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Engineering-Informed, Data-Driven Degradation Modeling, Prognostics and Control for Radiation-induced Void Swelling in Reactor Steels

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ABSTRACT:

The goal of this research is to advance the capability to model, predict and control void swelling in irradiated structural components through developing engineering-informed, advanced data-driven statistical and machine learning techniques. One of the most challenging engineering consequences of high-energy neutron irradiation to fuel cladding and structural materials is void swelling. Excess swelling not only leads to dimensional instability, but also can cause severe embrittlement of internal materials. Void swelling is a complex process depending on many input conditions, such as alloy composition, material structure, processing conditions, and irradiation conditions. So far, significant efforts have been attempted to develop physics-based models that describe how all these input conditions affect the swelling process. However, due to *the long development time frames and the necessary simplifications of physics-based models, and the large number of input conditions with complex relations* vs. *the limited availability of the experimental data in practice*, it has been very challenging for using these physics-based models to provide adequate guidance and interpretation on what will happen to materials during a reactor irradiation. These same constraints have also contributed to the current limitations in attempting to directly translate ion irradiation data to in-reactor conditions.

To address this fundamental issue, this project will establish new engineering-informed, data-driven methodologies for degradation modeling, prognostics and control of void swelling. The key to our innovative ideas is a novel machine learning concept called *transfer learning*, aiming to leverage the knowledge gained through analyzing the swelling of a sample with specific material and irradiation conditions to enhance the modeling and analysis of other samples with similar characteristics. With this approach, degradation modeling, prognostics, and control of sample volume changes can be understood across many different variables associated with a single alloy class.

The potential impact of the project will be significant and transformative. *First, from the methodological viewpoint*, this research will significantly enrich the existing literature by establishing a new integrated suite of transfer learning-enabled analytical methods, which can essentially transform our current practices in degradation modeling, prognostics, and control for applications with sparse data. *Second, from the application viewpoint*, this research will bring fundamental new knowledge and understanding of void swelling process, ensuring more effective aging management and license extension approaches. While we focus on void swelling, the proposed methods can be also applied to other degradation of materials in nuclear applications, e.g., changes of fracture toughness in reactor pressure vessels, corrosion in cladding, and fission-product swelling of fuel. Such efforts will lead to enhanced equipment safety, improved operation and maintenance, and ultimately help the U.S. gain a competitive advantage in nuclear power. Our team has the necessary collective expertise to execute the proposed project—involving data analytics, statistical learning and machine learning, condition-based monitoring, prognostics and control, and radiation damage and corrosion of materials for nuclear systems, as well as experience in leading breakthrough research initiatives. We have crafted a shared vision and a carefully developed plan to test the proposed methods and maximize the chances of success of the project.