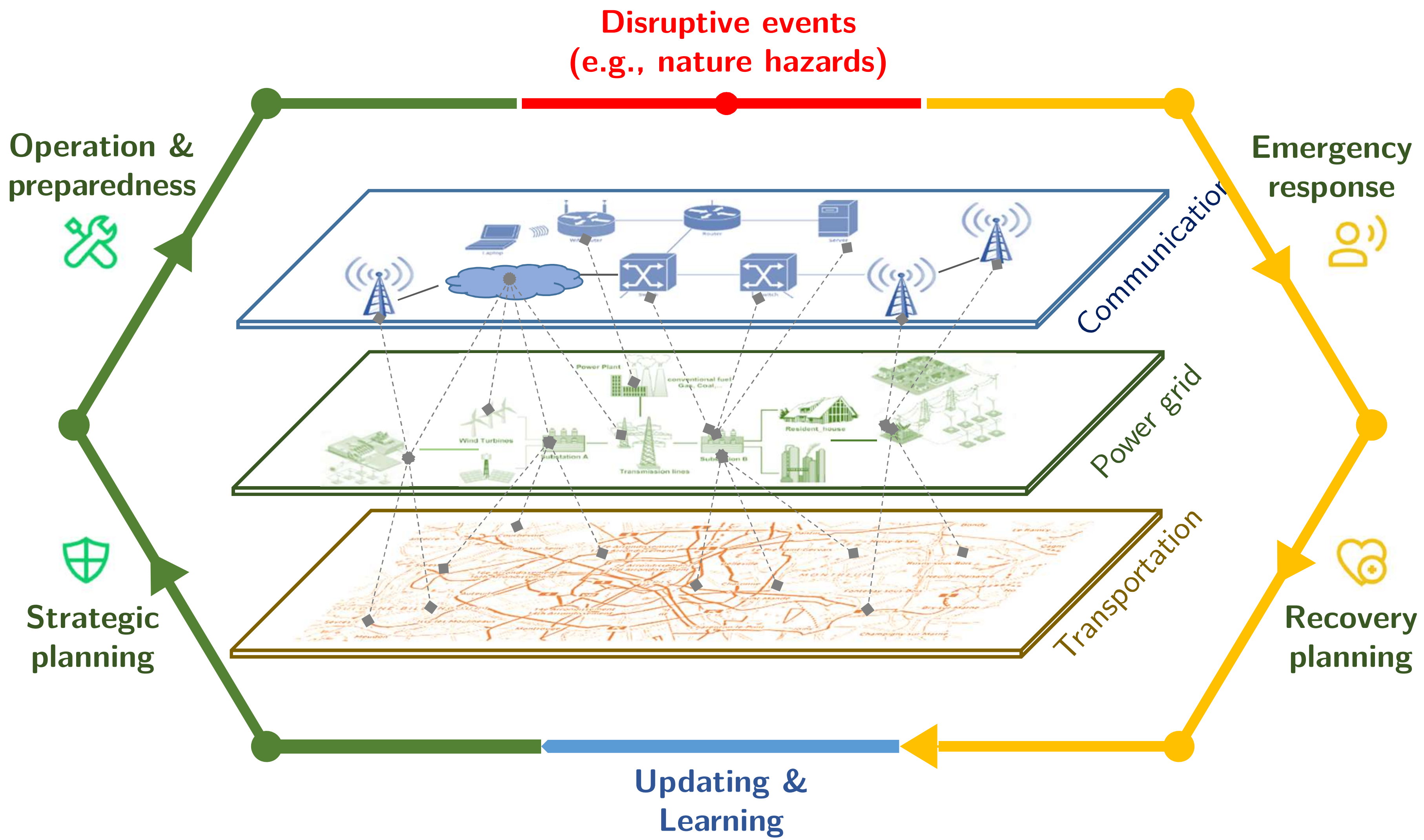
Resilience: symptom-wise



survivability + recoverability

+ adaptive/transformative capability

Resilience: prescription-wise



Strategic planning

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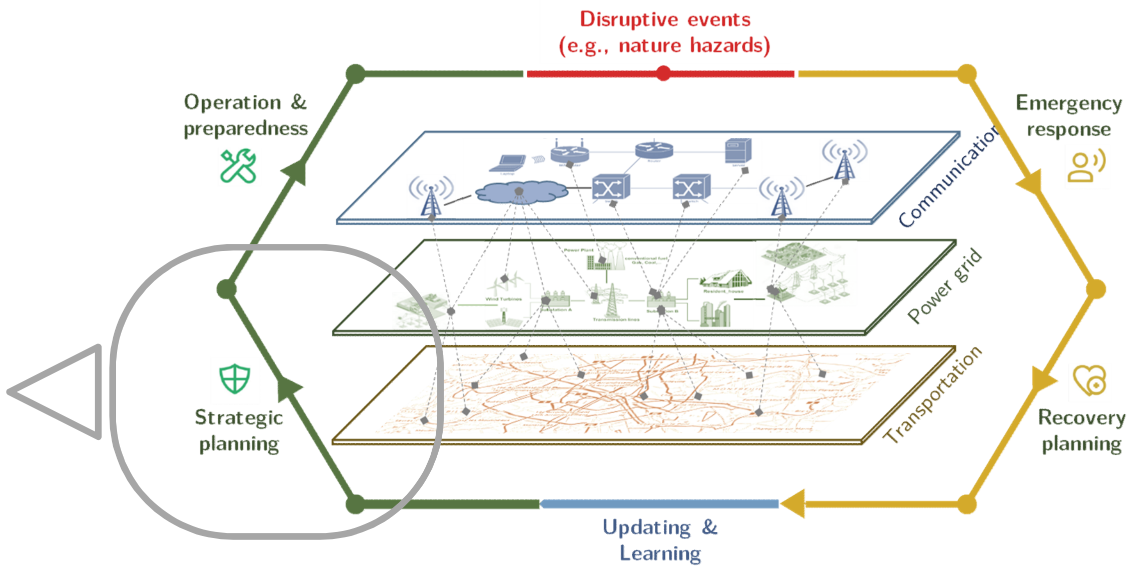
Consider resilience when making decisions that have mid-/long-term effects?

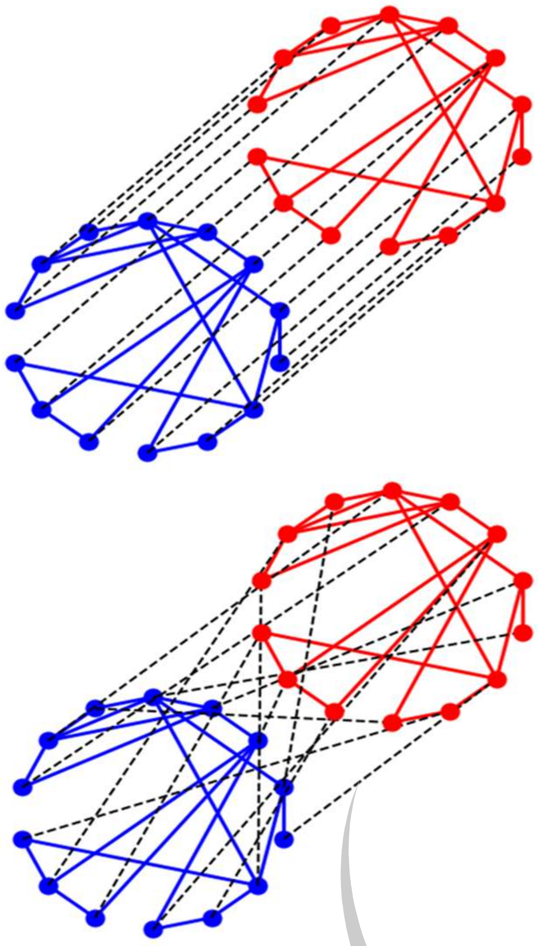
- → structure (re)design
- → integration of new techologies
- → maintenance strategy



Decision-making under uncertainty, key challenges:

- → deep uncertainty of future risk scenarios
- → need of having robust solutions & computational tractability

Example: coupling interface design



Interdependent links

Select coupling interface

- ↑ Survivability under uncertain components failures
- ↑ performance & ↓ cost in normal operation

Bellè, A., Abdin, A. F., Fang, Y. P., Zeng, Z., & Barros, A. (2023). A data-driven distributionally robust approach for the optimal coupling of interdependent critical infrastructures under random failures. *European Journal of Operational Research*, *309*(2), 872-889.

Theoretical frameworks

Stochastic program (SP) & Robust optimization (RO)

Recourse function

$$\textbf{SP}: \max_{\boldsymbol{x}\in\mathbb{X}} \mathbb{E}_{\mathbb{P}}[\mathcal{Q}(\boldsymbol{x},\boldsymbol{u})] \qquad \textbf{RO}: \max_{\boldsymbol{x}\in\mathbb{X}} \min_{\boldsymbol{u}\in U} \mathcal{Q}(\boldsymbol{x},\boldsymbol{u})$$

Design variables

Failure scenario

Uncertainty set: all feasible failure scenarios

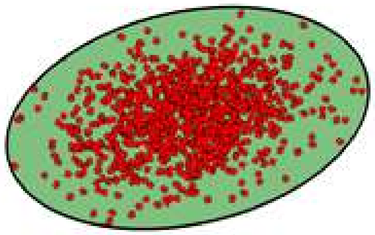
- Probability distribution of the set of all feasible failure scenarios
- Difficult to estimate due to lack of data & environment variability

- No need to estimate the probabilities of failure scenarios
- Too conservative/costly

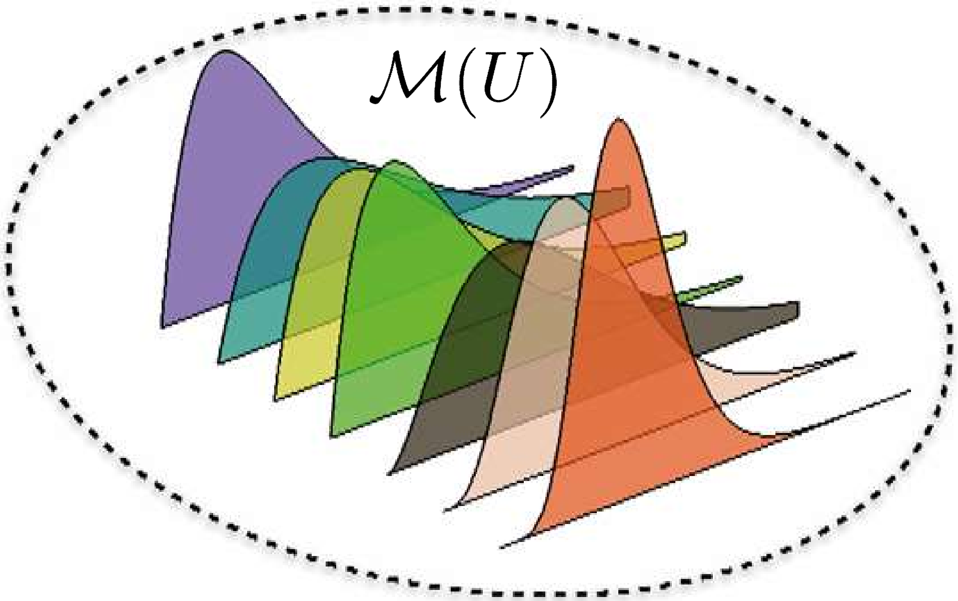
Distributionally robust approach

$$\textbf{SP}: \max_{\boldsymbol{x}\in\mathbb{X}} \ \mathbb{E}_{\mathbb{P}}[\mathcal{Q}(\boldsymbol{x},\boldsymbol{u})]$$

$$\textbf{DRO}: \max_{\boldsymbol{x}\in\mathbb{X}} \boxed{\min_{\mathbb{P}\in\mathcal{M}(U)}} \mathbb{E}_{\mathbb{P}}\left[\mathcal{Q}(\boldsymbol{x},\boldsymbol{u})\right]$$



Empirical failure data



DRO approach

- Ambiguity set

$$\mathcal{M}(U) = \{\mathbb{P} \in \mathcal{P}(U) : \ \mathbf{0} \leq \mathbb{E}[1 - \boldsymbol{u}] \leq \boldsymbol{\pi}^{max}\}$$

$$U = \left\{\boldsymbol{u} \mid \boldsymbol{u} \in \{0, 1\}^N, \|\boldsymbol{u}\|_1 \geq N - k\right\}$$

  - ▷ Set of multinomial distributions on the set of feasible failure scenarios
  - ▷ Upper bound on the marginal probability of component failure

DRO approach

for optimal coupling interface design of IPGNs

$$\max_{\substack{\mathbf{h}^0,\boldsymbol{\delta}^0\in\{0,1\}^{N_d}\\ \mathbf{y}\in\{0,1\}^{N_c}}} \min_{\mathbb{P}\in\mathcal{M}} \mathbb{E}_{\mathbb{P}}\left[\mathcal{Q}(\mathbf{y},\boldsymbol{\xi})\right]$$

s.t.

$$\sum_{j\in V_{PN}} y_{ij}^1 \le 1, \quad \forall i\in V_{GN}$$

$$\sum_{j\in V_{GN}} y_{ij}^2 \le 1, \quad \forall i\in V_{PN}$$

$$\sum_{\substack{i\in V_{GN}\\ j\in V_{PN}}} y_{ij}^1\, d_{ij}^{km}\, c_{km}^1 + \sum_{\substack{i\in V_{PN}\\ j\in V_{GN}}} y_{ij}^2\, d_{ji}^{km}\, c_{km}^2 \le B_c$$

$$\mathbf{R}^0\mathbf{h}^0 \le \mathbf{q}^0 - \mathbf{H}^0\mathbf{y} - \mathbf{W}^0\boldsymbol{\delta}^0 - \mathbf{y}^T\mathbf{D}^0\boldsymbol{\delta}^0 - \mathbf{y}^T\mathbf{G}^0\boldsymbol{\delta}^0\mathbf{c}^{0T}\mathbf{y}$$

$$\mathbf{b}^T\mathbf{h}^0 \ge 1$$

$$\max_{\mathbf{h},\boldsymbol{\delta}\in\{0,1\}^{N_d}} \mathbf{b}^T\mathbf{h}$$

s.t.

$$\mathbf{R}\mathbf{h} \le \mathbf{q} - \mathbf{T}\mathbf{u} - \mathbf{H}\mathbf{y} - \mathbf{W}\boldsymbol{\delta} - \mathbf{y}^T\mathbf{D}\boldsymbol{\delta} - \mathbf{y}^T\mathbf{G}\boldsymbol{\delta}\mathbf{c}^T\mathbf{y}$$

Solution strategy

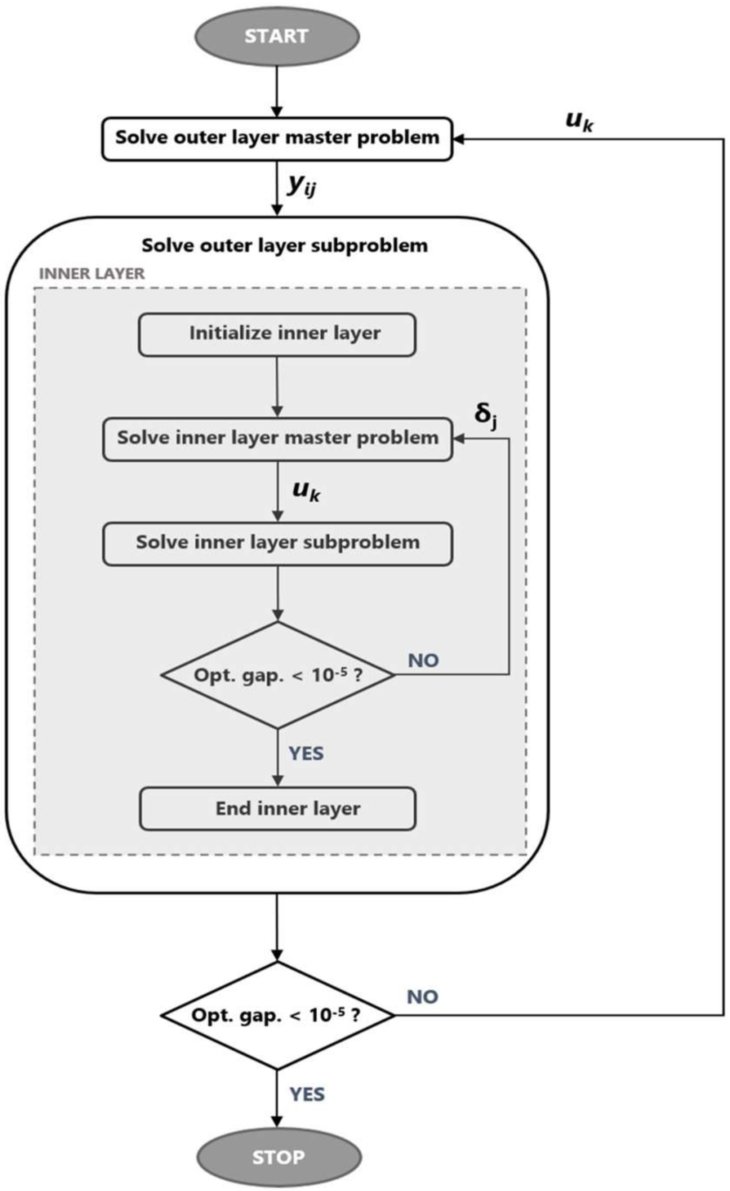
$$\max_{\boldsymbol{y}\in\mathbb{Y}} \min_{\mathbb{P}\in\mathcal{M}(U)} \mathbb{E}_{\mathbb{P}}\left[\mathcal{Q}(\boldsymbol{y},\boldsymbol{u})\right]$$

Proposition 1: dual counterpart

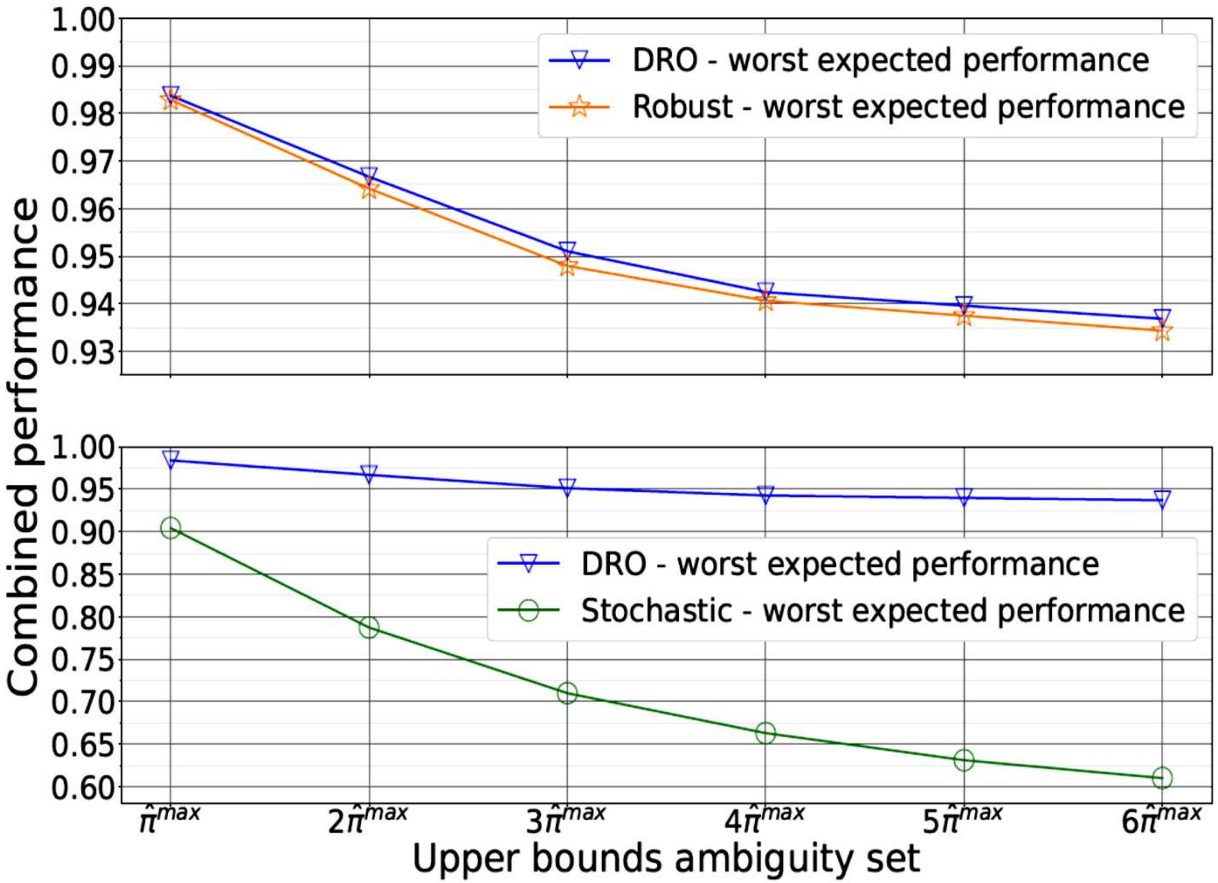
$$\max_{\boldsymbol{y}\in\mathbb{Y}} \min_{\boldsymbol{u}\in U} \mathcal{Q}(\boldsymbol{y},\boldsymbol{u}) + \sum_{n\in\mathcal{N}} \beta_n(1-u_n-\pi_n^{max})$$

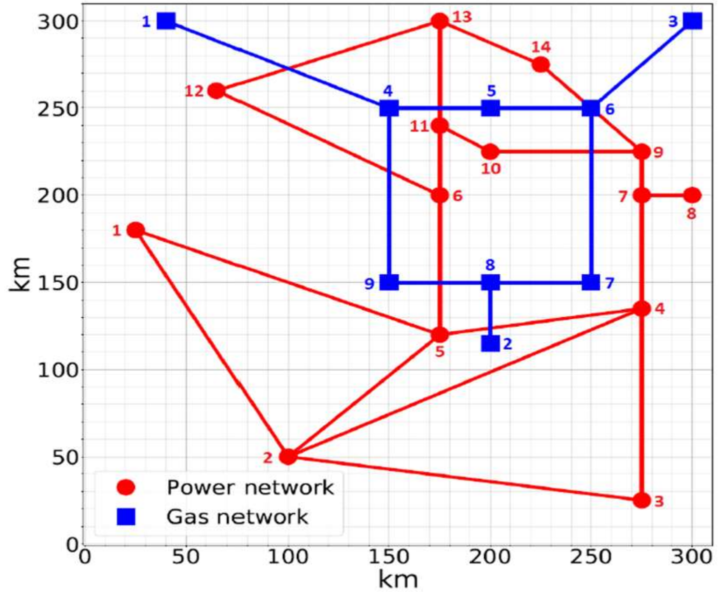
Proposition 2: Equivalent monolithic MILP

Nested column-constraint-generation algorithm



Key results





- ▷ RO solutions are suboptimal in terms of their expected performance in the worst-case distribution $\mathbb{P}^{\star}$
- ▷ SP solutions perform very poorly when tested under $\mathbb{P}^{\star}$

More studies

- Power grid protection investment with endogenous uncertainty

  Bellè, A., Fang, Y. P., Zeng, Z., & Barros, A. (2022). *IFAC-PapersOnLine*, *55*(16), 122-127.

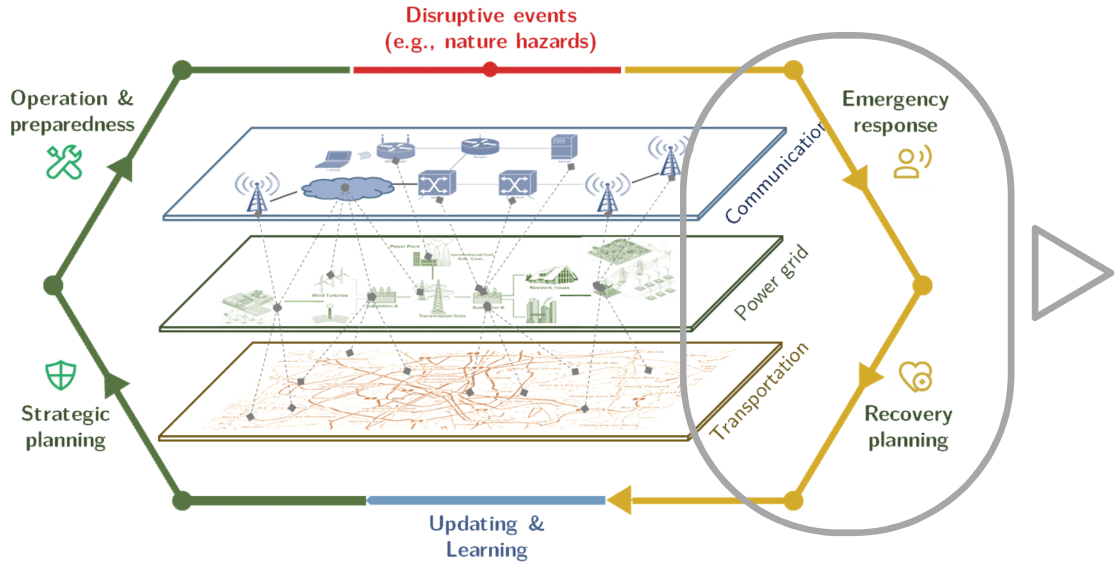
- Optimal siting & sizing of DESs for grid resilience against wind storms

  Yin, Z., Fang, C., Yang, H., **Fang, Y.**, & Xie, M. (2023). *Risk Analysis*.

- Robust day-ahead flight planning in ATM considering extreme weather events

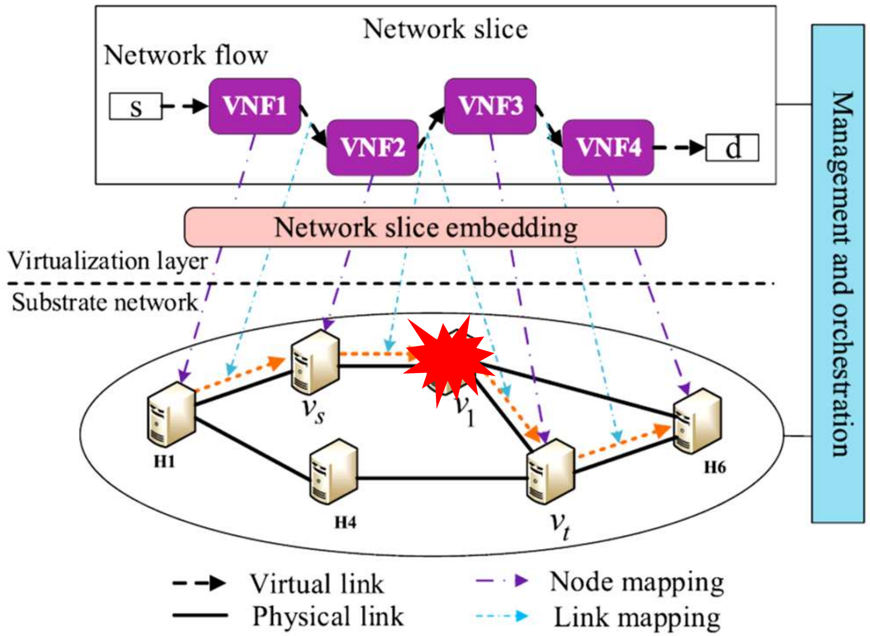
  Hao, B., Cai, K., **Fang, Y. P.,** Fadil, A., & Feng, D. (2021, October). In *2021 IEEE/AIAA 40th Digital Avionics Systems Conference (DASC)* (pp. 1-7). IEEE.

Emergency response & recovery planning

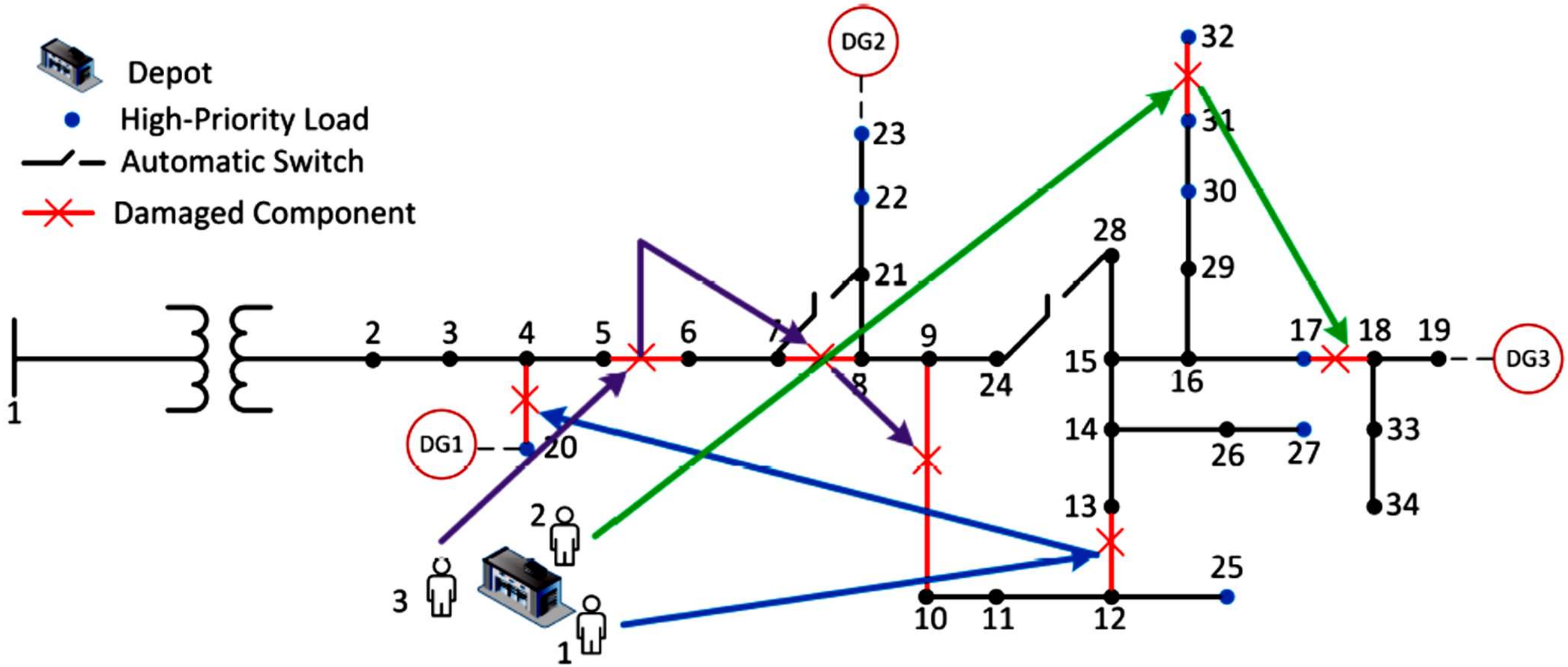


Mitigate service loss and speed up system recovery by leveraging flexibility/ maintenance resources

- Examples:
  - → Reconfiguration of network slicing in 5G
  - → Integrated reconfiguration and recovery in power distribution grids
  - → ...



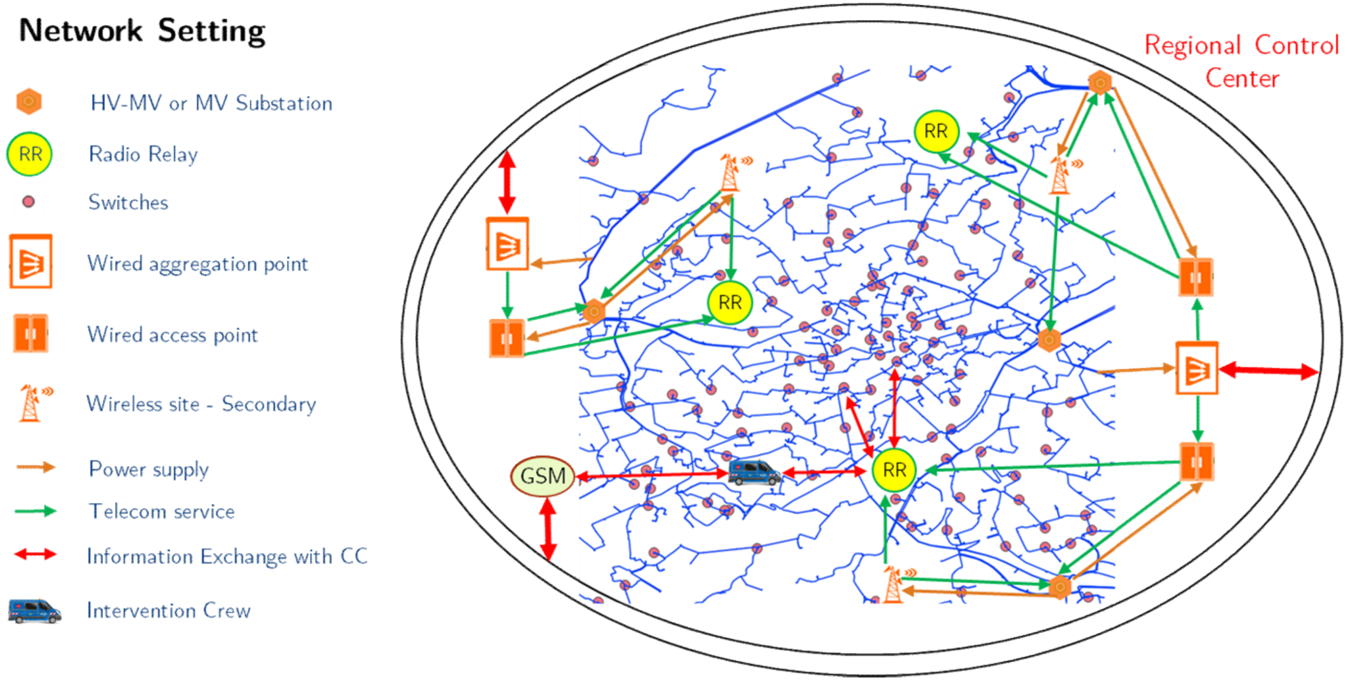
Example: distribution grid recovery



- Flexibility resources: automatic/manual switches → control decisions), DGs → allocation
- Maintenance resources: repair crews → scheduling

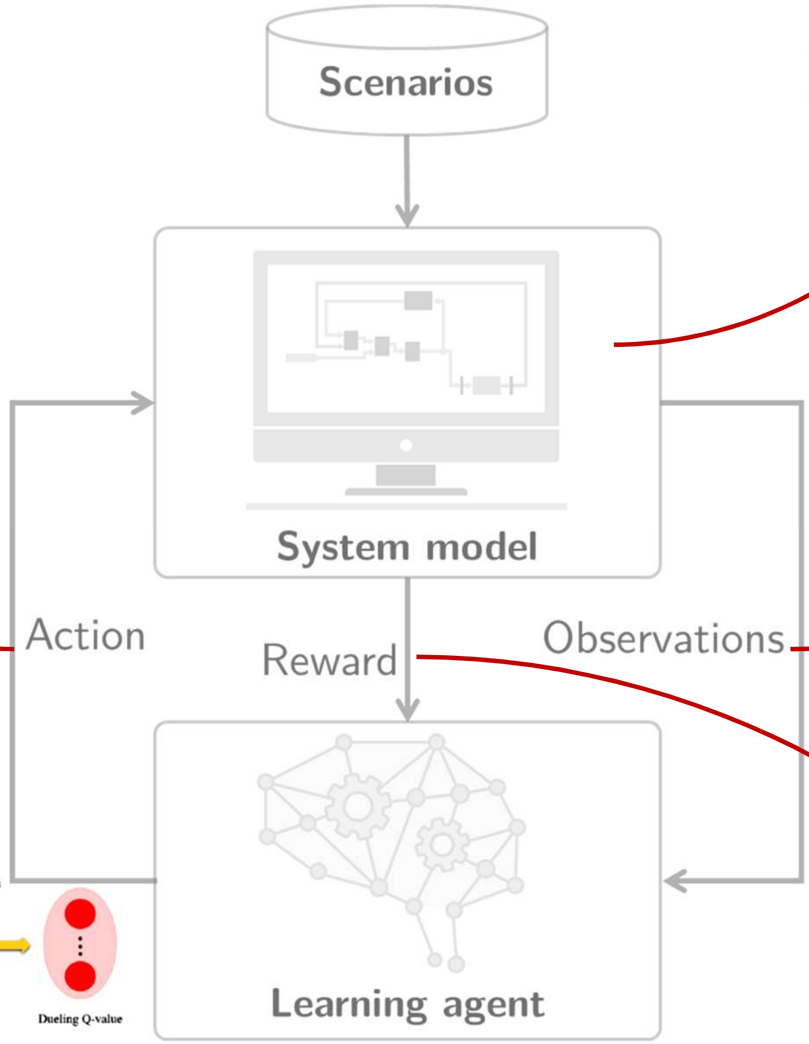
Modeling methods

- MILP for communication-aware restoration (Belaid et al. 2023)



- Stochastic MILP to consider uncertain times of individual repair tasks (Fang and Sansavini, 2019)
- Key challenge: combinatorial nature v.s. highly time-critical in ex-post stage $\rightarrow$ scalable method

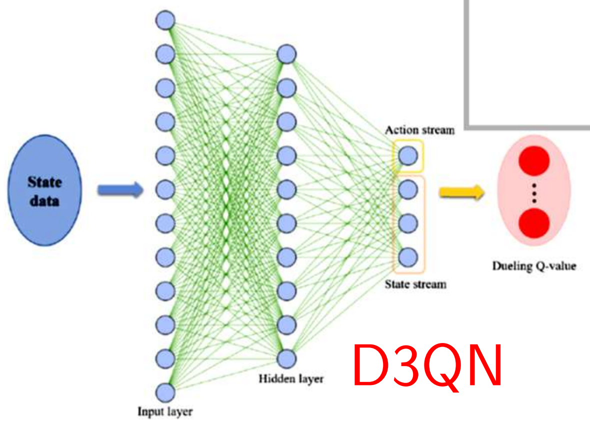
DRL for scalability



DC-OPF $\mathcal{R}(\boldsymbol{s})$

Choose failed items to be repaired

$$\boldsymbol{s} = \underbrace{[0, 1, 0, \ldots, 1]}_{\text{availability}}$$

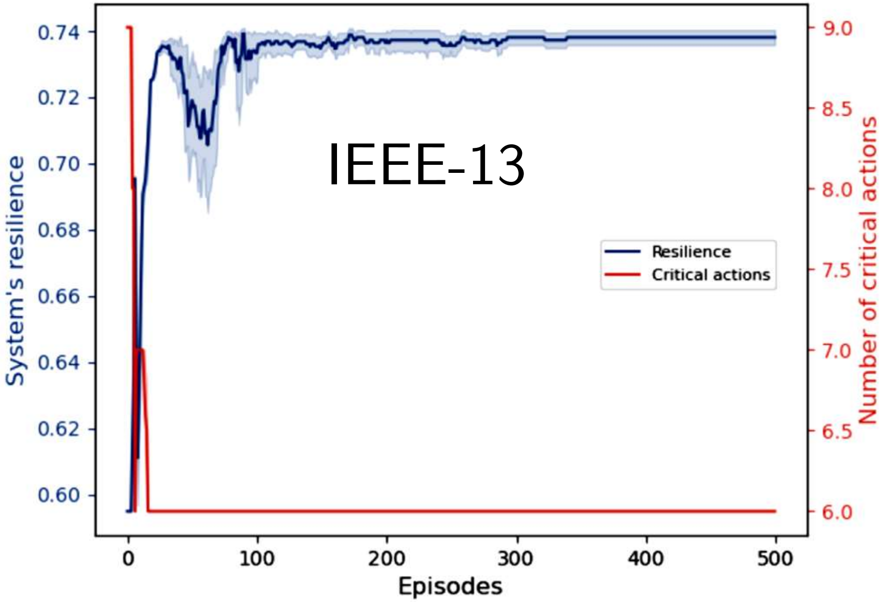


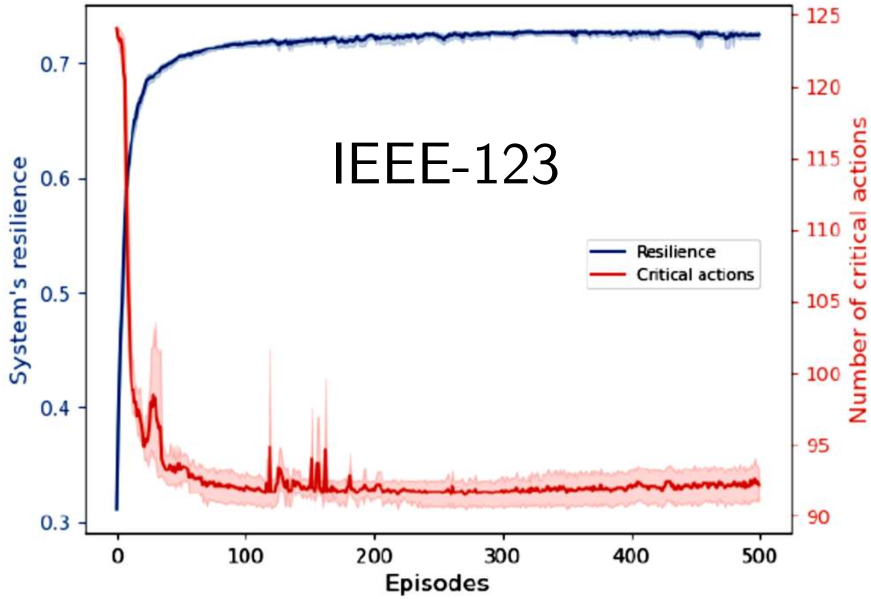
D3QN

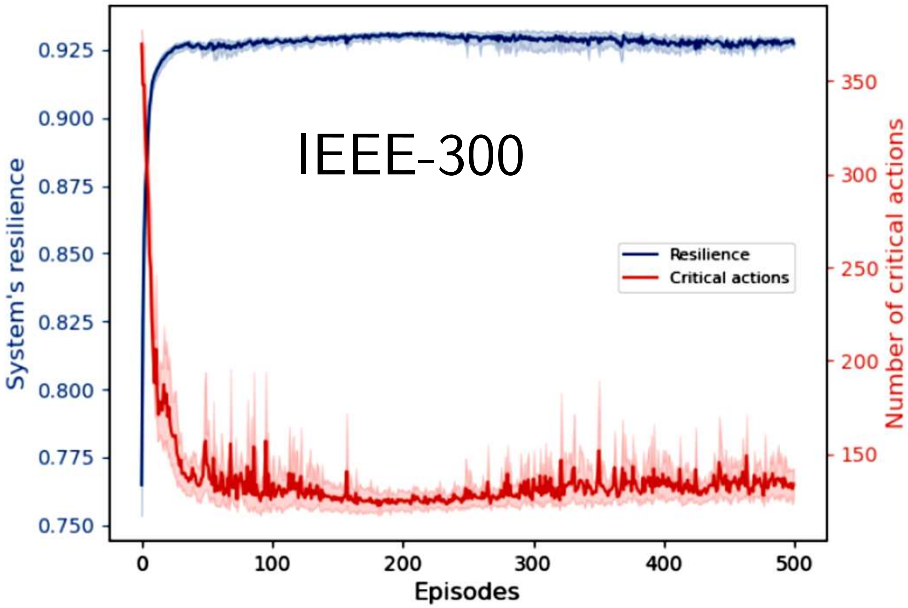
$$R(\boldsymbol{s}, a, \boldsymbol{s}') = \mathbb{E}_{T_a}\left[\frac{\mathcal{R}(\boldsymbol{s}') - \mathcal{R}(\boldsymbol{s})}{T_a}\right]$$

Z.-Y. Yin, C. Fang, Y.-P. Fang, M. Xie. (2023) "An optimization-driven deep reinforcement learning framework for distribution grid recovery planning with large action space"

Key results


IEEE-13
System's resilience
0.60 0.62 0.64 0.66 0.68 0.70 0.72 0.74
Number of critical actions
6.0 6.5 7.0 7.5 8.0 8.5 9.0
Episodes
0 100 200 300 400 500
Resilience
Critical actions


IEEE-123
System's resilience
0.3 0.4 0.5 0.6 0.7
Number of critical actions
90 95 100 105 110 115 120 125
Episodes
0 100 200 300 400 500
Resilience
Critical actions


IEEE-300
System's resilience
0.750 0.775 0.800 0.825 0.850 0.875 0.900 0.925
Number of critical actions
150 200 250 300 350
Episodes
0 100 200 300 400 500
Resilience
Critical actions

Key results

Trained DRL (D3QN & DDQN) vs. SO

Failure scenario	System	Method	Average CR	Time
50% damaged	13-node	D3QN	85.29%	$<$1s
		DDQN	85.29%	$<$1s
		SO	89.29%	$<$1s
	123-node	D3QN	76.72%	1.06s
		DDQN	75.79%	1.71s
		SO	74.98%	1h
	300-node	D3QN	95.25%	5.13s
		DDQN	93.79%	5.32s
		SO	None	None

▷ Near optimal performance with much less computational time

II. Ongoing projects and opportunities

Ex-ante prescriptive analysis

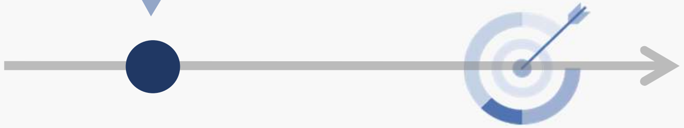
Pascal Quach

Stochastic optimization for the resilience of networked infrastructures against climate change, ANR JCJC Thesis

- Integrate historical & predicted data
- Compare/unify different approaches: RO & DRO & Robust Satisficing
- Develop tailored model & algorithm for energy systems (and other systems?)

$$\mathcal{Q}_N^\star = \min_{\boldsymbol{x}\in\mathbb{X}} \mathbb{E}_{\mathbb{P}^N}\left[\mathcal{Q}(\boldsymbol{x},\boldsymbol{\xi})\right]$$

$$(1+\alpha)\mathcal{Q}_N^\star$$



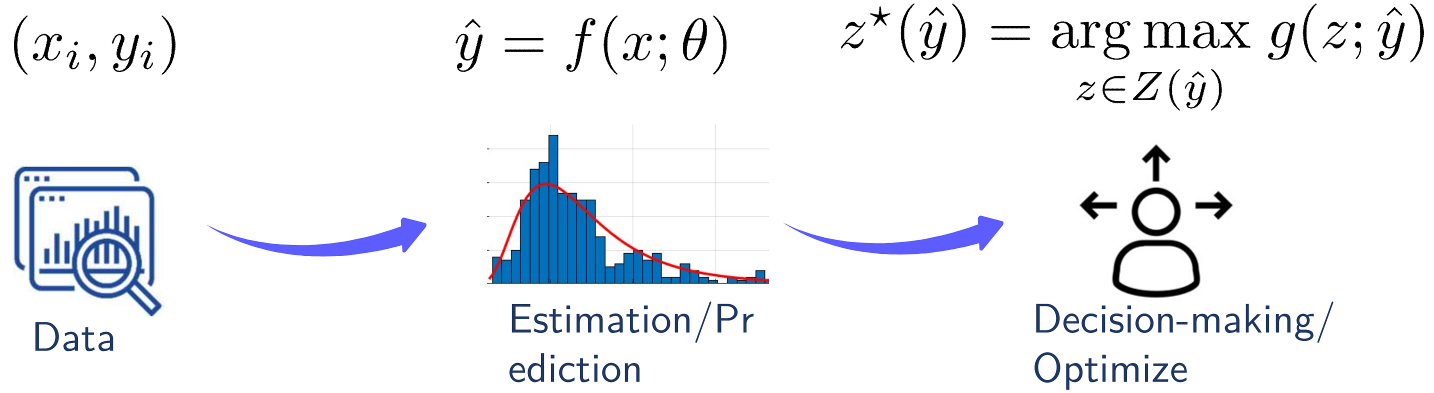
$$\max_{\boldsymbol{x}\in\mathbb{X}} \epsilon$$

$$\text{s.t. } \mathbb{E}_{\mathbb{P}}\left[\mathcal{Q}(\boldsymbol{x},\boldsymbol{\xi})\right] \le (1+\alpha)\mathcal{Q}_N^\star, \quad \forall \mathbb{P}\in\hat{\mathcal{P}}_N(\epsilon)$$

Ex-ante prescriptive analysis

Zhuojun Xie

Decision-focused learning and optimization for resilient system design and operation, CSC Thesis



Predict: RUL (Days)

	WT1	WT2
Ground truth	100	100
Pred. 1	110	90
Pred. 2	90	90
Pred. 3	110	110

Optimize: maintenance time to minimize cost

10k 10k 30k

2x + + = 60k

1x + 2x = 30k

1x + 2x = 70k

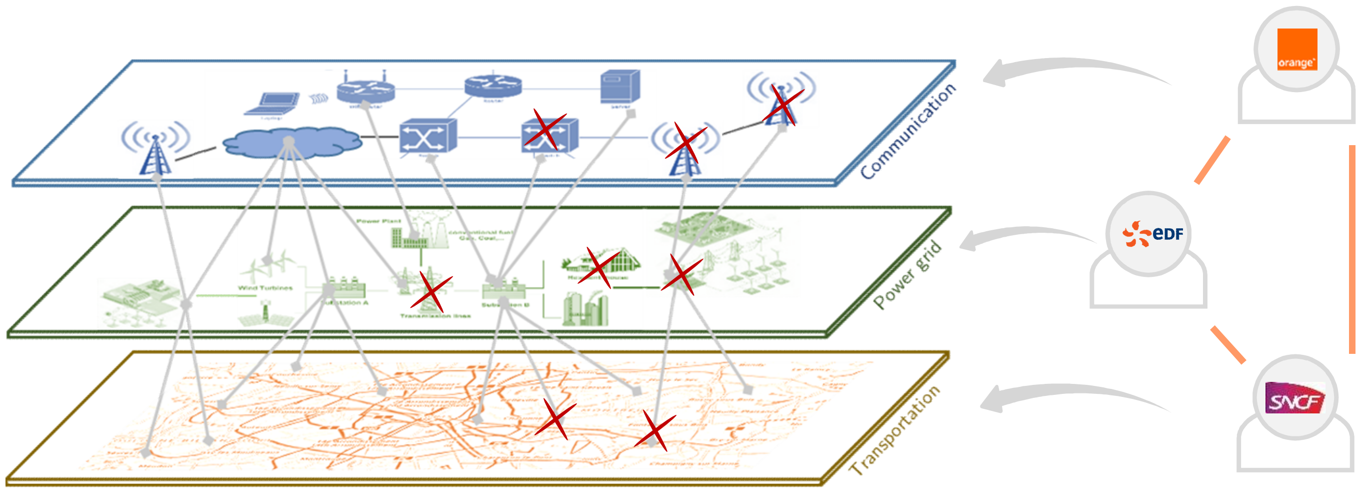
Decision awareness in learning could be of high value!

Ex-post prescription

Modelling aspects:

- Failure state *not fully known*, e.g., blocked/ damaged roads / failure in dependent systems; *Exploration takes resources* (e.g., drone inspection)
- *Decentralized* response & recovery planning with multiple operators

Postdoc to be recruited, ANR JCJC

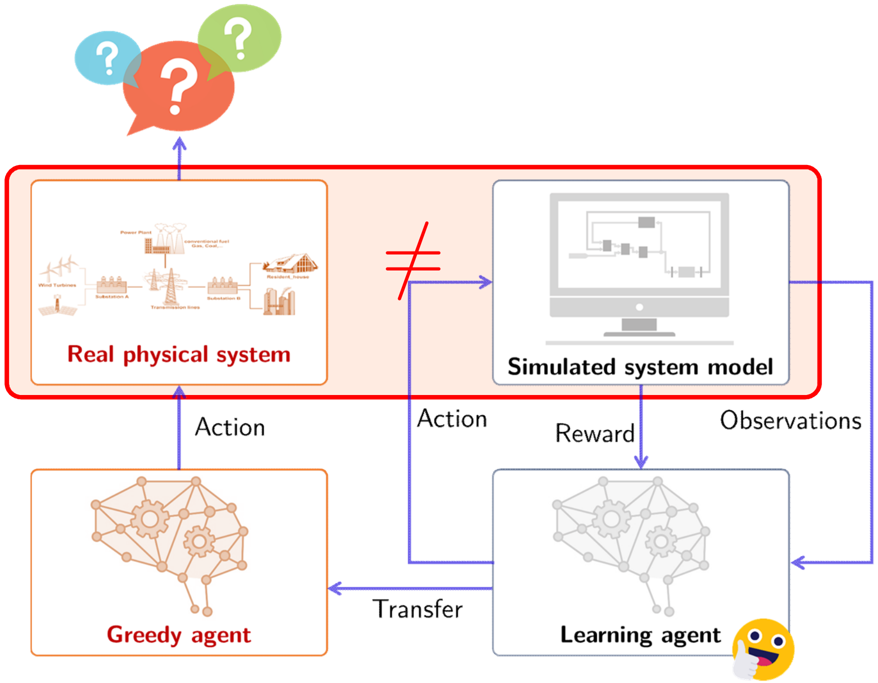


Wang, H., Fang, Y. P., & Zio, E. (2022). Resilience-oriented optimal post-disruption reconfiguration for coupled traffic-power systems. Reliability Engineering & System Safety, 222, 108408.

Ex-post prescription

Algorithmic: learning robustness and interpretability

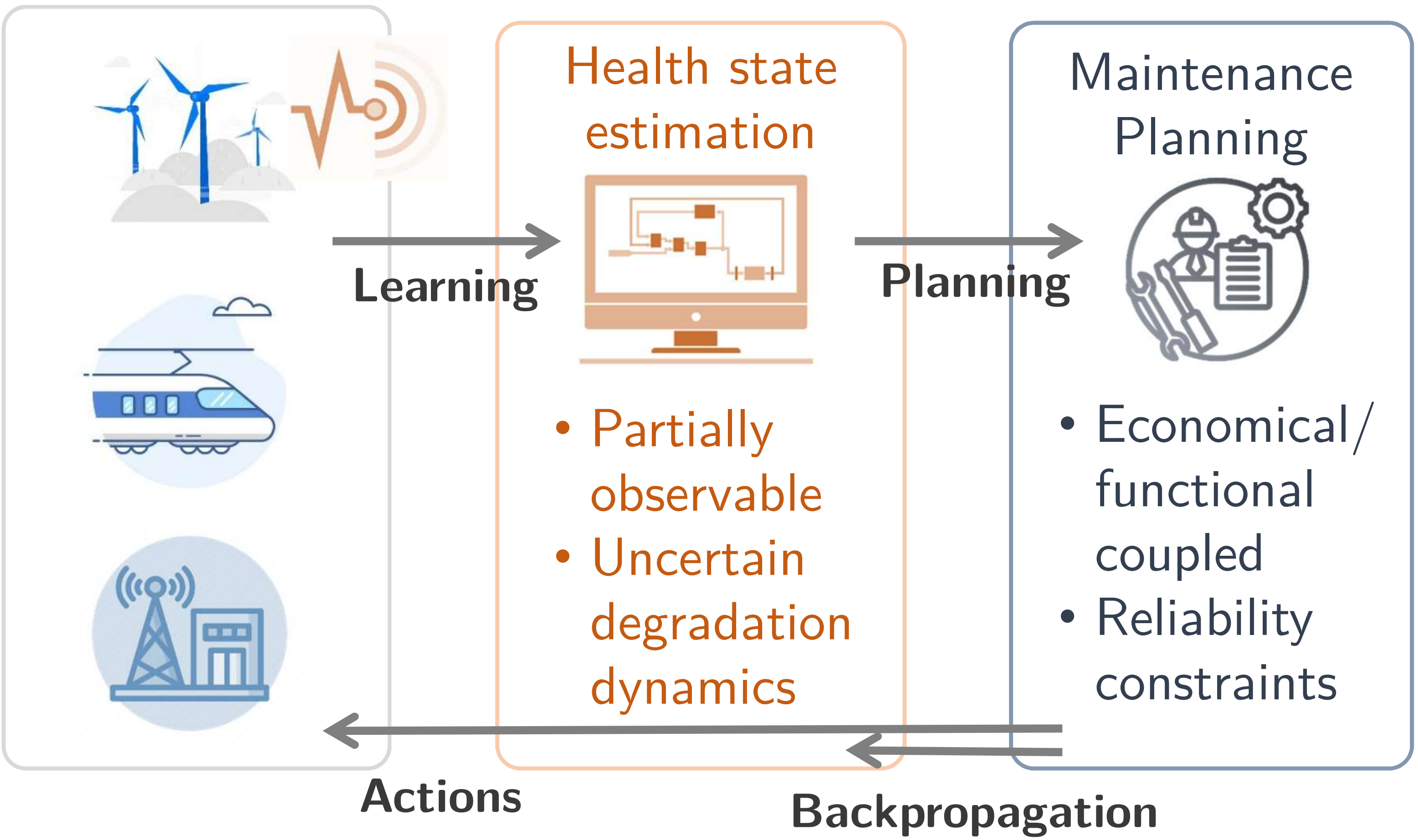
- **Trustfulness** in DRL
  - → *Simulation-to-reality gap*: distributional RL with risk-averse (Dulac-Arnold et al. 2019)
  - → *Safety*: constrained DRL incorporating domain-expert knowledge in training (Corsi et al. 2022)



- **Interpretability**:
  - → More interpretable model in RL, e.g., tree, rule-based
  - → Visualization, attention/saliency maps...

Updating and learning

Integrated machine learning and optimization for dynamic decision-making in continuously monitored systems, RRCS Chair Thesis, 10/2023



Zehui Xuan

Opportunities

- Systemic roadmaps to map from symptoms to prescriptive actions?

- Resilience cost models: cost sharing/allocation

Thanks for your attention!

Chair Risk and Resilience of Complex Systems

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