



Deep Reinforcement Learning for Power Grid Control

Final Project Report

S-93G

Power Systems Engineering Research Center
*Empowering Minds to Engineer
the Future Electric Energy System*



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Executive Summary

Power grid operation and control research has gained a lot of traction due to the high penetration of distributed energy resources in power grids. These emerging distributed energy resources and their sub-optimal integration planning result in the underutilization of the power grid's transfer capability. An ample amount of research is conducted to maximize the transfer capability by using demand-side management, load shedding, generation redispatch, etc. However, these methods are more costly from a transmission system operator point of view. A more economical and effective method to maximize the transfer capability while reducing both losses and contingencies is by using the topology reconfiguration techniques. These techniques include the switching of transmission lines using the breakers (line switching - changes the total number of edges in a graph) and switching of elements at a substation between two different busbars (bus switching - may change the total number of nodes in a graph).

However, historically, when specific important lines in the power grid, either lightly or heavily loaded lines become out-of-service, it resulted in numerous power grid outage events. This inability of the transmission and generation infrastructure to support the total load on the power grid results in the long-term voltage instability (LTVI) phenomenon. This can ultimately result in a system-level blackout, islanding, or trigger other instability mechanisms. Thus, the power system operators need to assess the occurrence of the LTVI phenomenon when topological actions are performed to mitigate the thermal limit-based contingencies in the power grid.

The topology reconfiguration problem translates to a time-series planning problem for the power grids and it is computationally infeasible to obtain the global solution due to the combinatorial nature of the action space (topological actions and time-dependent loading conditions on the power grid). In addition to the high complexity of the topology reconfiguration problem, one must also track/assess the LTVI phenomenon. Unfortunately, the existing methods to track voltage instability require multiple power flows to be computed and this adds more complexity to the original topology reconfiguration problem. The proposed method helps to convert heavy time intensive deep reinforcement learning (DRL) based topology controllers to that of a moderate one to address both safety and optimal control problems in power grids as a real-time application. Hence, this project focuses on the machine learning that can learn the generalized physical laws such as distance to collapse while using only a limited amount of data.

In this project, a fast and accurate machine learning-based method is provided. This method generalized its learning by observing the small subset of the solution space to a superset of the same solution space. This enables the development of futuristic topology controllers that can assist the power system operators in real-time while also considering the aspect of voltage instability in addition to thermal-based contingencies which cause cascading events. The proposed method uses graph neural networks (GNNs) to predict the distance to LTVI phenomenon given the state of the power grid. The state of the power grid is a function of the loading at each substation as well as the topological actions performed by the operator at that current time step. Therefore, the inputs of the GNNs are the adjacency matrix and loading conditions of the power grid. The outputs of the GNNs predict the distance to LTVI phenomenon given the input information. The training dataset included only a subset of the solution space i.e., topological actions that impact only one substation at a time. However, two testing datasets are used to evaluate the performance of the trained model.

Testing dataset-1 has unseen scenarios from the training dataset. Testing dataset-2 is a superset of the training dataset i.e., topological actions that impact two substations at a time. It is highly desired for the machine learning model to not only be very fast but also highly accurate and generalize its learning to unseen scenarios. Thus, high accuracy on both testing datasets indicates the best performance of the trained machine learning model. The intuition behind using the GNNs for generalization is due to its message-passing feature which uses the computational graph derived based on the neighborhood of a given node in the graph.

The trained GNNs have 94% accuracy on testing dataset-1 and surprisingly it also generalizes well for the unseen superset scenarios i.e., 93% accuracy on the testing dataset-2. It is shown that the proposed model using GNNs is 1440 times faster than the state-of-the-art recently published methods with an accuracy of 94% and especially, it generalizes very well for new topologies. Thus, making the proposed method more attractive to be used in developing the real-time topology reconfiguration controllers for power system operators in control centers. This not only optimizes the transfer capability of the power grid, but it also ensures the safety of the operation of the power grid.

The proposed method is added as a feature to an existing open-source software called Grid2Op, developed by the RTE, a utility based out of France. Grid2Op helps the users to develop both expert systems as well as reinforcement learning-based topology controllers for power grid operation and control. This research-grade software along with the added feature from this project can now enable to development of an AI recommendation system in control centers for topology reconfigurations while also considering the safe operation of the power grid.