# Learning-Accelerated ADMM for Stochastic Power System Scheduling with Numerous Scenarios

**Ali Rajaei**, Olayiwola Arowolo, Jochen L. Cremer

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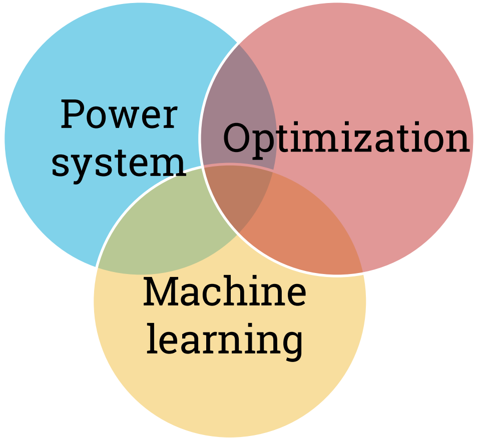
https://www.tudelft.nl/ai/delft-ai-energy-lab

# Ali Rajaei

PhD student at Delft AI Energy Lab,

Delft University of Technology.

Research focus: Machine learning for power system optimization.




M.Sc. & B.Sc. at Electrical Engineering, Sharif University of Technology, Iran (2019, 2017).

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# Motivation

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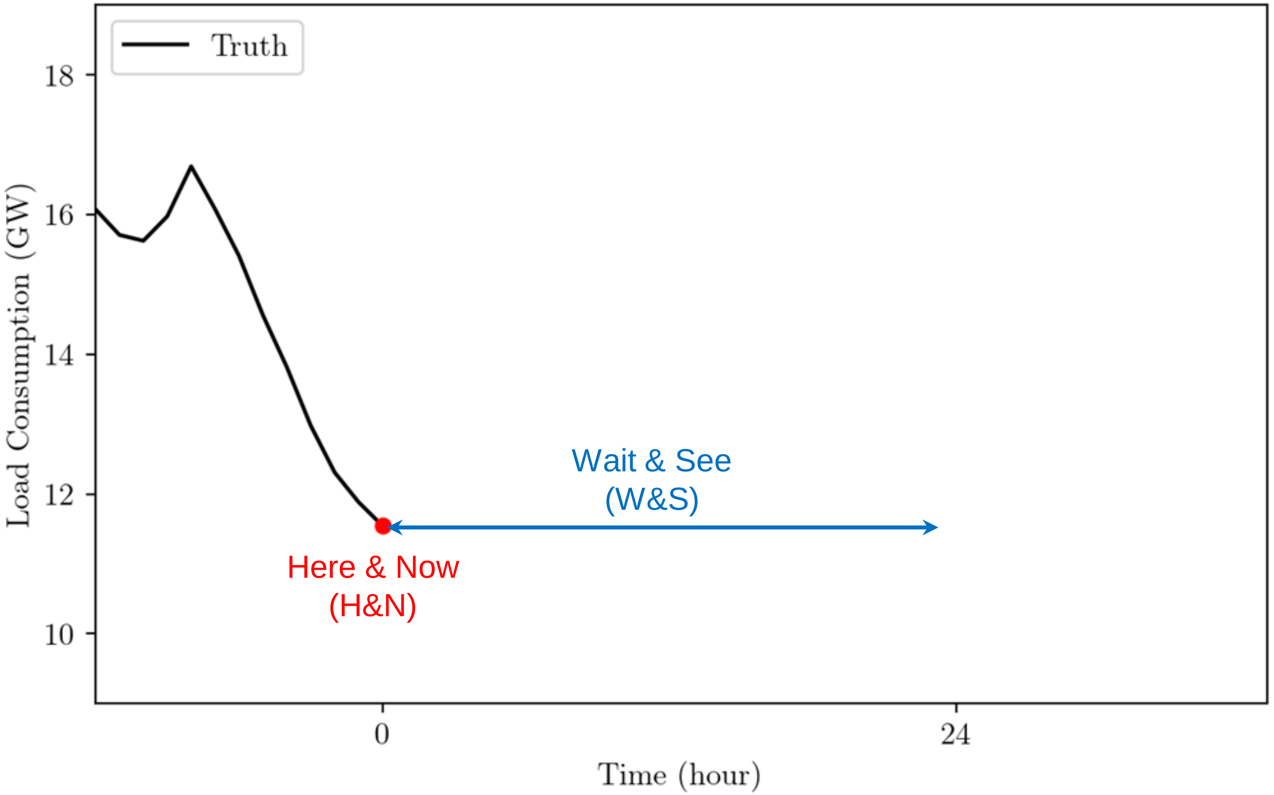
- Two-stage stochastic scheduling
  - Stochastic multi-period optimal power flow (St-MP-OPF)



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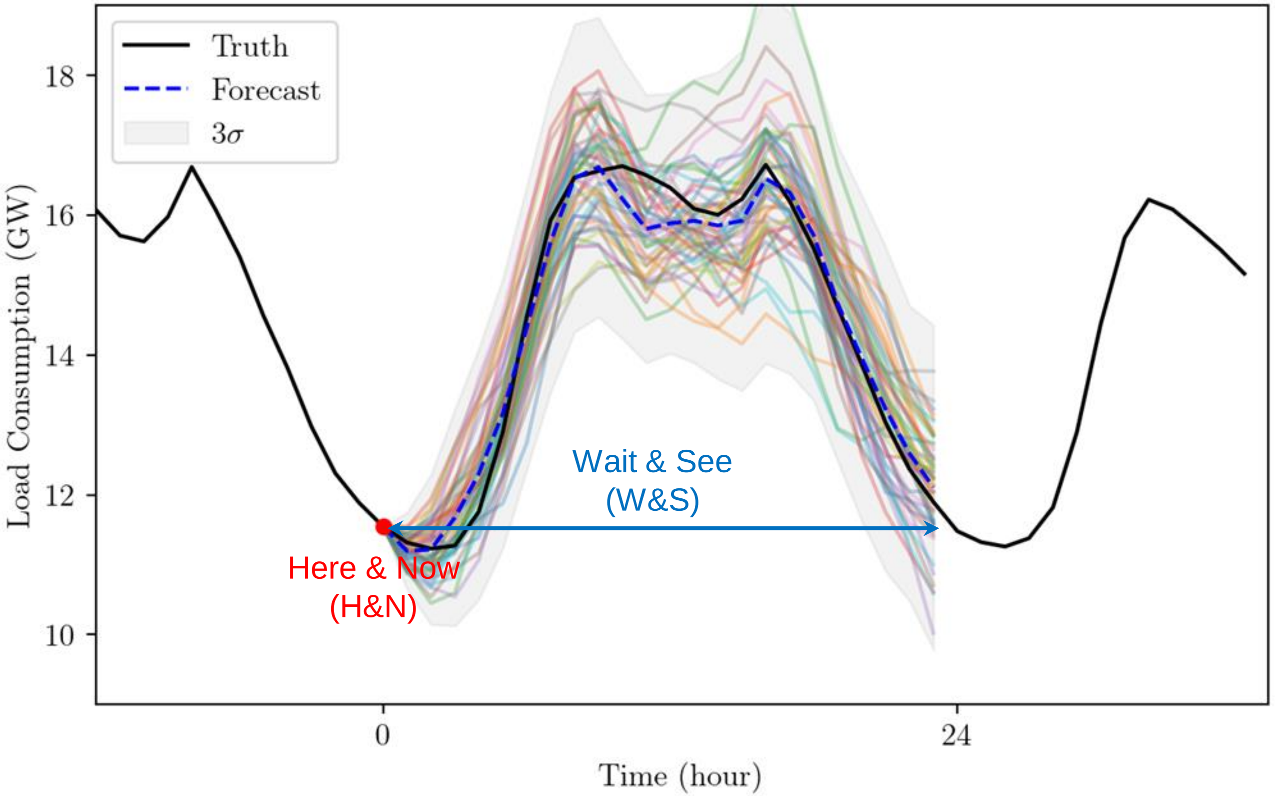

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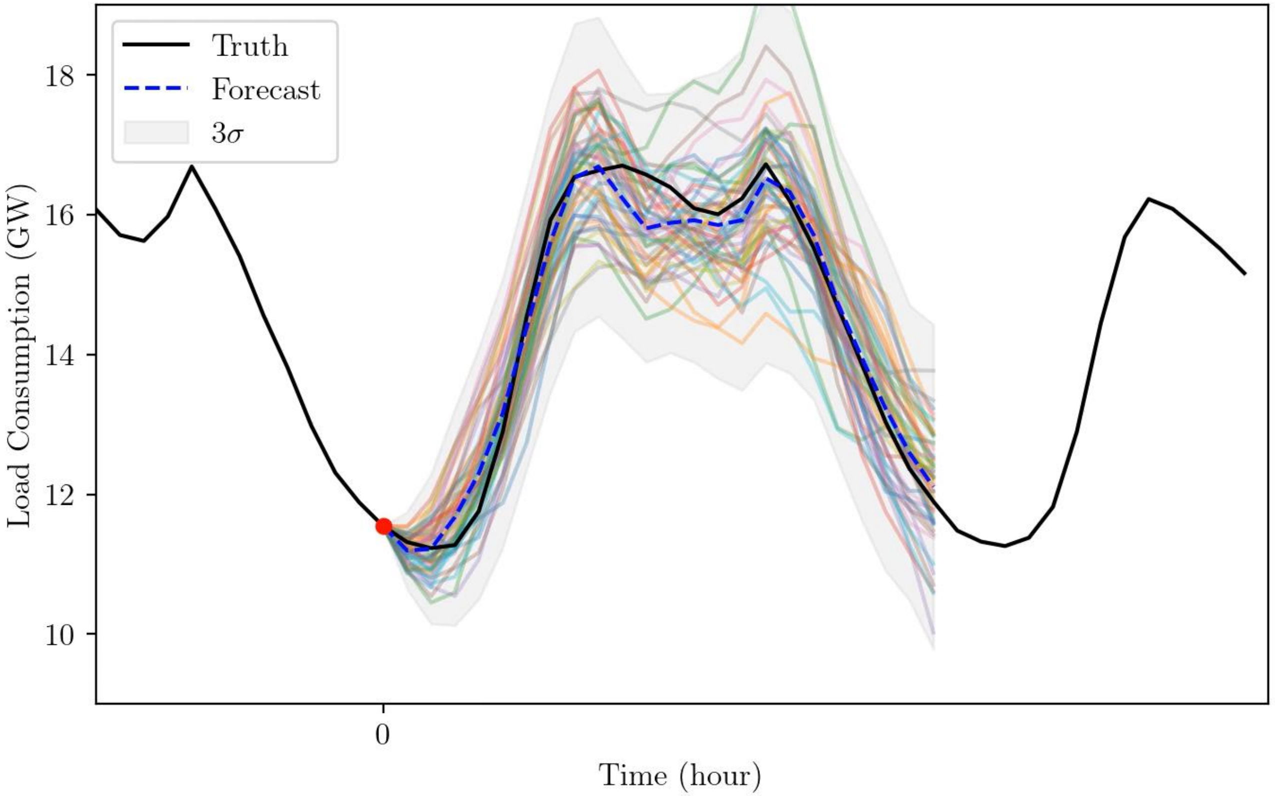

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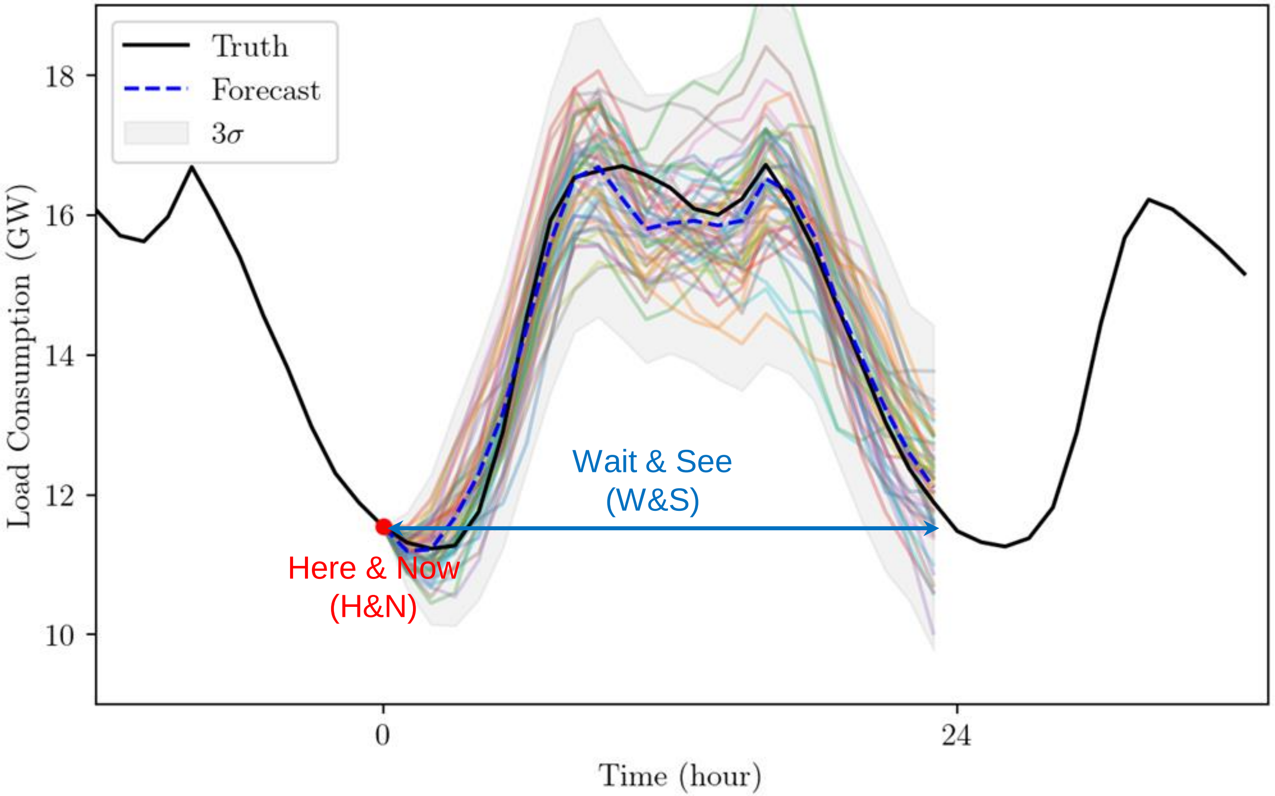
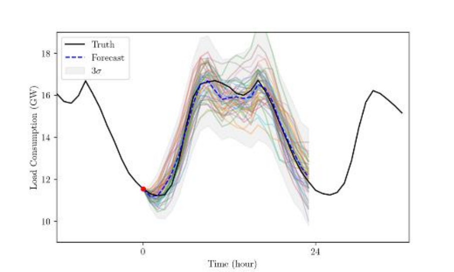
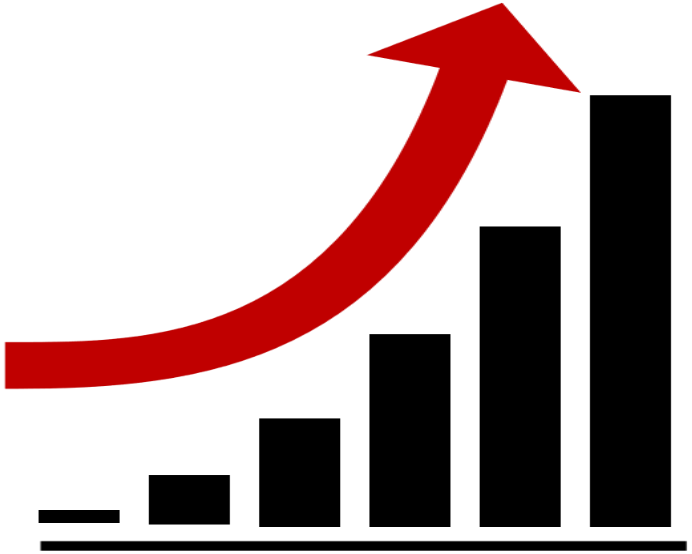


# Motivation

- RES integration and uncertainty
- Two-stage stochastic scheduling
  - Stochastic multi-period optimal power flow (St-MP-OPF)
- Computational complexity in large-scale systems with numerous scenarios



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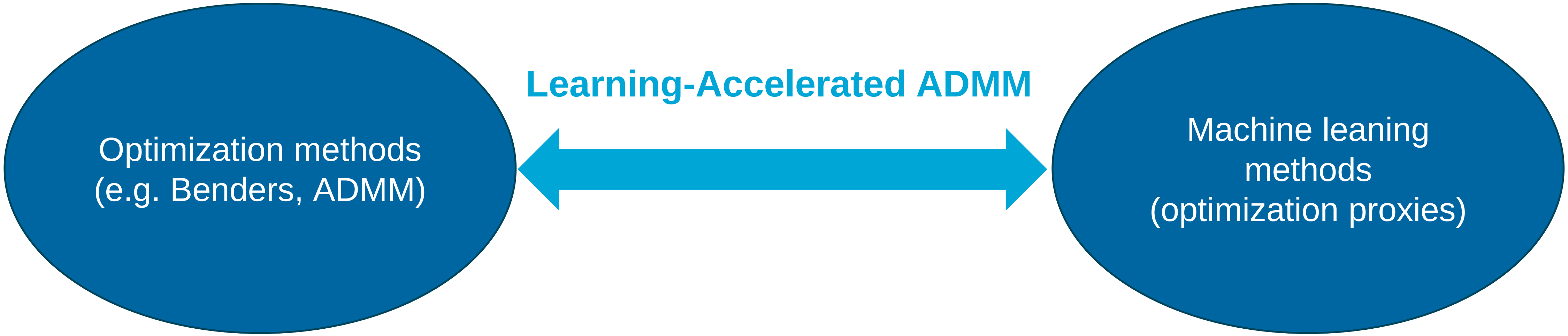


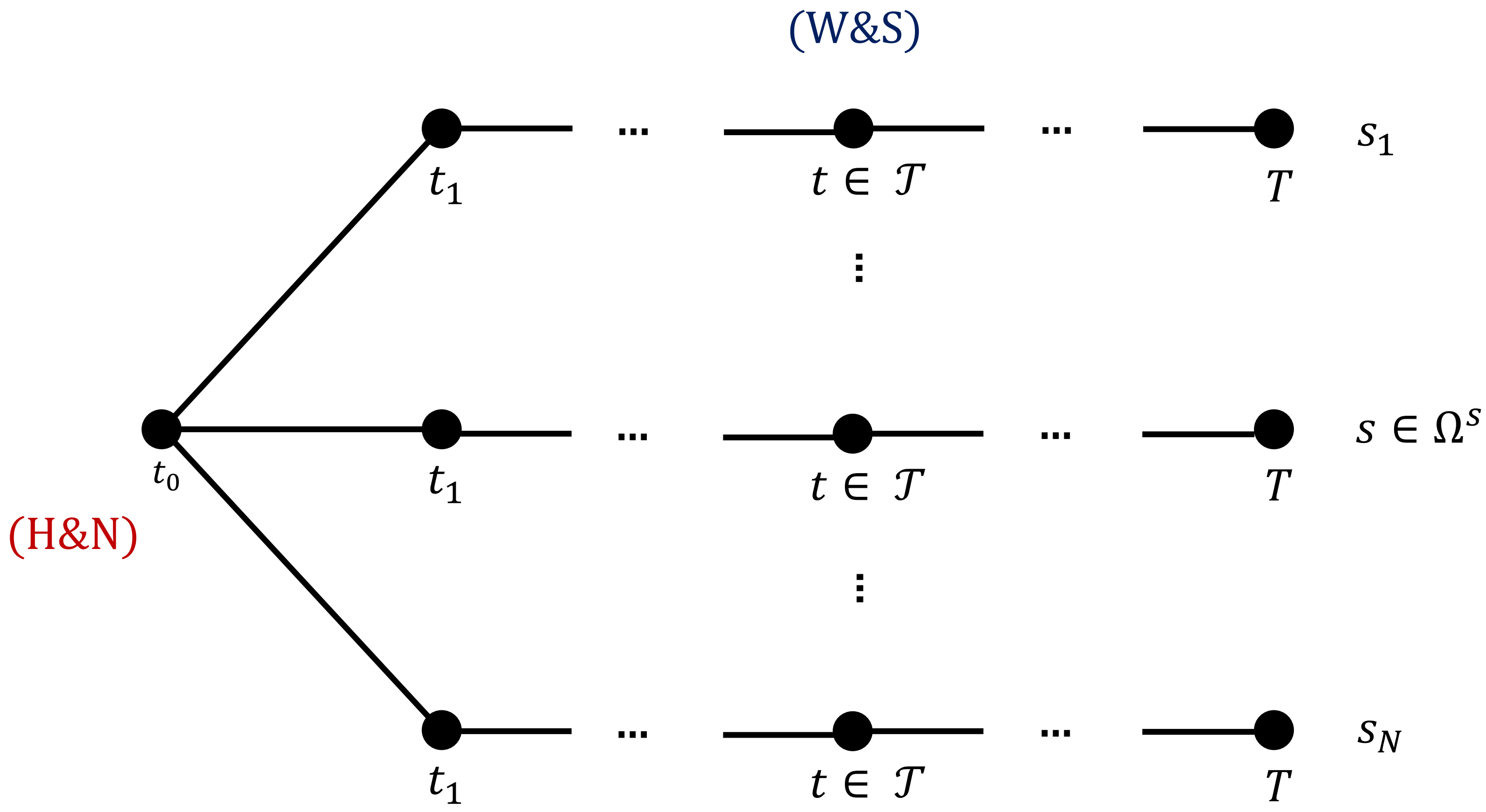

Guarantees
Slow

No guarantees
Fast

# Stochastic scheduling

$$\min \sum_{s\in\Omega^s} \sum_{t\in\mathcal{T}} f(z_{t,s})$$

$$\text{s.t. } h(z_{t,s}) \leq 0 \qquad t \in \mathcal{T}, s \in \Omega^s$$

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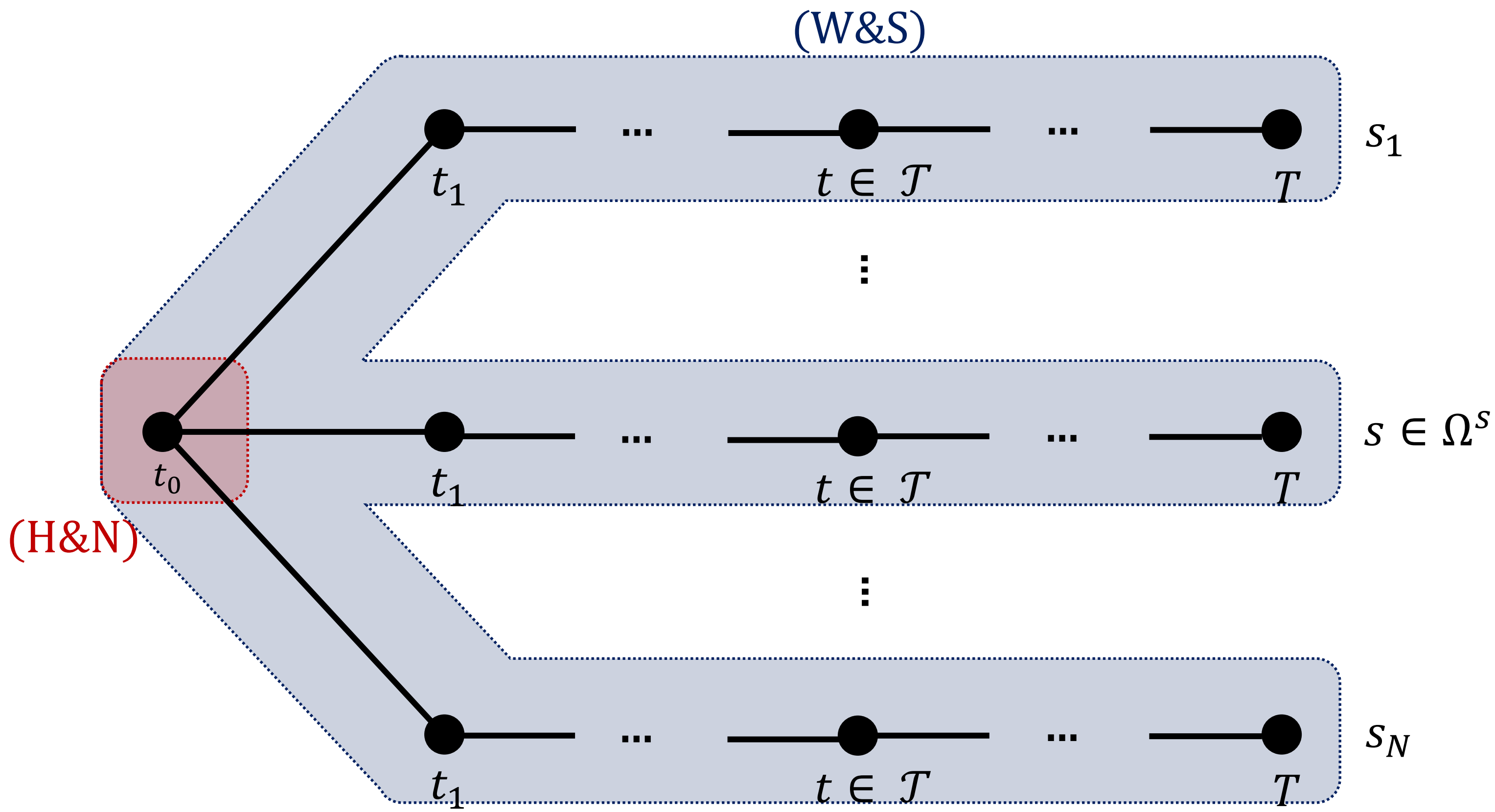
# ADMM-based Stochastic scheduling

$$\min \sum_{s \in \Omega^s} \sum_{t \in \mathcal{T}} f(z_{t,s})$$

$$\text{s.t. } h(z_{t,s}) \leq 0 \qquad t \in \mathcal{T}, s \in \Omega^s$$

$$x = z_{t0,s} : \lambda_s \quad t \in \mathcal{T}$$

Consensus constraint

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# ADMM-based Stochastic scheduling

$$\min \mathcal{L}_\rho = \sum_{s\in\Omega^s}\left(\sum_{t\in\mathcal{T}} f(z_{t,s}) + \lambda_s(x - z_{t0,s}) + \frac{\rho}{2}(x - z_{t0,s})^2\right)$$

$$\text{s.t. } h(z_{t,s}) \le 0 \qquad t\in\mathcal{T}, s\in\Omega^s$$

$$\cancel{x = z_{t0,s} : \lambda_s \quad t\in\mathcal{T}}$$

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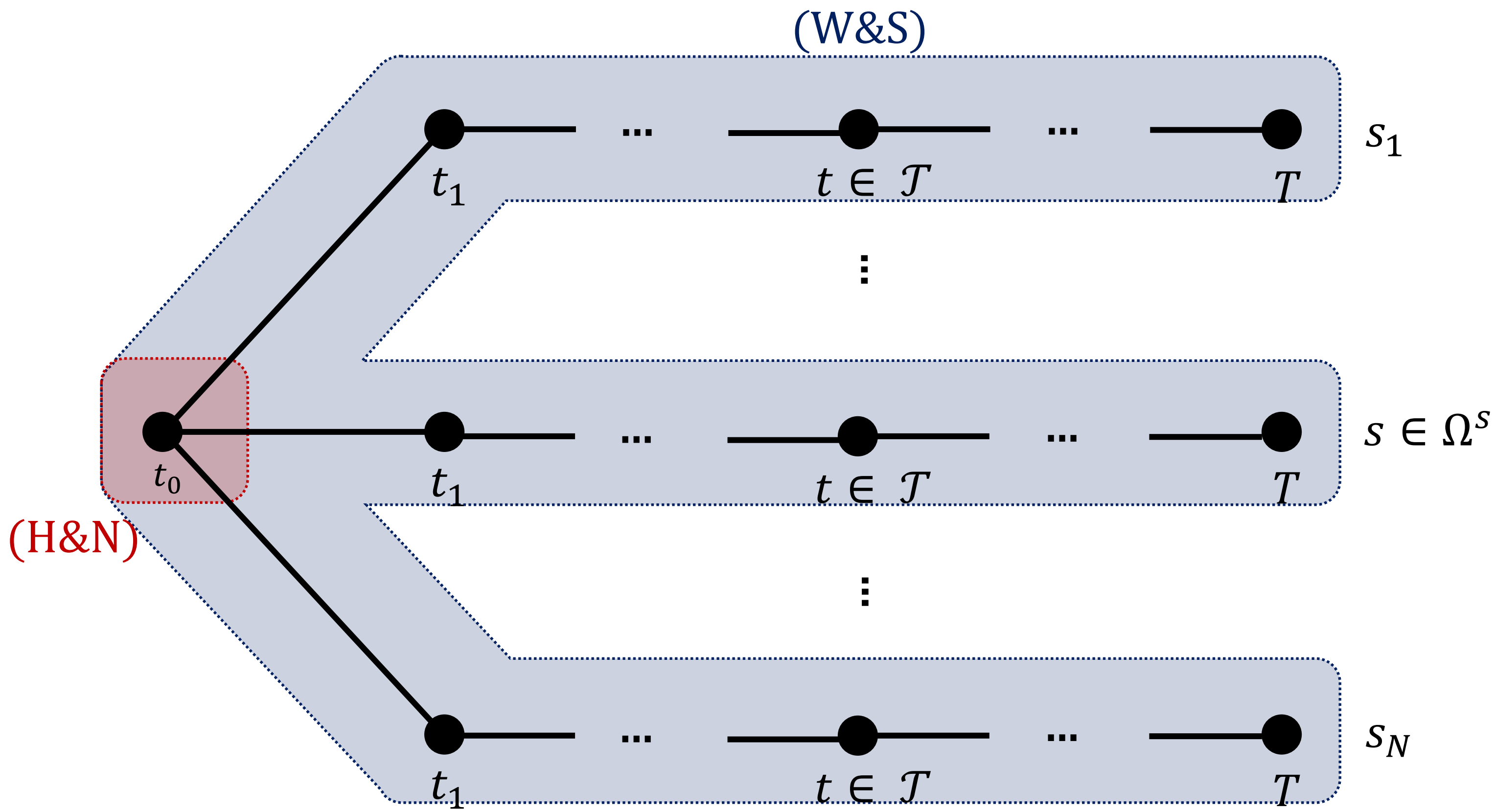


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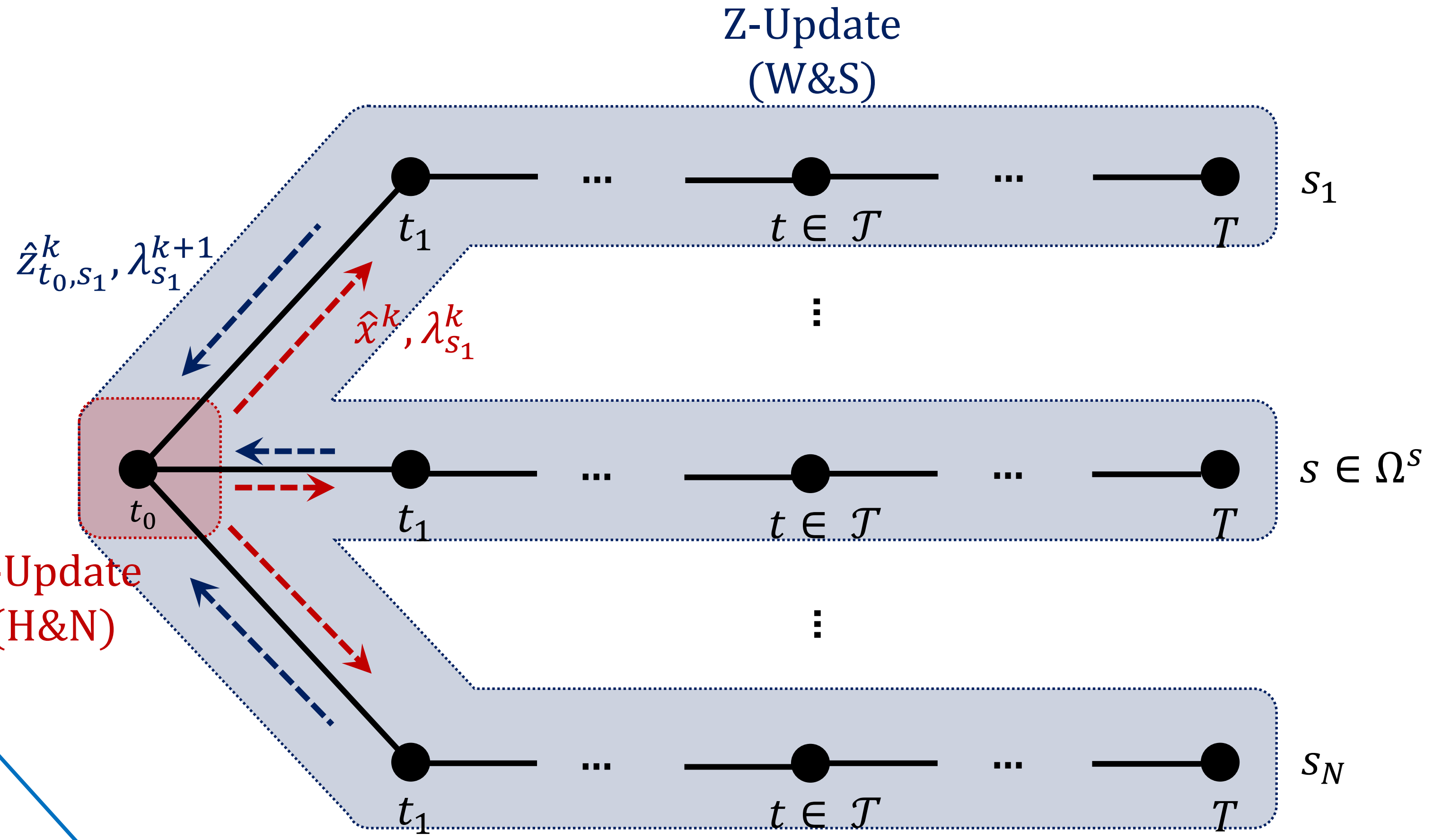
$$\text{s.t. } h(z_{t,s}) \leq 0 \qquad t \in \mathcal{T}, s \in \Omega^s$$

1. $x^{k+1} = \operatorname{argmin}_x \mathcal{L}_\rho(x, z^k, \lambda^k)$

2. $z^{k+1} = \operatorname{argmin}_x \mathcal{L}_\rho(x^k, z, \lambda^k) \quad s \in \Omega^s$

3. $\lambda^{k+1} = \lambda^k + \rho(x - z_s) \qquad s \in \Omega^s$




Each Z-update is MP-OPF.
While computationally expensive, needs less accuracy.

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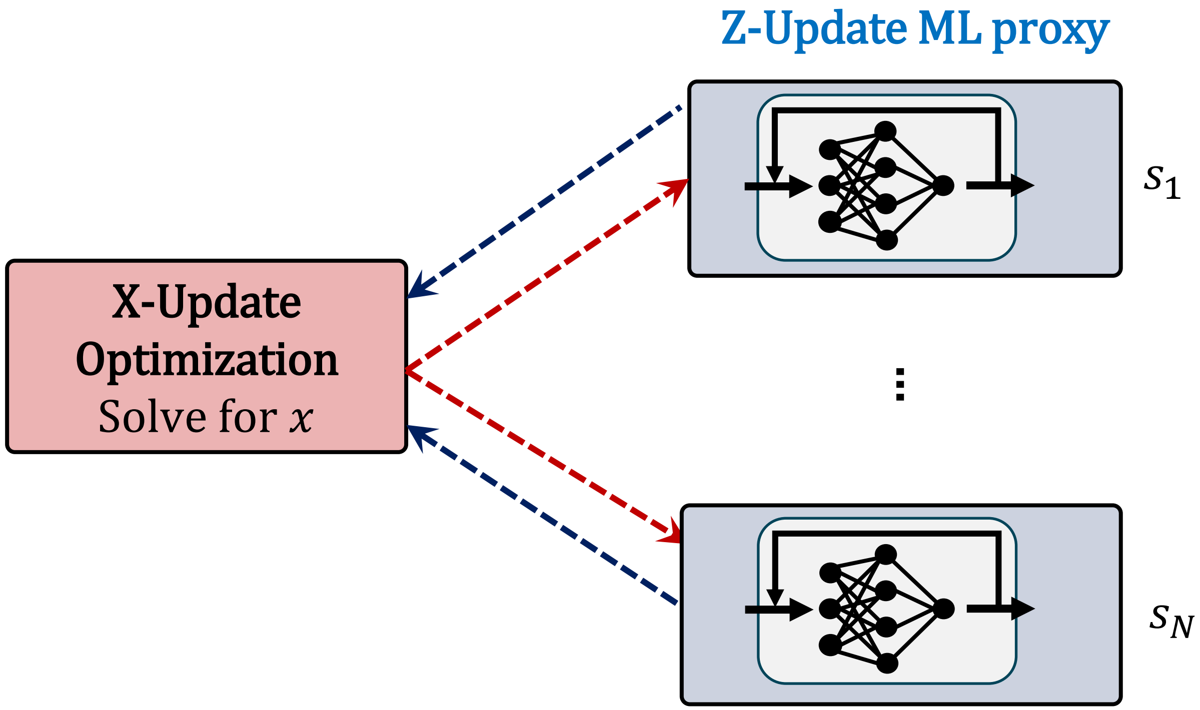
# ADMM-ML

- H&N decisions by X-update optimization.
- Future W&S decisions by Z-update **ML proxy.**
  - Recurrent Neural Networks (RNN)

$$h_t = \sigma(Ax_t + Bh_{t-1})$$

$$z_t = \sigma(Ch_t)$$

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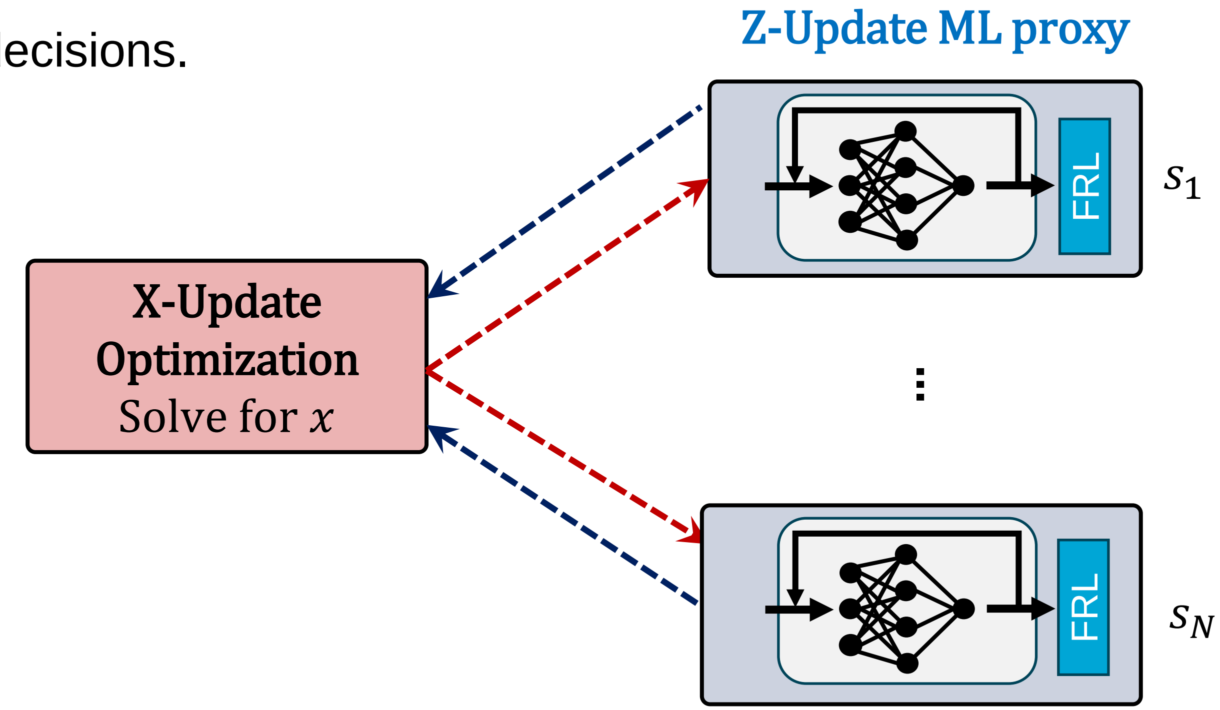
# Properties of ADMM-ML

- **Physical Feasibility**
  - X-update optimization ensures feasibility for H&N decisions.
  - Feasibility restoration layer for RNN.

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# Properties of ADMM-ML

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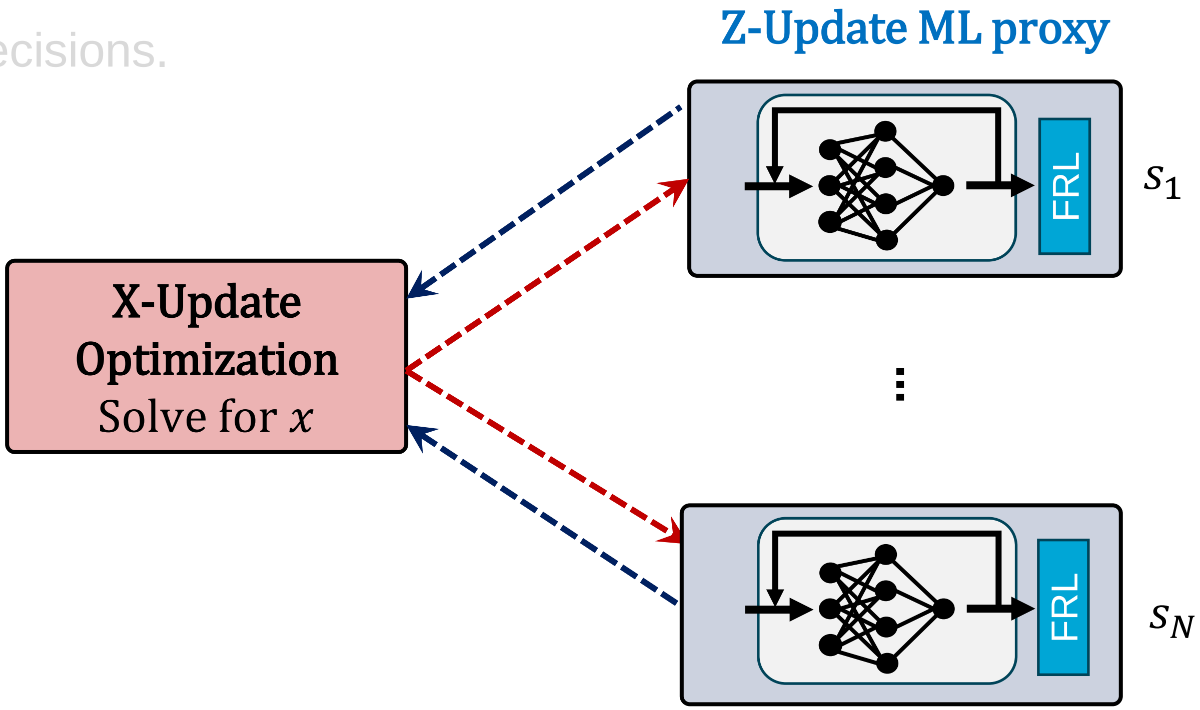
- **Fast & Parallelizable Inference**
  - RNN enables fast z-updates.
  - Scalable to long time horizons.
  - GPU parallelization.

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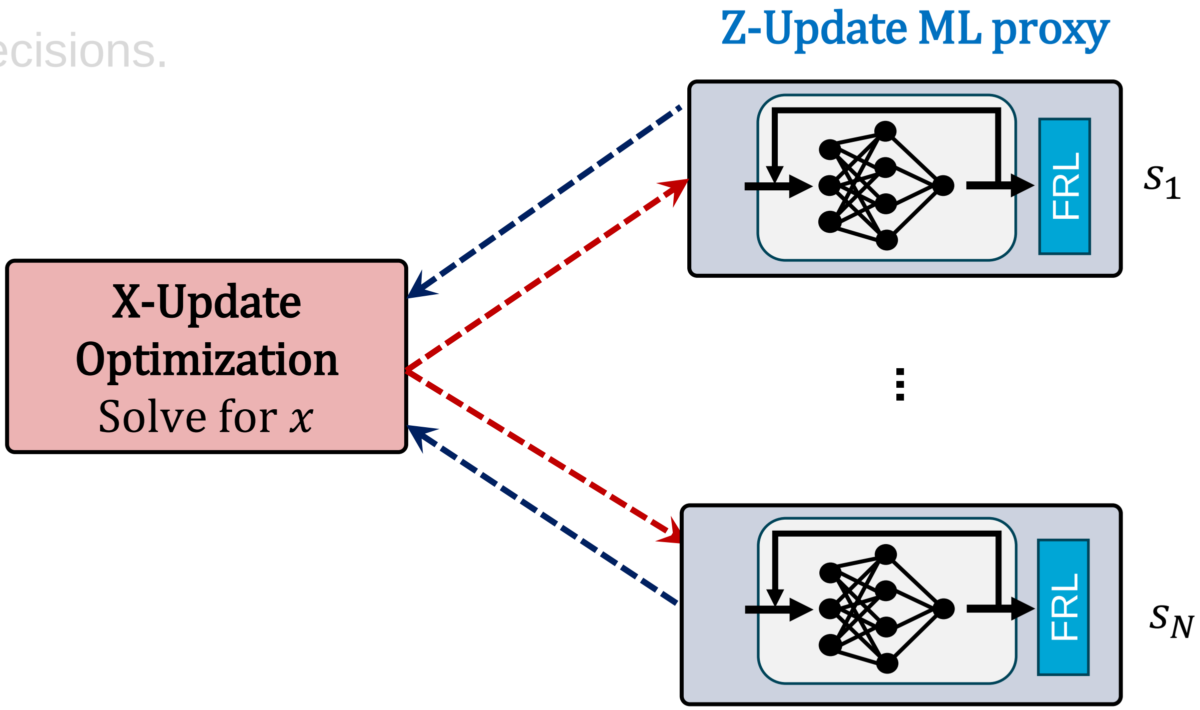

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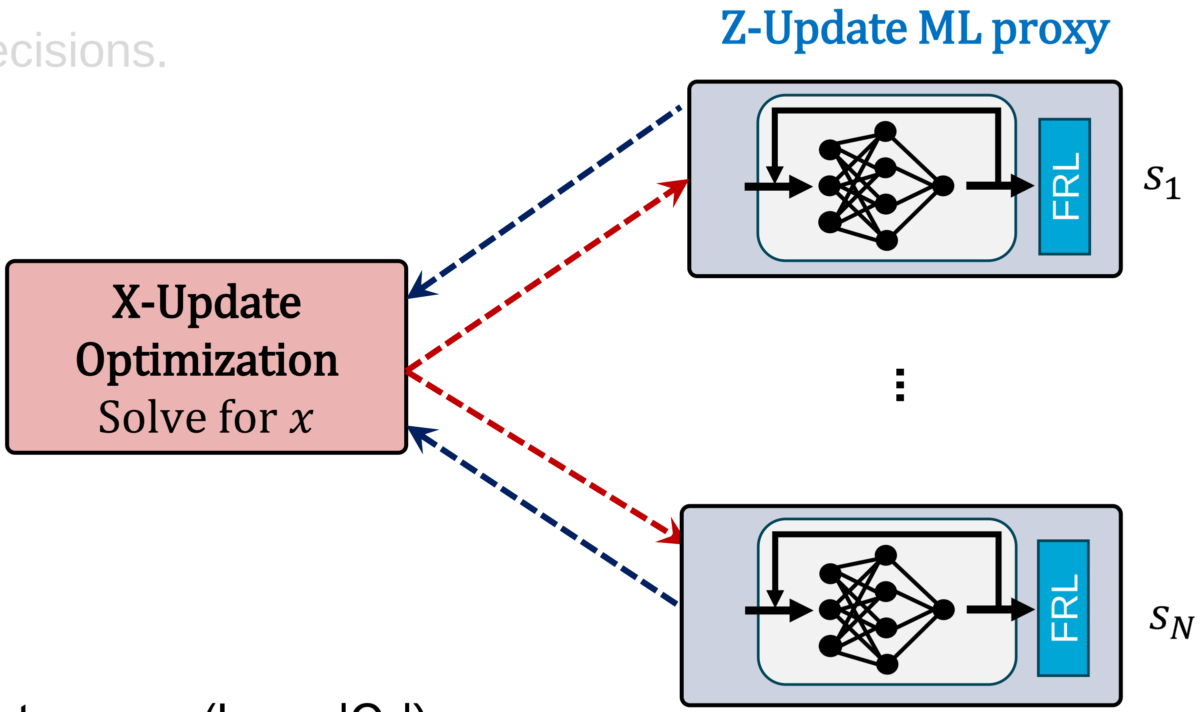
- **Generalization Across Scenario Sizes**
  - Same RNN used across all uncertainty scenarios.
  - Trained on few scenarios (small $|\Omega_s|$), but applicable to many (large $|\Omega_s|$).



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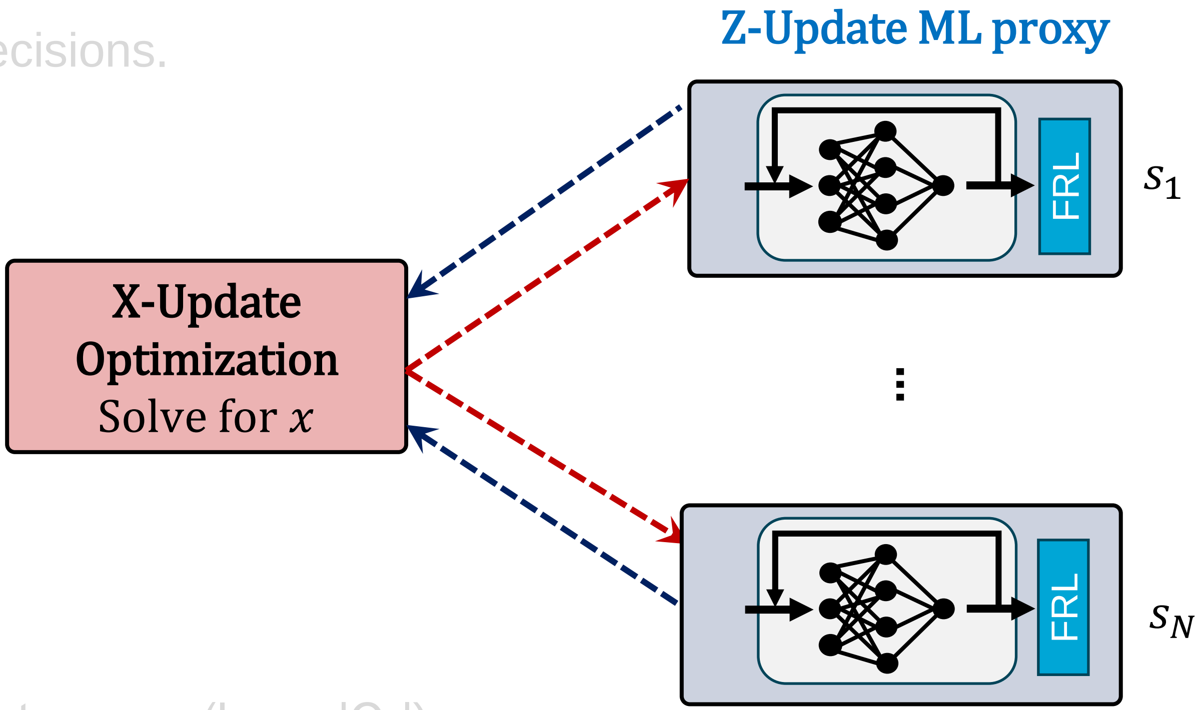
- **Warm Start for ADMM (Hybrid ADMM-ML).**

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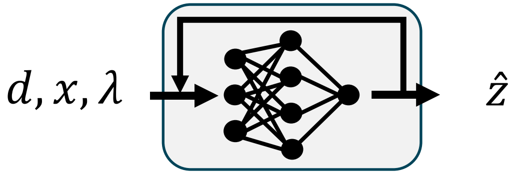
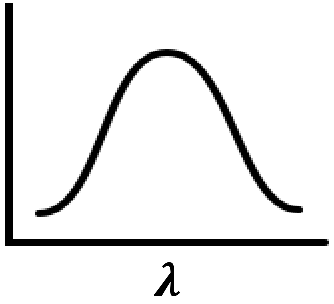



# Training data generation

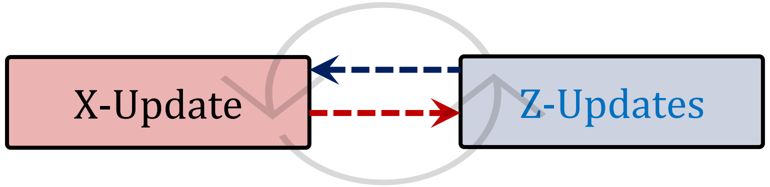
- Approaches:

1) Full exploration




$\epsilon$-greedy exploration

2) Full exploitation



# Case studies

- 14-bus, 118-bus, 1354-bus systems.
- 1-year NL load data.
- ARIMA scenario generation.
- For each training sample $n$, $|\Omega_n^s| = 10$ uncertainty scenarios.
- For each testing sample $n'$ , $|\Omega_{n'}^s| = 100 - 1000$ scenarios.

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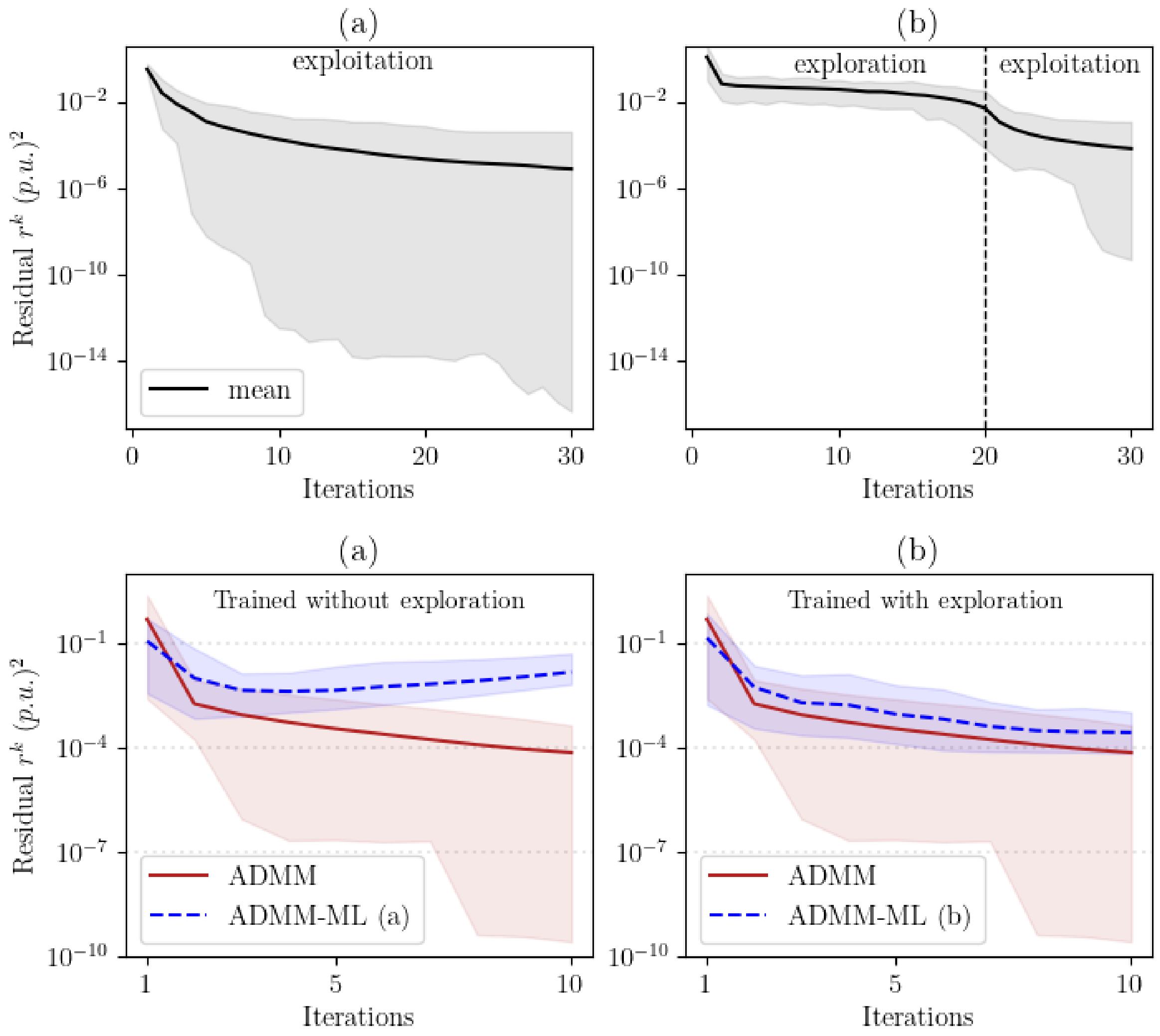
# Training data generation

Training

Testing

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# Accuracy and time

- 118-bus St-MP-DCOPF.
- Test on samples with 500 scenarios.

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| CO |
| ADMM |
| ADMM-ML |
| ADMM-ML-H |

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# Conclusion and future work

- Key message: Combination of distributed optimization and ML can overcome the challenges of operational feasibility and scalability to numerous scenarios.

- Remaining challenges:
  - Practical applications: topology and system generalization.
  - Distribution shifts during online implementation.

# Check out our paper

- A. Rajaei, O. Arowolo, and J. L. Cremer, “Learning-accelerated ADMM for stochastic power system scheduling with numerous scenarios,” IEEE Transactions on Sustainable Energy, 2025. (Link)

- Codes available on Delft-AI Lab GitHub. (Link)

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# Thank you for your attention!

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