ETH zürich

Chair of Intelligent Maintenance Systems

Master Thesis in Machine Learning for Intelligent Maintenance:

Data-Driven Methods for Power System State Estimation with Inductive Biases

Motivation:

Power system state estimations provide critical reference for secure system operation. The recent developments of new technologies in power systems, such as the integration of renewable energy sources, have brought more uncertainty into the system operation, as well as more challenges to state estimation. Inspired by the fact that the Phasor measurement units (PMUs) in the system provide large amount of redundant data, we propose to training models directly using measurement data for power system state estimations.

The standard end-to-end learning approaches are deficient in approximating the functions in large state spaces and complex systems and they often trade off generality for data efficiency. Furthermore, they suffer from the limited interpretability because of their ’black-box’ properties. To address this challenge, researchers proposed to combine the physical models or incorporate physical information into standard machine learning models to increase their generalizability for approximating complex dynamics, such as physics-informed neural networks, graph-network simulators. We are motivated here to build data-driven models for power system state estimations, also investigate introduce physical priors or inductive biases into the models.

Task description:

The goal of this project is to develop models for power system state estimation using the large amount of condition monitoring data in networks based on deep learning methodology. The student will first study the power system model and simulate data with functions or simulation tools. In the second stage, the student will investigate Graph Neural Networks for state estimation with inductive biases and evaluate the model performance. In the third stage, the student will explore methods to further incorporate physical information or introduce inductive biases into data-driven estimators.

References:

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