Learning Power Flow Mappings for Power Grid Simulation

Presentation Link: https://youtu.be/9vA_WmSLdqY

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Motivation and Project Objective

- Power system simulation engines are essential tools for power grid operation and planning.
- Simulations are computationally expensive for large networks and utility model accuracy can be limited.

Project Objective

- Develop deep learning framework for learning 3-phase unbalanced power flow simulation outputs.
- Analyze how knowledge about network characteristics improves performance.

Datasets and Features

Dataset:

- Generate data for each power network with GridLAB-D simulator [1].
- 82,080 samples training, 2,880 samples validation, 2,880 samples testing.
- Calibrate power networks to be in nonlinear power flow regime.

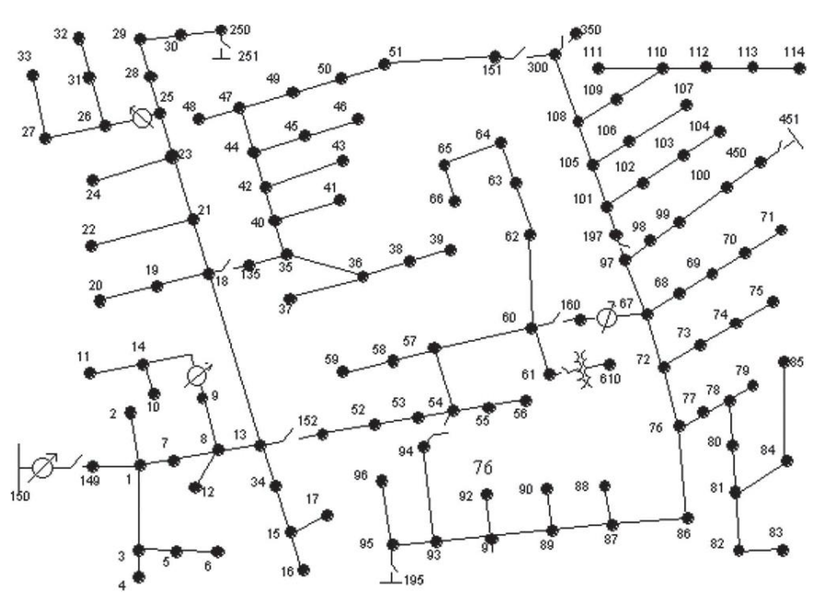
Features:

- Inputs: Real power injections at nominal voltage at each bus
- Outputs: Voltage magnitude at each bus in power network
- Other information: adjacency matrix of power network and phase of power injections

Power network case studies

Power network	Voltage (output) dimension	Power (input) dimension
IEEE 4	12	3
IEEE 13	48	22
IEEE 123	402	95
GC-12.47-1	108	9
R1-12.47-3	297	37
R2-12.47-2	2553	214

IEEE 123 bus power network topology



Models

Baseline models:

- Fully connected network (L=1,2,3)
- Linear regression

Model	# of Parameters
Linear regression	$(n_x+1)n_y$
Fully connected, L=1	$(n_x+1)n_h+(n_h+1)n_y$
Convolutional NN	$(n_x+1)n_y+9+n_y^2$

Convolutional NN:

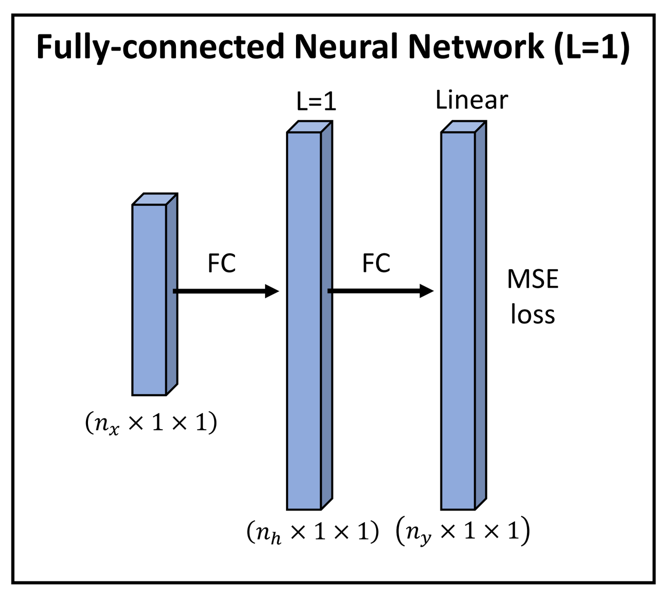
- Incorporate knowledge of the phase of the power injections using channels and apply convolutions to learn dependencies between the three phases of power distribution.

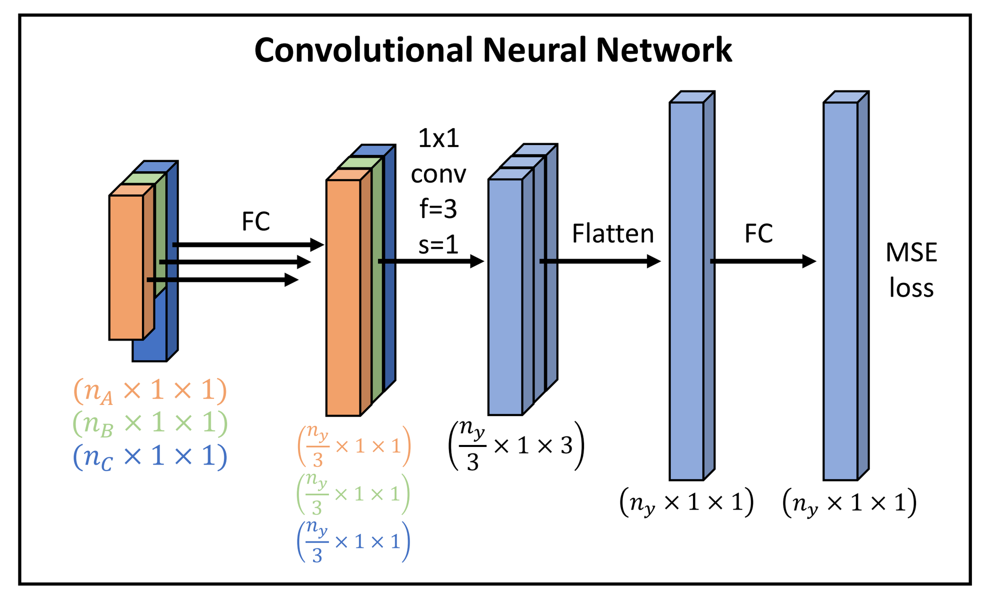
Graph Convolutional Network [1]:

- Utilize information about network topology/sparsity
- Poor preliminary results due to (1) model not capturing spatial differences and (2) large # of layers needed to propagate information for large power networks.

Model Training:

- Adam optimization, mean squared error loss
- Hyperparameters: activation (tanh and ReLU), L2 regularization, # of FC layers, # of hidden units





Performance Metrics

- Normalized voltage magnitude error: worst case voltage prediction over all buses for sample i

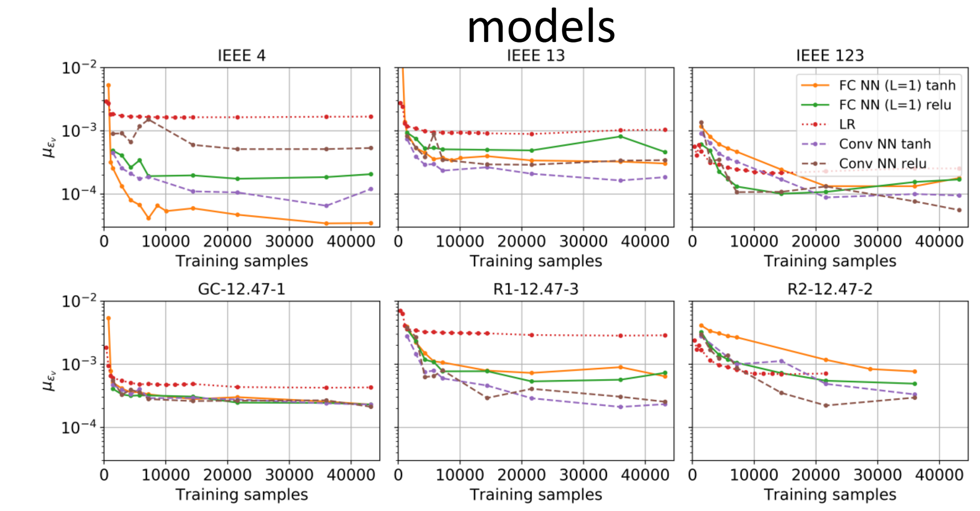
$$\epsilon_v^{(i)} = \left\| \frac{\hat{V}^{(i)} - V^{(i)}}{V^{(i)}} \right\|_\infty$$

- Mean over m samples:

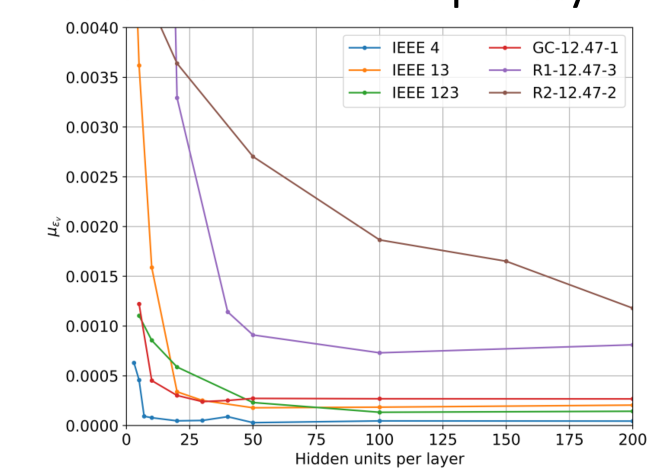
$$\mu_{\epsilon_v} = \frac{1}{m}\sum_{i=1}^{m} \epsilon_v^{(i)}$$

Results

Prediction errors vs. training set size for all models

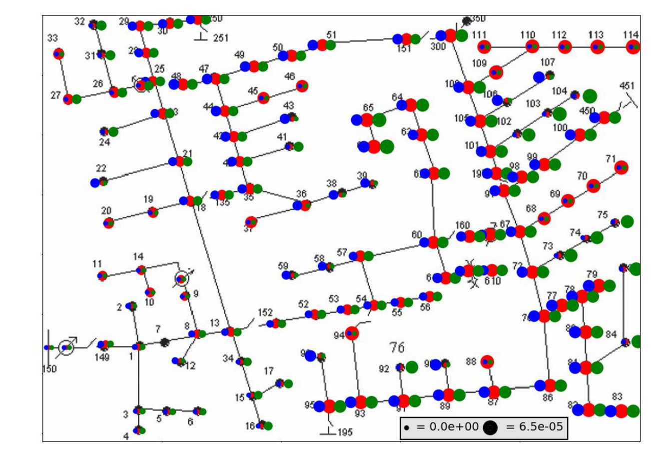


Fully-connected model: error vs. hidden units per layer



- Convolutional model outperforms other models in almost all cases.
- Tanh activation most reliably produces best results.
- Training data requirements scale with power network size.

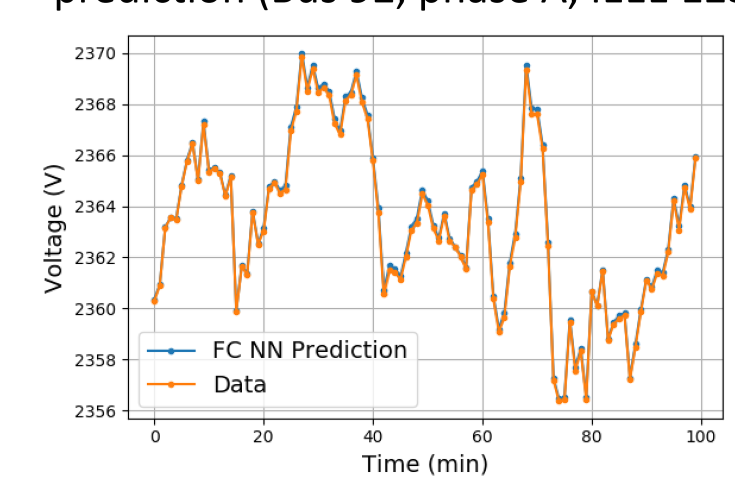
Spatial dependency of voltage magnitude prediction error



Validation and test prediction errors

Power network	Validation error μ_{ϵ_v}	Test error μ_{ϵ_v}
IEEE 4	1.103e-4	1.027e-4
IEEE 13	1.771e-4	1.718e-4
IEEE 123	9.552e-5	9.936e-5
R1-12.47-3	2.684e-4	2.586e-4
R2-12.47-2	4.627e-4	4.775e-4

Timeseries voltage magnitude prediction (Bus 92, phase A, IEEE 123)



Conclusions and Future Work

- Convolutional model significantly improves performance by accounting for the phase of the power injections and is scalable
- Error rate of convolutional model (μ_{ϵ_v}<0.0005) is appropriate for many power system simulation applications.
- Future work: Complex-valued neural networks, incorporate voltage regulators and capacitors into deep learning model

References

[1] D. P. Chassin et al., "GridLAB-D: An open-source power systems modeling and simulation environment," in 2008 IEEE/PES Transmission and Distribution Conference and Exposition. IEEE, 2008, pp. 1–5.
[1] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," arXiv preprint arXiv:1609.02907, 2016