Program on Technology Innovation: Landscape of Automation in Nuclear Power Plants

Technical Brief — *Advanced Nuclear Technology*

Executive Summary

Utilities are looking to increase the degree of automation in nuclear power plants (NPPs) to reduce their operating and maintenance costs. The technology to enable automation at NPPs has matured significantly in the last decade, and the nuclear fleet is embracing this shift to remain competitive with other power sources. This report describes the current landscape of automation in the nuclear power industry. It provides benchmarks for research and development and for implementation of automation technologies at NPPs. This report also identifies technical, regulatory, and design considerations that present hurdles to increased automation.

NPPs have demonstrated interest in automating tasks spanning operations, maintenance, and a variety of supporting processes. Most NPPs have taken at least initial steps to implement digital online monitoring. Data generated by online monitoring is processed in recently established monitoring and diagnostic (M&D) centers, where NPPs have also been able to start automating real time data analysis. NPPs are also exploring artificial intelligence and machine learning (AI/ML) to inform maintenance activities and automate workflows. Automating functions in these areas is intended to improve the reliability and performance of critical assets and reduce personnel time spent on administrative activities. Additionally, robotic technologies including tooling and remotely-operated vehicles are being used to reduce risk to plant personnel for inspection and surveillance activities.

Most automating technologies currently being leveraged by NPPs rely on human input and oversight. Current areas of research include developing new AI/ML tools for a variety of NPP applications, identifying new sensors and applications for monitoring and inspection technologies, and addressing challenges to broader implementation (e.g., cybersecurity). Operating NPPs are investing in both developing and implementing automating technologies and recognize the need for greater automation to remain economically feasible such that they can provide reliable base load power.

To evaluate the current state of automation for NPPs, this report uses a categorization framework based on whether four generic functions are met by the automating technology or by human counterpart(s). Across all implementations discussed, responsibilities are shared between the technology and the human. While many NPPs have identified areas where automation provides significant potential for improved performance and safety, confidence in the technology will need to grow to enable increased adoption by NPPs.

Overall, there are significant barriers for implementing broader automation in NPPs that require dedicated research and development. However, there is also great promise for automation to support the overall industry objectives to reduce operating costs, increase reliability, and improve personnel safety.

1 Introduction

1.1 Purpose

This report describes the current landscape of automation in the nuclear power industry. It provides benchmarks for research and development and for implementation of automation technologies at nuclear power plants (NPPs). This report also identifies technical, regulatory, and design considerations that present hurdles to increased automation in NPPs.

1.2 Background

Utilities are looking to increase the degree of automation in nuclear power plants (NPPs) to reduce their operating and maintenance (O&M) costs. The technology to enable automation of plant processes is well developed, and the nuclear fleet is starting to embrace automation as part of its efforts to remain economically competitive with other power generation sources. Industries such as oil and gas have leveraged digital technologies and process automation in their drilling, production, processing, and storage facilities to optimize operations [1], and new gas-fired power plants that plan to implement automation and advanced control systems will require far fewer staff for operation [2]. NPPs have lagged behind these other industries in research and implementation for several reasons, including the unique culture, safety consciousness, and regulatory environment associated with nuclear power.

For the purposes of this report, automation is defined as technology that performs a task or part of a task that was previously carried out manually, i.e., a task that now requires no or reduced manual oversight or input. Automation can provide the following benefits to utilities:

- Decrease calendar time and labor hours to complete certain tasks
- Decrease the exposure of personnel to a variety of industrial and radiological hazards
- Gather information and perform work while equipment is online (rather than necessitate an outage or downpower)
- Increase the quality and consistency of data collected from an inspection or walkdown
- Decrease opportunity for human error and improve plant reliability and safety
- Enable new or improved capabilities
- Increase scheduling flexibility among personnel

Table 1-1. Kaber and Endsley's Levels of Automation Taxonomy, Adapted from [4]

Level of Automation	Process Roles			
	Monitoring	Generating	Selecting	Implementing
(1) Manual Control	Human	Human	Human	Human
(2) Action Support	Human/Computer	Human	Human	Human/Computer
(3) Batch Processing	Human/Computer	Human	Human	Computer
(4) Shared Control	Human/Computer	Human/Computer	Human	Human/Computer
(5) Decision Support	Human/Computer	Human/Computer	Human	Computer
(6) Blended Decision Making	Human/Computer	Human/Computer	Human/Computer	Computer
(7) Rigid System	Human/Computer	Computer	Human	Computer
(8) Automated Decision Making	Human/Computer	Human/Computer	Computer	Computer
(9) Supervisory Control	Human/Computer	Computer	Computer	Computer
(10) Full Automation	Computer	Computer	Computer	Computer

Advanced reactor designers are seeking to build automation into their plant designs, which is a paradigm shift from the currently operating nuclear fleet [3]. Typical operating light water reactor (LWR) power plants were designed in the 1960s and are facing challenges backfitting automation technologies into their plants due to technical, regulatory, and infrastructure considerations.

1.3 Scope

This report characterizes the current state of automation in the operating nuclear fleet, both with regards to research and development and current implementation in NPPs. It focuses on automation technologies that are intended for or potentially applicable to the currently operating LWR fleet.

The automation technologies discussed in this report are evaluated through the framework of the Kaber and Endsley automation scale [4], where the functions in a process with potential for automation can generally be categorized as:

- ***Monitoring:*** Data collection and monitoring
- ***Generating:*** Generation of options for potential actions through data analysis
- ***Selecting:*** Selection of appropriate action out of given options
- ***Implementing:*** Implementation of the selected action(s)

Based on the degree of automation across each of these functions (i.e., whether the human or computer is responsible for the function), a single rating is assigned on a scale from 1-10 to classify the automation technology. This approach is shown in Figure 11. Note that each Level of Automation (LOA) rating represents a specific combination of human/operator control, and a higher score is not necessarily an indication of a system being closer to full automation.

1.4 Approach

To assess the current state of automation in the nuclear industry, input was gathered through several different paths, including:

- A review of literature and recently published papers,
- Interviews with power generation modernization and innovation leaders, including NPP personnel, and
- Discussions with vendors and subject matter experts (SMEs) in automation.

The literature review included the Nuclear Energy Institute (NEI) Top Innovation Practice (TIP) Awards from the past three years. To provide one perspective on the state of automation in the industry, the submittals from 2019 to 2021 were surveyed. Candidate innovations are submitted by NEI members. Results from this survey are provided in Appendix A.

Using information gathered from the listed sources, the current state of automation technology being researched and implemented at NPPs is described. The automation technologies are evaluated using the Kaber and Endsley LOA classification framework shown in Figure 11. Additional topics of discussion include limitations preventing wide-scale deployment and the specific benefits NPPs can achieve from automation.

In this report, automation at NPPs is discussed in the context of three areas: plant operation (Section 2), maintenance and inspection (Section 3), and business process automation (Section 4). While there are consistent themes within these areas, there are distinct use cases that demonstrate the potential value of automation and merit separate discussions. Common hurdles to further implementation of automation at NPPs are summarized in Section 5.

2 Plant Operations

2.1 Overview

Automation of plant operations is defined in this report as implementing technologies, devices and processes that support or replace traditional operator and other plant personnel tasks in a NPP. The main drivers for automating plant operations include:

- Improved staff productivity and optimized allocation of personnel to support tasks that require manual input/action, rather than lower-value, repetitive tasks that can be automated [5]
- Availability of real time data for insights to plant health, including quicker and more accurate identification of equipment issues [6]
- Reducing opportunities for human error

In general, automation of activities for plant operations is in the initial stages of development at NPPs. This is supported by the results of Appendix A, where only approximately 20% of TIP awards submitted were related to automating plant operations. The current focus of automation is to support operators instead of replacing their role. Per discussions with modernization leaders and vendors, and supporting input from literature, utilities are prioritizing digital upgrades and the installation of enabling systems for improved data collection, such as installation of plant networks through distributed antenna systems (DAS) and wireless monitoring devices [7]. NPPs are preparing standardized documentation and specifications to outline the required steps to install automated monitoring and digital controls and reduce the process-related barriers to implementation. Utilities are executing pilot programs to explore implementation and savings related to increased data collection [8].

In the future, the automated technology used to support or replace plant personnel can be leveraged for more complex tasks. These tasks can transition from simply notifying operators of issues to utilizing predictive analytics with machine learning models to detect anomalies early and influence operation of the plant. Leveraging more complex automation technologies introduces heightened regulatory and cybersecurity concerns when safety related equipment is involved. Artificial Intelligence (AI) and Machine Learning (ML) are being investigated for applications at NPPs, as evidenced by the recent Nuclear Regulatory Commission (NRC) strategic plan to support evaluation of those new advanced technologies [9] and supporting research from a national lab [5].

Some specific examples of automation for plant operations are discussed in detail below.

2.2 Collecting Data from Plant Systems and Components

2.2.1 Summary

Gathering and recording data on various plant systems and components is one of the tasks operators execute during daily rounds. By automating this monitoring process, the operator can redirect time from low-value, repetitive tasks towards higher value tasks requiring greater critical thinking (e.g., tasks to improve plant performance). Research, demonstration, and implementation of automation enabling technologies has been performed to support monitoring of NPP components including instrumentation for oil reservoirs, heat exchangers, pumps, compressors, couplings, condensers, air handling equipment, control rod drive mechanisms, and the turbine-generator shaft.

In recent years, NPPs have made progress towards implementing advanced online monitoring (OLM) of plant systems and components [6, 10]. OLM programs automate gathering, recording, and trending of data related to performance of equipment and plant health. Some of the devices which support advanced OLM include wireless gauge readers, vibration sensors, and ultrasonic sensors for corrosion monitoring [11, 12, 13].

Currently, NPPs are expanding their capabilities to support trending and other instantaneous health monitoring by increasing the availability of data via new sensors and devices. Many plants have setup monitoring and diagnostics (M&D) centers to consolidate data streams and perform data analysis. NPPs that do not have the resources to create and maintain internal M&D centers have turned to external companies to fill this role. Typically, data analysis is limited to advanced pattern recognition against normal equipment performance to provide alerts to operators for further investigation of off-nominal conditions [7]. Per discussions with plant personnel involved with such trending, this data analysis is only feasible for well-understood and closely monitored component behavior; for example, deviation from a setpoint is more readily implementable than diagnosing degraded motor performance based on vibration data. Insights from this data analysis approach are not typically used to make real-time decisions on plant operations but do provide additional insights to support overall plant health.

2.2.2 Example – Continuous Online Monitoring of Oil Reservoirs

A successfully piloted example of continuous OLM is sensors in large oil reservoirs [14]. One specific application is monitoring the lubrication oil supply for the main turbine system to ensure the critical rotating machinery operates efficiently and safely. Online sensors can monitor oil properties such as water content, oil cleanliness, oxidation, base/acid number, additive concentration/degradation, and viscosity. Utilizing automated monitoring enables more consistent data collection by eliminating variables that affect data quality, such as variation in time of measurement and amount of oil drained before collection. The continuous or semi-continuous online measurements enable increased insight into equipment health since data can be collected more frequently, providing an opportunity for early detection of failures that could disrupt plant operation [14].

This technology has been successfully demonstrated at NPPs and is being used as a benchmark for similar technology installations [15]. Additionally, there are many guidelines that exist and have been published in the recent past to provide guidance on instrumentation and analysis methods for other specific components of interest (e.g., [16]).

2.2.3 Challenges to Adoption

Despite the advances in sensor technology and data analysis methods in recent years, there are still challenges associated with OLM such that most utilities are still in the early phases of implementation. For example, electromagnetic and radio-frequency interference (EMI/RFI) from newly installed wireless equipment such as OLM sensors can impact existing equipment and must be evaluated. Additionally, sensor performance could be affected by existing equipment [17, 18]. Further, the business case for implementing OLM for only a single piece of equipment may not be favorable. Project initiatives for installing sensors on multiple equipment pieces can provide higher ultimate cost savings, but also require significant up-front investment [19]. Additional general hurdles which are applicable to other automating technologies are summarized in Section 5.

2.2.4 Level of Automation

Collecting data from plant systems and components, such as OLM of oil reservoirs, is best categorized as an LOA of 2, or action support. In the context of the overall scenario, the data being collected and analyzed by the computer is fulfilling the monitoring function (with oversight from the human as to what should be monitored), but the human is currently responsible for generating and selecting options to address the response from the monitoring role (i.e., inspect the component, perform maintenance, or shut down based on an irregular indication), and implementing the option via submitting a work order or other process step to address the monitored condition.

It is noted that a low LOA does not necessarily mean that the automation technology is not mature, just that the computer has a limited role in the framework proposed by Reference 4. In fact, the monitoring equipment successfully performs the role of analyzing the monitored information and sending an off-normal indication (in many instances), and operating NPPs are widely interested and actively adopting this technology.

2.2.5 Future Direction

Realizing the full benefit of OLM may eventually require reliance on data gathered by sensors and transmitted wirelessly. In the future, data collected from OLM systems could be used to inform NPP operator action without manual data collection from operator rounds. This will likely require further validation efforts and broad instrumentation to ensure NPP operator and regulator confidence in the reliability of OLM technologies.

2.3 Camera-Based Monitoring

2.3.1 Summary

More complex monitoring systems that allow for greater automation are being researched and implemented, including the use of camera-based data streams to support multiple applications at NPPs. Monitoring activities, such as regular visual inspections of components, are currently performed manually and in-person. Utilities have started exploring the benefits associated with using camera-based solutions to automate monitoring, for example via thermography or motion-amplification technology. The technology required for camera-based monitoring has successfully been used in other industries including steel and chemical production for continuous vibration monitoring and thermography [21, 22]. However, discussions with utilities indicated that few permanent installations have been piloted in NPPs due to the effort required to support installation.

There are many potential use cases for camera-based monitoring systems to support plant operations, including fire watch, vibration monitoring, machine verification, radiation monitoring and physical security. A key example of automated camera-based monitoring that is being implemented by NPPs is thermal imaging and monitoring.

2.3.2 Example – Camera-Based Thermal Imaging and Monitoring

Camera-based thermal image monitoring could be applied to monitoring electrical equipment (e.g., transformers) in switchyards and diagnosing steam leakage from piping systems. Steam leak monitoring is of particular importance because a small leak can cause a significant damage [23] and presents a notable safety concern to personnel manually searching for leaks. NPPs contain a large amount of balance-of-plant (BOP) piping so identifying the precise location of a leak can be time-consuming. Additionally, if the leak occurs in areas with high radiation levels, the time spent identifying the leak can result in significant personnel dose or require a downpower to access the area.

Monitoring for steam leaks can be performed with an infrared or thermal camera, both of which are commercially available. The analysis software for detecting heat transients on video has already been implemented at NPPs (e.g., transformer monitoring in switchyards). Some commercially available thermal imaging cameras can set regions of interest and define ranges of allowable temperatures to be read before alerting an operator [21]. If installed with pan-tilt-zoom (PTZ) cameras, this technology can effectively monitor for leaks using temperature or infrared energy values read from the equipment of interest. NPP operators have used camera-based thermal imaging to support manual walkdowns for leaks, but permanently installed cameras have not yet been implemented.

2.3.3 Challenges to Adoption

Camera-based monitoring presents several notable challenges: 1) a challenging business case since reductions in staff are limited by minimum operator requirements (per 10CFR50.54), 2) privacy concerns related to inadvertent continuous monitoring of personnel, and 3) challenges related to the management and analysis of data rich inputs. However, the technology is promising in helping to reduce operations costs for operating NPPs. Regulators are currently developing methodology to address the acceptance of camera-based monitoring technologies to aid adoption [5]. See further discussion on general barriers and barriers specific to AI/ML in Section 5.

2.3.4 Level of Automation

Similar to Section 2.2.4, the LOA is best defined as a LOA of 2, per the Kaber and Endsley framework [4]. However, it is less mature than a technology such as OLM, because there is much more manual effort to assist the system in performing the monitoring function; i.e., because the analysis tools are not currently fully automated.

2.3.5 Future Direction

In the future, AI/ML algorithms could be refined to use solely visual data to automatically accomplish complex visual monitoring tasks, such as detecting steam leaks in NPPs [24], automatically analyzing leak rates in an accident scenario, or supporting automatic condition evaluations for multiple pieces of equipment in a given room. Cameras could be setup in challenging-to-access locations to support machine verification (instead of manual verification or even remote verification) of personnel activities, and the data could support automated work packages (described in Section 4.3). Improved image processing algorithms could additionally allow NPPs to take advantage of existing plant cameras with adequate plant computer interfaces without installing new application-specific cameras (such as thermal imaging devices). Further, an automated camera system could be paired with other technologies such as acoustic monitoring to enable even greater insights and analysis of plant data.

2.4 Digital Instrumentation and Controls

2.4.1 Summary

Instrumentation and controls (I&C) systems provide operators information on important plant parameters and performance, allowing operators to control plant systems as required during operation and automatically respond to abnormal or accident conditions. Digital technologies are replacing some legacy I&C equipment to provide numerous benefits, including improved plant safety, improved self-diagnostics, and improved controls and reliability. Digital I&C also supports increased integration of data and analysis to the control room. This provides operators better insight for in-situ plant conditions and operations [25]. Digital technologies are also more robust than legacy systems for more extreme operating conditions and transients. Digital I&C is also an enabler to further automation of operator tasks to realize significant benefits.

2.4.2 Example – Digital Feedwater Level Control System

A successful example of implementing digital I&C at a NPP with a benefit for automation is a digital feedwater level control system. Legacy feedwater control systems were also automated but have been the cause of a significant number of plant trips, due to issues with the electronic control system and air operators for feedwater control valves [27]. As discussed in Reference 26, changing to digital feedwater control system technologies that allow for greater automation more effectively maintains water levels in the reactor or steam generator during normal operation and steam demand transients. Digital feedwater level control utilizes a redundant digital level sensor and electric valve positioner suite to facilitate correct automated response, as opposed to analog sensors and traditional air-operated valves. The digital control system can perform self-diagnostics and more precisely maintain optimal conditions for thermal performance of the plant. In this application, the improved controls system automatically selects the best reading from the sensors in case of a single sensor failure and adjusts the appropriate value (average or median) for control. This same technology can be applied to feedwater heater level controls to extend the life of feedwater heaters and therefore lower lifecycle costs because of the more precise control of the water level in each heater.

2.4.3 Challenges to Adoption

The complete benefits of digital I&C upgrades are still far from being realized; in addition to the substantial up-front cost, there are many other challenges facing implementation of digital I&C to enable automation. The technology is mostly proven, but installation is complex, expensive, and time-consuming [29]. For some projects, implementation can require multiple outages, and there is a significant personnel burden to support the required design work, documentation and execution.

Increased automation reduces the level of interactions operators have with the systems, which could negatively impact knowledge of plant staff and reduce operators' situational awareness. Furthermore, the phased transition in control rooms to increase automation is challenging from a human systems interfaces perspective, as operators must become familiar with multiple hybrid interim configurations [28].

Regulatory approval is expected to be required for digital I&C upgrades to safety-related equipment. While guidance exists for U.S. plants submitting license amendment requests through DI&C-ISG-06, Digital Instrumentation and Controls Licensing Process Interim Staff Guidance, there is no experience with regulatory approval of safety-related digital I&C upgrades [36]. Additionally, the current guidance from the NRC on regulations for digital I&C updates under 10CFR50.59 has not kept pace with advances in the technology. For example, the current NRC position on demonstrating protection against common cause failures, included in SRM-SECY-93-087, was issued in 1993, and the current guidance in Branch Technical Position BTP 7-19 on addressing common cause failure for digital safety systems [34] does not currently support industry needs [35]. However, the regulator is actively working on guidance to support the direction of the industry. Per SECY-18-0090 (Reference 35), the NRC is working to update BTP 7-19 to support a risk-informed graded approach for evaluating software. Additionally, DI&C-ISG-06 Revision 2 [36] supports an alternate review process for safety-related digital I&C upgrades and, per discussions with industry, has been successfully implemented on a small scale.

Additional general hurdles which are applicable to other automating technologies as well as barriers specific to AI/ML are summarized in Section 5.

2.4.4 Level of Automation

Digital I&C technology is one of the most automated technologies being implemented by NPPs currently. Implementation typically involves a human/computer shared responsibility for monitoring, such that the operator could manually intervene if needed to select the appropriate option for input to the control loop [4], but typically the computer is generating, selecting, and implementing options for adjusting the system parameters to meet the desired control band acceptance criteria. Therefore, most digital I&C technology that has been implemented for non-safety applications is categorized as Level 9, or Supervisory Control, on the Kaber and Endsley LOA categorization scale [4]. In the specific example above, the digital feedwater level control system performs self-diagnostics to generate, select, and implement the desired reading for input to the control loop. Note that for many digital I&C technologies supporting safety-significant BOP control functions, and eventually those supporting safety-related systems, it is likely that any automated system implemented in the near future will require manual oversight.

2.4.5 Future Direction

Specific digital controls modernizations, such as the digital feedwater level control system, serve as an enabling technology to more broad automation of plant operations. Currently, some plants have successfully transitioned many balance of plant systems to utilize digital technologies. However, because these digital I&C improvements require significant upfront investments, implementation is not widespread. Several plants are currently undergoing projects to modernize their control rooms via digital I&C upgrades. Control room modernization projects typically include safety-related digital I&C upgrades in the planned scope, and as mentioned above it is recognized that regulatory approval will be a significant challenge to the cost and schedule of the project.

Plants are working on integrating the outputs of newly implemented digital systems with automated data management at the control interface to improve operator efficiency [28]. In the future, a goal reiterated by multiple utilities was to use automation to reduce opportunities for human error and to improve plant reliability. An example is automatic alignment of the fluid systems in plants to meet various operating scenarios (e.g., startup, shutdown). Reference 28 provides detailed discussions of the required steps to analyze allocation of functions to automation and many other important considerations for designing automation.

3 Inspection and Maintenance

3.1 Overview

Automation of inspection and maintenance activities is defined as the implementation of technologies to reduce the burden of or improve capabilities related to performing preventive and corrective measures to ensure that structures, systems, and components (SSCs) are able to perform their intended functions. Motivations for automating inspections and maintenance activities include [40, 41]:

- Allowing for greater consistency in task execution, which supports high accuracy in trending degradation or conditions over time
- Expanding capabilities, particularly in accessing new areas using tooling or robotics and gaining new insights from AI/ML that are not manually identifiable
- Reducing burden to plant personnel, both those who would be performing the maintenance or inspection activity manually or at greater frequencies, and those responsible for the administrative burden of preparation and oversight for manned access to hazardous areas
- Increasing performance and availability of plant SSC by improving reliability.

NPPs are in the early stages of implementing automation technologies for inspections and maintenance in operating NPPs. As discussed in Appendix A, approximately 30% of the TIP award submittals that discussed an automating technology were implemented to improve inspections and maintenance activities. Multiple sources, including utility interviews, TIP award submittals, and published news articles and papers, discussed increasing adoption of and forward momentum for the implementation of automated tooling for inspections. On the other hand, only a few utilities discussed automated repair activities and testing. Automation of data analysis has also garnered wide interest among NPPs. Many utilities and vendors are investigating and demonstrating automating technologies to support inspection and maintenance data analysis and generation of insights. These technologies include analytics to process inspection data and to support predictive maintenance.

To increase the degree of automation for inspection and maintenance activities, interviewed utilities have demonstrated an interest in 1) using robots to perform inspections and maintenance tasks to reduce risk to plant personnel and outage costs and 2) using ML/AI to optimize inspection and maintenance planning. Online monitoring to enable automation of inspection and maintenance activities is discussed in Section 2. Automation of reporting to support inspection and maintenance is discussed in Section 4.

Specific examples of automation for inspections and maintenance in operating NPPs are discussed below.

3.2 Robotic Technologies for Inspection and Maintenance Activities

3.2.1 Single-Purpose Robotic Platforms and Tooling

Investments in robotics technologies for applications in NPPs have largely been limited to development of specific platforms or tools for individual use cases [42]. This approach is time and cost intensive but has yielded robotic platforms capable of high value activities including decontamination, containment structure inspections, underground piping inspections, and foreign material extraction [40, 43, 44]. These technologies are well developed as tools to reduce human exposure to hazardous environments. However, they do not fully automate power plant inspection and maintenance activities and are largely designed to allow manual tasks to be performed remotely, rather than without manual input.

Utilities regularly leverage vendors to perform these high-value specific tasks. Since developing a tool for a specific purpose is time and cost intensive, and high-value use cases are performed with low frequency at any one site, presenters at the 2021 Robotics for Inspection and Maintenance Summit noted that the business case for internal research and development at NPPs is limited [42].

One example task is to use remote tooling and/or submersible robots to decrease exposure to radiological hazards and reduce critical path for reactor internals inspections (Reference 45). This is a task that was traditionally performed by divers. Multiple utilities have taken the remote tooling and/or robotics approach to reactor internals inspections. When a platform exists for the particular reactor internals configuration at a site, the vendor owning and operating that platform is brought in during the outage. When tooling is not available, a partnership may be formed between the utility and vendor to develop the right tool for the particular job.

The number of applications for which specific tools are developed and degree of automation leveraged continues to grow, as indicated by the TIP award survey (see Appendix A). Approximately 40% of the TIP award submittals related to inspections and maintenance are about automated tooling for inspections. Additionally, all but one were developed for use in radiologically hazardous locations. This means that significant benefit is gained despite the low LOA present in the specific tool. Personnel safety continues to be a driving force for new use cases.

3.2.2 Multi-Purpose Robots for General Activities

Recently, investments in robots for operating NPPs have expanded to include general purpose platforms as a means to 1) advance the development of the technology and 2) identify future use cases. A typical general-purpose robot is a land rover, drone, or submersible remotely operated vehicle that can use various payloads to perform tasks like collecting visual inspection data, creating three-dimensional radiation maps, or identifying steam leaks [47, 48, 49].

Pilot programs to expand use cases for robotics and NPPs are underway with several utilities, who have implemented such programs to explore the technological maturity of commercially available general-purpose robots [50]. Various activities have been identified by utilities as having good potential for automation, and, with manual input and oversight, many automation capabilities have been demonstrated. Some examples are highlighted in the following paragraphs.

One utility used a land rover to monitor a weld that was degrading, allowing operators to run the plant while waiting for replacement parts without increasing risk to personnel [51]. Another utility has used drones to inspect their waterbox for leaks during normal operation and the main condenser and drywell equipment during an outage. This allowed for risk and cost avoidance in reducing the need for scaffolding, climbing, and fall protection [52]. At a third utility, a land rover has been used to disconnect a breaker and perform inspections [53].

One of the popular general-purpose land rovers has a built-in functionality for obstacle avoidance and adaption to varied terrain. In areas where human activity is infrequent, impractical, or hazardous that can be readily accessed by the robot, some utilities have begun to investigate the maturity of autonomous navigation and demonstrate the robot's object avoidance and terrain adaption capabilities. A use case being explored is performing walkdowns of switchyards with human supervision. This task is accomplished by manually creating a path using posted indicators for the robot to use for navigation; along this path, the robot collects data using visual, thermal, and/or gas detecting sensors [54]. Two utilities have reported using this robot to perform pre-job and post-job surveys for transmission sites and substations.

A developer of submersible remotely-operated robots that are used for underwater inspections in NPPs reported progress in reducing the need for the operator to define waypoints at the Robots for Inspection and Maintenance Summit. Their goal is to reduce the need for manual input in piping and intake structure inspections. Mission planning capabilities are an important step toward full automation; implementation of automated mission planning in an operational capacity at NPPs is expected to follow adoption by other industries.

3.2.3 Challenges to Adoption

One challenge to adoption that is particularly significant for robotic platforms used in containment and other controlled NPP areas is the automation of data transfer and availability of supporting infrastructure. While this hurdle exists for most automating technologies, the use cases that are particularly well suited to robotic platforms present significant challenge to full automation. Since there is no data transfer infrastructure in-containment, data transfer becomes more manually-intensive. One interviewee discussed the need to manually download and upload data from a robot using a flash drive. This is burdensome and increases risk to the security of the data since its retrieval requires additional transfer points.

3.2.4 Level of Automation

For both categories of robotic technologies, the current state of implementation heavily leverages personnel for manual input and oversight. Most decision making and implementation efforts are manual, aligning with action support (LOA of 2), batch processing (LOA of 3), or shared control (LOA of 4) on the Kaber and Endsley LOA scale.

Remote tooling and robots used in NPPs for specific high value tasks typically have a LOA of 2 or 4, since implementation typically involves human and computer monitoring of data streams and human or shared control of tooling and/or robot actions throughout the activity (generating, selecting, and implementing actions in response to a data feed, [46].

Using a general-purpose robot to collect inspection data or perform simple maintenance tasks is also best characterized as having a LOA between 2 and 4 (action support, batch processing, or shared control) since a human operator is usually required to control or provide direction to the robot or robotic tooling while it the performs the action per interviews with NPPs. In cases where the degree of automation is greater (e.g., putting out a fire, see Section 3.2.5) robotics have only been used in controlled environments, rather than within a normally operating NPP [53]. Manual input, testing, and oversight are seen as necessary steps to enable the development of the technology to allow for more automation in the future.

3.2.5 Future Direction

For specific high-value activities performed in operating NPPs, manual control is used where robotics tooling and platforms are leveraged to ensure risk is minimized [46]. However, during the 2021 Robotics for Maintenance and Inspection Summit, several vendors described efforts to move from human-planned and -navigated missions to human supervision of robotic mission planning and execution.

For pilot projects, utilities are focused on expanding the degree of automation and use cases for which robots are considered. One utility's robotics pilot program recently partnered with a university to test the ability of a ground-based robot to autonomously detect and extinguish a diesel fire using an infrared camera in a controlled environment [55]. It included the robot assessing the location, positioning itself, and extinguishing the flames. Through such activities that test greater degrees of automation, utilities are helping vendors to identify gaps, enabling future use cases as the technology becomes more versatile and better proven. Researchers are spread across many different areas of development including autonomous navigation [56], identification and implementation of new capabilities [51], and analysis of data rich sensor outputs [57].

In parallel with robotics technologies designed for and being leveraged by utilities, there have been investments in automation for inspection and maintenance by many programs globally. A few examples specific to nuclear power generation are [42]:

1. ***International Atomic Energy Agency (IAEA)*** robotics challenges to incentivize the development of robots for tasks to reduce risk to NPP personnel
2. ***Robotics for Inspection and Maintenance (RIMA)*** a 4-year project to provide funding, training, and facilitate communication between stakeholders for the development of robotics for inspections and maintenance
3. ***Robotics and Artificial Intelligence for Nuclear (RAIN)***, a collection of research institutions collaborating to accelerate the development of robotics for the nuclear industry

3.3 Automated Equipment Monitoring for Predictive Maintenance Using AI and ML

3.3.1 Summary

Time-based preventive maintenance has been the standard approach to establish maintenance intervals for systems and components in NPPs [58]. This approach uses conservative maintenance intervals to identify and correct equipment issues. Not performing maintenance frequently enough can lead to degraded performance and unplanned failures, increasing operational and safety risk. However, this approach is challenged when there is limited data on equipment reliability, a high degree of system complexity, or limited equipment accessibility [59]. Additionally, significant conservatism in maintenance frequency increases operational costs and places an increased burden on plant personnel away from higher value tasks. NPPs often must use conservative time-based maintenance frequencies unless a technical basis can be provided to justify longer periodicity [60].

Data-driven predictive maintenance offers an advantage to time-based maintenance because it optimizes the frequency at which an asset is serviced based on key indicators, including data from the asset of interest. This is an appealing strategy for many assets, particularly those that have a significant impact on a larger system or power generation capacity, take a long time to repair, or are costly. Gaining insights from asset monitoring is discussed in this section; monitoring of critical assets is discussed in Section 2.

Use of AI/ML technology can allow for automated analysis of NPP data to optimize maintenance activities and avoid unplanned repairs and outages. One advantage of AI/ML is its ability to develop models for systems that are challenging or infeasible to characterize using conventional algorithms. Instead of relying on prescriptive intervals, AI/ML algorithms can capture non-linear or complex relationships between measured parameters and component or system performance. In a 2021 NRC survey, participants identified SSC monitoring as the business or technological area that could benefit the most by AI/ML applications. SSC monitoring was followed closely by predictive maintenance, which is informed by SSC monitoring [61].

Currently, most utilities are focusing on enabling technologies, such as installing advanced sensors and instrumentation, digital computing capabilities, data transfer infrastructure, and a variety of modeling and simulation capabilities (see Section 2 and Reference 62). Some utilities have also established efforts to research, develop, and test AI/ML models in-house or with vendors to better understand the performance of a specific asset. Others are looking at plant health holistically, using AI/ML to predict system reliability through standard reporting tools.

3.3.2 Example Applications

One utility is experimenting with using natural language processing to identify maintenance rule function failures from incident reports and advanced pattern recognition on data from monitoring equipment. Some example inputs include bearing temperatures, vibration data, and steam and shaft pressure for various components [62]. Another utility reported that they are working with a vendor to develop a digital twin for their site. The digital twin is a software representation of the physical plant that is designed to inform and improve plant performance. While the digital twin will initially rely on physics-based analytics, the plant intends to use AI/ML algorithms within the digital twin to allow for early detection of anomalies and potential failures in the future. The digital twin will ultimately be used to inform maintenance and operations decisions. AI/ML models within the digital twin are expected to use both live data and historical information, such as maintenance records, to assess when maintenance should be performed [63]. Once AI/ML is adopted by operating NPPs, many have expressed a desire to automatically generate work orders in response to AI/ML based insights (see Section 4.3).

3.3.3 Challenges to Adoption

Data availability and quality drive AI/ML models. An important challenge to training models for NPP applications is finding a sufficiently broad data set from operating NPPs that includes both normal operation and upset conditions. The absence of this information requires developers to make assumptions, which can impact the accuracy and applicability of model. Further, this can delay adoption of the model [59]. As an illustration of this point, a 2021 NRC evaluation of AI/ML for NPPs contains a list of recent applications of advanced computational tools in NPP operation and maintenance. Within the 23 studies that were listed, only 4 used solely plant or test facility data, while 19 leveraged simulated data (note that one study used both plant data and simulated data, [61]).

Additionally, there is a lack of literature on using AI/ML to develop and update maintenance programs in a normal operating environment. Rather, it is currently being explored as a potential tool to inform maintenance practices. Efforts are being made to address specific concerns related to leveraging AI/ML in operating NPPs (i.e., through working groups and industry surveys). For example, a recent NRC publication benchmarked cybersecurity concerns and how industry actors are approaching risk mitigation. They found a high awareness of the importance of proper controls for an ongoing effort to strengthen cybersecurity for AI/ML. More information can be found in Reference 61.

Barriers to the implementation of automating technologies and those specific to AI/ML are further discussed in Section 5.

3.3.4 Level of Automation

Despite these barriers and the barriers discussed in Section 5.1 and 5.2, progress towards adoption in NPPs is being made. Many operating NPPs and vendors have or are currently exploring various AI/ML methods, and typically leverage a mixture of internal and contracted SMEs [61]. However, most models have been developed and tested in controlled environments and have limited or no experience integrated with normal plant operations. The maturity of these models is varied [59].

While the technology is not mature in terms of implementation for NPP inspection and maintenance, the LOA is best described as Shared Control or Decision Support (LOA of 4 or 5). For most applications being developed and tested for use in NPPs, the model is responsible for monitoring incoming data, generating expected outcomes, and weighting and reporting the most likely outcomes. The human counterpart is also responsible for monitoring the data through pre-processing and model training and for generating actions to take in response to model insights, but typically has full ownership over the selection and implementation of an action in response.

3.3.5 Future Direction

Researchers are using AI/ML to develop and improve models to optimize maintenance and predict failures and component degradation. Some specific applications are as follows:

- A predictive maintenance mechanism for small steam sterilizers has been proposed that uses AI/ML to categorize the health condition of two important components [61].
- To advance the generation of insights for failure prediction, researchers at a national lab are developing a model to analyze the crack growth of turbine blades using AI/ML to predict turbine blade failure and inform operator action [64].
- AI/ML is also being used to extract centrifugal pump bearing degradation features from large volumes of vibration data to predict remaining useful life [61].

Accident detection, diagnosis, and mitigation has also been approached using AI/ML methods. Researchers have developed an automated fault detection tool using an artificial neural network regression model for very small loss of coolant accidents in PWRs without data from an actual loss of coolant accident, verifying their results against Loss-of-Coolant Accident simulations [61]. Additionally, researchers at a national lab are working on a project to develop and demonstrate an integrated risk-informed condition-based maintenance capability. The project diagnoses pump failures using vibration data collected from the circulating water system at an operating NPP. Natural language processing was then performed on work orders to establish the reliability of various circulating water system components [62].

As a precursor to leveraging AI/ML, NPPs are expected to implement physics-based models to optimize maintenance. These models are currently being researched and prototyped for use in operating NPPs. In the future, ML algorithms can improve the ability of physics based models to optimize maintenance intervals, detect and diagnose accidents, and predict failures in operating NPPs. Ultimately, AI/ML models for inspections and maintenance are expected to be leveraged in conjunction with other automation technologies. For example, AI/ML capabilities to identify the required maintenance action in response to monitoring data may be leveraged on a robotic tooling platform, allowing the combined technologies to perform tasks required by each LOA role.

4 Workflow and Business Processes

4.1 Overview

One of the most accessible forms of automation to NPPs is workflow and business process automation. Automation of workflow and business processes is defined in this report as the use of software or other algorithms to augment or replace manual effort to accomplish administrative-type tasks. Typically, these processes are not associated with safety systems or directly impact critical assets at NPPs, so there is a low barrier to entry. There are notable benefits that can be gained from automation of workflow and business processes for repetitive or time-intensive activities performed on a recurring basis, including:

- Significant time savings for personnel to focus on areas of higher importance requiring more critical thinking [28]
- Improved repeatability of the outcome of the task and reduced opportunity for error through process standardization
- Capturing knowledge of processes and systems from trained personnel to support knowledge transfer during staff turnover [65]
- Increased quality of task outcomes due to sophisticated analysis techniques and the ability to incorporate greater amounts of inputs

As discussed in Appendix A, many NPPs have successfully implemented solutions, including novel AI/ML algorithms, to support automation in workflow and business processes. The approach to implementation has varied between utilities, depending on their resources. For example, one utility has successfully used open-source code to develop software and other technologies for administrative process automation without relying on commercial products [65]. Other utilities do not have the resources to support these R&D tasks, and have contracted out development work or purchased software solutions developed by vendors.

Current research is focused on automating additional steps of workflow processes, improving integration with the data outputs discussed in Sections 2 and 3, and increasing the confidence in the outputs to support more widespread use of the results to inform decisions.

Specific examples of successful implementation at NPPs and current research are discussed below.

4.2 Example – Automated Cap Review

As mentioned above, one key opportunity for automated workflow processes is automation of record and data management and analysis. In addition to operational, maintenance and inspection data, discussed in Sections 2 and 3, there are other sources of significant amounts of data that NPPs must manage and effectively utilize. Examples include corrective action program (CAP) condition reports and component data and safety categorization information (e.g., to support the 10CFR50.69 process). Automation of the CAP review process is discussed in detail to highlight the use of AI/ML techniques in NPPs.

4.2.1 Summary

INPO reviews and analyzes NPP operating experience to identify areas for improvement at NPPs across the industry. To support INPO reviews, NPPs must review their CAP data and provide a report to INPO summarizing insights and trends from their recent operating experience. NPPs typically have thousands of condition reports (CRs) generated over this time frame, all of which required individuals in different departments to review and assign problem or cause codes. Per an interview with plant personnel, the process for reviewing the data from the previous 18 months and summarizing insights is time and resource intensive: the manual process took three to four man-months of effort.

Some NPPs have successfully automated portions of this process using a software solution that assigns codes to CRs and automatically outputs the results in just a few minutes. The software uses a natural language model trained on validation from plant personnel reviewing recommended code assignments. Once the NPP has sufficient confidence in program outputs, the process of assigning problem or cause codes, screening based on priority and severity, and packaging the results to easily derive insights on performance can be fully automated. The software was developed in-house by a utility, and other NPPs that want to leverage this work can outsource the entire process or license the software and run it on in-house servers through 'cloud native' technologies [65]. This automated process saves utilities significant personnel hours which would otherwise be spent reviewing the data manually. Additionally, automating the problem/cause code assignment process, which originally would take place on an individual CR basis during the initial screening process, reduces human bias and inconsistencies resulting from multiple individuals and organizations applying the codes. Altogether, the process affords NPPs flexibility in resource management and improves reporting consistency and insights to INPO.

Note this implementation is just one example of automating a CAP process. Reference 71 provides the results of an industry survey which covers additional approaches and utility objectives.

4.2.2 Challenges to Adoption

Limitations associated with fully automating the CAP review and reporting processes include integration with utility software infrastructure, automation of importing historical CR data, and uncertainty quantification. Backwards compatibility of the software to import problem/cause code assignments back into the enterprise asset management software is limited. Additionally, the software package solution does not automate the pulling of historical CR data. Instead, it is manually imported by information technology staff per interviews with a utility implementing the software. Lastly, the interviewed utility was currently working to better quantify the accuracy of the results to inform discussions around the outputs with key personnel and build trust in the application. Quantifying and ensuring model accuracy is a challenge faced by multiple utilities implementing automation [71]. This barrier, in addition to other AI/ML specific barriers, are discussed in Section 5.2.

4.2.3 Level of Automation

CAP automation software currently being researched, developed, and implemented in NPPs typically addresses a subset of the tasks required for full automation of the CAP review process. At several utilities, the software is used to provide recommendations to a human counterpart who is responsible for manually performing the review. Human input is required to gather and input data into the model, the model and human both assess the information, the human provides a decision and both the human and software contribute to the report. This is best categorized as shared control (LOA of 4). For utilities using automating software to also evaluate CRs, blended decision making (LOA of 6) is more appropriate since the role of providing a decision (i.e., selecting) is shared.

4.2.4 Future Direction

Technology to automate CAP code assignment and reporting is highly desirable to operating NPPs and is feasible with current technology. Plants are largely focused on improving accuracy through improved model training and other layered approaches so that it can be deployed with confidence. Next steps for the interviewed utility also include using their technology to automate the process of trending data over many years. Ultimately, utilities would like to fully automate CAP assessment and reporting by improving outcomes and integrating data collection with analysis and reporting. Full automation of the CAP review process and reporting will require coordination effort across departments (e.g., information technology) and development of a package specific to the specific interfacing programs (e.g., data visualizer).

4.3 Example – Automated Work Packages

Within the last decade, many NPPs have successfully shifted to using electronic work packages (eWPs) to support maintenance work instead of paper-based work packages. The work package process is performed thousands of times annually for a single unit. As such, modernization efforts to digitize WPs have significantly improved personnel efficiency and resulted in cost savings [66]. Automated work packages (aWPs) would take this one step further to include unsupervised generation of the packages and other automated processing steps, and represents an opportunity to integrate several of the automation technologies described in the previous sections.

4.3.1 Summary

EWPs can vary from smart PDFs to fully integrated computer-based procedures [67]. At their most advanced, eWPs integrate data from multiple sources and can be accessed via devices with a wireless connection to the plant network to allow for workers to view the most up-to-date information for a package [68]. This digital foundation provides numerous possibilities to increase automation in the work package process, which is a current focus of research and an area of interest for utilities [68].

Reference 68 identified a number of steps in the work package workflow which have functions that could be automated. Per discussions with utilities, personnel envision automated initiation and screening of work requests based on input from plant monitoring technologies, which is only feasible if a plant has implemented wireless monitoring. Another potential input to initiate work requests is from the predictive maintenance models, described in Section 3.3. Initiating work packages using predictive maintenance insights would allow utilities to more effectively plan and schedule required maintenance. Per the user needs survey from Reference 68, there is greater interest in automating aspects of the work process which are less complex and are more administrative in nature, such as filing quality assurance records, archiving work packages, and managing clearances and permissions from appropriate personnel. These suggestions are from participants familiar with current NPP work processes and are likely are viewed as the most realizable tasks using currently available technologies.

4.3.2 Challenges to Adoption

While the framework for aWPs has been clearly laid out through the current research, many proposed functions are conceptual and require further research and development to be deployed [68]. Also, each NPP has a unique digital foundation of eWPs and existing monitoring infrastructure, so the level of effort and investment costs to realize the full benefits of aWPs will vary significantly between plants. Additionally, challenges associated with the AI/ML models such as accuracy and uncertainty in model outputs need to be further developed, as discussed in Section 5.2.

4.3.3 Level of Automation

The fully automated process is still in the research phase and has not been implemented at operating NPPs. However, many are looking into automating certain aspects of the process. Assuming the most likely state of an automated work package process at an NPP, as described in Reference 67 and discussed in Section 0, the computer and human would share responsibility for monitoring the various system parameters that may result in either a work order request being generated, or an indicator that the next step in the process can be completed, and then the computer would generate the proposed options for what should occur as a result of that indicator. It seems most likely that at least initially, the human would share responsibility for confirming that the option which the computer selects is indeed the correct approach; as models develop, this approach may shift to the computer retaining responsibility for selecting the approach and implementing the action (e.g., sending out the work order request). Therefore, initially the process would have an LOA of 6, blended decision making. As additional steps are automated and confidence is gained in the model, the process may achieve a LOA of 9, only requiring human participation in monitoring activities to enable intervention if correction was required.

5 Barriers to Implementation

Significant progress has been made to increase automation in operating NPPs. However, several common barriers exist that need to be addressed for maximum potential benefits from automating technologies to be realized. Common barriers that apply to all areas of automation benchmarked for this report (see Section 2 through Section 4) are summarized in Section 5.1. Additionally, there are several barriers that are specific to implementation of AI/ML technologies in NPPs that apply for other areas of automation discussed. Barriers specific to AI/ML are summarized in Section 5.2.

5.1 Common Barriers

- ***Cybersecurity:*** Realizing the maximum potential benefit from OLM possible through automation will require reliance on data gathered by sensors and transmitted wirelessly to make operational decisions. In the U.S., this will require compliance to 10 CFR 73.54, “Protection of Digital Computer and Communication Systems and Networks.” The most recent guidance issued by the U.S. NRC on these requirements was published in 2010, in Regulatory Guide 5.71, “Cyber Security Programs for Nuclear Facilities.” The guidance addresses modernization technologies and processes that were current at the time of publication [32]. Additionally, NEI published implementation guidance in NEI 08-09, “Cyber Security Plan for Nuclear Power Plants.” Modernization technologies and processes have matured and NEI is preparing an update to their guidance that is expected to include broader usage of wireless technologies. Cybersecurity continues to be a current topic of research in the industry and by the regulator [33].
- ***Challenging business case:*** The business case for implementing some automation projects, such as OLM systems or robotics technologies, usually depends on saving money through reduced maintenance, avoided trips, reduced person-hours, or a reduction in personnel exposure to hazards to offset the cost of installation. Taking credit for savings in these areas can be complicated: e.g., how to claim savings for an avoided trip. Even if these savings are quantifiable, upfront and ongoing costs can be high. As an example, digital I&C projects cost plants millions of dollars, and because of the extended timeline required for implementation, a high level of cost and schedule certainty (and therefore certainty in scope and requirements of the upgrades) is required at the start of the project [30]. The overall return on investment for projects such as digital I&C upgrades is typically very strong, but the payback period can be multiple years [26].

- ***Limited NPP personnel support:*** A significant time investment from utility personnel is often required to pilot and deploy the proposed automation technologies for each NPP. Utilities often do not have engineering resources to dedicate towards automation projects due to the other operation, maintenance, and administrative demands. Additionally, the level of experience among the available engineering resources is declining as highly experienced personnel approach retirement, making efficient implementation more challenging [31].
- ***Staffing hesitancy:*** There is some hesitancy in adopting new technologies in NPPs, which is attributed to the risk averse culture of the nuclear industry. For example, discussions with operators indicated a lack of trust in digital platforms to output accurate values, due to the familiarity with traditional analog system outputs. Typically, new technologies are rigorously proven both safe and effective before implementation is considered at NPPs. This may be accomplished by waiting for operating experience in other NPPs to evaluate the ROI and for endorsement by regulatory and advisory bodies before implementation is considered. As a result, not all NPPs have management who are currently willing to invest time and money to develop new automation technologies and processes. While this approach reflects the importance of safety to the nuclear energy generation industry, it challenges timely adoption.
- ***Site-specific infrastructure:*** Each NPP has a unique layout, variations in existing monitoring and wireless infrastructure, and different design and licensing considerations. While the automation technology being considered for implementation may be similar from plant to plant, each deployment requires considerable site-specific tailoring. E.g., for NPPs with limited existing wireless infrastructure, utilities must weigh the benefits and costs of either updating the existing infrastructure, sacrificing capability of the automation technologies, or identifying and implementing an alternate approach to what is described in existing guidance or operating experience.

5.2 AI/ML BARRIERS

For automation technologies that leverage AI and/or ML, the following additional challenges may apply:

- ***Explainability:*** Challenges in the transparency and trustworthiness of AI/ML results are present due to the perceived "black box" nature of the technology. This is an especially important issue when implementation may affect decision making for safety-related or safety-significant systems. The ability to clearly explain the AI/ML decision-making, conclusions and recommendations as well as any downstream impacts is important to winning support among personnel in the operating fleet and gaining regulatory acceptance [61, 63].
- ***Data quantity and quality:*** AI/ML algorithms require large volumes of data for training of models to ensure reliable results are produced. In addition, many researched AI/ML applications specifically for NPPs are performed based on simulated data, because 1) operating NPPs currently lack large volumes of historical digital sensor data and 2) some data which would support AI/ML applications cannot be shared outside of a plant to build a large enough dataset (e.g., camera footage for automated condition evaluation of sensitive components). To enable AI/ML to be effectively implemented in NPPs, data quality and volume requirements must be well understood. Additionally, data that meets these requirements must be available in appropriate formats [59, 61, 63].
- ***Uncertainty quantification:*** Model performance must be quantifiable in order to assign uncertainty to model results. Failure modes captured by AI/ML may not be well enough understood physically to determine the appropriate uncertainties present in the model inputs or results. Due to the low availability of fault data and potential lack of transparency in the AI/ML decision making process, defining uncertainty for each output may be challenging. The model may be asked to predict the occurrence of a random event, potentially one that has not occurred in the operating history of the plant, adding to the challenge of uncertainty quantification [59, 63].
- ***Verification and validation:*** A benefit of leveraging AI/ML for maintenance is the ability to predict a failure or degradation in performance or reliability before it has occurred. However, as mentioned previously, this includes events that occur rarely, or have never occurred, for which there is no baseline to compare against or minimal historical data for model training. AI/ML is also intended to be leveraged for equipment that has a complex relationship with the other systems or components. These models may not have an analogous manual evaluation or physics-based approach that can be used to prove the outcome is accurate [63].

While the barriers for implementing broader automation in NPPs are substantial and require dedicated research and development, there is great promise for automation to support the overall industry objectives to reduce operating costs, increase reliability, and improve personnel safety.

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A Nuclear Energy Institute (NEI) Top Innovative Practice (TIP) Award Submittals

A survey of NEI TIP award submittals from 2019, 2020, and 2021 was performed to provide an indication of the types of automation recently implemented by utilities [69, 46, 70]. Submittals are made by NEI members to document new practices, enhanced processes, and improvements to technologies that resulted in direct benefits to the utility or site.

To inform the state of automation in NPPs, each entry was evaluated to determine: 1) whether it is describing the automation of an activity, 2) what is being automated, and 3) the level of automation (LOA) for the activity, defined using the Kaber and Endsley scale [4].

Approximately 20% of all entries submitted by utilities between 2019 and 2021 explicitly discussed using automation to realize benefits. The results of the TIP submittal review are reported in Figure A-1 and Table A-1.

In general, automation described by TIP submittals between 2019 and 2021 is most readily characterized as Action Support (LOA 2) or Shared Control (LOA 4). Batch Processing (LOA 3) was much less frequently applicable because the TIP submittals typically relied on both a human and automating technology for implementation of the actions resulting from a decision, rather than on the automating technology solely.

For lower LOAs, the innovations were described as providing supporting information to personnel, who would then generate actions, select an action, and/or implement the action. No utilities reported full automation (which would correspond to LOA 10) of an activity that is currently performed manually: i.e., an activity for which no personnel oversight is required, and the automating technology is making the decisions required for the task and implementing the decision without human intervention. The submittals evaluated to have higher LOAs tended to involve controls or automating data analytics, reporting, and resource management. Reporting tasks tended to inform or provide recommendations for decisions, but in most cases a human was still responsible for the decision made or for providing oversight.

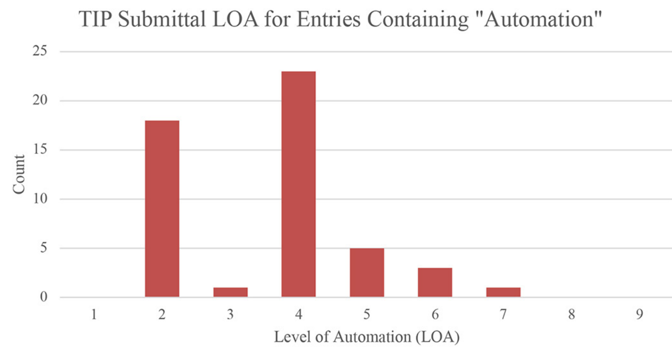

Figure A-1. Distribution of TIP LOAs for Submittals Crediting Automation

Table A-1. NEI TIP Award Submittal LOA

Area of Automation	Activity Automated	Number of Submittals[1]	Average LOA Characterization[2]
Plant Operations	Controls	2	5.0
	Data Collection/Monitoring	6	2.3
	Analysis	3	4.0
	Subtotal	**11**	**3.8**
Inspection and Maintenance	Inspection Tooling	7	2.3
	Repair/Maintenance	3	3.7
	Testing	3	4.0
	Analysis	4	3.5
	Subtotal	**17**	**3.4**
Workflow and Business Processes	Reporting	14	3.8
	Resource Management	3	4.7
	Validation/Verification	4	4.5
	Analysis	8	4.8
	Subtotal	**29**	**4.4**
Total Number of Submittals Discussing Automation			**57**
Total Number of Submittals			**261**

Notes:

1. Some submittals included multiple automated activities. Those activities may be counted towards several "Activity Automated" classifications within the same "Area of Automation" when relevant. For example, the TIP submittal for *Automated Testing of Open Phase Detection System (OPDS) Multifunction Digital Protective Relays Using Simulated and Actual Event Data* was counted towards subtotals for both Testing and Reporting in the Inspection and Maintenance Area of Automation, since it included automatically testing the relays and reporting a variety of key metrics as well as event reports and anticipated state change reports [69].
2. Activities that do not require decision making were assigned a LOA as a subset of the automation realizable for a task. For example, the TIP award submittal *Outage Milestone Analysis* allows for reduced manual reporting by automating key outage readiness performance indicators. However, manual reporting is still required, and no options for implementation are generated, selected, or implemented. A future goal for this activity may include generating high impact actions based on key indicators, then selecting and implementing the actions without human support [69]. Considering the limited scope of automation, this submittal is assigned a LOA of 2 to reflect shared monitoring and human generating, selecting, and implementing.

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