Integrating Graph Neural Operator with MOOSE Framework for Enhanced Transient Modeling and Real-Time Data Assimilation

PI: Yang Liu, Texas A&M University

Collaborators: Romit Maulik, Pennsylvania State University; Ling Zou, Argonne National Laboratory; Som Dhulipala, Idaho National Laboratory

Industry Collaborator: Patrick Everett, Oklo Inc.

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ABSTRACT:

Advancements in nuclear reactor technology hinge on the ability to accurately model and simulate complex systems to ensure safety, efficiency, and regulatory compliance. The Multiphysics Object-Oriented Simulation Environment (MOOSE) framework has been instrumental in this endeavor, offering robust capabilities for modeling advanced nuclear systems. However, current MOOSE-based modeling and simulation tools face significant challenges when dealing with long-duration transient simulations of advanced reactors. These challenges arise due to the complex geometries and tightly coupled multiphysics phenomena that demand multi-dimensional models, leading to computationally intensive and time-consuming simulations.

To address these critical challenges, we propose a transformative approach that integrates Physics-Informed Machine Learning techniques directly into the MOOSE framework. Specifically, we introduce the GNO-MOOSE differentiable hybrid solver, which incorporates Graph Neural Operators (GNOs) into MOOSE's existing capabilities. This integration leverages MOOSE's built-in automatic differentiation features and Libtorch integration, aiming to significantly enhance computational efficiency without compromising accuracy. By embedding GNOs within the numerical solver, we aim to reduce computational time by allowing larger timestep sizes and coarser mesh requirements. This solver efficiently solves complex partial differential equations over extended simulation periods, which is crucial for capturing dynamic behaviors during long transients.

Furthermore, we plan to implement real-time data assimilation by coupling the GNO-MOOSE solver with Ensemble Kalman Filter (EnKF), a tool that updates model predictions by assimilating new observational data, effectively handling nonlinear systems with non-Gaussian uncertainties common in reactor operations. By incorporating the EnKF, our simulation framework can adjust model parameters on the fly, ensuring that predictions remain accurate as new data becomes available. This integration allows the simulation to refine itself based on actual reactor data, enhancing predictive accuracy and reliability.

The integrated GNO-MOOSE-EnKF framework will be applied to two challenging benchmark cases: i). a sodium fast reactor during a Loss of Flow Without SCRAM (LOFWOS) transient based on the Fast Flux Test Facility LOFWOS Test #13; and 2). molten salt reactor case based on the Molten Salt Reactor Experiment. These case studies will demonstrate improved predictive capabilities and computational performance, validating the effectiveness of our approach. This developed framework promises a transformative advancement in reactor modeling and simulation by enabling computational efficiency and real-time predictive capabilities for next-generation nuclear systems.