The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

Climate Change AI

Tackling Climate Change with Machine Learning workshop @ ICML 2021

Graph Neural Networks for Learning Real-Time Prices in Electricity Market

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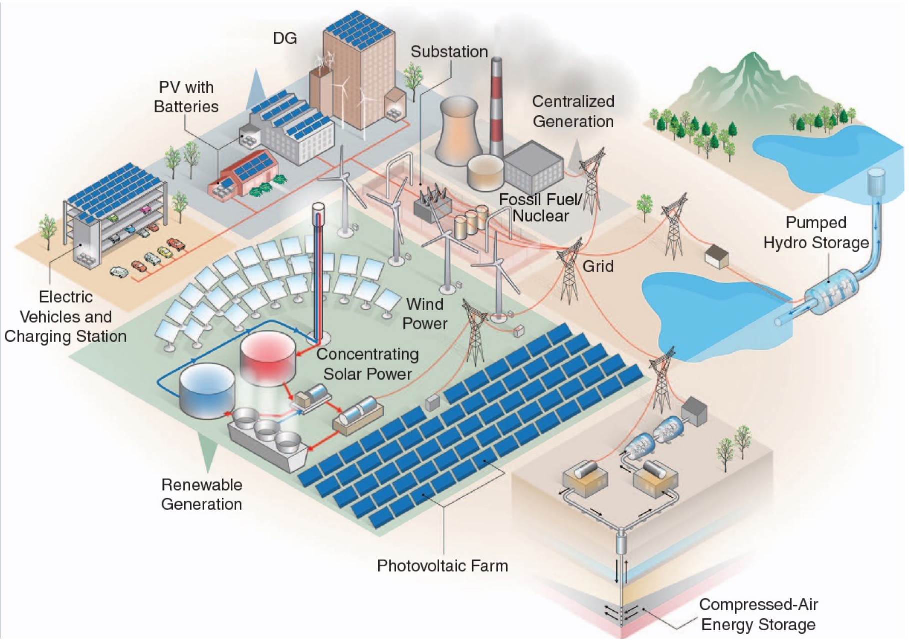
Motivations

- Optimal scheduling of grid resources reduces operational costs and Greenhouse Gas (GHG) emissions [Yang et al., 2015]
- Integration of renewable resources increases variability of the power grid that requires real-time, adaptive solutions
- Leverage the grid structural properties to learn optimal dispatch of energy resources in real-time [Owerko et al., 2015; Geng & Xie, 2016]



Grid Integration of Renewable Energy Sources
(Source: Alfred Hicks, NREL.)

Optimal Power Flow (OPF)

- Optimal nodal (generation) injections and corresponding power (line) flows for stochastic system profile that minimize the cost

$$\min_{\mathbf{p},\mathbf{q},\mathbf{v}} \quad \textstyle\sum_{i=1}^{N} c_i(p_i) \tag{1a}$$

$$\text{s.t.} \quad \mathbf{p} + \mathrm{j}\mathbf{q} = \mathrm{diag}(\mathbf{v})(\mathbf{Y}\mathbf{v})^* \quad \textbf{Flow balance} \tag{1b}$$

$$\underline{\mathbf{V}} \le |\mathbf{v}| \le \bar{\mathbf{V}} \tag{1c}$$

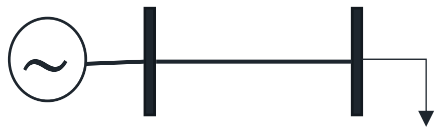
$$\underline{\mathbf{p}} \le \mathbf{p} \le \bar{\mathbf{p}} \tag{1d}$$

$$\underline{\mathbf{q}} \le \mathbf{q} \le \bar{\mathbf{q}} \tag{1e}$$

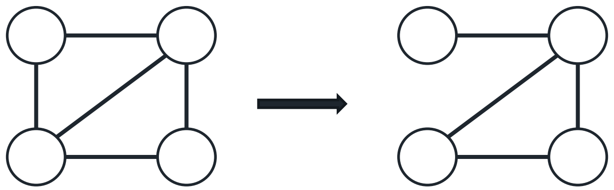
Nodal constraints:
- **Voltage**
- **active, reactive power**

Flow limits

$$\underline{f}_{ij} \le f_{ij}(\mathbf{v}) \le \bar{f}_{ij}\,, \quad \forall (i,j) \in \mathcal{E} \tag{1f}$$



Power Network



Topology Change

Optimal Power Flow (OPF)

- Optimal nodal (generation) injections and corresponding power (line) flows for stochastic system profile that minimize the cost

- Linearized DC-OPF problem:

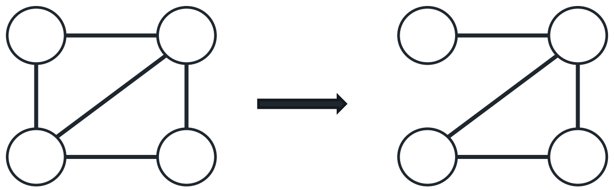
$$\min_{\mathbf{p}} \quad \sum_{i=1}^{N} c_i(p_i) \tag{2a}$$

$$\text{s.t.} \quad \mathbf{1}^\top \mathbf{p} = 0 \tag{2b}$$

$$\underline{\mathbf{p}} \leq \mathbf{p} \leq \overline{\mathbf{p}} \tag{2c}$$

$$\underline{\mathbf{f}} \leq \mathbf{S}\mathbf{p} \leq \overline{\mathbf{f}} \tag{2d}$$

Power Network



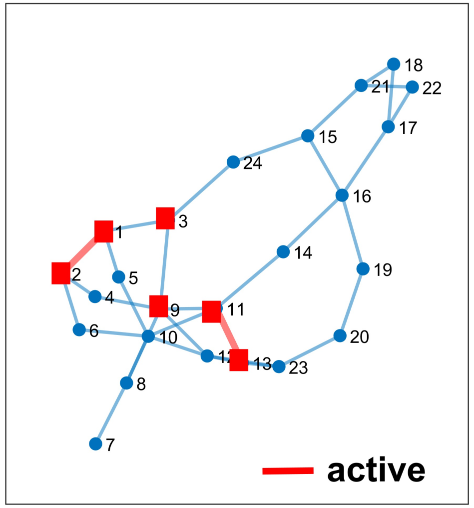
Topology Change

Topology Dependent Market Prices

- Locational marginal price (LMP) by solving dual problem

$$\boldsymbol{\pi} \triangleq \lambda^* \cdot \mathbf{1} - \mathbf{S}^\top(\bar{\boldsymbol{\mu}}^* - \underline{\boldsymbol{\mu}}^*) \quad (3a)$$

  - $\overline{\boldsymbol{\mu}}^* - \underline{\boldsymbol{\mu}}^*$ indicates the network congestion patterns
  - ISF $\boldsymbol{S}$ strongly depends on topology thus $\boldsymbol{\pi}$ has locality property



Line congestions and affected nodes

- LMP generated by the eigenspace of the graph Laplacian

$$\mathbf{S}^\top = \mathbf{B}_r^{-1}\mathbf{A}_r^\top\mathbf{X}^{-1} = \mathbf{U}\mathbf{\Sigma}^{-1}\mathbf{V}^\top\mathbf{X}^{-\frac{1}{2}} \quad (3b)$$

  - Weighted Laplacian $\boldsymbol{B_r} = \boldsymbol{A_r^\top X^{-1} A_r}$ given graph incidence $\boldsymbol{A_r}$ and reactance $\boldsymbol{X}$
  - Assume SVD $\boldsymbol{A_r^\top X^{-\frac{1}{2}}} = \boldsymbol{U\Sigma V^\top}$

Topology-aware Learning for Market Prices

- Solution chain of OPF problem:

$$\mathbf{X} \xrightarrow{f(\mathbf{X};\boldsymbol{\theta})} \hat{\boldsymbol{\pi}} \xrightarrow{\text{argmin}\, \boldsymbol{p}(\hat{\boldsymbol{\pi}})} \mathbf{p}^*(\hat{\boldsymbol{\pi}}) \xrightarrow{\mathbf{S}} \hat{\mathbf{f}}^*(\hat{\boldsymbol{\pi}}) \tag{4}$$

- Loss function with regularization on feasibility:

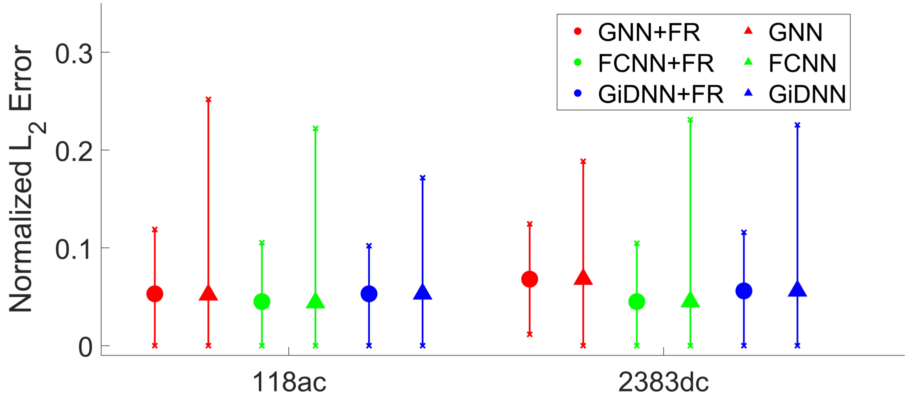
$$\mathcal{L}(\boldsymbol{\theta}) := \|\boldsymbol{\pi} - \hat{\boldsymbol{\pi}}\|_2^2 + \lambda \|\sigma(|\hat{\mathbf{f}}^*(\hat{\boldsymbol{\pi}})| - \bar{\mathbf{f}})\|_1 \tag{5}$$

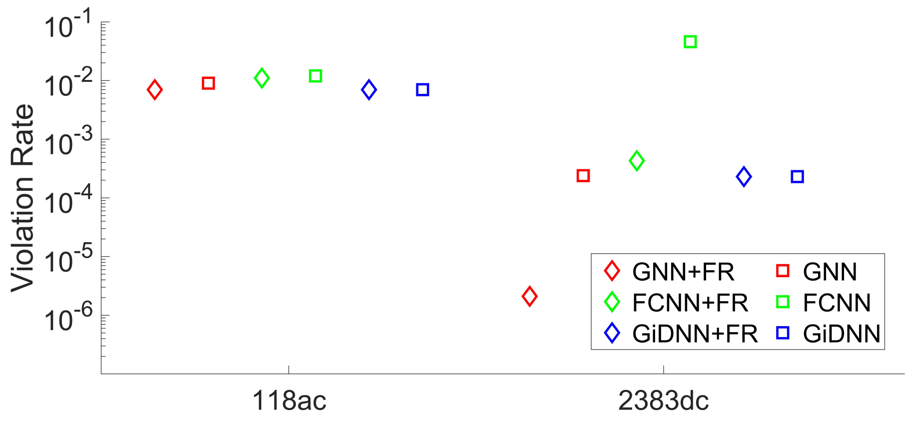
- Graph neural network (GNN) model:

$$\mathbf{X}_{t+1} = \sigma\left(\mathbf{W}\mathbf{X}_t\mathbf{H}_t + \mathbf{b}_t\right) \tag{6}$$

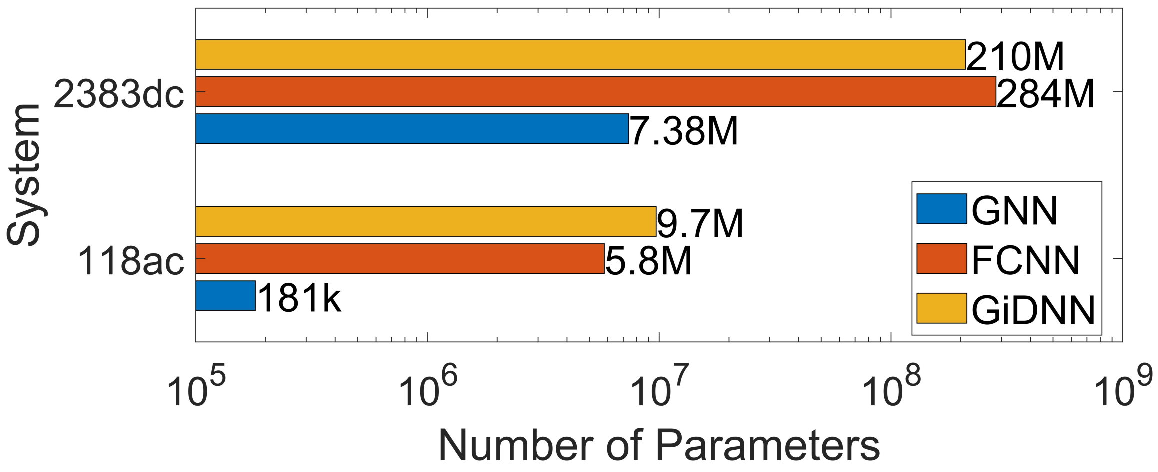
  - Topology-aware with graph convolution filter *W*
  - Reduce the number of parameters per layer significantly

Numerical Validations

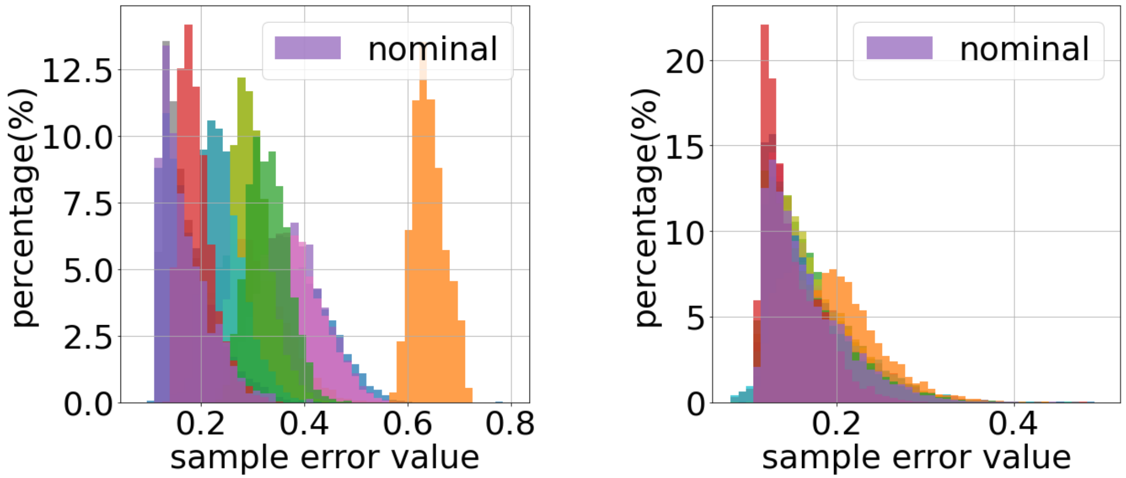




Validation error and feasibility



Scalability



Topology adaptivity

Future Work

- ❑ Incorporate environment effects in the formulation and quantify impacts on reducing GHG emissions
- ❑ Analysis of topology adaptivity for the efficiency of resource dispatch
- ❑ General optimal resource allocation problems in networked systems

Thank you!

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