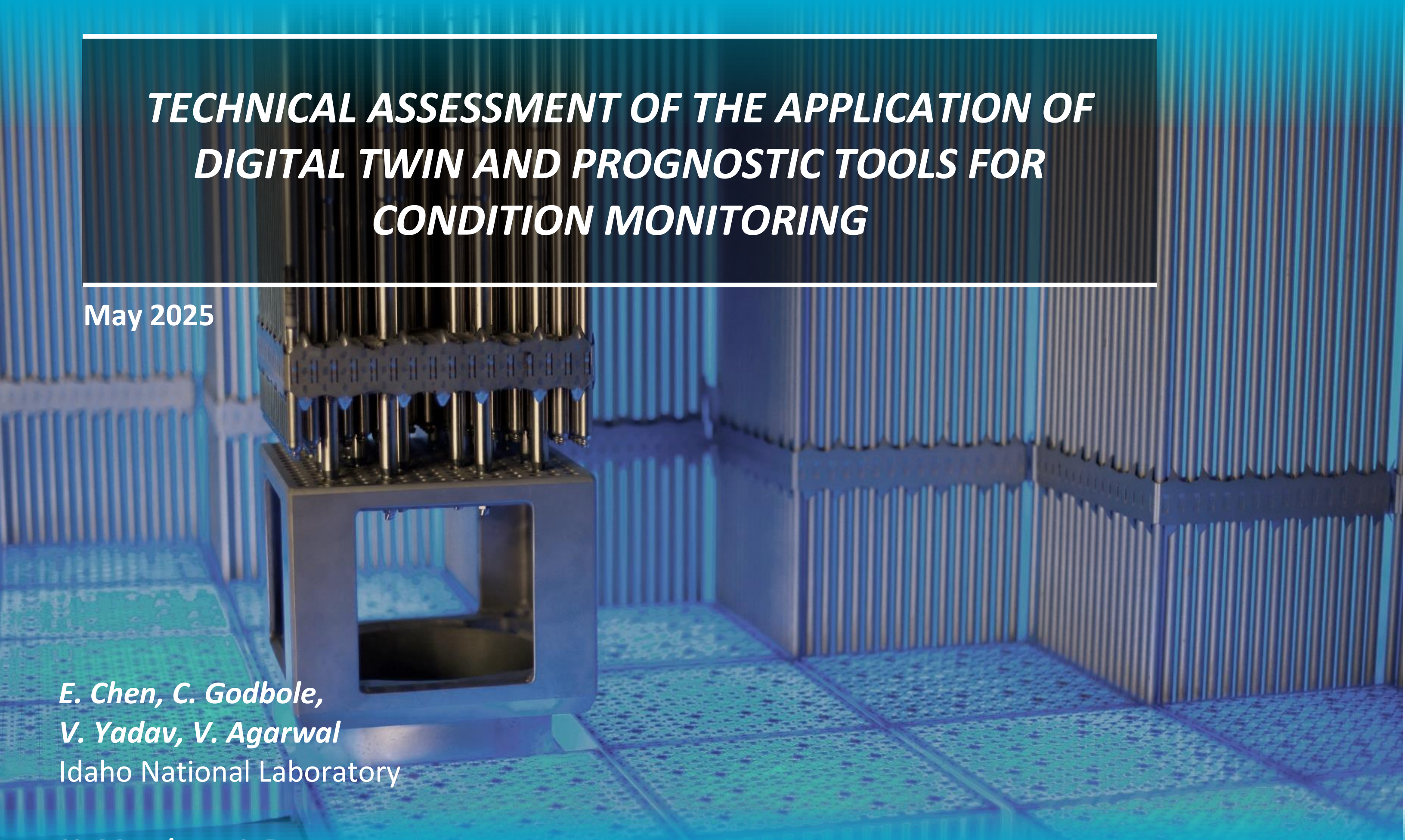
Letter Report
TLR-RES/DE/REB-2025-09



# TECHNICAL ASSESSMENT OF THE APPLICATION OF DIGITAL TWIN AND PROGNOSTIC TOOLS FOR CONDITION MONITORING

**May 2025**

***E. Chen, C. Godbole,***
***V. Yadav, V. Agarwal***
Idaho National Laboratory

***H. Mendoza, J. Bass,***
***J. Matrachisia, T. Hathaway,***
***C. Nellis, C. Ulmer, J. Tokey, E. Cohn,***
***D. Eskins, T. Scarbrough,***
***R. Iyengar***
U.S. Nuclear Regulatory Commission

**Division of Engineering**
**Office of Nuclear Regulatory Research**
**U.S. Nuclear Regulatory Commission**
**Washington, DC 20555–0001**

*Prepared as part of the Task Order 31310023F0029, "Enabling Technologies for Plant Modernization and Applications of Digital Twins"*

**This report does not contain or imply legally binding requirements. Nor does this report establish or modify any regulatory guidance or positions of the U.S. Nuclear Regulatory Commission and is not binding on the Commission.**

*Page intentionally left blank*

INL/RPT-25-84268

# Technical Assessment of the Application of Digital Twin and Prognostic Tools for Condition Monitoring

MAY 2025

Edward Chen
Chaitee Godbole
Vaibhav Yadav
Vivek Agarwal

*Idaho National Laboratory*

H. Mendoza, J. Bass,
J. Matrachisia, T. Hathaway,
C. Nellis, C. Ulmer, J. Tokey, E. Cohn,
D. Eskins, T. Scarbrough,
R. Iyengar

*U.S. Nuclear Regulatory Commission*

Idaho National Laboratory

INL/RPT-25-84268

# Technical Assessment of the Application of Digital Twin and Prognostic Tools for Condition Monitoring

**Edward Chen**
**Chaitee Godbole**
**Vaibhav Yadav**
**Vivek Agarwal**
**Idaho National Laboratory**

**H. Mendoza, J. Bass,**
**J. Matrachisia, T. Hathaway,**
**C. Nellis, C. Ulmer, J. Tokey, E. Cohn,**
**D. Eskins, T. Scarbrough,**
**R. Iyengar**
**U.S. Nuclear Regulatory Commission**

**May 2025**

**Idaho National Laboratory**
**Idaho Falls, Idaho 83415**

**http://www.inl.gov**

**Prepared for the**
**U.S. Department of Energy**
**Office of Nuclear Energy**
**Under DOE Idaho Operations Office**
**Contract DE-AC07-05ID14517**

*Page intentionally left blank*

# SUMMARY

This report was prepared for the U.S. Nuclear Regulatory Commission (NRC) to present use cases of applying advanced technologies to meet the current and future regulatory requirements for the maintenance and condition monitoring of structures, systems, and components. The advanced technologies considered in this work, collectively referred to as digital twin technologies, are advanced sensors and instrumentation, data analytics, machine learning and artificial intelligence (ML/AI), and physics-based models. This report presents two use cases: reactor coolant pumps and heat pipes in nuclear power plants (NPPs), along with technical and regulatory considerations and opportunities for using advanced technologies in condition monitoring. Key findings from exploring these considerations are as follows:

- Uncertainties in sensor data and model predictions must be rigorously addressed through validation and verification processes.
- For safety-significant applications, regulatory implications on NRC guidelines for current and advanced reactors need to be considered. Such considerations may necessitate the development of sound data-driven models consistent with codes and standards.
- Explainability and transparency in ML/AI models are essential for developing operator trust and regulatory review, including methods that enhance the interpretability of complex data-driven predictions.
- Condition monitoring programs must be evaluated for their effectiveness in reducing maintenance-preventable function failures and aligning with plant performance criteria.
- The deployment of advanced technologies for condition monitoring could lead to a transition from periodic to continuous monitoring, thereby optimizing maintenance schedules.
- Collaborative efforts between industry stakeholders, regulatory bodies, and technology developers are crucial for the successful adoption of advanced technologies for condition monitoring systems in nuclear facilities.

In summary, the introduction of advanced technologies to condition monitoring programs represents a significant leap forward in the domain of NPP maintenance. By harnessing the capabilities of advanced sensors, data analytics, and ML/AI, NPP operators can transition from a time-based to a condition-based maintenance approach. This shift can potentially enhance the reliability and safety of crucial plant components while optimizing maintenance efforts and minimizing unnecessary outages. The NRC is continuing to explore the regulatory aspects of advanced technologies as part of inservice inspection and inservice testing programs by pursuing additional research in this technical area.

*Page intentionally left blank*

# CONTENTS

# FIGURES



# TABLES

*Page intentionally left blank*

# ACRONYMS

| | |
|---|---|
| AI | Artificial intelligence |
| ASME | American Society of Mechanical Engineers |
| BPV | Boiler & Pressure Vessel |
| DT | Digital twin |
| EDA | Exploratory data analysis |
| FBG | Fiber Bragg grating |
| ICE | Individual conditional expectation |
| INL | Idaho National Laboratory |
| ISI | Inservice inspection |
| IST | Inservice testing |
| LBE | Licensing basis events |
| LIME | Local Interpretable Model-agnostic Explanations |
| LMP | Licensing modernization program |
| LWR | Light-water reactors |
| ML | Machine learning |
| MOOSE | Multiphysics Object-Oriented Simulation Environment |
| MPFF | Maintenance-preventable function failure |
| NPP | Nuclear power plant |
| NRC | Nuclear Regulatory Commission |
| ODFR | Optical frequency domain reflectometry |
| OM | Operation and Maintenance of Nuclear Power Plants |
| PDP | Partial dependence plot |
| PWR | Pressurized-water reactors |
| RCP | Reactor coolant pumps |
| RCS | Reactor coolant system |
| RG | Regulatory Guide |
| SPHERE | Single Primary Heat Extraction and Removal Emulator experiment |
| SPR | Special Purpose Reactor |
| SSC | Structures, systems, and components |
| V&V | Verification and validation |

*Page intentionally left blank*

# 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 (DTs). For more information on what comprises a DT, refer to Reference [1].

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 [2]. The workshop focused on developing 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. A report was recently published on this effort and provides an assessment of technical challenges, considerations, and opportunities associated with applying advanced condition monitoring technologies to address certain inservice inspection (ISI) and inservice testing (IST) activities [3].

This current report presents a broad approach for the application of advanced technologies intended to potentially meet the regulatory requirements associated with condition monitoring of SSCs at NPPs. The scope of this report encompasses identifying the scope of monitoring, determining safety classifications based on existing guidance, monitoring degradation modes, and selecting appropriate monitoring parameters. Two use cases, reactor coolant pumps (RCPs) in pressurized-water reactors (PWRs) and heat pipes in microreactors, are discussed in detail to present the possible implementations of a condition monitoring approach using advanced technologies.

For RCPs, the focus is on safeguarding the pump's operation within design parameters—a critical aspect for the reactor's safety and efficiency. This first case study focuses on the onset detection of thermal barrier leakage, a significant degradation mode, by closely tracking process variables (e.g., bearing temperature) to indicate the pump's health. Discussion of advanced monitoring technologies in this case study is to evaluate its impact on IST and ISI activities for active components.

For the second case study, heat pipe condition monitoring is explored. Heat pipes are novel heat removal components actively explored for advanced microreactors applications and are instrumental in transferring heat away from the reactor core. A key feature of heat pipes is their lack of moving parts to achieve heat removal, leveraging the principles of phase transition and capillary action (i.e., wicking structure) of a working fluid (e.g., sodium) to facilitate efficient and reliable heat transfer. As such, the heat pipe case study focuses on thermal performance condition monitoring to ensure that the heat pipe can function as designed within acceptance criteria. In addition to thermal performance, a condition monitoring program may also take into account the structural integrity (e.g., ISI activities) of the heat pipe as maintaining integrity (i.e., wicking structure corrosion) directly affects heat transfer performance. This case study investigates how advanced monitoring technologies may impact IST and ISI activities.

Section 2 provides a background and overview of the condition monitoring approach using advanced technologies. Sections 3 and 4 discuss the RCP and heat pipe use case, respectively, along with the technical and regulatory considerations and potential challenges for the successful deployment of these use cases. Section 5 presents some generic considerations for condition monitoring, which are common considerations regardless of a specific application or use case.

# 2. BACKGROUND

This section introduces a broad and general approach for applying advanced technologies toward condition monitoring of an SSC at an NPP. Table 1 illustrates the development stages for condition monitoring, detailing each stage for the two use cases presented in this work. Within each stage, key information is identified that is expected to be integral for developing DT models for condition monitoring. These stages may refine the existing major steps required for developing a condition monitoring program. For example, American Society of Mechanical Engineers' *Operation and Maintenance of Nuclear Power Plants* (hereafter referred to as ASME OM Code), Division 2, Part 24, "Reactor Coolant and Recirculation Pump Condition Monitoring" [4] provides guidance for condition monitoring of pumps. The first step is to identify the potential pump faults that the program can detect, and the symptoms produced by those faults [4]. In this work, this single step is broken down into five stages: (1) identifying the scope of condition monitoring, (2) determining the safety class of the SSC, (3) determining the degradation mode monitored, (4) determining the objective of the condition monitoring program, and (5) selecting the relevant parameters for condition monitoring (see Table 1).

Table 1. DT development stages for condition monitoring under different example use cases.

| DT Development Stage | Use Case Application | |
|---|---|---|
| | **Case 1** | **Case 2** |
| Identify scope and reasoning for condition monitoring | RCP ensuring normal anticipated operating condition | Heat pipe ensuring normal anticipated operating condition |
| Determine the safety class of the SSC | Safety-related | Safety-related* |
| Determine degradation mode monitored | Thermal barrier leakage | Structural integrity |
| Determine the objective of condition monitoring | Detection of the onset of thermal barrier leakage | Detection of degradation and leakage of heat pipe |
| Select parameters for condition monitoring | Bearing temperature, motor vibration signature, flow rate | Ultrasonic vibrations for structural integrity monitoring |
| *Dependent on final heat pipe reactor design. | | |

The first step of the DT development process is an organizational decision to implement a condition monitoring program for a target SSC and what capabilities the program may offer. This organizational decision evaluates what SSC is targeted, whether a condition monitoring program is necessary for the SSC, the expected benefits derived from its implementation, and the scope of the program. In essence, it should answer fundamental questions such as why a condition monitoring program is necessary, what component is assessed and under what conditions, and what benefits it can bring to the organization. Techno-economic analyses may also be performed in this step to evaluate the feasibility of implementation. In this work, it is assumed that the organization has determined that a condition monitoring program is necessary; decision support for this determination is not investigated in this work. The next step is to identify the scope of the condition monitoring program after selecting an SSC, determining the intended operational conditions monitored and identifying the available sensors and technology used to monitor that SSC. This step is fundamental as it sets the boundaries of what needs to be monitored and why. For the RCP (i.e., Case 1), the scope is to ensure that it operates within designed parameters at normal operating conditions, which is crucial for reactor safety and efficiency. Similarly, for the heat pipe (i.e., Case 2), the scope is to assure its proper function in transporting heat away from the reactor core, a key aspect of the reactor's cooling system. Note that defining the scope of the monitoring task is not limited to a single operating condition and may span a variety of anticipated operational occurrence.

Determining degradation modes monitored is a stage that involves understanding how a component might fail or underperform. There can be several degradation modes for each SSC in an NPP. For this report, one degradation mode is considered in each use case; other modes may be added following a similar approach. For Case 1, thermal barrier leakage is a concern, as it could signal a breach in the RCP's ability to maintain a thermal boundary. In Case 2, the degradation mode of interest is an event that affects the structural integrity of the heat pipe. Note that structural integrity condition monitoring may either be inferred through heat transfer performance (e.g., decreased heat transfer performance implying structural degradation of heat pipe) or through conventional structural monitoring (e.g., crack detection)

The objective of condition monitoring is closely tied to the identified degradation modes and specifies what the condition monitoring program is intended to do, whether for the prediction of onset of failure, recommendation for preventive maintenance action, or detection of structural integrity, etc. For the RCP, the aim is to detect the onset of thermal barrier leakage early. Timely detection allows for maintenance actions before leakage exceeds limits or negatively affects component performance. In the case of the heat pipe, the objective is to identify any cracks and signs of leakage that could jeopardize the reactor's cooling capabilities. Both objectives are geared toward preemptively identifying issues to maintain the uninterrupted, safe operation of the nuclear facility.

Finally, the parameters that correlate the degradation to the functional reliability of the SSC are identified. Selecting parameters for condition monitoring is a technical decision based on what best indicates the health of the SSCs. For instance, the RCP's bearing temperature is an indicative parameter, as it can reflect various issues, including potential thermal barrier problems. For the heat pipe, ultrasonic vibrations serve as a parameter for monitoring. This method is sensitive to changes in material integrity, making it suitable for detecting structural discrepancies that could lead to leaks. Note that this stage is focused on the completeness of indicative parameters rather than down-selecting to a limited number of parameters to monitor. Multiple parameters may be selected as degradation indicators if evidence exists to support their use.

# 3. PUMP CONDITION MONITORING

In both existing light-water reactors (LWRs) and certain advanced reactors, pumps are crucial components that maintain flow circulation (i.e., core reactor cooling). Some examples include integral reactors that rely on horizontally mounted coolant pumps and LWRs that utilize large vertically oriented centrifugal pumps. In these configurations, pumps act as the primary method to achieve a variety of performance and safety goals of the reactor design.

While smaller novel reactor designs may utilize different passive safety features for operation (e.g., natural circulation) to reduce reliance, pumps may still play an integral part in other systems of the nuclear facility. For instance, pumps may still be used as feedwater and condensate pumps [5], circulating water system pumps [6], and injection pumps for borated water for the chemical volume control system [5], etc. As such, pumps remain relevant to the current and future fleet of NPPs; the ability to monitor their condition will also be important, whether they are involved in a safety function or are important for power operation (i.e., intermittent operating pumps). To support operation, IST and ISI activities as well as condition monitoring may be performed on SSCs related to the pump (i.e., RCP thermal barrier).

## 3.1. Motivation for Condition Monitoring of Pumps

Maintaining performance and scheduling appropriate maintenance for certain pumps in some nuclear facilities are necessary for meeting plant operational and safety goals. The NRC regulations in Section 50.55a, "Codes and standards" in Title 10 of the Code of Federal Regulations (10 CFR 50.55a) [7] incorporate the IST requirements for pumps by reference in ASME OM Code, Division 1, OM Code: Section IST, 2020 Edition [4]. Conventional methods are provided for pump condition monitoring (e.g., motor current signature analysis) and are well-established in guidance documents.

### 3.1.1. IST Activities and Condition Monitoring of Pumps

IST activities, as required in ASME OM Code, Division 1, Subsection ISTF [4], include periodic testing to ensure that a pump meets its performance goals. ASME OM Code Case OMN-29 [8], "Pump Condition Monitoring Program" provides alternative requirements for condition monitoring of pumps in NPPs as part of the IST program required by 10 CFR 50.55a [7]. Different types of pumps are identified that may or may not be within the scope of the ASME OM Code IST program. For example, guidance for RCP condition monitoring is provided in ASME OM, Division 2, Part 24 [4] and describes in-situ monitoring for the detection or prediction of pump and driver degradation and equipment faults prior to functional failure. As each pump type and application will have a different monitoring and performance requirements, this report will focus on IST and condition monitoring activities for the vertical line shaft centrifugal pumps to provide an illustrative overview.

Before implementing an IST program for a pump, a preservice test must first be conducted to establish the initial baseline behavior for each pump. This baseline test must be performed under conditions as near as practicably possible to those expected during subsequent IST activities. For instance, for vertical line shaft centrifugal pumps, the baseline test must include (a) flow rate and differential pressure at a minimum of five locations and (b) vibration measurements at specified reference points [4]. If the pump is capable of variable speeds, then monitoring speed is also required in the baseline test. Baseline tests are reconducted if the existing reference data no longer represent the installed pump following replacement, major maintenance, or routine service.

Following the preservice test, an IST activity must be conducted periodically in accordance with the ASME OM Code as incorporated by reference in 10 CFR 50.55a. Specific testing conditions for vertical line shaft centrifugal pumps are identified in ASME OM Code, paragraph ISTF-5220 [4]. By following the acceptance criteria and testing conditions outlined in the ASME OM Code [4], a license holder can develop an IST program that complies with 10 CFR 50.55a.

A condition monitoring program may also be implemented for the advanced detection of faults and degradation. The major steps to implement a condition monitoring program include the following, derived from guidance in ASME OM, Division 2, Part 24 [4] (note that Division 2 provides guidance but not requirements):

1. Identify the potential pump faults that could be detected by the program and the symptoms produced by these faults
2. Determine the analysis techniques that are appropriate for the faults monitored
3. Establish the monitoring program necessary for the advanced detection of equipment degradation or faults early enough to prevent functional failure
4. Apply the evaluation criteria for the pump.

Implementing advanced technologies for online condition monitoring could follow similar steps, with the actual model development and integration occurring in steps 2 and 3. Existing guidance on a condition monitoring program covers vibration analysis, seal monitoring, thermography, motor current signature analysis, and lube oil analysis. In addition, a condition monitoring program may have set intervals in which data are collected depending on the startup monitoring schedule. Monitoring schedule and data collection guidance is found in ASME OM, Division 2, Part 24 [4]. Alarm setpoints guidance is also provided in ASME OM, Division 2, Part 24 [4].

Advanced technologies such as data analytics and ML/AI for condition monitoring may assist operators by continuously and more frequently assessing the condition of the pump in contrast to the periodic monitoring schedule. Automated and continuous, as opposed to manual and periodic, analysis can provide more timely insights into the condition or the pump.

### 3.1.2. Monitoring the Effectiveness of a Condition Monitoring Program

In addition to the IST requirements in 10 CFR 50.55a, the evaluation of condition monitoring programs and their effectiveness is specified under 10 CFR 50.65 [9] also known as the Maintenance Rule. This rule specifies the requirement for condition monitoring of safety and non-safety-related SSCs. Section (a)(1) of 10 CFR 50.65 [9] states that NPP license holders "shall monitor the performance or condition of structures, systems, or components…in a manner sufficient to provide reasonable assurance that these structures, systems, or components…are capable of fulfilling their intended functions" [9]. Alternatively, if it is demonstrated that the performance or condition of the SSC is effectively controlled through appropriate preventive maintenance to perform its intended function, then monitoring, as specified in Section (a)(1), is not required because requirements are satisfied as part of Section (a)(2) [9]. Regardless of a licensee's use of Section (a)(1) or (a)(2), a condition monitoring and/or preventive maintenance activity must be conducted at least once every refueling cycle or within 24 months, whichever is shorter [9]. Specific SSC evaluation intervals may be more often than once per refueling cycle. Last, the licensee shall assess and manage the risk that may result from the performed maintenance activity [9].

Regulatory Guide (RG) 1.160 [10] further describes methods that the NRC accepts and endorses under NUMARC 93-01, Revision 4F [11] to comply with the Maintenance Rule. Methods or solutions that differ from those described in RG 1.160 may be acceptable if sufficient basis and information are provided to the NRC [10]. In general, the Maintenance Rule for an SSC may be satisfied by using performance criteria or goals or by condition monitoring [10]. The performance criteria for evaluating SSCs should be either availability, reliability, or condition [11].

The performance criteria can be quantified as a single value or ranges of values [11]. For example, maintaining wall thickness of a piping system to comply with ASME *Boiler & Pressure Vessel Code* (BPV Code) requirements could be a performance criterion [12]. A licensee would establish an acceptable value for wall thickness and monitor it by an approved means [11]. Plant-level performance criteria may also be used to determine the effectiveness of the maintenance program as equipment performance is a major contributor [11]. For instance, a plant-level performance criterion may include "no unplanned reactor scrams per 7000 hours critical" [11].

NUMARC 93-01 identifies the maintenance-preventable function failure (MPFF) as an indicator of SSC reliability and performance [11]. An MPFF is an unintended event or condition such that the monitored SSC is not capable of performing its intended function, which should have been prevented by appropriate maintenance actions [11]. MPFFs identify whether the root cause of a component failure was preventable through maintenance or if external factors were the cause. If the failure of the SSC was not an MPFF, the licensee may continue to perform the existing maintenance program [11]. Examples of MPFF include failures that occur due to the failure to perform a maintenance activity that are normal and appropriate (e.g., application of lubrication at appropriate frequencies) [11]. If the MPFF approach is utilized, the licensee must demonstrate how the number of MPFFs allowed per evaluation period is consistent with the assumptions in the risk analysis and plant performance goals.

One way to assess the analytics applied for online condition monitoring is to consider to what degree MPFFs are reduced over an operational period when compared against the conventional condition monitoring program. A lower MPFF due to maintenance recommendations from the analytics suggests the new program may be more effective at identifying the onset of RCP faults and anomalies.

From an organizational perspective, comparing the level of effort spent (e.g., work hours) when conducting preventive vs. corrective maintenance activities can also indicate the effectiveness of a pump condition monitoring program. Other economic factors may also play a role in the decision-making process; however, this is not explored in this report. A cost impact analysis of the application of DTs for maintenance optimization can be found in Reference [13].

In summary, NUMARC 93-01 [11] specifies methods to evaluate whether a condition monitoring program is effective at preventing failure events, whereas the ASME OM Code specifies requirements for an IST program that may include condition monitoring. Developing a DT for condition monitoring (e.g., for pumps) must therefore take into consideration how it may impact the existing condition monitoring program (e.g., operationally, economically) as well as the impact to plant/component performance metrics (e.g., MPFF). Validation that a DT for condition monitoring is effective may assess whether the MPFFs over an operational period are reduced on average in comparison to previous operational periods MPFFs.

## 3.2. Relevant Technologies for Pump Modeling and Condition Monitoring

Enabling technologies that are anticipated to play an important role in developing DT models include sensors, data storage, preprocessing, and analytics, ML/AI, and physics simulators. These technologies ensure that a DT for condition monitoring can continuously maintain digital state concurrence with the physical process, in this case, detecting the early onset and occurrence of degradation or faults in pumps.

For a DT developed for pump condition monitoring to be successful, it is important to determine what type of information can be collected to build and operate a DT. Sensors (e.g., vibration and temperature) monitor the different condition indicators of a pump and play a crucial role at fault detection. For instance, deviations in recorded sensor data can be precursor indicators for pump faults or irregularities. Some key features measured by sensors include inlet and outlet pressure, pump vibrations, pump flow rate, pump impeller speed, electric current, bearing temperatures, motor winding temperature, power consumption, and lubricant quality. Sensors in multiple locations may also be used for a single feature measurement. For instance, pump vibrations are usually measured in at least two locations (typically in different orientations) to measure horizontal and vertical vibrations (i.e., on the pump shaft).

A condition monitoring DT would rely on a source of real-time data to supply analytics and/or ML algorithms that detect degradation/fault within the pump. An ideal suite of sensors to support condition monitoring functionality may vary from the current standard suite of sensors used today (e.g., additional sensors and varying placement locations). The intent is to transition from time-based periodic monitoring to condition-based continuous monitoring to reduce the likelihood of corrective maintenance activities and reduce unnecessary maintenance activities.

With respect to pumps, a wide variety of sensors, measuring different parameters, can capture real-time data characteristics of a wide variety of failure modes across a pump. Pressure sensors, such as pressure transducers, are used to measure inlet and differential pressure, typically at three different locations per shaft seal [14]. Changes in pressure values can indicate hydraulic degradations within a pump such as cavitation, recirculation, and loss of flow. Differential pressure transmitters may also be used to derive flow rate in and around the pump. These sensors may also be placed on auxiliary system loops, such as the component cooling water return line and in the controlled bleed-off line in the chemical volume and control system, as indicators for pump coolant leakages. In addition, tachometers may be used to measure the pump impeller rotational speed [15]; variation in rotational speed can be used to gauge pump performance trends. Finally, pump component temperature may be measured at various bearing locations and on the motor winding via direct measurement (e.g., thermocouples) or indirectly (e.g., infrared detectors). Typically, RCPs have six detection locations within each motor and a sensor for each bearing location [14]. Thermographic imaging (i.e., infrared detectors) may also be used to detect areas of high temperatures and is a developed form of condition monitoring. Temperature measurement can be used in several different ways, such as detecting bearing failures and reactor coolant leakages.

Another useful parameter that can indicate degradations is motor current conducted via motor current signature analysis. Motor current is useful for detecting any developing degradation and failure within the motor electrical system. It can detect various hydraulic and component degradations (e.g., broken rotor bars) and can indicate occurrences of overcurrent or undervoltage before the pump trips. Gross load and power evaluations can detect the occurrence of trips due to improper power distribution to the motor.

Motor current analysis may also be supplemented with vibration analysis. As degradations in the motor structure (e.g., broken rotor bar) result in additional side-band vibration signatures, this type of analysis can provide additional early fault identification signatures. Vibration analysis commonly measures three dynamic quantities: displacement, velocity, and acceleration. Vibration data can also be used in detecting degradations like bearing misalignment, recirculation, shaft breaks, improper suction, axial and radial thrusts, pressure changes within the system, improper lubrication, mechanical damages to bearings, and unbalanced power supply. Vibration can be measured using accelerometers, permanently mounted transducers, or advanced acoustic emission monitoring transducers [16].

It is expected that these sensors will produce a large quantity of data that needs to be processed. As such data storage is projected to be a key enabling technology for online condition monitoring. It is essential to store all real-time sensor data as well as previous plant and pump change information, such as previous work orders correlated to pump degradation, equipment data containing design information, pump performance curves, and inventory data. An example of data storage for a circulating water system in an accessible digital form is an Azure cloud-based web application written in JavaScript to support large-volume data storage [6]. This web application can also be used for data preprocessing along with analytics and visualization models for work order data [6].

Data preprocessing is the act of data preparation and cleaning into a usable format and can include outlier removal, noise reduction, and detrending, but also may be used to inform when sensor drift is occurring. First, real-time data can contain noise that can obscure indicative signs of degradation; for example, vibration data achieved through acoustic emission transducers are susceptible to background noise. Equipment data and previous storage of faulty and normal data can be used in this instance to understand if data is noisy or if the data contains faults (e.g., sensor drift). A few examples of data preprocessing for vibration data are fast Fourier transform, wavelet transform, S-transform, and cyclic spectral analysis [17].

A more pertinent example is exploratory data analysis (EDA), which is used to discover correlations in the data (e.g., Pearson correlation, pairwise plots) and irregularities. EDA usually consists of capturing trends in data and removing any existing outliers within the data. EDA can be used to analyze both textual and numeric data and summarize the major aspects of them. For instance, EDA is used in Reference [13] to categorize and analyze pump maintenance work order and inventory data. In this study, methods, such as Latent Dirichlet Allocation, along with natural language processing, were used to conduct topic analysis to correlate the work order equipment condition to degradation states [13].

Fault and degradation detection and modeling can be conducted via conventional analytical methods and data-driven methods (e.g., ML/AI). Analytical methods include, but are not limited to, the parity space method [18] and the auto-associative kernel regression [19]. The parity space method relies on checking for parity of measurements from the system processes and generating a residual comparison between an input-output linear model and process behavior [18]. Auto-associative kernel regression is, essentially, a signal reconstruction method used to identify irregularities in the data when compared to a known historical database [19]. These methods rely on historical data to inform on the anticipated performance of the SSC.

ML/AI-based models may also be used to predict and detect faults in pump data as well as classify the type of fault within a pump based on the real-time data received. The primary benefit ML/AI-based models have over conventional analytical methods is their ability to summarize vast quantities of data into fast and succinct relationships. There are two possible configurations for supervised ML/AI models: classification and regression. Classification models output a single class decision based on a limited number of possible distinct classes (e.g., binary) whereas regression outputs a continuous value across the parameter range. For instance, a classification model can be used to determine the overall state of a pump (e.g., if it is healthy or if there is incipient degradation). In contrast, regression algorithms can be used to understand the root cause of anomalies in data by comparing the current or future state of a parameter to a baseline. Artificial neural networks and their variations are widely used ML/AI algorithms that can be used for both fault classification and degradation degree in pumps.

Previous work in Reference [6] used ML methods to detect if a circulating water pump was healthy or unhealthy and, if unhealthy, what type of fault occurred. This was done using XGBoost (eXtreme Gradient Boosting) as a prognostic and diagnostic model [20]. The diagnostic model was implemented using XGBoost as a binary classifier to detect whether the circulating water system was healthy or unhealthy. The prognostic model also used XGBoost but in a multiclass classifier configuration to identify which type of fault occurred given an unhealthy diagnostic. The prognostic model was able to consider a variety of faults including but not limited to waterbox fouling, pump diffuser failure, pump bellmouth failure, pump shaft misalignment, motor air intake screen clogging, motor winding moisture and salt contamination, pump low oil level, bearing failure, etc. [6]. The input data used by the diagnostic and prognostic XGBoost models consisted of plant process data like differential temperature, motor inboard and outboard temperature, motor stator temperature, motor current, motor and pump age, historical replacement/refurbishment data, temporal domain features (e.g., time stamp, uptime) as well as frequency domain features (e.g., diffuser vane vibration). Fundamentally, ML models are capable of diagnosing fault occurrence and fault type but may require a variety of input data ranging from sensory to maintenance logs.

## 3.3. Case Study on Condition Monitoring for Pumps

This section showcases how a condition monitoring program for RCPs can be set up following similar guidance presented in ASME OM, Division 2, Part 24. The first subsection discusses the potential pump faults and symptoms that should be detected by a condition monitoring program. The second subsection presents appropriate analytical techniques to identify faults. An RCP is used for the case study with the lessons learned intended to be applicable to all important pumps in nuclear facilities.

### 3.3.1. Degradation Modes for a Reactor Coolant Pump

An RCP in a large water-cooled PWR NPP circulates the reactor coolant and transports heat from the reactor to the steam generators. The major components of an RCP include the pump case assembly, pump cover, heat exchanger assembly, the mount and rotating assembly like the shaft, impeller, and associated coupling as well as the shaft seal assembly [21]. Degradations can occur in any part of the RCP, which can then have the potential to cause a failure of the RCP and can thus have a negative effect on the operation of the NPP.

There are various causes of degradation that can be detected through improper vibrations within the RCP. The most common vibration-related problems within an RCP can be due to: (1) improper suction conditions, (2) improper operating conditions, (3) misalignment of pump components, (4) improper fitting of couplings and bearings, (5) leakages and lubrication issues, and (7) seal failure [22].

Improper suction conditions refer to a hydraulic condition of the pump operating conditions. These degradations can manifest as pump recirculation issues, where partial reversal of flow back through the pump impeller is due to the reduced flow rate through the pump at the suction/impeller region of the pump [22]. Recirculation can damage the inlet of the casing and the thrust bearings, causing erosion of impellers and diffusers as well as mechanical failures in the bearings and seals.

Another hydraulic condition causing pump degradation is cavitation, which is the rapid formation and collapse of vapor bubbles that occur at ambient pressure less than or equal to the liquid vapor pressure. Collapsing cavitation bubbles on metal surfaces can cause damage in the form of pitting [22]. Cavitation can cause severe deterioration of pump internals and is usually detected by steady crackling noises around the pump suction, as well as an increase in vibration and noise level and a reduction in the net capacity and pressure head. Cavitation can be prevented by operating the RCP at a net positive suction head greater than the required net positive suction head as recommended per the manufacturer [22].

Aside from operating conditions, misalignment of pump components can cause extreme heating in couplings, wear and fatigue of rotating components, and bearing failures, along with thrust transmission issues through couplings [22]. Misalignment may refer to a situation where the pump and driver shafts are not perfectly straight and concentric with each other, resulting in non-parallel thrust forces along the axis of rotation. Misalignment may also refer to a situation where the motor stator is not concentric with the motor cage, manifesting as static or dynamic eccentricity in alignment [23]. These misalignments generate additional vibrations in the motor that are anomalous when compared against trending data. Other signs of misalignment include excessive acoustic noise, increased energy consumption, and reduced flow rate.

RCP degradation may also be caused due to a variety of leakages, such as oil leakage, thermal barrier leakage, and seal leakage. An identified leakage is a leakage that can be captured, flow-metered, collected in a sump, tank, or a collection system or moves from a known primary to secondary system without being considered a reactor coolant pressure boundary leakage. The identified leakage can also be a leakage that goes into a containment atmosphere of a known source and does not interfere with the operation of unidentified leakage monitoring systems or does not affect the reactor coolant pressure boundary [24].

Oil leakage is where oil in the upper bearing heat exchanger, used to cool the bearings, leaks from the exchanger. A drip pan is positioned at the base of the motor to catch any leaks from the oil heat exchanger at bearing components. The RCP oil system components are also enclosed to catch any oil leaks. Accumulated oil in either the drip pan or enclosure is emptied into a collection tank, reducing the chance that oil comes into contact with the reactor coolant system (RCS) pipework. An oil leakage of the heat exchanger can cause high temperatures of the upper bearing, ultimately increasing the vibrations within the RCP [25]. If the oil leakage is not properly collected within the reservoirs and comes into contact with the insulation or high-temperature surfaces, it can easily ignite, causing a fire [25]. When an oil leak occurs, the standard procedure is to reduce power or trip the reactor, helping isolate and address the pump oil leak [25].

Another common type of leakage that can occur is due to seal failure. Leakage along the shaft of an RCP is controlled by shaft seals located at the top end of the pump shaft. For instance, the Westinghouse AP1000 [14] RCP contains three shaft seals; the first one is a controlled leakage seal while the next two are rubbing face seals. All seals are located within the main flange and seal housing. Seal injection water is supplied to the RCP from the chemical and volume control system. Of the 8 gallons per minute (gpm) seal injection flow, 3 gpm flows upward through the radial bearings and pump seals, and 5 gpm flows downward through the heat exchanger into the reactor coolant flow, which is considered normal. This downward flow prevents the coolant from entering the seal areas of the pump. The thermal barrier heat exchanger is located at the interface between the reactor coolant and controlled leakage seal and is usually used as a backup source of cooling if there is a loss of seal injection flow. During a failure of the seal injection system (e.g., no water is provided to seals), reactor coolant flows upward through the thermal barrier heat exchanger to provide temporary cooling for the seals. This operating mode is limited only to short durations as unfiltered reactor coolant will damage the seals. In the event of a seal failure, the upper seals convert to film riding seals from rubbing face seals due to an increase in pressure, which forces the majority of the leakage to enter the component cooling return line instead of further up the pump shaft [14]. As such, this type of leakage is sensed by a high flow alarm in the component cooling water return line. The response to this alarm is to isolate the component cooling water return line to stop the leak flow and results in the high-pressure piping of the component cooling water system serving as a part of the RCS pressure boundary.

### 3.3.2. Reactor Coolant Pump Condition Monitoring

There are a large variety of technologies that can help with detecting degradations within the RCP, such as vibration spectral analysis, thermography, lubricant analysis, modal analysis, acoustic emission analysis, motor current, and power analysis [22].

Monitoring vibration through methods such as vibration spectral analysis is a powerful tool for pump analysis and diagnosis, which can be used to detect numerous types and causes of pump degradation like misalignment, unbalance, and various anomalies that can occur within the bearings of the RCP. Early detection can thereby help in preventive maintenance as opposed to corrective maintenance to prevent degradation from causing any type of failure within the RCP. Spectral analysis, by transforming a signal from a time domain to a frequency domain, is also more useful than vibration amplitude measurements for detecting pump failure in its early stages [22]. Spectral analysis can distinguish between various pump degradations like misalignment, unbalance, looseness, and different bearing anomalies [22].

Thermographic measurement equipment has also been used to detect anomalies as they are not intrusive and can scan hot spots, indicating degradation like misaligned couplings causing excessive friction, overheated bearings, misaligned and rubbing shafts, and lack of lubrication within the RCP [22]. Limitations of thermographic measurements are dependent on the material that it is used on; for example, highly reflective surfaces can interfere with the thermal imaging process leading to inaccurate results.

Lubricant analysis can also be used to detect the presence of particulates generated through wear or mechanical damage within the motor or pump's rotating parts (e.g., bearings). Common measurement techniques include particle count, kinematic viscosity, Fourier Transform Infrared spectroscopy, etc. For instance, rotating bomb oxidation test is a useful lubricant analysis method used to determine the remaining life of the lubricant [22]. However, rotating bomb oxidation test does not capture insoluble particles and sludge.

Motor current analysis and power analysis techniques can be used to help analyze impending faults and degradation in the motors of the RCP. Motor current monitoring can detect rotor faults as well as hydraulic degradations. Motor current monitoring through motor current signature analysis has limitations because it cannot capture all types of degradations (e.g., mechanical faults).

Acoustic emission analysis can be used to detect defect growth in metals, inadequate lubrication, overloading, misalignments, damage due to fatigue, rubbing between rotor and surfaces, and different friction-caused wears. Acoustic emission analysis is most useful when overall mean values and spectral signatures are stored for trend analysis. Acoustic emissions do not necessarily require direct attachment to the pump components for measurements and are advantageous for monitoring concealed or covered components. A disadvantage of acoustic emissions is their susceptibility to contamination from external noises.

Modal analysis is often used to understand the dynamic interactions and behavior of pump, motor, and piping through vertical, horizontal, and axial movement analysis to detect deteriorations. Modal analysis can provide additional insight into the causes of degradation that other methods can miss and can identify resonant frequencies that exist above operational speed. A limitation of modal analysis is the functional necessity of using multiple sensors to obtain accurate results and for transducers to be specified at a frequency response within an anticipated range.

Pump curves may also be used as a method for pump analysis and are mathematical relationships that correlate flow, discharge pressure, suction pressure, atmospheric pressure, suction temperature, discharge temperature, pump speed, and input power with each other. Given certain measurable parameters, other key parameters can be calculated. The onset of faults will change the mathematical relationship and can be used as an advance indicator for corrective action. However, pump curves require the knowledge of subject-matter experts to analyze and determine when anomalies occur, especially when compared against real-time pump performance data.

Pump condition monitoring consists of developing an equipment file on the RCP-containing design and manufacturers specifications such as a homologous pump curve [26]. Equipment files also contain previous history (e.g., seen in work orders) to understand the type of degradations and the data associated with them. Useful stored historic information contains operating temperatures, vibration data, power consumption, lubrication analysis, and performance indices. Regularly performed general observations are useful for predictive and preventive maintenance. Expert systems like computerized problem analysis programs are also needed to embody the knowledge basis for the RCP and sensor performance.

It is anticipated that both real-time and historical data from RCPs will be used to develop condition monitoring tools for preventive maintenance. Real-time data consists of motor current, gross load, inlet and outlet temperatures, motor-bearing temperatures, stator winding temperature, thrust-bearing temperature, upper and lower radial bearing temperatures, vibration data from distributed array of probes, etc. These measurements, collected within the seals and secondary systems of pumps, can be used to detect different potential degradations and leakages while simultaneously providing a continuous observation of the motor pump state. Historical data, such as plant processes, maintenance logs, operator logs, or work orders containing maintenance records, can provide information including, but not limited to, correlations between past degradations and repairs with associated sensor data, limits that trigger alarms for a particular degradation, and the duration of maintenance that causes the pump to be shut off.

## 3.4. Technical Considerations and Opportunities for Pump DT Condition Monitoring

In this section, a discussion on the technical considerations and opportunities for developing and deploying a DT condition monitoring program specific to RCPs is provided. General considerations for a DT condition monitoring program are discussed in Section 5.

### 3.4.1. Pump Condition Monitoring Sources of Uncertainties

There exist several sources of uncertainty that need to be addressed at various stages in the DT development pipeline. Assuming that historical, experimental, and simulation data are used to train the DT for pump condition monitoring, each of these sources contains their own epistemic and aleatoric uncertainties that may contribute to the final DT prediction uncertainty.

One potential uncertainty from using historical data arises from its collection and storage method. Real-time sensors generate a vast amount of data, and collecting data, such as long recordings, is generally infeasible due to physical storage limitations [4]. For instance, ASME OM, Division 2, Part 24 [4] provides guidance for a vibration monitoring system for pumps with a specified sample rate per instrumentation channel and collected for a sufficient period of time to ensure maximum vibration amplitudes are captured. As such, most plants implement a compression or data management tool to manage file sizes and simplify data processing. For instance, signal averaging or maximum/minimum data is recommended for RCP condition monitoring as provided in ASME OM, Division 2, Part 24 [4]. This process may remove spurious peaks due to electrical noise or eliminate specific frequencies that are not representative of a monitored response [4]. While removal of these frequency sources from the historical data can improve training efficacy, it may also eliminate potentially relevant hidden information in the data and force a specific function to the DT model. As such, utilizing data-compression tools and methods to efficiently store and collect data is still currently an issue as it may subsequently mask underlying fault signatures [27, 28, 29]. Furthermore, signal accuracy for analysis from historical data, especially from analog to digital formats, can introduce reconstruction uncertainty. As existing requirements on data storage and collection are developed for legacy condition monitoring methods, they may be less applicable when data-driven models are considered. For instance, ASME OM, Division 2, Part 24 Section 6.3.2 specifies the sensor channel accuracy over the frequency range. This form of uncertainty is where the reconstructed signal by the model incorporates sensor inaccuracy resulting in predictions that do not accurately reflect the state of the pump.

These various sources of uncertainty are implicitly built into the DT model during training. It is challenging to separate and quantify the degree to which these uncertainties affect DT model predictions. While model performance can be determined through test cases, these cases may not fully represent the intended operational condition and provide only a partial idea of how well the model will perform. For instance, consider the possible defects that may be considered in bearing condition monitoring. ISO 15243 [30] identifies six main damage modes for bearings: fatigue, wear, corrosion, electrical erosion, plastic deformation, and fracture/cracking. Generating enough data to sufficiently investigate each mode to train a DT model is challenging as varying operational and equipment specifications will result in different defect characteristics [31]. In use, variations between the training data and operational data will result in prediction uncertainty.

The degree of prediction uncertainty may be holistically quantified using popular existing methods. Sensitivity analysis, for instance, may be used to evaluate the effect each data feature contributes to model performance and to a certain degree establish model uncertainty. However, sensitivity analysis cannot determine how uncertainty from data sources will impact model prediction uncertainty. This is also true for popular ML methods, such as Monte Carlo dropout, k-fold cross validation, and Bayesian inference methods, which determine the model's uncertainty and not underlying data uncertainty. In this respect, an approach to propagate uncertainty from data inception to model construction is needed to create a more comprehensive understanding of the sources of uncertainty encountered in a DT.

### 3.4.2. Regulatory Consideration for Pump Condition Monitoring

A pump condition monitoring program may exist to address several different organizational and operational goals, such as reducing unnecessary maintenance frequencies, reducing MPFFs, and improving plant economics. These goals are driven by NRC regulations (e.g., 10 CFR 50.65 [9] and 10 CFR 50.55a [7]) and through IST requirements, incorporated by reference. For example, in NUMARC 93-01 [11] endorsed through RG 1.160 [10], MPFF is used to describe preventable SSC failures through maintenance actions. In this sense, a successful pump DT condition monitoring program may be used to reduce MPFF occurrences over the operational life of a component. Specifically, a pump DT for condition monitoring may provide more robust insight into when preventive maintenance activities need to be conducted through more frequent automatic analysis of pump trending characteristics such as vibration, temperature, and motor current and voltage. In addition, a pump DT may be used to reduce unnecessary maintenance frequency without compromising safety. Currently, IST for pumps is performed at set interval frequencies as per regulation under ASME OM Code, Table ISTB-3400-1 [4] or if unusual trending is observed as per guidance under ASME OM, Division 2, Part 24 [4]. Pump condition monitoring may be one way to demonstrate the pump is operating at reference. Through frequent automatic analysis, a DT for pump condition monitoring can continuously verify that the pump is operating at an established baseline and thus operating within reference conditions and quantities.

DT for condition monitoring can be further improved by incorporating evidence from multiple sources of plant data. For instance, it is identified that while one technology alone may convey some evidence of a defect condition, incorporating other technologies (e.g., thermography, oil lube analysis, and motor current signature analysis) may provide a more complete and accurate diagnosis of the pump condition (see guidance in ASME OM, Division 2, Part 24). A method to incorporate these technologies would improve the reliability of DT predictions for condition monitoring as various pieces of evidence can be utilized to make a deduction on the state of the RCP.

# 4. HEAT PIPE CONDITION MONITORING

Heat pipes are a type of heat transfer device primarily used for cooling. They utilize the thermal conduction of the pipe shell and phase transition of a working fluid (e.g., sodium) sealed in an elongated pipe to transfer large amounts of heat between the heat source and sink. Heat pipes have several benefits. They have excellent heat transfer rates, are completely, requiring no power source or moving parts (other than the working fluid), and are completely sealed from the interfacing system. The two most common types of heat pipes are identified by how heat is transferred within the pipe. Gravitational heat pipes (also known as a Perkins tube or thermosyphons) rely on the gravitational convection between liquid and vapor phases of the working fluid in upright tubes to transfer heat [32]. In contrast, capillary heat pipes can operate in any orientation (typically horizontal) and rely on the wicking effect of liquids and vapor pressure differentials between the hot and cold leg of the pipe to transfer heat [32]. Either heat pipe type may employ a range of working fluids and cladding material (e.g., steel 316). Some commonly used working fluids for high-temperature applications (e.g., 400 to 1200$^{o}$C) include sodium-potassium alloy, sodium, or lithium [32, 33]. Examples of heat pipe reactor designs include the eVinci microreactor [21], the Special Purpose Reactor (SPR) [34], and the KiloPower reactor [35].

In this report, the technological and regulatory considerations of reactors that employ monolithic steel blocks to house heat pipes are considered. This reactor type is used as an example as several designs and concepts exist that can be referenced (e.g., SPR and eVinci). Different heat pipe reactor designs will require different condition monitoring strategies, and the discussions presented in later sections may not be applicable. In a monolith steel block heat pipe reactor, the fuel pins and heat pipes are arranged in a hexagonal pattern within channels of the monolith. Each heat pipe is potentially surrounded by up to six adjacent fuel pins as shown in Figure 1 [36].

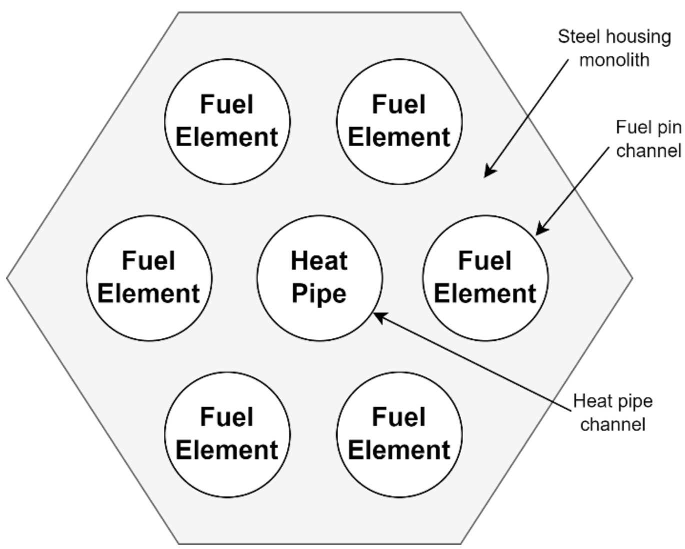



Figure 1. Cross section of a subsection of a steel monolith with one heat pipe surrounded by up to six fuel pins [36].

## 4.1. Motivation for Condition Monitoring in Heat Pipes

### 4.1.1. IST Activities and Condition Monitoring of Heat Pipes

Heat pipes contain no moving parts unlike RCPs. However, due to the importance in maintaining core temperature, their function may still involve protecting the reactor whether as a safety-related or non-safety-related SSC. The exact determination will depend on the final reactor design. Even if heat pipes are considered structures as opposed to systems and components, the Maintenance Rule may still apply as heat pipes will play a crucial role in reactor cooling [10]. Condition monitoring of heat pipes may be required under 10 CFR 50.65 [9] following NUMARC 93-01, Section 9.4.1.4, which discusses structural monitoring [11]. Section III, Division 5 of the ASME BPV Code [37] is also anticipated to apply to heat pipe reactor designs as it specifies relevant material limits, welding processes, and inspection requirements. Alternatively, a heat pipe reactor licensee may refer to guidance in Regulatory Guide 1.233 [38], known as the licensing modernization program (LMP), as heat pipe reactors are classified as non-LWRs. LMP provides an alternative pathway for licensees to identify licensing-basis events, classification, and special treatment of SSCs and assess defense-in-depth of non-LWR designs. An LMP case study with the eVinci microreactor was conducted to examine how licensing could be conducted [39]. The LMP pathway may be more relevant as the types of LBEs encountered by a heat pipe reactor will be significantly different than an LWR. For instance, in Reference [40], it is identified that the failure of a single heat pipe over the lifespan of the SPR is highly probable and a design should account for this type of failure. Within NUMARC 93-01, Section 9.3.3 [11], it is mentioned SSCs that have little to no contribution to system safety function could be allowed to run until failure (i.e., a heat pipe), such that only corrective maintenance is performed rather than preventive maintenance. As the events that a heat pipe reactor would encounter in comparison to LWRs would be substantially different, the effects of a single heat pipe failure could be limited and have little contribution to overall plant safety function. This would be highly dependent on the types of LBEs identified in the event of a heat pipe failure.

IST programs for heat pipes may be implemented following guidance under ASME OM-2 Code [41], a standard developed specifically for advanced reactor components (i.e., heat pipes). In OM-2 Code Section GR-1.2, a heat pipe can be considered a component that generates, allows, throttles, or isolates a fluid [41]. Note that due to the novelty of heat pipes in nuclear power plants, a specific section discussing IST guidance within OM-2 Code is not currently available. Rather, new ASME guidance may be developed within OM-2 Code, with specific applications depending on the adopted design [41].

In the SPR reactor, for example, the tight configuration of the heat pipes within the steel monolith block might challenge individual heat pipe testing as surrounding heat pipes highly influence the behavior of any individual heat pipe [42]. Variations in surrounding heat pipe performance could result in variations of individual heat pipes. A heat pipe reactor may also plan for individual heat pipe failures [40]. This is because heat pipes may act as a distributed redundant cooling system, such that the failure of any individual heat pipe does not compromise system safety [40]. Therefore, establishing a consistent performance baseline for heat pipes (whether individual or for groups) may be challenging.

Although heat pipes may act as redundant cooling structures, a minimum number of heat pipes over a specific core volume must be operational to maintain safety. For example, multiple heat pipe failures in a single location (or within proximity of each other) might exceed local allowable thermal limits, but multiple heat pipe failures in multiple locations might not. Monitoring the integrity of individual heat pipes or specific distributed locations can provide an estimate on the number of remaining heat pipes that are operational even in the event of single heat pipe failure. In addition, condition monitoring might also be necessary to demonstrate inherent safety and maintenance of defense-in-depth principles. For example, in SPR reactor design, it is anticipated that the core monolith structure will be operating at elevated temperatures (i.e., 700–800°C) [42]. At these temperatures, most practical metals suffer from some degree of material property change, loss of strength, increased grain growth, migration of elemental constituents, and thermal creep under load [42]. The ASME defined that the maximum allowable stress for 316 stainless steel, an approved alloy for nuclear applications, at 700°C is 29.6 MPa [37]. However, it was found, through thermo-mechanical analysis of the SPR reactor, that the heat pipe housing structure may reach a peak stress of 37.1 MPa if surrounding heat pipes fail [34]. The exact threshold (e.g., percent of surrounding heat pipe failures) may vary between designs; more experimental or simulation evidence is required before a determination can be made. This is concerning because this may result in radioactive containments leaking into heat pipe channels, causing external corrosion of the heat pipes and potentially leading to the release of radioactive material into the heat exchanger region of the reactor. Condition monitoring may inform licensees of locations within the housing structure where this event occurs.

Non-water-cooled reactors will be required to develop an IST program for components that provide for the movement or cessation of the movement of reactor cooling system fluid. Heat pipes might be included in the IST program for such non-water-cooled reactors. Ultimately, condition monitoring of heat pipes is important and might be required by the NRC regulations (such as new Part 53 or 10 CFR 50.65). The exact regulatory requirements for condition monitoring would be dependent on the applicable NRC regulations and LBEs identified along with the anticipated design of the reactor.

### 4.1.2. Monitoring the Effectiveness of a Condition Monitoring Program

Due to the relative novelty of using heat pipes to cool reactors, the exact criteria for success of a condition monitoring program are not known and highly depend on the operational and design goals. For instance, the use of MPFF may not apply as an evaluation metric if the reactor internals (i.e., heat pipes) are not planned for maintenance and are allowed to fail. Previous reports [34, 42] discuss that the heat pipe microreactor is intended to operate for an extended period of time (i.e., 5-year sustained operation [42]) with minimal maintenance activities. Once the operation period has ended, the reactor is intended to be sent back to the manufacturing floor for refueling and servicing (i.e., eVinci [21]). Replacement or maintenance of heat pipes is not discussed in the operation of microreactors. Certain structural components within the reactor may not need a condition monitoring program if they are planned to fail. For instance, the monolith housing structure, although exceeding ASME-defined stress limits, may not apply if the monolith is not designated as a pressure vessel boundary [42]. In a similar manner, some number of heat pipes may be permitted to fail over the anticipated reactor lifetime [40]. This may not be concerning given that heat pipes are intended to operate independently of each other. The large number of in-core heat pipes would thus provide built-in redundancy and a theoretically large safety margin [40]. In the event of a local failure of one or more heat pipes, the surrounding heat pipes may still operate normally and can theoretically avoid serious accidents (e.g., core damage) [40]. As such, developing a method to evaluate the effectiveness of a heat pipe condition monitoring program must factor in the operational and design goals of the reactor.

The evaluation of a heat pipe condition monitoring program may fall under Section 9.3.3 of NUMARC 93-01, which discusses new plants with no operating history [11]. In essence, the licensee establishes an acceptable baseline performance goal for the condition monitoring program by referencing similar designs used in other applications. This comparative goal setting and process applies to preventive maintenance programs, corrective actions, cause determination, and operating experience. While there is very little operating experience with commercial heat pipe reactors, experience may be transferred from other piping applications, such as ultrasonic testing of buried pipes and bobbin probes for U-tube steam generator assemblies.

## 4.2. Relevant Technologies for Heat Pipe Modeling and Condition Monitoring

Referencing Figure 1, all instrumentation as well as the heat pipe must fit within the center channel. Several sensor technologies can be employed to monitor the temperature of the heat pipe in different sections (i.e., condenser and evaporator). In the Single Primary Heat Extraction and Removal Emulator experiment (SPHERE) [36, 43, 44], based off the configuration in Figure 2, researchers utilized a combination of multipoint type K thermocouples, fiberoptic temperature sensors, and an ultrasonic temperature sensor to measure temperature at discrete points along the heat pipe. The length of the monolith was 19.5 inches long and made from 316-stainless steel with heat pipes approximately 36 inches long [44]. In Figure 2, the un-instrumented SPHERE experimental setup is presented, with a single heat pipe resting in a vacuum chamber.

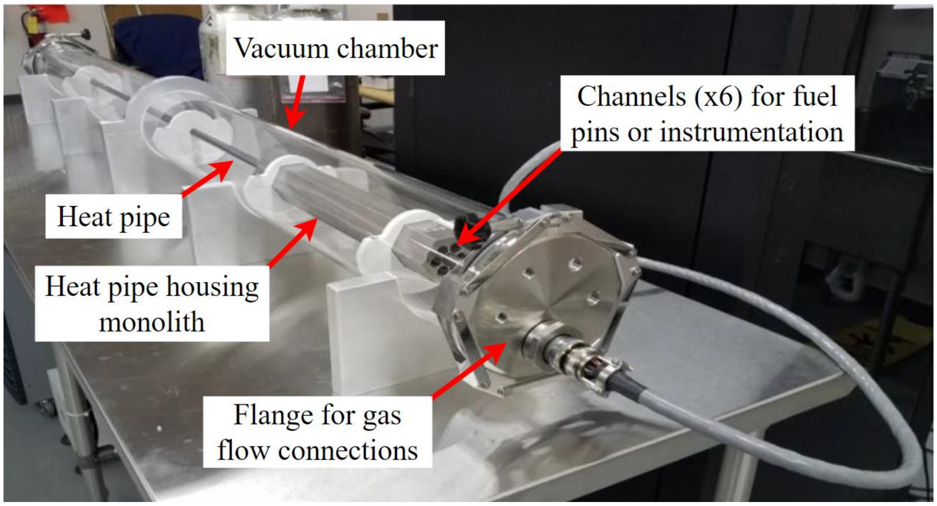


Figure 2. SPHERE test bed and seven-hole test article [36].

The fiberoptic temperature sensors run down the axial length of the heat pipe and are capable of recording temperature along the entire length (at discrete locations) of the monolith block [36, 43]. Two different fiberoptic sensors were tested: (1) a fiber Bragg grating (FBG) sensor with nine FBGs equally distributed along the fiber and (2) an optical frequency domain reflectometry (ODFR) distributed temperature sensor with spatial resolutions every 0.65 mm (0.0256 inch) [36, 43, 44]. Both sensors have been demonstrated in the Transient Reactor Test Facility [36, 44]. The FBG sensors permit measurements up to 1kHz and can provide stable measurements at high temperatures above 700°C. The ODFR sensor will fail above 700°C but can use an adaptive reference technique to compensate at higher temperatures [36, 44]. However, there are several challenges with fiberoptic temperature sensors that affected temperature sensing accuracy and consistency. For example, the ODFR sensor is highly sensitive to material defects, density changes, and annealing inconsistencies [44].

The ultrasonic thermometer utilizes a magnetostrictive alloy to generate and sense ultrasonic waves along a waveguide to detect temperature [44]. Five measurement zones are possible, separated by 3 inches per detection zone [44]. The ultrasonic thermometer can record data up to 10 Hz, which is more applicable for steady state conditions. However, there are several challenges associated with the ultrasonic thermometer, namely environmental radio frequency noise, which interferes with and partially obscures the recorded signal [44]. It was found that at power levels of 500 W and greater, the associated noise makes the recorded temperature signals unusable [44]. Calibration of the ultrasonic thermometer may also be an issue as the entire length must be calibrated before use. In the experiment, this was a challenge as the furnace used for calibration of the 15-inch-long thermometer was too short to adequately calibrate the sensor [44].

These temperature sensors would be important for monitoring the effectiveness of heat transfer by the heat pipes. Furthermore, if the axial power along the heat pipe is known, it may be possible to calculate axial heat flux. In combination with axial temperature, the operating profile (see Figure 3) of the heat pipe at different sections can be derived. This would be relevant in monitoring when heat pipes limits are reached and have potentially failed.

In addition to sensing technologies, heat pipe modeling and simulation can be utilized for DT development. For instance, Sockeye, a simulation software based on the Multiphysics Object-Oriented Simulation Environment (MOOSE) [45], can be used to model high-temperature liquid-metal heat pipes with annular or porous wick structures. Sockeye specializes in modeling heat pipes that are sealed cylindrical tube containing a wicking structure along the inner surface, saturated with working fluid [45]. Different wicking structures can also be modeled, such as wire screens, sintered metal, or open annulus screens [45]. Sockeye currently supports two-phase flow modeling, vapor-only flow modeling, and conduction modeling and can be used to investigate all heat transfer limits shown in Table 2 [45]. However, Sockeye cannot currently be used to evaluate certain accident scenarios, such as dryout, which may occur during leakage of working fluid or heat transport limitations (shown in Table 2). In addition, Sockeye cannot be used to model startup or shutdown transients [45].

## 4.3. Case Study on Condition Monitoring for Heat Pipes

A case study is presented for structural integrity condition monitoring of heat pipes. The process for developing the condition monitoring DT follows the steps provided in Table 1.

### 4.3.1. Degradation and Failure Modes of Heat Pipes

An understanding of degradation and failure modes of heat pipes can be derived from similar experiences with other piping components used in NPPs as well as other industries. ASME BPV Code, Section III, Division 5 [12] is anticipated to contain design rules that apply to heat pipe reactors. For instance, within the standard, Nonmandatory Appendix HBB-T describes deformation and fatigue limits of components at elevated temperatures (i.e., creep-fatigue evaluation) [12]. In general, heat pipes are anticipated to have two different pathways that can lead to inoperability: heat transport limits and environmental degradation.

Heat transport limits describe the physical limitations of heat pipes for heat transfer. For instance, if the temperature differential between the hot and cold ends of the heat pipe is significant, this may lead to the phenomenon of entrainment [46, 47]. This is where the high vapor velocity of the working fluid strips liquid from the walls, preventing rewetting of the hot-end heat pipe wicks, and impedes convective heat transfer. This phenomenon is self-sustaining and compounding in the sense that as heat transfer capability is lost, entrainment is exacerbated as vapor velocity grows with temperature differential [46, 47]. Entrainment is analogous to the countercurrent flow limitation in LWRs [46]. Another physical limitation is the viscous limit of the working fluid [48]. On cold startup, the operating temperature may be close to the freezing temperature of the working fluid; in such conditions, the vapor pressure and density are very low, and the viscous forces dominate flow behavior preventing circulation of the working fluid [48]. In Table 2, heat transport limits of heat pipes are summarized; while in Figure 3, a plot of the limits is provided. Lastly, while heat transport limits may describe global conditions that can lead to failure of heat pipes (i.e., during cold startup), they may also exist locally (e.g., individual heat pipes) due to the loss of operable heat pipes over the operational lifespan of the reactor.

Each heat transfer operating limit has a different physical phenomenon; indirect methods must be used to determine which limit has been reached. In general, the operating limits are characterized by abrupt increases in the overall thermal resistance of the heat pipe, resulting in rapid temperature increases [49]. As such, temperature measurements can generally be used to determine the power at which a limit is reached [49]. Further analytical and physics-based reasoning (i.e., using heat pipe evaporator region temperature) can be employed to determine the exact limiting factor and can be used to determine operational limits. However, it should be noted that operating limits can change under both short-term transient conditions as well as long-term due to degradation/corrosion of the channel or structure, or through the intentional (i.e., design choice) or non-intentional (i.e., fabrication error) introduction of non-condensable gases [50].

Table 2. Heat transport limitations for heat pipe operation. Derived from Reference [48].

| Phenomenon | Description |
|---|---|
| Viscous Limit | Insufficient pressure differential between evaporator and condenser to overcome viscous forces of working fluid |
| Sonic Limit | Vapor flow reaches sonic velocity, choking flow of working fluid |
| Capillary Limit | Capillary force is insufficient to overcome pressure drop |
| Entrainment Limit | High vapor velocity strips working fluid from heat pipe walls |

| | |
|---|---|
| Boiling Limit | Rapid boiling and surface bubbles in the evaporator prevents rewetting |

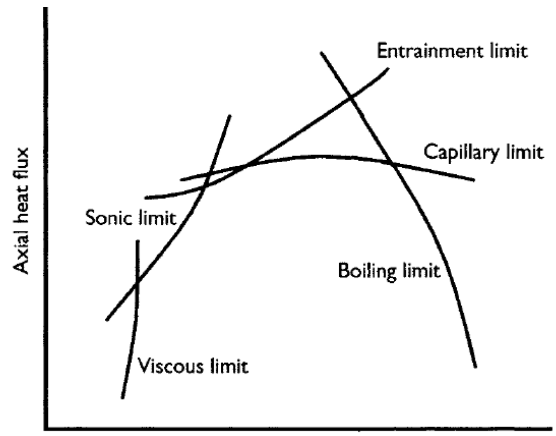


Figure 3. Heat transport limitations on heat pipes based on temperature and axial heat flux [48].

Environmental degradation describes changes to the heat pipe over the long-anticipated course of operating heat pipe reactors. For instance, heat pipe locations, for the SPR, are adjacent to fuel rods and will be subject to long-term irradiation. The working fluid may undergo transmutation into non-condensable gases from activation product decay, reducing heat transfer efficacy. Long-term irradiation can also lead to impurity-induced corrosion, especially within the wicking structure of capillary heat pipes. Impurities, such as oxygen, can be introduced during manufacturing, carried during charging of the working fluid, or found within the wicking structure [51]. For instance, in Reference [51], it is identified that heat pipes in high-power applications (e.g., 75 kW) require 4 to 8 micron fibers to construct adequate wicking structures. This fine wicking structure is highly susceptible to corrosion damage and plugging, as dissolved containments plate out on to the evaporator surface [51]. Even if heat pipes are not initially designated to transfer large quantities of heat, failure of surrounding heat pipes may result in an environment condition that forces higher heat transfer requirements. Normal operation of heat pipes can also concentrate contaminants in the evaporator region where heat fluxes are highest, ultimately degrading the heat transfer performance of heat pipes over long periods of time [51]. Prolonged irradiation can also lead to crack formation along welds and blemishes of the heat pipe material. Neutron-induced swelling of the heat pipe tubing material can result in working fluid leakage and failure [34]. In Table 3, a summary of environmental degradation modes of heat pipes is provided. Note, the table list is not exhaustive and focuses specifically on heat pipe failures. Other external factors, such as the containment vessel (e.g., steel monolith), may also contribute to heat pipe failures but are not explored in this work.

The effect of environmental degradation on heat pipes, while considered a local effect on individual heat pipes, can result in a global effect such as a cascading loss of surrounding heat pipes initiated by the loss of an individual heat pipe [34]. A cascade failure may result from a mechanistic or heat transfer limit standpoint. For instance, in the event of a single heat pipe failure within the SPR design that reduces its heat transfer capabilities, it is anticipated that the surrounding mechanical stress would increase to 154.6 MPa [34], significantly higher than ASME-approved stress limits for 316 stainless steel, increasing the potential for subsequent heat pipe failures. Alternatively, a cascading failure may result from insufficient margin in the heat transfer capabilities, which may be unable to carry the additional thermal load, leading to the entrainment or boiling limit [40]. The development of a condition monitoring program may be applied to evaluate heat transport limits or environmental degradation that may occur in heat pipes.

Table 3. Degradation phenomenon of heat pipes [34].

| Phenomenon | Description |
|---|---|
| Impurity-induced corrosion | Impurities within the heat pipe leading to corrosion of the wicking structure. |
| Crack formation and leakage | Material cracks form in the tubing structure of the heat pipe leading to leakage of working fluid. |
| Weld degradation | Failure of heat pipe welds, either through prolonged exposure to contaminants or radiation or through a shaking event (e.g., earthquake, transportation). |
| Irradiation-induced working fluid transmutation | Conversion of working fluid into non-condensable gases from activation product decay, depending on working fluid composition. |
| Irradiation-induced embrittlement/swelling | Changes in tensile strength and volume of tubing material due to localized displacements in atomic structure by neutrons. |
| Thermal aging-induced embrittlement | Changes in tensile strength of tubing material. |
| Support weld and coupling age-based degradation | Welding heat pipes to the housing structure (i.e., monolith) has very limited physical access and would be challenging for IST and ISI. For long-term operation, heat pipe coupling and welds may degrade if maintenance cannot be performed. |

### 4.3.2. Heat Pipe Monitoring and Maintenance

Considering available maintenance methodologies applicable for heat pipes is relevant for the development of a heat pipe condition monitoring methodology. This is to ensure that the condition monitoring method utilized aligns with current maintenance practices that can be applied for heat pipes. Due to the working fluid of heat pipes being sealed and generally inaccessible for inspection, different conventional, non-invasive, and invasive monitoring strategies could be deployed for detecting defect and anomalies within heat pipes. It is anticipated that instrumentation will have to be installed in dedicated channels to continuously monitor heat pipe conditions in the event of defect growth. These defects include, but are not limited to, corrosion and cracking of the cladding structure or plugging of the wicking structure. The objective of monitoring is to ensure that the heat transfer capabilities of the heat pipers are maintained.

This section is separated into in-process and inservice monitoring and maintenance to differentiate the state of plant operation in which a method can be applied. *In-process* refers to when the reactor is operating. This includes during startups, normal operations, transients, and accident scenarios. IST activities are permitted to be performed in-process (i.e., valve testing). *Inservice* refers to when the reactor is undergoing maintenance and is not operating. This includes during shutdown, refueling, and planned/unplanned outage. These terms are used only to help readers differentiate when an activity is performed and is not regulatory terminology.

#### *4.3.2.1. In-Process Monitoring and Maintenance*

Conventional methods, such as temperature, flow rate, and pressure sensing, are anticipated to be crucial to ensure that heat pipes can maintain the intended heat transfer rates. For instance, thermocouples can inform on the temperature distributions around fuel pins and heat pipes which can be used to detect the onset of heat transfer limits (shown in Figure 3). Heat flux, the other important parameter in determining the presence of transfer limits, may be measured directly via thermoelectric modules [52] or calculated indirectly using temperature difference between the hot end (i.e., evaporation region) and cold end (i.e., condensation region) of the heat pipe. Alternatively, if pressure difference along the heat pipe can be measured, heat transfer limits may also be inferred [53]. However, instrumenting heat pipes channels for in-situ monitoring is an active research field; there are limited publications that discuss potential configurations. Two different experimental case studies are presented from References [54] and [55] to demonstrate how sensors may be configured into a heat pipe reactor to determine performance.

In Reference [54], researchers integrate optical fiber and thermocouple temperature and strain sensors in milled channels along the monolith block to record axial temperature of heated channels. Two different integrations were tested, floating, where sensors are placed in larger milled channels without attachment to the monolith, and embedded, where sensors were fused with the monolith via sonotrode [54]. Monolith surface thermocouples and strain gauges were also attached. Figure 4 and Figure 5 provide a top-down and cross section of the monolith illustrating where sensors are placed. Cartridge heaters were used as a heat source in place of fuel rods. A boron nitride past was used as a gap filler between the cartridge heaters and the wall of the monolith to provide better heat transfer. A single sodium heat pipe is inserted into the center channel of the monolith as the heat exchanger, with an external water-cooled chiller at the condenser end of the heat pipe.

The researchers were able to monitor the strain and temperature response along the axial length of the monolith. These detailed temperature measurements enable the temperature distribution within the monolith to be more accurately mapped, which is necessary for determining thermal stress. In Figure 6, a temperature distribution is mapped from the various temperature sensors at specific axially locations.

During the experimental process, certain challenges occurred [54] that should be considered when developing a heat pipe condition monitoring program. One of the key issues encountered was sensor reliability; specifically, the fiber optic strain sensor failed after 140 minutes of operation due to a mechanical break at the fiber sensing head [54]. The result was that the entire sensing length of the strain gauge was broken and could not be used. The root cause of the failure was that fiber optic sensors can be easily strained at the entrance of the embedded region during handling and installation. Sensor sensitivity was also identified in References [56, 57, 58]. Reference [54] implements redundant sensors to partially address this issue. In essence, a condition monitoring program receiving signals from the reactor will need the capability to detect and handle sensor values that degrade or break over time, whether in redundant or non-redundant configurations. Another lesson learned was that improper filling of the boron nitride paste in the heater cartridge channels increased the local temperature by ~$30^oC$ [54]. A similar geometry fabrication issue was also identified in Reference [55] that led to localized hotspots in the monolith. Variations in temperature due to geometry or fabrication can impact the longevity of heat pipes and other structural components. Establishing baseline performance testing and trend analysis (i.e., IST) through embedded thermocouples and stress gauges may help identify the onset of component failure. While long-term reliability and handling procedures are still undergoing research, it is anticipated that as more experience is gained and processes are refined, these challenges can be resolved.

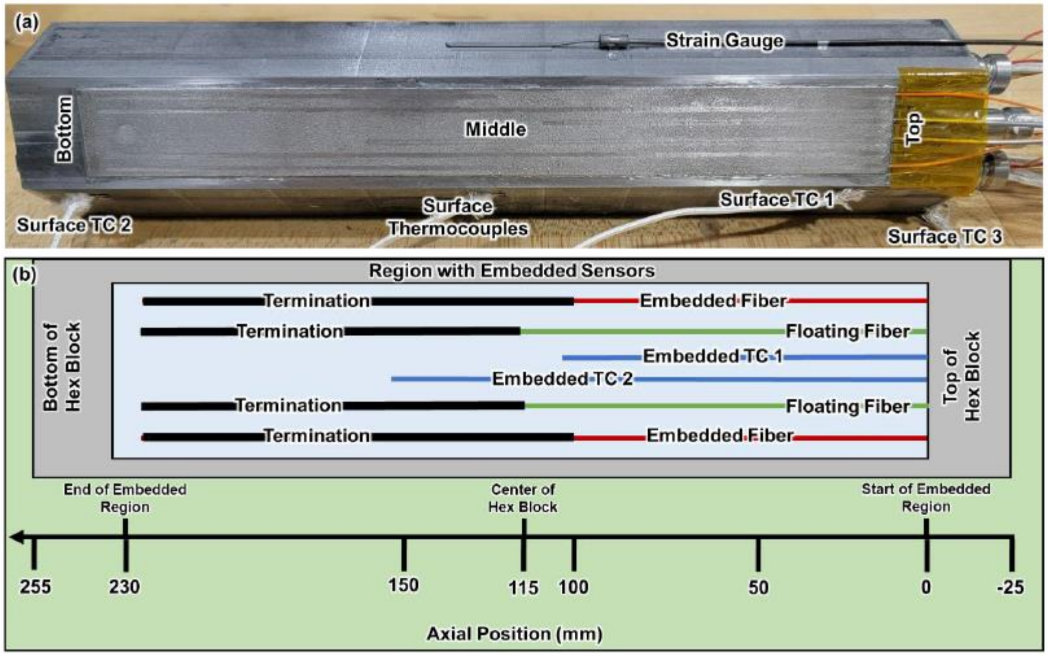



Figure 4. (a) Photo and (b) schematic of the sensor placement along the hex block test article. The red/green segment of the embedded/floating fibers indicates usable sensing range. Black bands at fiber ends indicate termination where no sensing data can be acquired. The hex block is 280 mm long, and the embedded region is situated 25 mm from either end of the block. Reproduction from Ref. [54].

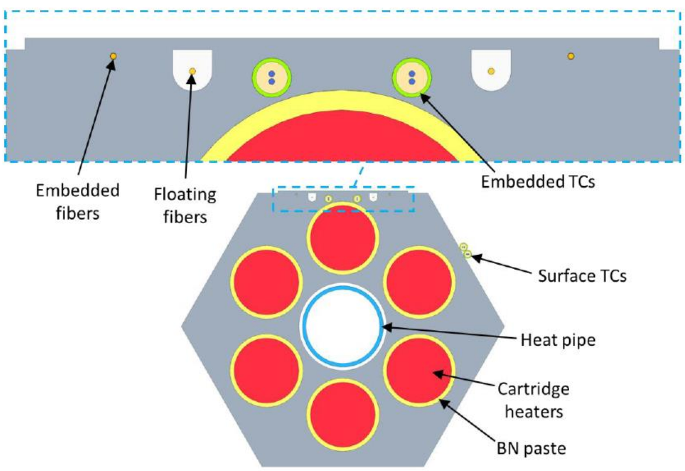



Figure 5. Transverse cross-sectional view of heat pipe monolith showing sensor position. Reproduction from Ref. [54].

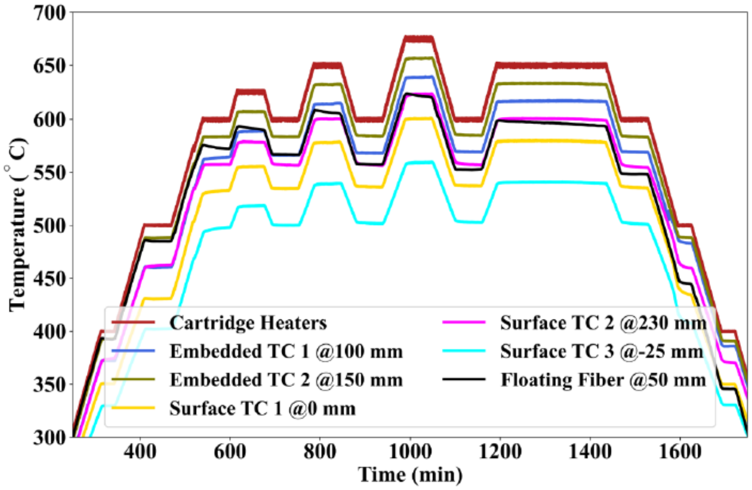



Figure 6. Temperature recorded by floating fiber, embedded, and surface thermocouple temperature sensors mapped over heating cycles and at specific locations along the monolith [54].

In Reference [55], a similar heat pipe monolith experiment was conducted, where type K thermocouple sensors were placed in milled notches within the heat pipe channel as opposed to embedding on the exterior side of the monolith. This experiment also utilized heater cartridges to control and heat the monolith. In Figure 7, the cross-sectional view of the heat pipe and notch placement is shown. In Figure 8, the axially positioning of thermocouples is shown. Each *point* indicates a probe location. To remove heat from the system, a water-cooled gas-gap calorimeter is setup at the condenser end of the heat pipe.

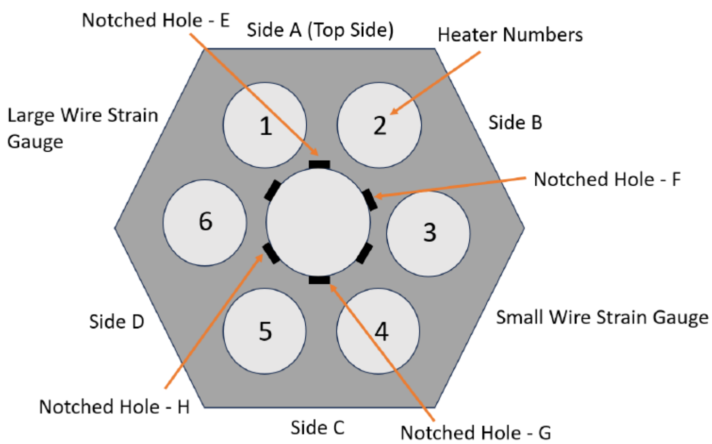



Figure 7. Transverse cross-sectional view of heat pipe monolith with milled notches in center heat pipe channel. Reproduced from Reference [55].

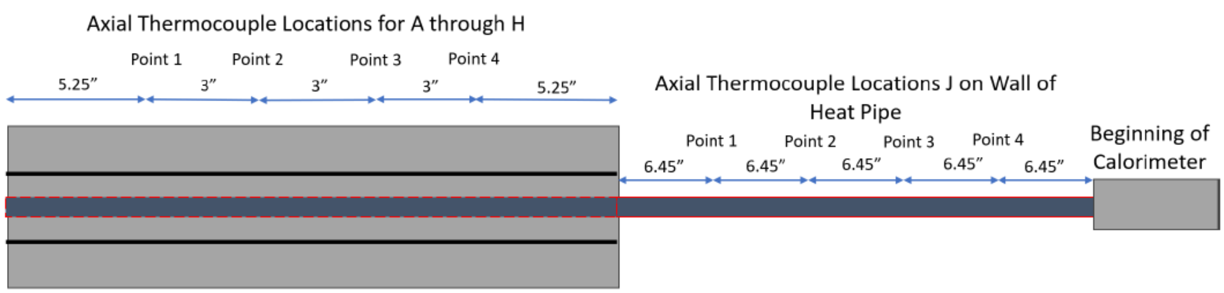



Figure 8. Positioning diagram of thermocouples along heat pipe. Reproduced from Reference [55].

In this experiment, researchers were able to collect the axial temperature profile at steady state and transient conditions of the heat pipe. These values are important as they may be used to determine thermal heat transfer performance of the heat pipe along the length of the channel. In Figure 9, the temperature profile at different radial separations at the same axial location is shown. Discrepancy between the radial temperature sensors was due to slight geometric variations in the installation of the heat pipe to the core block.

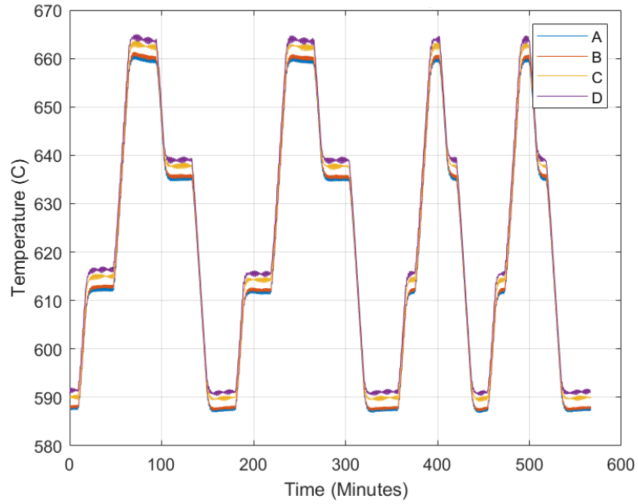



Figure 9. Temperature profile of heat pipe in evaporator region across core block during heating cycles. Reproduced from Reference [55].

#### *4.3.2.2. Inservice Monitoring and Maintenance*

Non-invasive methods for defect detection include ultrasonic imaging, acoustic emissions, thermography, laser ultrasonics, eddy currents detection, and X-radiography [59]. The usage of non-destructive methods for detecting external and internal defects is crucial for detecting degradations to ensure safe and reliable operation and maintenance of heat pipes [60]. Regardless of the type of instrumentation, qualification to ensure that these sensors are also operational over the extended operational period is anticipated. Note that these technologies are presented based on experience from other industries (e.g., oil and gas and sewage) as heat-pipe-specific monitoring technologies are still under development.

Ultrasonic inspections use sound signals above the normal human range (>20 kHz) to estimate properties of irradiated materials by analyzing the reflected or transmitted signal from the materials [61]. Ultrasonic inspections consist of units like pulsers, receivers, transducers, and devices to display the signals [60]. For example, a pulser produces high-voltage electrical pulses that drive a transducer, which then generates high-frequency ultrasonic waves. Ultrasonic data is usually collected in three formats: A-scan, B-scan, and C-scans. A-scan gives an amplitude scan, B-scan provides cross-sectional views of materials to show trends, and C-scan shows three-dimensional ultrasonic scans in horizontal and vertical directions across material thickness [60]. In Reference [62], non-destructive pipeline testing was conducted using ultrasonic imaging and a generalized neural network for regression. The aim of using the ultrasonic scan in conjunction with the neural network model was to determine the dimensions of the corrosion and to generate entire images of the internal and external walls of oil pipeline.

In addition to the model, the authors also introduced a neuro-fuzzy decision-based algorithms that can detect and classify the corrosion occurring in the oil pipes [62]. Due to the necessity to reduce noise in ultrasonic signals and enhance even small defects, wavelet transformation may be used to enhance flaw location information from ultrasonic signals, while showing good localization of defects [63]. The results were then sent to an artificial neural network that can detect and classify faults. Thus, ultrasonic methods can be useful as a non-invasive testing method to detect anomalies in heat pipes, while also having potential to develop automated methods for condition monitoring by using data from ultrasonic testing for the development of data analytics models. However, some limitations of ultrasonic testing include its susceptibility to external noise and its need for a relatively smooth surface, and it can produce incorrect results for materials with low thickness.

Acoustic emission is another non-destructive method for fault detection that can be used for heat pipes. Acoustic emissions generate stress waves by sudden movement in stressed materials that can help in detecting deformations or crack growths. Sudden movement caused through transient elastic waves produces stress waves that radiate into the component to excite a piezoelectric transducer [64]. This raises stress in the component, which generates different emissions in the form of signals captured by sensors. These data from the sensors can be analyzed to understand defects within the component. Cracks and material defects of even relatively small magnitudes in heat pipes can be detected using the passive acoustic emissions method. Acoustic emission testing has also been used to detect leakages in pipe. However, acoustic emission testing is limited since it does not work over long detection ranges and is sometimes complex to interpret. The length of detection is determined by a variety of factors including but not limited to material properties, shape of the acoustic waveguide (e.g., heat pipe shape), touching surfaces (e.g., support structures), frequency of acoustic emission, intermediate interfaces (e.g., attachment material between the transducer and the heat pipe), and strength of transducer (e.g., amplitude of probing acoustic wave). Note that acoustic emission testing is also very prone to environmental interference and noise, which may limit the range of detection. Optimization techniques like using wavelet threshold functions could be a useful addition to ensure noise is removed from the data generated by the acoustic emission testing. These data can then be used to train ML/AI models that can be used for fault detection, classification, and prediction for condition monitoring of heat pipes.

X-radiography can be used by generating ionizing radiation to produce images of the internals of a component to detect faults. X-radiography consists of two parts: a radiation source and a detector. When X-rays pass through an object, the difference in mass attenuation coefficient as the X-rays pass through generate different imaging responses. As such, X-radiography testing can be used to detect shape defects, shrinkage defects, cavities in materials, or sponge shrinkage defects while providing information on their intensities, orientations, sizes, and shapes [65]. X-radiography is a popular technique for pipeline and piping inspection. However, a key limitation of X-radiography is the penetration depth and potential invisibility of heat pipes. For example, one report suggests that the penetration depth of solid steel 316 is between 3–20 mm [66]. In addition, if both the heat pipes and housing monolith are both constructed using 316 stainless steel or similar materials, X-radiography may not be able to distinguish the components apart for defect analysis. In addition, if X-radiography is intended to be used while the plant is in service, other high energy radiation given off by nearby fuel pins may completely obscure the X-ray image (e.g., high noise). Lastly, X-radiography requires a receiver that is typically positioned opposite to the radiation source to generate the image. Assuming a penetration depth of 20 mm, this would imply that sources and detectors would have to be installed in close proximity to heat pipes to be able to capture the structural condition; therefore, limitations in space are a concern. While small detectors do exist (e.g., semi-conductor X-ray detectors [67]), these detectors are highly sensitive to environmental degradation (e.g., radiation-induced crystal-lattice defects) and may not survive if within close proximity to heat and radiation sources (e.g., fuel pins) [67].

Similarly, thermography can be used to capture hot spots [22] within the heat pipe, detecting various operational limits of the heat pipe, such as the boiling limit. This helps with condition monitoring to determine whether the heat pipe is functioning within the normal operational limits. Thermography can also be used to detect corrosion, flow erosion at high temperatures, and hidden material defects [68].

Defects in electrically conductive materials can also be detected using eddy currents. Alternating current-driven coils, delivered via a bobbin probe (or other sensor heads), induces eddy currents within the material via electromagnetic coupling. This eddy current circulation, in turn, produces a secondary magnetic field. The characteristics of this field vary depending on the existence of flaws or defects within the material that impede the eddy current flow. These variations are detected by either coil or magnetic sensors [69]. Any small defects within the components can influence and vary the eddy currents, which can be monitored. Eddy current testing has only a single frequency, whereas pulsed eddy current testing has a broadband of frequencies increasing its applicability in capturing various frequency-dependent defects [69]. Eddy current methods can thus detect small cracks and material defects including corrosion, but defects that do not come in direct contact with the probe cannot be detected and are thus not viable for large area applications. However, a significant limitation of this method for condition monitoring is the reliance on a physical sensor head to sweep across the material surface for detection. For instance, it is unlikely that a probe can be used to examine the internal structure of sealed heat pipes. In addition, eddy current probes are conventionally used to assess smooth surfaces (e.g., steam generator piping). It is unknown what effect an irregular wicking structure of the heat pipes will have on eddy current measurements. All such methods can generate data to develop a data analytics model that can be used for condition monitoring of heat pipes.

## 4.4. Technical Considerations and Opportunities for Digital Twin Deployment

In this section, a discussion on the technical considerations and opportunities for developing and deploying a DT condition monitoring program specific to heat pipes is provided. General considerations for a DT condition monitoring program are discussed in Section 5.

### 4.4.1. Heat Pipe Modeling Challenges

Simulation codes (e.g., Sockeye [45] and HTPIPE [70]) of heat pipe reactors may be used to address design, testing, and operating experience inadequacies. There are three general categories to describe heat pipe codes: full two-phase, gas-only, and super thermal conductivity codes. Basically, the differentiator between the codes is the number of material phases modeled.

In full two-phase code [45], both the gaseous and liquid forms of the working fluid are modeled, allowing for more comprehensive physical phenomenon simulation, such as capillary action, evaporation, and condensation, etc. While computationally expensive, these codes can be used to model transient and startup events in addition to heat transfer limits. However, at scale (e.g., multiple heat pipe or large geometry), full two-phase codes can have slow computational performance (e.g., cannot be run in real-time). Furthermore, additional code validation for two-phase codes is still required, especially under varying thermal and pressure conditions.

In gas-only codes [50, 70], typically a non-condensable gas emulates the working fluid’s convective and conductive heat transfer mechanisms. Gas-only codes may be used to model steady state operating conditions. While validation for gas-only codes is more mature than the full two-phase codes, they cannot be used to model transients and startups, and the heat transfer limits must be determined analytically. A key benefit to gas-only codes is that they are relatively faster than full two-phase codes, especially when scaled to full reactor size or multiple heat pipe bundles.

Lastly, in super thermal conductivity codes [71], the heat pipe’s heat transport model (i.e., convective vapor flow) is replaced with a high-efficiency heat conductance material model (i.e., conduction model). While super thermal conductivity codes have certain benefits (e.g., computational speed and scale) over the gas-only and full two-phase codes, they do not capture realistic heat pipe physics and may introduce model uncertainty. For heat transfer limits (e.g., viscosity, entrainment), these limits are analytically derived. The model itself cannot be used to derive the limits or determine damage incurred on the heat pipe when a limit is reached [71] as neither the geometry nor model physics accurately reflect the heat pipe.

These codes, while helpful at identifying the thermal characteristics and properties of heat pipe reactors, may introduce unrealistic assumptions and uncertainties if they are also subsequently used to train DT models for heat pipe condition monitoring. This is especially true for heat pipe reactor designs, as a lack of operational experience impedes accurate model development. Parameters, such as geometric dimensions, material density, and nuclear data, can all introduce uncertainty, significantly impacting modeling and simulation data. Transient behavior of heat pipes is also not well understood, and important research in phase change (e.g., solid to liquid and vapor) modeling is being conducted.

In Reference [72], it is identified that liquid-metal heat pipes on startup typically involve a number of nonlinear mass and heat transport processes undergoing various phase changes. As such, there are major modeling difficulties when it comes to simulating multiphase interaction of the working fluid, microporous wick flow, and compressible gas dynamics [72]. Typically, a sophisticated model with multiple sub-model implementations is required to accurately simulate the phase change physics within heat pipes. On the other hand, lump modeling approaches, while computational efficient at exploring the macro characteristics of the heat pipe physics, overlook key driving effects that contribute to heat transfer limits. For instance, in Reference [73], a lumped heat conduction model was used to simulate heat pipe startup and working fluid evaporation. However, this method neglects the modeling of the working fluid vapor region and the vapor's thermal resistance within the heat pipe, potentially resulting in highly inaccuracy as flowing vapor contributes to convective heat transfer. These model simplifications contributed significantly to wall temperature prediction inaccuracy when compared to experimental data, specifically within the adiabatic region (i.e., between the evaporation and condensation ends of the heat pipe) [72].

Experimental evidence is also not free from uncertainty. In previous heat pipe experimental studies [74, 75], variations in heat-pipe wall emissivity, thermal mass of structures, wicking structure construction imperfections, and reference temperatures to determine radiation heat loss were identified as potential sources of uncertainty. In Reference [55], they identify that minor variations in the experimental setup resulting in geometric asymmetry of the monolith block had meaningful temperature impact on the heat pipe. In Reference [55], this variation was at most $\pm 5°\text{C}$ between the sensors placed at the same axially location. Ultimately, the implication of experimental data uncertainty on model development is that some degree of aleatoric uncertainty is present and potentially unquantifiable, impacting validation efforts.

Modeling uncertainty is not limited to the working fluid heat transfer dynamics. In Reference [76], it is discussed how there is significant uncertainty in the high energy region of $^{235}U$ reactions that can impact core physics calculations, especially within the SPR design. This is also identified in Reference [34], which states that fast reactor $^{235}U$ nuclear reaction cross sections have uncertainties on the order of the beginning-of-life excess reactivity (i.e., 2,000 pcm). As certain microreactors are planned to be fast reactors, this uncertainty can impact core simulation calculations. This is a concern as heat pipes are anticipated to undergo radiation-induced corrosion due to their close proximity to fuel pins; inaccurate modeling of reactor physics can alter the rate of anticipated degradation of heat pipes (and support structures) [77].

Lastly, these simulator codes and models themselves need further validation and verification work. For instance, only preliminary verification, validation, and uncertainty quantification on Sockeye was performed in References [78, 79] on a limited set of experimental data from the SPHERE experiment. Until further simulation validation can be completed, Sockeye is limited to modeling heat pipe internal fluid and heat transfer properties. Simulation experience with defects and degradations and their impact on the heat pipe is limited; corresponding validation data is limited as well. However, as Sockeye is a thermal fluids code, it can model the effects of a degradation or defect on heat transfer performance as long as the input parameters for the defect are provided. Determining the correct input parameters requires experimental data collection. In essence, additional maturity is required should Sockeye be used to generate data for DT condition monitoring programs.

### 4.4.2. Qualification of Reactor Technologies for Deployment Length

Sensors and other instrumentation will be crucial for advanced condition monitoring activities. Sensor qualification is the process of testing and ensuring that a sensor meets certain performance criterion under a specified environmental condition. Note that while testing is not the only method of qualification, under limited/no operating experience or analytical methods, it is a comprehensive method. There are two particular issues associated with sensor qualification: identifying the test environment sufficient for the operational environment and ensuring these sensors meet requirements.

Identifying a test environment involves determining how long a test will be conducted on a sensor and under what conditions, analogous to the intended operational environment. However, due to the lack of operational experience for heat pipe reactors, determining the right set of conditions may be challenging. For instance, microreactors are anticipated to operate for extended periods of time without active maintenance [21]. Ensuring that these sensors are usable and capable of maintaining operability over extended periods of time in high-temperature and irradiated environments while also in unique geometries is still an active area of research [80]. While sensors exist that are qualified for other industrial applications and may be postulated to be usable for advanced reactors, the potential for radiation-driven corrosion and transmutation of sensor materials introduces uncertainty in their lifespan. Sensor failure modes novel to nuclear heat pipe environments may complicate qualification and require novel methods to address the uncertainty in their lifespan and reliability. Ensuring sensor operation ensures the availability of the monitoring program to assess the heat pipe condition.

Finding an appropriate test environment may be also difficult if the chosen sensors are also classified as important to safety. These sensors would require, but not be limited to, additional qualifications under accidents, anticipated operational occurrences, external events, and natural phenomena scenarios beyond normal operating conditions. However, it is important to keep in mind that the requirement for highly qualified sensing must consider the safety determination of the associated condition monitoring program. If the conditioning monitoring program is not important to safety[a] and the sensors it utilizes are also not used for other important safety systems, a high criterion for sensor qualification is not necessarily warranted.

Generating experimental data to justify component reliability may also be completed through accelerated testing methods (ATM) [49, 81]. ATM is the process of magnifying life-limiting effects during component testing to accelerate aging degradation (e.g., at high operating temperature or mass fluence) [81]. The immediate benefit of ATM is the faster generation of realistic heat pipe defects, from 10 years of operational life to 3 years under accelerated aging. To conduct ATM, typically one relevant material stressor is identified (e.g., temperature) and varied, while other stressors are held constant. The increased stress state is held until the component fails or cannot work properly. In essence, ATM tests how individual stress factors can lead to component failure. However, realistic component failures may result from a combination of multiple (individually benign) stress factors. Selecting the correct accelerating test conditions to extrapolate component reliability is difficult, especially if the environmental condition has multiple input parameters (e.g., temperature, pressure, moisture).

### 4.4.3. Regulatory Considerations on Heat Pipe Condition Monitoring

New and advanced reactors that use heat pipes may be required to develop IST programs. ASME has developed new guidance for IST programs (referred to as the OM-2 Code [41]) in new and advanced reactors. The NRC staff is considering the preparation of an RG to accept the new ASME OM-2 Code with applicable conditions for reference by applicants in their licensing documents. Applicants for reactors that use heat pipes could consider the new ASME guidance in developing their IST program. A key feature discussed in microreactor design is the implementation of safety function through inherent safety measures, which include non-actuated safety systems (i.e., heat pipes). These systems are designed on naturally occurring physical processes to achieve crucial safety functions. However, non-actuated safety systems may challenge traditional methods to evaluate the level of safety of reactor design [82]. Reactor designs that utilize heat pipes are planned for operating at sub-atmospheric pressure [82]. The total volume of primary coolant is divided into hundreds of individually self-contained heat removal devices [82]. These

[a] SSCs "important to safety" as defined in 10 CFR 50 Appendix A are structures, systems, and components that provide reasonable assurance that the facility can be operated without undue risk to the health and safety of the public.

heat pipes may be designed to act as redundancies to each other such that the loss of one heat pipe is not crucial. This differs from conventional reactors with a single large volume of coolant and will make loss-of-coolant transient analysis different. In this respect, the loss of a single heat pipe or a cascading failure of multiple heat pipes may be an important license basis event [82]. Evaluation of other effects relevant to the identification of LBEs will also be required and may consist of the following categories seen in Table 4.

Table 4. Relevant considerations in selecting LBEs.

| Phenomenon | Description |
|---|---|
| Evaluation of heat-pipe heat transport limits and safe operating regimes | Heat pipes may functionally fail due to one of the heat transport limits discussed in Table 2. |
| Demonstration of inherent safety | Inherent safety depends on several factors:<br>• Reversible return to safe operation once the heat transport limit is exceeded<br>• Confirmation of no single failure or common mode failure in LBEs. |
| Separate effect heat pipe performance versus integrated heat pipe performance | Evaluating heat pipe performance goals across either individual or grouped heat pipe performance. Depends on the design chosen. |
| Heat pipe construction | Reliable construction of vacuum-filled heat pipes, welding, and quantification of impurities in working fluid and internal structure (e.g., wicking). |
| Corrosion and chemistry issues | Evaluation of the aggregation of working fluid impurities over the lifespan of heat pipe operation and the impact on performance. |
| Testing of functional containment defense-in-depth elements | Characterization of heat pipe leakage and LBE response to failures of identified containment barriers. |

# 5. GENERIC CONSIDERATIONS FOR DT CONDITION MONITORING PROGRAMS

This section discusses generic considerations for developing a DT for a condition monitoring program. These considerations may apply to either of the case studies presented above.

## 5.1. Digital Twin for Condition Monitoring Verification and Validation

Currently, RG 1.168 [83] discusses the verification and validation (V&V) of software used in safety systems. This also applies to all activities in the installation, testing, operation, maintaining, or modifying of the safety-related functions of an SSC [83]. It is anticipated that a DT for condition monitoring of safety-related SSCs (i.e., RCPs) is a software model that would impact the maintenance scheduling and would be subject to RG 1.168 [83]. This RG may also be applied for non-safety-related but "important to safety" systems [83]. Furthermore, RG 1.170 discusses software unit testing of digital computer software used in safety systems of NPP. This RG also applies to non-safety-related but "important to safety" systems.

Verification of a DT for condition monitoring is the act of confirming with objective evidence that the specified requirements have been fulfilled (e.g., for correctness, consistency, accuracy). Validation is the act of confirming that the DT satisfies end user needs. These definitions are derived from IEEE 1012-2004, endorsed in RG 1.168 [83]. V&V does not refer to the underlying software or operating system that executes the DT functions. This report does not cover the V&V of these subsystems. V&V of condition monitoring DTs is an important activity both in licensing and development as it can validate the veracity of the model, providing confidence in its functionality through observation of modeling and algorithmic error. However, there are several challenges when conducting V&V for condition monitoring DTs, namely: (1) uncertain consistency of fault signatures, (2) inadequate experimental or operational data, (3) combinatorial damage, and (4) model reverification and maintenance.

Uncertain consistency of fault signature data refers to the condition where the identifying signatures (e.g., vibration spectral side bands) for the same fault condition may change over time. Note that the nature of the fault does not change; rather the instrumentation monitoring the condition of the component may change over time, due to wear, environmental degradation, or small changes to performance caused by maintenance. For instance, sensor drift, the gradual change in sensor output deviating from originally calibrated values, can impact the predictive output of DT condition monitoring models. Verification work, conducted during model development, to determine whether a DT satisfies specified requirements may be incomplete, and the detection effectiveness may decrease as plant conditions change. This issue arises as relevant fault data is difficult to collect [31]; the addition of sensor drift would further complicate this collection issue. While methods exist to detect sensor drift, such as discrete average block-based methods, cumulative sum, and exponentially weighted moving average algorithms, these methods only detect the onset of drift and cannot be used to "correct" the input for the DT models [84]. Furthermore, these methods are insensitive to very noisy or prolonged drift conditions, which can hinder detection of drift [84].

Operational data, while available, may not be useful in the verification process as (a) fault signatures are not collected in completeness due to proactive maintenance, (b) are one-off scenarios that are not comparable, and (c) are collected under different conditions [31]. To ensure continued operation of the component, an operator may choose to proactively replace or repair the component at the earliest signs of performance deviation, regardless of the degree or presence of a fault. As such, data on these fault conditions are partial and cannot be used for verification. Furthermore, faults may be one-off conditions and non-repeating. For instance, improper bearing loading is a one-off condition that can be resolved by reloading the bearings appropriately. V&V partially relies on repetitive confirmation that the model meets requirements; verification on one-off examples may make it hard to justify that the model performs well on a class of faults. This further extends to the condition that the fault was collected and corrected. True faults are "far and few between." Plant conditions during a fault are not guaranteed to be the same for each condition. When monitoring conditions are inconsistent, it is difficult to justify that the model performance will also be consistent, especially when the data is limited [85]. While experimental data can address some of these issues, it is imperfect. Namely, faults generated under laboratory conditions may not represent realistic fault conditions. For instance, in Reference [31], it is identified that methods of generating damage artificially (e.g., electric discharge machining, drilling, or manual engraving) to simulate bearing damages are typically uncharacteristic of real bearing damages. Verification using experimental data may provide a skewed perspective on the true performance of the DT.

Another potential challenge is the presence of multiple faults. Typically, model V&V in literature is conducted on a single phenomenon to identify efficacy and does not include multiple faults, which can detract from the intended model function. In reality, faults are not necessarily single point damages and may be distributed across different sites [31]. The consideration here is no single site may be significant enough to be clearly identifiable, but rather the combination of multiple minor fault sites may lead to the determination that a fault is present [85]. It is not clear how the current V&V for DT would approach multi-site faults, especially if each fault individually is insignificant. This issue may be partially resolved if the scope of the DT is to determine whether a component is faulty or not, instead of determining the exact root cause of the fault. While a loss of resolution is anticipated, the simplified V&V process may be more achievable.

While preliminary V&V data, regardless of how it was generated (e.g., experimentally or derived from historical databases), may not be initially available, developers may assume that operational data can be used to refine and further validate the model. The premise being that operational data is more relevant to the intended function of the DT condition monitoring model. Aside from the operational data challenges mentioned above, this may present a potential conflict between initial V&V data and collected operational data. Assuming that operational data is "more relevant" than the initial dataset, it is unclear how conflicting evidence should be addressed. For instance, consider the bearing damage example from Reference [31]. If an initial DT model is verified on this particular fault type, how should more realistic bearing damage data be used and should the original dataset be integrated or disavowed? Furthermore, as more information becomes available, what approach should be utilized to maintain and update these models with more relevant information?

A/B testing, also known as bucket testing or split testing, is one approach proposed to address model maintenance [86]. A/B testing is used to evaluate the difference between a new and old model version in terms of performance or impact by exposing the models to a small representative dataset [86]. A/B testing is used routinely in software development (e.g., websites) to ensure that the new version improves upon the existing version [87]. *A* refers to the original model while *B* refers to the revised model. In DT for condition monitoring, A/B testing may take the form where an *A* is compared against *B* for a period of time, where *B* has no impact on operation until it can be shown to improve upon performance. However, A/B testing for condition monitoring DTs has some additional considerations. A challenge related to A/B testing is the duration of the test [86]. Feedback on A/B testing for websites is nearly spontaneous, and performance changes can be gauged quickly. However, for condition monitoring, as true component faults are rare, A/B testing would have to be conducted for an extended period of time before it can be confirmed that the new model is better. Over this period of time, more operational data will become available; A/B testing may result in models that are always out-of-date, inflexible to the up-to-date operational conditions [86]. Furthermore, A/B testing only reveals holistic level performance and cannot reveal how multiple individual model changes affect performance. For instance, retraining may change all weights and biases within the model. The holistic impact may be positive, but there is the potential that the model becomes more/less sensitive to specific scenarios [86].

Essentially, many of the challenges associated with V&V of DT for condition monitoring is the difficulty in acquiring relevant data in the necessary quantity to adequately understand a phenomenon. The drivers of this issue are associated with the uniqueness and rareness of true faults in components. Devising a method to integrate this new data with existing data is also perceived to be a challenge.

## 5.2. Model Explainability

Development or deployment of models based on data analytics like statistical and/or ML models require some extent of explainability such that the model responses are understandable to operators. Understanding model response is important as it can provide confidence in prediction reliability [88] and may be used to further diagnose degradation issues [89]. Different models have different levels of explainability. When considering ML/AI-based models, deep learning models like neural networks can have very good accuracy and predictive capabilities but lie low on the explainable scale, while linear regression models may have performance capability lower to neural networks but land high on the explainable scale. The extent of explainability depends on the complexity and degree of nonlinearity of the problem modeled. For example, highly nonlinear problems may require vast neural networks with multiple hidden layers to adequately model them. Ultimately, explainability can be incorporated through a variety of ways, such as surrogate modeling, data visualization, performance metrics, and using explainability tools/interfaces.

Surrogate modeling is where a simple model is constructed to explain a limited set of outputs of a complex model (e.g., neural network). The premise is that the surrogate model provides information on how an output was generated based on the locality of the data source. Some examples of surrogate modeling include linear regression and decision tree.

In linear regression, it is assumed that the phenomenon near the test data point is approximately linear (e.g., the decision boundary); such nonlinearities in the complex model can be approximated with a linear model. For example, Local Interpretable Model-agnostic Explanations (LIME) is a commonly used model-agnostic local method that works by locally creating small perturbations around the test sample to see how model predictions change and assigning weights to linear ridge regression model to explain the output [90]. However, it must be understood that LIME is a post hoc method and not intended to be used in real time, a criterion for DT. Furthermore, parametric selection of kernel size and perturbation generation range is a significant concern (see Figure 10). There is active research into discovering: (1) the best method for selecting the range to generate perturbations around the test point and (2) how to choose the correct value for kernel width in model construction. First, the range to generate perturbations determines the linear model used for explanation and is dependent on the local curvature of the complex model regression line [91]. Insufficient or too large ranges lead to unstable LIME explanations as either scenario leads to misconstruction of the linear regression line around the test point [91]. This leads to the second challenge of kernel width selection, which confines the generated perturbation range to a subset of the most relevant datapoints (see the green area in Figure 10). Poor kernel width selection can result in meaningful explanations even if the model is noncoherent [92].

Decision trees are a non-parametric learning method that predicts a value based on a set of binary decision rules (e.g., yes/no, higher than/lower than). Like a tree structure, each decision rule leads to subsequent, more refined decision rules. An output may be explained based on the answers to these set of rules. The assumption here is that if a decision's tree output matches a complex model's output, the complex model's output can be explained to some degree by the decision trees decision rule answer. However, a key limitation to decision trees is the inflexibility of updating the tree to new information. For instance, when a new more relevant dataset is presented and integrated into the existing dataset, the structure of the tree is not maintained, and an entirely new set of decision rules are created that match the combined dataset. Existing answers are no longer relevant, and a new set of answers can be used to explain both old and new samples. In such cases, two different sets of decision rules may be used to justify the same outcome, presenting potentially conflicting information.

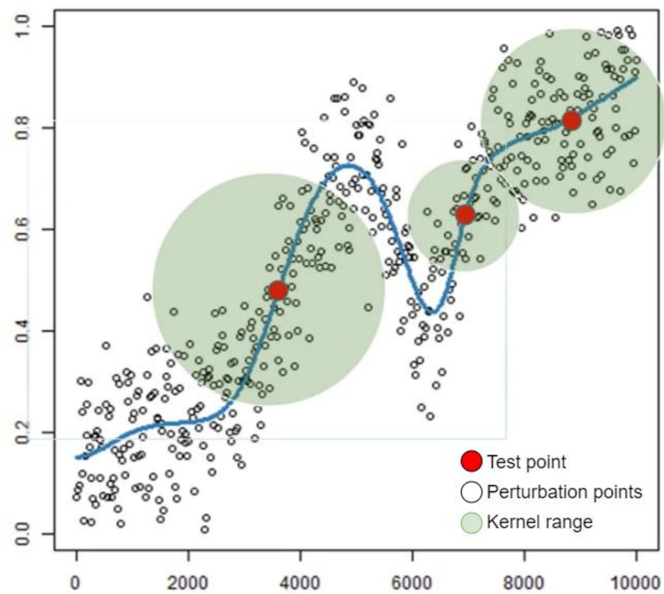



Figure 10. Selection of perturbation and kernel range when deriving LIME model. Original image modified from Reference [93].

Aside from surrogate modeling, Shapley Additive exPlanations (SHAP) [94] is a popular approach for explanations. SHAP scoring is a model-agnostic method that determines the degree of contribution that a feature makes to a model output. SHAP is a popular method as it achieves three desirable properties: local accuracy, missingness, and consistency [94]. Local accuracy refers to the requirement that the explanation model output at least matches the output of the complex model. Missingness is the quality where missing features will have no impact on the explanation. Lastly, consistency is the property where if a model changes such that the input feature's contribution increases or stays the same (regardless of the other features), that feature's attribution should also increase or stay the same (or at least not decrease). However, recent published papers have identified that SHAP scores may yield misleading information about the relative importance of features for predictions [95]. In a range of classifier experiments performed in Reference [95], it was shown that high SHAP scores (i.e., highly relevant) can be assigned to irrelevant features. No special treatment or modification of the dataset was needed to generate this outcome, rather this misassignment is related to how SHAP scores are inherently computed. The opposite can also be true, where a relevant feature is assigned a zero SHAP score (i.e., not relevant) [95]. The implication is that SHAP may be misused in communicating the explainability of a model outcome.

Partial dependence plot (PDP) [96] and individual conditional expectation (ICE) [97] are two global model-agnostic graphical visualization tools to analyze the interaction between the target response and a set of input features of interest. PDP shows the average effect of input features on the target output; ICE visualizes dependency for each sample separately, generating a different visual response per sample. While PDP is good at showing the average effect of target features, it may obscure heterogenous relationships caused by interactions. For instance, for a PDP plot showing positive correlation between an input feature and target growth, some feature samples may be negatively correlated, but the average over all feature samples is positively correlated [96]. ICE does not have this limitation as each feature sample is individually modeled. However, an issue with PDP and ICE is the visualization ability in high dimensions [97]. Typically, PDP and ICE only plot one or two features at a time, where the x-axis is the domain of the feature and the y-axis is the strength of dependency. For two features, the x-axis is feature one, the y-axis is feature two, and the z-axis is the strength of dependency. Investigating interaction between three or more features is a visualization limitation.

# 6. SUMMARY

In this report, two different use cases for condition monitoring were presented, along with how advanced technologies, such as sensing instrumentation, data storage and analytics, and ML/AI modeling methods for DTs, can be applied to augment existing condition monitoring approaches. For each use case, the report covered identifying the scope of monitoring, determining safety classifications based on existing guidance, monitoring degradation modes, and selecting appropriate monitoring parameters. The two use cases, RCP and heat pipes, were discussed in detail to present the implementation of the condition monitoring approach using advanced technologies. Such technologies may improve existing regulated maintenance practices while simultaneously improving overall plant performance by reducing unnecessary plant outages. There are also several challenges and considerations for the successful implementation of advanced condition monitoring systems. Therefore, key considerations include:

- Addressing verification, validation, and uncertainty in condition monitoring data, simulation models, and predictive algorithms
- Balancing the predictive capabilities of complex ML/AI models with the need for model explainability and interpretability of model outcomes
- Aligning the existing inspection, testing, non-destructive examination, and other maintenance techniques with the advanced condition monitoring program
- Developing methodologies for performance assessment of the advanced condition monitoring approaches.

The use cases presented in this report underscore the need to address several considerations associated with condition monitoring DTs that are anticipated to integrate ML/AI models, such as the construction of data collection, modification, and integrity management methods as well as trustworthiness and explainability of model predictions. There is much expressed interest in using advanced condition monitoring techniques to meet IST requirements and improve operations and maintenance efficiency. The NRC is preparing to effectively and efficiently evaluate using these technologies through research activities.

# REFERENCES


[1] V. Yadav, H. Zhang, C. P. Chwasz, A. V. Gribok, C. Ritter, N. Lybeck, R. D. Hays, P. K. Trask, V. Jain, P. Badalassi, D. Ramuhalli, D. Eskins, R. L. Gascot, D. Ju and R. Iyengar, "The State of Technology of Application of Digital Twins," US Nuclear Regulatory Commission, Washington, 2021.

[2] V. Yadav, J. Matrachisia, B. Cohn, B. Lin, T. G. Scarbrough, J. Tokey, C. Ulmer and R. Iyengar, "Proceedings of the Workshop on Conditional Monitoring and Structural Health Managment for Nuclear Power Plants," U.S. Nuclear Regulatory Commission, Washington, DC, 2024.

[3] E. Chen, C. Godbole, V. Yadav, V. Agarwal, J. Matrachisia, D. Eskins, C. Nellis, J. Tokey, E. Cohn, H. Mendoza, T. Scarbrough and R. Iyengar, "Assessment of Condition Monitoring Methods and Technologies for Inservice Inspection and Testing of Nuclear Power Plant Components," U.S. Nuclear Regulatory Commission, 2024.

[4] The American Society of Mechanical Engineers, "Operation and Maintenance of Nuclear Power Plants," The American Society of Mechanical Engineers, 2022.

[5] NuScale Power, LLC, "NuScale Plant Design Overview," NuScale Power, LLC, Corvallis, 2012.

[6] V. Agarwal, A. Gribok, K. M. Araseethota, J. A. Smith, N. J. Lybeck, V. Yadav, M. Yarlett, B. Diggans and H. Palas, "Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 3," Idaho National Laboratory (INL) , Idaho Falls, 2022.

[7] U.S. Nuclear Regulatory Commission, "50.55(a) Codes and standards," U.S. Nuclear Regulatory Commission, 2023. [Online]. Available: https://www.nrc.gov/reading-rm/doc-collections/cfr/part050/part050-0055a.html. [Accessed 2024].

[8] The American Society of Mechanical Engineers, "Case OMN-29 Pump Condition Monitoring Program," The American Society of Mechanical Engineers, 2022.

[9] U.S. Nuclear Regulatory Commission, "50.65 Requirements for Monitoring the Effectiveness of Maintenance at Nuclear Power Plants," U.S. Nuclear Regulatory Commission, 2021. [Online]. Available: https://www.nrc.gov/reading-rm/doc-collections/cfr/part050/part050-0065.html. [Accessed 2024].

[10] U.S. Nuclear Regulatory Commission, "Regulatory Guide 1.160, Revision 4 - Monitoring the Effectiveness of Maintenance at Nuclear Power Plants," U.S. Nuclear Regulatory Commission, Washington, 2018.

[11] Nuclear Energy Institute, "Industry Guideline for Monitoring the Effectiveness of Maintenance at Nuclear Power Plants, Revision 4F," Nuclear Energy Institute, 2018.

[12] American Society of Mechanical Engineers, "ASME Boiler and Pressure Vessel Code - Section XI Rules for Inservice Inspection of Nuclear Reactor Facility Components," American Society of Mechanical Engineers, 2023.

[13] V. Agarwal, K. A. Manjunatha, A. V. Gribok, J. A. Smith, V. Yadav, N. J. Lybeck, M. Yarlett, S. Yurkovich, B. Diggans, N. Goss, N. Zwiryk, H. Palas and M. Pennington, "Machine Learning and Economic Models to Enable Risk-Informed Condition Based Maintenance of a Nuclear Plant Asset," 2021.

[14] Westinghouse Nuclear Energy, "Westinghouse Technology Systems Manual Section 3.2 Reactor Coolant System," U.S. Nuclear Regulatory Commission, 2002.

[15] R. M. Singer, K. C. Gross, M. Walsch and K. E. Humenik, "Reactor coolant pump monitoring and diagnostic system," Argonne National Laboratory, 1990.

[16] G. Mousmoulis, C. Yiakopoulos, I. Kassanos, I. Antoniadis and J. Anagnostopoulos, "Vibration and acoustic emission monitoring of a centrifugal pump under cavitating operating conditions," *IOP Conference Series: Earth and Environmental Science*, vol. 405, 2019.

[17] S. Tang, S. Yuan and Y. Zhu, "Data Preprocessing Techniques in Convolutional Neural Network Based on Fault Diagnosis Towards Rotating Machinery," *IEEE Access,* vol. 8, pp. 149487-149496, 2020.

[18] R. J. Patton and J. Chen, "A Review of Parity Space Approaches to Fault Diagnosis," *IFAC Proceedings Volumes,* vol. 24, no. 6, pp. 65-81, 1991.

[19] S. Jung, M. Kim, J. Kim and S. Kim, "Fault Detection Method based on Auto-associative Kernel Regression and Interval Type-2 Fuzzy Logic System for Multivariate Process," in *2021 IEEE International Conference on Fuzzy Systems*, Luxembourg, 2021.

[20] XGBoost Developers, "XGBoost Documentation," Sphinx, 2024. [Online]. Available: https://xgboost.readthedocs.io/en/stable/. [Accessed 2024].

[21] Westinghouse Electric Company LLC., "eVinci Microractor," Westinghouse Electric Company LLC., 2024. [Online]. Available: https://www.westinghousenuclear.com/energy-systems/evinci-microreactor/. [Accessed 2024].

[22] R. C. Greene and D. A. Casada, "Detection of Pump Degradation, NUREG/CR-6089," Oak Ridge National Laboratory, 1995.

[23] E. T. Kartal and F. K. Arabul, "Diagnosis of a mixed eccentricity fault in a squirrel-cage three-phase," *Effects of air gap eccentricity on different rotor structures for PMSM in electric vehicles,* vol. 14, 2024.

[24] "Regulatory Guide 1.45, Guidence on Monitoring and Responding to Reactor Coolant System Leakage," United State Nuclear Regulatory Commission, 2008.

[25] A. M. Judd, "Leakage of pump bearing oil into the PFR sodium," in *International Atomic Energy Agency*, 1991.

[26] K. R. Guy, "Pump Monitoring and Analysis," in *Proceedings of the Second NC/ASME Symposium on Pump and Valve Testing*, Washington, DC, 1992.

[27] Liang, Z.-P. Liang and P. C. Lauterbur, "Constrained imaging: overcoming the limitations of the Fourier series," *IEEE Engineering in Medicine and Biology Magazine,* vol. 15, no. 5, pp. 126-132, 1996.

[28] E. Hopper and M. Newberry, "Some Applications and Limitations of the Fast Fourier Transform," National Aeronautics and Space Administration, 1970.

[29] T. Thayaparan and A. Yasotharn, "Limitations and Strengths of the Fourier Transform Method to Detect Accelerating Targest," Defense Research Establishment Ottawa, Ottawa, 2000.

[30] International Standards Organization, "Rolling bearing - Damage and failures - Terms, characterisitics, and causes," International Standards Organization, 2017.

[31] C. Lessmeier, J. K. Kimotho, D. Zimmer and W. Sextro, "Condition Monitoring of Bearing Damage in Electromechanical Drive Systems by Using Motor Current Signals of Electric Motors: A Benchmark Data Set for Data-Driven Classification," *PHM Society European Conference,* vol. 3, no. 1, 2016.

[32] H. Jouhara, A. Chauhan, T. Nannou, S. Almahmoud, B. Delpech and L. C. Wrobel, "Heat pipe based systems - Advances and applications," *Energy,* vol. 128, pp. 729-754, 2017.

[33] P. Wallin, "Heat Pipe, selection of working fluid," Lund University, Lund, 2012.

[34] J. W. Sterbentz, J. E. Werner, M. G. McKellar, A. J. Hummel, J. C. Kennedy, R. N. Wright and J. M. Biersdorf, "Special Purpose Nuclear Reactor (5MW) for Reliable Power at Remote Sites Assessment Report," Idaho National Laboratory, Idaho Falls, 2017.

[35] P. R. McClure, D. I. Poston, M. A. Gibson, L. S. Mason and C. R. Robinson, "Kilopower Project: The KRUSTY fission power experiment and potential missions," *Nuclear Technology,* vol. 206, no. 1, pp. S1-S12, 2020.

[36] P. Sabharwall, J. Hartvigsen, T. Morton, Z. Sellers and J. S. Yoo, "Sphere Assembly and Operation Demonstration, INL/EXT-20-60782," Idaho National Laboratory, 2020.

[37] The American Society of Mechanical Engineers, "Section III Rules for Construction of Nuclear Facility Components," The American Society of Mechanical Engineers, 2023.

[38] U.S. Nuclear Regulatory Commission, "Guidance for a Technology-Inclusive, Risk-informed, and Performance-based Methodology to Inform Licensing Basis and Content for Applications for Licenses, Certifications, and Approvals for Non-Light-Water Reactors," U.S. Nuclear Regulatory Commission, 2020.

[39] A. Maioli, H. L. Detar, R. L. Haessler, B. N. Friedman, C. A. Belovesick, J. H. Scobel, S. T. Kinnas, M. C. Smith, J. v. Wyk and K. Fleming, "Westinghouse eVinci Micro-reactor Licensing Modernization Project Demonstration," Southern Company, 2019.

[40] Y. Ma, E. Chen, H. Yu, R. Zhong, J. Deng, X. Chai, S. Huang, S. Ding and Z. Zhang, "Heat pipe failure accident analysis in megawatt heat pipe cooled reactor," *Annals of Nuclear Energy*, vol. 149, 2020.

[41] The American Society of Mechanical Engineers, "Component Testing Requirements at Nuclear Facilities, ASME OM-2-2024," The American Society of Mechanical Engineers, Little Falls, 2024.

[42] J. W. Sterbentz, J. E. Werner, A. J. Hummel, J. C. Kennedy, R. C. O'Brien, A. M. Dion, R. N. Wright and K. P. Ananth, "Preliminary Assessment of Two Alternative Core Design Concepts for the Special Purpose Reactor," Idaho National Laboratory, 2018.

[43] H. C. Hyer, D. C. Sweeney, C. M. Petrie, J. L. Hartvigsen, Z. D. Sellers, T. C. Unruh and T. L. Phero, "Performance of Microreactor Test Article with Embedded Sensors during Testing in the Single Primary Heat Extraction and Removal Emulator," Oak Ridge National Laboratory, Oak Ridge, 2022.

[44] T. Unruh, J. Daw and K. McCary, "Summary report of INL sensors and Instrumentation activities in SPHERE and MAGNET," Idaho National Laboratory, Idaho Falls, 2022.

[45] J. E. Hansel, R. A. Berry, D. Andrs and R. C. Martineau, "Sockeye Theory Manual," Idaho National Laboratory, 2020.

[46] C. L. Tien and K. S. Chung, "Entrainment Limits in Heat Pipes," *American Institute of Aeronautics and Astronaustics*, vol. 17, no. 6, 1979.

[47] G. P. Peterson and B. K. Bage, "Entrainment Limiations in Thermosyphons and Heat Pipes," *Journal of Energy Resources Technology,* vol. 113, no. 3, pp. 147-153, 1991.

[48] D. Reay, R. McGlen and P. Kew, Heat Pipes - Theory, Design, and Applications, Butterworth-Heinemann, 2006.

[49] I. Yilgor, Z. D. Sellers, J. L. Hartvigsen, K. M. Sweetland, P.-H. Huang, T. Ahn, J. Seo, A. Manera, V. Petrov, M. Anderson, Y. Hassan, S. Shi and P. Sabharwall, "Recent Developments and Findings of Heat Pipe Experiment for Microreactor Applications," *Nuclear Technology,* pp. 1-35, 2024.

[50] M. Tano, P. Sabharwall and K. Sweetland, "Modeling Heat Pipes with Non-Condensable Gases," Idaho National Laboratory, Idaho Falls, 2023.

[51] D. R. Adkins, S. K. Rawlinson, C. E. Andraka, S. K. Showalter, J. B. Moreno, T. A. Moss and P. G. Cordiero, "An Investigation of Corrosion in Liquid-Metal Heat Pipes," Sandia National Laboratory, 1998.

[52] E. Guinan, J. Punch, C. Butler and V. Egan, "A novel method of accurately characterizing heat pipes using thermoelectric modules," *Experimental Thermal and Fluid Science*, vol. 153, 2024.

[53] Advanced Thermal Solutions, Inc., "ATS Engineering eBook," in *Collection of Technical Articles on Heat Pipes and their Roles in the Thermal Management of Electronics*, 2024.

[54] H. C. Hyer, D. C. Sweeney, C. M. Petrie, J. L. Hartvigsen, Z. D. Sellers, T. C. Unruh and T. L. Phero, "Performance of Microreactor Test Article with Embedded Sensors during Testing in the Single Primary Heat Extraction and Removal Emulator," Oak Ridge National Laboratory, Oak Ridge, 2022.

[55] Z. D. Sellers, J. Hartvigsen and P. Sabharwall, "Single Primary Heat Extraction and Removal Emulator (SPHERE) Power Transient Testing," Idaho National Laboratory, Idaho Falls, 2024.

[56] C. M. Petrie, N. Sridharan, A. Hehr, N. Norfolk and J. Sherifan, ""High-Temperature Strain Monitoring of Stainless Steel Using Fiber Optics Embedded in Ultrasonically Consoldiated Nickel Layers," *Smart Materials and Structures,* vol. 28, no. 8, 2019.

[57] C. M. Petrie, N. Sridharan, M. Subramanian, A. Hehr, M. Norfolk and J. Sheridan, "Embedded Metallized Optical Fibers for High Temperature Applications," *Smart Materials and Structures,* vol. 28, no. 5, 2019.

[58] H. Hyers, D. Sweeney and C. Petrie, "Functional Fiber-Optic Sensors Embedded in Stainless Steel Components Using Ultrasonic Additive Manufacturing for Distributed Temperature and Strain Measurements," *Additive Manufacturing,* vol. 52, 2022.

[59] Y. D. Huang, L. Froyen and M. Wevers, "Quality control and nondestructive tests in metal matrix composites," *Journal of Nondestructive Evaluation,* vol. 20, pp. 113-132, 2001.

[60] T. D'Orazio, M. Leo, A. Distante, C. Guaragnella, V. Pianese and G. Cavaccini, "Automatic ultrasonic inspection for internal defect detection in composite materals," *NDT & E International,* vol. 41, no. 2, pp. 145-154, 2008.

[61] A. P. C. 1. :. 2017, "Appendix III, Ultrasonic Examination of Vessel and Piping Welds," in *BOILER AND PRESSURE VESSEL CODE - RULES FOR INSERVICE INSPECTION OF NUCLEAR POWER PLANT COMPONENTS*, 2017.

[62] H. Ravanbod, "Application of neuro-fuzzy techniques in oil pipeline ultrasonic nondestructive testing," *NDT & E International*, vol. 38, no. 8, pp. 643-653, 2005.

[63] F. Bettayeb, T. Rachedi and H. Benbartaoui, "An improved automated ultrasonic NDE system by wavelet and neuron networks," *Ultrasonics*, vol. 42, no. 19, pp. 853-858, 2004.

[64] A. A. Pollock, "Acoustic Emission Inspection," in *Nondestructive Evaluation of Materials*, DOI: https://doi.org/10.31399/asm.hb.v17.a0006454, 2018.

[65] Q. Huang, Y. Wu, J. Baruch, P. Jiang and Y. Peng, "A template model for defect simulation for evaluating nondestructive testing in X-radiography," *IEEE Transactions on Systems, Man and Cybernetics-PartA: Systems and Humans*, vol. 39, no. 2, pp. 466-475, 2009.

[66] H. V. Gomez, L. Korner, R. Leach and S. Smith, "Amplitude-wavelength maps for X-ray computed tomography systems," *Precision Engineering,* 2020.

[67] D. Pennicard, B. Pirard, O. Tolbanov and K. Iniewski, "Semiconductor materials for X-ray Detectors," Material Research Society , 2017.

[68] P. W. Tse and G. Wang, "Sub-surface defects detection of by usig active thermography and advanced image edge detection," *Journal of Physics: Conference Series,* pp. DOI 10.1088/1742-6596/842/1/012029, 2017.

[69] A. Sophian, G. Tian and M. Fan, "Pulsed eddy current non-destructive testing and evaluation: A review," *Chinese Journal of Mechanical Engineering,* vol. 30, pp. 500-514, 2017.

[70] F. Prenger, Jr., "Heat Pipe Computer Program (HTPIPE)," Los Alamos National Laboratory, Los Alamos, 1979.

[71] Y. Guo, Z. Su, Z. Li and k. Wang, "The Super Thermal Conductivity Model for High-Temperature Heat Pipe Applied to Heat Pipe Cooled Reactor," *Frontiers in Energy Research,* vol. 10, pp. 1-11, 2022.

[72] J. Yoo, M. Song, S. Qin and P. Sabharwall, "A Conduction-Based Heat-Pipe Model for Analyzing the Entire Process of Liquid-Metal Heat-Pipe Startup," in *Transactions of the 19th International Topical Meeting on Nuclear Reactor Thermal Hydraulics*, Brussels, 2022.

[73] M. Ma, W. Liang, S. Wang, Q. Xie, D. Qian, Z. Bai, T. Zhang and R. Zhang, "A pure-conduction transient model for heat pipes via derivation of a pseudo wick thermal conductivity," *International Journal of Heat and Mass Transfer,* vol. 149, 2020.

[74] A. Faghri, M. Buchko and Y. Cao, "A Study of high-temperature heat pipes with multiple heat sources and sinks: Part I - Experimental methodology and frozen startup profiles," *Journal of Heat Transfer*, vol. 113, no. 4, 1991.

[75] R. Ponnappan, "Studies on the Startup Transient and Performance of a Gas Loaded Sodium Heat pipe," Universal Energy Systems Inc. , Dayton, 1988.

[76] K. Qin, B. Yang, Y. Liu, H. Liu, Y. Qian and K. Li, "Uncertainty quantification and target accuracy assessment of nuclear data to effective neutron multiplication factor of heat pipe cooled reactor," *Annals of Nuclear Energy,* vol. 190, 2023.

[77] S. Chen, B. Cai, C. Yuan, Z. Li and C. Zhang, "Evaluation of Neutron irradiation-induced displacement damage in heat pipe reactor," *Nuclear Materials and Energy,* vol. 32, 2022.

[78] J. Hansel, J. Hartvigsen, L. Ibarra, P. Sabharwall and B. Feng, "Sockeye Validation Support Using the SPHERE Facility," in *International Conference on Physics of Reactors*, Pittsburgh, 2022.

[79] J. E. Hansel, M. Charlot and L. Cecile, "Sockeye Heat Pipe Analysis Code Verification and Validation," in *International Topical Meeting on Nuclear Reactor Thermal Hydraulics*, Brussels, 2022.

[80] T. L. Phero and M. D. McMurtrey, "Strain Gauge for Testing Microreactor Hexagonal Core Blocks in the Single Primary Heat Extraction and Removal Emulator," Idaho National Laboratory, Idaho Falls, 2022.

[81] J. J. Martin and R. S. Reid, "Life Test Approach for Refractory Metal/Sodium Heat Pipes," in *Space Technology and Applications International Forum*, Albuquerque, 2006.

[82] A. Clark, B. A. Beeny, K. C. Wagner and D. L. Luxat, "Technical and Licensing Considerations for Micro-reactors," Sandia National Laboratory, 2020.

[83] U.S. Nuclear Regulatory Commission, "Verification, Validation, Reviews and Audits for Digital Computer Software used in Safety Systems of Nuclear Power Plants," U.S. Nuclear Regulatory Commission, Washington, 2013.

[84] A. Estaji, M. Gotzinger, B. Tutzer, S. Kollmann, T. Sauter and A. Jantsch, "Evaluation of Drift Detection Algorithms in the Condition Monitoring Domain," *IEEE Transactions on Industrial Informatics,* pp. 1-10, 2024.

[85] I. Ahmed, "Investigation of Single and Multiple Faults Under Varying Load Conditions using Multiple Sensor Types to Improve Condition Monitoring of Induction Machines," University of Adelaide, 2007.

[86] R. Kohavi, D. Tang and Y. Xu, Trustworthy Online Controlled Experiments, A Practical Guide to A/B Testing, Cambridge: Cambridge University Press, 2020.

[87] M. Conti, A. Gangwal, S. P. Gochhayat and G. Tolomei, "Spot the Difference: Your Bucket is Leaking," in *Fourth Workshop on Security and Privacy in the Cloud*, 2018.

[88] E. Chen, H. Bao and N. Dinh, "Evaluating the Reliability of Machine-Learning-based Predictions used in Nuclear Power Plant Instrumentation and Control Systems," *Reliability Engineering & System Safety,* vol. 250, 2024.

[89] E. Chen, L. Lin and N. Dinh, "Advanced Transient Diagnostic wwith Ensemble Digital Twin Modeling," in *American Nuclear Society Mathematics and Computation Conference*, Virtual, 2021.

[90] M. T. Ribeiro, S. Singh and C. Guestrin, "High-precision model-agnostic explanations," in *Proceedings of the AAAI conference on artificial intelligence*.

[91] T. Laugel, X. Renard, M.-J. Lesot, C. Marsala and M. Detyniecki, "Defining Locality for Surrogates in Post-hoc Interpretability," in *ICML Workshop on Human Interpretability in Machine Learning* , Stockholm, 2018.

[92] G. Visani, E. Bagli and F. Chesani, "OptiLIME: Optimized LIME Explanations for Diagnostic Computer Algorithms," [Online]. Available: https://arxiv.org/abs/2006.05714.

[93] G. Visani, "LIME: Explain Machine Learning Predictions," Towards Data Science, 2020. [Online]. Available: https://towardsdatascience.com/lime-explain-machine-learning-predictions-af8f18189bfe. [Accessed 2024].

[94] S. M. Lundenberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in neural information processing systems*, 2017.

[95] X. Huang and J. Marques-Silva, "On the failings of Shapley Values for Explainability," *International Journal of Approximate Reasoning,* vol. 171, 2024.

[96] T. Hastie, R. Tibshirani and J. Friedman, The Elements of Statiscal Learning 2nd Edition: Data Mining, Inference, and Prediction, Springer Series in Statistics, 2017.

[97] A. Goldstein, A. Kapelner, J. Bleich and E. Pitkin, "Peeking inside the black box: visualizing statistical learning with plots of individual conditional expectation," 2014. [Online]. Available: https://arxiv.org/abs/1309.6392.