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Topology-aware Graph Neural Networks for Learning Feasible and Adaptive ac-OPF

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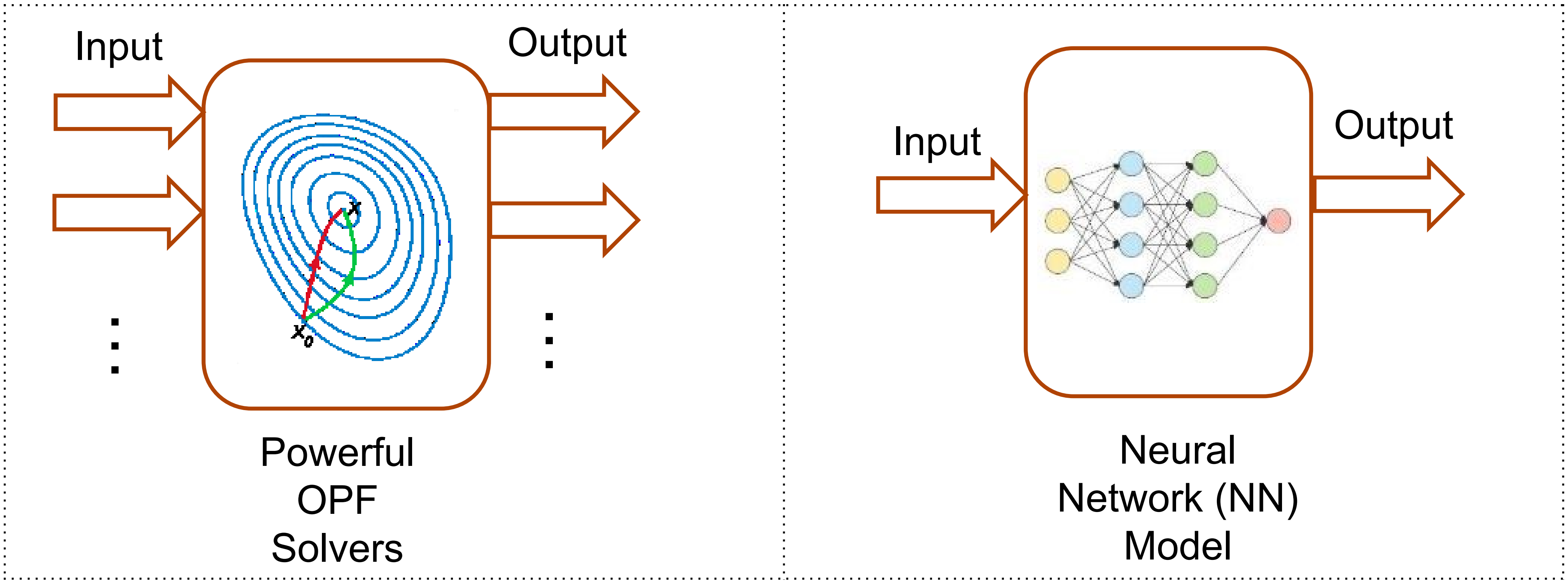
Machine learning for optimal power flow (OPF)



➢ Attain a pre-trained OPF input-output mapping from available samples

Existing work and our focus

- Integration of renewable, flexible resources increases the grid variability and motivates real-time, feasible OPF via training a neural network (NN)
  - Warm start the search for ac feasible solution [Baker '19]
  - Feasible domain to reduce limit violation [Zamzam et al'20][Zhao et al'21]
  - KKT conditions based regularization [Zhang et al'22] [Nellikkath et al'22]
  - Connection to the duality analysis of convex OPF [Chen et al'20] [Singh et al'20]
- Rely on FCNN architecture and cannot adapt to varying topology

Focus: graph learning approach for *complexity reduction & topology adaptivity*

Real-time ac-OPF

- Power network modeled as a graph [redacted] with N nodes
- ac-OPF for all nodal injections

[redacted]

- Nodal input:

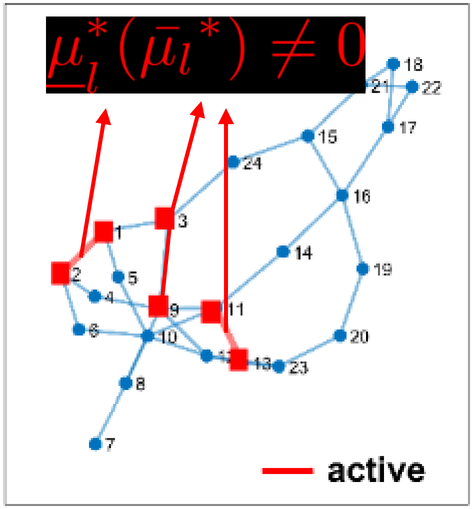
  [redacted]

  power limits + costs

- Nodal output: optimal p/q

Each FCNN layer has [redacted] parameters!

Topology dependence



- [Owerko et al'20] using graph learning to predict p/q
- But topology dependence (locality) of output label is crucial!
- Locational marginal price from (very few) congested lines
- Voltage magnitude [redacted] approximated using q injection

[redacted] $: \lambda$ $: [\underline{\mu}; \bar{\mu}]$

[redacted] $(\bar{\mu}^* - \underline{\mu}^*)$

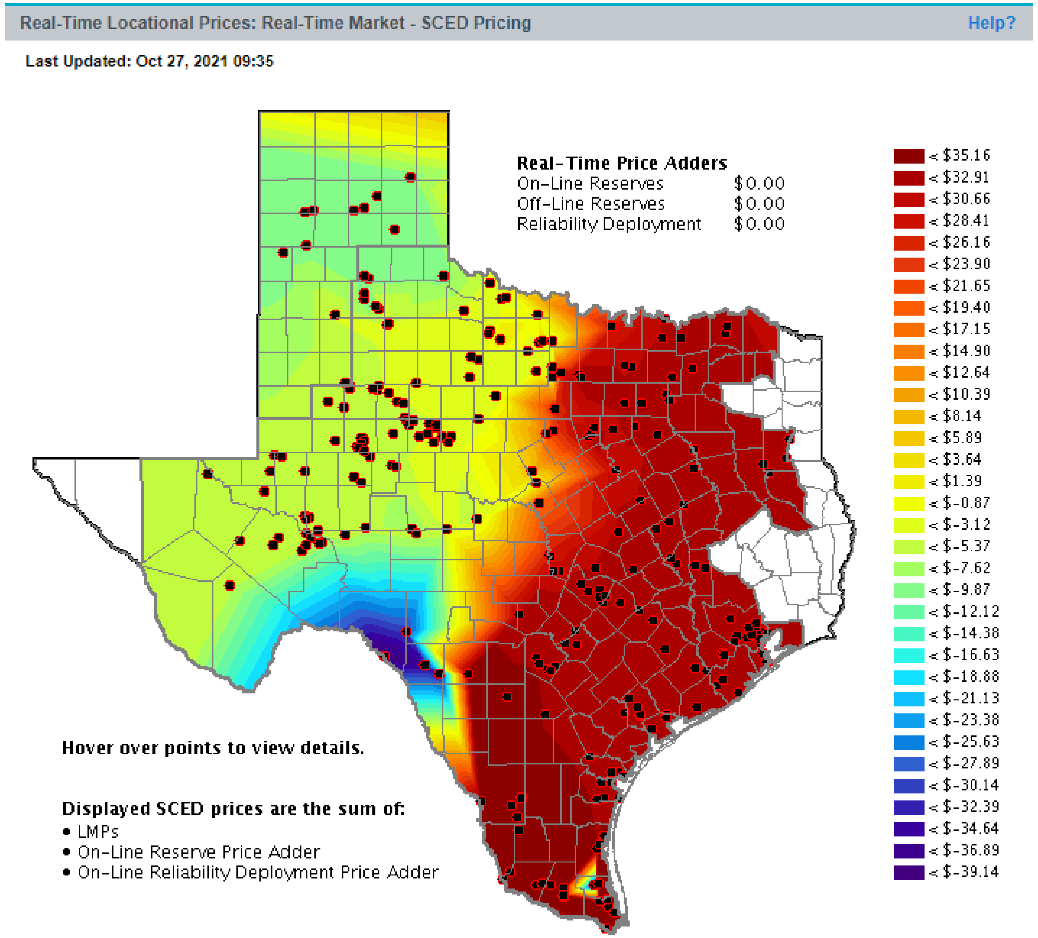
[redacted]

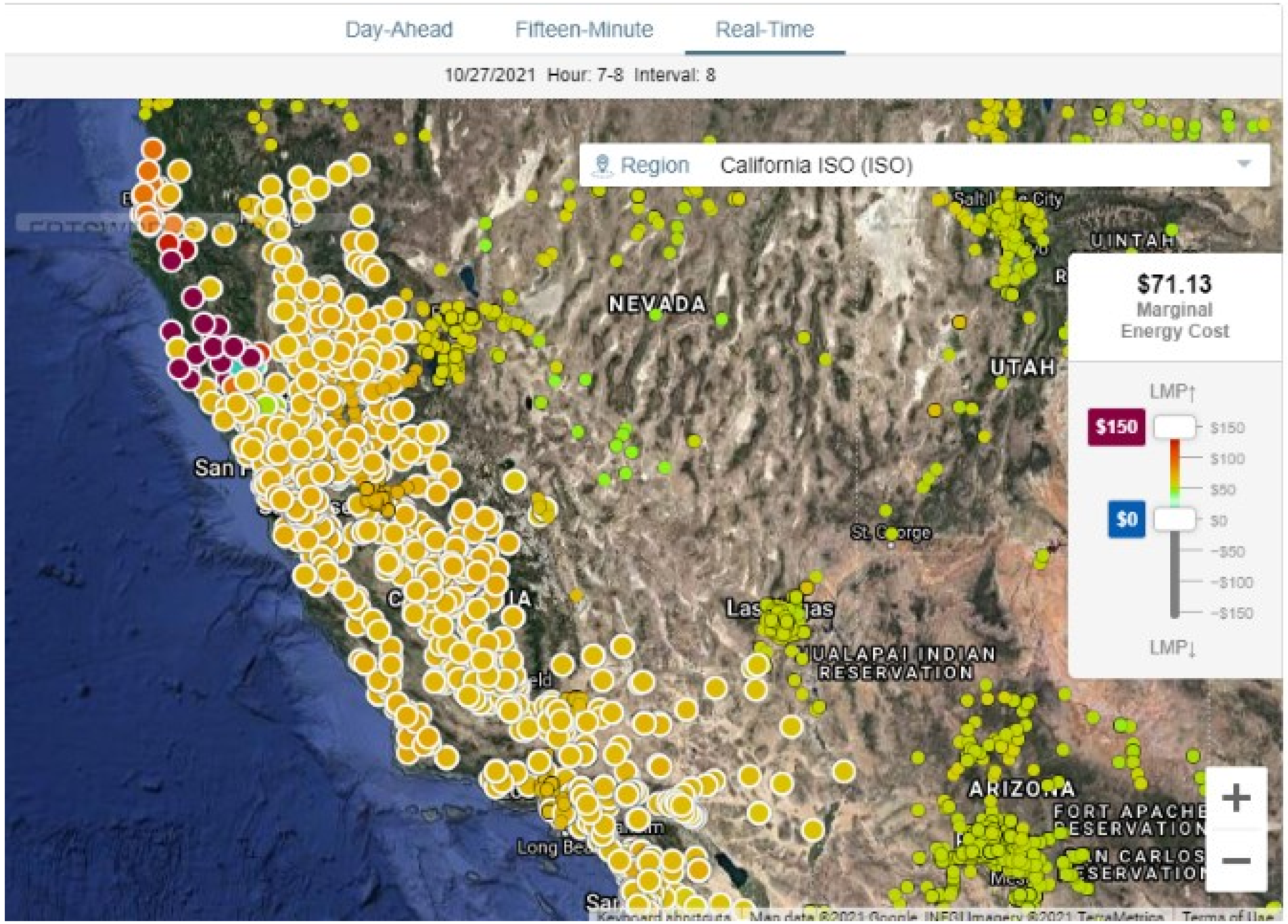
Spanned from the eigen-space of Bbus matrix [redacted] (graph Laplacian)

[redacted]

[redacted]

Locational marginal price (LMP) map





Graph NN (GNN)

➢ Input formed by nodal features as rows

[redacted]

➢ GNN layer l with learnable parameters

[redacted]

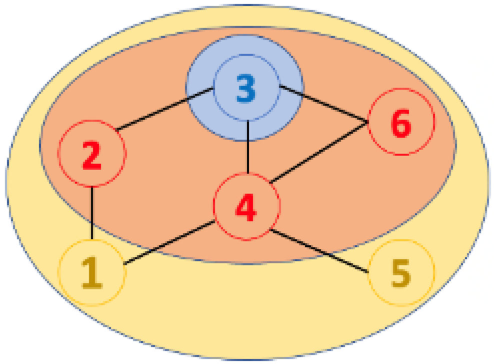
- Topology-based *graph filter* [redacted]

[redacted]

- Feature filters [redacted] for higher-dim. nonlinearity

➢ GNN used for grid fault location [Li-Deka'21]

Hamilton, William L. "Graph representation learning." 2020.
https://www.cs.mcgill.ca/~wlh/grl_book/



$$\mathbf{W} = \begin{bmatrix} W_{11} & W_{12} & 0 & W_{14} & 0 & 0 \\ W_{21} & W_{22} & W_{23} & 0 & 0 & 0 \\ 0 & W_{32} & W_{33} & W_{34} & 0 & W_{36} \\ W_{41} & 0 & W_{43} & W_{44} & W_{45} & W_{46} \\ 0 & 0 & 0 & W_{54} & W_{55} & 0 \\ 0 & 0 & W_{63} & W_{64} & 0 & W_{66} \end{bmatrix}$$

Input feature X^0 is a 6xd matrix

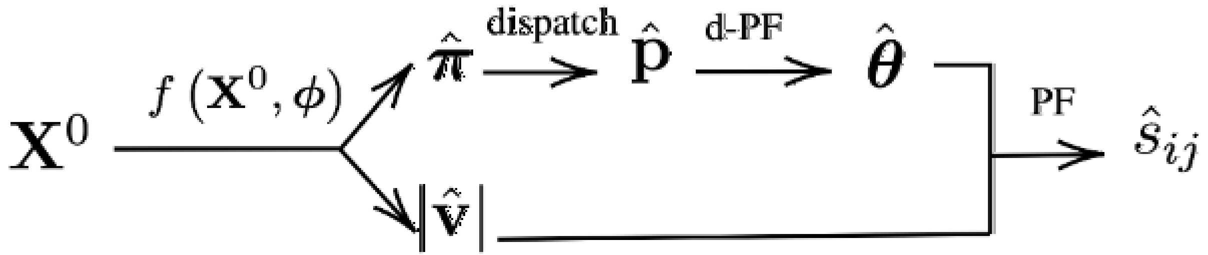
Prop. 1 *(GNN complexity)*:
If lines are sparse [redacted] and let [redacted], then the **number of parameters** for each GNN layer is [redacted]

Compared to FCNN's [redacted]

From GNN outputs to OPF variables

- ➢ LMP decides (feasible) p from economics [redacted]
- ➢ Decoupled (d-)PF approximates angle [redacted]

- ➢ GNN outputs of LMP and [redacted] can fully determine the power flow



Liu, Shaohui, Chengyang Wu, and Hao Zhu. "Topology-aware Graph Neural Networks for Learning Feasible and Adaptive AC-OPF Solutions," submitted. https://arxiv.org/pdf/2205.10129

Feasibility regularization (FR)

- Loss function for predicting LMP and [redacted]

[redacted]

  - Infinity-norm on LMP due to its larger variability than [redacted]

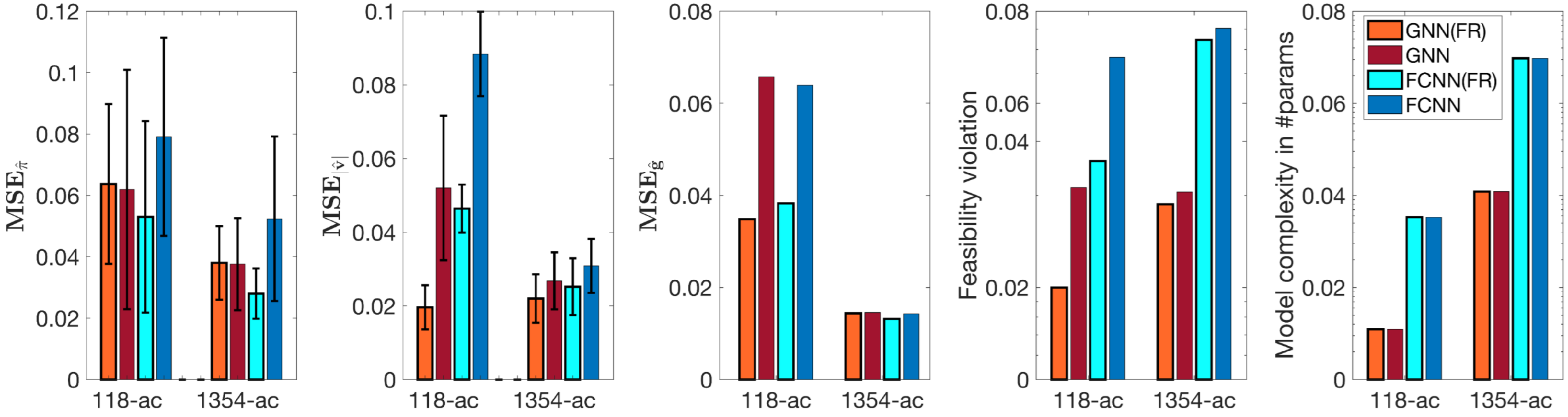
- Network-wide line limits are difficult to satisfy
- FR to reduce line flow violations: [redacted] $\lambda \left\| \mathbb{P}_{[\mathbf{0},\infty]} [\hat{\mathbf{s}} - \bar{\mathbf{s}}] \right\|_1$

Prop. 2 *(Feasibility):* ac-FR based OPF learning is a *fully feed-forward* NN. The proposed FR term still allows for efficient using ***autograd*** and ***backpropagation***. The feasibility of both predicted [redacted] and [redacted] can be strictly enforced via projections, as well.

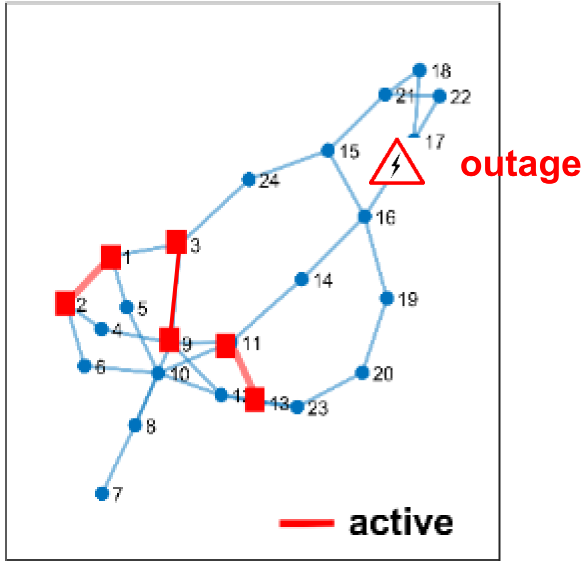
Liu, Shaohui, Chengyang Wu, and Hao Zhu. "Topology-aware Graph Neural Networks for Learning Feasible and Adaptive AC-OPF Solutions," submitted. https://arxiv.org/pdf/2205.10129

Benchmark results

- 118-bus and 1354-bus for ac-opf
- **Metrics:** normalized MSE; line flow limit violation rate; model complexity
- GNN, FCNN, both + feasibility regularization (FR)

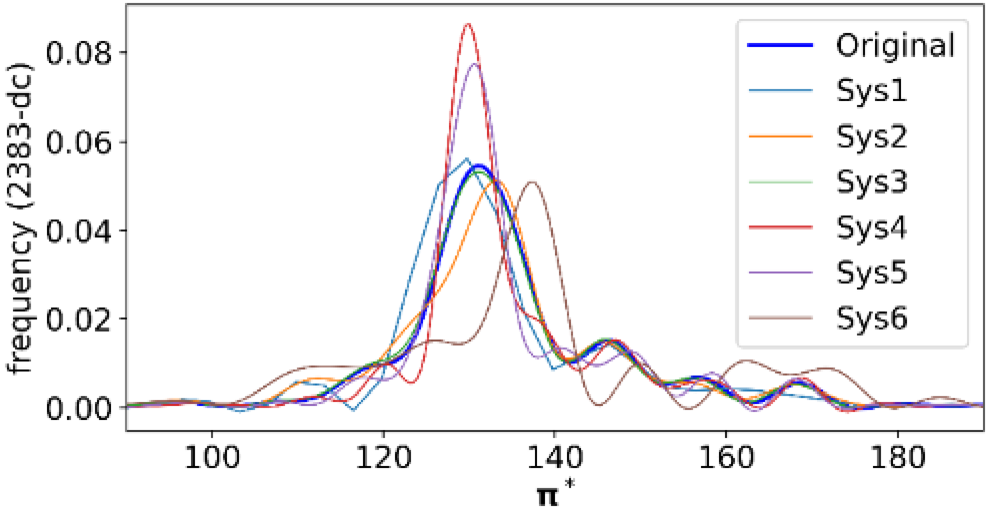


OPF learning under contingency



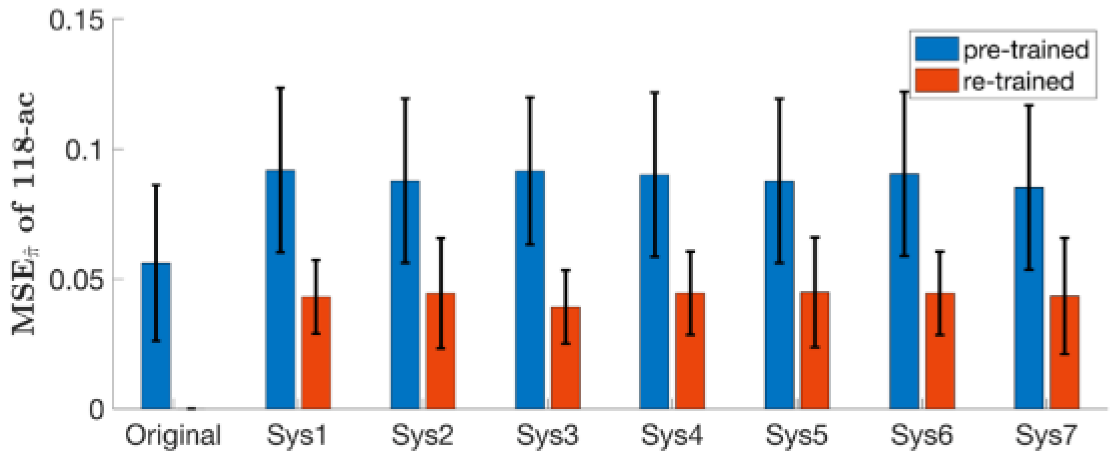
- Topology-agnostic NNs lack in transfer capability
  - Sample re-generation and re-training are time-consuming
- OPF outputs tend to be stable under line outages
  - Thanks to stability of the eigen-space

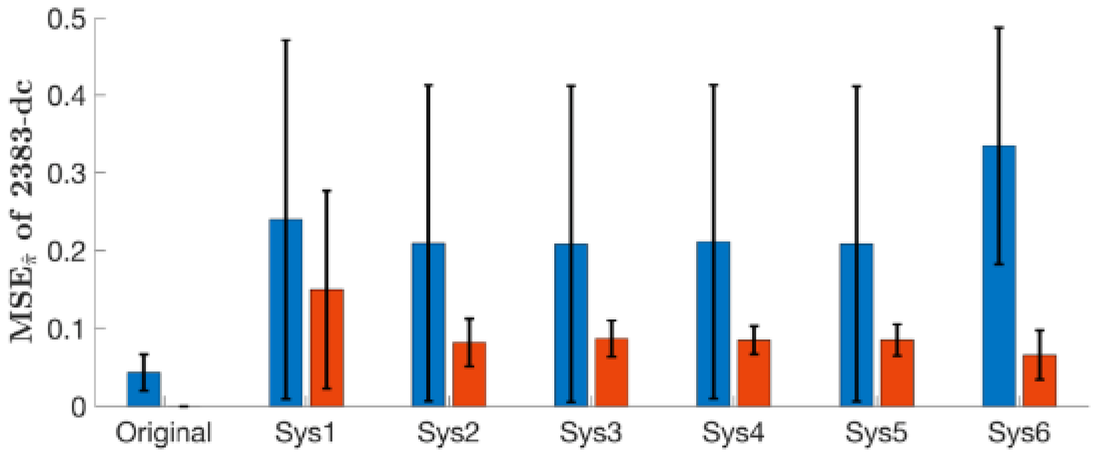
    [redacted] with [redacted]
  - LMP outputs slightly vary with the outages of multiple lines (of high capacity)
- We have established analytical bounds for this perturbation on graph subspace



GNN topology transfer learning

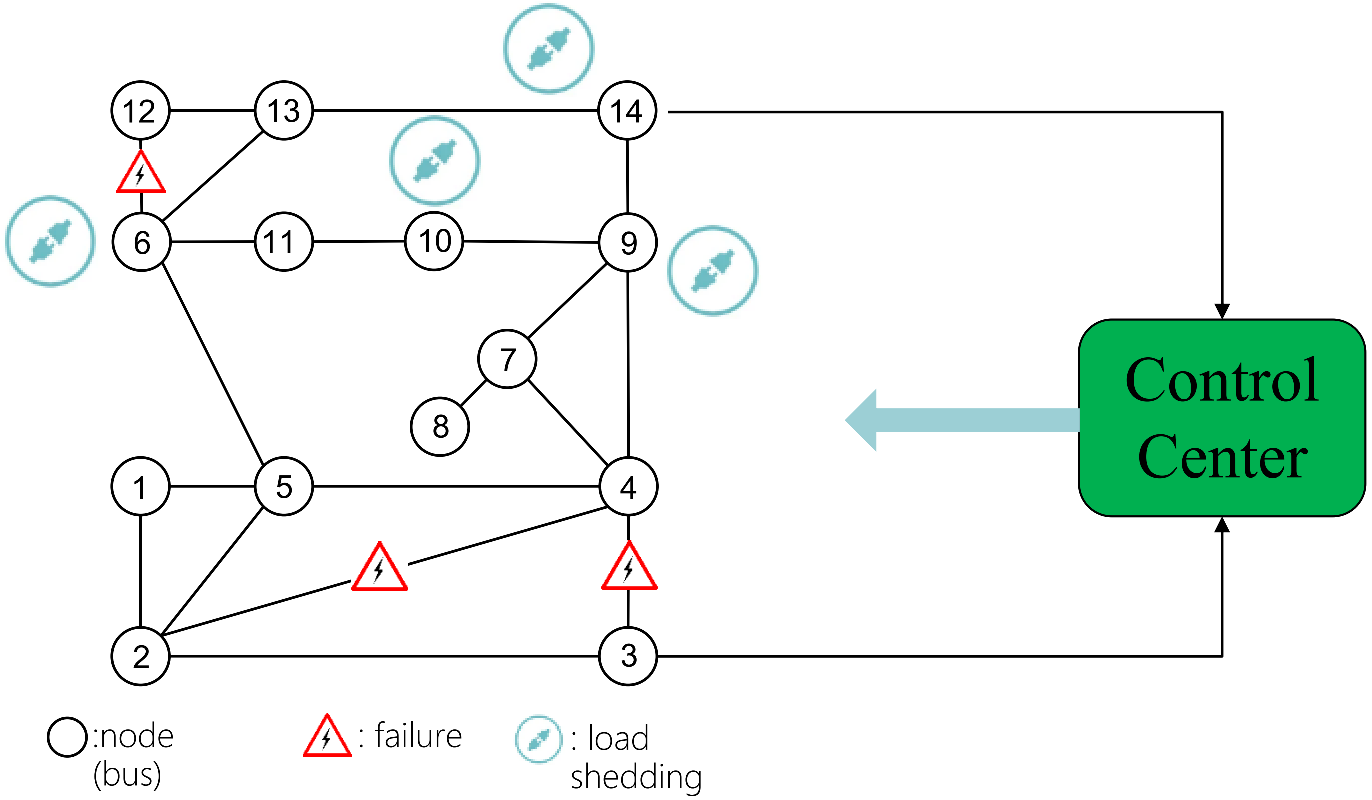
- Perturb the original system with the outages of 2-4 lines of high capacity
- Pre-trained GNN for the original system has reasonable error rates
  - warm-start the re-training using only half of samples
- GNN exhibits excellent adaptivity to the varying grid topology
  - Re-training takes *only 3-5 epochs* to converge to the original performance





Learning for resilient operations

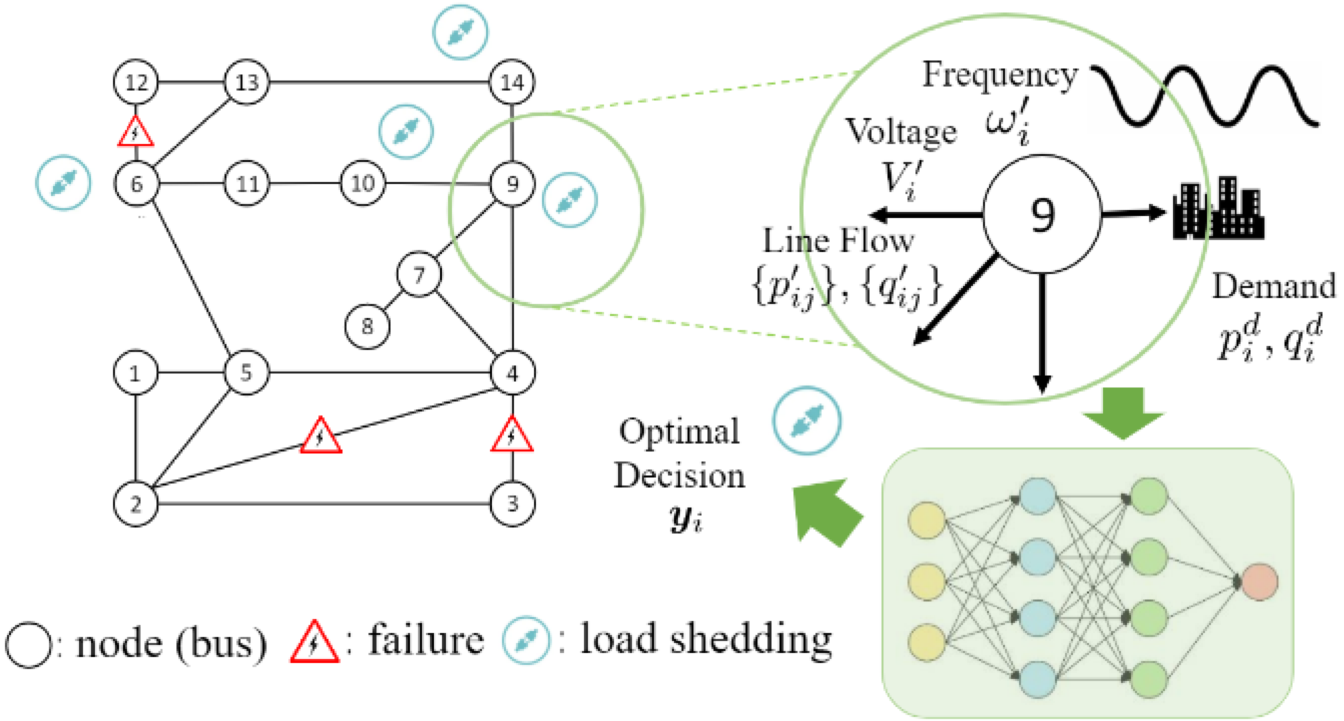
- Grid resilience challenged by resource variability and extreme weather
- Optimal load shedding (OLS) is a special case of ac-OPF



- Centralized optimization using system-wide information
- However, need very fast-speed communication links and computation capability
- Can we use ML to enable *scalable OLS* at each node using *local information* only?

ML for decentralized load shedding

- Each load center learns the decision rule from historical or synthetic scenarios



- Input feature:

$$\boldsymbol{x}_i = [p_i^d, q_i^d, V_i', \{p'_{ij}\}, \{q'_{ij}\}, \omega_i']$$

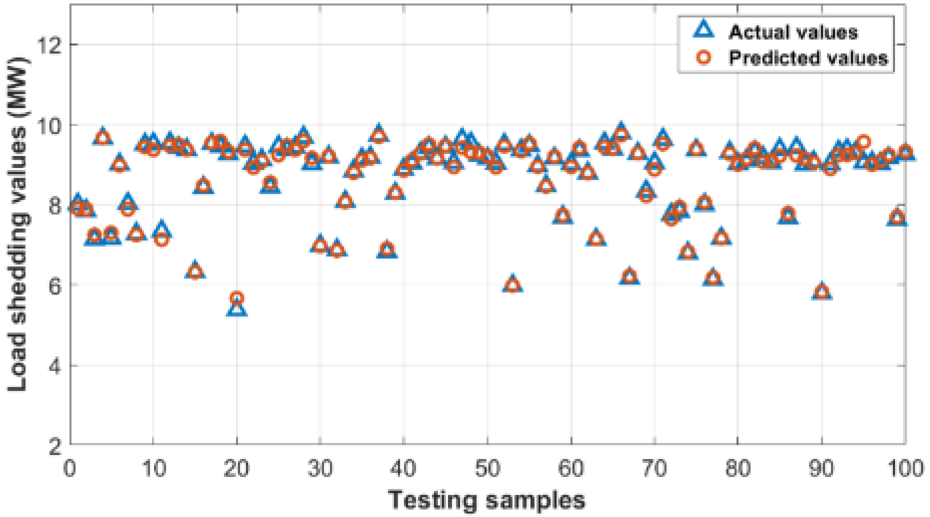
- Local reduction solutions:

$$\boldsymbol{y}_i = [p_i^s, q_i^s]$$

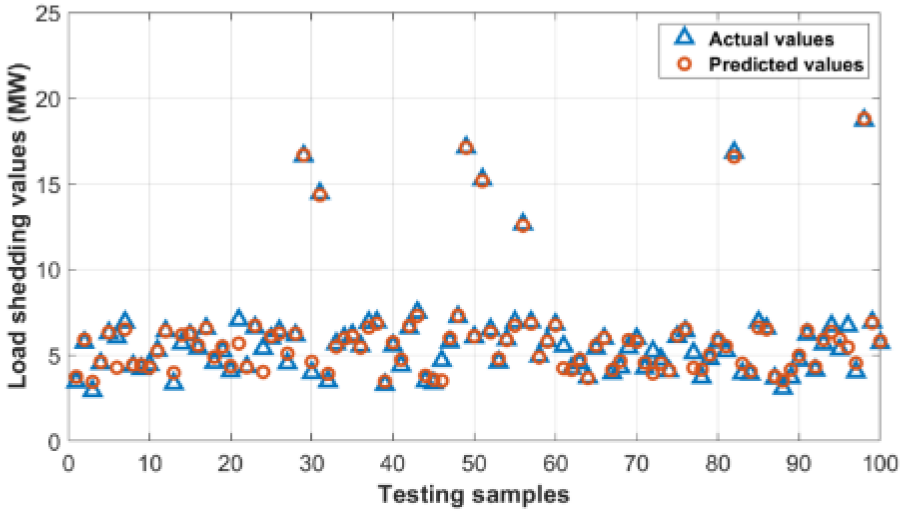
Yuqi Zhou, Jeehyun Park, and Hao Zhu, "Scalable Learning for Optimal Load Shedding Under Power Grid Emergency Operations," *PES General Meeting (PESGM)* 2022 (accepted) https://arxiv.org/abs/2111.11980

Prediction under single line outage

- IEEE 14-bus system; quadratic cost functions
- All $(N-1)$ contingency scenarios, under different load conditions (1000 samples for each scenario)



(a) Load center at bus 10



(b) Load center at bus 14

Learning and Optimization for Smarter Electricity Infrastructure

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Learning for grid resilience

Learning for dynamical resources

Learning for inverter-based resources

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Thank you!