



(REVIEW ARTICLE)



AI-driven real-time diagnostics and self-correcting control schemes for next-generation nuclear energy systems

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World Journal of Advanced Research and Reviews, 2025, 27(03), 1550-1557

Publication history: Received on 16 August 2025; revised on 23 September 2025; accepted on 25 September 2025

Article DOI: <https://doi.org/10.30574/wjarr.2025.27.3.3294>

Abstract

The advancement of Next-Generation Nuclear Energy Systems (NGNES) requires intelligent, adaptive control mechanisms to enhance operational reliability, safety, and efficiency. Artificial intelligence (AI)-driven real-time diagnostics and self-correcting control schemes are emerging as transformative solutions in nuclear energy infrastructure. These systems integrate machine learning, predictive analytics, and automation to continuously monitor reactor performance, detect anomalies, and autonomously adjust control parameters in response to dynamic operational conditions. This review examines the application of AI-driven models in fault detection, predictive maintenance, and automated response mechanisms within advanced nuclear power plants. It explores key methodologies such as deep learning-based anomaly detection, reinforcement learning for optimal reactor control, and digital twin simulations for predictive diagnostics. By leveraging these AI technologies, nuclear energy systems can improve safety margins, reduce downtime, and optimize energy output, aligning with U.S. Department of Energy (DOE) priorities in nuclear modernization and energy security. However, challenges remain in AI model interpretability, regulatory compliance, cybersecurity risks, and data integration with legacy nuclear infrastructure. Future research should focus on enhancing the robustness of AI models, integrating real-time sensor fusion techniques, and developing standardized frameworks for AI-driven automation in nuclear power operations. By synthesizing recent advancements, this paper provides a comprehensive analysis of the role of AI in real-time diagnostics and self-correcting control schemes, offering insights into how intelligent automation can revolutionize the next generation of nuclear energy systems.

Keywords: Artificial Intelligence; Real-Time Diagnostics; Self-Correcting Control; Next-Generation Nuclear Energy; Predictive Maintenance; Digital Twin; Automation; Energy Security

1. Introduction

The increasing global demand for clean, reliable, and efficient energy has accelerated the development of Next-Generation Nuclear Energy Systems (NGNES) to enhance sustainability, safety, and operational efficiency in nuclear power generation [1]. Traditional nuclear energy systems rely on manual monitoring and periodic inspections, which are often time-consuming, prone to human error, and unable to detect real-time anomalies [2]. The integration of artificial intelligence (AI)-driven real-time diagnostics and self-correcting control schemes has emerged as a transformative approach to improving reactor safety, predictive maintenance, and autonomous response capabilities in nuclear energy facilities [3]. By leveraging machine learning, digital twin technology, and intelligent automation, these AI-enhanced systems can continuously analyze sensor data, detect early warning signs of equipment failures, and autonomously adjust reactor control parameters to maintain operational stability [4].

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Ensuring the safety and efficiency of nuclear power plants is a critical national priority, as outlined by the U.S. DOE's Advanced Reactor Technologies program [5]. The Next Generation Nuclear Plant (NGNP) initiative seeks to develop nuclear reactors that incorporate advanced instrumentation and control systems to improve reliability, reduce human intervention, and enhance resilience against operational uncertainties [6]. However, existing monitoring and diagnostic frameworks in nuclear energy infrastructure lack real-time adaptability, often leading to delays in fault detection, unplanned shutdowns, and increased maintenance costs [7]. Addressing these challenges requires the development of self-learning AI models capable of adaptive anomaly detection, predictive failure analysis, and autonomous decision-making to optimize reactor performance [8].

AI-driven diagnostics and self-correcting control schemes have demonstrated significant potential in enhancing nuclear plant resilience by integrating sensor fusion, deep learning algorithms, and reinforcement learning-based optimization [9]. These technologies provide real-time insights into reactor behavior, enabling precise control adjustments to mitigate performance deviations, radiation hazards, and system failures [10]. Moreover, the adoption of digital twin simulations—which create virtual models of physical nuclear reactors—allows for scenario testing, predictive maintenance, and proactive risk mitigation in nuclear facilities [11]. Despite these advancements, challenges remain in deploying AI-based automation in high-risk environments, particularly concerning model interpretability, cybersecurity threats, and regulatory compliance in nuclear operations [12].

This review paper synthesizes recent research on AI-driven real-time diagnostics and self-correcting control schemes within Next-Generation Nuclear Energy Systems, evaluating their effectiveness, challenges, and future research directions. The study explores current applications of AI in nuclear diagnostics, the role of predictive maintenance in minimizing reactor downtime, and advancements in self-learning control mechanisms. Additionally, it highlights key barriers to implementation, including regulatory considerations and technical limitations, while discussing strategies to enhance AI adoption in nuclear power generation. By presenting a comprehensive analysis of AI-driven innovations, this review aims to contribute to the development of intelligent, resilient, and sustainable nuclear energy systems that align with national energy security and clean energy goals.

2. Literature Review

2.1. AI-Driven Real-Time Diagnostics in Nuclear Energy Systems

Real-time diagnostics are fundamental to ensuring the safety, reliability, and efficiency of nuclear reactors by continuously monitoring system parameters and enabling early fault detection. Advanced monitoring technologies have significantly improved reactor performance, prevented catastrophic failures, and optimized maintenance schedules [13]. The integration of artificial intelligence (AI) in fault detection has enhanced conventional diagnostic methods by providing faster anomaly identification and reducing false alarms, thereby increasing operational reliability [14]. Machine learning (ML) and deep learning (DL) have become essential tools in nuclear diagnostics, offering sophisticated techniques for fault detection and predictive maintenance. Supervised learning models, such as support vector machines (SVMs) and artificial neural networks (ANNs), have demonstrated high accuracy in classifying reactor anomalies, while unsupervised learning methods, including clustering algorithms and autoencoders, facilitate the identification of unknown or rare faults within reactor systems [15]. These AI-driven approaches continuously analyze sensor data, detecting early indicators of system degradation and contributing to more effective maintenance strategies.

The adoption of digital twin technology has further revolutionized nuclear facility operations by enabling real-time simulation of reactor performance and predictive failure analysis. By integrating physics-based models with AI-driven analytics, digital twins enhance predictive maintenance, optimize operational efficiency, and minimize unexpected downtimes [16]. Case studies have demonstrated the effectiveness of digital twins in reducing unplanned outages and strengthening safety protocols in nuclear power plants [17]. Furthermore, sensor fusion and advanced data analytics have significantly improved reactor monitoring capabilities by integrating diverse sensor data sources, such as thermal, acoustic, and radiation sensors, to provide a comprehensive assessment of reactor health [18]. The application of big data analytics has been instrumental in processing vast amounts of operational data, facilitating trend analysis, and enabling proactive anomaly detection [19]. As nuclear facilities continue to adopt AI-powered diagnostics, the synergy of real-time monitoring, digital twin technology, and sensor fusion will be critical in enhancing fault detection, mitigating operational risks, and ensuring the long-term sustainability of nuclear reactors.

2.2. Self-Correcting Control Schemes in Nuclear Reactors

The integration of self-correcting control schemes in nuclear reactors has become a critical advancement in enhancing operational safety, efficiency, and resilience in high-risk environments. These mechanisms leverage artificial

intelligence (AI) and machine learning (ML) algorithms to autonomously detect anomalies, adjust system parameters, and improve reactor stability in real time. By minimizing human intervention and reducing error rates, AI-driven self-correcting systems enhance the reliability of nuclear reactors under varying operational conditions [20]. Autonomous decision-making, enabled by predictive analytics, plays a vital role in anticipating and mitigating potential system failures before they escalate into critical incidents, thereby optimizing reactor operations and ensuring long-term sustainability [21].

One of the most transformative AI models for adaptive control in nuclear power plants is reinforcement learning (RL), which enables systems to continuously interact with the reactor environment and refine optimal control strategies. RL-based models have demonstrated remarkable efficacy in enhancing operational efficiency and safety, particularly in dynamic and uncertain reactor conditions where traditional control mechanisms may struggle to adapt. Recent studies have shown successful applications of RL in nuclear automation, such as optimizing coolant flow regulation and managing reactor core temperature fluctuations [22]. Deep reinforcement learning (DRL) further refines these adaptive capabilities, allowing AI-driven algorithms to fine-tune control actions in response to real-time changes in reactor conditions, thus improving energy production stability and efficiency [23].

Beyond optimization, autonomous fault recovery systems contribute significantly to reactor resilience by employing AI-based response mechanisms that detect, diagnose, and correct system deviations in real-time. Self-healing control loops, a critical component of these systems, continuously monitor reactor performance and implement corrective actions without human intervention. These AI-driven loops integrate sensor fusion techniques to analyze multi-modal data streams, ensuring precise anomaly detection and rapid fault resolution [24]. The implementation of such self-correcting control schemes has been shown to significantly reduce reactor downtime and mitigate the risk of cascading failures in nuclear operations, reinforcing overall system stability [25].

However, the increased reliance on AI in nuclear automation presents substantial cybersecurity challenges, necessitating robust security measures to safeguard reactor control networks from potential cyber threats. AI-powered automation expands the potential attack surface, making it imperative to implement advanced encryption protocols, real-time anomaly detection systems, and AI-driven threat intelligence frameworks to protect against malicious intrusions [26]. Additionally, evolving regulatory frameworks and risk mitigation strategies are essential to ensure the secure integration of AI in nuclear control systems, thereby minimizing vulnerabilities and enhancing resilience against cyber threats [27]. In conclusion, self-correcting control schemes represent a significant advancement in nuclear reactor automation, offering enhanced safety, efficiency, and operational resilience. The integration of AI-driven reinforcement learning, autonomous fault recovery systems, and robust cybersecurity measures is instrumental in shaping the future of reliable and secure nuclear energy operations. As research in this field continues to evolve, addressing emerging challenges and refining AI-driven control technologies will be essential in ensuring the safe and sustainable deployment of nuclear reactors in an increasingly complex technological landscape.

3. Challenges and Limitations in AI-Driven Nuclear Automation

The integration of artificial intelligence (AI) in nuclear energy systems presents significant opportunities for improving safety, efficiency, and operational reliability. AI-driven automation can enhance fault detection, optimize maintenance schedules, and reduce human dependency in reactor operations. However, its adoption faces several challenges, including technical limitations, regulatory concerns, and infrastructure barriers. Addressing these issues is critical for ensuring AI's safe and effective implementation in nuclear power plants.

3.1. Technical Challenges

One major technical limitation is the interpretability and trustworthiness of AI models. Most AI-driven nuclear automation systems rely on deep learning algorithms, which often function as "black boxes," making it difficult to explain their decision-making processes. This opacity hinders the ability to predict and understand AI behavior, raising concerns about system reliability, particularly in safety-critical environments like nuclear reactors [28]. The lack of transparency can delay fault detection and compromise safety by limiting the ability of engineers to diagnose and respond to anomalies in real time. Therefore, the development of explainable AI (XAI) models is essential to improve trust and reliability in nuclear automation. Computational complexity and data processing constraints also pose significant challenges. Nuclear reactors generate vast amounts of operational data, requiring robust computational infrastructure to process and analyze information efficiently. Existing frameworks often struggle with real-time adaptability, limiting AI's ability to dynamically adjust to changing reactor conditions [29]. Implementing AI solutions requires high-performance computing resources, cloud-based data storage, and advanced predictive analytics. However, these advancements introduce cybersecurity vulnerabilities, as AI-driven control systems may become

targets for cyberattacks. Ensuring that AI algorithms remain adaptable and secure against evolving threats is crucial for long-term sustainability in nuclear energy systems [28].

3.2. Regulatory and Safety Concerns

The integration of AI into nuclear operations must comply with stringent safety regulations. However, existing regulatory frameworks were primarily designed for traditional nuclear technologies and may not fully address the unique challenges posed by AI. Regulatory bodies are now assessing whether current guidelines are sufficient or if new safety standards are needed to govern AI applications in nuclear energy [29]. The challenge lies in developing regulations that balance technological innovation with rigorous safety requirements, ensuring that AI-driven systems adhere to the same high standards as conventional reactor control mechanisms. Human dependency remains a critical concern in nuclear automation. While AI has the potential to reduce human interventions, complete automation is not yet feasible. Ethical considerations and accountability issues arise when delegating nuclear safety decisions to AI systems. Excessive reliance on AI without human oversight could increase the risks of errors, particularly in emergency scenarios [30]. Therefore, hybrid models that integrate AI with human decision-making are necessary to maintain operational safety and public trust in nuclear energy systems.

3.3. Infrastructure and Implementation Barriers

The high cost of integrating AI into existing nuclear infrastructure presents another significant barrier. Retrofitting conventional nuclear power plants with AI-driven automation requires substantial investment in hardware, software, and workforce training. Many nuclear facilities operate under tight budgets, making it difficult to justify the cost of AI implementation without clear evidence of long-term benefits [31]. Developing phased implementation strategies and securing funding for AI research and development will be crucial in overcoming these financial obstacles.

Additionally, workforce training and industry acceptance pose challenges to AI adoption. The nuclear sector relies heavily on experienced engineers who may be resistant to adopting AI technologies, particularly if they lack familiarity with advanced machine learning models. Comprehensive training programs are essential to equip nuclear professionals with the necessary skills to integrate AI into reactor operations. Incorporating AI education into nuclear engineering curricula and professional development programs can help bridge this knowledge gap and facilitate smoother adoption [31]. Collaboration between AI specialists and nuclear engineers is also essential to develop automation solutions tailored to industry needs and safety standards.

Despite its potential to enhance nuclear energy systems, AI-driven automation faces significant technical, regulatory, and infrastructural challenges. Issues such as model interpretability, real-time adaptability, compliance with safety regulations, and workforce acceptance must be addressed to ensure AI's effective implementation. Moving forward, research and policy development should focus on mitigating these challenges through transparent AI models, adaptive regulatory frameworks, and strategic investment in AI-enabled nuclear technologies. By addressing these limitations, the nuclear industry can leverage AI to improve safety, efficiency, and reliability in future energy systems.

3.4. Case Studies and Current AI Initiatives in U.S. Nuclear Energy

The integration of Artificial Intelligence (AI) into the U.S. nuclear energy sector is emerging as a transformative advancement, offering significant improvements in safety, operational efficiency, and cost optimization. Recent initiatives spearheaded by the U.S. Department of Energy (DOE) and its national laboratories demonstrate the growing application of AI in modernizing nuclear infrastructure and processes. A notable example is the development of AI-powered tools designed to streamline the siting and permitting processes for clean energy infrastructure. In partnership with Pacific Northwest National Laboratory (PNNL), the DOE is currently working on Policy AI, a large language model testbed aimed at supporting National Environmental Policy Act (NEPA) reviews. This initiative is expected to accelerate environmental policy analysis and improve decision-making efficiency in the nuclear sector [34].

Further advancements in AI applications are being explored at Argonne National Laboratory (ANL), where researchers are developing AI-driven diagnostic systems for real-time monitoring and predictive maintenance of nuclear reactors. These systems leverage generative AI models to analyze vast operational datasets, detect potential anomalies, and provide reactor operators with real-time insights to enhance situational awareness and safety [33]. Similarly, Idaho National Laboratory (INL) is implementing machine learning algorithms to strengthen fault detection and predictive maintenance strategies in nuclear plants. Such proactive interventions are crucial in minimizing operational risks, reducing unplanned outages, and extending the overall lifespan of nuclear reactors [34].

The private sector is also playing a critical role in advancing AI-driven innovations within the nuclear energy industry. For instance, Blue Wave AI Labs has successfully deployed machine learning models at two Constellation-operated nuclear power plants in the United States. These applications have resulted in significant cost savings by optimizing reactor operations, improving fuel efficiency, and reducing downtime due to unplanned outages [5]. Additionally, as the demand for reliable and clean energy sources increases, private technology firms are collaborating with nuclear energy providers to support energy-intensive operations, particularly AI-driven data centers. A notable case is Microsoft's recent agreement with nuclear power suppliers to secure clean energy for its expanding data center facilities, illustrating the evolving synergy between AI technologies and nuclear power generation [35].

The application of AI in nuclear systems has provided critical lessons that further validate its role in enhancing the industry's resilience. AI-driven predictive maintenance has proven effective in identifying potential equipment failures early, allowing for timely intervention and substantial cost reductions [5]. Moreover, machine learning models have demonstrated their capacity to optimize reactor performance, leading to improved fuel utilization and operational longevity [33]. Furthermore, AI has enabled more sophisticated data analysis capabilities, equipping operators with the tools to uncover patterns and anomalies that conventional monitoring systems might overlook [34]. Overall, AI is steadily becoming a cornerstone of innovation in the U.S. nuclear energy landscape. The combined efforts of government agencies, national laboratories, and private sector partnerships are driving the adoption of AI technologies that significantly enhance safety protocols, operational efficiency, and cost-effectiveness. These initiatives not only support the sustainable development of nuclear energy but also strengthen the sector's capacity to meet future energy demands. Continued investment in AI research and integration within nuclear systems remains vital to securing a robust, efficient, and clean energy future for the United States.

3.5. Future Directions and Recommendations for AI in Nuclear Energy Systems

The growing integration of Artificial Intelligence (AI) into nuclear energy systems presents transformative potential for enhancing reactor safety, operational efficiency, and predictive maintenance. To fully harness these benefits, however, it is essential to improve the adaptability and reliability of AI models, particularly given the complexity and high-risk nature of nuclear environments. Developing robust AI algorithms capable of learning from diverse datasets that reflect various operational scenarios, including rare system failures, is critical to minimizing false alarms and ensuring system resilience [36]. In addition, the incorporation of explainable AI (XAI) methodologies is increasingly necessary to enhance transparency and build trust in AI-driven systems. By enabling clear and interpretable decision-making processes, XAI enhances the reliability of AI applications in safety-critical operations like nuclear reactor management [37].

A promising future direction for ensuring nuclear safety lies in hybrid AI-human oversight models, which balance the analytical power of AI with human expertise. While AI excels in processing vast data streams and detecting anomalies in real-time, human operators bring indispensable contextual understanding, particularly when facing unforeseen scenarios. Scholars have argued that AI should function primarily as a decision-support tool rather than a fully autonomous system, allowing human operators to interpret AI-generated insights and intervene when necessary [21]. Such collaboration ensures operational decisions maintain both technical accuracy and contextual relevance, thereby reducing risks and fostering public confidence in AI-enabled nuclear operations.

Despite these advancements, significant infrastructure and financial challenges continue to impede widespread AI adoption in the nuclear sector. Retrofitting aging nuclear facilities to support high-performance computing capabilities, sensor networks, and advanced cybersecurity measures demands substantial capital investment [19]. Moreover, the financial burdens associated with data acquisition, model training, and comprehensive system validation further complicate implementation, particularly for smaller utilities. Public-private partnerships and targeted government incentives could play a pivotal role in addressing these barriers and accelerating the integration of AI technologies across the sector.

Equally vital to AI deployment is fostering interdisciplinary collaboration among AI developers, nuclear engineers, and policymakers. Successful integration requires not only technical advancements but also the establishment of regulatory frameworks that prioritize safety, ethics, and industry compliance. Collaborative research initiatives can promote knowledge sharing, bridge existing gaps, and support the development of standardized AI validation protocols essential for safe deployment [38]. Engaging policymakers early in the innovation process will be critical to ensuring that AI integration aligns with national energy strategies and public interest, ultimately securing a safe and resilient future for AI-driven nuclear energy systems.

4. Conclusion

The implementation of AI-driven diagnostics and self-correcting controls is poised to transform the future of U.S. nuclear energy. These technologies enhance the reliability of nuclear systems by reducing human error, enabling proactive interventions, and supporting autonomous operations during complex scenarios. The adoption of digital twins, in particular, allows continuous virtual monitoring of reactors, improving efficiency and safety through predictive simulations. As the demand for clean and reliable energy grows, AI's role in optimizing reactor performance and supporting advanced nuclear designs like small modular reactors (SMRs) will become increasingly critical. Therefore, policymakers should prioritize funding for interdisciplinary research, focusing on explainable AI (XAI), cybersecurity, and AI validation protocols specific to nuclear environments. Additionally, collaboration between AI experts, nuclear engineers, and regulatory bodies is essential to ensure that AI systems are trustworthy, interpretable, and aligned with industry needs. With sustained investment and coordinated efforts, AI technologies can significantly advance the safety, efficiency, and sustainability of U.S. nuclear energy systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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