

## Harnessing AI and Robotics-Assisted Automation for Predictive Maintenance of Next-Generation Nuclear Energy Infrastructure

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**Abstract:** The pursuit of reliable, carbon-neutral energy sources has placed next-generation nuclear energy systems such as small modular reactors (SMRs), advanced fast reactors (AFRs), and molten salt reactors (MSRs) at the forefront of global energy strategy. Ensuring the long-term safety, operational efficiency, and cost-effectiveness of these systems necessitates a paradigm shift from traditional reactive or scheduled maintenance approaches toward intelligent, data-driven predictive maintenance (PdM) frameworks. Predictive maintenance, underpinned by artificial intelligence (AI) and robotics-assisted automation, has the potential to revolutionize nuclear infrastructure management by enabling real-time diagnostics, early anomaly detection, and adaptive response capabilities. This review provides a comprehensive analysis of current advancements in AI-enabled predictive maintenance technologies as applied to nuclear energy infrastructure. We examine the deployment of machine learning (ML) models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and reinforcement learning algorithms for equipment health prediction, failure mode classification, and condition-based monitoring. Special attention is given to the role of digital twins and physics-informed ML models that integrate real-time sensor data with high-fidelity simulations to forecast system behavior under various operational conditions. Additionally, we discuss the use of computer vision and natural language processing (NLP) for automated visual inspections, incident report mining, and safety compliance verification. The review further explores robotics-assisted automation, particularly the development of radiation-hardened autonomous and semi-autonomous robotic platforms for remote inspection, precision repair, and maintenance task execution in hazardous or inaccessible zones. These robotic systems, ranging from aerial drones to articulated manipulators and crawling robots are integrated with AI to enable perception, planning, and control functions in dynamic environments. Challenges such as high-radiation tolerance, data interoperability, sensor fusion, and cyber-physical security are critically evaluated.

**Keywords:** Artificial Intelligence, Nuclear Energy Infrastructure, Machine Learning, Digital Twin, Condition-Based Monitoring, Next-Generation Reactors, Anomaly Detection.

### INTRODUCTION

Nuclear energy constitutes a significant component of the global clean energy portfolio, currently providing approximately 10% of worldwide electricity and representing nearly one-third of global low-carbon electricity generation (International Atomic Energy Agency [IAEA], 2025). The capacity of nuclear power to deliver reliable, dispatchable energy makes it an essential complement to variable renewable sources such as wind and solar. Historical data demonstrate that nuclear energy has prevented roughly 70 gigatonnes of CO<sub>2</sub> emissions over five decades, highlighting its substantial contribution to climate change mitigation efforts (IAEA, 2025). Despite these advantages, the nuclear sector faces considerable challenges, particularly regarding infrastructure maintenance and operational longevity. Nuclear power plants (NPPs) in industrialized nations are increasingly characterized by aging reactor fleets, with average operational ages reaching 35 years in the European Union and 39 years in the United States (International Energy Agency [IEA], 2019). These aging systems exhibit growing operational inefficiencies, elevated safety concerns, and escalating maintenance requirements. Furthermore, the decommissioning of older reactors without

corresponding capacity replacement has contributed to a declining share of nuclear power in the global energy mix, potentially undermining broader decarbonization objectives (IEA, 2019).

In response to these challenges, predictive maintenance has emerged as a critical strategy for ensuring the safe, reliable, and cost-effective operation of nuclear facilities. Traditional maintenance approaches in nuclear power plants (NPPs) have typically followed reactive or time-based paradigms. Reactive maintenance addresses equipment failures after they occur, frequently resulting in unplanned outages and increased risk exposure. Time-based or scheduled maintenance, while more proactive, often fails to accurately reflect the actual condition of equipment, potentially leading to unnecessary interventions or overlooked degradation issues (Ucar *et al.*, 2024). Predictive maintenance represents a fundamental shift, employing real-time data analytics and continuous condition monitoring to anticipate equipment failures before they occur. This data-driven methodology enhances operational safety parameters, minimizes facility downtime, and optimizes resource allocation. In the nuclear context, where system failures can have profound

safety, environmental, and economic implications, predictive maintenance constitutes a transformative evolution in maintenance philosophy (Ucar *et al.*, 2024).

Artificial intelligence and robotics technologies have significantly advanced the implementation and effectiveness of predictive maintenance in nuclear settings. AI methodologies, particularly machine learning algorithms, enable the analysis of extensive datasets collected from sensor networks and monitoring systems to identify anomalous conditions, forecast equipment degradation trajectories, and optimize maintenance scheduling (Abdel-Rahim, 2024). For instance, AI-driven computer vision systems are increasingly deployed for automated inspection processes, capable of detecting microscopic cracks, corrosion indicators, or operational irregularities without human intervention. Robotics technology complements these AI capabilities by facilitating physical access to hazardous or high-radiation environments, enabling remote inspection procedures, manipulation tasks, and even repair operations. These robotic systems substantially reduce human radiation exposure while increasing operational efficiency in otherwise inaccessible areas. Moreover, the integration of digital twin technology creating virtual replicas of physical assets with AI and robotics systems enables comprehensive real-time monitoring, predictive simulation, and scenario planning. The iFANnpp project exemplifies this integration through its development of a comprehensive digital twin of a nuclear facility that supports robotic interaction and autonomous decision-making capabilities for maintenance operations (Do *et al.*, 2024).

## METHODOLOGY

This review synthesizes recent literature on predictive maintenance applications in nuclear energy systems published between 2019 and 2025. The analysis focuses on peer-reviewed journal articles, conference proceedings, industry reports, and technical documentation from leading nuclear energy organizations and regulatory bodies. Literature was identified through systematic searches in scientific databases including IEEE Xplore, Science Direct, and Scopus, using keywords related to nuclear maintenance, artificial intelligence, machine learning, robotics, automation, and digital twins. The selected publications were analyzed to identify emerging technological trends, implementation challenges,

regulatory considerations, and performance outcomes.

## LITERATURE REVIEW

### Predictive Maintenance in Nuclear Facilities: Concepts and Importance

Predictive Maintenance (PdM) refers to a data-driven maintenance strategy that anticipates equipment failures before they occur by monitoring the actual condition of assets in real time. Unlike traditional maintenance, which is either reactive (fix after failure) or preventive (routine servicing), PdM uses advanced sensor technologies, machine learning algorithms, and historical performance data to predict the remaining useful life (RUL) of components and schedule interventions only when necessary (Khamis *et al.*, 2023). This condition-based approach allows for timely maintenance, reducing unplanned outages and optimizing the allocation of resources in high-stakes environments like nuclear power plants (NPPs).

Implementing PdM in nuclear facilities poses unique challenges due to the highly complex, hazardous, and tightly regulated nature of these environments. One of the most significant barriers is the presence of ionizing radiation, which not only affects human safety but can also degrade sensor systems and electronic components, compromising data accuracy (Liu *et al.*, 2022). The intricate design and interdependence of nuclear systems further complicate fault diagnosis and failure prediction. Moreover, stringent safety and regulatory standards demand that any maintenance system, including PdM technologies, undergo thorough validation, qualification, and compliance with international norms such as those established by the International Atomic Energy Agency (IAEA) and Nuclear Regulatory Commission (NRC) (Goyal *et al.*, 2023). These factors necessitate highly robust, interpretable, and fail-safe predictive models to support critical decisions in NPPs.

Despite these challenges, the benefits of adopting PdM in nuclear energy infrastructure are profound. First, PdM enhances operational safety by identifying degradation patterns before they evolve into critical failures, thus reducing the risk of accidents or radiation leaks. For instance, early detection of micro-cracks in reactor components can prevent catastrophic failures (Ucar *et al.*, 2024). Second, PdM significantly improves cost-efficiency by minimizing unnecessary preventive maintenance and extending the lifespan of aging

components. Third, it reduces downtime, which is crucial in an industry where even short outages can result in substantial economic losses. Lastly, PdM supports long-term sustainability goals by maintaining system reliability and performance, enabling older plants to continue operating safely and efficiently while the world transitions to next-generation nuclear technologies.

## ROLE OF ARTIFICIAL INTELLIGENCE IN PREDICTIVE MAINTENANCE

Artificial Intelligence (AI) has revolutionized the field of predictive maintenance (PdM), especially within complex and high-risk sectors like nuclear energy. AI offers the computational capability to analyze vast amounts of operational data, identify patterns, and make real-time maintenance predictions, enhancing the safety, efficiency, and cost-effectiveness of nuclear power plant (NPP) operations. Among the core AI techniques employed in PdM are machine learning (ML) models, which include supervised learning, unsupervised learning, and deep learning. Supervised learning algorithms, such as decision trees, support vector machines, and random forests, are widely used for equipment health classification and remaining useful life (RUL) estimation by learning from labeled historical data (Zhao, *et al.*, 2023). Unsupervised learning, including clustering and dimensionality reduction techniques, is essential when labeled data is scarce, helping identify operational anomalies without predefined fault types. Deep learning models, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), are adept at handling time-series sensor data for trend prediction and fault detection, offering high accuracy in dynamic and nonlinear systems (Ucar, *et al.*, 2024).

AI-driven PdM systems are underpinned by the integration and processing of diverse data sources. Key inputs include data from Supervisory Control and Data Acquisition (SCADA) systems, Internet of Things (IoT) devices, and embedded sensors that continuously monitor variables such as temperature, pressure, vibration, and radiation levels. These data streams form the basis for anomaly detection, classification, and failure prediction models. Anomaly detection methods use statistical and AI-based techniques to identify deviations from normal operating patterns, which can indicate early signs of system degradation (Khamis *et al.*, 2023). Classification models categorize equipment states (e.g., normal, warning,

failure), while failure prediction models estimate the likelihood and timing of specific faults. These insights enable plant operators to initiate timely interventions, preventing unplanned outages and enhancing asset longevity. However, the success of AI-based PdM hinges on the quality and reliability of the underlying data. Nuclear environments present challenges such as data sparsity, noise, sensor drift, and communication delays. Preprocessing steps such as data cleaning, normalization, feature extraction, and dimensionality reduction are critical to ensure the robustness and accuracy of AI models (Liu *et al.*, 2022). Moreover, the high-stakes nature of nuclear operations demands transparent and interpretable AI systems to satisfy regulatory requirements and gain operator trust. As such, explainable AI (XAI) techniques are increasingly being incorporated to elucidate model predictions and facilitate human-in-the-loop decision-making. Through intelligent data interpretation and actionable insights, AI serves as a cornerstone of next-generation PdM systems for nuclear energy infrastructure.

## ROBOTICS-ASSISTED AUTOMATION IN NUCLEAR MAINTENANCE

Robotics-assisted automation has become a critical enabler for safe and efficient predictive maintenance (PdM) in nuclear energy infrastructure. Due to the hazardous nature of nuclear facilities, including high radiation levels, extreme temperatures, and confined spaces, robotic systems are increasingly deployed to perform inspection, maintenance, and repair tasks that would otherwise pose significant risks to human workers. Several types of robots are utilized in nuclear environments, each tailored to specific functions. Inspection robots often wheeled, tracked, or snake-like are designed to navigate complex reactor geometries and provide real-time visual, thermal, or radiation data (Fukuda *et al.*, 2021). Manipulators, including robotic arms and teleoperated systems, are used for handling radioactive components, replacing valves, and conducting maintenance in glovebox environments. Aerial drones are also emerging as tools for overhead inspections in containment buildings and storage facilities, offering high maneuverability and wide-area coverage (Shin *et al.*, 2023).

The key capabilities of these robotic systems extend far beyond mobility. Advanced robotic platforms are equipped with high-resolution cameras, LIDAR sensors, radiation detectors, and

force-feedback tools, enabling precise, non-invasive inspection of reactors and associated equipment. In radioactive zones where human access is restricted, robots can perform critical functions such as corrosion detection, weld inspections, pipe thickness measurements, and leak detection (Choi *et al.*, 2022). Some systems also facilitate minor automated repairs, such as applying sealants or replacing small components, significantly reducing downtime and minimizing radiation exposure to maintenance crews. These capabilities not only improve safety and operational reliability but also support compliance with stringent regulatory frameworks by enabling more frequent and thorough inspections.

A major advancement in robotics-assisted PdM is the integration of these platforms with Artificial Intelligence (AI) and digital twin technologies. AI enhances the autonomy of robotic systems by enabling real-time decision-making, adaptive navigation, and anomaly detection based on sensor feedback. For instance, machine learning algorithms can help robots identify deteriorating equipment and prioritize inspection routes (Yang *et al.*, 2023). Moreover, the concept of digital twins virtual replicas of physical assets allows robots to simulate maintenance scenarios, validate repair procedures, and optimize operational strategies before physical execution. This synergy enables predictive and prescriptive maintenance that is not only data-driven but also dynamically responsive to operational changes. As robotics and AI technologies continue to mature, their combined application in nuclear maintenance promises a transformative shift toward safer, smarter, and more sustainable nuclear energy systems.

## INTEGRATION OF AI, ROBOTICS, AND DIGITAL TWINS AND SIMULATION ENVIRONMENTS

Digital twin technology has emerged as a transformative framework for integrating artificial intelligence (AI), robotics, and real-time data analytics in the maintenance of next-generation nuclear energy infrastructure. At its core, a digital twin is a high-fidelity virtual replica of a physical asset, process, or system that synchronizes with real-world operations through continuous data exchange. In nuclear environments, digital twins are particularly valuable due to their ability to consolidate complex and heterogeneous data, such as real-time sensor readings, design blueprints, operational parameters, historical maintenance

logs, and environmental conditions into a unified, dynamic model. This integration not only enhances situational awareness but also enables predictive insights that are critical for safe and efficient operations. The use of digital twins in nuclear infrastructure has evolved to support simulation-based decision-making, enabling operators to anticipate equipment degradation, evaluate potential fault scenarios, and prioritize predictive maintenance (PdM) actions before issues escalate. For instance, advanced simulation capabilities allow stakeholders to test multiple maintenance strategies in a risk-free virtual environment, identifying optimal timing for interventions and forecasting the effects of operational changes on equipment life cycles (Khajavi *et al.*, 2022). Such simulation-driven foresight is especially crucial in nuclear power plants, where unplanned shutdowns or reactive maintenance can result in substantial safety risks and economic losses.

A notable implementation of this approach is seen in the iFANpp (Intelligent Framework for Autonomous Navigation in Nuclear Power Plants) project. This initiative illustrates how digital twins can facilitate virtual commissioning of maintenance tasks, enabling operators to rehearse and validate procedures digitally before deploying physical interventions. The iFANpp digital twin integrates real-time feedback from sensors and AI-driven analytics to assist robotic systems in autonomous navigation and adaptive task execution within radiation zones (Tariq *et al.*, 2023). Such integration not only accelerates maintenance planning and improves procedural accuracy but also significantly reduces human exposure to hazardous environments.

The synergistic interplay between AI, robotics, and digital twin technologies forms a robust ecosystem for PdM in nuclear infrastructure. AI algorithms embedded in digital twins analyze incoming data streams to detect anomalies, predict equipment failures, and support adaptive control decisions. Robotic systems, equipped with AI, execute maintenance tasks based on these insights, feeding new data back into the digital twin to refine its accuracy and responsiveness. This feedback loop facilitates continuous learning and optimization, enabling scenario testing and decision support in real-time. Ultimately, this triad empowers nuclear operators to transition from reactive or scheduled maintenance to a fully predictive, data-driven paradigm enhancing operational reliability, safety, and cost-effectiveness across the facility lifecycle.



## CASE STUDIES AND PERFORMANCE METRICS

The integration of artificial intelligence (AI), robotics-assisted automation, and digital twin technologies into predictive maintenance (PdM) frameworks has yielded substantial improvements in the operational efficiency, safety, and cost-effectiveness of nuclear energy infrastructure. Across various global nuclear power plants (NPPs), case studies provide compelling evidence of the value these advanced technologies deliver when systematically implemented.

A notable multi-country study involving 12 nuclear power plants that adopted machine learning-based PdM techniques for critical systems—specifically primary coolant pumps—demonstrated remarkable performance improvements. By analyzing real-time sensor data and applying supervised learning algorithms for early fault detection, these facilities reported an average reduction of 37% in unplanned outages over a three-year period. The ability to identify equipment degradation trends before critical failure allowed operators to schedule timely interventions, thereby preventing costly shutdowns and reducing maintenance costs by an average of 22% (Zhou *et al.*, 2022). These figures highlight the effectiveness of AI models in enhancing predictive capabilities and optimizing maintenance cycles in high-stakes environments.

In addition to AI, robotics-assisted inspection has significantly transformed nuclear facility operations, particularly in environments with elevated radiation risks. For instance, a major European nuclear site deployed a fleet of autonomous robotic crawlers and aerial drones for periodic inspection of reactor containment structures and steam generator compartments. These robots were equipped with high-resolution cameras and radiation sensors, enabling detailed real-time data acquisition from hazardous zones. The implementation led to a 45% reduction in radiation exposure for human maintenance crews and increased inspection coverage by 30%, as robots could access hard-to-reach or high-radiation areas previously avoided or inspected less frequently (Wang, *et al.*, 2021). Such advancements underscore the critical role of robotics in enhancing personnel safety while expanding the scope and quality of condition monitoring. Another impactful example comes from a Canadian nuclear generating station that integrated digital twin technology to streamline

preventive maintenance efforts. The digital twin model synchronized real-time operational data with historical maintenance records and component design specifications, creating a dynamic and continuously updated representation of the facility's infrastructure. By simulating various maintenance scenarios, the plant was able to fine-tune preventive schedules and allocate resources more efficiently. As a result, the facility experienced a 15% improvement in key reliability indicators, such as mean time between failures (MTBF), and projected a 7 to 10-year extension in the service life of essential reactor components (Khajavi *et al.*, 2022). These outcomes illustrate the profound impact digital twins can have on strategic planning and asset longevity.

Collectively, these case studies demonstrate that while the initial capital expenditure for deploying AI, robotics, and digital twin technologies can be significant, the long-term returns are often compelling. Beyond tangible cost savings, the benefits include enhanced predictive accuracy, reduced human risk exposure, improved asset utilization, and overall performance optimization. As the nuclear industry continues to modernize, these technologies are increasingly seen not just as enhancements, but as essential tools for achieving the resilience, safety, and sustainability goals of next-generation nuclear infrastructure.

## CHALLENGES AND LIMITATIONS

Despite the promising advances in artificial intelligence (AI) and robotics, several significant challenges continue to constrain their widespread adoption in the maintenance of nuclear infrastructure. One of the foremost issues is data quality and availability. Many legacy nuclear power plants were not originally designed with advanced sensor networks, limiting the data necessary for developing and training predictive maintenance algorithms (Zio & Aven, 2022). Without robust, real-time data inputs, AI models cannot reliably detect anomalies or forecast equipment failures. Moreover, the data that does exist is often siloed, inconsistent, or restricted due to national security concerns, further complicating AI deployment (Lu, Zhang, & Hu, 2023).

Regulatory frameworks also pose a substantial barrier. Existing maintenance protocols and safety regulations were developed with deterministic, human-supervised procedures in mind and are not always suited to the probabilistic nature of AI systems. As a result, integrating new technologies into nuclear operations requires navigating a

complex landscape of certification, validation, and compliance measures, which can delay implementation (Kumar & Nambiar, 2024). These issues are compounded by the nuclear industry's inherently conservative safety culture, which, while crucial for minimizing risk, often resists rapid innovation. AI systems, particularly those employing deep learning or opaque algorithms, are sometimes viewed with skepticism due to their limited explainability raising concerns among regulators and operators who prioritize traceability and transparency in decision-making (Shah & Mohan, 2023). Technical limitations present further obstacles. Robotic systems must be engineered to withstand high-radiation environments, necessitating advanced materials and radiation-hardened electronics that can be cost-prohibitive or complex to develop (Choi *et al.*, 2021). In addition, reliable communication within reinforced concrete containment structures remains a challenge, often requiring novel wireless or fiber-optic solutions. Robotic manipulators also need to be sufficiently versatile to handle a broad range of inspection, maintenance, and decommissioning tasks, which vary in complexity and environment.

## FUTURE RESEARCH DIRECTIONS AND INNOVATIONS

The future of predictive maintenance in next-generation nuclear energy infrastructure is poised for transformation through cutting-edge research in artificial intelligence (AI), robotics, and regulatory development. One of the most promising areas is the evolution of emerging AI methodologies. Explainable AI (XAI) is gaining traction for its potential to provide transparent decision-making processes in high-stakes environments such as nuclear facilities, where accountability and interpretability are essential (Lu, Zhang, & Hu, 2023). Reinforcement learning, with its ability to improve decision-making through trial-and-error interactions with dynamic systems, offers a path to autonomous maintenance optimization (Zhao *et al.*, 2022). Federated learning, which enables AI models to be trained across decentralized data sources without compromising data privacy, is particularly relevant for nuclear facilities that operate under strict confidentiality protocols (Kairouz *et al.*, 2021).

In robotics, future innovations are expected to center around enhanced human-robot collaboration, allowing workers and robots to perform complex maintenance tasks more safely

and efficiently in shared environments (Ajoudani *et al.*, 2018). The development of soft robotics presents opportunities for delicate operations in confined or hazardous areas of nuclear reactors, where conventional robots may be too rigid or large. Additionally, swarm robotics coordinated robotic units that mimic biological swarms could revolutionize inspection and repair procedures by offering scalable, redundant, and adaptive maintenance solutions (Brambilla *et al.*, 2013).

Another critical research avenue involves the establishment of standardized protocols and comprehensive regulatory frameworks tailored to AI and robotic applications in nuclear maintenance. This includes defining best practices for system validation, cybersecurity requirements, and ethical guidelines, which are essential for gaining public trust and regulatory approval (IAEA, 2023). Lastly, fostering international collaboration will be vital for knowledge sharing, benchmarking innovations, and developing harmonized global standards. Cross-border initiatives can facilitate joint research programs, data sharing agreements, and capacity building, ultimately accelerating the safe and effective integration of AI and robotics in nuclear energy sectors worldwide (OECD NEA, 2022).

## CONCLUSION

This review has explored the transformative potential of artificial intelligence (AI) and robotics-assisted automation in enhancing predictive maintenance for next-generation nuclear energy infrastructure. The integration of AI technologies such as machine learning, reinforcement learning, and federated learning offers unprecedented capabilities in fault prediction, anomaly detection, and decision optimization. Concurrently, advances in robotics, including human-robot collaboration, soft robotics, and swarm robotics, are enabling safer, more efficient maintenance operations in hazardous nuclear environments. Despite these advancements, significant challenges remain, including data limitations, regulatory uncertainty, technical constraints, and workforce adaptation.

The potential impact of AI and robotics on the future of nuclear maintenance is profound. These technologies promise to increase operational efficiency, enhance safety, reduce unplanned downtimes, and extend the lifespan of critical assets. They also support proactive risk management by enabling real-time monitoring and predictive diagnostics, fundamentally shifting

maintenance strategies from reactive to anticipatory modes. However, for these benefits to be fully realized, efforts must be made to foster innovation through collaborative research, international standardization, and policy reform. Encouraging widespread adoption will require not only technological readiness but also cultural and organizational alignment. Investments in workforce training, regulatory adaptation, and explainable AI systems will be essential for building trust among stakeholders. Furthermore, global partnerships and knowledge-sharing platforms can accelerate the development of robust, scalable solutions tailored to the unique safety demands of the nuclear sector. By embracing these strategies, the nuclear industry can harness AI and robotics to drive a safer, smarter, and more sustainable energy future.

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**Source of support:** Nil; **Conflict of interest:** Nil.

**Cite this article as:**

Opoku, J. A. and Adeoye, M. B. "Harnessing AI and Robotics-Assisted Automation for Predictive Maintenance of Next-Generation Nuclear Energy Infrastructure." *Jr. Inn. Sci.* 1.2 (2025): pp 1-8.