**Regulatory Implications of Advanced Technologies for Component Condition Monitoring in Nuclear Energy Systems**

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**Abstract**

With the increased interest and activities in the development of commercial advanced reactors and their fuels, the U.S. Nuclear Regulatory Commission (NRC) is assessing potential use of advanced technologies to minimize risk and uncertainties related to reactor operations and maintenance, within its flexible regulatory framework. To aid this assessment, the NRC staff is engaged in several research activities to expand their understanding of the key technical and regulatory considerations for use of advanced modeling and simulation and digital twin methodologies for condition monitoring of reactor structures, systems, and components (SSCs). The outcome of these activities is intended to ensure NRC staff readiness to review near-term licensing/certification actions, support pre-application engagements, and inform guidance development, as needed. The paper will highlight opportunities afforded by digital twin enabling technology, such as condition monitoring for mechanical SSCs, verification and validation and uncertainty quantification for advanced modeling and simulation, explainability and trustworthiness for artificial intelligence/machine learning.

## INTRODUCTION

The U.S. Nuclear Regulatory Commission (NRC) initiated the Digital Twin (DT) - Regulatory Viability research project beginning in 2020 under the Future-Focused Research Program. The Future-Focused Research Program was established by the NRC Office of Nuclear Regulatory Research to support the identification, prioritization, performance, and monitoring of research activities: a) intended to help the NRC prepare for upcoming challenges, and b) having longer term horizon and greater risk opportunities than considered in typical activities addressing program office needs. The goals of the DT project are to identify technical aspects of a nuclear DT, such as the state of technology and technical issues, to explore their intersection with regulated activities and regulatory infrastructure needs. As of May 2024, the project has included two public workshops [1][2] and six technical letter reports [3][4][5][6][7][8], with additional research in progress. These reports and stakeholder engagements have identified the spectrum of DT technologies and current efforts in the nuclear industry, focused on DT-enabling technologies, challenges and gaps for implementing DT-enabling technologies in current and advanced reactor applications, and regulated activities that may be impacted by DT-enabling technologies.

### The Nuclear Digital Twin System

Initial literature reviews made it clear there was no single industry-wide definition for digital twin. To better understand the nuclear DT problem space, the project team engaged extensively with stakeholders and experts in DT-enabling technologies to develop a description of a DT and a DT system for nuclear power plant (NPP) applications. A DT, as part of a DT system, is a virtual representation of an entity, process, or system, synchronized at a frequency and fidelity sufficient to maintain state concurrence. A DT leverages various types of models, data, and frameworks to produce knowledge/insights about the represented entity, process, or system to fulfill an intended purpose. An NPP DT system of this type broadly comprises four elements: (a) NPP (or subsystem of), (b) DT, (c) data and NPP response flowing from NPP to DT, and (d) actions and recommendations flowing from DT to NPP. As information flows from the NPP (i.e., the physical plant) to the DT, that information is processed and analyzed through various methods (e.g., data analytics and data-informed models), and then ultimately returned to the NPP in useful forms such as diagnostics, visualizations, operation and maintenance (O&M) recommendations, and control signals. A visualization of this DT system is provided in *FIG. 1*.

Graphical user interface, application, website

Description automatically generated

*FIG. 1. Nuclear Power Digital Twin System [7]*

### Application of Digital Twins in the Nuclear Industry

One of the potential near-term applications of DT and DT-enabling technologies identified from the research and stakeholder engagement is condition monitoring of mechanical systems and components. Nuclear facility designers and operators are developing new methods for monitoring the condition of systems and components in new and advanced nuclear facilities as well as for operating nuclear power plants. These new condition monitoring methods provide opportunities for more efficient operations, potential reduction in risk and uncertainties, and early detection of operational anomalies, while ensuring reasonable assurance of adequate protection. These methods may include DT and machine learning (ML) technologies to support condition monitoring of systems and components in nuclear facilities. With the increased interest in improved condition monitoring methods, the NRC has initiated efforts to prepare for the review of these methods as part of the licensing process when proposed for application in nuclear facilities in the United States.

### Regulatory Context

Research activities are underway at the NRC to assist in understanding applications of DT and ML analytic tools for condition monitoring of plant structures, systems, and components (SSCs) in nuclear facilities. These research activities will help provide NRC staff with the necessary information and knowledge to support regulatory review of the application of ML tools to support advanced modeling and simulation techniques for condition monitoring of mechanical systems and components to meet inservice testing (IST) regulatory requirements.

The regulatory role of the NRC staff will be to review and approve any DT and ML approaches used to meet the NRC regulations for the safe operation of nuclear facilities. The NRC regulatory staff efforts are focused on preparing to make a reasonable assurance finding on the use of such technologies at nuclear facilities. Along those lines, the NRC staff can best focus their current efforts if they are able to obtain information via early engagement on the possible applications of these technologies. The more prepared the NRC staff are for a particular type or method of application, the more efficient and effective the NRC staff can be in terms of time and resources to reach a safety finding.

The NRC specifies regulatory requirements in Title 10 of the *Code of Federal Regulations* in Section 50.55a, “Codes and standards,” (10 CFR 50.55a) for applicants and licensees of nuclear facilities to establish IST programs for pumps, valves, and dynamic restraints (snubbers) to provide reasonable assurance of operational readiness to perform their safety functions in nuclear power plants that use water in their cooling systems [9]. The American Society of Mechanical Engineers (ASME) established provisions for IST programs for pumps, valves, and dynamic restraints that perform safety functions for water-cooled reactors in the ASME *Operation and Maintenance of Nuclear Power Plants*, Division 1, OM Code: Section IST (OM Code) [10]. The NRC incorporates by reference the ASME OM Code in 10 CFR 50.55a with applicable conditions for water-cooled nuclear power plants. Current U.S. water-cooled nuclear power plants typically operate for 18 to 24 months before shutting down to perform refueling activities and to test components that cannot be tested during plant operation.

Some new and advanced designs of nuclear reactors vary significantly from current water-cooled reactors with fewer opportunities for testing components during plant operations or refueling outages. Condition monitoring rather than specific testing of components might be needed or proposed by new and advanced reactor applicants or licensees based on the reactor design or operations. The NRC is working to prepare for the use of condition monitoring in new and advanced reactors.

The ASME is preparing a new OM-2 Code for IST programs in new and advanced reactors for components that (a) generate, allow, throttle, or isolate fluid flow; (b) provide pressure relief; or (c) establish dynamic restraint to ensure the structural integrity of piping systems and their components. The scope of the OM-2 Code is broader than pumps, valves, and dynamic restraints in ASME OM Code because new and advanced reactors might use different components than current water-cooled reactors. The OM-2 Code will allow condition monitoring of components that could include DT technology where justified by applicant or licensee and approved by the NRC. The ASME is working to issue the new OM-2 Code in 2024.

The NRC is preparing a new Regulatory Guide to accept the ASME OM-2 Code with applicable regulatory positions. Applicants and licensees for new and advanced reactors may specify use of ASME OM-2 Code as accepted in the NRC regulatory guide for IST programs in their licensing applications. Applicants and licensees for new and advanced reactors may propose the use of DT technology as part of their IST condition monitoring programs for review and approval by the NRC. Licensees of current water-cooled nuclear power plants might request use of the ASME OM-2 Code as part of their IST programs.

The NRC staff continue to assess the regulatory viability of DT and ML technologies for monitoring systems and components at nuclear facilities by evaluating the technical and regulatory challenges associated with the implementing these technologies in nuclear applications. Additionally, the NRC is developing staff knowledge of these advanced technologies to facilitate effective and efficient reviews of DT and ML applications.

## Research activities

The NRC is supporting several research activities studying the use of DT and ML enhanced condition monitoring for mechanical systems and components. These activities are intended to inform regulatory decision-making and develop staff knowledge in these technical areas.

### Machine learning anomaly detection and classification case study

This research activity investigated the use of ML methods to monitor the health of a pump. The study used a boiling water reactor (BWR) simulator to generate data from a subset of normal operations and abnormal operations. The synthetic data from the simulator was used to develop two ML models to (a) detect deviations from normal operations, and (b) to identify/classify the fault inserted into the simulated component.

#### Methodology

A combination of preprocessing, training, and optimization techniques were explored. The approach to demonstrate the potential application of ML for condition monitoring of NPPs started with the curation of a dataset. Using the simulator as a substitute for a real BWR plant, a subset of relevant plant parameters was captured in time-series datasets. After samples were collected, preprocessing techniques including feature and prediction label selection, sample splitting and shuffling, and data binning were applied to ensure that the data was in a suitable form for model training and testing. Seven plant parameters relevant to the operation of the selected pump and seven different faults were selected for inclusion into the ML model.

After obtaining trainable datasets, the next step was to select the proper ML algorithm. The selection was informed by the characteristics of the data, the objective, and the desired output. Two ML models were trained and tested independently and then combined to demonstrate limitations based on the failure of one or both models.

**LSTM-Autoencoder Anomaly Detector**. The first ML model was developed using a long short-term memory (LSTM) autoencoder, which uses an unsupervised learning algorithm that can accommodate time-series data. An autoencoder only relies on input data for the model thus, during training, the input data is set as the ground truth for the prediction. The neural network compresses the input data into a reduced dimension space and reconstructs the data into the output, which in theory, should closely match the input data [11]. As the neural network trains, the predicted value back propagates to fit the input by minimizing the loss function, in this case, the mean squared error (MSE). The MSE is based on the residuals between the input, and the autoencoder’s predicted output. When new datasets like the training dataset are fed as inputs into the model, then the MSE of the predicted outputs will be low; however, when new datasets quantitatively differ from the training dataset, the MSE will be relatively high. An MSE threshold was set based on the MSE observed during normal conditions to differentiate between normal conditions and anomalous conditions.

The autoencoder used here has a symmetrical neural network architecture composed of an encoder, a latent space, and a decoder. By implementing LSTM as the main neural network, the model can detect an anomaly from a window of sequential data. An LSTM neural network is a type of recurrent neural network (RNN) that has special gates which can feed output back to themselves and forget information from the previous state [12]. Due to their nature, LSTM neural networks work well for processing time-series data. With the combination of the LSTM neural network within the structure of an autoencoder, the model can train with a window of multivariate sequential data, such as a time series.

**LSTM-Softmax Anomaly Classifier.** The second ML model was developed using a LSTM-Softmax neural network, which uses a supervised learning algorithm. Like the LSTM-Autoencoder, the LSTM-Softmax neural network takes in a window of sequential data, but instead of outputting the reconstructed sequential data, it outputs a vector of probabilities from zero to one using the softmax function, which correlates with the respective labels. As the neural network trains, the predicted value back propagates to fit the input by minimizing the loss function, or in this case, the categorical cross-entropy (CE) function [13].

The initial hidden layer comprises LSTM neural nodes, while the softmax layer generates probabilities using the softmax function for the associated index labels. With the combination of the two, the model can train with a window of multivariate sequential data and a correctly labeled vector. Once the model is fully trained, the maximum value of the output vector is traced back to identify the corresponding label. Initially, there were seven different faults the model could choose from when making a prediction.

#### Results and discussion

Overall, the models performed well for the test cases used, with the anomaly detector flagging anomalies quickly and the classifier predicting the correct fault 99 percent of the time during testing. It should be noted that the scope of this case study was limited, with a primary goal of developing staff experience with ML methods for engineering applications. The anomaly detector training data was limited to one specific normal operating condition; any different normal operating condition would flag as an anomaly despite being within normal operating space. This would cause excessive nuisance alarms and have the potential to desensitize personnel monitoring the system. Because this case study was restricted one normal operating condition, it is difficult to draw broad conclusions on the effectiveness of this approach to anomaly detection across varying operational states. Additional normal operational states would need to be considered to fully evaluate this methodology.

During evaluation of the classifier model, it was determined that one of the seven faults had little influence on the plant parameters selected as input features of the model. Including this fault negatively impacted model performance. When that fault was removed from the dataset and the model was retrained using only six fault classes, the model performance improved. This underscored the importance of the application of domain knowledge when selecting features to include in ML models to ensure they are relevant to the process and faults being monitored. It also highlighted how explainability of ML models can support troubleshooting performance issues and building trust. In this case, due to the limited number of input features and faults, it was easy to tie key input feature movements to the faults they would be indicating.

### Pump and heat pipe case studies

Two additional case studies were conducted to demonstrate the potential application of advanced technologies for meeting the IST and condition monitoring requirements of SSCs at nuclear facilities. The components considered in the two case studies are (a) reactor coolant pump (RCP) of a pressurized water reactor (PWR), and (b) heat pipe concept in microreactors, see FIG. 2.



FIG. 2 The components considered in the two case studies. (a) Reactor coolant pump [15], and (b) A design concept and operation schematic of heat pipe in microreactors [16][17].

The first case study is focused on RCPs for which the IST activities include periodic testing of pump performance requiring pumps to be taken out of service at fixed intervals. DT-enabling technologies such as advanced sensors and instrumentation (ASI), data analytics, ML, and others could be utilized for performing online condition monitoring and transition the current periodic approach of maintenance and testing to a predictive approach. Current condition monitoring activities for an RCP are aimed at detecting common degradations in the RCP such as leakage, seal failure, bearing failures, shaft misalignment or cracking, erosion of impellers and diffusers, and motor damage. Some of the existing technologies which are applicable for detecting degradations in an RCP include vibration spectral analysis, modal analysis, acoustic emission analysis, motor current and power analysis, thermographic measurement, and lubricant analysis.

The first step in creating a DT for condition monitoring of an RCP is determining the source of data needed to parameterize and build a successful DT. Sensors play a crucial role in condition monitoring by measuring various features such as inlet and outlet pressure, vibration, flow rate, speed, current, bearing temperatures, and motor winding temperature. These data features can be direct or indirect indicators of faults and ensure the system is functioning smoothly. Data preprocessing is essential to clean and convert data into a usable format. Real-time data can contain noise, and equipment data and previous storage of faulty and normal data can be used to understand if data is noisy or contains faults. Methods like parity space method, auto associative kernel regression, and fast Fourier transform are used for data preprocessing and/or anomaly detection. ML based models are effective enabling technologies for fault detection and classification in pump data. Various ML algorithms like artificial neural networks, support vector machine, ensemble learning algorithms, and k-nearest neighbors can be used for fault detection or classification. Previous work used ML methods to detect and classify faults in a circulating water system using XGBoost, as a prognostic and diagnostic model applied to active components in commercial nuclear power plants [18].

Heat pipes are passive cooling systems, typically an annular pipe containing a small amount of working fluid, which are being considered in several microreactor concepts and designs for maintaining core temperatures and might be subject to maintenance requirements under various regulations. The core monolith structure in heat pipes operates at high temperatures, causing material property changes, and potential stress concerns. Heat pipes could become inoperable due to heat transport limits or environmental degradation. Heat transport limits refer to physical limitations of heat pipes for heat transfer, such as entrainment and the viscous limit of the working fluid. Entrainment occurs when the temperature differential between the hot and cold ends of the heat pipe is significant, causing high vapor velocities that strip liquid working fluid from the walls and impede convective heat transfer. Environmental degradation refers to changes in heat pipes over long-term operation in heat pipe reactors. This includes irradiation effects, such as transmutation of working fluid into non-condensable gases, impurity-induced corrosion in wicking structures, and contaminant concentration in the evaporator region (FIG. 2(b)). Long-term irradiation can also cause crack formation, neutron-induced swelling, and weld blemishes, leading to working fluid leakage and failure. Environmental degradation can result in cascading failures, affecting multiple heat pipes mechanically or thermally.

Several physical parameters and associated sensor technologies are currently being explored for condition monitoring of heat pipes including thermocouples, fiberoptics and ultrasonic temperature sensors [19]. Due to the sealed working fluid in heat pipes, non-invasive methods are preferred for detecting defects and anomalies. Ultrasonic imaging, acoustic emissions, thermography, laser ultrasonics, eddy currents detection, and X-radiography could be considered for non-invasive condition monitoring in heat pipes. Acoustic emissions detect stress waves generated by sudden material movement to identify deformations or crack growths. Thermography can capture hot spots within the heat pipe to detect operational limits. Eddy currents can identify defects in electrically conductive materials by monitoring the interaction between the magnetic field and the component. X-radiography uses ionizing radiation to produce images of the component internals to detect faults. All these methods can provide insights and data for developing analytics models for condition monitoring of heat pipes.

## Considerations for the use of machine learning for condition monitoring of mechancial systems and components

One of the primary considerations in the application of DT-enabling technologies in nuclear facilities could be the lack or absence of data. For the available data, it is important to perform uncertainty quantification of the input data and understand uncertainty propagation across models and analytics within a DT. ML-based models used for condition monitoring could contain both epistemic and aleatory uncertainties. Techniques like sensitivity analysis, Monte-Carlo dropout, k-fold cross-validation, Bayesian inference, and Bayesian neural networks can be used to quantify these model uncertainties.

Explainability of ML-based models is critical for understanding the workings of the input-output mapping within the models, and to develop trust in the model output and predictions. Explainability can be improved through model simplification, visualization, or using explainability tools. Model simplification can be used to make models more easily explainable. Examples of explainable ML models include linear regression, decision trees, and Generative Additive Models (GAM). To improve the trustworthiness of ML/AI algorithms, application of domain knowledge can be incorporated. If data scarcity exists, advanced data-driven models that can handle sparse data may be required, but they can affect model explainability. Model-agnostic local methods, such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive exPlanations (SHAP), can help improve model explainability by understanding how the model input features influence a model’s output. Partial Dependence Plot (PDP) and Individual Conditional Expectation (ICE) are global model-agnostic methods that provide graphical information on partial dependence of each variable, but they can be computationally expensive.

## Conclusion

There is much expressed interest in the use of advanced condition monitoring for the purpose of meeting IST requirements and improving operations and maintenance efficiency. The NRC is preparing to effectively and efficiently evaluate the use of these technologies through research activities. Licensees and potential applicants are encouraged to engage with the NRC early to ensure that research activities are aligned with expected industry use cases.

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