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Development of a Technology Roadmap for Online Monitoring of Nuclear Power Plants

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ABSTRACT

The nuclear power industry has recently recognized the potential cost savings that can be achieved from migrating the current manual and labor-intensive surveillance and preventive maintenance activities to data-driven online monitoring methods. Consequently, several efforts have been launched with various degrees of momentum to tackle specific surveillance or preventive maintenance activities. The U.S. Department of Energy's Light Water Reactor Sustainability (LWRS) program has anticipated this need and launched an effort aimed to develop a technology roadmap for the nuclear power industry. A holistic technology roadmap will reduce long-term investment costs by prioritizing improvements that support the end-state vision rather than just the next incremental capability. Because a comprehensive roadmap has to be focused towards the plant's needs, and because nuclear power plants (NPPs) have different process efficiencies and deficiencies, the extent of details described by this technology roadmap was optimized to be plant-independent. The roadmap, therefore, is developed to describe processes and equipment, regardless of an NPP's specific need to target a certain process or equipment sequence. For example, the steps required to migrate the inspection of a pump are plant independent. However, defining that the migration of feed water pump inspections to online monitoring should be performed before inspections of feed water valves is dependent on multiple plant factors such as the plant requirements, labor work capacity, and process or equipment conditions.

The technology roadmap was broken down into six elements, four of which have a sequential path of advancement, while the other two are supporting elements to the sequential elements. The sequential part of the roadmap consists of data collection, analytics, visualization, and management. For these elements of the technology roadmap, the adoption of the technology to perform an activity is defined by the availability and usage of the technology in one of three states. The base state is defined as the most primitive, manual, and/or labor-dependent process used by some NPPs. The modern state is defined as the state that can be achieved if the activities are augmented or replaced by current technologies that are either commercially available or soon to be available. The state of the art is defined as technologies of the future (i.e., concepts and technologies that are being researched).

The data collection element of the technology roadmap is described in terms of a process. However, the data analytics element is described in terms of equipment, because automating an activity performed on one piece of equipment requires considering multiple data sources from various data collection processes. The visualization and data management elements are process and equipment independent. Visualization describes the effective use of human factors science and technological advancements to present the collected data and data analytics results. Data management targets storage, communication, and computational power needs in addition to data integration and sharing. Because storage, communication, computational power technologies, and their path for deployment are known to information technology organizations, this effort targets the cost of data management, which has a direct impact on the feasibility of the automation effort.

The supporting elements of the technology roadmap examine the value of automating the activity as well as the challenges associated with implementing the necessary changes to the plant. The value element of the roadmap describes how to analyze cost savings and associated risk. The change management element identifies multiple factors to consider such as regulation, cybersecurity, resources, supporting infrastructure, feasibility, and

cultural change. The combination of the sequential and supporting elements defines a plant-independent roadmap for migration from current manual processes to online monitoring.

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ACRONYMS

AE	acoustic emission
AR	augmented reality
CAFTA	computer aided fault tree analysis
CM	condition monitoring
COA	course of action
COSS	computerized operator support system
CPU	computer processing unit
DCS	distributed control system
DGA	dissolved gas analysis
EAB	elongation-at-break
EID	ecological interface display
EPRI	Electric Power Research Institute
ETL	extract, transform, load
GA	gas analysis
GB	gigabyte
GC	gas chromatography
GPU	graphical processing unit
I&C	instruments and control
IR	infrared
ISI	in-service inspection
LWRS	light water reactor sustainability
MBVI	model-based voltage and current systems
ML	machine learning
NDE	nondestructive examination
NEI	Nuclear Energy Institute
NPP	nuclear power plant
O&M	operation and maintenance
PRA	probabilistic risk assessment
RFID	radio-frequency identification
RT	radiography technique
RUL	remaining useful life
SAPHIRE	Systems Analysis Programs for Hands-on Integrity Reliability Evaluation
SHM	structural health monitoring

SOC	state of charge
SPDS	safety parameter display system
SSC	structure, system, or component
TCO	total cost of ownership
UGW	ultrasonic guided wave
U.S.	United States
UT	ultrasonic technique
VR	virtual reality

Development of a Technology Roadmap for Online Monitoring of Nuclear Power Plants

1. INTRODUCTION

Operation and maintenance (O&M) costs represents the main disadvantage of the nuclear industry compared to other energy sources. Maintaining a nuclear power plant (NPP) depends on very labor-intensive activities required to meet high safety standards. Under current energy-market conditions, the nuclear industry must innovate and move towards a more economically viable approach that requires less O&M cost by reducing labor frequency of O&M activities and automating activities, such as the maintenance work processes, operations surveillances, or support activities such as administration, security, and radiation protection.

To achieve the vision of online monitoring of an NPP, guidelines need to be developed. The Nuclear Energy Institute (NEI) recognized this need and has generated multiple efficiency bulletins to guide the industry towards developing a process for migration to implement the necessary capabilities to enable effective online monitoring. NEI 2017 surveyed some of these efforts to achieve value-based maintenance approach, which results in variable- or fixed-time based maintenance, depending on the condition of the equipment, its importance, impact of risk on the plant, and the value added by performing the maintenance. This approach generates cost savings when compared to the classical time-based preventive or post-failure corrective maintenance approach. NEI also created efficiency bulletins for high-cost, noncritical preventive maintenance reduction (NEI 2016a), and critical component reduction (NEI 2016b). The Electric Power Research Institute (EPRI) has also developed a report to describe methods and examples for applying online monitoring to reduce or eliminate various maintenance tasks (Kerr and Taylor 2018). A list of sensor cases used for each type of equipment and expanded discussion on maintenance automation can also be found in nuclear and non-nuclear industries as well (NASA 2008, Sullivan et al. 2010, EPRI 2018).

NPPs are aware of the main cost contributors. Common high-cost contributors to NPPs are often associated with sophisticated or complex equipment, and are harder to automate due to the safety and economic risks associated with modifications. Other high-cost contributors are dependent on plant-specific efficiencies or deficiencies due to equipment condition, manpower portfolio and skills, and processes and procedures. It is therefore not possible to design a comprehensive technology roadmap that fits every NPP. A specific and comprehensive technology roadmap should be created by each plant; however, it is possible to develop a generic path for the common processes and equipment that are used in NPPs. Some of the previous efforts provided an equipment-specific roadmap but none proposed a systematic approach to creating a technology roadmap for the nuclear industry. This effort describes an approach for the development of a comprehensive technology roadmap. The approach describes the migration sequence needed to automate an NPP process and/or equipment activities, but does not describe the specific sequence of processes or equipment to target. Each plant must individually decide which process or equipment would demonstrate the best value proposition and enable the plant to operate more competitively. For example, the steps required to migrate the inspection of a pump are plant independent. However, defining that the migration steps for a feed water pump to enable online monitoring should be performed before inspections of the feed water valves is dependent on the plant.

The technology roadmap to migrate plants from manual processes to data-driven online monitoring is a systematic guideline to prioritize resource utilization and the amount and/or type of data collected, while taking advantage of improved analytical and visualization techniques to extract better insights from the data. The flow chart in Figure 1 shows the main elements that must be addressed to enable migration to a data-driven approach. These main elements are:

- *Data collection*: Measurement-acquisition methods to automate the data-acquirement process in time and space.
- *Data analytics*: Whether using trending, statistical analysis, or intelligent methods, methods to analyze collected data and make informed decisions on plant performance or equipment condition.
- *Data visualization*: Human-factors methods to optimize the human perception of highly dimensional data to make a decision on plant performance or equipment condition and actions needed. Visualization methods are useful for activities where human-assisted decision-making is essential.
- *Data management*: Methods of data storage to preserve the acquired data, communication to transfer the data from the field to the various users of the plant, and computational power needed to analyze the data. This also targets development of methods for data integrations and knowledge sharing.
- *Value*: Methods to achieve high benefit and cost savings and low deployment cost without changing the risk on the plant.
- *Change management*: Methods to enable successful adoption of process and organizational changes. This includes ensuring regulation compliance, cybersecurity evaluations, resource availability (staff, training, spare parts, etc.), and supporting infrastructure availability; ensuring feasibility (power, fitness, environment tolerance, facilities); and enabling cultural change.

The elements are categorized into elements that have a sequential path of advancement towards the end state of online monitoring and those which provide support to the primary sequential elements. The sequential elements of the roadmap include data collection, analytics, visualization, and management. The two supporting elements are value analysis and change management. Data collection methods were analyzed on a process basis, while data analytics were analyzed on an equipment basis because automating an activity performed on one piece of equipment required considering multiple data sources. The visualization and data management elements are process or equipment independent. A guideline for the value and change enablement of migrating a process to an automated approach is presented.

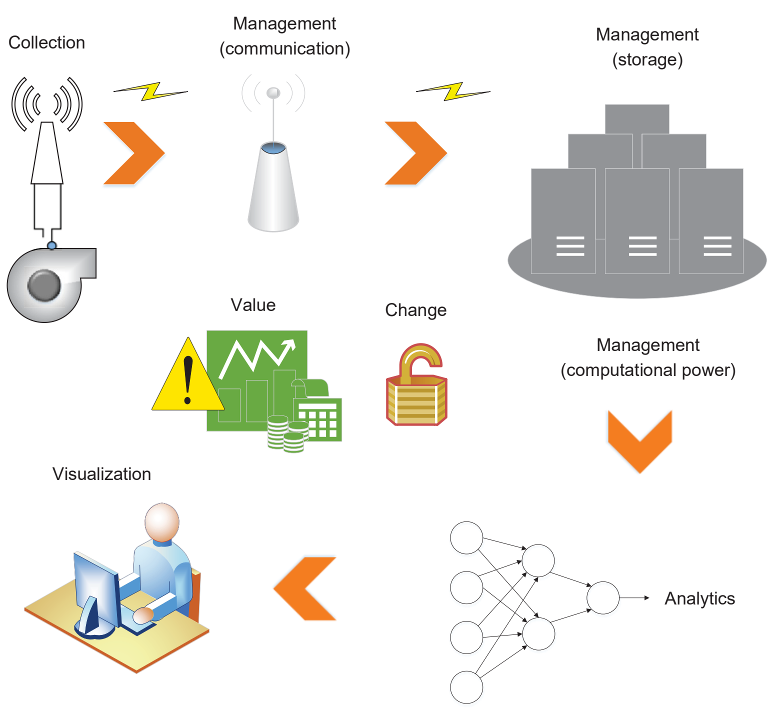

Figure 1. Main elements to enable data-driven online monitoring.

The approach used in this report followed the approach introduced by Al Rashdan and St. Germain 2018. Each O&M migration element must be considered independently and in the context of the overall process. Three states need to be defined for each element:

1. *Base state*: describes how the activity (in any of the defined four elements) is typically performed in NPPs today. This represents the least capable state within the spectrum of methods.
2. *Modern state:* Reflects a state achievable with currently available technology or recognized best practices currently in place at some NPPs or related industries.
3. *State of the art*: Represents a future state, using future technologies or emerging through research and development.

The plants should develop a strategy similar to Figure 2 for every process, equipment, and every element of the technology roadmap using the state definitions described later in this report. The definitions are time dependent because today's state of the art will likely be the modern state years from now. A plant developing a specific technology roadmap should:

1. Identify the category that the plant falls in (dashed curve at t_0) for each of the four sequential elements of the roadmap using the definition of this report.
2. Identify the states to be achieved after a period of time $t_0+\Delta t$ using the definition of this report.
3. Identify the value and change requirements to achieve the new state using the guidelines of this report.
4. Develop a plan to get to the new state based on the process or equipment using Items 1 through 3.
5. Develop a plan to get to the new state of multiple equipment. The plan will be plant specific and depend on the plans defined in Item 4 while considering the bigger picture of how each advancement benefits other advancements.

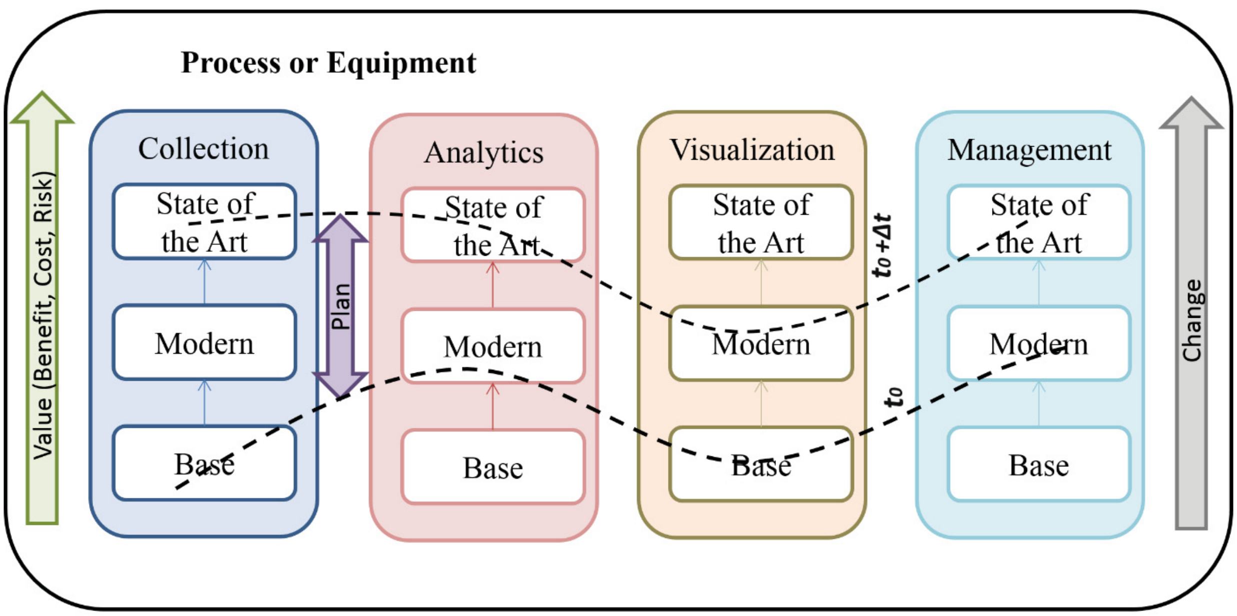

Figure 2. Process- or equipment-based strategy development.

2. DATA COLLECTION

The data at an NPP are typically available in dedicated paper or electronic data forms, but not necessarily easily available outside of their native use. There exists a potential for data collection automation and data fidelity improvement that can be realized by evolving current industry data collection methods. The information captured in this section are selected and summarized from an earlier dedicated study of data collection processes (Al Rashdan and St. Germain 2018). The fifteen identified data sources are:

1. Process instruments and control
2. Maintenance
3. Equipment performance testing
4. Calibration
5. Operator rounds
6. Radiation protection
7. Security
8. Condition reporting system
9. Work orders
10. System engineer’s notebook
11. Schedule
12. Logistics (procurement)
13. Clearance orders
14. Vendor and plant documentation
15. Industry operating experience.

Seven of the fifteen identified data sources are summarized in the following sections for illustration. For more details, refer to Al Rashdan and St. Germain 2018.

2.1 Process Instruments and Control

Process instruments and control (I&C) data include data that are logged into the plant computer and data that are available in the main control room, but not on the plant computer.

Base State

Most control rooms in United States (U.S.) NPPs currently use analog boards and analog instrumentation. Extensive amounts of information in an analog control room are manually logged. The logging includes switches, breakers, knobs, gauges, and chart recorders. Remote or field controls include levers, handles (for valves), switches, gauges, and breakers. Control room indicators are often manually logged, even though many of the indicators are recorded into the plant computer. Remote or field indicators that are not available in the control room are also manually logged by operators. The plant computer is connected through the input and output panels of a plant. It stores data for various plant systems and processes. This data collection process does not require manual activities aside from computer maintenance, and the only cost of this process arises from the cost of upgrading or maintaining the plant computer. The plant computer is primarily used for trending process data when needed. Almost all data coming into the plant computer are from analog devices.

Modern State

In the control room, evolution to distributed control systems (DCSs) replaces manual logging of indicators and controls with an electronic, integrated, historical-trending capability in addition to an alarm- and event-logging system. The role of the plant computer would be integrated into the plant DCS. Because plants will still rely, to various extents, on different systems to supervise or control specific parts of the plants, the plants might include system-specific controllers and recorders. For field I&C, retrofit devices can be attached to analog field indicators to digitize and process images of the gauge reading or to track actions by retrofitting a sensor to track movement of equipment. It is also possible to directly replace local analog instruments with wireless transmitters. If additional monitoring instruments are deemed necessary and cable infrastructure does not exist, wireless instruments may be used. The DCS should be able to connect and log wireless instruments.

State of the Art

A dedicated platform would integrate and analyze data from multiple sources described in this report. The platform could be part of a dedicated monitoring center that has responsibility for one or multiple plants. The plant would add environmental and indirect-measurement instruments to more typical process I&C to capture currently unacquired information, including visual, infrared (IR), acoustic, and electromagnetic spectra of the plant. In addition to these instruments, it is possible to augment the plant with assistive technologies, such as visual data acquisition technologies and image processing methods to automate logging of data and to track staff actions. The monitoring center would integrate this multisource and multi-spectrum data (visible spectrum, IR-thermal, acoustics including outside of human range, and electromagnetic field) with traditional process data for the monitoring center watch staff, as well as single-spectrum plant-wide monitoring for individual spectrum staff. Advanced machine learning (ML) tools will correlate these additional data with currently collected process data to predict or diagnose even more accurately system or component failures.

2.2 Maintenance

Maintenance includes both preventive and corrective maintenance. Preventive maintenance includes testing, adjustments, cleaning, lubrication, and replacement of parts. The data collected are mainly focused on the use of inspection instruments to collect data related to the performance of plant components. These instruments capture time- and space-dependent measurements of a certain physical phenomena to provide insight into equipment condition for diagnostic and prognostic purposes. Validation of equipment performance is often verified by conducting periodic test runs that include both the initiation of equipment and the performance of the equipment. These test runs produce data important for monitoring the long-term health of these components.

Base State

The base-state process relies on manually installing a sensor to capture data on a local device. These sensors or devices are periodically and temporarily installed on equipment of interest. The data are transferred manually to a subject-matter expert to evaluate the measurement with respect to equipment history and conditions. Any change of the inspection frequency requires an extensive review by a dedicated committee. Examples of inspection types of measurement include:

- Sensing vibration using accelerometers or piezoelectric sensors for pumps performance
- Thermography for abnormal heated spots
- Ultrasonic subsurface inspection
- Resistance for materials integrity
- Oil analysis for viscosity and impurities measurement

- Radiography for pipe thickness
- Visual inspections of cables and concrete
- Electric-current measurement of equipment (e.g., motor-circuit evaluation or batteries)
- Physical parameters such as valve clearance.

The above-performed measurements could require certain equipment conditions to be present. For example, a pump may need to be running to capture vibration information.

Modern State

Migration to a continuous measurement is the key aspect of the modern state. This implies refinement of processes to include detailed recording of sensor data covering more parameters and at a higher collection rate than current methods. Raw data are stored and fed into predictive models. To achieve this, fixed sensors would be installed and connected through a wired connection if cabling infrastructure exists, through wireless connection if wireless infrastructure exists, or enabled continuously to store data in onboard memory to be periodically transferred into an external storage medium. For the wireless or onboard memory scenarios, the sensor data could be downloaded, either manually or automatically, using technologies such as "Wi-Fi direct" to send data to passing personnel with Wi–Fi-enabled devices.

State of the Art

The state-of-the-art capability would replace individual sensors with a suite of sensors that provide multiple forms of measurement to enable high-confidence decision making. For example, instead of measuring pump vibration and using it independently as the decision-making data source, other sensors, such as temperature, acoustic, thermography, and electromagnetic measurements, can be combined to evaluate equipment performance. Future maintenance-activity sensors would couple equipment data with other equipment and process data to provide additional benefit from the existing sensor data in the plant. For example, the vibration of one pump might be due to a problem in an upstream or downstream process that is associated with another equipment item, such as a generator in proximity, and the only means to isolate the two causes is to use the holistic data view of the process and plant. Future maintenance measurements enable high-fidelity spatial coverage of equipment. For example, instead of sampling pipe-wall thickness at specific locations, researchers envision optimizing future sensor locations to provide a continuous measurement of wall thickness between the sensors. It is also possible to follow a proactive approach, to replace current equipment with equipment that provides both real-time condition monitoring and a complete picture of equipment health.

2.3 Operator Rounds

Data gathered from observant staff touring plant spaces also contributes to diagnosis and prognosis. Operator rounds for the main control-room staff are set to comply with certain surveillance requirements and create data that are required by the plant's operating license, but also potentially useful for trending and correlating with other operating data of equipment status. Whether accidently or intentionally observed, the human element acts as a mobile sensor in the plant. Predefined routes are established for equipment operator rounds, security rounds, fire-watch rounds, or health-physics monitoring. Ad hoc inspections by various plant staff cover nearly every physically accessible space in the power plant.

Base State

Operators log the information on a paper form or with electronic tools, and then transfer that information into a dedicated database that is used to demonstrate the plant is within compliance limits. The process is manual and requires operators to walk throughout the plant in order to capture the information. Some tours capture very little data other than to determine that no problems currently exist.

Modern State

All operator log entries are accomplished using wireless mobile tablets to capture surveillance observations and to access checklists and reference data. The information captured is supplemented by video and still-picture capture using the mobile tablet. This provides a visual context to the collected data points. These structured and unstructured data are then immediately available for additional analysis and parsing for critical operational data. Additional passive sensors such as thermal or radiation detectors could also be added to create additional data streams without increasing labor costs.

State of the Art

To eliminate the need for operator rounds, drones or moving robots would follow preconfigured or on-demand routes of movement such as stopping, sensing, and logging. Drones or robots would also monitor spaces that are not accessible to humans, such as areas with high radiation exposure or high temperatures during plant operations. The drones or robots would be equipped with multispectral continuous environment sensors along with application-specific sensors, such as air-chemical sensors for fire detection or gas- and liquid-leak detectors. They could also be equipped with props to conduct vibration measurements or sense surface temperature along with location-identification technologies such as GPS, Wi-Fi triangulation, radio-frequency identification (RFID), or beacons (Al Rashdan et al. 2017). Baseline profiles would be established for all equipment types for each of these spectra, with alerts established for out-of-limit alarms. The drones can be equipped with wireless communication modules or transfer their captured data when they return to the drone charging station. These drone inspections will require an additional layer of intelligence in order to optimize their inspection capability. For example, image processing may be needed in addition to IR-thermal sensors to detect fire during fire watches.

2.4 Radiation Protection

One unique data source in NPPs is radiation levels and contamination. Though currently used for regulatory compliance and safety purposes, radiation and contamination monitoring provides another source of data that could indicate plant performance or equipment condition. Radiation data are used to detect off-gassing or leakage and can be used to detect steam or water leakage, even at a level that is hardly detectable by the current approach.

Base State

Radiation data are collected by both fixed and mobile dosimeters and periodic, on-demand, manual contamination surveys. Mobile dosimeter data are acquired periodically and logged into a dedicated system that is primarily used by radiation control staff for compliance and safety verification. Contamination surveys are performed on a periodic and as-needed basis as well, and logged into dedicated databases.

Modern State

The mobile dosimeters are coupled with the plant wireless network or mobile devices carried by the staff to stream real-time radiation data into a central dedicated database. To enable the coupling of radiation with other plant-process data, the data will be timestamped, and the location will be logged (using the location-identification technologies described in the previous section). Contamination surveys are performed by wireless-enabled survey coupon analyzers or are manually logged into portable tools that log the survey results with a timestamp and transmit data in real-time through a wireless network or when in range of a wireless access point.

State of the Art

The plant would be entirely covered by fixed radiation dosimeters that feed into radiation-monitoring systems. Each fixed or mobile dosimeter would be identified with a location and would continuously stream the radiation data into a central tool that uses radiation data as another indicator for equipment issues.

To increase the collection frequency of contamination data, tasks conducted by radiation control staff could be augmented by drones or robots conducting inspection rounds and collecting contamination samples from predefined locations within the plant. As described earlier, drones can be equipped with wireless communication modules or can transfer their captured data when they return into the drone charging station. They can use coupons to collect the surveys or, alternately, be equipped with survey meters to determine and log the contamination level.

2.5 Condition Reporting System

Every plant maintains a robust corrective-action program, which provides a mechanism for any plant staff member to report a deficient condition. Each condition report is evaluated by dedicated staff and assigned to the appropriate organization for disposition. These data could be extremely valuable if available to an advanced data-integration system because they capture important events that can used for online monitoring.

Base State

Plants rely on a system to manually log a wide variety of notes from plant staff. These notes are analyzed by dedicated staff and filtered to determine whether further action is needed. In some cases, a data source triggers other actions in the plant. However, a significant portion of these data do not result in any action and are simply archived. The fundamental capability presented by human monitoring relies on sensing an anomaly by:

- Listening for local alarms, an increase of acoustic emission (AE) level, or changes in the tone of equipment audio emissions
- Making visual examinations for misalignment, deformation, or damage
- Smelling for abnormal overheating, burning materials, or abnormal chemical odor
- Touching to detect increased vibration, temperature, and/or mechanical resistance.

The current process does not systematically require a human to observe and log all of these observations. However, a human observation can be logged into an action system that initiates further investigation of the observed issues. The baseline used in this process is solely based on human experience and memory.

Modern State

Processes and tools are used to streamline all data logging into categorized data sets to be directly used in condition monitoring. To better use the data collected by the plant staff, action logging by the plant staff depends on plant staff to log an event or condition observed in preset conditions. The condition reporting relies significantly less on generic text to describe the issue. This ensures the data are in a form that can be directly coupled to plant data and, therefore, result in a useful data stream. Tagging, such as bar codes or RFID tags, could also be affixed to the item of interest in order to alert others that issues have already been detected.

To complement, improve, and log human observations, it is possible to consolidate human senses by equipping personnel with multisensor suits (e.g., visual and IR helmet cameras, haptic sensing gloves for thermal and vibration measurements, chemical sensors, dosimeters, and acoustics recording devices). The benefit of these sensors is not only higher accuracy and reduced reliance on the human, but also an ability to automatically log and store the data. This creates a new valuable data source and reduces the need for operators to manually log anomalies. The location of the measurements can be logged concurrently with the measurement data using location-identification technologies described earlier. For areas that require more-frequent rounds, a fixed wireless unit with a suite of the aforementioned sensors can be installed in optimal locations to eliminate the need for operator rounds.

State of the Art

All logged data are categorized and sorted. Text-mining methods can be used to convert generic text data into an actionable data source. In addition, the data collection process can be automated by enabling new technologies to automate condition reporting. For example, mobile tablets with visual recognition systems could match a picture of a piece of equipment with items in an image database to automatically identify the equipment item. Observations using the sensors described in the modern state could then be recorded. Equipment-relevant information would be presented to the operator immediately to help create the condition report as soon as an anomaly is observed or to provide information on current issues already logged for that item.

2.6 System Engineer's Notebook

System engineers at NPPs are decision makers on equipment condition and maintenance activity frequencies. They conduct inspections, review documentation, and capture measurements or information in dedicated notebooks. Unfortunately, these data are not often available for automated process evaluation and consolidation.

Base State

The system engineer manually logs the measurement into spreadsheets or notebooks, manually trends the data, and makes decisions on system conditions accordingly. The engineer uses vendor or custom-made tools and procedures to determine whether equipment is in satisfactory condition or needs replacement. No prognostic analysis is performed, and raw data are usually not available to other applications.

Modern State

Data captured by the system engineer's inspection tools include raw data, equipment identification, and time stamp. The tools transmit captured data remotely, or they may store the data and then allow them to be uploaded into a structured database on a server when the job is complete. The tools have screens to guide the system engineer on where to inspect and adaptively decide on the next point of inspection based on the data collected. Also, as part of the modern state, fixed sensors need to be installed and connected, as explained in Sections 2.1 and 2.2.

State of the Art

The system engineer's data acquisition process is replaced by a suite of sensors that enable continuous spatial measurements of the equipment in addition to environment sensors that provide additional insights that would not be captured by more typical sensors (as described in Section 2.2). Human decision making (human knowledge) is automated by creating a fully autonomous decision-making system that learns from the system engineer's decision-making process and replaces it.

The system-engineer function can also be performed using extended decision-support systems to incorporate engineer log data into virtual decision environments. A virtual-decision environment is enabled by a software platform that provides interactive modeling, "what-if" simulation, and advanced analysis/decision making using dynamic simulation and artificial intelligence (Bishop, Stock, and Williams 2009). It specifies prospective courses of action (COAs) for issues that require resolution by generating and evaluating the strengths and weaknesses of those COAs. What-if simulations are used to present possible outcomes using projected performance metrics to allow subject-matter experts to evaluate and choose a final COA.

2.7 Procurement

NPPs have a systematic approach to manage procurement, tracking, stocking, performance, and need for parts and materials. The management of these parts and tools can be correlated with the performance of equipment and are, therefore, an important source of data to improve the condition of the equipment. For example, spare-part stocking conditions can be correlated to a certain type of equipment failure. This type of data is currently not coupled to equipment condition.

Vendor information contains multiple forms of data that are directly relevant to equipment condition. Relevant information available in vendor documentation largely relates to failure-rate testing, calibration requirements, drawings and schematics, and procedures and manuals for maintenance and inspections.

Base State

The procured parts are logged into an enterprise asset management system database that is managed by warehouse workers and logistics staff. The procurement process is triggered by the planners or schedulers. The parts data are often comprehensive, but are not tracked after arrival or coupled with the work process data, except for cases where tools need to be calibrated or for expensive equipment.

The vendor and plant documents are manually read by the system engineer or planner to extract information such as steps in inspection procedures. Once extracted, these data are included in the system engineer's documents and used in the work-order development process. Sophisticated analyses are sometimes listed in the vendor documentation, but are normally not used.

Modern State

A comprehensive list of parts information must be created. Parts are tracked as they are used in the plant. Technologies such as bar codes and RFID are used to automate this process (Al Rashdan et al. 2017). The parts storage and transportation conditions, usage, events, and feedback are tracked. Parts removed from failed equipment are also logged to enable the development of patterns for high- and poor-quality parts. Vendor data related to equipment performance is also made available for comparison by equipment health-monitoring systems.

A data structure is defined for the key information that applies to the main type of plant equipment. This structure is used to store the most-relevant vendor and plant information. This enables the availability of a consistent level of data from all parts that can be utilized. For more-comprehensive documentation, paper documentation is digitized and indexed using optical character and shape recognition. This enables easier access to the documentation for data collection.

State of the Art

All parts information would be provided by suppliers in a unified electronic form that can be automatically logged into the enterprise asset management system with minimal human interaction. This should include the part's specifications, usage requirements, and limitations. In addition, image recognition methods are used to track parts used in the plant. The craft or warehouse staff would be required to take a picture of a part that does not have bar code or RFID tag as it is being checked out, checked in, or used. Visual parts patterns would be created to identify parts and categorize them. This would help automate the parts data-logging process and allow tracking part specifications with minimal human actions.

Documents would be automatically mined, indexed, and stored in a ready-for-use format. This applies methods similar to internet search engines. It uses textual-analysis methods to comprehend the text context and provide meaningful data for documentation use, when needed. For example, the mined data can be useful when certain vendor documents are missing information that is available in other vendor documents for similar equipment. The mined data can be used to compare vendor specifications and provide missing performance insight to improve decision making regarding equipment condition.

3. DATA ANALYTICS

With modern data acquisition systems and techniques, the amount of data available for decision making can be overwhelming and paralyzing. Effective interpretation of data leads to visions that plant operators can turn into decisions and actions that improve operations and maintenance activities without the need for an expert interpretation of data. Data analytics are the techniques used to facilitate effective data interpretation that enables detection, interpretation, and communication of valuable patterns in data. Data analytics should be at the center of the strategic maintenance decision-making process.

The diversity and quality of data collected provide a key element to data analytics. As a result, data analytics should integrate data from disparate sources. The choice of the data to use will depend upon the application. This implies that unlike the data collection process, which is defined on process bases, data-analytics needs are defined on equipment bases. The following sections will discuss some of the common equipment used in NPPs. The equipment discussed are those that have high cost-saving potential and are highly dependent on data analytics. The sections will discuss the potential applications for data analytics to specific equipment without the details of the methods. The data-analytics methods to be used for each type of equipment are being researched on a case-by-case basis and are not yet in a state to make a conclusion on the ideal methods to use. A summary of equipment-independent methods that can be used is described next.

3.1 Equipment Independent Methods

Base State

Regardless of the equipment targeted, the current approach is highly dependent on human decision making. System engineers combine decades of experience and manually resort to data across multiple systems used in the plant to visually compare the values acquired from an activity with a baseline that is manually created. If a deviation is observed, the system engineer investigates other plant systems to rule out that the deviation is due to another plant condition, or to determine if it is actually an anomaly.

Modern State

This state applies statistical methods to classify the measurement as normal or anomaly. In general, the distortion of the pattern's shape provides insight to the condition of the component being monitored. Statistics are used to determine whether the changes in the patterns are real or caused by plant noise and quantify uncertainty levels. Algorithms form the data-analytics process to automate decision making with operations knowledge as a key factor to understand the operational context of the data.

Instead of manual, human-based analysis, correlation and regression analysis are used to determine equipment condition. These can be based on signal shape and/or time of one or more data sources. Correlation and regression analysis are related in the sense that both deal with relationships among variables. The correlation coefficient is a measure of linear association between two variables. Values of the correlation coefficient are always between -1 and +1. A correlation coefficient of +1 indicates that two variables are perfectly related in a positive linear sense, a correlation coefficient of −1 indicates that two variables are perfectly related in a negative linear sense, and a correlation coefficient of 0 indicates there is no linear relationship between the two variables. The most popular forms of correlation analysis used include Pearson product-moment correlation, Spearman's rank correlation, and autocorrelation. The Pearson product-moment correlation is calculated by taking the ratio of a sample of the two variables to the product of the two standard deviations and illustrates the strength of linear relationships. In the Pearson product-moment correlation, the correlation coefficient is not robust due to the fact that strong linear relationships between the variables are not recognized. The correlation coefficient is sensitive to outlying points; therefore, the correlation coefficient is not resistant.

Spearman's rank correlation requires data to be sorted and the value to be assigned a specific rank, with 1 assigned as the lowest value. Moreover, in cases in which a data value appears more than once, equal values will be specified their average rank.

Autocorrelation (serial correlation) implies the correlation among the values of the same variables but at various times. Autocorrelation coefficient is calculated by changing lagged data with the formula for the Pearson product-moment correlation coefficient. Also, because a series of unshifted data will express perfect correlation, the function begins with the coefficient of 1.

State of the Art

Analytics depend on the concurrent application of mathematics, statistics, risk, algorithms, and operations research to quantify performance that transforms raw data into beneficial decisions. The patterns or clusters observed while the plant is operating under preset conditions define process states. The patterns are mathematically manipulated to highlight changes when they are detected. If enough historical data or accurate models exist, data analytics can predict the next state change when there is a change in the process or component. The key contributor of the state of the art is ML. ML algorithms provide dynamic mathematical means that can understand the present state and predict the next state with a degree of certainty. The term ML can be understood as a computer program that is executed on a machine to learn the interdependencies in the data and progressively improve the performance of the program, as additional data become available, to arrive at a decision. To learn and improve over time, the computer programs utilize mathematical models and theories from the fields of statistics.

The ML approach can be placed into three categories based on the decision: supervised learning (classification), unsupervised learning (clustering), and reinforcement learning. The decision and selection of the ML approach is application specific. In this section, a brief background on each category is provided. Prior to this, it is important to define some of the commonly used ML terminologies.

Input space refers to a representative input data or input feature (sample) that is part of the universal input space (population) and is used to learn interdependencies in the data or features. Input space could be a singular numerical value, a vector, or a matrix.

Training refers to a learning process wherein a certain portion of the input space is used to understand the interdependencies or functional relationship between the data or features to construct a training mathematical model.

Validation refers to an evaluation process where an independent portion of the input space is used to evaluate the performance of the trained mathematical model and perform optimal parameter selection to construct an optimal trained mathematical model.

Testing refers to an evaluation process of an optimal trained mathematical model on previously unseen input space. Here, the previously unseen input space could be an independent portion of existing input space or completely new input space (sample) drawn from same universal input space (population).

Output space refers to the expected outcomes of the optimal trained mathematical model during the testing process. Output space could be a singular numerical value, a vector, or a matrix.

Target refers to a known set of outcomes known *a priori* and could be a singular numerical value, a vector, or a matrix. It is well-defined in the case of supervised learning and undefined in the case of unsupervised learning.

Supervised learning is a category of the ML approach wherein the input space is paired with known target values during training, validation, and testing. This is the most common and practical category of the ML approach for solving practical problems. In most cases, the desired outcome is known for a given set of inputs. Even if the desired outcome is unknown, *a priori*, an estimate of the expected outcome can at least be obtained. The supervised learning approach is generally used to solve classification problems, but the approach is also applicable for regression analysis.

Unsupervised learning is a category of the ML approach wherein the input space is not paired with known target values during training, validation, and testing. The most common unsupervised learning approach is clustering; this is defined as finding a natural grouping that exists in the input space. To achieve this grouping, data descriptions are required. Statistics provides assistance, along with similarity measures, in identifying clusters. The most obvious similarity measure is the distance between samples in the input space. If distance is a good measure of similarity (or dissimilarity), then one would expect the distance between samples in the same group (cluster) to be less than the distance between samples in a different group (cluster). There are many distance-matrices developed, and their performance is application and data dependent. Some examples of similarity metrics are Minkowski metric, Tanimoto distance, minimum variance metric, Bhattacharya metric, and so on.

Reinforcement learning is a category of the ML approach where the inference between input space and output space is achieved from interaction to maximize the reward function. Reward function could be a metric to stop learning when prescribed reward level is achieved. In reinforcement learning, there is an intermediate agent that educates (or guides) the algorithm by providing clues as binary responses (for example, yes or no, right or wrong, up or down) to achieve the target outcome. As the learning algorithms adapt to the clues in moving in the right direction, the reward function starts to converge. Note, the agent never quantifies the extent (how much) that the learning output space is away from the target.

3.2 Rotating Machinery

Base State

Degradation of rotary machinery can comprise mechanical and electrical issues. The mechanical issues include imbalance, misalignment, and bearing problems in motors and driven equipment. Electrical issues include insulation breakdown, loose stator windings, rotor-slot problems, current or voltage imbalance, and harmonic distortion. Whether for pumps or turbines, manually or through system-engineering tools, analyzing vibrations and emissions coming from rotating machinery is performed by monitoring the frequency spectrum from the acquired data. The continuous nature of rotating machinery is ideal for Fourier analysis and other frequency-based techniques (Lee et al. 2013). In the base state, the vibration spectrum is passed to the system engineer to perform threshold-based evaluation of the equipment condition. The system engineer extracts through tools the vibration magnitude at the frequencies resulting in the highest oscillation magnitudes and compares these magnitudes to the historical baseline of the equipment or the vendor manual. If an abnormality is observed by the magnitude's deviating significantly from the historical behavior or vendor's specification, the system engineer explores the cause of this deviation by inspecting the maintenance logs of activities performed at the equipment to determine if this is due to some recent or planned work, investigates other vibration sensors adjacent to the equipment to isolate calibration issues, and attempts to manually correlate the measurements to other process parameters to determine the abnormality cause.

Modern State

The frequency spectrum obtained from Fourier analysis contains frequency signatures that correspond to specific mechanical components (e.g., a shaft or turbine) or malfunctions (e.g., shaft flexure or balance). By examining these frequencies and their harmonics, the sites, type of issues, and root causes can be determined. As an illustration, a large amplitude vibration at the frequency that matches the rotation rate can be due to residual imbalance and corrected by balancing the rotating component. A rolling-element bearing that is degrading has a different frequency signature. The wearing rolling-element bearing generates vibrational motion at specific frequencies, which increases in amplitude as the element wears. Effective instrumentation and analysis can detect wear and degradation months prior to failure. Age and run time of equipment are not significant indicators of pending failure as more than 80% of complex mechanical machinery break down irrespective of their life-cycle period (Kaboli and Oraee 2016). Frequency analysis is also beneficial on machines that have rolling-element bearings with failure modes related to wear. The resulting frequency signatures show increases in characteristic frequencies linked to bearing geometries and construction.

State of the Art

The addition of diagnostic measurements and algorithms to form distinct data clusters that identify discrete process states is the goal of data analytics. Additional data can be time-domain signatures, phase relationships between vibration components and the motor shaft (keyphasor), past trends of vibration amplitude, vibrational mode shapes, and other measurements, such as current and acoustics. It is important to realize that process measurements play a critical role in defining the state of the process. Thus, process measurements such as load, bearing temperatures, flow rates, valve positions and pressures are necessary to provide effective understanding of the current process state and determine an accurate diagnosis.

Model-based voltage and current systems (MBVIs) are examples of using process measurements for health monitoring. MBVI is a data-analytic method that uses the measurements available from the input current and voltage buses across all three phases simultaneously in motors. Model-based systems generate a model of the relationship between current and voltage while the motor is in operation. The model uses the measured voltage as input and generates a predicted current compared against the measured current. Differences between the measured current and the predicted current identify deficiencies in the motor and drive system. Analysis can use a variety of techniques to determine the state of health of the motor, such as Park's vector, to reduce three-phase currents into two orthogonal phases, and Fourier analysis to generate power spectral density graphs and algorithmic assessment of the processed spectrum to classify definite faults or failure modes. When both current and voltage are monitored, power is also monitored. Power identifies issues initiated by abnormal operating conditions and determines origins of lost efficiency. Because MBVIs are based on the relationship between voltage and current, they deal well with inverter-driven systems where the input voltage may be of a variable frequency and there may be a noisy waveform high in harmonic components. Model-based systems efficiently filter out noise and variable frequencies in the voltage signal from the subsequent current signal, which emphasizes primary degradations. This leaves a much simpler set of signals to analyze (ISO 2013).

3.3 Transformers

Base State

Power transformers undergo degradation over time due to the substantial workload placed on them by operator business interests and lack of capital for new electric-power infrastructure in a highly competitive market. Power utilities have been monitoring faults and degradation in power transformers using predictive maintenance techniques. Most of these methods characterize various material properties of the insulation subsystem such as insulation degradation compounds and physical or chemical parameters (Faria, Spir Costa, and Mejia Olivas 2015). Some of the standard characterization techniques currently in use are given below (Faria, Spir Costa, and Mejia Olivas 2015):

- Physical–chemical analysis: Characteristics of insulating oil, such as dielectric strength, moisture content, color, acidity, interfacial tension, are evaluated
- Furfural: Furfuraldehyde content dissolved in the oil is verified, with the aim of detecting the aging of insulating paper
- Particle analysis: Suspended particles in insulating oil are identified, compared, and classified according to size.

Gas analysis (GA) characterization technique is performed in the laboratory on oil samples that are manually collected from the operating transformer due to the complexity of the technique. Because of time and cost considerations, GA is generally performed infrequently or when indications warrant the effort.

Modern State

Of the different transformer characterization techniques, dissolved gas analysis (DGA) provides the superior diagnostic and prognostic information and, specifically, uses gas chromatography (GC) (Faria, Spir Costa, and Mejia Olivas 2015, Abu Bakar , Abu-Siada, and Islam 2014). A significant number of common failure modes such as corona, overheating, and arcing cause degradation in the insulation oil. By determining the relative concentrations of signature gases, the most threatening failure mode can be determined (Faria, Spir Costa, and Mejia Olivas 2015). Wireless-enabled real time DGA evaluation to perform the inspections of the base state would provide continuous insight that moves the inspection process from the threshold-based approach in the base state to a trending-based approach that can be coupled with other equipment and sensors to identify the transformer condition.

State of the Art

The use of other available sensor information to extend the testing interval will be a significant advancement. The key is finding the right features to extract from the data. The choice of the features to generate and use from existing data is dependent on the practitioner's expertise. Some methods that can be used to transition to online monitoring with diagnostic and prognostic capabilities can be found in Agarwal et al. 2013. The characterization data that support data analytics for power transformers are real-time data, such as vibrational, thermal (thermocouples), electromagnetic, AE, and some types of DGA, such as hydrogen online monitoring and photo-acoustic spectroscopy (Abu Bakar, Abu-Siada, and Islam 2014). Real-time DGA techniques do not supply strong diagnostic information as compared to the GC results. They provides an opportunity for data analytics to pull in more information from other sensors to support the real-time DGA measurements. Additional data from the standard characterization techniques list can supplement real-time DGA sensors to provide better diagnostic and prognostic information. Vibration sensors are attached to the transformer to measure vibration during operation. AEs, through a set of high-frequency acoustic sensors, can locate and triangulate pulses to identify and locate faults in transformers. Also, AE sensors can be used to extract the sharp transient acoustic pulse caused by arcing. The amplitude, rate, and total number of arcs can be determined. Electromagnetic emissions can also directly indicate these phenomena, in addition to providing indicators on the transformer condition. The corona phenomenon has a steadier "white" noise emission that will look more like background vibrations. The amplitude and frequency content can be measured. Thermographic images provide the status of connections and internal overheating detection by comparing the temperature of the hot spots, room temperature, and normal operating temperature. A temperature sensor can monitor overheating of the transformer, but must be combined with historical-performance records to be useful. All these mode failures will have distinct temperature signatures. These features obtained from the selected data types are then passed to the correlation analysis and ML processes, where the diagnostic and prognostic value of chosen data will be determined. The sensor selection and reduction process are repeated until a set of sensor features is found that provides significant value to the power plant.

3.4 Valves/Valve Assemblies

Base State

Monitoring the condition of valves, both manually and motor operated, is accomplished using physical visual observations by plant operators made during scheduled rounds, when plant operators manipulate valves for process control, and during valve disassembly following manufacturer's predictive-maintenance recommendations. Valve degradation is indicated by leaks, either external or internal. Valve degradation is also observed when there is difficulty manipulating a valve. The time between valve inspections varies due to valve function, type, location, and process or safety requirements. Complicating these observations, valves often have insulation or some other covering that cannot be removed that may lead to an incorrect assessment of valve condition.

Modern State

For motor-driven valves, the modern state is based on measuring the current and comparing it to a baseline from previous operations of the valve, in addition to the voltage profile, which implies looking at the power spectrum of the valve (Granjon 2011). The increase of current needed to operate a valve is an indication of valve-stem degradation. For both manual and motor-driven valves, thermography, using mobile or fixed cameras coupled with image processing methods is used to detect leaks. Mobile AE props are used too to inspect valves for leaks or detect an anomaly. AE detection is based on finding significant signals in unusual frequencies that could be associated with an internal or external issue. Radiography techniques (RT) are also performed sometimes to inspect the internals of the valve.

State of the Art

To compile a complete understanding of a plant's valve condition, a monitoring system should be implemented on valves. For the internal integrity of the valve, advancements in new miniature and energy-efficient sensor technologies will enable them to be packaged together to measure valve and other parameters in the immediate ecosystem surrounding the valve. In specific, the sensors that present high success potential to monitor valves are permeant acoustic detectors to capture valve failures. AE detectors are most efficient in capturing internal abnormalities (Lee et al. 2003). Signatures need to be developed for each type of failure that include leakage (internal or external), obturator broken or locked, valve plugged (with dirt or impurities over time), and valve internally corroded (see Greenstreet et al. 1985 for details on failure modes). AE (Gribok et al. 2016, He and Shen 2012) has also the potential to be a real-time monitor of chemical degradation. For example, the concept of predicting cavitation erosion via an AE technique has had several successful data-analysis techniques prototyped for the determination of cavitation erosion rate (He and Shen 2012). Real-time feedback will provide operators the ability to change process parameters to reduce the corrosion rate. The magnitude and frequency content of an AE signature can change in real time due to process changes. Additional sensor information will therefore be used for coupling data from the valve AE with the overall flow, temperature, pressure, and other process data. Applying methods to identify the main correlations (if any) will enable better classification of failure mode presence. Acoustic methods often require knowing the state of the valve, so valve-position indication devices should be retrofitted on valves that do not have limit switches or when a continuous range of valve opening measurements is desired.

Physical observations are labor intensive and costly, with no guarantee of detecting a degraded or failed valve, because many of these failures are internal. For the external integrity of the valve assembly, optical automated image processing inspections, coupled with thermal gradient detectors on valves, enables detection of external cracks and corrosion in addition to detecting leakage. Image processing methods such as change detection or object recognition (for cracks) can be used to detect the stem deviation from a norm or capture external valve anomalies that cannot be detected by the human eye.

3.5 Piping

Base State

The most common mode of failure in pipes is corrosion. The technical basis for the inspection period could be based on predictive analysis or operating experience. The current approach consists of applying different nondestructive examination (NDE) methods to different piping components. Components can be inspected for degradation using wearable, portable ultrasonic techniques (UTs), RTs, or visual observation. Both UT and RT methods can be used to determine whether or not wear is present. However, the UT method provides more-accurate data for measuring the wall thinning rates of large-bore piping. RT is commonly used for complex geometries and components with irregular surfaces, such as valves and flow nozzles. RT has the advantage of providing broad coverage with a visual indication of current metal loss. An additional advantage is the ability to perform RT without removing the pipe insulation when the plant is online and, in some cases, with reduced scaffolding needs. Although there may be advantages to applying radiography, it may have impacts on other outage and non-outage tasks due to radiological exposures. Nearly all utilities are using the manual UT method with electronic data loggers to perform most large-bore inspections. Visual observation is often used for initial examination of very large-diameter piping (e.g., cross under and cross over piping), followed by UT or RT examinations of areas where significant damage is observed or suspected. The results of all inspections are back fed into a predictive algorithm to produce an updated forecast. The current accuracy of some common tools is believed to be ±50%. Small-bore piping systems in boiling water reactors have been investigated using pulsed x-ray equipment that performs radiography. In addition to UT and RT methods, the surface examination technologies (e.g., magnetic particles, liquid penetrant, eddy currents), and a recently arrived AE testing are deployed to evaluate different piping components.

Modern State

Because of the significant length of piping systems, the problem of identifying specific piping components that need to be inspected during an outage remains a challenge. Traditional UT inspections are highly localized and can only detect flaws within proximity of the sensor location. Thus, many unnecessary inspections are performed, which adds to planned downtime and lost revenue. The well-established technology of ultrasonic guided waves (UGWs) offers new possibilities in the inspection of large portions of piping systems with few sensors. UGWs are mechanical waves that propagate at low frequencies—either sonically or ultrasonically through the walls of a pipe—and bounded and guided by those walls. The velocity and wave modes of guided waves are strongly influenced by the geometry of the guiding boundaries. In the pipe, the UGWs exist in three different wave modes—longitudinal, torsional, and flexural. Because the guided waves are mechanical waves, they are generated either through piezoelectric or magnetostrictive transducers that convert electrical magnetic fields into mechanical energy. Once the mechanical wave is generated with a set of piezoelectric or magnetostrictive sensors arranged in a collar around the pipe, it is transmitted through the walls of the pipe and reflected from any discontinuities (i.e., flaws) of the surface of the wall. In contrast to conventional UT inspections, the UGW technology can cover tens of meters in one inspection session.

Provided the UGW technology can overcome the limitations of complex geometries, it is a perfect tool for determining where to inspect. At present, guided-wave acoustic sensors have been shown to be effective to monitor straight pipes; however, the guided-wave approach is inadequate to monitor other pipe components, such as a large variety of pipe components—joints, T-, L-, and U-bends, regulating valves, etc. For pipe structures with complex shapes, multiple hardware factors (e.g., locations of sensors, number of sensors) and human factors (how sensors are mounted) all have significant influence on measurement outcomes. Further, due to the complex shape of pipe components, corrosion-induced defects often generate complex acoustic and thermal signatures that cannot be easily delineated or diagnosed by conventional pattern classification.

State of the Art

To be competitive, a technology in the nuclear industry needs to overcome several shortcomings, such as low sensitivity to minor degradation, dependence on geometry, and a low signal-to-noise ratio in a heavily degraded environment. Despite many benefits, UGW technology is challenged when applied to power plants in general and NPPs in particular. Piping systems in electric power plants come in various configurations and geometries; for example, they have thousands of elbows, bends, tees, valves, nozzles, and flanges. Full circumference inspection systems in nuclear reactors are being developed for power plants (Gribok and Agarwal 2018, Puchot 2013). Other secondary components, such as heat exchanger shells, have welds, nozzles, and piping components attached to them. These geometries are not friendly media for UGWs. Geometries other than straight pipe attenuate and distort UGWs, making inspections beyond them difficult. Also, while being a perfect tool for locating the damage in pipes, UGWs cannot determine the size of the flaw with acceptable accuracy. Because corrosion and crack growth can take a substantial amount of time to modify signals, ultrasonic monitoring is, in general, poorly suited for real-time monitoring and providing the basis for corrective actions.

For an online piping-monitoring system to be effective and cost efficient, it should be able to cover different piping geometries besides straight piping. Thus, UGW systems need to be augmented with other sensor modalities such as high-spatial-resolution fiber sensors as tools capable of handling complex piping configurations and improved pattern recognition for corrosion-induced defect identification. Through high-spatial-resolution data gathering using distributed fiber sensors (acoustic, temperature, and strain), vibration sensors, and thermography coupled with ML, it is possible to significantly improve cost effectiveness and measurement efficacy for multimodal sensing systems for pipeline monitoring. Knowledge gained through the ML process will be used by computers to classify and identify subtle signal patterns produced by defects in term of temperature and strain profiles and acoustic signatures. The successful rate of defect recognition through ML and sensors will be correlated to the locations, mounting approach, and minimal number of sensors needed for successful detection. This will allow engineers to determine the best location, installation practices, and number of sensors needed for corrosion detection. New ML techniques will also enable more effective ultrasonic characterization in the future.

3.6 Batteries

Base State

The base approach used to inspect batteries is manual for aqueous systems such as lead-acid or nickel-cadmium batteries.. Discharging current, voltage, resistance, and/or temperature are logged for basic monitoring. A low voltage indicates the battery is losing its charge while a large voltage indicates that it will discharge faster than planned. A high temperature decreases battery life while a low temperature decreases battery capacity. The associated ampere-hours or specific gravity can be used to determine battery capacity. The type of activities performed in an NPP varies depending on the battery. Whether for vented lead-acid batteries, vented nickel-cadmium batteries, or valve-regulated lead-acid batteries, the type of activities can be summarized as a simple or detailed visual inspection (for obvious signs of electrolyte leakage or cell damage), float voltage checks, electrolyte checks, battery-ground checks, connection or internal-resistance measurements, battery rack integrity inspection, or a comprehensive performance test. Details about the types of measurements acquired and why they are needed can be found in Johnson 2002.

Modern State

Battery condition monitoring is performing by battery management systems (BMSs). A BMS is primarily responsible for battery safety and reliability by monitoring the charge and discharge cycles and evaluating individual battery cells on several metrics. The key objectives of a BMS are to:

- Protect the battery backup power (BBP) systems from damage caused by electrical shocks and fluctuations
- Provide adequate control of the performance of the BBP system when needed
- Maintain the battery system in an accurate and reliable state of functionality
- Diagnose and indicate any abnormalities in the performance of the entire system or a particular cell.

A number of state-of-the-art BMSs are available commercially. These systems may be adapted for NPP operation using data-driven monitoring. In general, these systems monitor key parameters in the batteries, such as terminal voltage, temperature, internal resistance, and current or capacity, depending on the chemistry and design, to enable estimations of the state of the battery system and to assess the system's readiness for services. More advanced systems can use current, ambient room temperature, humidity, and hydrogen gas and electrolyte levels to actively manage batteries to increase reliability and extend life. These systems advance beyond detecting the crossing of a set threshold into predictive models that can anticipate battery performance. Advanced systems can be installed on new or old batteries, and the modular design allows the system to fit applications of any size and configuration, including monitoring many separate battery systems simultaneously.

Besides the state function of the battery systems that needs to be monitored, there are other hazards that could impact the performance and reliability of the systems. For example, the physical or mechanical integrity of the system, including interior and containment of the system, also needs to be monitored for reliability and safety concerns. Degradation due to corrosion, chemical reactions, and other environmental stresses could cause system deteriorations that might not be easily detectable during standby. These detections might include gas and pressure monitoring, physical inspection of leakage, bulging, deformation of the physical shape of the systems, etc. Some of these effects may be passive or incubated during standby, but they will become hazards or failures upon engaging in active operation.

State of the Art

As we transition from aqueous systems to more advanced lithium-ion batteries, more active detection, diagnostics and prognostics during standby and operation are also necessary to estimate time to failure, maintenance requirements and schedule, and need to implement preventive protocols to ensure reliable function at events. One example is lithium plating in lithium-ion batteries (LIB). As LIBs are becoming more favorable for BBP applications, due to cost benefits and reliability, than conventional aqueous systems, new safety hazards and failure modes and effects need to be understood and managed. A BMS in these LIB systems is more complicated in function and service than those in the lead-acid or Ni-Cd. New, more sophisticated advanced battery diagnostics and prognostics approaches are being developed (Wood et al. 2018, Tanim et al. 2018).

One of the most critical battery control and monitoring parameters is the state of charge (SOC) of the battery. Correct estimation of the SOC has become crucial for BMSs (Mastali et al. 2013). Disregarding the complexity in the energy balance in the determination of battery state functions, the empirical Ah-counting method to obtain SOC remains a practical solution used by a majority within the battery technology industry (Lu et al. 2013). Nonetheless, some critical issues associated with Ah-counting remain unsolved (Li et al. 2017). The problems of the Ah-counting method include:

- Uncertainty and inherent errors in the determination of the initial SOC
- Accumulative errors over a long period of time due to the imprecision introduced by the time counters and current-measuring transducers, as well as the coulombic efficiency
- The use of rated capacity Q_{rated} as the denominator in the SOC calculation, since Q_{rated} is determined more or less arbitrarily by test protocol and procedure used by the cell manufacturers or device original-equipment manufacturers
- Systematic errors introduced by the tests (Li et al. 2017).

Steady progress has been made in regression methods to provide more precise estimates of the SOC in the past three decades. Suitable battery models and regression techniques can be used as a powerful approach to achieve viable results in SOC determination and, therefore, more accurate battery monitoring. To date, a significant level of effort has been engaged on building accurate models. These efforts include those using various types of multi-physics framework to couple principal system properties, such as those governed by electrochemical and thermal processes—utilizing simplified mechanism descriptions, dimensional reduction, and efficient parameter identification—and engaging sufficient validation of model precision and accuracy. A typical exercise in most regression methods from modern control theory includes those using least square (Wu et al. 2011; Hu et al. 2011; Li et al. 2012; Zhu et al. 2013) filters (Plett 2004; Sun et al. 2011; Sepasi et al. 2014; Sepasi et al. 2015), estimators (Kalawoun et al. 2015), artificial neural network (Urbina et al. 2002; Jungst et al. 2003; Li et al. 2007; Shen 2007; Xu et al. 2012; Cheng et al. 2008), genetic algorithms (Luo et al. 2009; Ting et al. 2014), and so on. These exercises demonstrate improved precision. By and large, without any adequate validation with SOC values determined separately from reliable empirical techniques such as open-circuit voltage measured after equilibrium establishment, the accuracy remains undetermined. This is an important aspect that future modeling work should strive to understand and address properly.

Self-discharge is another issue that continues to undermine battery monitoring accuracy. For instance, disperse self-discharge among cells could cause serious constraints on battery performance. To measure self-discharge accurately is challenging. Recently, an expeditious self-discharge measurement method has been developed (Sazhin et al. 2016, Sazhin et al. 2017, Sazhin et al.2018) branded as Battery Health Sentry. It offers the ability to quickly detect elevated self-discharge, not just in single cells, but also with more complicated topologies consisting of several parallel strings. Once properly validated, these new techniques could greatly enhance the reliability and safety aspects of the battery system.

3.7 Instruments and Control

Base State

The majority of NPPs rely on analog instrumentation and control to various extents. As described earlier, these systems present a valuable source of data. In terms of data analytics, the main activities that are performed as part of these systems and can be automated by data analytics involve calibration of instruments by maintenance. In terms of control, functionality tests of equipment are performed by operations, and I&C breakers are tested through continuity tests by maintenance. Process tuning by adjusting proportional, integrator, and differentiator controllers are sometimes performed by operators. These processes are based on specific equipment response behavior and operator experience.

Modern State

Smart instruments exist in other industries and have eliminated the need for several calibration activities that are a core part of the NPP operations. These instruments have self-regulating capabilities and can detect when a drift of measurement occurs. They are also enabled with digital communication modules (e.g., field bus or HART) and microcontrollers that can be tuned, thereby enabling remote calibration of instruments when needed. Smart instruments perform needed data analytics to determine their condition and recommend the best form of action using digital error codes. However, for analog instrumentation, and once the data collection process is automated by means explained in Section 2 of this report, the amount of data present enables the use of statistical methods to determine deviations of an instrument from the norm at various time scales. For example, instruments with higher-than-normal and unexplained variation can be an indication of a loose component, while instruments with low variation are an indication of degrading sensor sensitivity. Wiring and connector panels can be inspected using thermography for an apparent visual anomaly. For controls, the functionality evaluation process by testing relays or state switching can be replaced by commercially available self-monitoring relays that have additional self-sensing capabilities.

State of the Art

In addition to the self-regulating capability of the instrument, calibration is performed by comparing the measurement from one instrument with broader process parameters to evaluate the instrument condition. ML methods to define dynamic-correlation methods can be used to ensure that, as the process state changes, the correlations are identified, and deviations are classified as an anomaly that could be due to a process or an instrument issue. The tuning process of controllers is replaced by autonomous control methods that optimizes the equipment performance based on historical data.

3.8 Heat Exchangers

Base State

Inspections of a heat exchanger, such as steam generator or condenser, are similar to pipes in terms of their monitoring activities. While pipes leak to the environment, heat exchangers can leak from one side of the process to another (high-pressure to low-pressure side) or to the surrounding environment. Both failure modes occur mainly due to mechanical precursors in the form of wear, fatigue or impingement, or corrosion in the form of pitting, flow-accelerated corrosion, and stress corrosion cracking. A detailed description of the types of steam generator failure can be found in EPRI 1994.

The external inspection of a heat exchanger is performed using different methods. Visual inspections capture leakage and surface degradation of the equipment or structure and are performed as an in-service inspection (ISI). However, advancements resulted in ultrasound's replacing visual inspections because it can be used to detect damage that cannot be seen by identifying acoustic signatures. This can be used for fittings or welds of the heat exchanger. It enables pinpointing the location of the issue.

Traditionally, borescopes were used to inspect the internal integrity of the heat exchanger tubes while the heat exchanger was out of service. Ultrasonic methods have replaced borescopes because of their ability to detect leaks that are visually undetectable. When the heat exchanger is offline, pressure can be applied to one side of the heat exchanger using a testing gas. The flow of the testing gas (i.e., helium) in the other side can be detected by using ultrasonic or ultrasound probe or gas sampling. In addition to leakage, acoustic methods can detect thinning tubes because they generate a different acoustic signature than a normal tube. The same approach can be used to inspect the casing of the heat exchanger tubes.

Eddy current (mainly using bobbin coil) is the most common inspection approach used to detect cracks, erosion, and corrosion of the heat exchanger tubes. It is considered faster and more reliable than the ultrasonic approach described above (Stanic 1996). The use of a rotating probe, an array of probes, or a plus-point probe can improve inspection accuracy and detect circumferential cracks that are not easily detected by the bobbin coil. Other methods that are used to various extent in the nuclear power industry, such as magnetic-particle and radiographic testing, can be found in Sollier 2017.

Modern State

The modern state would use sensors or cameras to replace visual shell ISIs. In some cases, radiation detectors can note the transfer of contamination from the primary to the secondary side of the heat exchanger. The offline inspection is performed by new means of analyzing the probe's data by enabling multiple-frequency inspection and automated calibration algorithms to streamline the inspection process. This improves the measurement interpretation in terms of the measurement, the damage location, its depth, shape, and nature. The data analysis also facilitates easier comparison of historical or adjacent captured baselines and more informed decision making. Examples of the use of probabilistic models or Monte Carlo methods to quantify the process uncertainties by modeling can be found in IAEA 2007. Analysis methods have also advanced to using intelligent methods of failure diagnosis by using methods such as fuzzy logic and ML. These methods require a centralized approach to data analysis, rather than the probe-based method. Examples of the methods can be found in Upadhyaya et al. 2005.

Due to the large number of instruments, the approach of inspection can move from on-the-spot measurement and decision making by a human to a robot's acquiring the data and transferring it to a centralized location for data analysis and baseline establishment. Examples of the technologies developed mainly for steam generators in the nuclear power industry can be found in Obrutsky et al. 2009.

UGWs were successfully applied to monitor corrosion degradation in low-pressure feedwater heaters (Puchot 2013). The UGW sensors were permanently installed on the heater shell and correlated well with ultrasonic thickness-measurement data which served as ground truth measurements. However, the UGW system, while being able to locate corrosion activity in a heat exchanger shell, was unable to estimate the magnitude of corrosion activity.

State of the Art

The state of the art for inspecting heat exchangers is envisioned by enabling ISIs that do not rely on the human elements. High sensitivity acoustic and vibration probes are used in an array set up to develop a spectrum surrounding the heat exchanger that enables the detection of extremely low deviations of the acoustics or vibration signature. The data collected from the sensors are analyzed using correlation methods to isolate noise contributors from actual flow acoustics. For offline inspections, methods such as laser scanning can assist in reconstructing the inspected surfaces to provide a visual profile of the inspected tube after an eddy-current inspection has identified a region of interest. This reduces the uncertainty of the inspected surface.

All inspections are performed by robots, with a programmed routine, that perform the inspection and analyze the data collected by ML classification methods that contain a profile of both intact and failed components. The ML classifies encountered conditions into bins of various states of failure, based on an existing training set, and decides to perform additional inspections using the same or a different inspection method to confirm or reject the state identified. For example, fouling can be detected by analyzing the heat exchangers performance data using ML methods (Radhakrishnan et al. 2007). The methods to fuse measurements and aggregate their insight to introduce confidence in the identified state need to be developed.

3.9 Cables

Base State

Cable failures, although rare, are serious events that need to be prevented, and are therefore subject to regulation by the Nuclear Regulatory Commission (NRC 2010a, NRC 2013). An aging cable management program is currently used. It includes a database of cables chosen for testing and trending by the appropriate cable characterization technique based on accessibility, risk, and environment. The active concern of the aging cable management program is the ability of the cables to withstand extreme stresses, such as in a design-basis event that may not be covered under typical system tests as per Regulatory Guide 1.128 (NRC 2012). As the cable deteriorates, several alterations in properties occur within the cable insulation as a consequence of thermal and radiation damage. Key indicators (Glass et al. 2015) include changes in chemical, physical, mechanical, and electrical properties that can be characterized.

At present, the gold standard for determining cable insulation deterioration is either visual or through the elongation-at-break (EAB) (Glass et al. 2015, Ramuhalli et al. 2015) measurement, which is a measurement of cable elasticity. EAB is an *ex situ* measurement that entails removing a sample of cable insulation for testing in the laboratory. EAB quantifies mechanical toughness of the insulation that is closely related to the critical damage mechanisms in a design-basis event. The removal of an insulation sample from the cable and testing it in the laboratory does not make for a practical plant-characterization technique.

Effective guidelines are in place and evolving that rely on sampling and screening cables. The selection of cables to be tested are evaluated on accessibility, risk, history, and other factors. Structured programs for aging cable management are in use throughout the NPP industry. Glass et al. 2015,Villaran and Lofaro 2009 have developed an explicit nine-step aging management program, NUREG/CR-7000, for condition-based qualification of cables. The data collected from this program is strategic, broad, categorized, and accessible, which makes for effective use in data analytics. Cables to be monitored are specifically selected to provide pertinent data and then stored in databases.

Knowing the cable environment helps to identify potential stressors and aging mechanisms affecting cable lifetime. It is intuitive to believe that the longer the cable has been in service, the higher the probability that the cable should be replaced. The same goes for cables experiencing high temperatures and stress for prolonged periods. To be effective, the environment that the cable lives in needs to be accounted for in the condition-monitoring (CM) assessment. Depending on the qualitative inputs, the CM assessments may be substantially different for similar characterization signatures.

Based on the likely cable stressors and aging mechanisms, cable testing and CM inspection techniques are selected. The cable assessment will start from the condition that the cable is in at the start of a CM inspection. Degradation will be tracked from the initial existing state forward. The interval at which the CM inspections take place will depend on the cable being monitored, and its environment and application. The CM interval are based on periodic schedule. The CM data are reviewed against cable-related operating experience to note trends and address applicable issues that are discovered. Adjustments are made at this time to the CM inspections, as necessary. The last step combines the data collected from the previous steps and determines the overall quality of the information, trends, and prognostic assessments of cable condition, expected service life, and program changes and activities to effectively manage aging.

Modern State

Characterization approaches are categorized into two classes: bulk electrical tests, and local tests (Glass et al. 2015). Bulk electrical tests consist of time-domain reflectometry, tan δ, frequency-domain reflectometry, and additional tests that can be operated *in situ* from cable terminations within NPPs. Most of these electrical techniques generate data regarding the position of the damaged sections of cable, along with an assessment of the cable's overall state of health. Fourier transform IR spectroscopy, indenter, dynamic mechanical analysis, and capacitance probes assess the jacket and insulation conditions at the tested location. Localized testing can only serve as a stand-alone characterization and evaluation of cable condition when the test site is clearly the most vulnerable to damage. In general, bulk electrical tests are the more practical industrial techniques.

Table 1 and Table 2, from Glass et al. 2015, list a few techniques to characterize cable insulation and go into detail about the different characterization techniques. Table 1 lists the bulk-characterization techniques. Table 2 lists the local characterization techniques. Although bulk-characterization techniques are preferred, the data obtained from local methods can be used to help access the condition of the cables. Because the data from these measurement techniques cover the four key indicators of cable condition, the normal data-processing methods will be quite broad and sensor dependent.

State of the Art

The data pool in the aging cable management program contains quantitative and qualitative data. The quantitative data come from instrumentation, and the qualitative data can come from process and operation logs. Qualitative data can be salient to the CM assessment, but is often underutilized because it is difficult to incorporate. To help lower the uncertainty in the interpretation derived from the quantitative data, qualitative data or experience can be used. The goal of advanced data-analytic techniques such as ML is to incorporate qualitative (experience) information in a rigorous manner with quantitative data that brings consistency and predictability to interpretation from the totality of available information.

A successful NDE technique will effectively and accurately characterize one or more key indicators for cable aging: chemical, physical, mechanical, or electrical. Although it is preferable to perform bulk assessment in situ with limited disruption of plant operation, local testing can still provide valuable information. The characterization data can then be integrated with the plant process and operation data to be input into developing models and ML algorithms to accurately predict remaining useful life (RUL) of aging cables. In situ NDE techniques will need to be correlated with the EAB technique to accurately assess cable condition. Correlation of NDE techniques to EAB measurement and other characterization techniques, including observations, will be enabled by data analytics including ML.

Table 1. Common bulk electric-cable characterization techniques from Glass et al. 2015.

Inspection Method	Advantage	Disadvantage
Time-Domain Reflectometry	Commonly used for determining the condition of instrumentation, control, and power cable conductors where full-length cables are relatively inaccessible. Test uses low voltages and is completely nondestructive.	Intrusive—requires disconnecting at least one end of the cable perform the test. Only tests conductor. Not sensitive to insulation damage.
Frequency Domain Reflectometry	Low voltage, tests full cable including insulation, can identify flaw location.	Intrusive—requires disconnect. Works best for shielded cables. High noise on unshielded cables. Data interpretation challenging.
Partial Discharge	Stepped high-voltage test that identifies cable weakness up to the point of insulation breakdown.	May damage weak or compromised cable and potentially can cause noise and damage near-by circuits. Also does not specify discharge location.
Insulation Resistance (low voltage)	Commonly performed in industry to determine the condition of the cable insulation, primarily as a screening for other tests.	Inconsistent readings weaken broad acceptance of this test.
Inductance/Capacitance/ Resistance	Good for detecting changes in electrical circuit (cable and termination) by trending changes in inductance, capacitance, and resistance.	Currently intrusive—requires disconnecting cable at one end. Does not indicate location or cause of change in measurement.
Tan Delta (tan δ)	Determines changes in insulation (dielectric) properties by measuring change in dielectric loss angle. Can measure aging effects over entire cable length.	Intrusive—requires decoupling both ends. Only suitable for shielded cable and no information regarding degradation location of aged or damaged segment. Loss angle may be trended; however, single measurement insufficient to estimate remaining life.

Table 2. Common local cable inspection techniques from Glass et al. 2015.

Method	Advantage	Disadvantage
IR spectroscopy	Sensitive to chemical changes on the jacket and outer surface.	May over-predict jacket or surface damage, not indicative of full volume condition. Also sensitive to surface condition.
Visual walk-downs	Simple and low cost.	Not quantitative.
Elongation at break	Strongest direct indication of aging damage.	Not really a nondestructive technique.
Indenter	Simple test that is broadly accepted.	Does not work well for harder cables like XLPE.
Dynamic mechanical analysis	Promising and potential for broader application than indenter.	Although it could be adapted to in-situ test, currently a laboratory approach.
Interdigital capacitance	Promising and seems to have broad application.	Not fully commercial.
Ultrasound velocity	Works well for some materials, particularly jacket materials.	Not easily adapted to *in situ* field measurement and does not work well for some materials.
Imbedded micro sensor	Could be an easy test as a leading indicator of damage.	Too late to retroactively install in existing cable systems.

3.10 Reinforced Concrete Structures

Base State

Concrete structures are present in all NPPs and are grouped into four categories: primary containments; containment internal structures; secondary containments/reactor buildings; and other structures, such as spent-fuel pools and cooling towers (Naus 2007). The current aging management plan for passive structures includes the following steps: check, act, plan, and do. Under the check step, inspection, monitoring, and assessment activities are performed. In the act step, maintenance activities are performed. In the plan step, efforts to improve effectiveness of aging management programs are evaluated. Finally, in the do step, the process is improved based on the findings of the previous steps.

The reinforced concrete in NPPs undergoes degradation due to physical, chemical, and mechanical conditions, and under irradiation with an increase in temperature. Physical degradation includes thermal expansion and contraction, moisture shrinkage and expansion, and freeze-thaw cycles. Mechanical contraction or expansion, produced due to moisture transport, sustained or cyclic loading, pressure variations, and tensile stresses lead to the following types of degradation: shrinkage, creep, fracture, and internal-swelling reaction. The chemical reactions between the environment and cement paste or coarse aggregate typically occur at concrete surfaces and between cracks. The effect of chemical reactions could lead to the following types of degradation: chloride penetration, carbonation, corrosion of reinforcing steel, leaching, acid attack, and alkali-silica reaction. All of these sources of degradation can alter the porosity and permeability of concrete, cause or aggravate various material flaws (such as scaling and spalling, swelling and debonding, cracking and disintegration), impair the integrity and tightness of concrete structure, and lower the loading capacity of structural members.

The most common means of assessing reinforced concrete state of the health is periodic visual inspection of the surface of the concrete structures: marking crack development, measuring crack length and other dimensions, and collecting any samples for potential chemical analysis. In addition to visual inspection, NDE techniques utilize several UTs to assess different degradation states of the reinforced concrete. However, the current visual and inspection approach is only able to assess the extent of degradation after the damage is well established. The current approach is not scalable to identify the impact of multimodal degradation. There is large uncertainty associated with the measurement and analysis of UTs because there is no unified approach to combine different sources of uncertainty. More importantly, the NDE technique is impacted by human-factors errors, and fitness of service is unreliable.

Modern State

A reinforced-concrete structure undergoing different degradation mechanisms would benefit from the concrete structural-health monitoring (SHM) framework developed under the LWRS Program. The concrete SHM framework will investigate concrete structural degradation by integrating the following four technical elements: monitoring, data analytics, uncertainty quantification, and prognosis or damage modeling (Figure 3). For details on each element of the proposed framework, refer to Mahadevan et al. 2014. The framework will enable plant operators to make risk-informed decisions on structural integrity, RUL, and performance of the concrete structure.

The modern state approaches the concrete aging management from four perspectives: modeling, monitoring, data analytics, uncertainty quantification, and prognosis. The model element leverages the modeling of chemical, physical, and mechanical degradation mechanisms (such as alkali-aggregate reaction, chloride penetration, sulfate attack, carbonation, freeze-thaw cycles, shrinkage, and radiation damage) in order to assist monitoring and risk-management decisions. Alkali-aggregate reaction is currently receiving prominent attention; however, other appropriate damage mechanisms for NPP concrete structures can also be included. The interactions of multiple mechanisms need significant consideration. The task requires modeling and computational advances and combined-physics experiments and the integration of multiple models through an appropriate simulation framework.

The monitoring element explores an effective combination of promising SHM techniques for full-field multiphysics monitoring of concrete structures. Optical, thermal, acoustic, and radiation-based techniques are being investigated for full-field imaging. Examples of these techniques include digital-image correlation, IR imaging, velocimetry, ultrasonic, and x-ray tomography. A particular consideration is the linkage of chemical degradation mechanisms to observed degradation, which requires synergy between monitoring and prognosis. The data analytics information gathered from multiple health-monitoring techniques results in a high volume, rate, and variety (i.e., heterogeneity) of data. This element leverages big-data techniques to store, process, and analyze heterogeneous data (i.e., numerical, text, and image) and arrive at effective inference of concrete degradation. The data-analytics framework can also integrate information from model prediction, laboratory experiments, plant experience and inspections, and expert opinion. Data mining, classification and clustering, feature extraction and selection, and fault-signature analyses with heterogeneous data can be orchestrated through a Bayesian network for effective inference.

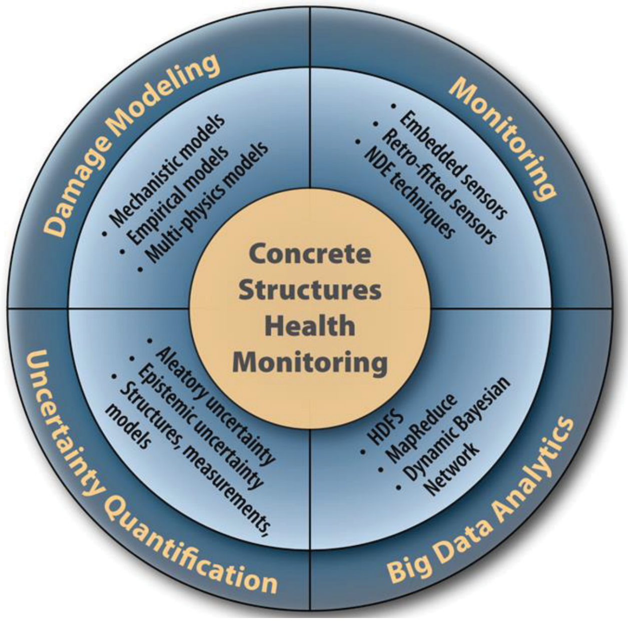

Figure 3. Elements of concrete structural health monitoring from Mahadevan et al. 2014.

Uncertainty quantifications in health diagnosis and prognosis is performed in a manner that facilitates risk-management decisions. Sources of natural variability, data uncertainty, and model uncertainty arising in both modeling and monitoring activities can be considered and their effects, quantified. In addition to measurement and processing errors, data uncertainty due to sparse and imprecise data for some quantities and due to large data on other quantities (i.e., data quality, relevance, and scrubbing) can be considered. Model uncertainty in multiphysics degradation modeling due to model-form assumptions, unknown model parameters, and solution-approximation errors can be included. Various uncertainty sources do not combine in a simple manner, and the Bayesian network offers a systematic approach for comprehensive uncertainty quantification in a manner that is informative to the decision maker for operation, maintenance, inspection, and other risk-management activities.

Prognosis leverages modeling of chemical, physical, and mechanical degradation mechanisms (such as alkali-aggregate reaction, chloride penetration, sulfate attack, carbonation, freeze-thaw cycles, shrinkage, and radiation damage) in order to assist monitoring and risk-management decisions. This element leverages modeling and computational advances and combined-physics experiments and integrates multiple models through an appropriate simulation framework. This combined model can be used for a prognosis of damage based on the present state of damage obtained from the diagnosis result. The uncertainty quantification in the diagnosis can be propagated through the prognosis model to quantify uncertainty in the prognosis. At present, the concrete SHM framework is applied to the alkali-silica reaction degradation mechanism and is evaluated using laboratory-scale experimental concrete-specimen data.

State of the Art

To be a competitive technology in the nuclear industry, it is important to scale and adapt the concrete SHM framework to work across multi-modal degradation mechanisms, to work on real plant-size concrete structures, and to be able to combine data or information coming from different monitoring techniques to enhance decision making. To enable this scalability and adaptability of the concrete SHM, an enhanced SHM framework needs to be developed using advanced data analytics and ML techniques that would provide a technical basis to augment or replace the current manual–inspection-based aging management plan. The enhanced SHM framework will enable development of diagnostic and prognostic models using advancements in data analytics and ML techniques. In addition, a Bayesian approach will be developed to enable systematic integration of different forms of uncertainty to support decision making under uncertainty.

3.11 Plant Thermal Performance

Base State

Plant performance is monitored in terms of process alarms and events due to process deviations and thermal performance indicators. The alarms and events generated can be due to operations actions, maintenance, or process-uncontrolled changes that require operations actions without a specific component causing the anomaly. These are usually tackled by indicators, such as annunciators, in analog systems or by a dedicated alarms-and-events system in digital control rooms. Thermal performance is performed by measuring the power megawatts (MWs) generated in time and comparing the generated power to the planned generation target. This analysis is often performed manually, by a specified system engineer, and performed on a periodic basis because specialized tools, data, and skills are required for the analysis.

Modern State

Advanced trending and statistical methods are used to improve the anomaly-detection process. Correlations can be incorporated in the models used to reduce the amount of unnecessary reported alarms and events. Additionally, thermal performance models become more sophisticated to combine factors such as environmental conditions and are augmented by process data and additional temperature and flow sensors and components thermography to identify areas of energy loss and address them. A small reduction of energy loss can result in significant cost saving. Modern tools should provide information directly to the operations staff, without requiring a specially trained engineer.

State of the Art

ML methods are implemented to categorize events. Classifications methods are used to train the alarms-and-events system to the sources of an anomaly before it occurs by detecting the patterns that precede the anomaly. If operators identify the anomaly once it occurs and feed it back to the process, a supervised learning classification method is created. For the anomalies that have not yet been identified, unsupervised learning methods are used. The same is applied to thermal performance. The environmental conditions, process data, and power generation can be fed into an ML method that is capable of identifying correlation between these inputs and predict the future performance outcome.

4. DATA VISUALIZATION

The difference between the currently available visualization techniques in other industries and that found within existing NPPs is great. With the introduction of online monitoring, it is essential to advance the visualization techniques in NPPs to a state that enables fusing various sources of data into an easily perceptible means for the plant workforce.

Each of the elements presented elsewhere in this report represents potential data that can be visualized. If the hardware or process collects data suitable for monitoring, these data can be represented visually. Considerable innovation comes from instrumenting plant components that are not currently instrumented or that must be manually or locally observed and cataloged. The automation of data acquisition begins the process of feeding data to the point where it may be put into an information dashboard and used by plant personnel to make maintenance or operational decisions. Likewise, instrumentation allows advanced prognostic and diagnostic systems to monitor and make decisions upon such information. This information must be conveyed to the human decision makers at the plant in a meaningful way. This process of disseminating raw and analyzed information is the heart of plant visualization.

Base State

Most light-water reactors comprising the fleet of U.S. NPPs were built between the 1960s and 1980s. Therefore, the visualizations included in the main control room and at local control panels are analog and quite limited in their capability to represent data in graphical forms. In most cases, the process value is represented by an analog gauge that displays the instantaneous value. Because of this, it can be quite difficult to detect subtle changes, and operators rely heavily on training to understand acceptable ranges. Additionally, the paper-based procedures used by operators contain ranges of values they can use to reference when reading a gauge to determine the value's acceptability for a given state or evolution for the plant.

Analog control panels do contain some paper chart recorders that are capable of displaying trend information to provide a historical context for the current process value. These chart recorders are dedicated to a few key indicators that are critical in nature and, as such, they are more the exception than the rule to the type of indication found on the analog control panel. They are somewhat limited in their visualization functionality since they are physical in nature. While many paper chart recorders have been replaced with like-for-like digital upgrades, the functionality of the digital recorders does not typically exceed that of its older siblings.

Paper-based procedures are another aspect of the limited visualization found within analog control rooms. The paper-based procedures contain graphics such as operating curves for operators to follow as they monitor and manipulate a process. However, the procedures themselves, in their structure, are a form of visualization to provide process context and serve as memory aids for operators, albeit in a paper and ink manner. In this sense, operators are visualizing the plant in line with the psychological definition of the term visualization. They visualize a mental image of the system or equipment. Through training and experience, operators have constructed many schemas that pertain to the plant operations and maintenance. In regard to operators, the accuracy of their schema is quite important to the correct functioning of the plant or equipment; therefore, the procedures are a critical tool to enable operators to mentally visualize the system or equipment they are working on.

Though the current fleet of NPPs in the U.S. is largely analog, these plants do have some digital systems that provide useful visualizations to operators. Most notable is the safety parameter display system (SPDS) that was installed at all plants as a result of the Three Mile Island accident (Kemeny 1979). The SPDS provides key parameters, known as critical safety functions, that correspond to plant safety and support accident-management decision making. The visualizations afforded by the SPDS are still quite limited. In many cases, the values represented by the system are purely digital readouts of the process value. Some plants do have the PI system, which is a software and hardware platform that enables the collection, analysis, and visualization of plant data from computer workstations. PI does provide trends and allow the operator to configure custom displays. However, operators are required to use this data purely as supplemental information because these trends are not considered qualified values that can be used to make decisions.

Last, some so-called digital islands adhere to some modern visualization methods. For example, several plants have begun adopting DCSs for non-safety-related equipment, such as the turbine. These digital interfaces are more advanced than the vintage SPDS. These are multi-windowed interfaces that provide historical data similar in manner to what PI provides. The focus is not on the visualization aspect, but rather typically on providing like-for-like replacements of the existing subsystem functionality such as turbine control systems. Through automation enabled by the digital nature of the control system, these displays do provide some automatic information processing to enhance the visualization to a limited extent. In particular, the system provides an alarm list with filtering capabilities. These alarm lists are useful for visualization because they show the first-in alarms and categorize alarms to aid operators in interpreting the cascade of alarms that typically occur in tightly coupled systems such as those found across the NPP. These visualization methods adopted by the few digital islands within nuclear process control are heading in the right direction to enable better sense- and decision-making, but there are more modern techniques that the nuclear industry could greatly benefit from adopting.

Modern State

Industries outside of nuclear have made advancements in visualization techniques that could be advantageous if adopted by the nuclear industry. The examples are numerous and, therefore, only the most beneficial examples will be described here. Perhaps the most pertinent visualization method is a four-tier hierarchical visualization framework described in Tharanathan et al. 2010. Level-one displays in this framework are categorized as large, panoramic overview displays positioned in the front of the room. They display functional representations of systems to support monitoring and provide a common operating picture for the entire crew. The functional representations of the systems serve as higher-order information to quickly assess the state of the plant without providing too many specific details concerning the exact values for each component's process values. Each operator has a console workstation, which provides level-two and three displays comprising schematic representations of individual systems. These displays allow operators to drill down to more-specific displays at the subsystem or individual equipment (e.g., level-two displays of unit-level graphics representing the schematics of the system or equipment and level-three displays support more-detailed diagnostics required for some specific operations and maintenance activities). A fourth-level display is accessible from the console workstations. It is purely for diagnostics and intended to support maintenance activities.

The overview-display framework hierarchy is a general method for designing the level and type of detail provided in the visualizations to represent the plant or equipment. The representation of individual indications is also important to creating effective visualizations. There are several different methods. Ecological interface displays (EIDs) aim to convey the constraints and relationships between indication and equipment (Burns 2000). The EID approach is based on the concept of ecological psychology, which focuses on basic human perception of affordances within the environment to drive the understanding of the relationship between elements. Within the context of complex sociotechnical systems, an example of an EID display would be a tank outline overlaid on a bar meter. This container information conveys the context of the level or pressure value since level and pressure may have vastly different meanings for equipment other than a tank. In this simple fashion, the graphic is able to convey the constraint of the level because the upper level is physically positioned near the top of the tank graphic surrounding the bar indicator. This follows natural perception of a tank and supports rapid sense making of this particular indicator.

In more-traditional visualization design approaches, conveying the context of the value is still important, but this is achieved through more abstract means. The high-performance human-machine interface approach adheres to the hierarchical overview display format, but also outlines good practices for process displays (Hollifield et al. 2008). The high-performance human-machine interface approach emphasizes visualizations that bolster situation awareness, particularly during abnormal operating situations in which time is critical and operators must act swiftly. As such, the approach mandates overview displays shall support at-a-glance monitoring to enable the different interactions or, more specifically, the decisions operators must make based on the information within the visualization. This visualization approach does not provide a solution; rather, it outlines a process for building effective visualization elements to support operator decision-making. The many details of this process are outside the scope of this report; however, a few examples of effective visualization requirements for individual display elements are worth noting for illustrative purposes. The following example requirements for effective visualizations come from an interaction analysis of a coker process plant console performed by Bullemer et al.2008:

- Show the process variable's current value relative to a target range (and if appropriate, alarm limits)
- Show the parameter's estimated value at time X, based on the actual value relative to the target value
- Show a parameter's current value as a deviation from normal variability in two directions as qualitative steps; larger deviations are more salient
- Show a parameter's current value relative to multiple instances of the same parameter type, such that any given deviation from the group is perceptible.

There is some experimental work done on computerized operator support systems (COSSs) that provides some useful visualization techniques. The concept of a COSS spans a number of technologies, but of paramount importance is effective information automation to provide the operator with a visualization that clearly conveys the actionable information at appropriate times in an intuitive and easily interpretable manner (Boring et al. 2015). The COSS is currently a purely experimental platform, but it has some useful visualization features that should be adopted by the nuclear industry as it moves toward digital interfaces that can support advanced visualizations. In particular, the method of an embedded visualization capability that intelligently displays itself to the operator only at appropriate times is a core visualization concept of the COSS. The COSS provides alerts to the operator in addition to highlighting the section of the system or specific equipment that has been diagnosed by the system as undergoing a potential fault. The potentially faulted component has yet to exceed a threshold for an alarm, but rather the physics convergence equation, model-based diagnostic system detects a mass or heat imbalance within the system that is unaccounted for by the process state. This type of intelligent diagnostic system is the driving force behind diagnostic and predictive visualizations that have tremendous potential for assisting operators in preventative maintenance activities. This area of advanced visualization represents a significant technological advancement beyond the current concept of operations found in existing plants. Other industries, such as oil and gas and aviation (e.g., remote engine monitoring) have adopted this approach, and the nuclear industry should and can leverage these technologies to its own benefit.

State of the Art

There are state-of-the-art visualization techniques that could enhance operators' ability to perform online monitoring. Virtual reality (VR) is a form of visualization that uses three-dimensional visual imagery, spatialized sound, and tactile feedback to create a sense of presence with a virtual environment. The current trend towards inexpensive VR equipment is ongoing, with a number of production-level systems available. One of the primary goals of VR is to create a sufficiently realistic experience so that the user has a sense of presence or feels fully immersed within the virtual environment.

VR provides a realistic ecological display to convey complicated equipment states to the operator through three-dimensional representations of the equipment. For example, instead of relying on a voltage meter to identify whether a pump is running, the operator can see the pump physically, turning through a cross section of the three-dimensional pump represented in the virtual environment. Furthermore, other sensory modalities can also be used in VR to convey the state of the pump. Vibration through vibrotactile displays can be used to allow operators to feel pump movement by virtually placing their hand on the outside body of the pump to understand that the parts within are moving. These VR methods of representing the state provide natural and intuitive interactive methods for the operator to inspect the components. Furthermore, they are able to virtually explore equipment in areas they couldn't otherwise inspect. For example, the operator can move through a virtual representation of the flux within the core or move through the steam-generator tube heat exchanger to examine the integrity of individual tubes. In all these examples, VR requires data to support the level of representation provided in the virtual environment. Current sensor technology limits the level of fidelity that may be possible for these monitoring purposes; e.g., online visual inspection of the tubes in the steam generator heat exchanger is likely not possible yet. However, as a concept for visualization, the potential for VR is, at the least, intriguing and certainly worth industry exploration. Furthermore, the effort to construct the VR world is reduced because the equipment, in most cases, already exists as a digital computer-aided drawing file that was created for the fabrication of the equipment. In the event that a digital replica does not exist, light detection and ranging mapping technology is sufficiently mature that it is not difficult to create the digital replica for VR simulation (Haala et al. 2008).

Another related technology that could prove more beneficial and easier to integrate to existing maintenance processes is augmented reality (AR). AR entails adding visual imagery, spatial auditory cues, and vibrotractile feedback overlaid on the physical world. AR holds significant promise as a visualization tool because it leverages some of the capabilities from VR while relying on the existing capabilities of modern visualizations. As a result, AR is much more readily adoptable as a technology for the nuclear industry, though there are still a number of technological issues that must be overcome before it could be commercially deployed. Fundamentally, object recognition is required for AR to work effectively. Assuming the system is capable of recognizing objects, the AR device can then access a database of known information regarding that object and provide useful information to the operator performing a round. Additionally, the procedure steps themselves can be overlaid within the operator's visual field and near the pertinent element so the operator can focus on the equipment and not have to consult a tablet or paper procedure to verify the step or check what information must be determined to proceed. Another visualization AR can provide is wayfinding. Wayfinding refers to the guidance provided by global positioning systems commonly found in cars so that drivers can reach their destination in the most expedient manner possible. Wayfinding within the plant can provide the operator with the quickest path towards the desired equipment or, when coupled with a diagnostic system, can even alert operators to faulted equipment and guide them to the problem without requiring them to trace the fault to its root cause. Lastly, AR can also help align the team members by providing the actions or even a video feed of the view of other operators. These are only a few of the possible visualization benefits AR could provide to the nuclear industry, but this limited account of AR demonstrates the potential for the nuclear industry to realize substantial efficiency and resulting economic gains by adopting these state-of-the-art visualization techniques.

It should be noted that advanced and three-dimensional visualizations are not necessarily synonymous. Data that can be distilled in simplified form, such as information dashboards, may prove more actionable to operators than a three-dimensional walkthrough of the plant. Recent advances in simplifying information, such as presentations in the form of infographics, illustrate the utility of combining complex information into a simple form. In many cases, effective visualization does not entail adding dimensions, but subtracting them. A multidimensional information field that can be represented as a single value can be better tracked by the human operator. Intelligent visualization requires finding the simple visual anchors that allow operators to monitor, detect changes, and take appropriate responses to changes. Finding understandable and traceable visual anchors becomes especially important when the information presented is not linked directly to current states. Prognostics systems will become especially important to maintenance forecasting, but must convey predicted fault states without confusing operators with current upsets. Visualization must therefore effectively differentiate planning activities from immediate-action requirements. This is a level of information abstraction that will require visualization technologies still in their infancy.

5. DATA MANAGEMENT

In order to enable a data-driven online monitoring approach, a data management plan needs to be established to transport data from the plant, and prepare, structure, store, retrieve at need, and analyze it. A data life-cycle infrastructure must be created. The infrastructure should be robust to minimize interruptions, and the data should be meaningful to increase storage efficiency. The infrastructure should be powerful to perform computationally expensive algorithms developed by the data analytics methods. It should also enable powerful and secure data communication to increase data availability and protection, and to reduce retrieval time. These requirements need to be quantified in performance metrics that depend on the specific migration process. The following steps introduce one approach for the development of a data management plan for migration of a process or equipment:

1. Identify the form of the data that are being collected and the size per data collection unit. For example, data can be in the form of a sensor measurement, a picture, a video, or a frequency spectrum.
2. Estimate the frequency of data generation. This sampling rate could be set by the data-analytics requirements, sensor limits, data infrastructure limitations, or a combination thereof.
3. Calculate the total data rate generated in time. This is found by multiplying the data size per unit of data from Step 1 by the frequency of Step 2.
4. Identify where data are being collected. This can be in locations such as on equipment, in local silos in the plant, in a structured database managed by the plant information-technology organization, or in a paper, non-structured form that is archived.
5. Identify the location options for data storage for immediate retrieval (i.e., hot access), and archival (i.e., cold access). This can be local where the data collection occurs, remotely in a centralized location, in an online monitoring center, or on a cloud.
6. Identify options for how the data are transferred from the data collection location to the hot- and cold-data locations. This can be wired using cables or wireless using the various technologies and associated bandwidth.
7. Identify options for where the data will be processed. The options include field processing, using dedicated hardware, local processing on tablets or mobile processing units, in a central processing unit, or in multiple units on dedicated server(s).
8. Develop scenarios for the combinations of how data can be transferred, stored, and processed. For example, if there is no means of communication to transfer data from the collection location to a storage and processing hub, local storage must be created as part of the sensor. Passing staff with tablets can be then used as the means to transfer the data.
9. Estimate the bandwidth needed for the transfer of data, the hot- and cold-storage requirements for the data, and the computational power needs for analyzing data based on the data-analytics algorithm for each scenario.
10. Estimate the current and projected cost of each scenario, based on the data-need estimates.
11. Select the option that provides highest cost saving without impacting the performance of the process or risk.

Steps 1 to 9 are application-specific. Steps 10 and 11 are fed into the value analysis of the online monitoring migration as will be discussed in Section 6.1. An optimal data infrastructure is one that increases data benefits while minimizing infrastructure cost.

The business model for establishing the data infrastructure can rely on an in-house approach with support of information-technology organizations, outsourcing the work to dedicated data life-cycle vendors, or combinations thereof. Similarly, the model can use a cloud or on-premises option for storage and computations. Each option has advantages that can have a different weight depending on the plant conditions (Table 3). Because the decision on whether to outsource work is a business decision, this section will focus on the technical aspects of using on-premises or off-site options. The technologies and path for both options are widely used in other industries and are trivial to information-technology organizations. They do not present an obstacle to the online monitoring vision. As a result, this section will present a summary of the cost of data management in terms of storage, computational power, and communication, because cost has a direct impact on the value of the automation effort.

The on-premises cost should be found using the total cost of ownership (TCO), which considers the cost for the hardware capital and hardware maintenance cost, resources to maintain the network, energy and cooling cost, and facility location and cost. Details and specific examples on the TCO can be found in Dutta and Hasan 2013 and Rasmussen 2011. Amazon offers a calculator that estimates the TCO for any defined specification for a data center (Amazon Web Services 2018a). Converting the TCO cost to a cost per gigabyte (GB) of data per unit of time is not trivial. Therefore, the cost estimation information followed in this section will rely on the pricing of common cloud service providers. An optimal TCO should result in comparable but higher costs, because cloud service providers have managed to optimized costs (especially energy cost). The provided costs will not be as low if a utility decides to proceed with an on-premises approach. Therefore, a larger than 1 multiplier need to be used in the cost estimation if the numbers are used for on-premises cost estimation.

The following section discusses options for each of the three factors considered and the cost associated. Though not relevant to a specific migration process, aspects of data integration and data sharing are discussed in a dedicated section, because they represent a data-use challenge for enabling online monitoring.

Table 3. Advantages of in-house or outsourcing options.

Option	Advantages
In-house	Direct oversight of data
	Less cybersecurity and data-sharing concerns
	Less communication infrastructure needs
Outsourcing or cloud	Faster deployment
	Enables gradual deployment
	Smaller financial commitment
	More economic
	Higher uptime
	No capital investment
	Lower overhead
	Better access to experts
	Benefit from other users experience
	Well suited for automation workflow

5.1 Data Storage

Efficient storage policies and processes are key factors to cost. Considering the enormous amount of data generated from a plant, storage is the fastest-growing cost in a data-driven online monitoring center. Storage needs are mainly influenced by the data collection method. The archiving strategy is influenced by the decision-making process to mainly determine the duration of historian data available for immediate access versus data that are accessed on an as-needed basis.

In today's marketplace, many options exist for optimal storage of information. Options can be broken down into two primary types of storage: binary bucket storage and database storage. Binary bucket storage is utilized for larger binary files: images, video, and logging information. Database storage is used to store metadata (source, timestamp, etc.) or data that are easily mapped by a time series.

Binary bucket storage can be stored into two distinct classes: real-time need and eventual need. Need is defined by the expected frequency to access the data. Frequently accessed data are optimally stored in standard cloud bucket storage or onsite solid-state drives. Infrequently accessed data can be stored into cold storage or slow hard drives. Cloud bucket storage is billed by the month per gigabyte stored; access to the data is typically free. Cloud cold storage is billed by the month per gigabyte stored (at a much-reduced rate), but access to the data is billed.

Database storage is offered in three subclasses: relational database, document database (NoSQL), and graph database. Relational databases are a classic storage mechanism that stores data into tables. These relational tables can be joined with minimal performance penalty to provide queries that span two or more sets of data. Document storage also stores data in tables; however, joins between documents are extremely expensive. As an example, log data are optimally stored in a document database as they are typically queried by date range or identification. A customer-relationship management tool will often relate customer tables to contacts, companies, and comment tables: these data need indexes for fast retrieval and are optimally stored in a relational database. Graph databases are a newly emerging technology that allow for relationships between data to be aggregated and queried with further simplicity and additional speed improvements of standard relational databases.

The cost of data storage has been rapidly dropping in an exponential pattern (Vachon 2018, McCallum 2018, and Komorowski 2018). As a result, storage is not anticipated to be an obstacle in introducing online monitoring in NPPs. A cost estimate of the various storage cost options is listed in Table 4.

Table 4. Cloud storage costs.

Type	Location	Cost ($/GB/m)	Retrieval ($/GB/m)	Early Deletion (days)
Standard Cloud Bucket Storage	Amazon AWS S3[a]	0.0230	0	0
	Microsoft Azure General Blob[b]	0.0208	0	0
	Google Cloud Storage[c]	0.0260	0	0
Cold Cloud Bucket Storage	Amazon AWS Glacier[a]	0.0040	0.0030 (Bulk) 0.0100 (Standard) 0.0300 (Fast)	90
	Microsoft Azure Cold[b]	0.0152	0.0100	30
	Microsoft Azure Archive[b]	0.0020	0.0200	180
	Google Cloud Platform[c]	0.0070	0.0500	90

a. From Amazon Web Services 2018b as of the date this information was acquired.
b. From Microsoft Corporation 2018 as of the date this information was acquired.
c. From Google 2018 as of the date this information was acquired.

5.2 Computational Power

Computational needs will depend highly upon the amount of stored data in combination with the data analytics methods implemented. For this effort, it is estimated that computational needs will be nominal with a resident instance with four virtual cores and 16GB RAM proving sufficient at this stage.

Today's computational workloads can be offered on demand via cloud services and statically via on-premises data centers. These computer workloads can be offered using graphical processing units (GPUs) for ML and model solving and computer processing units (CPUs) that are suitable for general processing. Cloud services offer computing in three distinct classes: reserved instances, standard on-demand instances, and spot instances. Reserved instances are committed for 1 to 3-year periods at a significant workload discount (up to ~65%). These instances are optimal for always-on computing needs (database servers, logging processes, application servers, etc.). On-demand instances are available to burst when computational power is needed at an instant; these instances are optimal for elastic scaling applications and high-performance workloads. Spot instances are available to workloads that can wait to execute until a desired price point is reached; these instances are often the cheapest class of computing, but require delay in execution to be acceptable. Cloud services additionally offer serverless computing through cloud functions. Cloud functions allow a single action to be performed; the execution of that action is billed by the millisecond. Cloud functions allow for elastic scalability without having to pre-plan or pre-warn instances. Cost estimate of the various cloud computational power options is listed in Table 5.Looking at the long time-frame behavior, the cost is expected to continue to drop in an exponential pattern (see Flop cost in Wikipedia 2018).

Table 5. Cloud computational costs.

Location	SKU	Cost ($/month)
Amazon AWS[a] (Northern Virginia, Reserved)	M5.large 2 vCores, 8GB RAM	44.53
	M5.xlarge 4 vCores, 16GB RAM	89.79
	M5.2xlarge 8 vCores, 32GB RAM	178.85
Microsoft Azure[b] (East U.S., Reserved)	D2.v2 2 vCores, 7GB RAM	44.64
	D3.v2 4 vCores, 14GB RAM	89.28
	D4.v2 8 vCores, 28GB RAM	178.56
Google Cloud Platform[c] (Iowa, Sustained Use)	n1-standard-2 2 vCores, 7.5GB RAM	48.55
	n1-standard-4 4 vCores, 15GB RAM	97.09
	n1-standard-8 8 vCores, 30GB RAM	194.18

a. From Amazon Web Services 2018b as of the date this information was acquired.
b. From Microsoft Corporation 2018 as of the date this information was acquired.
c. From Google 2018 as of the date this information was acquired.

5.3 Communication

An extremely high-bandwidth communication infrastructure is needed to handle expected data traffic, as well as to operate with minimal latency. The topology should be designed in a manner that enables scalability and introduces redundancy where needed to reduce downtime and prevent system loss. The impact of data loss due to any unanticipated interruptions should be analyzed. Network traffic should be monitored and continuously optimized by a centralized framework to predict infrastructure changes, detect anomalies in the infrastructure performance, and mitigate the consequences.

The options for network infrastructure depend highly on the end storage site. If data are stored in a local data center, the hourly cost of bandwidth will be nominal. If data are stored in the cloud, bandwidth will need to be purchased by the gigabyte to connect to the virtual private cloud network. Currently, bandwidth costs are nominal, with storage costs representing the largest cost of the data lake. This state could change if the associated data-lake application program interfaces are accessed frequently externally to the virtual private cloud network. A cost estimate of the various cloud storage options is listed in Table 6. In terms of cost, the data-transfer cost has been the slowest dropping cost of the three data-management factors considered.

Table 6. Cloud bandwidth costs.

Location	Cost ($/GB/month)
Amazon AWS[a]	0.081
Microsoft Azure[b]	0.087
Google Cloud Platform[c]	0.120

a. Amazon Web Services 2018a as of the date this information was acquired.
b. From Microsoft Corporation 2018 as of the date this information was acquired.
c. From Google 2018 as of the date this information was acquired.

5.4 Data Integration and Sharing

Enabling online monitoring of NPPs requires initiating a process for data from various sources to integrate in a common data repository. Growing and increasingly distributed data sources, driven by the diversity of locations, data types, and use cases, will require new methods to emerge as an architecture for connecting data creators and users. Introducing new data sources without proper planning can scale out of control in terms of cost, complexity, and inability to enforce governance controls. The data collected are diverse in nature and need to be normalized to some extent to enable the use of multiple data sources. Naturally, over-normalizing data is neither efficient nor always possible. As a result, data lakes that rely on increasing use of metadata and semantic contextualization should be considered. The decision on how to integrate the data is, therefore, a topic that needs to be developed. The nuclear power industry has realized this need, and efforts have recently launched to develop a common data architecture.

In addition, a data-sharing methodology needs to be developed around the concept of data warehouses, data hubs, data lakes, and enterprise data warehouses. This topic is evolving, but still faces challenges, such as cybersecurity or data classification among local servers or remote locations (cloud). Also, the shift from physical batch movements to virtualized and real-time data delivery creates challenges to combine multiple data delivery styles to cater to mission-critical data and analytics use cases. A portfolio-based approach is needed that extends beyond physical consolidation of data via extract, transform, load (ETL) to also include real-time data flows, data virtualization, message-oriented movement of data, and stream data integration. Making operational processes act on the data "at edge" is incompatible with the requirement of collecting all the data in a central place before taking action. Decisions need to be made on data migration optimization and policies, ownership and rights, and level of centralization. The location of data should be irrelevant, thereby allowing connection to any data asset, anywhere. Metadata describing locations, formats, semantics, usage, and worth should be more important than the data themselves. It provides knowledge of where data assets of interest reside and how they are related A roadmap needs to be developed to drive data aggregation standards and collaborative models.

6. VALUE ANALYSIS

The value of migrating a process to online monitoring is measured by estimating the cost savings that result from process automation and the increase of cost risk due to events, such as unplanned parts failure, and consequent impact on the plant. This section is, therefore, divided into two subsections: one that targets cost saving analysis, and another that targets economic risk evaluation.

6.1 Cost-Saving Analysis

Cost saving can be quantified in various forms that include direct and indirect benefits. Estimating the cost saving that could result from advancing one of the identified elements requires performing the following steps:

1. Specify the set of automation alternatives that may be implemented in the monitoring activity.

The first alternative that should be fully described is the monitoring activity itself. Special attention should be paid to document costs and benefits associated with the status quo. This will become the baseline point of reference. Labor costs, material costs, support-activities costs, loss of revenue, or any resource that is used to conduct the monitoring activity carries a cost. These should be well understood for how monitoring is conducted before automation.

In order to specify the alternatives to the status quo, the technology options should be articulated and options should be listed, as was presented earlier. Each way automation could be implemented becomes an alternative for analysis. Not all alternatives need to be evaluated, but the set of automation alternatives should be documented. Once the automation alternatives are identified, the set of alternatives for analysis can be finalized. The first alternative is the status quo—the monitoring activity itself. Then the automation alternatives can be included. At this point, alternatives might be eliminated for various reasons (e.g., "this option will simply never work"). Upon completion of this step, the set of alternatives will be well understood. The status quo will be well documented as will how automation alternatives would change the status quo.

2. Identify the reach of the monitoring activity; bound the analysis.

   Given a monitoring activity, how far are the impacts it generates realized? Is there something downstream in a supply chain that changes as a result of the monitoring activity? Does monitoring impact some part of the system that is not directly downstream from the monitoring activity itself? This step generates information that sets up the "how far and wide" of the analysis. Areas of potential benefit would include reduced detection time and diagnosis, streamlined corrective actions, improved long-term planning, maximized outage utilization, optimized periodic maintenance activities, reduced data management, and increased access to data-based insights. A checklist, similar to that shown in Table 7, can be used to identify the cost impact resulting from each migration activity and the extent of meeting that cost saving.

Table 7. Migration activity benefit development (should be performed for every migration process).

Value	**Extent of Meeting the Value**	**Cost-Saving Impact of Meeting the Value**
Reduced detection time	—	—
Reduced diagnosis labor and materials	—	—
Streamlined corrective actions	—	—
Lower quality requirements	—	—
Improved long-term planning	—	—
Maximized outage utilization	—	—
Optimized periodic maintenance activities	—	—
Reduced data management	—	—
Reduced engineering labor	—	—
Improved plant efficiency	—	—
Reduced probability of plant trip	—	—
Reduced probability of power reduction	—	—
Increased insights	—	—
Others (the list above is just an example)	—	—

One could consider historical data to see where impacts of monitoring (success or failure) have been realized. Similarly, this step should also include the timeframe over which the evaluation will be conducted. At this point, the information is not informing how the world will be different with automation; instead, it is forming the boundaries within which to consider the impacts of automation. If automating the monitoring activity will have a reach beyond what monitoring has historically had, then the boundaries should be adjusted to account for this.

3. Given the boundary of analysis, identify impacts.

   This step identifies the set of measurement indicators that will be used to quantify impacts (Table 7). For example, if the monitoring activity succeeds, what happens? One might ask, "consider two cases, one where monitoring works perfectly and one where monitoring partially succeeds. What is different?" Generating and answering questions like these will point to the measurement indicators that will capture the impacts of changes in monitoring technology.

   This step also identifies the cost of moving away from the status quo. Implementing automation into existing monitoring process will generate costs, including capital investment for enabling the use of the new process (e.g., hardware, software, labor, regulations review) and the cost to maintain the new process. This step should identify where, in the cost structure, benefits will be realized. If automation happens, identify which activities and resources will no longer be needed. Moreover, if expected benefits of automation are beyond cost savings only, indicators should be identified that capture improvements to systems or processes as a result of automation, such as reduced radiation exposure.

4. Predict quantitative impacts over automation alternatives. Value measured indicators.

   This step calls for modeling, simulation, forecasting, or using other analytical tools that can predict the implementation of automation. Using the measurement indicators identified in Step 3, prediction-modeling quantifies, by alternative, how impacts are realized over time.

   A simulation should be conducted for each of the alternatives identified in Step 1. Once simulations have been run, the measurement indicators should be used to quantify how each alternative for automation is different from the status quo.

   The prediction step generates information that identifies how automation alternatives differ from the monitoring activity itself. This information can now be valued. For indicators that can be valued in dollars, these should be monetized. Significant effort should be taken to monetize all impacts. Sophisticated methods exist to monetize what appear to be otherwise nonmonetary values. The reason to take great effort to monetize impacts is because costs and benefits are then in the same unit of comparison: dollars.

   If some measurement indicators cannot be monetized, then a systematic approach to identifying effectiveness will be called for. Here, the measurement indicators can be turned into units of effectiveness, in multi-attribute decision-making framework. The multi-attribute framework enables multi-criteria decision making. It is a process whereby noncomparable units are made comparable. The drawback of this approach is that units of effectiveness are preference-dependent. That is, preferences of an assumed decision maker must be imposed. But, doing so enables conversion of noncomparable units to comparable units.

5. Perform present value analysis on cash flows of benefits and costs.

   This step imposes a discount rate on the stream of benefits and costs such that units across different time periods can be systematically accumulated. As noted above, some indicators may not be conducive to monetary measurement. Discounting can still be applied so the impact of future effectiveness can be compared in terms of today's preferences.

   Now, for the status quo and by each automation alternative, the net present value of each alternative can be computed. The difference between the net present value of an automated alternative and the net present value of the status quo is a quantitative measurement of value.

6.2 Economic Risk Evaluation

Any change to the inspection strategy at a plant comes with some risk that equipment reliability could be negatively impacted due to causes such as unexpected recoverable or irrecoverable failure, loss of revenue, and unplanned resources demand (labor, materials). The probability of occurrence of these events and the consequence from such failure need to be analyzed as plants move towards online monitoring. A checklist, similar to shown in Table 8, can be used to identify the cost risk resulting from each migration activity. The ability to accurately determine occurrence probability and consequence of each of the table scenarios requires detailed probabilistic risk analysis (PRA). PRA has long been a popular techniques for formulating system- and plant-level risk scenarios in high-hazard facilities and, particularly, in the commercial nuclear industry (Apostolakis 1978). Event- and fault-tree-based PRA is commonly performed in the nuclear industry using tools such as Systems Analysis Programs for Hands-on Integrity Reliability Evaluation (SAPHIRE) (NRC 2011a) or the Computer Aided Fault Tree Analysis System (CAFTA) (EPRI 2014).

Historically, PRA techniques have been used to formulate system- and plant-level risk scenarios based on basic event probabilities that model a system's or a plant's response to component failures or initiating events and compute quantities ranging from probabilities of system failure to core-damage frequencies. U.S. commercial NPPs have developed and utilized comprehensive PRA models that extensively incorporate the various failure modes of components such as motors, pumps, transformers, diesel generators, valves, and pipes. The use of data from the sources (Section 2) and data analytics methods (Section 3), in a PRA in a manner similar to what is currently being performed requires a systematic approach to convert the outcome from data analytics into a probabilistic risk of system, structure, or component (SSC) failure. Approaches that quantify component degradation from measurement data to estimate the RUL, or performing prognosis for condition-based maintenance, are being researched (Yadav et al 2018, Kim and Heo 2018, Barbieri et al. 2015, Hu et al. 2016, Coble and Hines 2011). These methods would capture SSC performance and reliability parameters in real time and provide data-based knowledge, which can be used to enable better RUL estimation.

Table 8. Migration activity cost rise development (should be performed for every migration process).

Value	**Probability of Occurrence**	**Cost Impact of Occurrence**
Unplanned reactor trip	—	—
Forced mid-cycle maintenance outage	—	—
Forced power reduction	—	—
Refueling outage extension	—	—
Increased risk of industrial accident	—	—
Reduced plant efficiency	—	—
Increase in personnel radiation exposure	—	—
Increase in core damage frequency	—	—
Increase in large early release frequency	—	—
Others (the list above is just an example)	—	—

Additionally, existing PRA can be extended to use SSC-aging data. The failure rates or probability of failure for SSC across U.S. commercial NPPs can be obtained from databases such as the U.S. Nuclear Regulatory Commission's Reactor Operational Database (Eide et al. 2007) and used in the assessment of new online-monitoring technologies.The approach of incorporating SSC condition in PRA has been investigated to include physics-based models that are suitable for degradation phenomena with existing physical models of degradation, like corrosion and fracture (Smith et al. 2001), and logistic function-based approaches that assess the likelihood of a failure event given the degradation level (Xu and Zhao 2005).

To be able to systematically convert the results from data analytics and SSC aging and degradation data using an integrated approach into a probability of failure, and accurately optimize the use of this information to improve the online-monitoring migration value and enhance performance. The LWRS program recently launched an effort to research this topic. The details of the research will be available in the future as part of the LWRS program publications.

7. CHANGE MANAGEMENT

Beyond the economic risk of replacing the current process of manual inspection and monitoring with online monitoring, there are other challenges that require further study to enable migration. The most common challenge is related to regulations that are derived from security and safety concerns. Security concerns are mainly related to cybersecurity. While there is a lot of knowledge, experience, and technique to enforce cybersecurity for network applications or other industries, cybersecurity has an application-dependent element that can change over time when considering online monitoring. The amount and type of data that are introduced by online monitoring provides an opportunity for deeper insight on the plant.

The safety concerns can be tackled by proper examination of regulations. Each and every shift of an activity to an online-monitoring approach needs to be evaluated with respect to requirements, such as 10 CFR 50.69 (NRC 2004), associated regulatory policies and guidance, and existing license conditions, to identify the risk category of the impacted SSCs. If the equipment has a direct or indirect safety-related role, applicable requirements, such as 10 CFR 50.59 (NRC 2000), should be used to evaluate whether the activity impacts SSCs in a way that influences safety and require a license amendment. This will trigger a series of safety analyses and evaluations. Because automating activities on safety SSCs introduces a significant cost burden on the plants, the nuclear industry has focused most of the online-monitoring plans on systems that have no safety impact. These significantly reduce the regulations review needed to ensure existing plant safety conditions are not indirectly impacted. For example, electromagnetic or radio-frequency interference will require evaluation with respect to the impact on existing SSCs from newly introduced equipment and the counter effect using compliance guides such as Regulatory Guide 1.180 (NRC 2003). In addition, the cybersecurity aspect of introducing the new system needs to be evaluated in compliance with requirements, such as 10 CFR 73.54 (NRC 2009). Guides such as Regulatory Guide 1.152, Rev. 3 (NRC 2011b) and Regulatory Guide 5.71 (NRC 2010b) should be reviewed to meet the 10 CFR 73.54 requirements.

In addition to regulations, the supporting infrastructure to achieve the targeted online monitoring strategy should be evaluated. The data infrastructure was discussed in Section 5. Additional infrastructure that needs to be evaluated relates to the availability of power and space, and the feasibility of installing sensors on equipment. Modifications to surrounding structures to enable the migration should be evaluated. The feasibility of installing wired or wireless means of communication need to be verified. The ability to sustain the new components should be evaluated to ensure the plant will be able to replace failed sensors and update methods with minimal or no work redo if a component becomes obsolete. Also, the new components' ability to sustain harsh work environments need to be verified. This includes the ability of the components to reliability perform as planned with minimum calibration needs in environments that could accelerate component failure. Last, cultural change needs to be addressed. It is essential that the current workforce does not see online monitoring as a threat, but rather a tool to make their daily work processes more efficient.

8. CONCLUDING REMARKS

An optimal roadmap for the nuclear power industry should target the NPP. Each NPP sustains a record of its cost challenges and has some unique equipment conditions that necessitate prioritizing certain processes or equipment over others. It was therefore decided to develop a roadmap for processes and equipment in this report, regardless of the plant's decision to target a certain process or equipment over others.

The developed technology roadmap was split into sequential elements and supporting elements. Sequential elements need to advance in preset milestones. Supporting elements are performed as a whole every time one of the sequential elements is advanced. The roadmap identified data collection, analytics, visualization, and data management as sequential elements. Value analysis and change management are the supporting activities that need to be performed before any of the four sequential elements is advanced.

The technology roadmap identified a set of data sources in an NPP. The data collection element of the roadmap was found to be process dependent. On the other hand, data analytics is equipment dependent. Equipment dependence was deemed necessary since equipment analysis would require data from multiple sources. Data analytics identified the base methods used by the industry and methods that can be applied using available technologies. The state-of-the-art data analytics methods are being researched, so it is not possible, at this stage, to identify the specific methods that can be applied to the identified equipment. Instead, a summary of methods were discussed in an equipment-independent context. Visualization can be advanced regardless of the considered process or equipment because it is beneficial to have a unique and consistent visualization philosophy for the plant. Data management is similar to visualization in the sense that it needs to have a consistent deployment strategy with a futuristic vision, regardless of the process or equipment. This strategy should include a plan for data integration and sharing. The cost of computational power and storage was found to continuously drop. However, communication cost was found to be slower to drop. This cost, in addition to other costs of deploying an online monitoring technology, should be evaluated as part of the value analysis. In addition to the cost of deployment and cost saving resulting from the migration to an online monitoring process, the value analysis should consider the cost risk associated with the new process not performing as desired. This risk should be considered too when the change process is studied. Regulations should be reviewed to ensure the change does not impact the safety of the plant, and additional factors such as resource availability, supporting infrastructure, feasibility and enabling cultural change, need to be studied. Moving forward, it is desired to apply the results of this report to develop a customized roadmap with a collaborating NPP.

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