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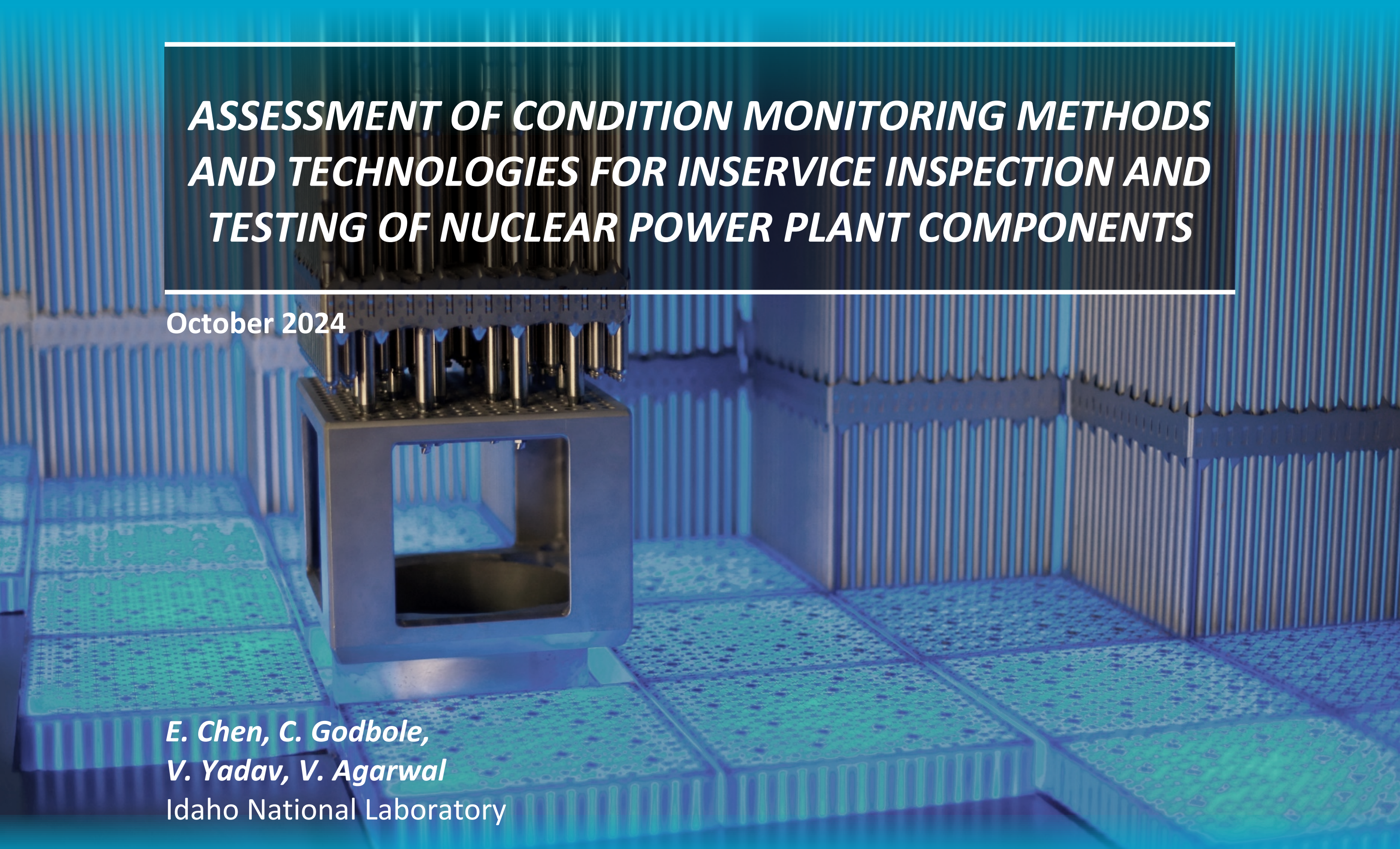

ASSESSMENT OF CONDITION MONITORING METHODS AND TECHNOLOGIES FOR INSERVICE INSPECTION AND TESTING OF NUCLEAR POWER PLANT COMPONENTS

October 2024

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EXECUTIVE SUMMARY

This report was prepared for the U.S. Nuclear Regulatory Commission (NRC) to explore the application of advanced technologies toward meeting the current and future regulatory requirements for maintenance and condition monitoring of structures, systems, and components. The advanced technologies considered in this work are advanced sensors and instrumentation, data analytics, machine learning and artificial intelligence (ML/AI), physics-based models, and digital twins (DT). The interest in the application of advanced technologies for condition monitoring in nuclear power plants continues to grow, and current and future licensees are expected to implement advanced technologies as part of their inservice inspection (ISI) and inservice testing (IST) programs.

This report delineates the outcomes of an exploratory investigation into the implementation of advanced condition monitoring technologies to address ISI and IST requirements. A thorough review was conducted of the existing regulatory requirements for ISI and IST, along with an analysis of associated industry practices. Additionally, a state-of-the-art assessment was performed on advanced condition monitoring technologies frequently employed in non-nuclear sectors. This research incorporated two nuclear-specific case studies to illustrate the application of these technologies within the current nuclear fleet. The report provides an exhaustive discussion on the technical challenges, considerations, and opportunities associated with the deployment of advanced condition monitoring technologies

The following are key considerations in the application of advanced technologies for the ISI and IST of nuclear power plant components:

- Developing adequate verification and validation procedures to confirm the functional and non-functional requirements
- Developing technical capabilities to conduct real-time asset condition monitoring
- Establishing guidance and protocol for modeling and simulation tools to continuously meet regulatory requirements
- Addressing trustworthiness, explainability, and interpretability of ML/AI methods
- Evaluating maintenance activities to maintain an adequate safety margin and avoid undesirable conditions
- Establishing cybersecure condition monitoring programs associated with a computer-based software system
- Establishing standardized evaluation metrics for advanced condition monitoring programs.

Interest in the use of advanced technologies for condition monitoring in ISI and IST programs continues to grow, and the technology is expected to experience rapid and wide industry adoption in the near future. Adoption of advanced technologies for condition monitoring could have novel and unique impacts on regulatory activities associated with ISI and IST programs. The NRC is continuing to explore the regulatory aspects of advanced technologies as part of ISI and IST programs by pursuing additional research in this technical area.

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FIGURES

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ACRONYMS

AI	Artificial intelligence
ANN	Artificial neural network
ASME	American Society for Mechanical Engineers
CCF	Common cause failure
CDF	Core damage frequency
CWS	Circulating water system
DRA	Dynamic risk assessment
DT	Digital twin
EDA	Exploratory data analysis
EMDAP	Evaluation model development and assessment process
FAA	Federal Aviation Agency
FBG	Fiber Bragg gratings
FDA	Food and Drug Administration
HSSC	High safety significant component
INL	Idaho National Laboratory
IR	Infrared
ISI	Inservice inspection
IST	Inservice testing
LERF	Large early release frequency
LSSC	Low safety significant component
MCSA	Motor current signature analysis
ML	Machine learning
MSE	Mean square error
MSET	Multivariate state estimation technique
NPP	Nuclear power plant
OM	Operation and maintenance
OLM	Online monitoring
SPHERE	Single primary heat extraction and removal emulator
SSCs	Structures, systems, and components
UUT	Unit under test
V&V	Verification and validation
WO	Work order

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Assessment of Condition Monitoring Methods and Technologies for Inservice Inspection and Testing of Nuclear Power Plant Components

1. INTRODUCTION

The Office of Nuclear Regulatory Research of the U.S. Nuclear Regulatory Commission (NRC) has initiated an effort to assess the regulatory viability of using advanced technologies for condition monitoring of structures, systems, and components (SSCs) at nuclear facilities. This effort is led by Idaho National Laboratory in collaboration with The University of Illinois Urbana-Champaign. The objective of this project is the identification and evaluation of technical challenges associated with advanced technologies when applied by an NRC applicant or licensee toward meeting the current and future regulatory requirements for maintenance and condition monitoring of SSCs. Condition monitoring incorporates signal data from sensors and instrumentation into computer codes and models that can be used to assess the state of system or component health. Some of the advanced technologies being considered for these uses are data analytics, machine learning and artificial intelligence (ML/AI), physics-based models, and digital twins (DT). For more information on what comprises a DT refer to [1, 2].

As part of this effort, the NRC sponsored a virtual workshop on Condition Monitoring and Structural Health Management for Nuclear Power Plants in November 2023 [3]. The workshop had three main purposes: (1) to gain a better understanding of industry activities and perspectives with respect to the application of advanced technologies and prognostic tools for condition monitoring of nuclear power plant (NPP) components, (2) facilitate the exchange of knowledge and research activities on topics such as online monitoring (OLM) techniques, predictive maintenance, structural health monitoring, diagnostic and prognostic health management, and (3) become aware of these advanced technologies and how these technologies could be used for lifecycle management of plant components. Some of the topics identified during this workshop related to the application of advanced condition monitoring technologies in the nuclear industry that need to be addressed in the near term include developing:

- Diagnostics and prognostics models capable of running in real time as part of condition monitoring programs
- Tools to characterize the interface between advanced condition monitoring technologies and human operators and end users
- Qualification requirements for advanced sensors and instrumentation
- Verification and validation (V&V) and uncertainty quantification for advanced modeling and simulation
- Explainability and trustworthiness for ML/AI.

This report presents an assessment of technical challenges, its considerations and opportunities, associated with the application of advanced condition monitoring technologies for meeting inservice inspection (ISI) and inservice testing (IST) requirements. Section 1 provides a background of the regulatory requirements associated with ISI and IST requirements and the current industry practices for meeting those requirements and a brief overview of the state-of-the-art of advanced condition monitoring technologies used in other non-nuclear industries. Section 2 presents a description of advanced condition monitoring enabling technologies. Section 3 presents two use cases applying advanced condition monitoring technologies for the current fleet. Section 4 presents a comprehensive discussion on opportunities and considerations in using advanced technologies for condition monitoring. Section 5 provides a summary and conclusions from this effort.

1.1. Regulatory Motivation

One of the regulatory motivations for condition monitoring of NPP components results from the NRC regulations in Title 10, "Energy," of the *Code of Federal Regulations*, Part 50, "Domestic licensing of production and utilization facilities," Section 65, "Requirements for monitoring the effectiveness of maintenance at nuclear power plants" (10 CFR 50.65) [4] that specify licensees shall monitor the performance or condition of specified SSCs in a manner sufficient to provide reasonable assurance that the SSCs can fulfill their intended safety-related or non-safety-related functions. In addition, 10 CFR 50.65(a)(3) specifies that condition monitoring and preventive maintenance activities (including, but not limited to, surveillance testing, post-maintenance testing, and corrective and preventive maintenance) shall be performed every refueling cycle or within a 24-month period (whichever is shorter) [4]. Adjustments to activity intervals shall be made when necessary to ensure that SSCs can perform their specified functions but must be balanced against minimizing unavailability of SSCs due to such activities.

Acceptable methods to comply with 10 CFR 50.65 [4] are described in Regulatory Guide (RG) 1.160 [5] and NUMARC 93-01 [6]. These guides establish the scope of SSCs covered, evaluation of risk significance and performance criteria for maintenance, the interval for periodic assessment, and evaluation of unavailability due to monitoring or preventive maintenance actions. Section 9.4.2 of NUMARC 93-01 [6] identifies condition monitoring of SSCs as a method to determine acceptable performance. The frequency of the specified monitoring program is dependent upon the licensee's goals of availability and performance and may be adjusted to allow for early detection and timely correction of negative trends [6]. Section 10.2.1.2 of NUMARC 93-01 discusses the use of predictive maintenance activities to assess equipment performance trends and includes methodologies such as vibration analysis, bearing temperature monitoring, thermography, and motor voltage and current analysis [6]. The predictive maintenance activities are intended to plan maintenance activities prior to equipment failure. In Section 11.2 and 11.3 of NUMARC 93-01, it is identified that maintenance activities must be carefully evaluated, planned, and executed to avoid undesirable conditions, transients, or a reduction in the margin of safety [6].

Another regulatory motivation for condition monitoring of NPP components results from the NRC regulations in 10 CFR 50.55a, "Codes and standards," [7], which requires NPP applicants and licensees to establish and implement ISI and IST programs for NPP components. The NRC incorporates by reference the American Society of Mechanical Engineers (ASME) *Boiler and Pressure Vessel Code* (BPV Code), Section XI, Division 1 [8] into 10 CFR 50.55a as a regulatory requirement for the establishment and implementation of ISI programs for NPP components [7]. The NRC incorporates by reference the ASME *Operation and Maintenance of Nuclear Power Plants*, Division 1, OM Code: Section IST (OM Code) [9] into 10 CFR 50.55a as a regulatory requirement for the establishment and implementation of IST programs for NPP components [7]. For instance, 10 CFR 50.55a(b)(3)(iv) describes the interval testing frequency of single or grouped check valves to ensure they remain capable at performing their intended function [7]. A condition monitoring activity for check valves that is implemented under Appendix II of the ASME OM Code must be performed within that specified interval [9]. In addition, the ASME has issued an OM Code Case that allows condition monitoring of pumps in NPPs (i.e., Code Case OMN-29 [10]).

The NRC regulations in 10 CFR 50.55a(z) allow an applicant or licensee to request alternatives to the requirements for ISI and IST programs [7]. The regulations specify that alternative requirements may be proposed that provide an acceptable level of quality and safety, or when undue hardships and unusual difficulties would occur through the implementation of existing requirements without a compensating increase in the level of quality and safety [7]. The NRC regulations in 10 CFR 50.55a(f)(6)(i) and (g)(6)(i) specify the NRC may grant relief if the IST or ISI requirements, as applicable, are determined to be impractical. Additionally, the NRC may impose alternatives that are authorized by law, will not endanger life or property, or the common defense and security, and are otherwise in the public interest [7].

The NRC regulations in 10 CFR 50.36, "Technical specifications," paragraph (c)(3) [11] specify surveillance requirements relating to the testing, calibration, or inspection of the quality of systems and components such that the operational and limiting conditions are met. Some organizations are developing proposed guidance for implementing technical specifications, such as the Analysis and Measurement Services Corporation [12], utilizing OLM methodologies as a technical basis to support plant-specific technical specification changes—under 10 CFR 50.36(3)—to switch from time-based surveillance frequency for sensor channels to a condition-based frequency based on OLM results.

Based on these regulatory motivations, condition monitoring is envisioned to play a critical role in transitioning from time-frequency-based inspection and testing to a condition-based maintenance schedule [13] through early fault detection, prognostics, and recommending corrective actions resulting in optimized ISI and IST processes while ensuring adequate safety and reliability.

1.2. Standards Motivation

The ASME developed the OM Code [9] to support the reliable and safe operation and maintenance of components in water-cooled NPPs. Division 1 of ASME OM (OM Code), as incorporated by reference in 10 CFR 50.55a, establishes requirements for IST activities to assess component operational readiness in water-cooled NPPs. Divisions 2 and 3 of ASME OM provide guidance for IST of components in water-cooled NPPs. The various components subject to testing and investigation are pumps, valves, pressure relief devices, and dynamic restraints, such as snubbers. The specified time between tests can be dependent on elapsed time periods (e.g., a quarterly test frequency of 92 days) or based on particular events occurring that affect the plant condition (e.g., cold shutdown, refueling outage, and following maintenance). The outputs from an IST activity may include the identification of the component, date and reason for test, the procedure and equipment used, calibration records used, values of measured parameters, comparison with reference values and analysis of any deviation, requirement of a corrective action, and the documentation mentioning the people responsible for analyzing and conducting the test as per the owners' quality assurance program. Pump IST activities, for example, may involve measuring parameters such as differential pressure, rotational speed, discharge pressure, flow rate, and vibration, depending on the test. Corrective action is then based on acceptable ranges, alert ranges, and required action ranges. For valves, the IST activities include leakage testing, stroke testing, position indication testing, and diagnostic testing, as applicable. If the valve does not meet the acceptance criteria for any specific test, the ASME OM Code includes requirements to resolve the test failure and implement corrective actions.

The ASME developed the ASME BPV Code, Section XI [8] for ISI of systems and components in water-cooled NPPs. As incorporated by reference in 10 CFR 50.55a, ASME BPV Code, Section XI requires periodic inspection activities to evaluate the structural integrity of NPP components. For example, ASME BPV Code, Section XI, Appendix VIII demonstrates the use of ultrasonic examination systems to detect and size service degradation-type flaws [8]. Where acceptance criteria are not met, the ASME BPV Code, Section XI [8] specifies corrective action to be taken to resolve the structural integrity issue. Based on these standards motivations, condition monitoring is envisioned to assist in the compliance with the IST and ISI requirements specified in the ASME OM Code and ASME BPV Code, Section XI.

1.3. Continuous Condition Monitoring in Non-Nuclear Industries

Condition monitoring using advanced technologies are currently prevalent in many non-nuclear industries that include, but are not limited to, aviation, automobile, manufacturing, oil and gas, and renewable energies like solar and wind. Most of these industries have evaluated the application of advanced technologies (i.e., ML/AI models and DTs) for condition monitoring, as part of their IST and ISI approaches, and especially within IST, advanced condition monitoring programs can be used to enhance reliability, efficiencies, and safety across different systems and components. Some examples from other industries are discussed here for completeness purpose and to highlight the potential benefits. Errandonea et al. [14] provide a detailed discussion on applications of advanced condition monitoring DTs for maintenance activities across several industries, highlighting three industries, aerospace, energy, and manufacturing (i.e., oil and gas). The paper presents a categorical review of maintenance case studies across many non-nuclear industries and again discusses how advanced condition monitoring programs incorporating DTs are influencing different maintenance strategies with predictive maintenance being dominant. Following the review in Reference [14], Bisanti et al. [15] compiled a systematic review of condition monitoring applications in aircraft lifecycle management (i.e., operation and maintenance). The Internet of Things (IoT), big data, and edge computing are some of the key technologies being explored as part of advanced condition monitoring programs for aviation, as they hold promise to enable real-time or even faster-than-real-time predictions. The paper discusses how information collected across different systems, components, and operation aspects of aircraft can be integrated to inform aircraft operation. The main benefit of using advanced condition monitoring technologies in aviation is in the faster identification of potential degradation or failure in aircraft components, which results in efficient maintenance scheduling and safer aircraft operations.

Within the energy industry, particularly wind energy, advanced condition monitoring programs have been applied for fault diagnosis, condition monitoring, and remaining useful life prediction of mechanical components like drivetrains [16]. Technologies that enable advanced condition monitoring offer unique benefits in condition monitoring of wind turbine components such as enhanced accessibility, visibility, and remote inspection, in addition to the typical outcomes, such as fault diagnosis and failure prediction. A unique challenge faced in developing such systems for a wind farm is in modeling the uncertainty associated with the wind and other environmental factors at the farm.

The oil and gas industry has adopted technologies that enable condition monitoring for a wide range of applications, such as asset monitoring, asset risk assessment, project lifecycle management, virtual training, virtual commissioning, and even certain novel areas such as exploration, geological studies and drilling [17]. In summary, there are several instances of DT applications for assessing asset condition and informing maintenance activities across non-nuclear industries. With these benefits, there are application-specific challenges in developing, deploying, and operating DTs that need to be understood and addressed to maximize the benefits. The challenges identified include, but are not limited to, lack of data standardization, data ownership, integration of business model with the monitoring strategy, model maintenance, and poor data storage.

2. ENABLING TECHNOLOGIES FOR CONDITION MONITORING IN NUCLEAR FACILITIES

Previous operational and research experience with sensor calibration-related condition monitoring, provided in NUREG/CR-6895 [13], can provide a basis for condition monitoring activities for other components. Note that NUREG/CR-6895 uses the term OLM to describe condition monitoring to support sensor calibration extension; however, many of the methods discussed are transferable to component condition monitoring applications. In essence, OLM describes a set of strategies which transitions time-frequency-based maintenance and calibration toward condition-based maintenance [13]. In OLM, sensor data are applied to an algorithm to estimate the normally operating or un-faulted state of a component, which are then compared against the measured values to assess performance and operational status [13]. Regardless of the underlying algorithm, all OLM systems construct models that estimate the target parameter [13]. In this sense, the term model describes the empirical (or in some cases physical) relationships between signals and the component for performance evaluation and validation [13]. While no generic OLM framework exists, an OLM methodology consists broadly of the following components as described in NUREG/CR-6895 [13]:

1. **Sensory information**: Sensors and derived information are critical for an OLM method to monitor variations in the target component. It permits the method to compare against the anticipated state of the component vs. the measured state [13].
2. **Parameter prediction algorithm**: All OLM systems construct models for predicting a parameter of concern. However, how the model is constructed varies significantly between methodologies. Empirical models, for instance, may incorporate historical plant data to construct predictive models, while first-principal models may incorporate physics equations [13].
3. **Response**: A response describes the goal of the OLM methodology. While not all responses will be the same for every OLM method (i.e., fault detection vs. anomaly detection), each OLM methodology incorporates a goal that it strives to achieve. A goal may be described with a quantitative metric such as the "allowable deviation value for on-line monitoring" (ADVOLM) [13].

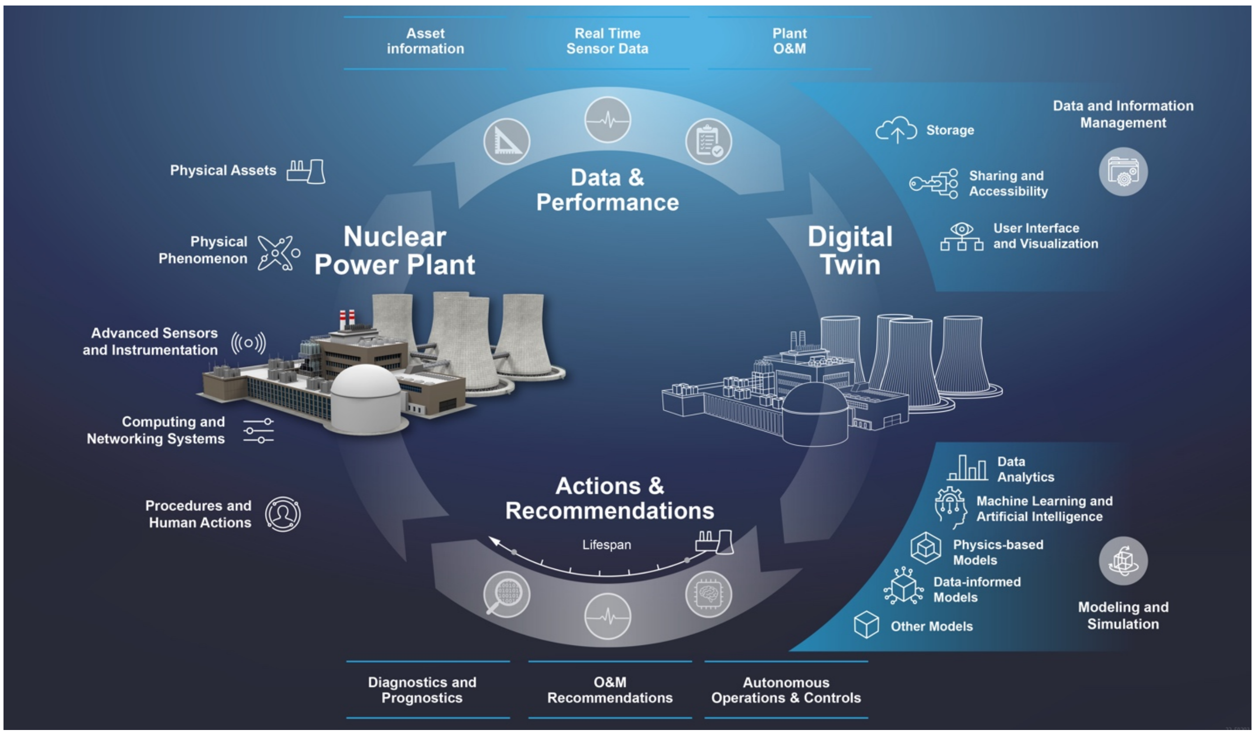

Figure 1. Overview of DT system in an NPP application [18].

DTs are anticipated to enhance and improve existing condition monitoring methods and may leverage experience from OLM. While various interpretations of DT exist, based on the functional requirements and implementation, area of application, criteria, or on the types of technologies included, a nuclear DT system may have the following four characteristics [1, 19]:

1. **Exists in digital form**: The technologies and information that form part of the DT must exist in a digital format that can be managed, processed, communicated, and executed using digital technology. It is important that this characteristic be explicitly defined for applications in the nuclear industry, which has a legacy of information sharing via nondigital formats (e.g., paper).
2. **Maintains state concurrence**: The DT must be able to update dynamically to represent the current state of a physical entity or phenomenon, and it must be able to maintain that state. This vital condition differentiates a DT from existing modeling or simulation capabilities that can run in digital form but do not maintain concurrence with the actual system in real time.

3. **Ensures state concurrence**: The DT must be able to provide new and integrated sets of insights, information, relationships, and outcomes—all pertaining to the physical entity being twinned, and all made possible, feasible, or efficient with DT technology. State cognizance is an important characteristic that ensures DTs do not simply recreate preexisting capabilities but add unique and novel value to the selected application.
4. **Serves an underlying purpose**: The technology must have an underlying purpose that relates to an NPP lifecycle activity, and that purpose should inform decisions about the system or component being represented.

Figure 1 illustrates an overview of a DT system for an NPP application as described in an NRC report [16] that broadly identifies DT-enabling technologies as advanced sensors and instrumentation; data and information management and storage; and modeling and simulation such as data analytics, ML/AI, and physics-based models.

2.1. Advanced Sensors and Instrumentation

Advanced sensors and instrumentation are crucial as they are needed to gather data from the physical realm and transfer it to the digital realm. The main parameters that may be monitored in an NPP include temperature, pressure, fluid flow and level, neutron flux, vibration, chemistry, and radiation. A system must be sufficiently instrumented to obtain measures of state useful for condition monitoring. An investigation into advanced sensors and instrumentation was previous conducted in Reference [18], which provides a detailed discussion on the challenges and gaps in developing and implementing sensor, instrumentation, and communication technologies relevant to implementing DT applications. Further, considerations, such as qualification of sensors or assuring sensor performance, are beyond the scope of this report but are discussed in Reference [18].

2.2. Condition Monitoring with OLM Data Analytics

As the field of OLM is not new, there are several companies that have developed OLM software systems that can be used to improve or augment condition monitoring. In this section, a brief overview of available OLM software is presented. These software systems are in use and have been demonstrated in several non-nuclear case studies. First, OLM parameter estimation software may utilize algorithmic or statistical analysis techniques of sensor and trend data to estimate the parameter of concern (i.e., data analytics). Some of the techniques utilized for OLM include but are not limited to: (a) parity space methods, (b) auto associative kernel regression, (c) multivariate state estimation, (d) rule-based logical detection, and (e) system state analysis.

The parity space method is an algorithm utilized by the Analysis and Measurement Service Corporation for their OLM software [13]. The parity space method relies on checking for parity of measurements from the systems processes and generating a residual comparison between model and process behavior [20]. Parity space approaches generally do not require knowledge of the component's behavior, where residuals are generated from a linear combination of sensor outputs and applied inputs, taken over a finite time window. This linear combination, also known as a parity relation, is chosen to yield zero when the components are functioning perfectly but deviate when a component is malfunctioning [21]. Constructing parity relations is subject to two requirements: (1) the relation is independent to the system modeled such that residuals are insensitive to noise and anticipated disturbances while sensitive to faults (e.g., robustness problem), and (2) each fault of the system should cause a distinguishably different combination of residuals to grow large (e.g., fault isolation problem) [21]. Parity space methods are useful as they can incorporate redundancies in sensor design within the parity relation and isolate a malfunctioning component among a set. However, to achieve this, the parity relation must generate a significant deviation along a known fault signature direction while subject to several sources of uncertainties, such as turbulence, parametric variation, and process noise [21]. Accounting for and limiting parity relation sensitivity to uncertainties may be difficult in highly complex systems that involve a large number of processes or interdependencies. As such, parity space methods have limited scalability to highly complex systems. Regardless, parity space methods have been successfully used for fault detection, isolation, and estimation of monitored parameters in a range of systems [22]. While difficult to apply to complex systems, parity space methods may be incorporated into DT as an evaluation technique to determine when individual or redundant parameter measurements deviate from model predictions.

Auto associative kernel regression (AAKR) is in essence a signal reconstruction method used to identify irregularities in the data when compared to a known database. Two different implementations are possible: memory-based learning and instance-based learning [23]. Both are nonparametric multivariate regression methods that compare the similarity between the training data stored in memory and the query vector and then assign weights to the vectors with high similarity to compute the anticipated vector [23]. As AAKR is based off a known database, it can capture complex relationships across a number of features and monitored variables. However, the requirement for training data to establish the known database is also one of its key limitations at identifying faults. Detection of faults is limited to the learned relationship established by the known database; identifying novel or unexpected faults may not be effective. When a novel fault is present, AAKR may not provide an accurate diagnosis of the exact fault. Furthermore, the relationship developed within AAKR across the different features may not be interpretable as the developed kernel function assigns weights that are not meaningful to the monitored process. Regardless, AAKR has been successfully used for a variety of NPP applications such as condition monitoring [24], early detection of abnormal conditions [25], and fault detection [26].

The multivariate state estimation technique (MSET), developed by Argonne National Laboratory, is a popular real-time process monitoring software system used for OLM [27]. This method consists of a state estimation model and a fault detection model; the combined models estimate what a signal “should be” and, through statistical hypothesis testing, determine at the earliest time possible whether a process is behaving as expected or anomalously. These residuals, calculated from the expected and measured process signal, can be used to detect the onset of faults. MSET can also be used to monitor multiple parameters simultaneously and is a powerful diagnostic tool. However, MSET relies on healthy historical data to determine when a fault state is present [28]. This may present two issues: (1) storage of potentially high dimensional healthy data and (2) training of models under measurement noise and uncertainty. For the former issue, an appropriate timescale must be chosen that can capture, to a sufficient degree of resolution, the characteristics of the monitored component. Time or other methods of data compression may obscure relevant information for the development of accurate MSET models. This leads to the latter issue where high-quality data may not be available resulting in undertrained or poor predictive models. While these challenges persist, MSET has been demonstrated on NPP sensor validation and early fault detection in Reference [29], prediction of remaining useful life, and development of component degradation models [28].

Curtiss-Wright developed the Fleet Asset Management & Optimization Solution (FAMOS) suite to address a variety of condition monitoring scenarios including, but not limited to, valve leakage monitoring, equipment anomaly detection, and fault diagnostics. Predictive Pattern Recognition (PdP) [30] is one of those tools within FAMOS, which utilizes system state analysis as an advanced patten recognition and parameter estimation software system for process monitoring [31]. The PdP system learns a number of observed states for various parameters to establish a range for different expected operations. Each monitored parameter is presumed to be correlated with one or more other variables such that when the process is operating correctly, all parameters are within the learned range [31]. When a fault is present, deviations from the measured and predicted parameters emerge as residuals and permit early detection, shifting unplanned outages to scheduled maintenance work. One important assumption of system state analysis within PdP is that the predicted state is a linear combination of the learned states, which yields a close approximation to the true state. PdP may thus be inaccurate for highly nonlinear systems where measurement and modeling uncertainties play a larger role in state prediction. However, the PdP system has been applied to a variety of nuclear and non-nuclear cases, which can be found in Reference [32]. For instance, the demonstration of condition monitoring and parameter prediction for the Experimental Breeder Reactor II can be found in Reference [30].

The SureSense software suite is another OLM approach developed by Expert Microsystems [33]. The software utilizes a variety of methods for process variable prediction including, but not limited to, AAKR, MSET, fuzzy inference, time series autoregression, and time series sensor averaging [33]. The software suite is intended for prognostic and health monitoring to detect and diagnosis faults in equipment and sensors before they can impact performance in critical systems. The diagnostic step correlates the observed sensor pattern with the most likely normal or abnormal state of the asset. The prognostic step then uses this condition information to determine the probable remaining useful life of the monitored asset [33]. SureSense is a combination of the aforementioned OLM methodologies and may be applied to a range of scenarios but is currently most applicable for sensor validation, fault detection, condition monitoring, and early detection of abnormal conditions.

2.3. Machine Learning and Artificial Intelligence

ML/AI has seen an exponential increase in its applications in a large variety of fields including the field of anomaly detection and classification for real-time monitoring and predictive maintenance, nuclear design, and thermal hydraulic computations [34] [35]. The rise in popularity is, in part, due to its capability and generalizability at processing vast quantities of data and providing useful regression insights quickly and computationally efficient that would otherwise require complex simulation models to derive. This is evident in its extensive use for reduced order modeling [36] and in applications where the underlying physics are too complex to model succinctly [37]. Due to its advanced computational capabilities, ML can play an important part as an enabling technology for condition monitoring applications.

Many ML/AI systems utilize an artificial neural network (ANN), which serves as a universal function approximator for a variety of nonlinear systems. ANNs relate input to output by using layers of elementary processing devices, called neurons. Each neuron contains an activation function, and depending on the type of activation function (e.g., ReLU), different nonlinear behaviors can be modeled [38]. Different ANN architectures exist, with two common ones being feedforward neural networks (e.g., multilayer perceptron) and recurrent neural networks (used widely for time-based series) [39]. ML/AI systems may be further classified by the type of model training regime—either being supervised or unsupervised. Semi-supervised learning is also possible and is a combination of supervised and unsupervised learning. The primary difference between the two training regimes is whether the data is labeled or not (labeled in the sense that a ground truth is known at the time of training). In this report, an emphasis is placed on supervised ML/AI systems as a considerable body of research exists to support their development and deployment for advanced condition monitoring.

Previous work, such as in Reference [40], mentions categories for ML applications for condition monitoring of mechanical and electrical systems. ML for condition monitoring may consist of a fault detection algorithm that compares current data from sensors to a baseline constructed from processed data followed by a fault classification stage that can extract information from identified anomalies between the current and baseline states, identifying the cause, nature, and the type of failure. A fault isolation and quantification tool may also be incorporated to understand and quantify the magnitude of the fault. In Reference [41], the authors utilized different types of a multilayered perceptron for fault detection in a three-phase induction motor. Another form of an ANN is the radial basis function neural network that has been used for fault detection to identify cracks in gears [42] as well as identifying faults in induction motor bearings [43]. Convolutional neural networks are another form of an ANN that has been used for fault detection-based real-time condition monitoring system [44]. A current challenge to ANNs is the difficulty in interpreting and explaining predictions. A specific prediction is difficult to explain and interpret as it is derived from matrix multiplication of non-descript weights and biases across several layers of neurons. Another challenge for ANNs is the complexity of the model with larger feature spaces. Typically, as the number of features increases, more neurons and hidden layers may be needed to obtain meaningful performance. While not a challenge in operation, the cost of training, maintaining, and updating these models with new data becomes a significant organizational burden.

Support vector machines (SVMs) are another type of widely used ML algorithm that are used for monitoring performance degradation in vessel propulsion [45] as well as detecting abnormal conditions of coal mills in thermal power plants [46]. Note that SVMs do not utilize neural networks but use points in the data, hence the name support vector, and a transformation kernel to establish a decision boundary. SVMs have several advantages over ANNs. The method can be applied to a variety of structured and unstructured datasets like text, images, and numerical values, which can be beneficial in incorporating different sources of knowledge. In addition, SVMs can scale well with high dimensionality data and do not require more complex architectures as data complexity scales. This contrasts with ANNs, which may require more hidden layers or nodes as more features are included in the dataset. However, there are several significant drawbacks to SVMs, namely interpretability and explainability of model hyperparameters and decision boundaries. For instance, there are no interpretable criteria for selecting a transformation kernel other than the performance of the model. Some kernels may perform well on certain datasets and poorly on others; incorporating logic into this selection is difficult as the parameters for each kernel have no real-world meaning. Minor calibrations to the model are also difficult as the decision boundary is determined by data points and not through calculation. Last, SVMs are primarily intended for classification tasks, where there is a clear margin of separation between distinct outcomes. As the number of classes increases, the performance of the model also tends to decrease as developing a clear decision boundary for all classes becomes difficult. In this respect, SVMs are susceptible to datasets that are noisy, where class outcomes significantly overlap with each other, or more than two classes exist within the dataset.

Ensemble learning is another popular approach to developing ML/AI models. Ensemble learning typically combines multiple predictive models together, all the same type (e.g., feedforward neural networks or decision trees), but trained on subsets of the original dataset (i.e., bootstrap aggregation). The outputs of these models are then averaged together to reduce training bias and variance [47] and can produce more robust predictions than what a single model trained on the entire dataset may produce. Ensemble modeling has been used to monitor hydraulic systems [48] and condition monitoring of diesel engines [49].

Extreme Gradient Boosting (XGBoost) [50] is one example of an ensemble learning model and is a popular ML technique to build a collection of decision trees for various regression and classification tasks. XGBoost has several advantages such as high accuracy, speed, and scalability but can have high training time requirements and may not be suitable for high dimensional data [50]. Note that decision trees do not use neural networks but may generate comparable predictive results. One of the primary benefits of a decision tree is its interpretability of predictions. A decision tree is interpretable by traversing the tree pathways and examining the decision criteria that has led to a specific prediction outcome. For instance, a node in a tree may ask the question "is the value X less than or greater than temperature T (e.g., X>$50^{o}C$)," for which exactly two outcomes are possible (i.e., yes or no). Through these series of simply binary questions, decision trees can successfully predict both classification and regression tasks. XGBoost is thus an algorithm that determines how to best construct these binary questions, the weights, and the structure to make predictions. XGBoost works well on structured datasets. However, there are several issues with decision trees related to the training dataset. A primary limitation is scalability and updatability. As the structure of a decision tree is established at the time of training, incorporating new data would require retraining on the entire dataset and redetermining all nodes and weights in the tree. Previously established decisions to support a prediction would thus change, and a new (potentially conflicting) interpretation of a prediction would exist. In this sense, decision trees are also hard to scale and do not perform well on sparse, unstructured, or large datasets. Datasets that contain outliers will also reduce the performance of decision trees. Regardless, XGBoost decision trees have been successfully demonstrated for online condition monitoring for fault detection and fault classification of circulating water systems in the Salem and Hope Creek NPPs [51]. Specifically, an XGBoost binary classifier was used to identify if the system was healthy or unhealthy, while an XGBoost multiclass classifier was used to detect what type of fault occurred given the system was detected as unhealthy [51].

However, ML/AI algorithms are not a panacea for every modeling problem. Data-driven ML/AI models may not be suitable for applications where (a) the training data is sparsely populated, and (b) multiple valid solutions exist for a single input [52]. The former condition is not uncommon and may emerge if the dataset is high dimensional such that the dataset is sparsely populated with data points (i.e., for most samples, the value of a feature is zero). Alternatively, if the dataset is small (i.e., few entries), the model may not develop an accurate estimator leading to poor predictive performance. There are currently no hard criteria for what defines a sparse dataset. One qualitative interpretation may be that if there are more zero entries than non-zero entries, a dataset may be considered sparse. The latter condition is also a problem of data inadequacy. Consider a function where for any input, x, two different output values, y, are possible and valid (e.g., multimodal). As ML/AI models are function approximators, without sufficient data, an ML/AI model may be challenged with identifying which of the two possible output values is the intended solution. However, it is important to note that while these are challenges to ML/AI application, there are methods to address both issues, such as principal component analysis and feature engineering/extraction [52].

2.4. Physics-Based Models

Physics-based models can be described as simulations that are driven by the inherent physics of a phenomenon (i.e., Navier-Stokes for fluid mechanics). Three separate categories may describe how physics-based models are used: (a) full physics-based models, (b) systems analysis models, and (c) physics-driven ML/AI models. The primary differentiator between the three categories is the scale of the simulation and accuracy of the derived results. Full physics-based models, such as direct numerical simulation and computational fluid dynamics, can provide detailed modeling of the micro-characteristics of a specific phenomenon, with capabilities such as observing fluid velocity vector fields, turbulence, etc. Commercial examples of full physics-based models include Nek5000 [53], COMSOL [54], and ANSYS [55]. While highly capable at simulating phenomenon, these models are typically computationally expensive and too slow to be used natively for condition monitoring activities, due in part to the refinement of the mesh needed for accurate modeling. While possible, full physics-based models of entire systems (i.e., entire coolant loops and core) are generally infeasible.

Instead, systems analysis models may be used to simulate the macro-characteristics of a system. While not as accurate as full physics-based models, system analysis models can simulate scenarios (i.e., transients) nearly in real-time and may be used as full plant simulators. Examples of commercial plant simulators include the Western Services Corporation 3KEYMASTER[42], a high-fidelity object-oriented graphic modeling tools for SSCs; RELAP5-3D [56], a modeling tool for coupled behaviors under different operating scenarios and transients in the nuclear reactor, reactor coolant system, and secondary coolant loop; MARS [57], used for thermal hydraulic system analysis of light-water reactor cores; and NESTLE [58], used for steady state and transient neutronic analysis. The Generic PWR Product is also a notable example as it is currently being used to develop plant simulators for the NuScale, AP1000, and pebble-bed modular-reactor types [59]. A diagnostic system has previously been developed [60] using the Parameter-Free Reasoning Operator for Automated Identification and Diagnosis (PRO-AID); a new version named PRODIAG [61] is also available for thermal hydraulic systems in commercial nuclear plants to detect both faults in equipment and instruments. However, the benefits in computational speed and simulation scale provided by system analysis models are limited by the level of detail that it can provide. For instance, GPWR can only simulate the macro-characteristics of a coolant pump (e.g., flow rate and speed) and cannot model how specific faults can generate coupling effects that lead to degradation signatures of a pump (e.g., increased vibration due to pump impeller degradation). This issue known as scale bridging is still under research.

One approach to resolve the scale bridging issue is the use of physics-driven ML/AI models to accelerate the computation of full physics-based models. Unlike data-driven ML/AI models, which rely on training data of a specific phenomenon to develop models, physics-driven ML/AI models directly integrate the physics equation into the training architecture. For instance, in Reference [62], the authors demonstrate a framework for integrating partial differential equations (i.e., Reynolds-averaged Navier-Stokes equation and heat conduction equation) into the training process of a deep feedforward neural network. This model was then demonstrated in several different scenarios such as those used to generate the temperature distribution of a heated block and the fluid flow velocity field of a two-dimensional lid-driven cavity problem [62]. There are several benefits to physics-driven ML/AI models that include, but not limited to, (a) capability to overcome the physics decomposition and scale separation assumption, where a single phenomenon has several different nonlinear contributors that can cause substantial uncertainties in modeling [62], (b) capability to accelerate the computational speed to derive accurate results while maintaining a comparable level of fidelity as full physics-based modeling, and (c) reduce the reliance on data preprocessing as training is conducted with the physics equation rather than through observational data [62].

In application, physics-based ML/AI models have been applied for health monitoring of turbines [63], structural components [64], anomaly and fault detection [65], etc. Physics-driven ML/AI models may also be used in other unconventional ways that are relevant to certain challenges in condition monitoring. For instance, in Reference [66], physics-based ML/AI models are used to reconstruct frequency spectrum information to recover information potentially lost through data compression. As collected sensor data grows in volume, especially with the advent of wireless and IoT technologies, compression may be necessary due to limitations in transmission bandwidth [66, 67]. As such, ensuring that compressed transmitted data is preserved, with all data characteristics, is relevant for both the development (using historical data) and deployment of advanced condition monitoring.

3. USE CASES FOR CONDITION MONITORING IN NUCLEAR FACILITIES

3.1. Pump Condition Monitoring

Condition-based predictive maintenance can ease the transition from periodic maintenance strategies to technology-driven and condition-based maintenance while also reducing operational and maintenance costs.

For instance, in previous work [51, 68], the authors examined the circulating water system (CWS) of the Salem and Hope Creek NPPs and showed that the application of condition-based predictive maintenance for plant assets can reduce operating costs without compromising safety or reliability. The goal was to identify if the CWS was healthy or unhealthy and whether a fault had occurred [51, 68].

First, exploratory data analysis (EDA) was conducted on work orders (WO) generated between 2009 to 2020 at the Salem and Hope Creek NPPs and used to remove duplicate WO [68]. From there, statistical testing (one-way analysis of variance) was conducted on both historical corrective maintenance and preventive maintenance tasks [68]. Over the years, it was observed that the corrective maintenance WOs had a statistically significant downward trend potentially attributed to preventive maintenance optimization. However, the authors also identify that further statistical analysis is needed to draw more meaningful conclusions about preventive maintenance optimization [68].

Topic analysis was also conducted to extract important words/information including equipment condition from WOs. This helped identify recurrent themes within textual data by assigning tags to each description. The model used for topic analysis in the work was the latent Dirichlet allocation. The data preprocessing stage of EDA consisted of word tokenization followed by stop word removal, lemmatization, and then topic analysis using latent Dirichlet allocation. Next natural language processing was used to classify equipment condition events of WOs as either related or unrelated to the degradation of the equipment by conducting text characterization using convolutional neural networks.

SSCs explored through the WO analysis were also equipped with sensors used to support maintenance activities during the operation of the Salem and Hope Creek NPPs. All the installed sensor data (from 2009 to 2019) were monitored using a monitoring and diagnosis center and consisted of data from motor temperatures, discharge pressures, breaker positions, fluid temperatures, etc. Sixty wireless vibration sensor nodes were installed across 12 pump motors and their associated bypass valves [68]. Three sensors were mounted on the external casing of each pump's motor, and two were mounted on the bypass valve [68]. These sensors were used to continuously monitor x and y directional vibration data including axial vibration and outboard and inboard bearing vibration.

The various faults and failure modes considered were waterbox fouling, pump diffuser failure, pump bellmouth failure, pump shaft misalignment, clogging in air intake screens of motors, moisture and salt contamination of the motor windings, low oil level in pump, bearing failure, or any pump failure diagnosed using vibration data [68]. The data used to train the models consisted of plant process data such as timestamped differential temperature, motor inboard and outboard temperature, motor stator temperature, motor current, motor and pump age, historical replacement/refurbishment, and overall run time. Vibration data in both the time domain and frequency domain for the four pump vanes and six diffuser vanes were also utilized.

To identify if CWS was healthy or unhealthy, a forest of decision trees was implemented as diagnostic and prognostic models for fault identification. The developed diagnostic model was implemented as a binary classifier to determine whether the CWS was healthy or unhealthy as well as the probability of an outcome and the time stamp of prediction. The prognostic model was implemented as a multiclass classifier and used to identify which fault had occurred if the system was deemed unhealthy. The outputs of the prognostic model were the type of fault along with the probability of the particular fault and the most significant features correlating to that fault. The evaluation of each model's performance during training was conducted using the F1 score and the area under the receiver operating characteristic curve. These performance metrics plot the true and false positive rates of predictions and are used to evaluate how well a model's predictions are when compared to the ground truth. Both the diagnostic and prognostic models were able to achieve a relatively high score (i.e., 98.5% and 99%), which demonstrates that it is possible to construct highly accurate random forests for fault identification and diagnostic tasks [51]. This case study also suggests that ML/AI-developed DT may be possible for optimizing maintenance tasks.

3.2. Motor Condition Monitoring

Motor condition monitoring applies to a variety of motor types used throughout an NPP including, but not limited to, pump motors or motor-operated valve assemblies [9]. Motor current signature analysis (MCSA) is one such technique to monitor and assess the health of three-phase induction motors [69]. MCSA is a mature technique and may detect faults at an early stage, thus avoiding damage and complete failure of the pump motor [70]. It may also be used to alert operators to changes in motor performance. MCSA is conducted by measuring the asymmetrical backward rotating electrical current frequency spectrum induced by the motor during normal operation [70]. In three-phase induction motors, up to three supply lines may be monitored. A reference signature is collected to establish normal healthy operation. Physical asymmetries that develop over the motor's life (i.e., broken rotor bar) change the induced magnetic field within the motor and appear as additional sideband frequencies in the current frequency spectrum [70]. The magnitude and variation of sideband frequencies are compared against the reference signature to determine the type and severity of the fault.

Typical parameters monitored by MCSA induced current amplitude waveform and frequency [70]. In addition to these parameters, the supply voltage may also be recorded to conduct supplemental instantaneous power frequency analysis to monitor operational health [70]. The types of motor faults that MCSA may be able to detect include, but are not limited to, power quality (e.g., voltage/current fluctuations and harmonic distortions), misalignment/unbalance (e.g., motor shaft to rotor bars), static and dynamic eccentricity, electrical faults (e.g., shorting of stator windings), and certain mechanical faults (e.g., broken rotor bars and defective bearings) [70, 71, 72].

The primary challenges of MCSA for condition monitoring include its sensitivity and identifiability to certain mechanical faults, variable load conditions, and the degree of expert knowledge needed for diagnostics [70, 73, 71]. Other challenges include external electromagnetic interference and data storage limitations associated with high sampling frequencies [70, 71]. Similar to vibration analysis, certain faults lack unique signatures and may be associated with a range of possible motor faults. In this respect, diagnostics using MCSA alone may not be sufficient at determining the root cause of the fault [70].

Electromagnetic interference, such as power and radio frequency interference, harmonics, and electromagnetic induction, may also change the recorded current frequency spectrum and increase the likelihood of spurious maintenance activities [70]. The impact of electromagnetic interference can be reduced with proper antialiasing filter selection but requires intimate knowledge of the motor operational conditions [70].

In addition, it is challenging to distinguish between normal variations in operating condition, load changes, and system transients to motor faults [70]. This is also an issue when MCSA is used to estimate the torque and thrust delivered by the motor actuator as various parameters must be evaluated when translating motor current to motor actuator output. Changes in the motor load and operating condition will alter the reference signature, which impacts the identification of associated fault signatures. Due to variable operating conditions and non-identifiability of faults, typically expert knowledge is needed to make accurate assessments of motor health [70]. For instance, faults of varying severity have different signatures that may coincide with other fault modes. Prioritizing and identifying fault severity will impact preventive maintenance optimization strategies and is not a straightforward task [70]. Root cause analysis through MCSA may also be challenging as faults may share signatures and may require ISI for proper diagnostics [70]. These challenges also affect fault identification via motor vibration analysis.

Another challenge to MCSA is the data requirements for fast sampling frequencies. MCSA typically uses frequency ranges within 1–5kHz, which necessitates a sampling frequency of 10,000 samples per second [71]. At lower sampling frequencies, detection of certain faults may be difficult due to insufficient resolution. The high volume of data requires significant storage capacity and a large data transfer bandwidth, which may make data storage and transferal challenging. Utilizing data compression methods to efficiently store data is still currently an issue as it may subsequently mask underlying fault signatures [74, 75, 76].

As discussed, significant expert interpretation of the frequency spectrum may be needed to diagnose faults. While the use of ANNs for MCSA is not novel and has been conducted in previous works (e.g., [77]), methods such as deep neural networks and image processing can improve fault diagnostics. For instance, in Reference [78], the authors utilize convolutional neural networks to conduct automatic image and fault classification of the motor current frequency spectrum. In Reference [79], the authors demonstrate various statistical classification algorithms to diagnosis different mechanical faults in pump motors. While promising, these methods are relatively novel and lack extensive operational experience and validation of their efficacy in realistic scenarios.

Thermography is another method identified for motor condition monitoring [10] and utilizes infrared (IR) imagining to assess the condition of pump motor components. IR imaging enables noncontact, real-time, and nonintrusive temperature measurements and does not require sensor placement near or on the pump motor component [80, 81]. In addition, IR measurement equipment is not impacted by electromagnetic interference or contact-related degradation mechanisms that other sensing strategies may be susceptible to [81]. IR imaging measures the black-body radiation emitted by a heated component and correlates it to a specific temperature. Typically, a reference knowledge base is collected on the component's physical properties and environmental conditions to establish a baseline for future comparison [81]. When a degradation of the component occurs, such as a broken rotor bar, additional friction caused by the fault generates heat, which when compared to the baseline, can be used as an indicator for maintenance action.

The types of pump motor faults that IR thermography can capture include, but are not limited to, bearing problems (e.g., insufficient lubrication), mechanical misalignment, damaged or degraded insulation, phase unbalance, overloading or overheated components, and seal failures [80, 81]. When a fault occurs, friction in the pump motor increases, which corresponds to an increase in temperature within the local proximity of the fault. Direct diagnostic of the root cause may not be readily available as the location of temperature increase may not be exact [80].

Challenges that impact IR thermography include, but are not limited to, delayed response time of measurements, variability in emissivity, uncertainty in correlated temperature, line-of-sight requirement, and significant expert knowledge needed for proper utilization [80, 81]. As IR thermography measures friction-induced temperature changes, larger components, components with poor heat transfer capability, or components with large thermal inertias may heat up slower, delaying the response time of temperature change [80]. In addition, IR imaging requires line-of-sight for temperature measurements [81]. Thermography of bearings and other pump motor components encased in housing may not be available without disassembly.

Adequate IR thermography requires extensive knowledge of the emissivity of materials and surface reflectivity (e.g., glare), as well as a detailed reference base on environmental factors such as protective coating (e.g., paint), ambient temperature, humidity, and air-circulation [81]. While reference data can be collected for healthy components as a baseline, this is not guaranteed to be consistent over the life of the component [80]. For instance, emissivity and reflectiveness may change over time due to corrosion or wear. These variations can make accurately determining temperature difficult and may be subject to large uncertainties [80]. As such, conducting proper IR thermography requires a strong understanding of material properties and may necessitate expert examination of IR data for correct fault diagnosis.

Various ML/AI models have been proposed to reduce the amount of effort needed to conduct IR thermography. The primary benefit of ML in IR thermography is the automation of fault diagnostics and interpretation of IR images. For instance, in Reference [82], the authors combine IR thermography with ensemble methods to diagnose three-phase induction motor phase imbalance caused by shorted stator windings. In Reference [83], the authors utilize convolutional neural networks to interpret IR images and diagnose rotating bearing faults of induction motors. In Reference [84], the authors apply various ML methods to IR thermography to anticipate maintenance activities. However, while promising, most ML/AI methods for IR thermography are conducted within laboratory settings with artificially manufactured defects. As of this report, ML/AI for IR lacks extensive field testing and may require additional industry-partnered studies for higher confidence in the methods. In addition, ML models developed for IR typically have strong limiting assumptions, such as the assumption that the target system does not change over time, which may limit their current application for condition monitoring [85].

4. TECHNICAL OPPORTUNITIES AND CONSIDERATIONS

In this section, various technical, development, licensing, and deployment challenges, considerations, and opportunities involving advanced condition monitoring are presented. It is anticipated that advanced sensors and instrumentation will be instrumental for advanced condition monitoring as they are the primary sources of information regarding the state of the component. Advancements in existing sensor technology may enable more robust and reliable sensing capability, whereas novel innovations in sensor technology may further enable additional capabilities in condition monitoring. However, there are several challenges and considerations associated with sensor instrumentation (i.e., sensor qualification) that may impact the performance of an advanced condition monitoring program. These challenges and gaps are detailed in a recent NRC report [18] and will not be discussed further in this report.

For the components involved in IST and ISI activities, an advanced condition monitoring program may be broadly used to inform ASME OM Code and ASME BPV Code, Section XI procedures in the following manner:

- Optimize component maintenance scheduling
- Improve confidence in fault detection and isolation
- Enhance analyses of existing condition monitoring algorithms and methodologies.

However, with these opportunities, there are also several considerations relevant to nuclear regulators, vendors, and developers that must be addressed before an advanced condition monitoring program may be viable. These considerations include, but are not limited to:

1. Establishing organizational guidance for data procurement, management, and interpretation
2. Identifying which active or passive components are candidates for an advanced condition monitoring program through the quantification of risks and benefits associated with its implementation
3. Developing an adequate V&V procedure to confirm the functional and non-functional requirements of an advanced condition monitoring program during development phases
4. Developing an adequate reverification procedure to confirm the advanced condition monitoring program is continuously meeting functional and non-functional requirements
5. Establishing cybersecure condition monitoring programs associated with a computer-based software system
6. Establishing standardized evaluation metrics for advanced condition monitoring programs
7. Developing an advanced condition monitoring program that provides guidance on key technical and regulatory aspects through application-specific scenarios.

4.1. Opportunities

4.1.1. Optimizing Component Maintenance Scheduling

ASME OM Code [9] specifies the current requirements for IST of components in water-cooled reactors. Division 1 of the ASME OM document requires IST that is typically performed at set interval frequencies identified in ISTB-3400-1 [9]. Division 2 of the ASME OM document provides guidance for IST activities, such as trending during a unit-under-test (UUT) (e.g., Division 2, Part 24, Section 8.7) [9]. If a developing undesirable trend is detected, an enhanced monitoring program may be enacted for the UUT to correct the problem. It is envisioned that a condition monitoring program may be used to optimize existing IST procedures by continuously evaluating the condition of the component and raising alerts if an unusual trend develop. This is accomplished through short- and long-term forecasting of developing degradations or faults of the UUT. In Reference [51], the authors demonstrate a Markov model for circulating water pump maintenance schedule optimization. They demonstrate that by considering the probability of a fault arising over future incremental periods of time, an optimal maintenance schedule can be achieved that considers different organizational goals in safety and plant availability [51]. Alternatively, if the condition of the component is unchanging or experiences only minor variations, there may be sufficient justification to extend the review period, reducing the amount of human effort needed for ongoing maintenance. This is similar to how OLM is used to extend sensor channel calibration intervals [12].

Different metrics may be used to optimize component maintenance scheduling. In Table 1, various potential optimization metrics are presented. Each of the metrics identified, aside from functional margin, describes the remaining utility or value of a component before a maintenance activity should be performed. For instance, technical value may be used to determine the optimal interval in which a component should undergo maintenance activities while minimizing the impact to operational goals. A reliability function may also be used which anticipates the probability that a component will survive over a specified operational period. Functional margin is another possible metric focused on safety as it determines the remaining excess capability of a component to operate at design-basis conditions.

Table 1. Commonly employed metrics for component operational analysis.

Metric Name	Description	Ref.
Mean Time Between Failure to Mean Time Between Unit Replacement Ratio	Measures the ratio between how long a component lasts and how long it is used before replacing it. Condition monitoring should enable the reduction of this ratio by allowing components to be used longer until they are closer to failure.	[86]
Remaining Useful Life	Amount of time left before the system health falls below a defined failure threshold.	[87]
Technical Value	The benefits achieved through accurate detection, fault isolation and prediction of critical failure modes are weighed against the costs associated with false alarms, inaccurate diagnoses/prognoses, and resource requirements of implementing and operating specific techniques.	[88]
Functional Margin	The increment by which a component's available capability exceeds the capability required to operate the component under design-basis conditions.	[9]

An optimized component maintenance schedule may also have the benefit of improving component operability and safety by automatically evaluating component performance on a more frequent basis (e.g., continuous or near continuous) as opposed to performing invasive checking and testing at predetermined intervals. This insight is drawn from existing OLM programs for sensor channel calibration extension [13]. Specifically, it was shown that the reduction in human reliant checking and testing activities through optimized maintenance scheduling simultaneously reduced the number of human errors and miscalibration events when compared to conventional periodically scheduled maintenance [12]. This may suggest that continuous evaluation via condition monitoring may also provide improvements to component operability and safety by reducing the number of unnecessary maintenance activities.

4.1.2. Improving Confidence in Fault Detection and Isolation

Certain faults are more difficult to detect than others due to various background noise and signal attenuation. For instance, the guidance in ASME OM, Division 2, Part 12, Section 1.2 [9], discusses how the loose parts monitoring program may experience high false detection rates and reduced confidence due to excess background noise from the reactor coolant system. In addition, locations far away from sensors may experience significant attenuation such that it is difficult to differentiate a true fault since normal background noise masks accurate detection. In this respect, an advanced condition monitoring program may enhance confidence in fault detection by implementing novel algorithms that combine various sensor signals to conduct diagnostics. Recent developments in multi-sensor fusion through ML models are promising as they enable more complex diagnostics. For instance, in Reference [89], the authors utilize principal component analysis and independent component analysis coupled with radial basis functions in a neural network to fuse multiple different forms of sensor information together. In Reference [90], the authors implement a convolutional neural network to process multiple vibration signals as representative two-dimensional images to enhance fault prediction. In essence, sensor fusion through ML models may provide a superior fault detection and diagnostic process while simultaneously lowering false detections as they utilize more information to identify the signatures of a fault.

4.1.3. Enhancing Existing Condition Monitoring Methodologies

The overall intent of a condition monitoring program as described in ASME OM Code [9] and the associated guidance documents is for the detection of equipment deterioration or faults early enough to prevent functional failure. The goals of diagnostic and prognostic methods must therefore be to (a) maintain or improve operability, (b) reduce plant downtime, and (c) increase productivity [9]. For instance, the guidance in ASME OM, Division 2, Part 24, "Reactor Coolant and Recirculation Pump Condition Monitoring," [9] discusses standardization of in situ monitoring methods for the detection of pump degradation and faults prior to functional failure. Code Case OMN-29, "Pump Condition Monitoring Program," [10] identifies an alternative approach to the ASME OM Code requirements that may be used to adjust the frequency of IST of pump operational readiness. The ASME OM Code [9] and its guidance documents identify commonly encountered faults, their typical symptoms, and the common analysis techniques employed to detect these faults. Relevant faults identified by the current program include pumpset mechanical faults (e.g., bent shaft, looseness, unbalance), seal faults (e.g., wear, cracked seal face), and electrical motor faults (e.g., broken rotor bars, insulation breakdown). It should be noted that the list of faults identified in ASME OM Code [9] and its guidance documents is not exhaustive, and other faults may be detected by the operator. Other faults and malfunctions may be more completely and accurately diagnosed by combining multiple different condition monitoring technologies as identified in the guidance in ASME OM, Division 2, Part 24, Section 11 [9].

In this respect, novel methods and algorithms that enhance diagnosis and prognosis of component condition and fault detection can be beneficial to the accuracy of the condition monitoring program and may reduce the number of false alarms triggered by the system. Certain challenges identified for MCSA, such as the need for significant expert interpretation of the frequency spectrum, may be addressed with ML/AI methods by automating the effort required for analysis. While the use of ANNs for MCSA is not a novelty and has been conducted in previous works (e.g., [77]), methods such as deep neural networks and image processing can improve fault diagnostics. For instance, in Reference [78], the authors utilize convolutional neural networks to conduct automatic image and fault classification of the motor current frequency spectrum. In Reference [79], the authors demonstrate various statistical classification algorithms to diagnosis different mechanical faults in pump motors.

4.2. Considerations

4.2.1. Establishing Organizational Guidance for Data

At the core of most condition monitoring methodologies is an algorithm that predicts a parameter of concern. While variations exist on how a model predicts this value, whether through empirical models, first-principal physics-informed models, neural networks, or statistical algorithms, all condition monitoring models will ultimately predict a value that informs on the condition, state, or health of a system, comprising of a single or multiple components. To make these predictions, the model requires knowledge of the current or past state of the system, which is provided in the form of sensor data, process information, historical databases, periodic reports, and/or alarms. Inaccuracies, inconsistencies, unavailable/missing, incorrect, untimely, or other forms of sensory data corruption can thus significantly affect a condition monitoring model's predictive fidelity, accuracy, and precision. Thus, establishing common organizational guidance on how sensory data is collected, used, modified, stored, and maintained throughout the lifecycle of a condition monitoring model will affect the overall program's efficacy.

The importance of adequate sensory data collection and storage is reflected in various sections of ASME OM Code [9] and its guidance documents. For instance, ASME OM Code, ISTA-4100, stipulates that instrumentation and test equipment used in performing the examination and testing of equipment shall have the necessary range and accuracy to demonstrate conformance to test requirements [9]. ASME OM Code, ISTB-3510-1 presents a further breakdown of the types of sensory data collected and the level of accuracy required to conduct an IST for a pump [9]. The types of sensory data collected include pressure, coolant flow rate, rotational speed, and vibration, all of which may be relevant input parameters to a pump advanced condition monitoring model. Initial baseline sensory data is also collected to provide the condition monitoring program, a reference point for the normal anticipated operation of the pump. The guidance in ASME OM Division 2, Part 24, Section 8.3.1 [9] discusses how a new baseline may be established for each pump after every outage where maintenance work is performed. A long-term trending database, specified under ASME OM, Division 2, Part 24, Section 7.3.3 [9] may also be collected to monitor long-term changes in the pump condition, provide an archive for past pump problems, and provide for statistical and other specialized analysis. At present, this data is also stored at intervals and resolutions to ensure no data loss and usefulness in diagnostics or trending, under guidance from ASME OM, Division 2, Part 24, Section 6.5 [9]. While the current version of ASME OM Code [9] and its guidance documents identify the data conditions sufficient to conduct the endorsed condition monitoring methods (e.g., MCSA), it is not known whether the existing data collection, usage, and storage conditions will be sufficient for advanced condition monitoring programs that incorporate DTs.

For example, a DT may combine multiple different functional modules together to address condition monitoring goals. For instance, in Reference [51], a multistage condition-based model is developed that combines various fault prediction models with risk assessment models to anticipate preventive maintenance scheduling. In the system, sensory information feeds into multiple models that in turn feed into other models. The models thus form dependencies with each other such that a modification or correction of one aspect will alter and affect the predictive capabilities of all other aspects of the system. Furthermore, it is identified in ASME OM Code [9] and its guidance documents that the act of component replacement, repair, or maintenance may impact its performance and baseline characteristics. This may subsequently affect the performance of the condition monitoring DT if sufficient difference between the original and post-modified condition exists. In the current requirements, such as OM Code, Division 1, Mandatory Appendix III, Section III-3400 [9], the performance of a component after a maintenance activity must be demonstrated to be within acceptable limits. Deviations in component performance from previous records shall be identified and analyzed. However, allowable acceptable limits and deviations for component performance may not be the same allowable limits and deviations for a condition monitoring program [13]. For instance, minor variations in sensory information may compound through the DT's various modules such that unexpected predictive performance may manifest. While uncertainty quantification and parametric sensitivity analysis can be conducted to evaluate the impact of changes, it is not clear how these changes should be applied to model predictions.

Condition monitoring models that generate data utilized by other parts of the system to conduct additional value analysis (e.g., risk-informed maintenance scheduling) may also lead to reduced interpretability of the end result. For instance, in ASME OM, Division 2, Part 24, Section 10.4 [9], it is discussed how the output of conventional condition monitoring programs is normally assessed by a human engineer who then makes an interpretation on the condition of the component and whether inservice activities are needed. By automating stages where humans may interpret data, the justification for a particular outcome of an advanced condition monitoring program may be unclear to support staff conducting the maintenance activity.

Ultimately, it is anticipated that for an advanced condition monitoring program to be successfully implemented, personnel from a plant's engineering and IT departments will have to be properly trained in its system theory, functionality, and maintenance [13]. Personnel interacting with the monitoring program must also have a strong understanding of the computational and data requirements. This may include the type, amount, frequency of collection, and any preprocessing stages for parameters utilized by the system. In addition, the appropriate utility personnel must also have a strong understanding of the operational conditions of the component monitored by the program both during the collection of baseline data serving as reference but also over the operational lifespan of the condition monitoring model [13]. Utility and IT personnel must also be aware of modifications or updates made to the architecture of the monitoring models, whether external or internal, as these changes can impact the performance of the system [13]. Developing clear organizational guidelines on identifying how data is collected, used, modified, and stored will be relevant for the deployment of an advanced condition monitoring program.

4.2.2. Identifying Candidates for an Advanced Condition Monitoring Program

Determining which SSC is ideal for which advanced condition monitoring program may include considering a variety of economical, operational, and safety factors. For instance, ASME OM Code, ISTE-4100 [9] identifies the risk of IST activities to a component on plant safety, which differentiates high-safety-significant components (HSSC) and low-safety-significant components (LSSC). The difference between HSSC and LSSC groupings are the types of IST activities conducted and their intervals, where HSSC components may have more stringent programs. The risk categorization of these components is further based on the assessment of the functional failure modes addressed by IST activities (e.g., pump failure to run). Fussell-Vesely and Risk Achievement Worth are the primary importance measures used to evaluate and separate plant SSCs into their corresponding risk groups, whereas core damage frequency (CDF) and large early release frequency (LERF) establish safety goals, as discussed in ASME OM, Division 1, Appendix L [9]. In ASME OM, Division 1, ISTE-4150 [9], additional studies are also conducted to determine the impact of an IST program on component unavailability, the probability of recovery from component failures, the change in common cause failure (CCF) rates, the impact of initiating events due to component degradation or failure, the potential consequences of shutdown (outage) conditions, and other considerations. Thus, the choice of implementing an advanced condition monitoring program for an SSC may be driven by safety considerations. Pilot candidates may initially include LSSC components if the monitoring program's maturity, operational experience, explainability, and uncertainty are not well established as the impact to plant goals may be less than for an HSSC component.

An additional concern associated with digital software systems is the possibility of CCFs. A CCF is the occurrence of failure of two or more components due to a single causal factor. While an advanced condition monitoring system may not necessarily interact directly with the instrumentation and control systems and thus does not necessarily impact plant functionality, a monitoring system that informs an IST program needs to be screened for CCF modes specifically within the context of defense-in-depth, as specified under ASME OM, Division 1, ISTE-4130 [9].

Introducing an advanced condition monitoring program may thus subsequently introduce additional risks to the operation of the UUT. For instance, an operator makes a misinformed decision based on erroneous condition monitoring data, such as shutting down the monitored process or switching to an inappropriate operating mode in lieu of a degraded mode [91]. Risks due to programmatic changes to the IST program are known as aggregate risks and are measured through figure-of-merits such as CDF and LERF [9]. Probabilistic risk assessment within condition monitoring is used to determine undesirable outcomes such as the potential consequences of shutdown (outage) and the impact of an initiating event when an IST activity is conducted. It is anticipated that changes to the IST program, for instance the inclusion of an advanced condition monitoring program, may need additional probabilistic risk assessment re-quantification as specified under ISTE-4420 Section (c)(2) [9].

The selection of an SSC may also factor in existing operational experience. Existing monitoring programs that have low confidence in efficacy (e.g., loss parts monitoring) may be optimal candidates if the condition monitoring program can improve upon the program's detection capabilities. Alternatively, components that are known to be continuously reliable over multiple IST intervals (e.g., channel calibration) may also be suitable if the condition monitoring program can extend maintenance intervals. A comparative cost-benefits analysis to safety or operational characteristics should be considered when choosing which SSCs are candidates for condition monitoring and may require factoring in how the monitoring program impacts the operational metrics (see Table 1) of the SSC in comparison to the original monitoring program.

Last, a feasibility study for implementing an advanced condition monitoring program may also consider organizational goals such as return-on-investment and lifecycle costs. These metrics determine the anticipatory cost of acquisition, operation, and continued maintenance of the monitoring program, weighing the cost of implementing over the benefits received from the program. For instance, a condition monitoring program may reduce maintenance efforts and possibly prevent outages or the loss of hardware over the system's life; however, if the new program's benefits are marginal compared to the original monitoring program, it may not make organizational sense to implement an advanced condition monitoring program. Interested parties may refer to *On-line Monitoring Cost-Benefit Guide* for more details on the direct and indirect organization benefits of implementing a condition monitoring program [92]. Ultimately, the selection of which component is suitable for a condition monitoring program is highly dependent on safety and risk factors of the component, existing operational experience with the condition monitoring program, and organizational goals for plant operation.

4.2.3. Developing Verification and Validation Procedure for a Condition Monitoring DT Program

As with any model development, V&V, uncertainty quantification, and other model quality assessment methods are imperative. These activities help users and developers determine the accuracy and precision of a model's predictions, which inform its relevancy and qualification for an intended operational environment. Under current regulations, a condition monitoring DT may be regulated under 10 CFR 50.55a(h) using guidance in RG 1.168 [93] with consideration for IEEE Std. 1012-2004 [94], "IEEE Standard for Software Verification and Validation" and IEEE Std. 1028-2008 [95], "IEEE Standard for Software Reviews and Audits." However, note that RG 1.168 and referenced IEEE documents are intended for software systems incorporated into the instrumentation and control systems of an NPP. As such, a condition monitoring DT, which may not have direct interaction with the instrumentation and control system, may not be subject to all the requirements under RG 1.168. A condition monitoring DT might also be required to comply with NQA-1 as specified under 10 CFR 50.55a(b) [7]. Regardless, in accordance with current standards, software developers of the condition monitoring DT must be able to demonstrate that the necessary V&V activities have been performed to meet functional and non-functional requirements. In addition, a condition monitoring DT software, like other forms of software, is subject to a quality assurance program as delineated under 10 CFR Part 50, Appendix B [96].

The specific issue is the use of ML/AI within the algorithmic processes of the system. In conventional software systems, the requirements of a system are specified in documents such as the "Software Requirements Specification" [97] and refined in the "Software Design Description" [97]. These documents describe exactly what the functional and non-functional requirements of a software system are, how these functions are achieved through algorithms, and, finally, the acceptance criteria of the software system. The function of an implemented algorithm is validated through tests (e.g., boundary value analysis) as the explicit form of the algorithm is known. In contrast, the explicit algorithmic form of an ML/AI algorithm is uninformative, and a function cannot be derived solely from its implemented mathematical equation. Instead, the function of an ML/AI algorithm is implicitly inscribed solely through training data that is postulated to be representative of the operational environment. Misinformed or underdeveloped training data can thus unknowingly corrupt the function of the ML/AI-driven condition monitoring DT. Furthermore, it is difficult to establish an acceptance criterion on an implicit function as its exact limits, domain, and applicable space can only be approximately inferred from the training data.

From this perspective, Regulatory Guide 1.203 [98] may be used to address some of the V&V issues associated with condition monitoring DTs that incorporate ML/AI algorithms as it specifies a procedure to evaluate models that utilize special methods and/or calculational models (however, from the perspective of transient analysis). In essence, RG 1.203 identifies the Evaluation Model Development and Assessment Process (EMDAP), which aims to describe an acceptable process for the development and assessment of evaluation models used to analyze transients [98]. EMDAP is divided into two parts; the first part evaluates the pedigree, applicability, and fidelity of the chosen algorithm, while the second part evaluates the performance at varying degrees of integration and scale. Finally, confirmatory supporting assessment, through known transients, is conducted to ensure that the model adequately meets regulatory requirements. This assessment is an important part of EMDAP and verifies the assumptions, limitations, and outputs of the model through scalability evaluations, convergence studies, etc., against experimental data. EMDAP differs from conventional software testing processes as it attempts to address implicit modeling issues discussed above. Note that EMDAP is intended for models that utilize closure models for a defined system and is not currently developed for unique ML/AI strategies (e.g., data-driven closure models). As such, adaptation may be necessary, such as those conducted in Reference [99], where the authors modify EMDAP with considerations for ML/AI modeling challenges.

Ultimately, when considering the V&V activities of a condition monitoring DT, not only are the explicit software requirements important but also the implicit modeling challenges associated with ML/AI-driven condition monitoring DTs. A combination of existing regulations might need to be met in the licensing and evaluation process of a condition monitoring DT and is thus not a straightforward task.

4.2.4. Developing Reverification Procedure for a Condition Monitoring DT Program

A condition monitoring DT after development and integration into an existing system may also undergo reverification and testing to continuously ensure that it meets specified functional and non-functional requirements. The reverification process is intended to ensure that changes to the condition monitoring DT pipeline (e.g., sensors and data collection) through IST activities do not fundamentally affect the system's capability at meeting specified functional and non-functional acceptance criteria. This aligns with IST guidance and might be needed, for example, see ASME OM, Division 2, Part 24, Section 8.3.1 [9]. This section identifies how a new baseline may be established after IST maintenance activities, which may modify the detection and diagnostics of the condition monitoring DT. Therefore, ensuring that the new baseline is compatible with an existing condition monitoring DT might also be needed. At present, the types of tests developed for a condition monitoring DT may be informed by Regulatory Guide 1.171 [100] "Software Unit Testing for Digital Computer Software Used in Safety Systems of Nuclear Power Plants" via IEEE Std. 603-1991 [101], IEEE Std. 279-1971 [102], and NQA-1. Once again, however, these regulations are geared toward safety instrumentation and control systems and may not be directly applicable to condition monitoring DT systems that do not have direct interaction. An EMDAP process, identified in RG 1.203 [98], may also be adopted to evaluate whether an ML/AI model within the condition monitoring DT system continuously meets implicit modeling requirements. However, it should be noted that implementing tests that the system has already passed (e.g., benchmarks) may provide misleading confidence in the capability of the system. Specifically, the output of a software system is deterministic once a specific configuration is set. Therefore, testing inputs and conditions on a specific configuration that is known to have passed previously will also pass thus providing limited useful information. In this respect, testing of a condition monitoring DT would require additional analysis of the new conditions presented in post-maintenance activities and are not completely reliant on previous benchmarking testing, which would only confirm known functionality. At present, developing an adequate reverification procedure post-development might be needed and is similar to IST confirmatory performance testing of components post-maintenance.

4.2.5. Establishing Cybersecure Advanced Condition Monitoring Programs

As advanced condition monitoring programs are projected to be digital computer-based systems, licensees may be required to develop and implement cybersecurity plans (CSP) that include protection of DT elements to meet the requirements of 10 CFR 73.54, "Protection of Digital Computer and

Communication Systems and Networks" [103]. Currently, CSPs are developed following the guidance in RG 5.71 [104] or NEI 08-09 [105], and if a DT element has the potential to affect a safety, security, or emergency preparedness function, it may have a set of associated cybersecurity controls to ensure a cyberattack could not adversely impact that function.

Compromising an advanced condition monitoring system may be accomplished by compromising one or more stages of the condition monitoring operational pipeline. Potential stages involved may include (a) sensing infrastructure, (b) networking services, (c) data and information services, (d) modeling and simulation, and (e) response and action recommendation [2]. The actual system may only consist of stages (c) through (e) and use existing sensing and networking infrastructure implemented by the plant for (a) and (b). However, cybersecurity vulnerabilities may appear at any stage of the condition monitoring data pipeline. For instance, an advanced condition monitoring system is expected to integrate novel instrumentation technologies, such as wireless sensors, which would require a wireless sensor network [18]. A compromised communication network may feed erroneous data to the condition monitoring DT model, which would make unreliable predictions without modifying or accessing the condition monitoring DT system itself. Furthermore, early detection of cyberattacks is difficult as the avenues of vulnerability are rarely known in advance. While measures may be taken to ensure proper operation, it is typically intractable to cover and consider all possible attack avenues. As such, cyberattacks are typically viewed as "when it will happen" not "if it will happen." A licensee's CSP would thus implement controls to identify such vulnerabilities and detect, protect against, respond to, and recover from condition monitoring attacks.

Cyberattacks can impact a condition monitoring program in a variety of ways. In coordinated attacks, an attacker may cause physical damage to the monitored facility by altering sensor readings (e.g., false readings of process variables) to confuse the operator of the actual plant's health conditions [91]. Alternatively, an attacker may choose to misinform operators on the true condition of the component monitored. The Stuxnet attack on uranium centrifuges is a prime example where attackers controlled the centrifuges to spin irregularly while simultaneously reporting that the system was operating normally [106]. This is especially relevant when the primary objective of a system is to report on component health.

While existing regulations identify the need for a comprehensive cybersecurity program in the mitigation of functional failure, it is unclear how that program will be implemented for advanced condition monitoring systems that include DTs. Furthermore, it is difficult to eliminate all avenues of attacks even with a comprehensive program. In addition, as advanced condition monitoring programs are intended to inform on condition and maintenance activities, the consequence of an attack may impact both operational and safety goals. Thus, a comprehensive understanding of the monitoring functions requiring protection, potential attack paths, system vulnerabilities, and consequences of successful attacks is needed to develop the set of cybersecurity controls to protect the condition monitoring program and models.

4.2.6. Establishing Standardized Evaluation Metrics for Advanced Condition Monitoring Programs

Part of the condition monitoring program development process is determining which derived quantitative metrics should be utilized such that the model is relevant and useful for the intended application. These quantitative metrics provide a basis for determining when maintenance activities should be performed, the anticipated impact of the activity, and the potential benefit of conducting the activity [13]. It is therefore a key step in the evaluation of an anticipated health management system [87]. In addition, it becomes imperative to establish confidence in the methodology and metrics before it can be incorporated within the decision-making process. For instance, a maintainer may need to know how good an estimate is before they can optimize the maintenance schedule [87]. Without reasonable confidence in the estimate, the prediction loses all significance and may be detrimental to organizational goals [87]. Identifying which metrics are relevant for DTs for a specific application is thus crucial if the condition monitoring is intended to improve or augment existing methodologies. Metrics that examine organizational (Table 1) and safety goals (i.e., CDF and LERF) are relevant and should be considered during the evaluation of the model. However, there are also a variety of developmental performance metrics that may also be used.

A developmental performance metric quantifies the error of a model and may be used to evaluate a prediction's accuracy, precision, and fidelity relative to a desired solution. In Table 2, a summary of current diagnostic and prognostic metrics for condition monitoring is presented. However, there is no common consensus in research or the commonly used standards on the best metrics [107], and as such, the table is not exhaustive. Each of the identified metrices can also be used in different applications and convey a different type of prediction error. There is no current practice of combining or comparing the metrics, which can result in conflicted conclusions about the performance of a model.

Table 2. Common metrics for determining a model's accuracy, precision, and robustness.

Metric	Description	Ref.
Average Scale Independent Error	Exponentially weighs error in remaining useful life (RUL) and averages them over all components (or predicted parameters) under test.	[108]
Average Bias	Average error of predictions made at all subsequent times after a prediction start time.	[88]
Timeliness	Weighs RUL predictions based on when they are made. Late predictions are penalized more than early predictions.	[88]
False Positive Rate & False Negative Rate	Assesses the ratio of false positive and false negative predictions made by the model against a user-specified acceptable range.	[109]
Mean Absolute Percentage Error	Averages the absolute percentage errors of predictions of multiple components (or predicted parameters) under test.	[108]
Anomaly Correlation Coefficient	Measures phase difference between predictions and observations, subtracting out the historical mean at each point.	[110]
Mean Squared Error	Averages the squared prediction error for multiple components (or predicted parameters) under test.	[88]
Standard Deviation	Measures the dispersion/spread of the error with respect to the mean of the error. The metric assumes a normal error distribution.	[88]
Mean Absolute Deviation from Sample Median	This is a resistant estimator of the dispersion/spread of the prediction error. It is used when there are multiple UUTs and when the error does not resemble a normal distribution.	[88]
Brier Score	In terms of health monitoring, the Brier score plots the observed frequency against predicted probability of a random failure event. Reliability is indicated by the proximity of the plotted curve to the theoretical perfect reliability line. If the curve lies below the line, this indicates over forecasting; points above indicate under forecasting.	[111, 87]
Receiver Operating Characteristic	A tradeoff comparison between false positive and false negative prediction rates against uninformed predictions.	[107]
Sensitivity	Measures how sensitive an algorithm is to input changes or external disturbances. Can be assessed against a performance metric of interest.	[88]

A particular issue with non-standardized developmental performance metrics is that different metrics may be used to provide a false sense of confidence in the performance of the model. Given a particular condition monitoring goal, metrics may be selected that misrepresent the actual performance of the model. This may be unintentional for developers unfamiliar with ML/AI performance assessment or intentional to generate more favorable results. For example, false positive and false negative rates, which assess the rate of unacceptable predictions, may be used to artificially misrepresent the performance of the model when an unbalanced test space is provided. Mean square error (MSE) is another metric that may be used to misrepresent the performance of a model. Fundamentally, this metric takes the averaged square error of a collection of predictions, which may mask single occurrences of significant prediction error. Misinformed MSE is prevalent when there is a combination of high-volume low-error predictions with low-volume high-error predictions. Misinformed MSE may also be present when the scale of the error relative to the prediction domain is not understood properly. These issues may be resolved by assessing the condition monitoring model across a range of performance metrics as listed in Table 2 but must be taken from the context of the condition monitoring goal as not all metrics are applicable in all scenarios. From a licensing perspective for predictive models, a common basis for analysis in the context of the condition monitoring goal may be needed to prevent unintentional or intentional manipulation of the reported developmental performance.

4.2.7. Developing Advanced Condition Monitoring Programs Addressing Technical and Regulatory Aspects

To ensure the smooth deployment of advanced condition monitoring programs, it is anticipated that more modeling and application experience is needed in relevant real-time condition monitoring scenarios and environments. Many published research projects on DT development for condition monitoring are based on datasets that artificially manufacture defects and degradations into the component under test [112]. Artificially generated degradations, either experimentally or simulated, are useful in the preliminary development of DT condition monitoring systems as they focus on the problem assessed. However, these datasets do not accurately reflect realistic degradation scenarios, which may vary in measurement, operating condition, machine types, and component types, all contributing to uncertainties in the condition prediction [112]. On the other hand, industry data is difficult to utilize for model training as it is complicated to receive systematic and comparable data for different damages (i.e., damages may vary in degree of severity and are not equal) [112]. In addition, data on specific defect states may be sparse as failures in components are not expected or are limited to a small number of defects and do not represent all possible defect states. The specific challenge here is that artificial data is an approximation of the degradation and are defect states postulated to be encountered by the condition monitoring model. However, this approximation may overlook specific operational conditions that contribute to uncertainties in the model's prediction in deployment. Ultimately, developing a robust and applicable model may require a combination of artificial data, to assess the macro-characteristics of the model, and realistic industry data, to assess the micro-characteristics of the model. For example, the development of a DT for condition monitoring of the circulating water pump system in the Salem NPP [51] provided invaluable deployment experience and lessons learned. These lessons learned related to data for model development include:

1. Plant processes may be measured by several sensor redundancies. While it is not necessary to incorporate redundant sensor information, as no new information is presented to the model, a method to integrate redundancy in model design may be needed to maintain the layers of defense.
2. Operational plant data may contain unexpected sudden spikes and transitions that may be due to servicing and inspection [68]. These anomalies can either be a false indication of events or the effect of real operational conditions, so careful considerations should be placed when filtering data. Developing the necessary filters for these spikes may be difficult in synthesized data as their occurrence is case-by-case.

3. Unexpected and periodically repeating operational events may exist that change the sensor data that are neither outliers nor an indicator of degradation. For instance, inlet pressure dropping to zero every 7 days [68]. However, these periodic drops will confound diagnostic models. Issues in initial model deployment will be expected, and modifications may be necessary; whereas, assumptions used to develop the model do not perfectly align with the operational environment.

These lessons highlight the usage of realistic industry datasets and how they may generate more useful and case-specific insights into the limitations and benefits of DT modeling within advanced condition monitoring.

Similar real-world demonstrations of a condition monitoring DT may be needed if the technology is to be deployed for other IST- and ISI-covered components, such as valves, dynamic snubbers, and pressure relief devices [9]. Other passive components may also be candidates for condition monitoring DT systems such as piping, tubing, and support structures [113, 114, 115] or in integral [116], helical [117], and conventional steam generators. These components are susceptible to chemically and mechanically induced corrosion, reducing wall thickness, and may be candidates for long-term degradation monitoring [114, 115]. They may be of specific interest for advanced reactor designs such as molten-salt reactors and integral reactor designs where maintenance access may be constrained.

4.2.8. Maintaining State Concurrence of the Condition Monitoring DT with the Physical Asset

Maintaining state concurrence with the physical twin is a key attribute of a nuclear DT system [2] which is critical for the time-sensitive applications of ISI and IST of SSCs and addresses a major limitation of the traditional, periodic, and manual approaches. Capable of updating dynamically to represent the current state of an SSC or a physical phenomenon, the condition monitoring DTs could maintain the state concurrence with the SSC in real time. The term “real time” implies update frequencies dictated by the purpose of the DT and the dynamics of the underlying physical system [2]. The update frequency needed to maintain state concurrence is dependent upon the rate of change of the represented physical system [2]. For instance, representation of highly dynamic systems such as pumps and motors may require state updates on the order of minutes, while systems with less dynamic change such as pipes may only require state updates on the order of weeks or months.

Developing DT-enabling technologies to ensure optimum state concurrence presents unique system constraints through design, development, and operation of condition monitoring DTs. The update frequency would determine the frequency and resolution in the sensors, instrumentation, communication, and data acquisition system. Maintaining state concurrence with the physical asset would require the physics-based and other models to reflect the true effects of aging and degradation of the physical asset in its DT. Certain models, such as high-fidelity physics models, could have limitations running in “real time” depending on their computational requirements. Addressing these limitations would entail making a choice of an appropriate model, or an efficient alternative such as a reduced order model. Data management infrastructure such as data storage servers or clouds, data sharing, as well as computational needs of a condition monitoring DT would also be determined by the necessary update frequency to maintain state concurrence.

4.2.9. Considerations for ML/AI as a Software Tool

There are several considerations in the licensing and continued maintenance process of ML/AI algorithms used for diagnostic and prognostic software tools (i.e., within condition monitoring DTs). The following section is adapted from lessons learned and considerations from the U.S. Food and Drug Administration (FDA) and the U.S. Federal Aviation Agency (FAA). The FDA has been focused on the licensing and continued maintenance of ML/AI algorithms as software medical devices for patient health predictions [118, 119, 120]. The FAA, on the other hand, has been investigating the integration of ML/AI algorithms into aircraft health monitoring to provide guidance on maintenance regarding system performance and structural condition [121, 122]. A brief discussion of the considerations made by both agencies is provided.

First, the FDA has cleared or approved several ML/AI-based medical devices used in the diagnostics and prognostics of patient health [118]. These devices have only included algorithms that are locked prior to distribution. Locked, or deterministic, refers to an algorithm that provides the same result each time when the same input is applied and is unchanging with use [118]. The FDA also recognizes adaptive ML/AI algorithms that continuously learn over exposure. The output from these algorithms is not guaranteed to remain consistent given the same set of inputs. The FDA's perspective on licensing of adaptive ML/AI algorithms is a new total product lifecycle regulatory approach is needed that permits algorithmic adaptation with consideration of risk management and continuous V&V [118]. Specifically, for adaptive ML/AI algorithms, a two-stage process is envisioned: learning and updating. In the learning phase, the model changes its behavior to better represent a use case. The update phase then occurs in batches where the new version of the algorithm is deployed [118]. V&V before and after the update ensures model quality does not degrade over time, whereas risk management is used to determine the impact of the software change. The intention is to enable evaluation and monitoring of the software product before and after deployment and for different risk categories [118].

The FAA has extensive experience with non-ML/AI condition monitoring programs and thus views ML/AI as an enabling technology for higher degrees of data analysis automation [122]. However, ML/AI algorithms are viewed as an additional monitoring activity to support the implementation of the existing condition monitoring program for non-critical components [123]. Existing procedures within a condition monitoring program cannot be substituted by an ML/AI algorithm. In addition, any implementation of ML/AI in a condition monitoring program must follow existing knowledge and IT technology of the 1980s and 1990s and can only be applied to non-critical components [123]. In essence, FAA guidance specifies that a condition monitoring program must consider qualification of associated hardware and software systems, data collection and traceability requirements, qualification of thresholds used for health determination, qualification of degradation parameters that drive maintenance, and qualification of the adapted maintenance procedure and service validation.

There exist significant parallels between the use of ML/AI algorithms for the diagnostic and prognostic programs used by the FDA and FAA vs. the same set of algorithms used to determine NPP component health. A summary of considerations is provided:

- In cases where the manufacturer/developer and user of the ML/AI software are not the same, the manufacturer/developer should consider how users will update and ensure that the ML/AI is up to date whenever a version update is released. Manufacturers/developers of ML/AI software should thus make appropriate mitigations to address any risk that arises from the existence of different versions of the software system either within a plant or across multiple plants.
- Due to its non-physical nature, a specific ML/AI software configuration may exist in numerous copies, be widespread across multiple plant components and sites, and potentially be outside the control of the original manufacturer/developer.
- The manufacturer/developer of an ML/AI software tool may be a third-party (e.g., commercial off-the-shelf) and may not have the same goals and objectives as the organization deploying the tool. A common management strategy should be implemented that defines direction, responsibility, authority, and communication to assure the safe and effective performance of the software tool.
- Software risk can never be totally eliminated as exhaustive testing and evaluation is computationally intractable. Manufacturers/developers should thus continuously monitor the users of ML/AI software (e.g., capture operational feedback and service performance) to maintain safety levels and be able to respond to failures in a quick manner. In the event of failures at one user of ML/AI software,

manufacturers/developers should inform all users of the failure and, if necessary, prepare an update to the ML/AI to all users.

- Incident investigation should consider any specific case or combination of use cases that may have contributed to the failure. To support incident reconstruction and investigation, appropriate data logging should be in place to resolve the discovered software issues.

With any software product lifecycle, modifications, updates, and changes are expected. Failures may occur due to errors, ambiguities, oversights, or misinterpretations of the functional specifications of the software. Failures may also arise from errors in code development, inadequate or incomplete testing, incorrect or unexpected usage of the software, or other unforeseen problems. These may also arise when developers of the software do not fully understand the scope and specification of the monitoring task, how the software may interact with the other components or systems, or how developmental assumptions may be unrealistic in an operational context. As such, it is anticipated that some degree of modification will be made after the software is applied to the intended operational environment, potentially as part of the maintenance of the system.

The nature of software maintenance can include adaptive, perfective, corrective, or preventive changes. Adaptive changes refer to modifications made to keep the software up to date with the current operational environment. For instance, as nuclear fuel is consumed within the reactor, from beginning-of-life to end-of-life, the power profile of the core may change and thus require different coolant pumping rates. For a pump condition monitoring program that utilizes an ML/AI in condition monitoring, these operational variations may need to be adjusted as they arise. Perfective changes refer to improvements made to the performance of the software tool. Recognize that ML/AI algorithms rely on data to make accurate predictions. During the developmental phase, highly relevant training data may not be available to produce highly accurate ML/AI models. However, during deployment of the ML/AI, as more context-specific operational data is generated, it may be desirable to update the model to derive more accurate and relevant predictions. Corrective changes refer to the correction of discovered bugs/problems in the ML/AI software. ML/AI software systems are anticipated to be highly complex; it thus becomes computationally intractable to test all possible states and branches to guarantee failure-free operation. Preventive changes refer to fixes to latent faults discovered in the software tool before they become operational faults. Regardless of the type of changes applied, the change and root cause of the issue should be clearly identified and defined with a method of tracing to the specific version of the affected software system. The newer version of the software should also undergo the appropriate V&V activities before being released.

It is anticipated that ML/AI software used to develop DTs for condition monitoring will have different versions as modifications are made over the lifespan of the component. This may include changes to the support functions of a software system or to the actual models used for prediction. What differentiates support functions and models may be how they implement a specified function. While no clear separation exists, it is generally interpreted that models implement functions that may be driven by data-informed ML/AI algorithms, whereas support functions may provide input/output conversion, formatting, and storage of results via conventional algorithms. Versioning of ML/AI software is potentially more convoluted as the difference between versions may be as minuscule as the training configurations. Technically, no code needs to be modified to obtain a different ML/AI versions, instead the weights and biases within the model are changed to obtain a different result. Furthermore, a solution derived from an ML/AI model is not unique in a mathematical sense; a different configuration of weights and biases may be used to obtain the same numerical output. For instance, obtaining more data and retraining the ML/AI model will result in a different model with different performance without any explicit change to the underlying architecture of the software. Alternatively, models that are permitted to change over time (i.e., adaptive) will have changing performance over time which is not guaranteed to be beneficial to the condition monitoring task. In continuously adapting models, what differentiates model versions may simply be changing weights and biases such that that the difference between two models may be quantitatively unmeasurable (in terms of quality metrics). Therefore, defining version control of data-driven models, whether adaptive or updated, will be an important task in initial and continued licensing.

In addition, it is not guaranteed that the developer of the advanced condition monitoring system will be the same as the operator of the tool, further complicating licensing. The SureSense software suite developed by Expert Microsystems [33] and the PdP monitoring tool developed by Curtiss-Wright [31] are two examples of third-party software systems that may be used for condition monitoring. In this sense, it is important to define the strategic direction, responsibility, authority and communication necessary for the deployment and continued management of the condition monitoring program within an organization. Third-party software systems can hide many of the underlying data analytics and prediction mechanisms, making the model partially or completely inaccessible and can make model maintenance difficult. Therefore, it is also important to identify roles and responsibility linked to the maintenance, modification, and usage of the software tool but also identifying liability of parties in postulated incident scenarios. This may also include the creation and establishment of appropriate quality objectives and policies through activities that systematically verify the effectiveness of the software tool (e.g., audits, tests, and reviews). A common management strategy ensures that the organization and all involved parties in the deployment of the condition monitoring program are invested in the safety and success of the software tool, aware of the potential risks associated with software tool, and provide communication over the entire software development and post-development lifecycle. Areas that a management strategy may impact include product planning, risk management, document and record control, configuration management, in situ measurement and analysis, and outsourced activity tracking.

Product planning involves developing a roadmap identifying and defining phases, activities, responsibilities, and resources needed to develop the monitoring program and the DT. Product planning is not static and is constantly updated as new information is gathered, milestones reached, or requirements refined. The intent of product planning is to develop a methodical and rigorous plan of action to reduce the likelihood of confusion or misunderstandings between the developer and the user of the monitoring program. This includes activities conducted post-development such as software updates, reverification testing, and maintenance.

Risk management involves identifying potential hazards involved with the implementation of the monitoring program, estimating and evaluating the associated risks, developing mitigation strategies, and methods for monitoring the effectiveness of the enacted strategies to control risk. As condition monitoring DTs are relatively novel, a comprehensive breakdown of all hazards and their likelihoods may not be initially available. As more experience is collected during the testing and deployment of the DT, identified risks may be updated to reflect a more realistic operational environment.

Document and record control is the process of generating evidence on the quality of the product as well as justifications behind organizational decisions made involving the monitoring program. Records demonstrate conformity to standards and regulations but also how the predictive models used in the monitoring program may evolve over time (e.g., retention of obsolete documentation) through maintenance or software updates. In addition, establishing an adequate document and records control program ensures against unauthorized or unintended changes to the condition monitoring program.

Configuration management involves controlling the source code, releases, options, and versions of the software tool to maintain integrity and traceability of configurable items throughout the development lifecycle. Systematic configuration documentation of its constituent parts, including a robust and documented change management process, is necessary to provide a history of changes made to it and to enable recovery/recreation of past versions of the software (i.e., version traceability). This may include how weights, parameters, and settings of a model are changed from version to version. In addition, it provides evidence of the correct installation and integration of the DT in the intended environment. This also assists maintainers to determine whether different routines and training are necessary to obtain new or reconfigure existing software or hardware systems.

In situ measurement and analysis involve the continuous surveillance of quality characteristics of the software tool. Surveillance of the DT model is intended to demonstrate it meets requirement specification objectives after development and during usage, while also monitoring and analyzing potential nonconformities to inform corrective or preventive modifications to the software. Trending may also be leveraged to identify irregularities in different versions of the DT model in a similar fashion to trend analysis in component monitoring.

Last, outsourced activity tracking takes into account and ensures the quality of activities and products developed by third parties. This includes identifying which commercial off-the-shelf software or hardware systems are integrated within the condition monitoring DT, how these components are maintained and managed, and understanding the inherent effects and risks associated with such outsourced processes, products, and activities. The key to outsourced activity tracking is understanding the capabilities and competencies, clearly defining roles and responsibilities, and establishing criteria for inspections/audits.

Even with a comprehensive management plan and version control, undesirable failures of the condition monitoring system may still arise. There are multiple reasons why perfectly developed software is unfeasible: the intractability of exhaustive testing, the unanticipated interaction between software and hardware systems, the emergence of unknown interactions in complex systems, etc. [124]. As such, devising a strategy to investigate incidents and reconstruct failures is prudent and avoids potential undesirable incidents in the future. A key part of incident reconstruction relies on historical data collection to rebuild the exact conditions that resulted in failure. This requires the collection of data as is. Modification of the historical data (i.e., compression for storage) will mask or change the conditions of failure and make incident reconstruction difficult. One idea presented by the FDA is to develop "black box recorders" for each condition monitoring system at the time of usage [118]. Black box recorders differ from historical data collection as they only record a short time range of data (e.g., 2 hours), reusing and wiping old data, but collect all parameters that are relevant to the monitored process.

4.2.10. Trustworthiness, Explainability, and Interpretability of ML/AI Methods for Advanced Condition Monitoring Programs

ML/AI is expected to be a key enabling technology for advanced condition monitoring programs. Thus, it is essential to incorporate methods and metrics that can improve the explainability of these models to see how an input influences the model during decision-making. Explainability can be incorporated through a variety of ways like using performance parameters, using existing methods, through visualization, through model simplification, and by using explainability tools/interfaces. Model simplification can be done to make the models easily explainable. Some examples of explainable ML models are linear regression, decision tree, or generative additive models, which are an adaptation of linear models that allow the modeling of nonlinear data while maintaining explainability. Another technique to improve the trustworthiness of the ML/AI algorithm is by incorporating the application of domain knowledge while building the ANN. This can be done by transforming input data using domain knowledge [125], transforming loss function using domain knowledge using penalty terms, or by transforming model parameters using domain knowledge by using methods like transfer learning to update a given model [126].

If model simplification cannot be done, there are a variety of global and local methods that can help improve explainability of the model. For example, Local Interpretable Model-Agnostic Explanations (LIME) is a commonly used model-agnostic method that works by locally creating small perturbations of the original data to see how the model predictions change based on weights assigned to the perturbations based on distance to the original data [127]. These variations then help in building a model that is locally interpretable. Shapley Additive exPlanations (SHAP) is another model-agnostic local method which explains a given output by showing contributions of each input feature for a given output value which helps in understanding how the model values some input features for a given output value [128]. Layer-wise Relevance Propagation (LRP) is a local model-specific method for ANN that determines the relevance of each neuron for a given output [129]. There are different versions of LRP; for example, LRP-ϵ is used when contributions are weak, and LRP-γ gives more relevance to positive contributions as compared to negative contributions. Contrastive Explanation Method (CEM) [130] generates instance-based local black box explanations for classification models in terms of Pertinent Positives (PP) and Pertinent Negatives (PN). CEM can generate clear explanations of the form: "[a]n input, x, is classified into class, y, because PP features are present and because PN features are absent" [130]. Counterfactual explanations can also be used locally to describe the smallest change to a feature value that changes a prediction which is done by simply changing the feature value of an instance before making the prediction and then analyzing the change in prediction [131]. Deep learning Important Features (DeepLIFT) is a deep learning local explainability method that uses backpropagation to find the neurons and weights that had major effects for a given output [132]. Partial Dependence Plot (PDP) and Individual Conditional Expectation (ICE) are global model-agnostic methods that provide graphical information on partial dependence of each variable and are computed by repeating the entire dataset for every unique value of a given features; for example, given 10 features with 20 data points, dependencies are computing by generating 20 copies of the dataset with 10 features, which can cause them to be computationally expensive. Both PDP and ICE show dependence plots between the input features with the output; however, PDP shows the average effect of the input feature while ICE accounts for each sample of an input feature. PDP can hide relationships between instances when they get canceled out by averaging out results while ICE prints out results for each instance without averaging. Accumulated local effects (ALE) is a variation of PDP and generates a small window on the features to take the difference in predictions instead of averages, which helps ALE to see feature interactions [133]. Another global method is permutation feature information [134] that computes feature importance of each feature by computing the difference in the loss function using the original feature set and the loss function when the original feature set is slightly perturbed.

Visualizations can also be used to promote explainability and interpretability of the ML/AI method by using graphical representations for LIME, SHAP, PDP, ICE, ALE, and loss function curves as well as visualizations for EDA. Performance parameters can also be used that can help with explainability as well as trustworthiness of the ML/AI model. Models that have higher values for accuracy or F1 score, precision, recall values for classification models may also be more trustworthy due to their pedigree of development and be an aspect in explainability. There are four explainable AI (XAI) evaluation metrics that can give an understanding on the explainability of a model which are D, R, F, and S [135]. The parameter "D" quantifies the change in performance of the model as compared to the best available transparent model. Parameter "R" helps to quantify the simplicity of a model, which is done by generating penalties based on the complexity of the model. Parameter "F" also penalizes the performance of a model based on the number of features used to generate an explanation. Parameter "S" quantifies the feature stability which can be implemented by creating perturbations through bootstrap method. There are a variety of explainable tools/interfaces that incorporate one or many methods to help with explainability. AI Explainability 360 [136] is an open-source software toolkit featuring a variety of explainability methods like LIME and SHAP along with evaluation metrics like faithfulness and monotonicity. Various Python packages exist like Skater, a model-agnostic tool that helps the user understand the internal workings of an algorithm, or explain like I'm 5 (ELI5), which is used to understand classifiers by offering various visualization techniques including implementing LIME and permutation importance [137]. Another example is the what-if tool, which uses an interface developed by TensorFlow for explainability using visualization for both classification and regression algorithms, allows users to move around data features to understand the impact on output while also visualizing behavior of different data subsets [138]. InterpretML is an open-source toolkit that combines global (i.e., PDP, ALE, and ICE) and local explanation metrics (i.e., LIME and SHAP) and helps with understanding model errors as well as methods for data analysis [139]. Alibi Explain [140] is another open-source software for Python which also contains various methods for explainability and interpretability like SHAP, ALE, LIME, etc.

Last, while a wide range of explainability and interpretability metrics exist that can help develop trust in ML/AI models, how these methods are integrated into the framework will also be a necessary consideration. For instance, examining the methods SHAP, ALE, and LIME, there is no way to determine whether one method is more useful or superior to the rest at explainability or interpretability than the other. In addition, there is currently no common framework that identifies the necessary and sufficient condition that an ML/AI model must achieve to be considered sufficiently explained or trustworthy. Direct comparison of the methods is also not a feasible approach. For instance, SHAP and LIME fundamentally assess different aspects of the development environment with no comparable attributes. As is the case with performance evaluation metrics for ML/AI models, there also exists a variety of methods to establish interpretability and explainability without a common acceptable standard or framework to guide development. For ML/AI to be integrated in advanced condition monitoring programs, standardizing the development framework may be necessary to ensure that all processes associated with the creation of models are performed within acceptable regulatory guidelines and requirements.

4.2.11. Evaluating Maintenance Activities for Adequate Safety Margin and Avoiding Undesirable Conditions

One possible objective of a condition monitoring program is to determine when maintenance should be conducted on a component based on its condition. A risk analysis perspective may be adopted that informs maintainers when an unacceptable level of degradation has accumulated in the component monitored. This is analogous to maximum component vibration thresholds used to determine unacceptable performance but may incorporate a larger range of data such as component maintenance and operational history. Afterward, a condition monitoring program could optimize maintenance scheduling based on a priority of work order. Modification of the maintenance schedule, through preemptive detection or optimization, should consider how it may impact existing plant safety margins to avoid undesirable or degraded plant operating conditions.

Determining when a component needs to be maintained from a risk analysis perspective may be accomplished through dynamic risk assessment (DRA), a branch of probabilistic risk assessment. DRA in condition monitoring determines the growth in failure probabilities of safety barriers of a component over time. Mechanical degradation, in the form of wear, fatigue, crack formation/growth, etc., as well as operational and environmental changes and inspection and maintenance data can be factored in for the calculation of failure probability. For instance, in Reference [141], a DRA using a hidden Markov-Gaussian model incorporating the aforementioned data, is utilized to calculate the risk of component failure in shaft bearing over an operational time. A benefit of DRA is that it allows failure probability trend analysis over time and may provide more insight into when a component requires maintenance within acceptable safety margins [141]. This type of modeling is especially useful when a component may have partial degradation states that do not impact safety margin. Graphite brick crack formation in the UK advanced gas-cooled reactor is prime example, as crack formation does not necessarily impact operational or safety goals (see Appendix A in Reference [142]). However, determining a threshold for safety is component specific and may be influenced by a range of factors such as manufacturer, operating history, environmental degradation conditions, etc. Furthermore, the accuracy of DRA analysis is heavily influenced by the available data on a component’s condition and history. It is acknowledged in Reference [141] that a challenge in using DRA for component failure risk quantification is to ensure accurate predictions since a sufficient quantity of degradation data is needed. Inaccurate models may lead to non-conservative confidence in the component’s reliability and unexpected failure events, leading to avoidable component outages. Assuming a condition monitoring program can determine when a component should be maintained; it should then initiate the process for maintenance or inspection.

A typical work management process for component maintenance includes six phases (1) screening, (2) scoping, (3) planning, (4) scheduling, (5) execution, and (6) post-work analysis [50]. Scheduling optimization may involve the first four phases, where the latter two phases are dedicated to conducting and checking the maintenance activity. Screening is the first phase and is the generation or recommendation of the work order when a fault is detected. The scoping phase is intended to refine the generated work order, aligning initial estimates to material and labor commitments. Following is the planning phase, which verifies the scoping phase and prepares work instructions for use by craft personnel. It is anticipated that the screening phase will be the most critical as it links the output of a condition monitoring program to the beginning of work order generation.

Work screening identifies the type of work needed and gives initial estimates on the complexity, involvement, and materials needed after a fault is identified. Integration of work screening with a condition monitoring program may allow for the generation of failure risk insights associated with maintenance of the selected components. Activity risk categorization may be utilized to evaluate the need for work order generation. For example, in Reference [51], a matrix-based scoring method was utilized to classify the urgency of maintenance work relative to the impact on plant safety goals. Examples of the plant impacts from [51] include minor disturbances (e.g., burden to organizational goals, and quality-related) to significant disturbances (e.g., technical specification and immediate threat to public health and safety), separated by operational groups (e.g., group A, continuous operation, and group B, standby). Matrix classification is intended to simplify scheduling decisions for work order generation while simultaneously identifying the priority of a work order. Note that certain WO involve scenarios that cannot be initiated through condition-based monitoring as it may require additional unique subject-matter knowledge. Examples include boric acid leak, radiological exposure risk, security, fire watch, impact to plant design-basis (e.g., modification of setpoints), etc. While it is possible to derive a solution to incorporate subject-matter knowledge into the work order generation process, investigation into how that knowledge is derived and used may require qualitative decision matrices that do not succinctly translate to quantifiable values. Therefore, it may be preferable to avoid components located in systems which impact specialty subject-matter topics when implementing maintenance schedule optimization. Furthermore, a condition monitoring program designed to address emergent degradation risks (as opposed to long-term degradation risks) would need to have more considerations in data refresh rates, plant stakeholder accessibility, architectural redundancy, and application availability in a different manner than one used to address lower priority WO.

4.2.12. Addressing Unidentifiability of Faults from the Available Condition Monitoring Methods

One of the main challenges toward condition monitoring is that certain faults cannot be identified solely through a single methodology. For example, vibration analysis for pump motor fault detection consists of basic methods (e.g., determining the magnitude of vibration) and complex (e.g., vibration spectral analysis). In basic methods, excessive vibrations are used to determine whether an issue is present in the pump motor [143]. However, multiple different components within a pump motor may contribute to vibrations making exact fault identification through basic vibration analysis difficult without IST activities [143]. Spectral analysis is more capable at fault detection and is highly sensitive to changes in the monitored pump's condition [144]. However, this sensitivity also has a drawback in that different faults may share the same characteristic fault signature which also makes exact identification difficult without expert analysis. Faults may share characteristics due to a range of reasons, such as varying magnitudes of fault severity, varying root causes that generate similar signatures, changing operational conditions, damage and sensor malfunction, etc. [144]. Furthermore, baseline signatures collected for a pump motor are not guaranteed to remain constant over the plant life even if the component monitored is unaltered mechanically. This implies that vibration sensors may require long-term monitoring and calibration to maintain efficacy [144]. Therefore, determining faults using vibration basic and complex analysis alone may be insufficient and may require subsequent IST activities [145]. Under conventional

IST procedures, this is addressed by supplementing multiple forms of condition monitoring activities such as lube oil analysis, thermography, motor electrical testing, and motor current analysis.

These supplemental methods can be integrated together within an advanced condition monitoring program to provide a more comprehensive understanding of the condition of the pump motor. There already exists the capability to measure multiple degradation parameters simultaneously (e.g., ABB Ability™ Smart Sensor [146]); condition monitoring DT can leverage these technologies by analyzing multiple parameters simultaneously. For instance, vibration and current analysis can be combined for the condition monitoring of centrifugal pump impellers [147, 148, 149]. Specifically, the equations for vane pass vibration and motor pole slip frequency are combined into a single frequency fault algorithm that can detect degradation of the pump impeller vanes. A benefit of combined methods is they may be more sensitive to specific faults (e.g., broken rotor bars) over usage of a single method and can increase the detection reliability (e.g., lower false positives) [148]. In the combined vibration and MCSA method, it was specifically found that detection reliability can be increased as each method supplements the limitations of the other. For instance, MCSA is highly sensitive to load variation, whereas vibration is not as sensitive. It was experimentally shown that the two methods can reduce false positive detection of rotor bar faults when motor load is varied [148]. Integrated condition monitoring methods are promising and can provide better assessment of the health of components, especially in pump motors, and can better improve the identification of the root cause of faults [149].

However, the implementation of a combined condition monitoring method for fault detection has several challenges. First, as there exists significant variation in the root causes of faults, there is no one method suitable for the detection of all possible faults. It is anticipated that multiple techniques must be combined for discriminating between faults [147]. How these techniques are combined is still an area of active research. Furthermore, while vibration analysis and MCSA are promising, there is no international standard for MCSA, which makes benchmarking and evaluation difficult when these methods are combined [147]. Different components and sensors will also require varying degrees of customization of the model used for advanced condition monitoring. As ML/AI models are data-driven, different sensor technologies will generate different operational data conditions, requiring specific model training and V&V efforts. As equipment used in NPPs is not standardized, this further limits the scalability of the condition monitoring DT technology. Furthermore, as condition monitoring methodologies are integrated together, calibration and maintenance of one set of sensors (e.g., vibration) will impact the overall methodology, requiring additional model maintenance and testing effort [150]. Additionally, safety in NPPs depends on the independence of systems. However, integration of monitoring activities may degrade the independence of analyses. For instance, if one set of vibration sensors fails, this may lead to the entire condition monitoring DT model being unusable. While virtual sensors may be incorporated to address this issue, this becomes another area where V&V activities are required and may complicate model maintenance [150]. While no single or combined method may address all related concerns, these methods may still be used to identify an unknown anomaly in component health, initiating subsequent maintenance activities. For instance, while a single advanced condition monitoring program for pumps may not be able to detect the full range of faults, there may be several potential merits to its implementation.

Table 3. Challenges and opportunities.

Challenges	Opportunities
Developing an advanced condition monitoring program to inform ISI and IST procedures to meet the requirements	• Establishing organizational guidance for data procurement, management, and interpretation. • Identifying which active or passive components are candidates for an advanced condition monitoring program through the quantification of risks and benefits associated with its implementation. • Developing an adequate V&V procedure to confirm the functional and non-functional requirements of an advanced condition monitoring program during development phases. • Developing an adequate reverification procedure to confirm the advanced condition monitoring program is continuously meeting functional and non-functional requirements. • Establishing cybersecure condition monitoring programs associated with a computer-based software system. • Establishing standardized evaluation metrics for advanced condition monitoring programs. • Developing an advanced condition monitoring program that provides guidance on key technical and regulatory aspects through application-specific scenarios.
Maintaining state concurrence of the condition monitoring DT with the physical asset	• Developing technical capabilities for real-time integration of asset condition in the condition monitoring program. • Developing guidance for implementing state concurrence capabilities.
Licensing and continuing maintenance of ML as software	• Developing guidance and protocol for modeling and simulation tools to meet and continuously meet regulatory requirements. • Evaluating the trustworthiness, explainability, and interpretability of ML/AI methods for advanced condition monitoring programs.
Evaluating maintenance activities for adequate safety margin and avoiding undesirable conditions	• Developing capabilities in condition monitoring DT to perform real-time safety analysis by incorporating existing risk assessment methodologies (i.e., probabilistic risk assessment).
Addressing unidentifiability of faults from the available condition monitoring methods	• Developing condition monitoring DT with capabilities of integrating and analyzing heterogeneous data such as historical data, real-time data, and multiple modalities.

5. SUMMARY

This report identifies how condition monitoring programs may utilize advanced technologies, such as DT, ML/AI, and data analytics, to augment routine IST and ISI activities on active and passive components within an NPP. IST and ISI are critical processes in the maintenance of plant operational performance and safety. Advanced technologies may enhance these activities through preemptive detection of degradation and component faults, increased confidence in the condition of a component, and may be utilized to optimize maintenance scheduling activities. Condition monitoring programs may accomplish this by leveraging DTs and advanced ML/AI methods that integrate multiple sources of information, from historical plant data to advanced sensor and instrumentation technologies. It is anticipated that such technologies may improve existing regulated maintenance practices while simultaneously improving overall plant performance by reducing unnecessary plant outages.

However, there are several challenges that must be considered to ensure advanced condition monitoring systems preserve organizational, regulatory, and operational goals. Key challenges include:

- Verification, validation, and reverification of ML/AI models used for degradation and fault prediction
- Initial and ongoing evaluation of condition monitoring program models under changing plant conditions
- Maintenance of condition monitoring program models—risk-informed decision-making both in the selection of the candidate component and the automated maintenance decisions of the condition monitoring system
- Cybersecurity concerns associated with computer-based condition-monitoring information systems.

Furthermore, significant effort may still be needed in the initial demonstration of advanced condition monitoring systems such as providing representative real-world case studies; developing the capability for real-time integration of plant data with condition monitoring program models; and developing the capability to integrate multiple sources of heterogeneous sources of information and methods. Finally, there exist several unaddressed challenges associated with condition monitoring DTs that are anticipated to integrate data- or physics-driven ML/AI models such as construction of data collection, modification, and integrity management methods; reliability, trustworthiness, and explainability of model predictions; and fragility and risk of CCFs in highly integrated software systems. If left unaddressed, these challenges may result in delays in the adoption and deployment process for nuclear energy applications.

While these challenges are daunting, the level of effort required in development and assurance should be commensurate to the degree of reliance and the impact which advanced condition monitoring program will have on existing processes. Potential applications with relatively lower risk significance could therefore be considered for early adoption of advanced condition monitoring program. Such applications would help in building trust in the technologies and the lessons learned could enable faster adoption among other applications including higher risk significant SSCs.

There is significant interest in using advanced condition monitoring techniques 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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