Active Learning Estimation and Optimization (ALEO) of Irradiation Experimental Design for Efficient Accelerated Fuel Qualification

PI: Adel Alaeddini – University of Texas at San Antonio

Collaborators: Elizabeth Sooby – University of Texas at San Antonio; Nathan Capps - Oak Ridge National Laboratory; Jacob Gorton (Co-PIs)- Oak Ridge National Laboratory

Program: RDO-5 Implementation of Artificial Intelligence and Machine Learning

ABSTRACT:

A collaborative program between the University of Texas at San Antonio (UTSA) and Oak Ridge National Laboratory (ORNL) is proposed to develop sample-efficient AI/ML methods of estimation and optimization of irradiation temperatures and fuel specimen burnups for accelerated fuel qualification. Specifically, the team will develop a novel active learning experimental design and optimization (ALEO) methodology for agile new fuel sample configurations of MiniFuel experiments in the High Flux Isotope Reactor (HFIR) at ORNL. This type of AI/ML-based methodology is not currently available in MiniFuel experiments in the High Flux Isotope Reactor (HFIR), while more agile methods for safety assessments are essential to accelerate the qualification process for fuel- beginning with irradiation test design. To achieve the best performance, a combination of preexisting simulated and real MiniFuel datasets is carefully identified. These datasets are complemented by new computational experiments guided by the proposed ALEO methodology and supervised by ORNL. Generative AI/ML models will be developed/employed to create additional data, paired with advanced deep transfer learning models to integrate different datasets. Complementing computational experiments are led by ORNL and data analytics are led by UTSA and advised by the ORNL analytics team. With the importance of efficiently accelerated fuel qualification with high accuracy at the forefront of irradiation design, planning, and analysis, it is the objective of the proposed work to complement and expand upon the current design and optimization of experiments and existing datasets by supplying:

- AI/ML-driven analog model of HFIR MiniFuel with uncertainty quantification and physics-based machine learning capabilities
- Sample efficient AI/ML-driven design of experiments (DOE) for rapid modeling of the irradiation temperatures and burnups in HFIR with high accuracy
- State-of-the-art AI/ML algorithms for rapid global optimization of sample configurations of HFIR MiniFuel along with performance analytics
- Generative AI/ML tools for creating realistic data to augment existing datasets
- AI/ML-driven methods for transfer learning from different types of simulated and actual experiments

Using these techniques systematically, the team will supply the most informative experimental settings for sample-efficient optimization of the irradiation temperatures and burnups in HFIR. The team will also create the analog model of the HFIR MiniFuel for sample-efficient simulation and optimization. The proposed work will additionally develop generative AI/ML and transfer learning arms to efficiently transfer the expensive knowledge between different yet related datasets. Furthermore, the proposed research will also include a physics-based AI/ML to bridge the gap between data and physics-driven models to further improve the sample efficiency, predictive accuracy, and explainability of the results.