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Application of Machine Learning for Enhanced Diagnostic and Prognostic Capabilities of Nuclear Power Plant Assets

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Pathway:
Advanced Reactor Development Projects

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Abstract

Nuclear power plays a vital role in satisfying the ever-growing global demand for low-carbon energy production. However, there are persistent economic pressures, most recently from the lower cost of natural gas, that have real potential to challenge the long-term economic viability for domestic nuclear power generation. Operations and Maintenance (O&M) currently comprise 60-70% of the overall generating costs of nuclear plants. These costs are expected to rise as the longer-term operation of the existing fleet will require increased monitoring and maintenance capabilities to address the ageing of key systems, structures, and components (SSCs). Development and implementation of enhanced diagnostic and prognostic methods for predictive maintenance are necessary for reducing O&M costs and critical to managing component degradation of ageing plants.

Recent trends in the nuclear industry have focused on advancing the online monitoring capabilities of plant components and processes, resulting in the collection and retention of vast amounts of plant data. This presents a major opportunity to improve the diagnostic and prognostic capabilities of nuclear power plant assets through advanced machine learning (ML) and deep learning techniques. Machine learning is a branch of artificial intelligence focused on learning from data, extracting information, and gaining a deeper understanding of complex relationships. Its applications are incredibly diverse, including things such as computer vision, driverless cars, and analyzing MRI and CT scans. ML is particularly well-suited for obtaining the group behavior of highly non-linear operational parameters, detecting anomalies, and revealing precursors to component failure.

This project will develop and provide ML solutions to improve and extend diagnostic and prognostic capabilities for predictive maintenance in nuclear plants. These solutions will integrate vast amounts of structured and unstructured historical data from ~15 boiling water reactors (BWRs), collected over multiple fuel cycles, in order to capture the complete operational and dynamic environment of plant components. Specific project objectives are: (1) develop enhanced diagnostic and prognostic models of equipment health, by applying ML techniques for the detection of incipient faults, characterization of latent fault signatures, and identification of higher-level features which represent an orthogonal basis of degradation indicators; (2) use the breadth of data to develop models for sensor calibration, and validation, which operate across the dynamic range of plant conditions (i.e. during reactor startup, coast down, and transients); and (3) develop a standard data dictionary for key SSCs that will establish the current state of "data coverage" within the industry and inform future "data needs."

The determination of which SSCs are modeled will be initially narrowed by data sufficiency criteria determined from the integrated and structured database. The candidate SSCs will then be prioritized by the economic impact incurred from

degraded SSC performance or failure, and by specific interests of utility partners. Deep structured learning will serve to determine relationships between redundant, correlated and covariant instrument channels, and to develop higher fidelity indicators of degradation. Predictive models for component failure will be developed from these higher-level features that will enable adaptive remaining useful life (RUL) estimates, as opposed to the basic statistical averages that are currently used. The developed approaches, models, and algorithms will be validated using independent data, and cross-validated with data from plants not used for training or model development. The direct benefits of this project are to increase situational awareness of the modeled SSCs, provide real-time health assessments that enable cost-savings, optimized maintenance, and improved component reliability through early detection of faults. The technologies developed for dynamic sensor calibration and validation are expected to provide significant cost-savings through extending the intervals between successive calibrations.

The capabilities developed in this project directly benefit the industry's push for increased operational efficiencies and reductions in O&M costs. The development of enhanced prognostic and diagnostic tools will enable adoption of predictive maintenance (and health management) strategies, opposed to more labor- and capital-intensive periodic maintenance. The benefits of enhanced diagnostic and prognostics capabilities include the elimination of unnecessary maintenance, reduction of unplanned outages due to equipment failure, intelligent maintenance scheduling and allocation of resources, and increased awareness of ageing-relating degradation that may threaten plant safety. The ML methodology developed will have significant benefit for other industry participants who may not have the resources, capabilities, or institutional support to undertake these activities alone. The data dictionary and other products developed in this project can be an invaluable resource for utilities looking to increase the capabilities of their existing online monitoring system, without the costs associated with installing new arrays of sensors.