Contingency Screening in Power Systems Using a Combination of Convolutional Deep Neural Network and a Self-attention Mechanism

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Total amount requested: $25,000.

Background and Vision: Power systems are fundamental for various critical services and infrastructures. Ensuring stability and reliability of power systems is essential to prevent disruptions that could lead to cascade failures. Due to the increasing diversity of resources and evolving operating paradigms, the current power system continues to approach its stability limit, while the demand for power keeps increasing. Moreover, due to climate change, power systems are experiencing more extreme weather-related events than ever. Therefore, it is important to develop an efficient tool that can predict and detect contingencies in power systems in an accurate and timely manner, and, at the same time, to recommend appropriate remedial actions to stabilize systems following contingencies. Iteration methods such as Newton-Raphson and Gauss-Seidel are often used to determine system stability. However, they are very time-consuming and have converging problems. When the topology of the system keeps changing, the iterative methods expose more drawbacks in dealing with nonlinearity and randomness of inverter-based resources [1-3]. Machine learning is emerging as a promising method to solve optimization in power systems. It can deal with nonlinearity of the system and have computational advantages [4-6]. Therefore, we propose a novel framework to screen system contingencies in real-time using a combination of convolutional deep neural networks and a self-attention mechanism. All parameters of the power networks are rearranged in an image-like shape of a multi-channel image where each channel is a two-dimensional matrix. The proposed approach is adaptive with every input size of power systems as well as frequent variations of network topologies without intervention to the framework core. The encompassment of all power system contexts in which all parameters of internal elements, and topology information are included, contributes to the higher accuracy of inference compared to other current machine-learning-based methods. Besides, the proposed framework established on ubiquitous platforms is effortlessly integrated into current infrastructures of power systems, and the great efficiency along with the computation speed may serve as a critical point for practical implications, such as enabling faster decision-making during real-time operations, predicting system contingencies, and remedial actions based on an offline pre-trained model.

Objectives and Plan: The objective of this project is to develop an advanced tool to screen contingencies in power systems using a combination of convolutional deep neural network and a self-attention mechanism. The project will be implemented based on the following thrusts.

Thrust 1. *Develop a dynamic model of power system*. This thrust includes the development of dynamic swing equations where the data of generations, transmissions, load systems, and damping mechanisms are required. The operating conditions and other impact factors such as the operation of inverter-based resources and energy storage systems with their ability to support the system by absorbing power and fast dispatching must be considered. (*Suresh, Ping, Nga*)

Thrust 2. *Sep up a list of potential contingencies in the system*: In the first step of this thrust, we will consider all N-1 contingencies that can happen. The main contingencies include loss of generators, loss of transmission lines, loss of load, which are the most popular and severe events. For N-1 contingencies that do not make the system unstable, N-2 contingency screening will be implemented. The screening will continue until N-n, when the events don't have significant impacts on the system stability. For unstable contingencies, remedial actions will be recommended as in Thrust 3. (*Nga*)

Thrust 3. *Develop the learning model combining convolutional deep neural network (CDNN) and a self-attention mechanism to find angle and voltage trajectories*: To determine if the system is stable following a contingency, a system of swing equations is solved. This solution nests a power flow

solution to determine the trajectory of the angle of each generation and voltage at each bus. The shortest time at which the remedial actions are implemented will be considered as fault-isolate time. CDNN and a self-attention mechanism will be used in this step to speed up the process of power flow solution. The steps of this thrust are as follows:
Step 1: Densely Connected Network can map a rule that is homologous with the non-linear equations of the Newton-Raphson method [7]. Its purposes are to indirectly find a solution via trainable layers' weights (e.g., weight, bias), and to directly find the solution of voltages and generation powers by the iteration procedure as for the Newton-Raphson method. (*Suresh, Ping*)
Step 2: The integration of a self-attention layer will cover the drawbacks of not catching the quantity of interdependence and the correlation between the network's features. This layer with the trainable weights constitutes the contribution of each feature to the rest, and it plays the role of the controller to adjust trainable weights, which maps a rule of the constraints of the power flow problem. From the results of power flow, angle and voltage trajectories of all buses in the system can be determined, which show the stability after each contingency. (*Suresh, Ping*)
Step 3: Recommend remedial actions: these actions include corrective actions and preventive actions. Preventive actions, which include generation shifting and load shifting, will first be implemented to prevent the occurrence of unstable events. If preventive actions cannot be applied, corrective actions will be implemented immediately following the unstable contingencies. The regulation for remedial actions will be determined based on the trajectories of the generator angles. (*Nga*)

Thrust 4. *Validation of the proposed tool on the miniWECC system* in a real-time and power hardware-in-the-loop simulator (The Opal-RT simulator). The EECS Department at UW has eight Opal-5700 real-time simulators (OPAL-RT) – one of the largest OPAL-RT systems owned by universities in the U.S. The simulator plays a critical role in performing demonstrations of system stability of large-scale power systems which include thousands of buses in real-time. The speed and accuracy of the proposed tool will be compared with the existing tools to prove the efficacy of the project. (*Nga*)

Technical Qualifications: The PI has participated in several grants related to power-system stability, modeling, and control, and is currently working on a DOE project and an NSF Career project. The co-PIs have been working in the application of machine learning in diverse areas and working on many DOE and NSF projects for many years. Our team has published more than 150 peer-reviewed articles in journals and conferences on power systems and computing.

Impacts: The proposal falls into two goals of the Tier 1 Engineering Initiative: 1) *Excellence in Undergraduate Education*: the project provides the students in the College of Engineering and Physical Sciences the chance to work and implement their project on a simulator that can model the real power systems (it is nearly impossible that they can test their experiments in real power systems). 2) *World-Class Research and Graduate Education*: The project can also potentially shape research in supporting the application of machine learning in power systems and can act as an initial step toward more early warning tools, operator decision support tools, and better grid asset management. In summary, the project will then be developed to become a full proposal to submit for external funding.

Potential partner: The PI has a strong connection with the power group at Sandia National Laboratories (SNL). The PI has been working with the University of North Dakota, South Dakota State University, Wichita State University, University of Utah, Michigan State University, Michigan Tech University, University of Connecticut in several other proposals. Therefore, these universities and SNL can be our potential partners in this project.

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References:

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Budget Justification

- 1 Master student (2024 – 2024):
  - Tuition and Fees: $7,470
  - Health Insurance: $2,855
  - Stipend: $12,825
  - Fringe benefit: $231

Total for one graduate student: $23,381

- Travel funding for one graduate student to go to conference to present the results: $1,619

Total = $25,000