



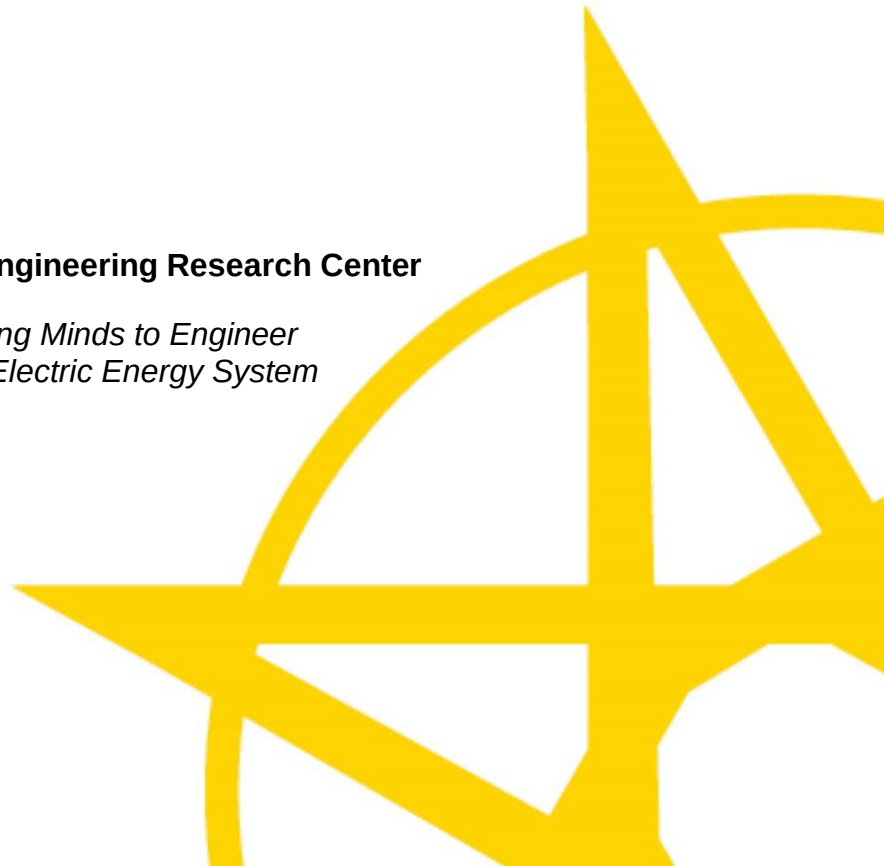
Machine Learning Based Preventive and Corrective Control to Prevent Cascading Failures Following Large Disturbances

Final Project Report

S-94G

Power Systems Engineering Research Center

*Empowering Minds to Engineer
the Future Electric Energy System*



Machine Learning Based Preventive and Corrective Control to Prevent Cascading Failures Following Large Disturbances

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Executive Summary

Power systems are becoming more complex due to the high penetration of renewable energy and integration of distributed energy resources. The introduction of electric vehicles, also increases the uncertainty due to the nature of the device characteristics and operation pattern decided by the user behavior increasing the complexity of system operation, especially emergency control. Reinforcement learning (RL) techniques now have been widely explored and applied to various electric power operation analyses under different control structures. With massive synchronized data from phasor measurement units (PMU), it is possible to explore the application of RL to ensure that electricity is delivered reliably.

Steady state stability control with RL has been studied by many researchers, while the system dynamic stability and performance after serious disturbances using RL has not been examined. However, the current control algorithms utilized in the power system dynamic control primarily utilize a discrete action space, the performance of which is not satisfactory when dealing with a parameter adjustment problem within a certain range. Hence, this project focuses on the continuous reinforcement learning methods to deal with system dynamic control problems after a disturbance.

This research applies the deep deterministic policy gradient (DDPG) approach integrated with detailed time-domain simulations to develop generator controls to prevent cascading voltage failures following large disturbances. The study in this report utilizes detailed time-domain simulations interfaced with reinforcement learning to determine appropriate generator control actions for voltage control. The DDPG controller regulates the magnitude of the voltage reference value of the generator's excitation system to achieve generator output regulation and bus voltage restoration in the vicinity of the disturbance area. In the DDPG algorithm, two hidden layers with rectified units of ReLU and Tanh are applied to the actor network and two hidden layers with ReLU are applied to the critic network to realize policy updates. The reward structure consists of accumulated voltage variations and generator regulation values in considering the system cost to realize voltage regulation. Historical data of voltage and voltage rate of change are also discussed when designing the reward function, to achieve a better voltage restoration level and dynamic performance.

The dynamic simulation and training platform is built based on the power system simulation software Siemens-PTI PSS/E and Python. The power grid operation environment is created through the API available in PSS/E to simulate dynamic changes on the power grid side. The IEEE 9-bus system and 2000-bus Texas synthetic grid system are used as the test systems, based on which time-domain simulations are conducted and interfaced with the reinforcement learning controller. The results show that the controller can provide accurate commands to the excitation system in real time based on the system operating conditions. The process of voltage recovery is stable and fast under the control of the DDPG controller, without which the system voltage would degrade slowly and enhance the risk of losing stability when only the conventional generator control is used.