INL/RPT-22-70350
Revision 0

Light Water Reactor Sustainability Program

Data Architecture and Analytics Requirements for Artificial Intelligence and Machine Learning Applications to Achieve Condition-Based Maintenance

November 2022

U.S. Department of Energy

Office of Nuclear Energy

INL/RPT-22-70350
Revision 0

Data Architecture and Analytics Requirements for Artificial Intelligence and Machine Learning Applications to Achieve Condition-Based Maintenance

Vivek Agarwal, Jeffrey Joe, Andrei V. Gribok, James A. Smith, Johanna Oxstrand, and Craig Primer

November 2022

Prepared for the
U.S. Department of Energy
Office of Nuclear Energy

ABSTRACT

There are several requirements associated with data, information, and artificial intelligence/machine learning modeling used to develop insights and inform decisions. These requirements must be given careful consideration to enable the design, development, and deployment of a condition-based maintenance strategy as part of automation and work reduction opportunities within the integrated operation of the nuclear concept. This report identifies some of the important requirements that need to be considered as part of the data evolution for the condition-based maintenance application on a circulating water system in an nuclear power plant. The concept of data evolution converts data into information which in turn is converted into insight, decision, and action. An overview of artificial intelligence design, development, deployment, and operation principles is introduced to support the lifecycle of artificial intelligence technologies. Towards the end of the report, we discuss how this condition-based maintenance can be realized in a seamless digital environment.

This report lays the foundation for developing more detailed industry guidance and a supporting data evolution path for other plant applications, like operations and plant support. These concepts will be developed as part of the path forward for ongoing research in Fiscal Year 2023.

ACKNOWLEDGEMENTS

This report was made possible through funding from the U.S. Department of Energy's Light Water Reactor Sustainability Program. We are grateful to William Walsh of the Department of Energy and Bruce P. Hallbert and Craig A. Primer at Idaho National Laboratory for championing this effort. We thank Alexandria N. Madden and Judy Fairchild at Idaho National Laboratory for the technical editing and formatting of this report and Barry Pike III and Lauren M. Perttula of RED, Inc. for some of the graphics contained in the report.

CONTENTS

FIGURES

ACRONYMS

AI	artificial intelligence
CBM	condition-based maintenance
CWP	circulating water pump
CWS	circulating water system
LWRS	Light Water Reactor Sustainability
M&D	monitoring and diagnostics
ML	machine learning
NLP	natural language processing
NPP	nuclear power plant
O&M	operation and maintenance
PdM	predictive maintenance
PM	preventive maintenance
PSEG	Public Service Enterprise Group
SDE	Seamless Digital Environments
SSC	structures, systems, and components
STAMP	System Theoretic Accident Model and Process
STPA	System Theoretic Process Analysis
VPI	valve position indication
VSN	vibration sensor nodes
WO	work order
TERMS	Technology-Enable Risk-informed Maintenance Strategy
XAI	explainable artificial intelligence

DATA ARCHITECTURE AND ANALYTICS REQUIREMENTS FOR ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS TO ACHIEVE SEAMLESS CONDITION-BASED MAINTENANCE

1. INTRODUCTION AND MOTIVATION

Operations and maintenance (O&M) activities are key aspects of ensuring the availability and reliability of energy generated by nuclear power plants (NPPs) [1],[2]. O&M costs—including activities such as inspection, calibration, testing, and replacement—are one of the major non-capital costs contributing to the overall operation costs of NPPs. There are three main maintenance strategies to ensure availability, reliability, and safety. These maintenance strategies are: (1) time-based periodic maintenance (referred to as preventive); (2) failure-based maintenance (referred to as corrective); and (3) condition-based maintenance (CBM) (referred to as predictive). Over the years, the nuclear fleet has relied on time-based and failure-based maintenance strategies across their structures, systems, and components (SSCs) to achieve high-capacity factors. This approach has also led to higher operating costs, presenting long-term economic sustainability challenges in the current energy market for the existing the fleet of light-water reactors.

An ongoing research and development project titled Technology Enabled Risk-Informed Maintenance Strategy (TERMS) under the U.S. Department of Energy's Light Water Reactor Sustainability (LWRS) Program is developing a well-constructed, risk-informed predictive maintenance (PdM) approach for the circulating water system (CWS) [3]. The research project is in collaboration with Public Service Enterprise Group (PSEG) Nuclear, LLC and takes advantage of advancements in data analytics, artificial intelligence (AI) and machine learning (ML), physics-informed modeling, and visualization. The research and development reported in References [3]–[5] describe in detail an approach developed to map data to actions (also referred to as data evolution) as part of the risk-informed PdM strategy.

Data evolution is a structured approach of transforming the embedded knowledge in heterogeneous data sources collected by NPPs across SSCs into usable information for decision-making with the human in the loop by mapping and managing the data. Data mapping refers to the pathways along which data flows. Data management refers to using appropriate structures, formats, tags, and transformation of those data. The structured approach may or may not include usage of AI/ML technologies as part of the modeling approach. In this research and report, AI/ML technologies are part of the modeling approach.

Figure 1 represents the general schematic of data evolution across three plant applications: operation, maintenance, and support. Figure 2 presents a data evolution specific to plant maintenance that considers risk modeling and predictive modeling to achieve preventive maintenance optimization, CBM, and asset management. An example of data evolution for CBM of the CWS (Figure 3) is represented as a variant of the System Theoretic Accident Model and Process (STAMP) [6] and System Theoretic Process Analysis (STPA) [7]. For details on the core concept of STAMP and STPA, see Appendix A.

In Figure 3, the CWS is a controlled process whose maintenance will be optimized to maximize availability and cost effectiveness. Multiple measurements (data) are collected at different temporal and spatial resolutions and with different formats (analog and digital). Data include real-time time series, static, text, visual, and others. Some of the analog data are digitized to be compatible with other digital data. These digital data are stored in a data hub and are analyzed using advanced data analysis techniques to develop fault signatures (i.e., digitalized information). The fault signatures are then used by AI/ML predictive models to diagnose and prognose the current and future health of the CWS, respectively.

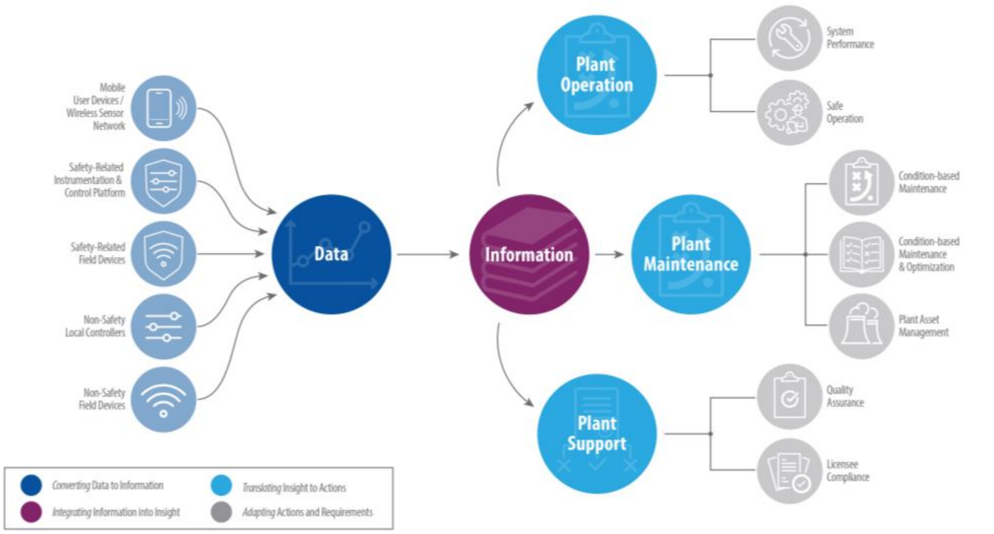

Figure 1. A general schematic of data evolution for three plant applications.

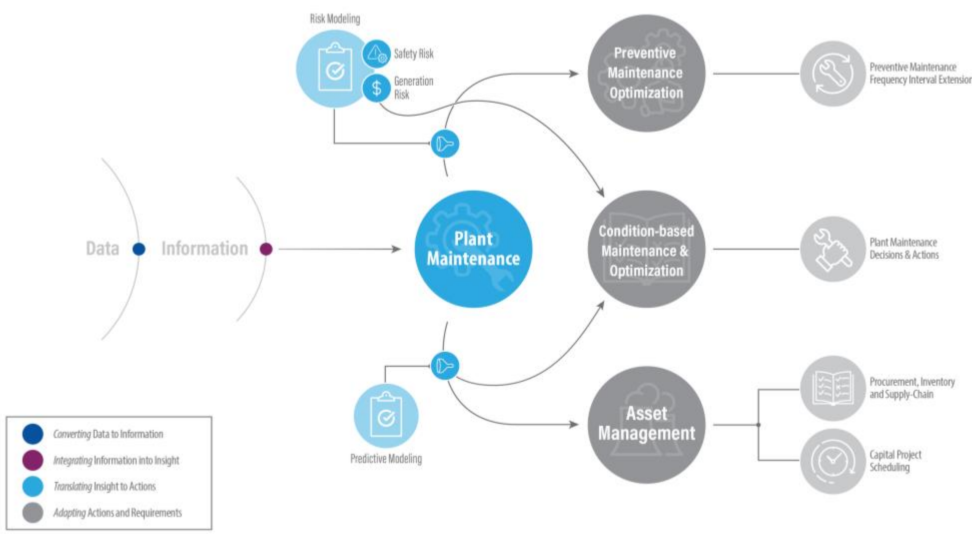

Figure 2. A general schematic of data evolution for plant maintenance application.

Action refers to the decision to perform or defer maintenance based on the CWS health state. In Figure 3, there are several directions for the flow of information and actions to and from different users in the loop. In STAMP and STPA, these are analogous to controller and control actions. See Appendix A for details.

There are several requirements associated with data, information, and AI/ML modeling used to develop insights and inform decisions. These requirements must be given careful consideration to enable the design, development, and deployment of a CBM strategy as part of automation and work reduction opportunities within the integrated operation of the nuclear concept [8]. This report focuses on identifying requirements for data evolution, where the CWS is the target system. However, the requirements developed in this report are generally applicable for the CBM of other plant SSCs with application-specific updates. The CWS is briefly described here. For more CWS details, see [4].

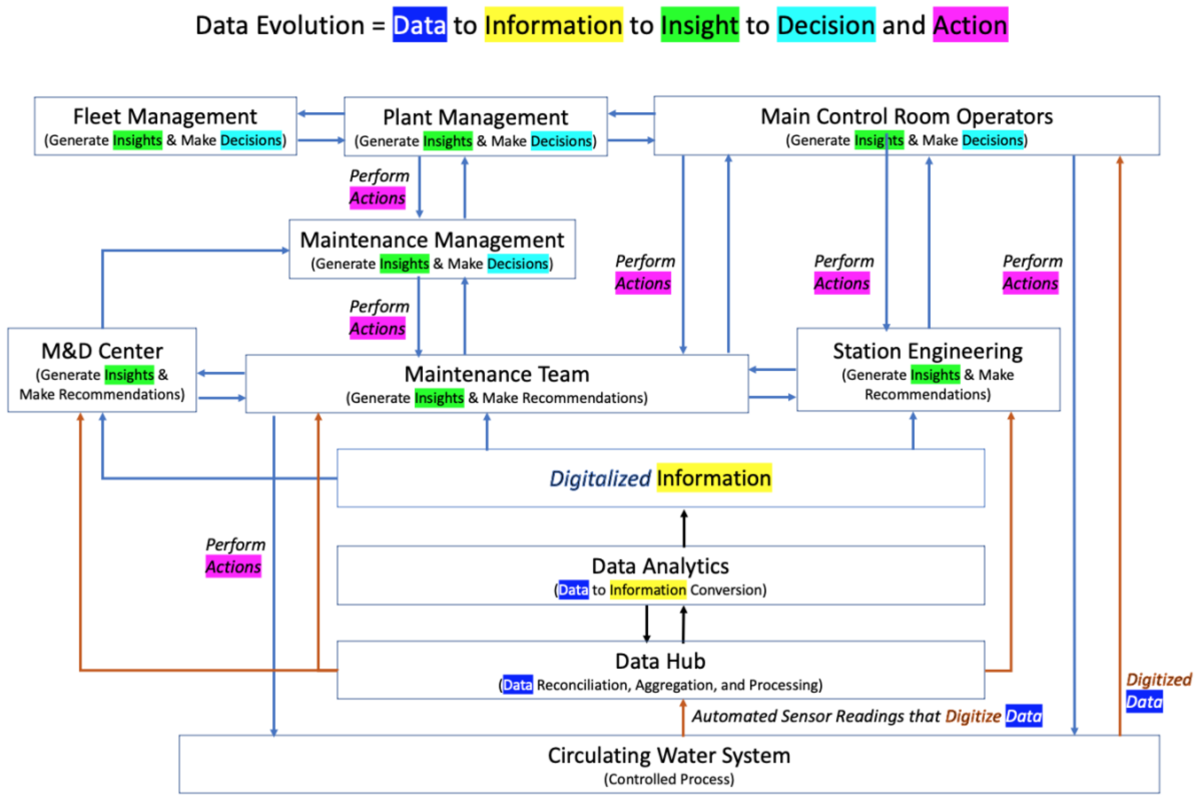

Figure 3. An example of data evolution for CBM of the CWS.

The CWS is an important non-safety-related system. As the heat sink for the main steam turbine and associated auxiliaries, the CWS at the Salem NPP is designed to maximize steam power cycle efficiency while minimizing any adverse impact on the Delaware River [9]. The CWS consists of the following major equipment [9]:

- Six vertical, motor-driven circulating pumps (or “circulators”), each with an associated trash rack and traveling screen at the pump intake to remove debris and marine life
- Main condenser
- Condenser waterbox air removal system
- Circulating water sampling system
- Screen wash system
- Necessary piping, valves, and instrumentation and controls to support system operation.

Figure 4 shows the pair of waterboxes associated with Condenser 1 of Unit 1 (i.e., 11A and 11B). Each of the two plant units has one main condenser with six waterboxes, circulators, trash racks, and traveling screens. For a functional description of the CWS, along with any other relevant details, see Reference [9]. Figure 5 shows different locations on the circulating water pump (CWP) motor where measurements are continuously collected as part of the plant OSIsoft PI historian.

In this report, Chapter 2 presents requirements associated with data collected for CBM. Chapter 3 briefly introduces the concept of information automation. Chapter 4 presents some the design, develop, deploy, and operate principles of AI/ML technologies. Chapter 5 briefly introduces the concept of a seamless digital environment. A report summary and the path forward are in Chapter 6.

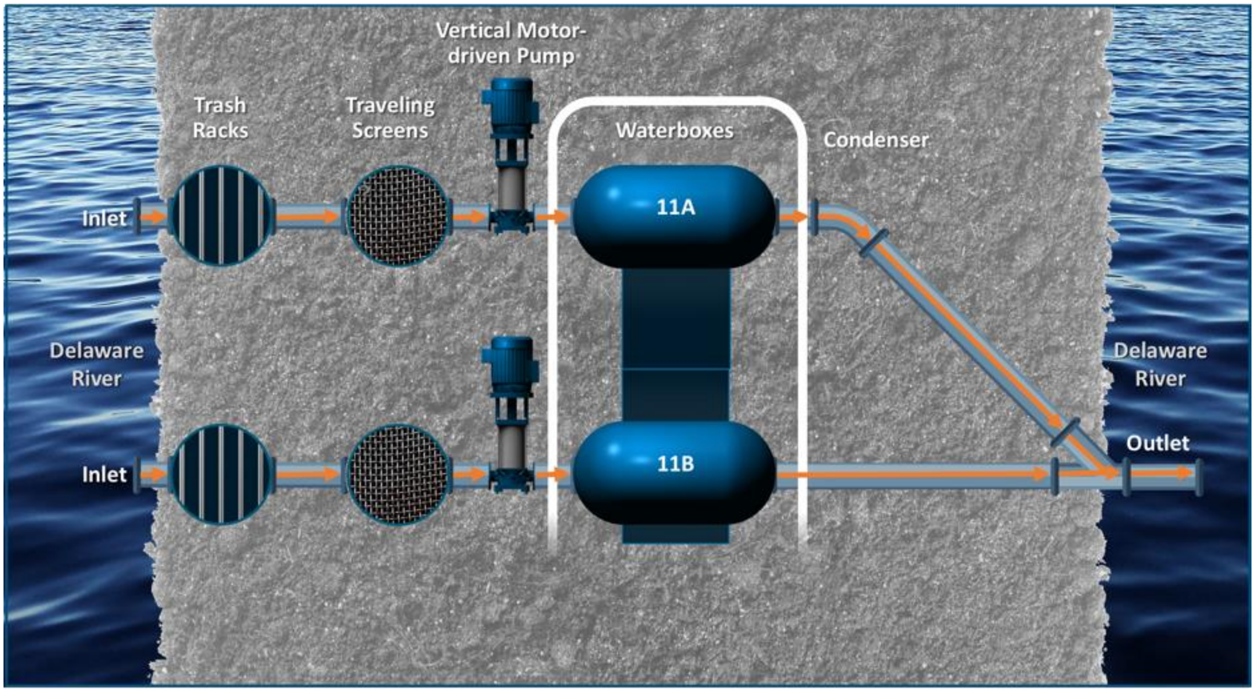

Figure 4. Schematic representation of the CWS at Salem Unit 1.

2. DATA

Data creates the underlying foundation for any work performed under CBM at a plant site, as the data drives the analytics and insight generation and review, as well as resulting actions or services. As the data utilized for the CBM application are diverse and sourced from many different locations, the structures used to store, retrieve, and modify the data must be suitable for the intended application. Each type of data has different requirements related to accuracy, reliability, responsiveness, accessibility, and integration into developed services and tools.

We collected data in an NPP at different resolutions and in a variety of formats using the following definitions for consistency. Raw data is the direct and original data generated at a source without any preprocessing. This raw data may be in a variety of formats, including numeric, handwritten text, audio, video, and visual. Raw data can be in analog or digital formats. There are technologies available to transform analog data into digital data (i.e., digitize). This in some ways standardizes the storage and processing requirements. In addition, data can be collected asynchronously, synchronously, and statically with time.

Data is asynchronous when the data collection is randomly delayed from the request to collect data or has no consideration for the timing within a process or event. Asynchronous data can be taken periodically. Manual surveillances are a good example of periodic asynchronous data.

Data is synchronous when the data collection is based on clock timing or is planned to coincide with the timing within a process or event. A good example of this is online collecting vibration or audio data. Although synchronous data is usually thought of being continuous within a finite time window, synchronized data can be collected on an aperiodic basis. In general, synchronous data requires significantly more storage space and computing power than asynchronous data.

Static data are intentionally set values by operators or other authorized personnel that are to remain in effect until they are changed. Examples of static data are process set points, process limits, and safety limits. Static data are usually used as checks on live sensor data to ensure efficient and safe operation.

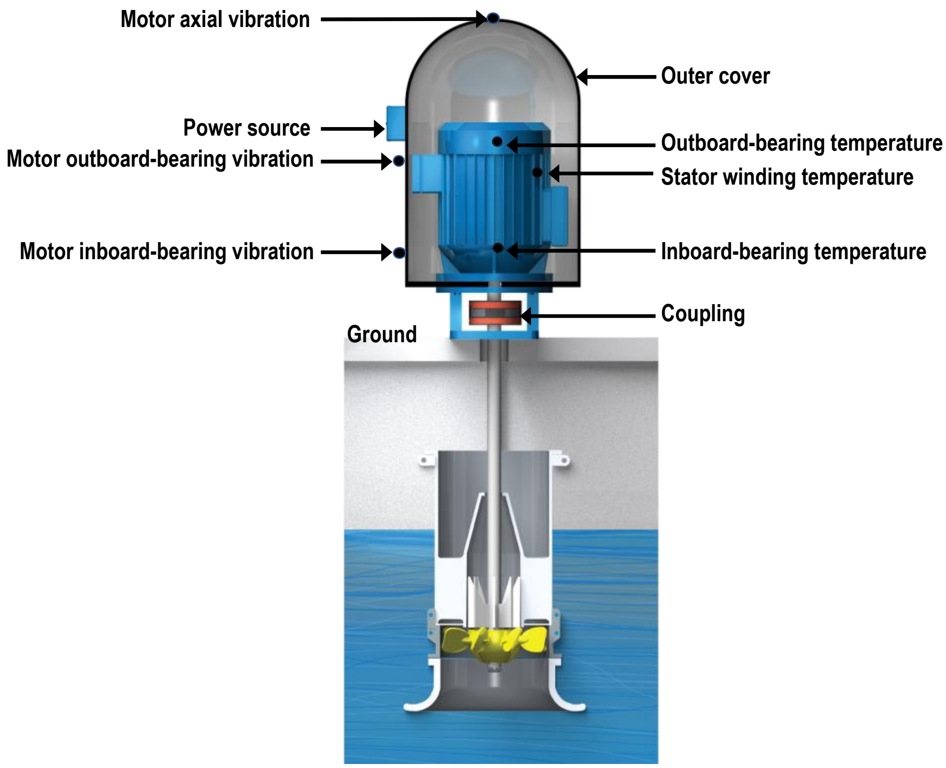

Figure 5. Schematic representation of a CWS motor and pump, along with measurement locations.

Collected asynchronous, synchronous, and static data must be reconcilable based on physical constraints to eliminate erroneous measurements and enhance data quality. In practice, data quality issues often directly impact information extraction and AI/ML model performance. Some of these aspects of data will be discussed in following sections of this report.

2.1 Data Types

To support the CBM of the PSEG-owned CWS, we received data from the Salem NPP presented in Sections 2.1.1, 2.1.2, and 2.1.3.

2.1.1 Process Data

The Unit 1 and 2 CWS process data are collected once every minute and stored in the Salem plant's OSI PI system. The raw process data from the plant first available includes:

- Gross load (MWe)
- River level (ft)
- Ambient air temperature (°F)
- CWP inlet river temperature (°F)
- CWP outlet water temperature (°F)
- CWP motor status (ON or OFF)
- CWP motor stator winding temperature (°F)
- CWP motor inboard bearing temperature (°F)
- CWP motor outboard bearing temperature (°F)

- CWP motor current (amps)

After an upgrade in 2015, continuously monitored measurement parameters associated with the main condenser for both Unit 1 and 2 have been available. The main condenser parameters for Unit 1 are listed below (the same parameters are available for Unit 2).

- CWP 11AB outlet temperature (°F)
- CWP 12AB outlet temperature (°F)
- CWP 13AB outlet temperature (°F)
- Main Condenser Backpressure 1
- Main Condenser Backpressure 2
- Low Pressure Turbine 11 exhaust temperature (°F)
- Low Pressure Turbine 12 exhaust temperature (°F)
- Low Pressure Turbine 13 exhaust temperature (°F)
- Low Pressure Turbine 11 exhaust hood temperature (°F)
- Low Pressure Turbine 12 exhaust hood temperature (°F)
- Low Pressure Turbine 13 exhaust hood temperature (°F)
- Condensate 11AB hot well temperature (°F)
- Condensate 12AB hot well temperature (°F)
- Condensate 13AB hot well temperature (°F)
- Vacuum pumps status.

Along with the process data, the CWP inlet pressure is collected every 12 hours in the electronic Shift Operations Management System.

2.1.2 Work Order Data

The collected CWS data contain metadata related to plant processes, maintenance logs, operator logs, work order (WO) documents, and condenser information. WOs for Salem Unit 1 and 2 CWSs contain useful information, including preventive maintenance (PM) and corrective maintenance WOs.

PM WOs are planned maintenance activities performed on a predetermined frequency based on the engineering review and maintenance strategy for a given type of equipment. Corrective maintenance WOs are reactive maintenance to resolve a nonconforming condition, such as a degradation or failure. Both types of maintenance activities are documented in WOs.

The details in a WO vary across the plant site, but at a minimum, they contain information such as WO number, order type, maintenance activity type, functional or equipment location, description, priority level, and approximate start and end date. For this reason, natural language processing (NLP) techniques are used to analyze WO database and categorize the resulting information. The CWS WOs can be used to perform parameter estimation as part of the risk modeling and PM optimization. For details, see Reference [10].

WO data NLP allows for effective and quick feedback on how well the maintenance activity or replaced component is working and its effect on the CWS. The replacement or refurbishment of a major asset, like a pump or motor, usually changes the baseline of the CWS process measurements. The ability to quickly identify, track, and compare significant baseline can help determine when maintenance actions were taken. WO NLP would help enable this capability.

2.1.3 Vibration Data

Online vibration data is an excellent example of synchronous data. Installing wireless vibration sensor nodes (VSNs) on CWP motors allows for continuous online monitoring. Sixty sensor nodes [4],[11] were installed across 12 CWP motors and associated bypass valves. Three wireless VSNs were installed at the plant site on each CWP motor (as depicted in Figure 5), and two VSNs were installed on each associated CWP bypass valve. The three VSNs installed on the CWP motors are referred as motor axial vibration, motor outboard bearing vibration, and motor inboard bearing vibration. The placement of the transducers on the CWP motors and bypass valves can be found in Reference [10]. Each sensor node consists of a temperature sensor and two accelerometers sensitive to orthogonal in-plane motions. The sensor nodes are mounted on the plant asset via a magnetic base in the node.

The vibration data consists of metadata, such as date (YYYY-MM-DD), time (in the Coordinated Universal Time format), and sampling rate of the vibration signal. The vibration signal is collected for 3.2 seconds at a sampling rate of 512 samples/second. For these sampling conditions, this works out to be 1.64 K of data per sampling period. Multiply this by 60 sensors, and this becomes 10 K of data per sample period. The data storage needs on a yearly basis for a periodic sample every hour would be on the order of 860 MB. Thus, the data storage infrastructure needs to be designed to handle this accumulation of data over the years. The vibration signal can be collected for different lengths of time and at higher sampling rates (up to 2,056 samples/second), which can push data storage needs significantly higher. Figure 6 shows representative vibration signals for both X and Y directions from the VSN located on the motor axial position.

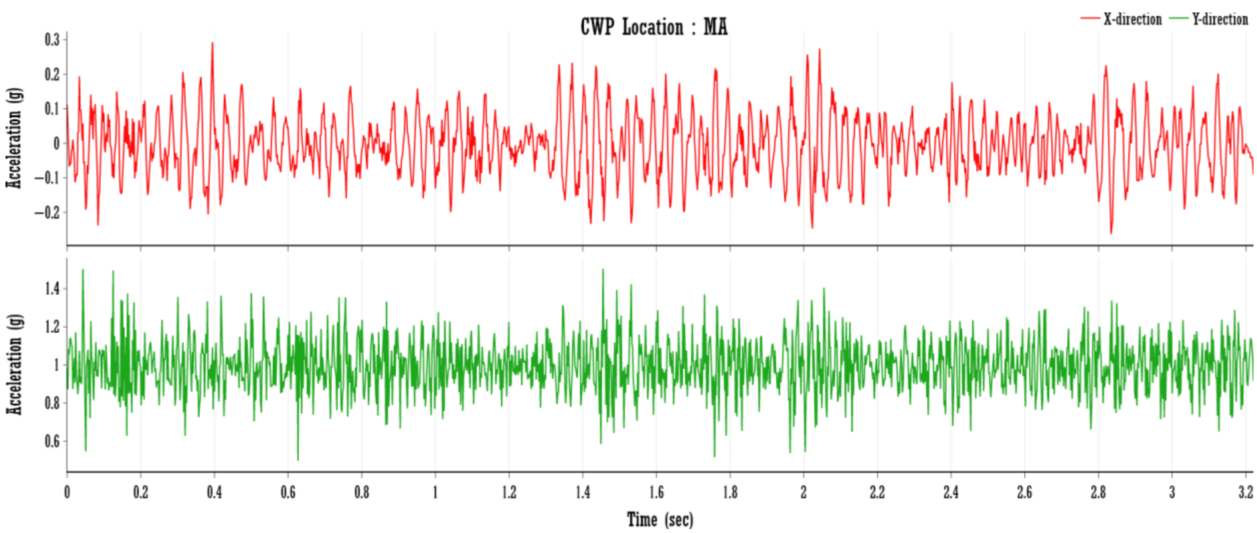

Figure 6. Vibration measurement collected at location motor inboard on a CWP motor for X and Y VSN directions.

2.1.4 Data Ingest

This section covers considerations of the data ingest required as the foundation for performing data analytics. The data ingest method should consider the specific use case(s) applicable to the data.

The best starting point for designing data ingest resources for a data analytics platform, see the data analytics box in Figure 3, is to verify that the data refresh frequency aligns with the frequency at which analytics are performed. For services that require real-time or near-real-time data in order to provide instant results and allow stakeholder organizations to respond immediately, the data ingest needs to match this frequency in order to support the intended responsiveness. Other analytics may not require real-time data, as they provide long-term trending insights or support processes that allow for slower response times. The intended frequency of data receipt is important in designing a streamlined process and is an important cost consideration. A delivery center platform can use both real-time sensor data and plant enterprise data extracted on a predetermined frequency (i.e., daily, weekly, or monthly) to identify insights into plant condition and processes.

It could be expensive to receive streaming data, as most cloud providers charge for the data transferred as well as the number of unique requests. The process of transmitting streaming data sends data requests as the data is received, resulting in a higher cost than data batch processing on an hourly or daily basis. Furthermore, an additional processing cost needs to be considered. Repositories or storage locations for streaming data are constantly changing. Processes for analyzing data must be designed in alignment with the frequency of data input (real-time or batch processes).

2.2 Data Hub and Data Quality Requirements

In this section, we discuss some of the requirements to be considered when developing the data hub used to store and process the collected data. The section also discusses certain requirements that data must fulfill as they are used for data analysis and predictive model development.

2.2.1 Digital Hub for Automated Access

It is critical that the infrastructure for handling and maintaining data be considered prior to implementing data analytics (as shown in Figure 3). The following is a list of primary considerations for data ingest, storage, and preprocessing:

- Identify security requirements to implement a security architecture that prevents unauthenticated or unauthorized access
- Understand the types of data required for analysis (e.g., time series, logs, WO, resource utilization)
- Understand the frequency at which data analytics must be performed to support stakeholder response
- Create “single-source-of-truth” verified data repositories that can interact with analytics models and AI tools
- Identify and plan for scaling needs, based on the full data quantities to be ingested
- Understand the costs and benefits of various technologies that handle large datasets.

2.2.2 Data Quality

As noted earlier, data quality issues often impact data analysis and model performance. Data quality issues can arise due to a number of reasons, including:

- How data is captured, transmitted, and stored
- Missing or incomplete data
- Inconsistencies between data sources (i.e., sensor measurement, maintenance record, and operation logs)
- Incorrect sensor settings and outliers (i.e., incorrect sensitivity, out of calibration, incorrect orientation, or incorrect sensor placement)
- Duplicate data
- Incorrect labeling
- Noisy data
- Human errors.

These data quality issues must be addressed. There are several ways to address data quality issues. Redundancy from multiple measurement sources on a system may address some of these issues but introduces new challenges, such as handling different timestamps and highly correlated data. There are several data quality measurement and improvement frameworks proposed and implemented for maintenance data [12]–[14]. The framework developed by Jai et al. [13] included recommended metrics for evaluating the suitability of the data for the purpose of diagnostic and prognostic model development. Griffith et al. [15] recommend best practices to align the time series variable, addressing sensors having different sampling rates and integrating contextual data sources with time series data. Lukens et al. [16] presented a data quality scorecard for assessing the suitability of data for diagnostics and prognostic modeling.

2.2.3 Data Balance

Imbalanced data is a form of between-class imbalance that arises when the number of samples in one data class dominates the samples in a smaller class [17]. This causes ML models to be more biased towards the predominant class. Omri et al. [17] present a metric to quantify data imbalance. Data balancing is a process to address the imbalance in data by using the Synthetic Minority Oversampling Technique [18], an oversampling method for imbalanced classification [19], or data augmentation with a balanced Generative Adversarial Network [20].

Class data sets generated from industrial processes are inherently imbalanced. For example, plants that are efficient, produce quality products, and have robust operations, by definition, spend the majority of the time in normal states. There can be multiple process states that can be classified as normal operations, such as startup, shut down, hold, and production. The abnormal states caused by equipment failures, events and asset wear occur randomly over long timeframes. Thus, process data sets are dominated by normal states of operation.

If this imbalance of normal data sets is not addressed by balancing the data sets prior to performing data analytics, the ML models will not be as accurate and tend to skew resulting classifications toward normal operating states. The imbalance may also obfuscate both superior and inferior operational states by blurring the fidelity of the ML models. Most industrial processes are complex and contain hysteresis (i.e., dependence on history) in process parameters during the transition between states. The ability to identify and classify these transitional data sets will help increase the effectiveness of classification and predictions by providing data classification sets that are more balanced. This leads to natural balancing since there will be more classes of process states that are considered normal for the same amount of data. The resulting increase in ML model fidelity from a better data balance will provide a means to identify, track, and predict complex state changes in processes.

2.2.4 Data Reconciliation

In practice, sensor measurements are noisy and have random errors, as identified as part of the discussion on data quality issues. Data filtering and reconciliation are two approaches used to address these data quality issues. One type of data filtering is the process of attenuating high-frequency components in the signal. Filtering can also target specific frequency bands if there is a reason to believe that the measurement noise is narrow band. On the other hand, data reconciliation is a data filtering and reconstruction technique that explicitly uses process constraints to eliminate erroneous measurements. These constraints normally include mass balance, energy balance, and material and flow balance. Graphically, the data reconciliation process can be represented as shown in Figure 7.

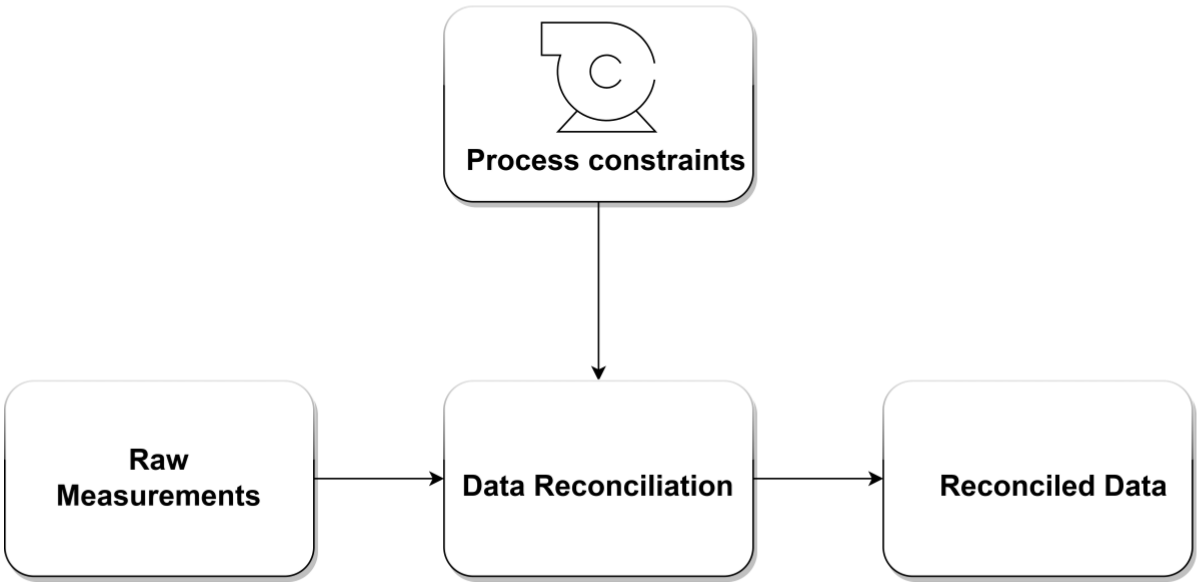

Figure 7. Schematic diagram of the data reconciliation process [21].

In the data reconciliation process, raw process variables can be classified according to the diagram in Figure 8 [21]. The first dichotomy is between measured and unmeasured variables. This dichotomy is based on the availability of sensor modalities to measure specific process variables (flow rates, pressures, concentrations). Obviously, due to economical and physical constraints, not all process variables can be measured. In reality, the majority of process variables are unmeasured; these variables are instead estimated through measured process variables. Further, the measured variables are dichotomized into redundant and nonredundant. Redundant variables can be estimated from other measured variables using the process models. If a variable is redundant, it doesn't have to be measured, although quite often engineering systems have numerous redundant measurements due to reliability considerations. The redundant measured variables are further split into spatially redundant and temporarily redundant. A measured redundant variable can be spatially or temporally redundant. A measurement is spatially redundant if its value can be completely and uniquely determined through measurements taken in other places and process model constraints. Flow measurements, for example, are often spatially redundant. The other type of redundancy exploited in data reconciliation algorithms is temporal redundancy, for when the process is predictable enough for its current or future values to be inferred from past values. Notice that spatial and temporal redundancy is only applicable to measured variables.

Data reconciliation cannot be performed without having spatial redundancy [22]. If there is no spatial redundancy, the system is determined or underdetermined and no unique measurement correction is possible. An equally important concept is the dichotomy of unmeasured variables into observable and non-observable. The unmeasured variable is observable if it can be estimated from measured variables and process models constraints, otherwise, the variable is non-observable. It should be noted that all measured variables are observable; redundant observable measured variables are redundant even if the measurement is unavailable [21],[22]. Observability and redundancy analyses are an integral part of the data reconciliation process [21],[22].

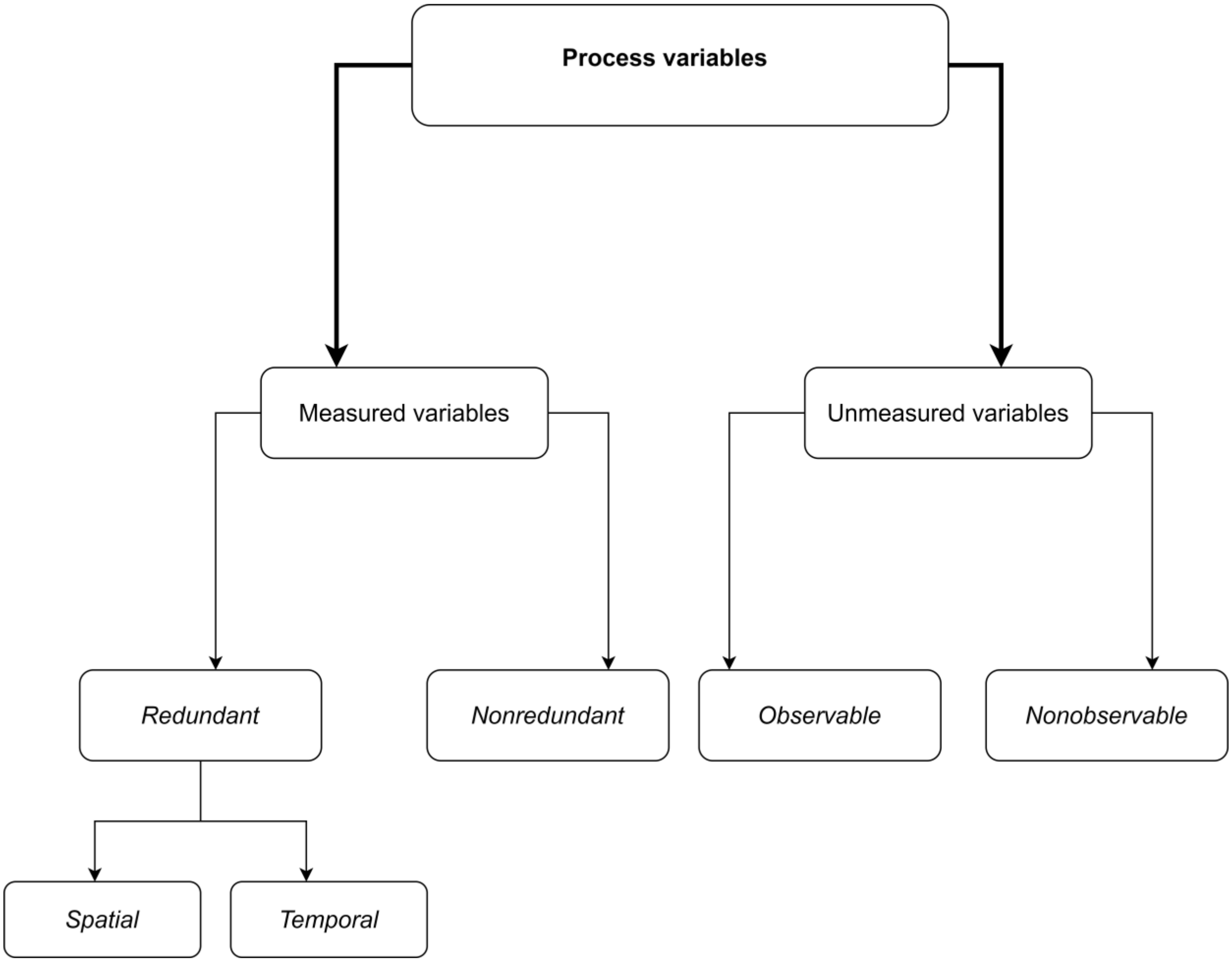

Figure 8. Dichotomy of variables in the data reconciliation process [21].

Another important aspect of the data reconciliation process is stationarity of a plant's operation. The majority of data reconciliation algorithms assume that the plant is in a steady state and thus stationary process models can be applied. However, quite often, it is necessary to reconcile the data during transient processes. Transient data reconciliation is a research gap that needs to be filled for an efficient implementation of data reconciliation strategies in NPPs.

For the data reconciliation approach to be effective, it should also address the systematic or gross errors that often happen during the recordkeeping of a plant's operational history. Similar to data reconciliation in the presence of random errors, gross error detection and elimination also requires an availability of constraints and redundant measurements. Normally gross errors are caused by two reasons: a combination of material loss such as piping leaks and either malfunctioning sensors or erroneous record-keeping. Dealing with gross errors requires addressing several interconnected problems, such as error detection, localization, identification, and correction. The detection problem is usually solved using statistical techniques of outlier detection. Having detected the gross error, the next step is identification, which is usually solved by calculating a sample statistic for each measurement and detecting values exceeding a preselected threshold. Error correction requires availability of redundant measurements, similar to data reconciliation, so the gross error can be replaced with an estimate from a redundant measurement. A general pipeline for first-principles-informed ML for CBM is shown in Figure 9.

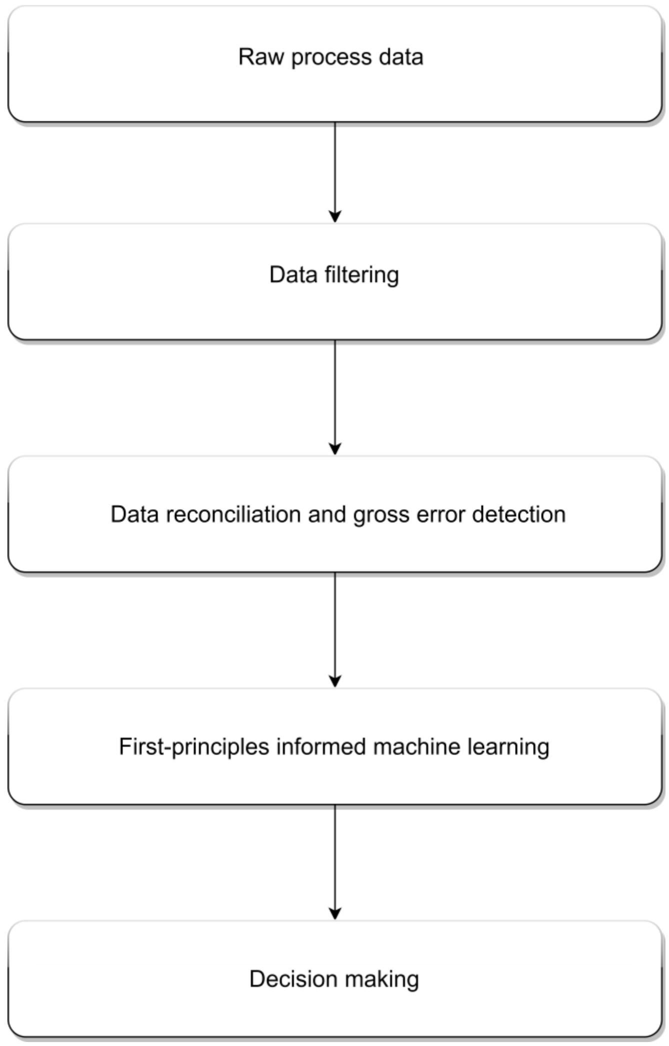

Figure 9. Steps to achieve CBM using ML [22].

As can be seen in Figure 9, data reconciliation and gross error detection is only a part of the data conditioning process necessary to achieve trustable and explainable solutions for CBM using ML approaches.

2.2.5 Data Completeness

Data completeness can be viewed from many perspectives, leading to different definitions. In Reference [23], data completeness is expressed as "the extent to which data are of sufficient breadth, depth and scope for the task at hand." Reference [24] identifies three types of completeness. Schema completeness is defined as the degree to which entities and attributes are not missing from the schema. Column completeness, at a data level, is a function of the missing values in a table column. This measurement corresponds to Codd's column integrity [25], which assesses missing values. A third type is called population completeness with respect to a reference population. In the case of CWS CBM [10], they assessed all three forms of completeness. However, the data required to generate representative fault signatures for different faults modes were incomplete and did not meet the population completeness requirements.

3. INFORMATION AUTOMATION

Information automation is the moving information and data from one underlying application to the other, supporting user decision-making. The information automation construct can be visualized in the context of a STAMP and STPA control loop simply as the **arrows** (i.e., → ↑ ← ↓) in Figure 3. Sometimes the movement of data and information in some commercial NPPs still occurs manually—meaning that the dynamic interaction between the controller and controlled process is done without the assistance of advanced automation.

For example, auxiliary or field operators currently perform manual walkdowns of the entire NPP's secondary infrastructure for inspections, security purposes, and reading and recording gauge values (e.g., surveillances). LWRS Program researchers have developed drones that can navigate their way around the plant to automate some of these manual activities, including inspecting hazardous locations. Computer vision solutions were developed and added to the drones to automate accurate gauge readings, even at oblique angles, thereby enabling an automation of gauge calibration and peer verification.

Another example of information automation is the wireless valve position indication (VPI) sensor technology developed by LWRS Program researchers [26],[27]. A significant amount of work manually performed at NPPs relates to ensuring or verifying that manually performed activities were accomplished correctly. For example, there are approximately 150–200 valves in a current commercial NPP that must be manually positioned and then verified, either independently or concurrently. The VPI technology enables the online monitoring and digital verification of valve positions, eliminating the need for manual verification. This technology can be nonintrusively retrofitted on valves without requiring them to be recalibrated or recertified. The technology also eliminates the need for periodic calibration. By automating this manual activity (i.e., enabling information automation), the wireless VPI sensor system provides continuously available and easily collectable verification data.

Information automation is also exemplified in LWRS Program research to detect degradation within NPP piping systems. The piping system is a critical NPP component, and maintaining this system is challenging due to the difficulty and high costs of assessing the extent to which it may have degraded [28]. During scheduled refueling outages, sections of the piping system are periodically inspected for degradation. For the reasons stated above, it is difficult to decide which sections to inspect. This problem is compounded by the amount of piping in an NPP. With safety in mind, the nuclear industry takes a conservative approach to piping inspections, but this likely leads to unnecessary inspections being performed, thus increasing the amount of downtime and affecting the economic competitiveness of the NPP. To address this, Gribok et al. [28] developed distributed fiber sensors that can withstand harsh NPP environments and continuously collect high-spatial-resolution data from throughout the entire plant. The data collected by the fiber sensors are analyzed [28] to identify pipe defects and assess pipe health (i.e., information automation).

A final example of information automation is the digitalization of paper-based procedures into computer-based procedures and electronic work packages [29]. The nuclear power industry is highly proceduralized in that very few critical work activities are performed by skill-of-the-craft. The paper-based procedures currently used by industry have a proven track record of ensuring safety, but they also present an excellent opportunity to apply information automation to O&M activities. Automating information in procedures by using computer-based procedures and electronic work packages means that information can be more dynamically presented, thereby enabling the operator to be better integrated into the work process and concept of operation, which then leads to increases in overall work efficiency and improvements in plant safety.

Some of the requirements considered for information automation are:

- Information Infrastructure: The infrastructure for handling and maintaining information must be considered prior to implementing information automation, including:

  - *Availability*: The degree to which the information infrastructure can support the frequency at which information automation is needed and be used to support a controller's ability to generate insights, make recommendations, and make decisions.
  - Timeliness: Requirements for how quickly automation information needs to be processed and made available to controllers (i.e., latency times in processing and converting data into information).
  - Information Quality and Integrity: Requirements for maintaining the quality and integrity of the information used. For example, an aspect of quality is the ratio of credible information to "noise" in the information. Additionally, a "single-source-of-truth" verified information repository for information storage is needed.
  - Scalability: The plan for scaling the needs of the information infrastructure based on projected use of automated information.
- <u>Information Security and Controls</u>: Identify the security requirements and implement a security architecture that prevents unauthenticated or unauthorized access.
- <u>Information Characteristics</u>: Identify and understand the characteristics of information used in analyses that automate information gathering, including:
  - Source: Requirements that specify how the information was acquired or derived from the data.
  - Format: Requirements that describe the general arrangement of the information.
  - Structure: Requirements that describe the general organization of the information.
  - Completeness: Requirements that characterize the scope the information covers.
  - Accuracy and Credibility: Requirements that describe the extent to which the information can be trusted.
- <u>Transformation Rules</u>: Requirements specifying how data will be converted into information, including:
  - Relevance: Requirements that describe what kinds of data will be used as the source for the derived information.
  - Data quality: Requirements describing the characteristics of data quality (e.g., readability, completeness, accuracy) needed to enable information automation.
  - Calculations: Requirements specifying what algorithms will be used in calculations needed to convert data into information.
- <u>Economic Considerations</u>: Identify and understand the costs and benefits of various technologies that enable information automation.

4. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING: DESIGN, DEVELOP, DEPLOY, AND OPERATION PRINCIPLES

The diagnostic and prognostic models developed as part of predictive modeling (Figure 2) for the CBM application take advantage of advancements in AI/ML technologies. There are numerous AI/ML models developed for CBM. However, despite recent impressive progress and success stories of applied ML, its actual use in the nuclear industry has been minimal. There are several reasons for such a reluctance to adopt AI/ML-based technologies in the nuclear industry. This section introduces the notion of RESET AI (Figure 10) that needs to be followed to lay the foundation for AI/ML technologies adoption in the nuclear industry. The notion of RESET AI is applicable to the design, development, deployment, and operation lifecycles of AI/ML technologies to optimize CBM in this report. However, the same principles are applicable for other applications, like plant operation and support (Figure 1) that use AI/ML tools. RESET AI is briefly elaborated in the following subsections.

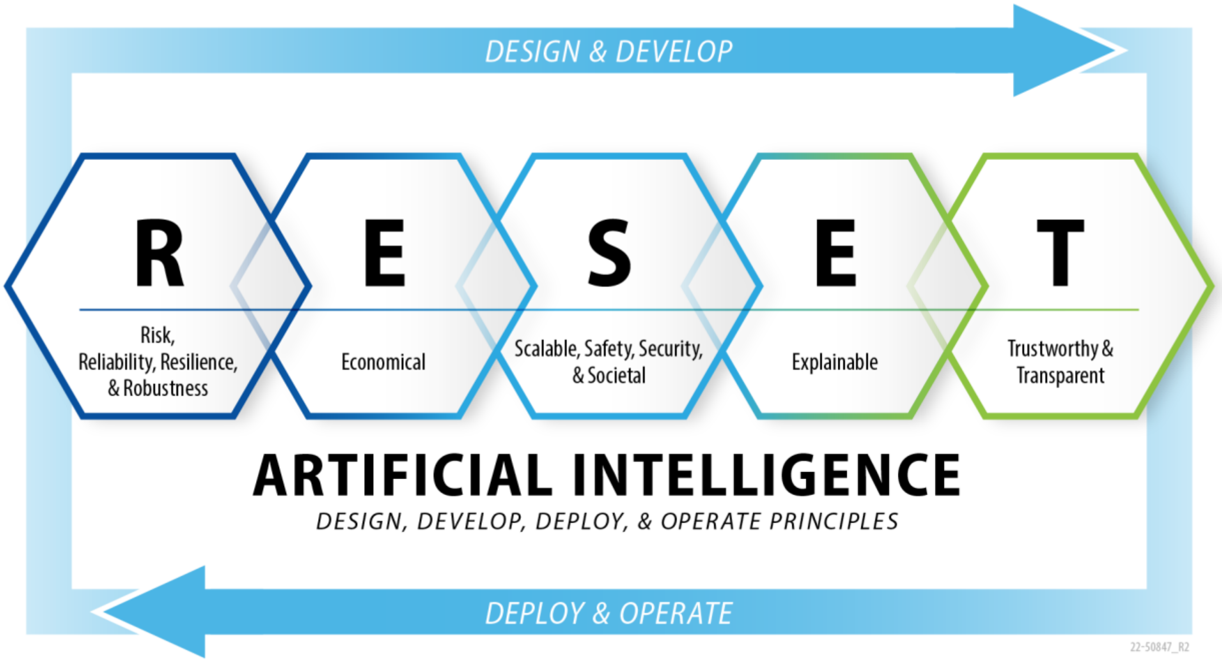

Figure 10. Design, develop, deploy, and operate AI/ML technology requirements.

4.1 Risk, Resilience, Robustness, and Reliability

Risk assessment is one of the most important requirements for any technology development and implementation in the nuclear industry. AI/ML is not and should not be exempted from this requirement. Risk assessment considers the probability of failure, consequences of failure, and scenarios under which a failure could occur. To reap the benefits of AI/ML, it is important to understand the risks and potential consequences of AI/ML failures, the use of AI/ML for malevolent purposes, and scenarios under which an AI/ML algorithm would fail. The risk assessment and management of AI failure should also consider the interaction of AI/ML with humans, organizations, and with other digital (AI/ML) technologies. Reference [30] provides insights on types of AI failures, risk assessment, and risk perception. A framework for AI system risk management across a wide spectrum of applications and maturity has been developed by the National Institute of Standards Technologies [31].

AI resilience refers to the ability to absorb, adapt, and recover from any anomalous behavior of the AI technology itself or of the system within which the technology operates [32]. This anomalous behavior could occur as the AI technology interplays with other technologies or with humans. Therefore, AI technologies must be able to absorb, adapt, and recover from such anomalous behaviors without breaking down and requiring a complete rebuild.

AI robustness is the ability of the AI technology to be invariant to any variations in hyperparameters or the data used for training purposes and ensure their estimates are within acceptable identification and prediction limits. It is very common in practical applications for training data to vary over time, as new data sources might become available or some of the existing data sources may be unavailable for a period of time.

The purpose of the reliability requirement for an AI technology is to ensure that the technology performs as intended—that is, within specified limits and without any failure, it consistently produces the same outputs for the same inputs [33]. If the performance of an AI technology is not reproducible over time, not only will it impact reliability but also other requirements like robustness, explainability, trustworthiness, safety, security, and economics.

4.2 Economic

In this section, we discuss the economics of AI/ML technologies by considering both financial and computational requirements. Ongoing digital transformation in the nuclear industry has led to the digitization of analog technologies, installation of digital sensors, online monitoring, information automation, high-performance computing resources, and others. These transformations have resulted in the generation of large volumes of new data and access to data, information, and other enterprise details that were previously unavailable to develop data-driven ML algorithms, physics-informed data-driven ML algorithms, and digital twins. While the development of AI/ML technologies for different plant applications (Figure 2) are in early stages, it is important for nuclear stakeholders to understand the level of financial investment required to deploy long-term sustainable AI/ML.

The first requirement is to have a data infrastructure that collects and organizes the data of interest (i.e., a data pipeline). For CBM in general, different types of data needs to be collected, as delineated in Section 2 for the CWS. These data need to be converted into a digital format suitable for storage, integration, analysis, AI/ML modeling, and visualization. Constructing this data pipeline is often the most labor intensive and expensive part of building a data infrastructure, since different plant sites have legacy systems that are difficult to connect. Traditionally, each nuclear stakeholder has developed their individual data center (also referred as data warehouse or data portal) due to privacy and cybersecurity concerns. Developing a data center requires a significant investment in hardware, software, and staff resources, including a substantial fixed capital expenditure, followed by subsequent years of operating expenditures. Once this data center is established, the next consideration is the development of an AI/ML repository that houses different AI/ML methods and tools per industry standards. These tools are subjected to version control and independent qualification processes, as their capabilities and applicability are expanded across different applications. This creates additional financial requirements, especially given that nuclear is a regulated industry and that regulatory requirements on AI/ML technologies are forthcoming [34].

An alternative approach to building a data center at each plant site or for multiple plant sites is to use cloud-based services to store, integrate, and analyze data. There are different cloud-based services available, and each has its own technical and economical pros and cons. The cloud provider takes care of managing and updating the hardware and software necessary to host the data and tools for data analysis. As pointed out in [35], what was previously a fixed cost to stakeholders (the data center) has now turned into a variable cost (renting time on the data center). A stakeholder can purchase virtually any amount of cloud services based on usage, and this could turn into a cost-effective alternative to a data center. In addition, these different cloud-based services also provide access to their AI/ML and visualization tools. These services can take care of the security, optimization, and qualification of hardware and software, ensuring service scalability.

Therefore, it is required for nuclear stakeholders to evaluate this requirement in detail and weigh the economical pros and cons of each approach to ensure the deployment of AI/ML technologies and its lifetime sustainability.

Another requirement for developing a deployable AI/ML technology is to minimize the dependency on high-performance computing resources and data centers. This could be true for even cloud-based services storing only minimal information and seeking additional details on an on-demand basis. Advancements in edge computing could be leveraged to reduce the need to store a large volume of data in a centralized location. A decentralized approach, taking advantage of federated and transfer learning, could eliminate the need to centrally store the data, addressing not only financial concerns but also data privacy and security concerns [36].

4.3 Scalability, Security, Safety, and Societal

AI/ML-based technologies developed for different applications in plants must be scalable across plant assets and the nuclear fleet [36]. Over the years, several application-specific AI/ML-based solutions have been developed, but their performance degrades significantly when applied to the same application at a different plant site or to a similar application within the same plant site. This is because the inherent design and development of the technology did not consider the need to consider the scalability requirement. Considering scalability requirements is essential for the long-term economical sustainability of NPPs. Scalability is defined as expanding the capabilities of a target entity to meet current and future application-specific requirements. "Entity" in this context is defined as an element of the suggested framework shown in Figure 11.

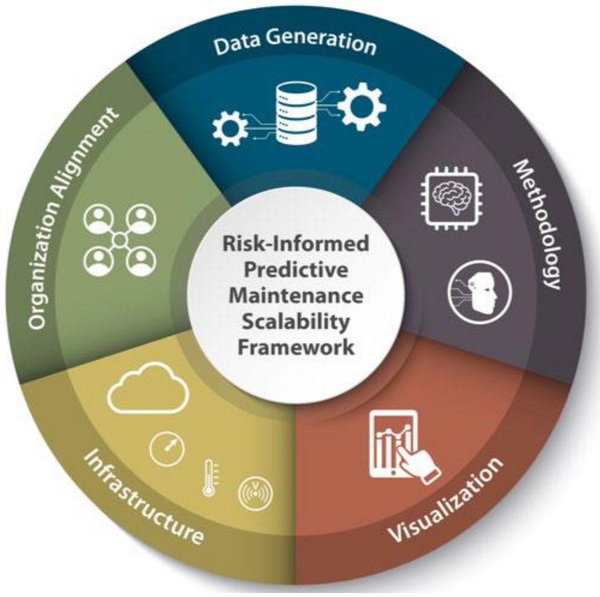

Figure 11. A framework to scale the risk-informed PdM strategy.

The elements of the framework shown in Figure 11 include data generation and governance, methodologies, visualization, infrastructure, and organizational alignment. For details on each element (i.e., entity) of the framework, refer to Reference [36]. The framework in Figure 11 is applicable to plant support and plant operation too.

AI/ML technologies are used to address several (physical and digital) security challenges in cyber-physical systems. On the other hand, is AI/ML technology itself secure? Again, going back to Figure 10, the security of AI/ML technologies must be considered at the design, development, deployment, and operation stages of their lifecycle. They need to be protected from interference, compromise, or misuse. This security requirement ties back to the risk assessment and management requirements.

AI/ML safety is another requirement to be considered to ensure that AI/ML do not lead to any harmful actions that could have societal impacts. This is particularly true in the nuclear industry, where any societal impact due to the unsafe operation or action of AI/ML could be catastrophic. The safety of AI/ML technologies should be established at the hardware, software, and human levels.

The societal requirement is about informing users and the public about their potential interaction with AI/ML technologies. Educating users and the public about AI/ML technologies creates awareness, and regulation on AI/ML technologies is a key step in establishing trust in interactions between users and the public with these technologies. In the nuclear industry, this is one of the most valuable requirements, as it can enhance public perspective.

4.4 Explainable

AI/ML-based applications are designed, developed, and used by humans, but their effectiveness is limited due to their inability to explain the outcomes and recommended actions to the human in the loop. This is a challenging issue in the adoption of AI/ML technologies in nuclear and other industries, leading to the requirement of explainable AI (XAI) methods. The Defense Advanced Research Project Agency recently led a significant effort on XAI [37]. Human-centered or user-centric AI is an emerging field of research focused on the role of humans within AI/ML solutions. Human-centered AI serves as a framework for managing the often-competing interests of ethics, practice, regulation, and assurance present in the deployment of AI/ML tools throughout our digital life and society [38][40].

In ongoing research, LWRS researchers developed their new explainability approach based on the closed-loop forward-backward process [41]. This process assesses outcomes using objective metrics, applies the user-centric interpretability of those outcomes, and then develops an approach to incorporate user interpretation as feedback to further simplify the process. As a result, researchers created an explainability prototype interface that provides a focused component-level display of the ML model outputs in a usable and digestible form to the user in the loop.

The forward process is a method that moves from data to decisions. The forward process entails a rigorous mathematical approach that accounts for data preprocessing; data integration; transforming the data into usable information to train, validate, and test ML models; uncertainty quantification of final outputs by accounting for the accumulation of errors; and presentation of the results to the end user. This approach explains AI/ML solutions by utilizing objective metrics, such as Local Interpretable Model-agnostic Explanations and Shapley Additive Explanations, that capture the rigorous mathematics. The metric-based approach quantifies the effectiveness of the explanation based on performance differences between the ML models, the number of features used to construct the explanation, and the stability of the explanation. For example, for a waterbox fouling (a fault mode of importance for the PSEG-owned Salem NPP), given all the key measurements and instances of waterbox fouling faults in the CWS, a global interpretation, as shown in Figure 12, is established for human interpretation. Figure 12 shows how different CWS parameters (such as differential temperature, motor stator temperature, motor current, and motor inboard and outboard temperatures) contributed to diagnosing whether the system is healthy or experiencing waterbox fouling. This global interpretation explains the significance of differential temperature, motor stator temperature, and motor outboard temperature in diagnosing waterbox fouling.

In the backward process, the objective metrics developed as part of the forward process to explain AI/ML technologies are verified by an end user. As part of the backward process, a user-centric visualization is developed to present AI/ML outcomes with objective metrics and other information to elicit user interpretation. Based on elicited input from end users with different levels of expertise and functional positions within the organization, objective metrics and visualization can be adapted to ease their interpretation and decision-making ability.

4.5 Trustworthy and Transparency

Trust is a complex phenomenon and has several definitions across different disciplines [42]–[44]. The National Institute of Standards and Technology [45] defines trust as "the confidence one element has in another, that second element will behave as expected." It is difficult to define trust. On that note, the trustworthy AI requirement cannot be bound by a definition but by answering: what are the necessary guidelines? References [46] and [47], present a trustworthy AI framework, shown in Figure 13. A detailed discussion on the trustworthy AI framework is beyond the scope of this report, see References [46] and [47] for more information. Observe that some of the guidelines presented in the framework tie back to robustness and societal requirements. The framework also highlights human oversight and involvement in achieving trustworthy AI. Requirements like AI fairness and ethics are part of the trustworthy requirement.

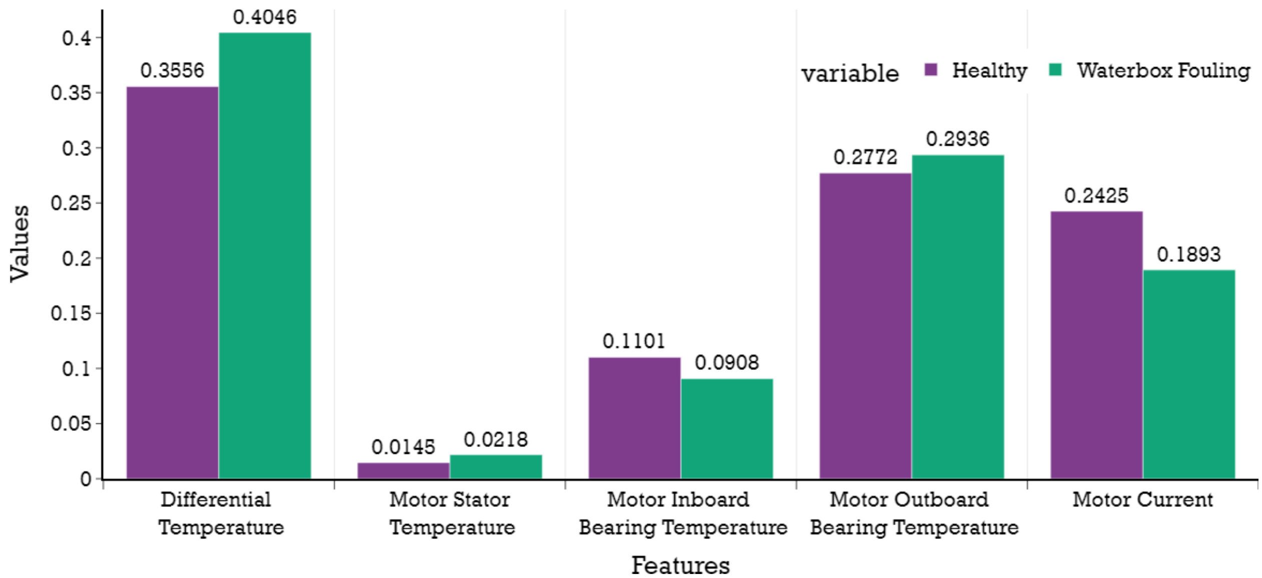

Figure 12. Feature importance of all the features used in differentiating between waterbox fouling and healthy condition of the CWS.

The transparency requirement of AI is also part of the trustworthy framework (Figure 13). The transparency of an AI technology refers to the need to explain, interpret, and reproduce its decisions [48]. It ensures that the different stakeholders using or impacted by the AI technology clearly understand its performance and limitations [49], which again ties back to the XAI requirement.

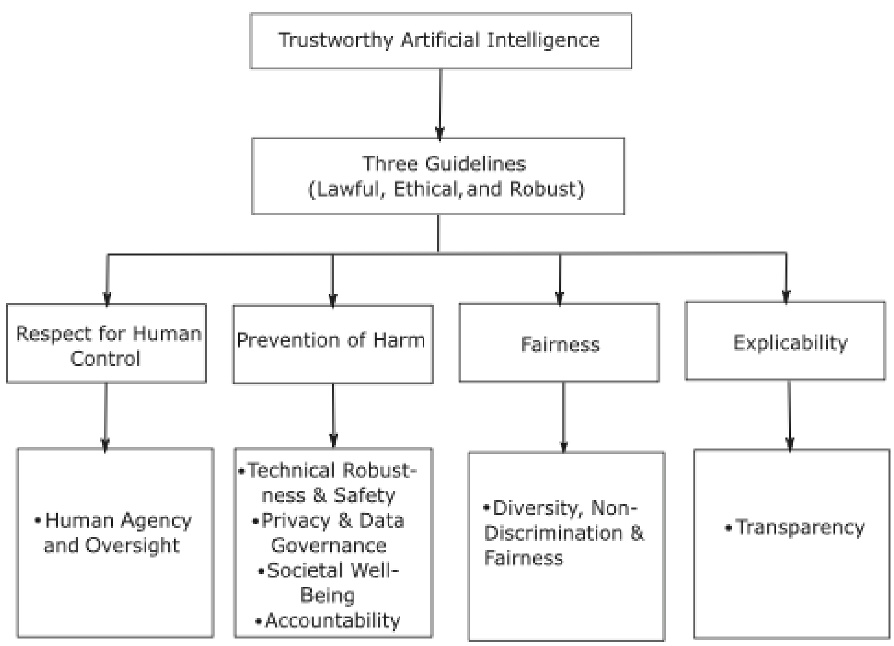

Figure 13. Trustworthy AI framework [46],[47].

In summary, this section on the notion of RESET AI has touched upon different requirements that are essential to design, develop, deploy, and operate an AI-based technology in a safety-critical industry. The section also highlights how these requirements interplay and should be treated in a mutually exclusive manner.

5. SEAMLESS DIGITAL ENVIRONMENT

In the nuclear industry, digitalization can, for example, improve planning, scheduling, and work management activities.

In the context of CBM, electronic work package solutions are an example of work digitization. In other words, the information in the work package and WOs that used to be in hard copies (i.e., printed on paper) has been digitized and is now available as electronic paper aka PDFs on handheld devices. Smart planning and scheduling tools and dynamic instructions are examples of work digitalization where these technologies pull and use data and information from other applications as well as push data back to appropriate applications. Work digitalization can be defined as the use of digital technology to transform work performance and related processes and interactions.

Information digitalization (and by extension, work digitalization) is realized using Seamless Digital Environments (SDEs). SDE is the integration of information from plant systems with operator processes through an array of interconnected technologies. In other words, data from digital instrumentation and control in plant systems are fed to various processes and applications. These processes and applications are then used by plant workers to execute work. This integration of information will save time, create significant work efficiencies, and reduce both system and human errors. The integration of information via SDEs includes:

- *Plant systems*. Beyond centralized plant condition monitoring and awareness, deliver plant information to digitally based systems that support plant work directly to the workers performing these work activities.
- *Plant processes*. Integrate plant information into digital fieldwork devices, automate many manually performed surveillance tasks, and manage risk through real-time centralized oversight and awareness of fieldwork.
- *Plant workers*. Provide plant workers with immediate, accurate plant information that allows them to conduct work at plant locations using assistive devices that minimize radiation exposure, enhance procedural compliance and accurate work execution, and enable collaborative oversight and support even in remote locations.

In the context of CBM, SDE is the mechanism that brings all the equipment data, processes, and workers together to ensure the correct maintenance is conducted on a specific piece of equipment at the optimal time.

More and more plants are installing advanced sensors, such as wireless vibration detectors, to gather detailed data about equipment health and performance. This performance data is commonly sent to staff for transcribing, screening, assessing, and trending the information to determine when to schedule maintenance—tasks that can be time consuming and are frequently added to existing staff workloads. Humans are also notorious for making unintentional mistakes, especially when working with larger amounts of information.

A more efficient and much less error-prone approach is to leverage digitalization of information and work and let technology do the tasks it's superior at compared to humans–in other words, utilizing an SDE. The SDE would automatically gather equipment performance data, perform relevant analytics, and feed the outcome to appropriate applications or management levels as suggested in Figure 14. If needed, the SDE would trigger the process to create a WO. The WO would be routed through the review and approval process as well as the planning and scheduling processes to ensure workers and tools are available in a timely manner to conduct the needed maintenance. In addition, the relevant instruction steps for the specific maintenance task along with drawings and applicable trends are automatically added to the WO. Hence, the SDE efficiently integrates the data and processes to ensure the workers have the information and tools they need to successfully complete the maintenance.

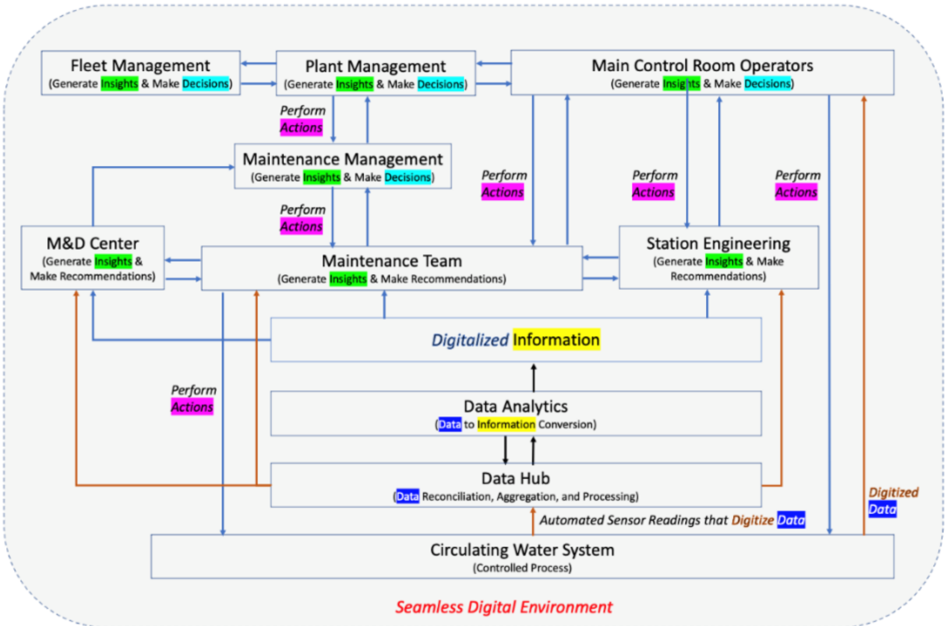

Figure 14. A seamless digital environment for TERMS within the context of a STAMP and STPA control loop.

6. SUMMARY AND PATH FORWARD

This report identified some of the important requirements that need to be considered as part of the data evolution for the CBM application on a CWS in an NPP. In the data evolution process, the information is converted into insight, leading into using advancements in AI/ML technologies. An overview of RESET AI design, development, deployment, and operation principles is introduced to support the lifecycle of AI technologies. Towards the end of the report, we discussed how this CBM can be realized in an SDE.

This report lays the foundation for developing more detailed industry guidance and a supporting data evolution path for other plant applications, like operations and plant support. These concepts will be developed as part of the path forward for ongoing research in Fiscal Year 2023.

7. REFERENCES

[1] Ngarayana, I. Wayan, Thi-Mai-Dung Do, Kenda Murakami, and Masahide Suzuki. 2019. "Nuclear Power Plant Maintenance Optimisation: Models, Methods & Strategies." Journal of Physics: Conference Series 1198, no. 2, (April). 022005. https://doi.org/10.1088/1742-6596/1198/2/022005.

[2] IAEA, "Plant Life Management Models for Long Term Operation of Nuclear Power Plants." IAEA Nuclear Energy Series, no. NP-T-3.18, IAEA, Vienna (2015). https://www.iaea.org/publications/10520/plant-life-management-models-for-long-term-operation-of-nuclear-power-plants.

[3] Agarwal, Vivek, et al. 2021. "Scalable Technologies Achieving Risk-informed Condition-Based Predictive Maintenance Enhancing the Economic Performance of Operating Nuclear Power Plants." INL/EXT-21-64168, Rev. 0, Idaho National Laboratory. https://doi.org/10.2172/1894498.

[4] Agarwal, Vivek, et al. 2021. "Machine Learning and Economic Models to Enable Risk-Informed Condition Based Maintenance of a Nuclear Plant Asset." INL/EXT-21-61984, Rev. 0, Idaho National Laboratory. https://www.osti.gov/servlets/purl/1770866.
[5] Yarlett, M., et al. 2021. **"**Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 3." INL/EXT-21-63561, Idaho National Laboratory.
[6] Leveson, Nancy G. 2011. "*Engineering a Safer World*." Cambridge, MA: MIT Press.
[7] Leveson, Nancy G., and John P. Thomas. 2018. *STPA Handbook*. http://psas.scripts.mit.edu/home/get_file.php?name=STPA_handbook.pdf.
[8] Remer, Jason, et al. 2022. "Integrated Operations for Nuclear Business Operation Model Analysis and Industry Validation." INL/RPT-22-68671, Rev. 0, Idaho National Laboratory. https://www.osti.gov/servlets/purl/1894935.
[9] PSEG Configuration Baseline Document for Circulating Water System. DE-CB.CW-0028(Z), Rev. 0, 1-1. https://www.nrc.gov/docs/ML1014/ML101440290.pdf.
[10] Goss, N., et al. 2020. "Integrated Risk-Informed Condition Based Maintenance Capability and Automated Platform: Technical Report 1," PKM-DOC-20-0013, Rev. 0, PKMJ Technical Services, June 2020. https://lwrs.inl.gov/Advanced%20IIC%20System%20Technologies/Hybrid%20Modeling%20of%20a%20Circulating%20Water%20Pump%20Motor.pdf.
[11] KCF Vibration Sensor Node SD-VSN-3. https://www.kcftech.com/wp-content/uploads/2020/11/VSN3_Data_Sheet-003.pdf.
[12] Hodkiewicz, M., Kelly, P., Sikorska, J., and Gouws, L. 2006. "A Framework To Assess Data Quality for Reliability Variables." In Engineering Asset Management. Mathew, J. Kennedy, J., Ma, L., Tan, A., Anderson, D. (eds.), 137–147, London: Springer. http://dx.doi.org/10.1007/978-1-84628-814-2_15.
[13] Jia, Xiaodong, Ming Zhao, Yuan Di, Qibo Yang, and Jay Lee. 2017. "Assessment of Data Suitability for Machine Prognosis Using Maximum Mean Discrepancy." IEEE Transactions on Industrial Electronics 65, no. 7, (Nov.) 5872–5881. https://doi.org/10.1109/TIE.2017.2777383.
[14] Lukens, Sarah, M. Naik, K. Saetia, and Xiaohui Hu. 2019. "Best Practices Framework for Improving Maintenance Data Quality to Enable Asset Performance Analytics." in: Annual Conference of the PHM Society 11, no. 1. https://www.researchgate.net/profile/Sarah-Lukens/publication/336217564_Best_Practices_Framework_for_Improving_Maintenance_Data_Quality_to_Enable_Asset_Performance_Analytics/links/5d94b964a6fdccfd0e710e67/Best-Practices-Framework-for-Improving-Maintenance-Data-Quality-to-Enable-Asset-Performance-Analytics.pdf.
[15] Griffiths, Toby, Débora Corrêa, Melinda Hodkiewicz, and Adriano Polpo. 2022. "Managing Streamed Sensor Data for Mobile Equipment Prognostics." Data-Centric Engineering 3, no. E11. https://doi.org/10.1017/dce.2022.4.
[16] Lukens, Sarah, et al. 2022. "A Data Quality Scorecard for Assessing the Stability of Asset Condition Data for Prognostics Modeling." Annual Conference of the PHM Society 14, no. 1. https://doi.org/10.36001/phmconf.2022.v14i1.3188.
[17] Omri, N., et al. 2021. Towards an Adapted PHM Approach: Data Quality Requirements Methodology for Fault Detection Application." Computers in Industry 127, (May), 103414. https://doi.org/10.1016/j.compind.2021.103414.
[18] Chawla, N. V., K. W. Bowyer, L. O. Hall, W. P. Kegelmeyer. 2002. "SMOTE: Synthetic Minority Over-sampling Technique." Journal of Artificial Intelligence Research 16, 321-357. https://doi.org/10.1613/jair.953.
[19] Zheng, Zhuoyuan, Yunpeng Cai, Ye Li. 2016. "Oversampling Method for Imbalanced Classification." COMPUTING AND INFORMATICS 34, no. 5, 1017-1037. https://www.cai.sk/ojs/index.php/cai/article/view/1277.
[20] Mariani, Giovanni, et al. 2018. "Bagan: Data augmentation with balancing GAN." arXiv: 1803.09655v2 [cs.CV]. https://doi.org/10.48550/arXiv.1803.09655.

[21] Introduction to Data Reconciliation Program for North American Mobility in Higher Education. 2003. North Carolina State University, USA: University of Ottawa, Canada, 2003. https://pdf4pro.com/amp/view/basic-concepts-in-data-reconciliation-module-introduction-570cca.html.
[22] Narasimhan, Shankar and Cornelius Jordache. 2000. "*Data Reconciliation and Gross Error Detection, an Intelligent Use of Process Data.*" Texas: Gulf Publishing, ISBN 978-0-88415-255-3NUREG/ CR-6895. https://doi.org/10.1016/B978-088415255-2/50002-1.
[23] Wang, J. R., S. E. Madnick. 1989. "The Inter-database Instance Identification Problem in Integrating Autonomous Systems." In proceedings of the 5th International Conference on Data Engineering (ICDE), California, USA: 46-55. https://doi.org/10.1109/ICDE.1989.47199.
[24] Pipino, Leo L., Yang W. Lee, R. Y. Wang. 2002. "Data Quality Assessment." Communications of the ACM 45, no. 4, 211-218. https://doi.org/10.1145/505248.506010.
[25] Codd, Edgar F. 1982. "Relational database: a practical foundation for productivity." The 1981 ACM Turing Award Lecture. Commun. ACM 25, no. 2, 109–117. https://users.dcc.uchile.cl/~cgutierr/cursos/BD/Relational_Database_A_Practical_foundation_For_productivity.pdf.
[26] Agarwal, Vivek, et al. 2017. "Wireless Online Position Monitoring of Manual Valve Types for Plant Configuration Management in Nuclear Power Plants," *IEEE Sensors Journal* 17, no. 2 (January): 311-322. https://doi.org/10.1109/JSEN.2016.2615131.
[27] Kovacevic, Sasa, Vivek Agarwal, and John W. Buttles. 2021. "Numerical and Experimental Vibration Analysis of an Additive Manufactured Sensor Mounting Unit for a Wireless Valve Position Indication Sensor System," *Nuclear Technology* 208, no. 3, (March): 468-483. https://doi.org/10.1080/00295450.2021.1905476.
[28] Gribok, Andrei, et al. 2020. "Concept for Integrated Multi-Modal Online Piping Monitoring System along with Data Fusion and Advanced Data Analytical Algorithms using High-Resolution Fiber Optics Sensors," INL/EXT-20-59810, Idaho National Laboratory.
[29] Oxstrand, Johanna, Katya Le Blanc, and Aaron Bly. 2013. "Computer-Based Procedures for Field Workers: Results from Three Evaluation Studies," INL/EXT-13-30183, Idaho National Laboratory.
[30] Mannes, Aaron. 2020. "Governance, Risk, and Artificial Intelligence." *AI Magazine* 41, no. 1, (Spring): 61-69. https://doi.org/10.1609/aimag.v41i1.5200.
[31] National Institute of Standards and Technology. 2021. "AI Risk Management Framework: Initial Draft." https://www.bsa.org/files/policy-filings/09142021nistairmf.pdf.
[32] European Commission. 2018. "Ethics Guidelines for Trustworthy AI." Retrieved November 2, 2021 https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai.
[33] ISOIEC TR 24028:2020. 2020. "Information Technology–Artificial Intelligence–Overview of Trustworthiness in Artificial Intelligence." Standard. International Organization for Standardization. https://www.iso.org/standard/77608.html.
[34] Dennis, M., et al. 2022. "Artificial Intelligence Strategic Plan Fiscal Years 2023-2027 (Draft Report)." NUREG-2261, U.S. NRC. https://www.nrc.gov/docs/ML2217/ML22175A206.pdf.
[35] Walker, Cody, et al. 2022. "Development of an End State Vision to Implement Digital Monitoring in Nuclear Plants." INL/RPT-22-66542, Idaho National Laboratory. https://www.osti.gov/servlets/purl/1860372.
[36] Agarwal, Vivek, et al. 2020. "Scalability of a Risk-Informed Predictive Maintenance Strategy," INL/LTD-20-58848, Rev. 0, Idaho National Laboratory.
[37] Defense Advanced Research Projects Agency, DARPA. 2016. "Explainable Artificial Intelligence (XAI)." DARPA-BAA-16-53. https://www.darpa.mil/attachments/DARPA-BAA-16-53.pdf.
[38] Shneiderman, Ben. 2020. "Bridging the gap between ethics and practice: Guidelines for reliable, safe, and trustworthy human-centered AI systems." ACM Transactions on Interactive Intelligent Systems (TiiS) 10, no. 4 (December): 1-31. https://doi.org/10.1145/3419764.

[39] Shneiderman, Ben. 2020. "Design Lessons from AI's Two Grand Goals: Human Emulation and Useful Applications." In IEEE Transactions on Technology and Society 1 no. 2 (June): 73-82. https://doi.org/10.1109/TTS.2020.2992669.

[40] Shneiderman, Ben. 2020. "Human-centered artificial intelligence: Reliable, Safe & Trustworthy." International Journal of Human–Computer Interaction 36, no. 6 (February), 495-504. https://arxiv.org/ftp/arxiv/papers/2002/2002.04087.pdf.

[41] Agarwal, Chirag, et al. 2022. "XAI: Towards a Transparent Evaluation of Model Explanations." arXiv:2206.11104v1 [cs.LG] 22 Jun 2022. https://doi.org/10.48550/arXiv.2206.11104.

[42] Granovetter, Mark. 2018. "Economic Action and Social Structure: The Problem of Embeddedness." In The Sociology of Economic Life, Mark Granovetter and Richard Swedberg (eds.), 22-45. New York: Routledge. https://doi.org/10.4324/9780429494338.

[43] Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. 2016. "Why should I trust you?" Explaining the predictions of any classifier." In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. (August): 1135–1144. https://doi.org/10.1145/2939672.2939778.

[44] Williamson, Oliver E. 1993. "Calculativeness, Trust, and Economic Organization. The Journal of Law and Economics 36, no. 1, (April): 453–486. http://www.jstor.org/stable/725485.

[45] Boyens, Jon, Celia Paulsen, Rama Moorthy, and Nadya Bartol. 2015. "Supply Chain Risk Management Practices for Federal Information Systems and Organizations." *NIST Sp Publication 800* 161, (April): 32. https://doi.org/10.6028/NIST.SP.800-161r1.

[46] Kaur, Davinder, Suleyman Uslu, and Arjan Durresi. 2020. "Requirements for Trustworthy Artificial Intelligence—A review." In Proceedings of the International Conference on NBi*S*. (Springer, Cham.): 105–115. https://doi.org/10.1007/978-3-030-57811-4_11.

[47] Kumar, Abhishek, Tristan Braud, Sasu Tarkoma, and PanHui. 2020. "Trustworthy AI in the Age of Pervasive Computing and Big Data." In Proceedings of the 2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops'20). Los Alamitos, CA: 1–6. https://doi.org/10.1109/PerComWorkshops48775.2020.9156127.

[48] Virginia Dignum. 2017. "Responsible Artificial Intelligence: Designing AI for Human Values." ICT Discoveries 1 (September): 1–8. https://www.itu.int/dms_pub/itu-s/opb/journal/S-JOURNAL-ICTF.VOL1-2018-1-P01-PDF-E.pdf.

[49] Donghee Shin and Yong Jin Park. 2019. "Role of Fairness, Accountability, and Transparency in Algorithmic Affordance." Computers in Human Behavior 98 (May): 277–284. https://doi.org/10.1016/j.chb.2019.04.019.

Appendix A
Core Concepts of STAMP and STPA

STAMP (Leveson 2011) and a hazard analysis tool based on the STAMP causality model called STPA (Levenson and Thomas, 2018) are core concepts for organizing the digitization, digitalization, data evolution, information automation, and a seamless digital environment construct. Specifically, the idea of modeling an engineered system and its safety constraints in terms of a control loop is central to both STAMP and STPA. A generic control loop is shown in Figure A-1 comprised of a controller with a control algorithm and process model, a controlled process (e.g., a CWS), and the interactions between the controller and controlled process, which are described in terms of control actions and feedback. At a high level, a control loop depicts the dynamic relationship between a controller and the process it is controlling—what Levenson (2018) calls a control structure.

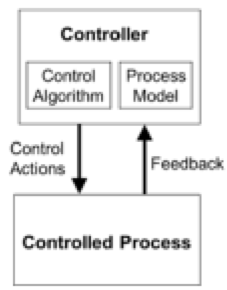

Figure A-1. Generic control loop ([7], Figure 2.6).

For the purposes of this research and report, modeling engineered systems in terms of a STAMP and STPA control loop, or series of control loops, produces an overall control structure that can be used to define and organize the digitization, digitalization, data evolution, information automation, and a seamless digital environment constructs.

Figure A-2 explicitly shows how the STAMP and STPA control loop concept can represent the TERMS [3][5] and how the digitization, digitalization, data evolution, information automation, and a seamless digital environment constructs are connected to what TERMS does in the case of a circulating water engineered system. TERMS is a scalable, risk-informed PdM strategy for commercial NPPs. TERMS uses data analytics, AI/ML, and visualization across plant systems and different NPPs to develop fault and predictive models that forecast the future health of the plant system(s) and then generates intuitive interactive visualizations of the data and fault signature trends to support overall situation awareness.

TERMS can also be described in the context of a STAMP and STPA control loop. In Figure A-2, the controlled process is the CWS at a commercial NPP. There are also multiple controllers of the CWS. In this depiction, TERMS mediates the interaction of the other controllers—namely the monitoring and diagnostics (M&D) center, maintenance, and station engineering—with the CWS.

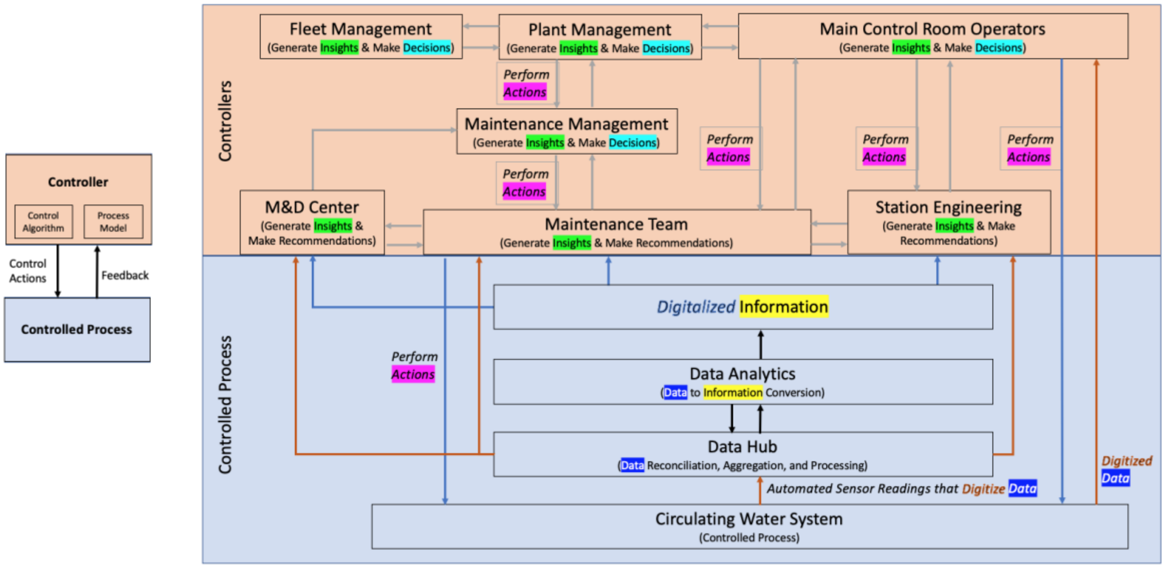

Figure A-2. TERMS represented as a STAMP and STPA control loop.

The main control room operators have both a direct interaction with the CWS and an interaction that is mediated by other controllers and TERMS. The M&D center, maintenance team, and station engineering also mediate the interaction of maintenance management, plant management, fleet management, and main control room operators with TERMS and the CWS. This is why Figure A-2 shows that the M&D center, maintenance team, and station engineering make recommendations and that maintenance management, plant management, fleet management, and main control room operators make decisions.

To *digitize* something is to convert information from an analog format into a digital format, but to *digitalize* is to use digital technologies (i.e., technologies based on that information in a digital format) to synthesize work processes as a means to integrate operations. Note that, in Figure A-2, brown arrows in the figure denote *digitized* data and blue arrows denote *digitalized* data.

Specifically, automated sensor readings of the CWS digitize data and provide that data as feedback to the data hub in TERMS. TERMS then uses data analytics, ML, and AI to digitalize the data to develop fault and predictive models that forecast the future health of the CWS and then generates intuitive interactive visualizations of the digitalized information to support overall situation awareness (i.e., converts data into information).

An important goal for effective and cost-efficient operations is to figure out how data is collected, stored, and organized in meaningful patterns so that it can be used as a basis for action. **Data evolution** is the effective mapping and management of plant data and is the construct the LWRS Plant Modernization pathway uses to describe how this goal is achieved. Data mapping refers to the pathways along which data flows, and data management refers to the appropriate structure, format, tagging, and transformation of that data.

Figure A-3 also shows that data evolution is comprised of converting data into information and then using that information to generate actionable insights to enable effective decision-making and actions. That is, data mapping and management can be thought of as the transformation of data into information into insight into decisions and then finally into actions.

Figure A-3 shows how the "data into information into insight into decision into action" sub elements of data evolution fit within a generic control loop.

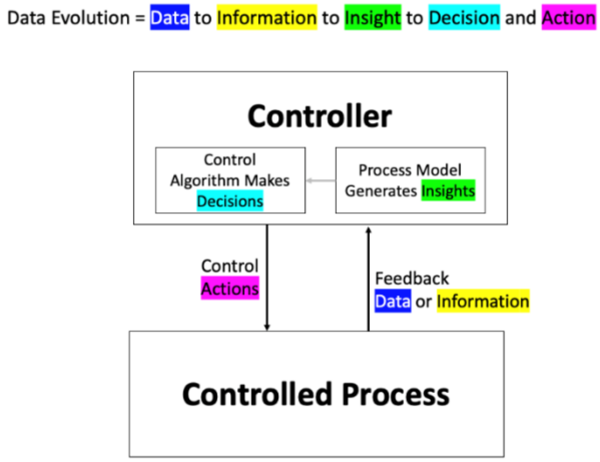

Figure A-3. Modified generic control loop to show data evolution ([7], Figure 2.6).

As the figure above shows, the controlled process generates the data or, in the case of this example, information—if the data is digitalized—and then sends the (digitized) data or (digitalized) information as feedback to the controller. The controller uses its process model to generate insights and its control algorithm to come up with key decisions that the controller then sends back to the controlled process as an action.