

Project Title: Extrapolation and Directional Anisotropic Behavior of Neural Operators for Power-Flow Applications

Project Type: Master's Thesis or Semester Project

Project Description: Neural networks (NNs) and Physics-informed NNs (PINNs) are increasingly used as surrogates for power flow (PF) and optimal power flow (OPF) solvers, promising substantial computational gains. While these surrogate models achieve high accuracies within their training data, their extrapolation behavior remains poorly understood [1]. In this work, we study how PF and OPF solution operators, such as NNs and PINNs, extrapolate beyond local training regions.

The objective is to characterize and quantify the prediction accuracy for which a neural surrogate remains reliable. The project will evaluate the reliability radius with increasing network width, its directional anisotropy, and perform a curvature-based analysis. These findings offer a system-theoretic explanation for the limits of neural OPF surrogates and motivate geometry-aware strategies for their deployment. The outcome of the project will guarantee the accuracy of the predictions based on the input data.

Key tasks during the project:

- Review the literature on neural surrogates for PF/OPF, PINNs, and existing work on extrapolation and out-of-distribution generalization in neural networks.
- Implement and train NN and PINN surrogates of varying width/depth for PF and OPF operators.
- Develop a methodology to quantify the maximal reliable perturbation radius (e.g., via adversarial or worst-case perturbation search).
- Analyze how the reliability radius and its anisotropy scale with network width, depth, and physics-informed regularization strength.

Useful skills software:

- Python, familiarity with power system analysis tools (e.g., pandapower, PyPSA, or MATPOWER),
- Background in Machine learning, optimization, and numerical linear algebra,
- Basic understanding of power flow and optimal power flow formulations,
- Familiarity with physics-informed neural networks is a plus.

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Reference:

[1] A. Venzke, G. Qu, S. Low, and S. Chatzivasileiadis, "Learning Optimal Power Flow: Worst-Case Guarantees for Neural Networks," in 2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), 2020, pp. 1–7.