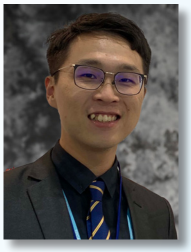
Machine Learning Emerges as a New Tool for Assessing Reactor Pressure Vessel Embrittlement

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All light water reactors in the United States (U.S.) went into service with 40-year licenses to operate. 94 reactors have had their licenses extended to 60 years, 6 have completed applications and 14 are in the review process to operate to 80 years. An important issue for extended operations is the reactor pressure vessel steel embrittlement due to high-energy neutron exposure. The reactor pressure vessel is the "outer shell" of a nuclear reactor that combined with the concrete biologic shield provides a barrier against the release of radiation and radioactive material in the event of a core-damaging accident. Over years of operation, the reactor pressure vessel steel is exposed to high-energy neutrons which can change the characteristics of the steel. For long-term life extensions of nuclear reactors, improved predictions of reactor pressure vessel embrittlement are needed.

Commercial nuclear reactors use ferritic low alloy steels for construction of the reactor pressure vessel. Assuring structural integrity relies upon accurate knowledge of the change in the materials toughness over the time the nuclear reactor will be in operation. Surveillance programs, using small samples, have been designed to assess changes in fracture properties. Test reactor data also provide valuable information on embrittlement trends, often over a wider range of fluence, but with higher flux values. All the data can be examined with physics-based models that offer excellent insights and predictive power, but they are time consuming to build and require large parallel efforts to support their underlying physical assumptions.

This is where machine learning is coming into play. Embrittlement has been extensively studied in accelerated, higher flux test reactor irradiations, but the use of test reactor data naturally raises the question of flux effects. The September 2023 study published in Acta Materialia, "Characterizing the flux effect on the irradiation embrittlement of reactor pressure vessel steels using machine learning," details a machine learning approach [1]. This approach is trained on a set of hardening data covering a wide range of flux, fluence, and steel compositions to determine the interactive effects of both irradiation and material variables on the increase in yield stress, which is the natural outcome of embrittlement.

Support for this research came from a wide variety of sources. The "ATR2 experiment," which was conducted through the Light Water Reactor Sustainability (LWRS) Program, contributed greatly to the post-irradiation examination of samples irradiated in the advanced test reactor (ATR) at Idaho National Laboratory (INL). The ATR2 experiment is a critical part in developing machine learning-based embrittlement trend curves. Furthermore, the LWRS Program is involved in initiatives to integrate machine learning models into the American Society for Testing and Materials (ASTM) E900 standard and the American Society of Mechanical Engineers (ASME) code case N-914.

Machine learning provides an advanced "data-centered" alternative approach, which reveals flux effects, without any guidance from a priori assumptions about mechanisms and models. Machine learning establishes the empirical relations between features (independent variables) and outcomes (dependent variables) based on being trained by "adequate" sets of data. Combined with improved algorithms and exponential growth in computing power, high-dimensional input data from test reactors can provide insights into the effects of combinations of variables, which might not be otherwise recognized. These new insights not only lead to better embrittlement predictions within the domain of the data, but they also inform the mechanistic approaches to dealing with possible unmodeled physics as observed in Figure 7.

The success of any machine learning model relies primarily on the depth and quality of the training data. For the study, data from the University of California Santa Barbara were used to train the model that came from the Belgian Test Reactor 2, ATR and the Irradiation Variables facility, as designed by University of California Santa Barbara and the Heavy Section Steel Irradiation program at Oak Ridge National Laboratory. In addition to various machine learning statistical tests, the research team carried out extensive analysis that included comparisons to physical models, as well as cross plot analysis for a representative set of six core steels, with systematic and controlled combined variations in their copper and nickel contents.

It is critical to emphasize that the two approaches are not an either/or issue. As noted by the authors, "The convergence of trends from both these very different approaches provides strong support for both of them." The authors point out that "Indeed, physics-based and machine learning methods are highly complementary. For example, the machine learning results provided a very useful, completely new, and quantitative insight regarding to the combined flux, fluence and alloy composition dependence of hardening."

This research holds significant practical importance and offers substantial insights into current efforts in physical modeling. Moreover, from an immediate practical standpoint, the results hold crucial significance for the life extension planning of LWR.

Reference

1. Liu, Y.-C., D. Morgan, T. Yamamoto, and G. R. Odette, 2023, "Characterizing the flux effect on the irradiation embrittlement of reactor pressure vessel steels using machine learning," Acta Mater., 256, 119144.

Figure 7. Machine learning model predicted trends are in good agreement with experiments and other physics-based models [1].