Physics-Guided Smart Scaling Methodology for Accelerated Fuel Testing

PI: Hany Abdel-Khalik,
Purdue University

Collaborators:
Anant Raj, Purdue University
Khafizov Marat, Ohio State University
Colby Jensen, Idaho National Laboratory
Aysenur Toptan, Idaho National Laboratory

Program: FC2.3

ABSTRACT:

Scaled experiments for accelerated fuel testing like MiniFuel and fission accelerated steady-state tests (FAST) are set to play a crucial role in accelerating fuel development and qualification to ensure the economic competitiveness of nuclear energy. However, constrained by the limited ability for a rigorous quantitative estimate of the uncertainties when scaling from experimentally-accessible states to application/prototypical states, the nuclear regulatory bodies frequently rely on artificial scaling distortion uncertainties. These are subjectively constructed by experts based on operational data, and are usually conservatively bound, resulting in significant cost inflation. Further, there is a heavy reliance on expensive experiments, undermining the massive investment in the development of modeling and simulation tools, which otherwise, integrated with state-of-the-art machine learning tools, can be employed to obtain physics-informed, scientifically defendable, quantitative estimates of scaling of uncertainties, with the potential of a drastic reduction in the time and cost of the development of new reactor designs and new fuel concepts.

The **primary objective** of this project is to address the above challenge by employing recent advances in machine learning techniques in a non-traditional manner, allowing for an optimal use of high fidelity simulation to enable a direct mapping of experimental biases and uncertainties to the prototypical state. While any simulation is expected to be plagued by uncertainties, machine learning can be used for extracting low-uncertainty recurring patterns -- as guided by the detailed physics simulation -- which allow for the construction of a rigorous mapping kernel to map biases and uncertainties between the two states. For demonstration, the project will focus on modeling the thermo-mechanical fuel response using a rate theory-based model to capture the scaling effects related to time-dependent burnup rate calculations and their impact on fuel performance as modeled by the BISON code under the INL's MOOSE environment. Given the quantitative nature of the mapping process, the project will also develop as a **secondary objective** an experimental relevance criterion, allowing analyst to measure the value of a new experiment and its associated measurements in terms of the potential reduction in prototypical state uncertainties. This capability will prove essential in driving down the overall cost of the experimentation, as it will allow measuring the value of an experimental setup before it is conducted.