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Idaho National Laboratory

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Digital-Twin-Enabling Technologies for Online Condition Monitoring of Nuclear Power Plant Components

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ABSTRACT

Online condition monitoring is an area of active research that may enable improved scheduling, maintenance, and safety of nuclear power plant components, reducing unnecessary derates while simultaneously improving operational capacity. Digital twins are one avenue to conduct online condition monitoring and are currently being explored by national laboratories and universities alike. Digital twins for online condition monitoring are, in essence, state concurrent models that emulate a physical process which predicts a parameter and compares it against a measured value. However, digital twins may also provide additional insights by combining and interpreting various sources of information. These insights may be used for preventative maintenance scheduling optimization or early fault detection and are projected to be valuable for meeting requirements under 10 CFR 50.55a. However, digital twin technologies are still under significant development; quantifying model uncertainties, improving unique fault identification, and multimodal sensor fusion are some areas under investigation. Therefore, in this work, we discuss and review the various enabling technologies, in the form of advanced sensors, instrumentation, and modelling methods, that may be used to implement and enhance digital twins for online condition monitoring. A potential use case for pump-motors is presented to demonstrate how these various pieces of enabling digital twin technologies may integrated together for online condition monitoring. Challenges and opportunities associated with the pump-motor digital twin enabling technologies are also identified and discussed.

Keywords: online condition monitoring, digital twins, advanced sensor instrumentation

1. INTRODUCTION

Commercial nuclear power plants (NPP) in the USA have implemented extensive operation and maintenance (O&M) practices such as preventive maintenance, in-service testing (IST), and in-service inspection (ISI). These practices have resulted in immense benefits for the fleet such as ensuring safe operations and maintaining high-capacity factors. However, many of these O&M practices are manual, time-consuming, and in some cases require plant derate or shutdown which drive up the O&M costs. The need for online condition monitoring, also known as online monitoring (OLM), is motivated by the regulations and standards established by the U.S. Nuclear Regulatory Commission (NRC) under 10 CFR 50.55a. Online monitoring code case 2022 (known as OM-2022) [1] developed by the American Society of Mechanical Engineers is one of the standards endorsed by the NRC to determine the requirements for pre-service and in-service testing. OM-2022 is used to assess the operational readiness of select components used in water-cooled reactor nuclear power plants [1]. The code case applies to pumps, values, pressure

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relief devices, and dynamic restraints (e.g., snubbers) and identifies the responsibilities, methods, intervals, and parameters that need to be measured and evaluated [1].

One potential application of OLM is the modification of the requirements of periodic maintenance outlined under OM-2022 ISTB-3400 [1]. Under current guidance, the interval for pump verification tests is biennial (for pumps identified under ISTB-1400) [1]. However, based on previous research in the application of OLM for pressure transmitter calibration intervals [2], it may be possible to extend the interval of pump testing without any significant impact to operation. Specifically, in [2], the authors identify that about 90% of the sensors maintained their calibration and, subsequently, did not need adjustment during the regularly scheduled maintenance activity. It is postulated that a significant amount of burden may be alleviated if sensor calibration is conducted with condition-based approach as opposed to fixed frequencies [2].

Digital twins (DTs) and associated enabling technologies such as advanced sensor instrumentation (ASI) and modeling and simulation (M&S) [3] may be one avenue to support such condition-based testing for passive and actives components in nuclear power plants. Recent technical reports published by the US Nuclear Regulatory Commission (NRC) provide a description of nuclear-DT system [3] challenges and gaps associated with DT enabling technologies [3, 4], regulatory considerations in nuclear-DT [5], and potential applications of DT in nuclear safeguards [6]. In this work, we examine the enabling technologies that may be used to develop DT for OLM and discuss how these technologies are applied for the maintenance activities in water-cooled pumps in nuclear power plants. Finally, we discuss the potential near-term opportunities and select challenges that affect DT for OLM in nuclear specific to pump-motors.

2. DIGITAL-TWIN-ENABLING TECHNOLOGIES FOR ONLINE CONDITION MONITORING

In summary, a DT developed for OLM represents one or more components within a nuclear power plant [4]. To develop a DT, two broad technological needs are required (1) M&S of the target component(s) and (2) data and information pipeline management [4]. Elements of M&S include, but are not limited to, statistical analytics, machine learning (ML), physics-based models, data-informed models, probabilistic models, and reduced-order-models [4]. In essence, these elements are used to predict metrics such as (a) the remaining useful life (RUL) of a component(s), (b) health and degradation states, and (c) mechanical or electrical faults experienced by the component. By anticipating these metrics, informed maintenance scheduling and operational performance may be achieved which may reduce plant maintenance activities and reduce cost of operation of target components [2]. Advancements in sensor instrumentation and modeling methods can broadly improve DT development by improving fault and malfunction detection, operational anomaly detection, reduction in useful metric uncertainty, and the real-time notification and recommendation of component condition and maintenance.

2.1. Advanced Sensor Instrumentation

Sensors have been used extensively in the existing fleet to measure a variety of parameters such as temperature, pressure, flow, neutron flux, level, etc. However, previous capability assessment suggests gaps still exist in the reliability to measure these quantities with sufficient resolution over an extended period [4]. Advances in sensor instrumentation is expected to enable a greater spatial density of measurements, an improved life span under degradation conditions, a reduced size/footprint, and the capability to measure multiple parameters simultaneously (e.g., multimodal) [4]. Together, these characteristics are expected to enable more detailed insights of component state—a necessary step for developing and maintaining a DT [4].

2.2. Advanced Modeling Methods

The explosion of artificial intelligence and ML development has prompted several investigative studies in the application for OLM. It should be noted that neural networks and many existing statistical methods are not novel and have been published extensively in the past. However, newer architectures that utilize multiple hidden neuron layers (e.g., deep neural networks) in combination with image transformation (e.g., convolutional neural networks for fault diagnostics [7]), time-based feedback loop models (e.g., long-short term memory for RUL prediction [8]), and statistical neural networks have permitted better predictions and modeling of conventionally difficult problems. More recent transformer models and improved natural language processing methods (e.g., automated work order classification [9]) have seen improvements in document processing and interpretation in lieu of expert elicitation. It is anticipated that these advancements will play a critical role in the future development of DT technologies for OLM such as sensor fusion (e.g., combining pressure, temperature, and vibration for fault detection [10]), improved prediction of useful metrics (e.g., RUL [8]), and interpretation of fault signatures from sensor readings (e.g., automated fault diagnostics of motor current frequency spectrum [11]).

3. ONLINE CONDITION MONITORING FOR PUMPS

Pumps and motors are key components within nuclear power plants, providing primary and secondary coolant flow through the core. Large centrifugal vertically mounted pumps have been used extensively in existing light-water-cooled reactors. Smaller horizontally mounted canned pumps have also been explored for newer reactor designs that have smaller thermal power outputs [12]. Due to their importance, maintaining the health of the pump-motors is a highly relevant task for the continued availability and operation of the reactor. Existing activities for pump-motor OLM include (a) vibration analysis, (b) motor current signature analysis (MCSA), and (c) thermography. These may be supplemented with lube oil analysis, motor electrical parameter monitoring, and process and equipment parameter monitoring to provide a comprehensive evaluation of pump-motor health [13].

3.1. Pump-Motor Vibration Analysis

As pump-motors are rotating machinery with repeating frequency spectrums, they are a candidate for vibration analysis for the identification of faults [14]. Vibration analysis is measured through wired or wireless accelerometers which record small changes in directional velocity due to vibrations. Recorded vibration data can then be used to monitor component health by examining changes in the time-frequency spectrum of the vibration data, where severity is usually expressed as variation in displacement, velocity, or acceleration [14]. Abnormalities in the time-frequency spectrum can be used to inform scheduling of maintenance activities [14]. An anomaly is typically identified when the recorded vibration data deviates from historical or baseline vibration data.

The types of data collected to conduct pump-motor vibration analysis include the axial displacement, velocity, and acceleration time waveforms and can be used to derive the velocity and acceleration frequency spectrums [15]. The types of pump-motor faults that may be detected with vibration analysis include, but are not limited to, general corrosion/wear induced performance degradation (e.g., excessive shaft bearing sleeve wear), cracks/damage of pump-motor components (e.g., casing, impeller), change in seal/lubricant material properties (e.g., viscosity and water-content), misalignment/unbalance of pump-motor components, structural support looseness, mechanical rubbing or friction, and obstructions in piping or intakes [14, 15].

3.1.1. Challenges in Vibration Analysis for OLM

Several challenges exist that may impact efficacy of vibration analysis, namely optimal positioning of vibration sensors, noise and interference, sensor drift, limited early detection capability, and limited detection of certain faults.

First, to adequately conduct vibration analysis, normal anticipated frequencies (e.g., fundamental harmonics of the pump) and operating conditions must be identified to characterize motor-pump frequency spectrums [14]. This baseline is important as while pump-motor vibration is usually lowest when operating at its ideal efficiency, variation in flow can significantly change the range of vibration levels even if the internal condition of the pump is unchanged [14]. Furthermore, it is important to note that no universal vibration severity limits exist [16], such that fault signatures will vary even for identical components.

The placement of sensors to measure baselines and fault signatures can be a challenge under certain design configurations. For instance, in reference [17], it was identified that optimal placement of sensors was a challenge as the types of sensors employed could not be installed around the pump where the impeller and casing were submerged in the coolant. Instead, vibration sensors were installed on the outer casing of the motor and used to indirectly monitor pump health. This was due to the limited accessibility of the pump as well as the potential long-term degradation effects of vibration sensors when exposed to coolant [17].

Another challenge is potential noise and interference from other active components and personnel that may be nearby. While antialiasing filters can be applied to remove irrelevant frequencies, selecting the proper filters requires intimate knowledge of the pump-motor's operational characteristics, including variation in day-to-day activities and potential transients [15]. Inadequate filtering of interference can result in higher false positive identifications of pump-motor faults leading to spurious maintenance activities [15].

Changes in the vibration spectrum may also be due to drift or decalibration of the sensors. First, accelerometer-based vibration sensors are sensitive to the axis of orientation (e.g., XY-axis); axial misalignment can thus alter axial sensor readings [14, 15]. Second, vibration sensors are placed on the target component via magnets or a mounting plate attached using epoxy [14]. Over time, excess vibrations of the component may displace the alignment of the sensor influencing sensor readings [15]. From this perspective, periodic calibration of vibration sensors may be required to ensure proper alignment and placement. However, more significantly, vibrations from faulty components (e.g., broken rotor bars) may not generate sufficient fault signatures for early diagnostics [18]. In many cases, the fault must be severe (e.g., multiple broken rotor bars) before vibration analysis can adequately identify a fault [18] and may impact the efficiency of maintenance activities.

Last, while pump-motor vibration analysis is a powerful tool, it can only detect a limited set of pump-motor faults [14]. Different fault modes may also exhibit similar vibration signatures, making exact diagnostics challenging [15]. For instance, excessive friction due to inadequate lubricant may share similar vibration signatures to general corrosion and wear [15]. Faults that cannot be detected include, but are not limited to, electrical and stator winding faults [18]. Currently, limitations in vibration analysis are supplemented with other types of condition monitoring programs such as oil-lubricant analysis, MCSA, and motor stator temperature analysis [13].

3.1.2. Enabling Technologies for Vibration Analysis OLM

Technological innovations of vibration sensors include integrating micro-electromechanical systems (MEMS) accelerometers, improving sensor fusion analysis, and applying ML methods.

MEMS accelerometers are part of the Internet-of-Things revolution and can overcome certain limitations associated with piezoelectric accelerometers; MEMS sensors consume less energy, are smaller in size, and are widely and cheaply available [19]. MEMS sensors can operate wirelessly for months under battery power reducing the need for periodic sensor maintenance [19]. In addition, their small size and wireless configuration permits the placement of sensors in tight spaced locations [19]. Finally, MEMS sensors can collect the same types of data collected by piezoelectric sensors, eliminating the need for new vibration analysis techniques.

As identified previously, vibration analysis alone may not yield unique fault signatures; utilizing multiple sensors may improve the identifiability of faults. Recent algorithmic improvements in empirical wavelet transform [20] and variance contribution rate in [21] may permit fusion of multiple sensor readings (e.g., vibration, pressure, flow, and temperature) to improve accuracy and range of fault detection.

Sensor fusion may also be accomplished with ML models. In [22], 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 [10], the authors implement a convolutional neural network to process multiple vibration signals as representative two-dimensional images to enhance fault prediction.

3.2. Motor Current Signature Analysis

MCSA is another monitoring technique used to assess the health and condition of motors such as three-phase induction motors typical in water-cooled nuclear power plants [23]. MCSA is a mature technique and can detect faults at an early stage, thus avoiding damage and complete failure of the motor [18]. MCSA is conducted by measuring the asymmetrical backward rotating electrical current frequency spectrum induced by the motor during normal operation [18]. 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 [18]. 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 include induced current amplitude waveform and frequency [18]. In addition to these parameters, the supply voltage may also be recorded to conduct supplemental instantaneous power frequency analysis to monitor operational health [18]. 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) [18, 24, 25].

3.2.1. Challenges in MCSA for OLM

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 required for diagnostics [18, 26, 24]. Other challenges include external electromagnetic interference and data storage limitations associated with high sampling frequencies [18, 24]. 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 [18].

In addition, it is challenging to distinguish between normal variations in operating condition, load changes, and system transients to motor faults [18]. Changes in the motor load will alter the reference signature which impacts identification of associated fault signatures. Due to variable operating conditions and non-identifiability of faults, typically expert knowledge is required to make accurate assessments of motor health [18]. 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 [18]. Root cause analysis through MCSA may also be challenging as faults may share signatures and may require in-service inspection for proper diagnostics [18].

Electromagnetic interference such as power and radio frequency interference, harmonics, and electromagnetic induction may change the recorded current frequency spectrum and increase the likelihood of spurious maintenance activities [18]. Similar to vibration analysis, the impact of electromagnetic interference can be reduced with proper antialiasing filter selection which requires intimate knowledge of the motor operational conditions.

Another challenge to MCSA is the data requirements for fast sampling frequencies. MCSA typically uses frequency ranges within 0–5kHz, which necessitates a sampling frequency of 10,000 samples per second [24]. 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 OLM challenging. Utilizing data-compression methods to efficiently store data is still currently an issue as it may subsequently mask underlying fault signatures [27, 28, 29].

3.2.2. Enabling Technologies for MCSA

Certain challenges identified for MCSA may be addressed with ML methods. As discussed, significant expert interpretation of the frequency spectrum may be required to diagnosis faults. While the use of artificial neural networks for MCSA is not a novelty and has been conducted in previous works such as [30], methods such as deep neural networks and image processing can improve fault diagnostics. For instance, in [31], the authors utilize convolutional neural networks to conduct automatic image and fault classification of the motor current frequency spectrum. In [11], the authors demonstrate various statistical classification algorithms to diagnosis different mechanical faults in pump-motors. While promising, integration of ML methods may require additional digital infrastructure to (a) pre-process sensor data, (b) implement a real-time input pipeline, and (c) a data storage method for input/historical data [4].

Aside from the implicit challenges posed by MCSA, modeling methods may improve how MCSA is used to inform scheduled maintenance. In [17], the developers implement a Markov Chain model to anticipate the reliability and availability of circulating water pumps in the Salem nuclear power plant. The Markov model was then used to inform on preventive maintenance optimization strategies to improve pump-motor maintenance scheduling economics.

3.3. Thermography

Thermography 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 [32, 33]. In addition, IR measurement equipment is not impacted by electromagnetic interference or contact-related degradation mechanisms that other sensing strategies may be susceptible to [33]. 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 [33]. 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 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 [32, 33]. 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 [32].

3.3.1. Challenges in Thermography for OLM

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 required for proper utilization [32, 33]. 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 [32]. In addition, IR imaging requires line-of-sight for temperature measurements [33]. 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 [33]. 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 [32]. 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 [32]. 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.

3.3.2. Enabling Technologies for Thermography

Various ML models have been proposed to reduce the amount of effort required 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 [34], the authors combine IR thermography with ensemble methods to diagnosis three-phase induction motor phase imbalance caused by shorted stator windings. In [7], the authors utilize convolutional neural networks to interpret IR images and diagnosis rotating bearing faults of induction motors. In [35], the authors apply various ML methods to IR thermography to anticipate maintenance activities. However, while promising, most ML methods for IR thermography are conducted within laboratory settings with artificially manufactured defects. As of this report, ML 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 target system does not change over time, that may limit their current application for condition monitoring [36].

4. CONCLUSIONS

In this work, we discuss various enabling technologies for digital twins for online condition monitoring. We discuss how these technologies are implemented from the context of light-water reactor pumps and motors. Finally, we discuss select challenges and opportunities that impact digital twins and advanced sensor instrumentation for condition monitoring. While digital twins are expected to enable condition-based maintenance and interval testing, there are several challenges and gaps that still need to be addressed before these technologies can be fully adopted. These challenges primarily include sensitivity of the modeling methods to specific faults, the long-term material and operational knowledge required for proper implementation, and data storage and processing requirements for models within digital twins. However, these technologies are seen to be promising and may be applicable to address certain requirements under ASME Online monitoring code case 2022 and 10 CFR 50.55a.

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