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# AI-Driven Fault Detection and Diagnostics in Nuclear Power Plant Control Systems: A Review

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**Abstract:** Nuclear power plants are among the most complex and safety-sensitive facilities in the world. The ability to quickly detect and diagnose faults within their control systems is critical for ensuring safe, stable, and uninterrupted operations. While traditional fault detection methods, like rule-based systems or physics-driven models, have served the industry for decades, they often fall short in responding to the increasingly dynamic, data-rich, and nonlinear nature of today's nuclear power environments. This growing complexity has created an opportunity for Artificial Intelligence (AI) to step in. Recent research shows that AI techniques, particularly those based on machine learning, offer powerful tools for identifying subtle anomalies, recognizing unusual system behaviors, and even predicting faults before they occur. From deep learning models and ensemble classifiers to digital twins and unsupervised anomaly detection, these innovations are helping engineers and operators improve reliability and reduce response times across a range of nuclear plant subsystems. This review explores the progress made so far in applying AI to fault detection and diagnostics (FDD) in nuclear control systems. It organizes the key techniques in use, highlights notable case studies and applications, and discusses both the benefits and challenges associated with deploying AI in this high-stakes setting. Issues such as data limitations, model transparency, regulatory concerns, and cybersecurity are also considered. The review concludes by outlining promising future directions, including the integration of explainable AI, edge computing, and collaborative learning methods. By consolidating existing knowledge and offering strategic insights into the state-of-the-art, this review aims to guide researchers, engineers, and policymakers in advancing safer, smarter, and more resilient fault detection frameworks for the next generation of nuclear power systems.

**Keywords:** Nuclear power, AI, fault detection, diagnostics, control systems, machine learning, anomaly detection.

## INTRODUCTION

Nuclear power plants (NPPs) play a vital role in the global energy mix, offering a low-carbon, high-efficiency source of electricity. Given the complex and tightly coupled nature of their operations, the control systems within NPPs are not only highly sophisticated but also inherently safety critical. These systems are responsible for regulating reactor operations, managing cooling systems, and ensuring protective shutdown mechanisms, all of which are crucial for safe and continuous plant function (International Atomic Energy Agency [IAEA], 2020). In such high-stakes environments, fault detection and diagnostics (FDD) are indispensable. A delay in identifying equipment malfunctions, control anomalies, or signal deviations can result in reduced operational efficiency, costly downtimes, or, in worst-case scenarios, catastrophic safety incidents (Lee *et al.*, 2021). Therefore, timely and accurate FDD mechanisms are essential for both preventive maintenance and real-time safety assurance in NPPs.

Historically, FDD in nuclear control systems has relied on physics-based models, rule-based algorithms, and expert systems. While these conventional approaches are grounded in domain expertise and deterministic logic, they often struggle with scalability, adaptability, and precision when dealing with increasingly complex system dynamics and large volumes of sensor data (Zio, 2016). These limitations expose NPPs to higher risks of undetected or misdiagnosed faults, particularly under novel or uncertain operating conditions. In response to these challenges, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as promising solutions for enhancing FDD capabilities in nuclear power environments. Leveraging data-driven models, AI systems can learn complex patterns, detect subtle anomalies, and even forecast incipient faults with greater flexibility and accuracy than traditional methods (Zhang *et al.*, 2023). From supervised classification models to unsupervised anomaly detection and deep learning-based digital twins, AI technologies are increasingly being integrated into nuclear instrumentation and control (I&C) systems to improve reliability, safety, and decision support (Park *et al.*, 2022).

This review paper aims to synthesize current research on AI-driven FDD systems applied to nuclear power plant control environments. It explores major methodological developments, application domains, challenges, and opportunities,





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with the goal of guiding future innovations in intelligent fault management for the nuclear sector.

## LITERATURE REVIEW

### Overview of Fault Detection and Diagnostics (FDD) in Nuclear Power Plants

Fault Detection and Diagnostics (FDD) is a critical domain in nuclear engineering, tasked with the timely identification, classification, and mitigation of system abnormalities to preserve operational reliability and safety. In the context of nuclear power plant (NPP) control systems, a fault refers to any unintended deviation or malfunction from the designed operational parameters of a component or process. An anomaly is a broader term, often used to describe unusual patterns or deviations that may or may not be directly caused by faults, but nonetheless warrant attention. Detection involves recognizing the presence of a fault or anomaly, while diagnostics focuses on determining its root cause, location, and severity (Zhou, *et al.,* 2020).

Nuclear power plant control systems—comprising thousands of sensors, actuators, and controllers—are susceptible to various fault types. Sensor faults are common and can include drift, bias, or complete failure, potentially leading to incorrect control decisions. Actuator faults may manifest as stuck or sluggish actuators that impact control responsiveness. System-level faults involve process deviations due to design flaws, software bugs, or hardware degradation, which can propagate across subsystems and compromise plant-wide safety (Gao, *et al.*, 2022). The high degree of interconnectivity and real-time requirements within these systems increases the complexity of fault propagation and detection.

Implementing FDD in nuclear environments presents unique challenges. Unlike in many industrial settings, false alarms or undetected faults in NPPs can have far-reaching consequences, including unscheduled shutdowns or radiation release. Furthermore, nuclear systems operate under stringent safety and regulatory constraints, where any modification to control algorithms or sensor networks must undergo rigorous validation and licensing processes (IAEA, 2015). Additionally, data scarcity due to infrequent fault occurrences and the limited availability of labeled fault data complicate the training and validation of AI-based FDD models (Zio & Baraldi, 2019). Regulatory bodies such as the U.S. Nuclear Regulatory Commission (NRC) and international entities like the International Atomic Energy Agency (IAEA) mandate high standards for safety, redundancy, and fault tolerance. These organizations require that any diagnostic system integrated into a nuclear facility must comply with established safety criteria, including deterministic failure responses, fault containment, and human oversight mechanisms (NRC, 2016). The effectiveness of FDD is also highly dependent on the underlying control system architecture, which typically includes Supervisory Control and Data Acquisition (SCADA) systems, Distributed Control Systems (DCS), and specialized Instrumentation and Control (I&C) systems. These architectures manage real-time data acquisition, process control, and automation. SCADA systems are often used for high-level monitoring and supervisory functions, while DCS and I&C systems handle core operations and feedback control within the plant (Wang & Li, 2021). The heterogeneity and complexity of these control frameworks necessitate FDD solutions that are scalable, interpretable, and capable of integration with existing safety protocols. Effective FDD in NPPs requires a multifaceted approach that addresses the diversity of fault types, ensures compliance with safety regulations, and is tailored to the architectural intricacies of modern nuclear control systems. The rise of AI and machine learning techniques offers promising pathways for overcoming many of these longstanding challenges.

## ARTIFICIAL INTELLIGENCE TECHNIQUES FOR FDD

### Machine Leanring Approaches

The adoption of machine learning (ML) in fault detection and diagnostics (FDD) has opened new frontiers in ensuring the safety and efficiency of nuclear power plant (NPP) control systems. Given the complexity and criticality of these environments, ML offers a significant advantage over traditional fault detection methods by enabling data-driven insights, pattern recognition, and predictive capabilities that improve system reliability and responsiveness.

Supervised learning remains one of the most commonly applied ML approaches in nuclear FDD. These techniques rely on historical, labeled datasets where known input-output relationships enable the model to learn fault classifications. Algorithms such as Support Vector Machines (SVM), Decision Trees, and Deep Learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)



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have shown strong performance in identifying and isolating faults within multivariate sensor data. For instance, SVMs are particularly effective in high-dimensional data environments, offering robust classification even when sample sizes are limited (Liu, *et al.,* 2020). Deep learning methods, on the other hand, excel at capturing complex temporal patterns and are increasingly being used for real-time anomaly detection in safety-critical NPP systems (Sun, *et al.,* 2022).

In contrast, unsupervised learning techniques are valuable when labeled data is scarce or unavailable—a common challenge in nuclear domains due to limited fault occurrence and proprietary constraints. Methods like clustering (e.g., k-Means, DBSCAN) can identify operational states and detect deviations that signal early-stage faults. Dimensionality reduction techniques such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) help distill key features from large datasets, enhancing model accuracy while filtering noise. Autoencoders—neural networks trained to reconstruct input data—are particularly effective for learning normal operational patterns. Reconstruction errors in these models often indicate anomalies, making them well-suited for fault detection in nuclear monitoring systems (Guo, *et al.,* 2021).

Reinforcement learning (RL) is another promising, albeit less mature, approach in this context. Unlike supervised or unsupervised learning, RL focuses on decision-making and optimal policy development through interaction with the environment. This makes it suitable for applications involving real-time system adjustments or fault-tolerant control. For example, RL algorithms can learn how to reconfigure control parameters after a fault occurs to maintain system stability (Chen, *et al.,* 2023). However, challenges related to training safety, convergence speed, and simulation requirements must be addressed before RL can be reliably deployed in operational nuclear facilities.

A critical component that cuts across all ML-based FDD approaches is the process of feature extraction and engineering. The effectiveness of any ML model is strongly influenced by the quality of its input data. In NPPs, features may include temperature gradients, pressure fluctuations, coolant flow rates, and vibration signatures. Advanced techniques such as wavelet transforms, time-frequency analysis, and statistical signal descriptors are often employed to enhance these features. Engineering domain-specific indicators, such as system residuals or thermal response rates, further strengthens the model's ability to differentiate between normal operations and incipient faults (Zio & Aven, 2019). In summary, machine learning presents a diverse and adaptable toolkit for fault detection and diagnostics in nuclear power plants. By tailoring these techniques to the unique constraints of nuclear control systems—ranging from data availability to regulatory compliance—researchers and practitioners can build smarter, more resilient monitoring frameworks that enhance safety and efficiency.

**Deep Learning Techniques**

Deep learning has emerged as a transformative approach in fault detection and diagnostics (FDD), particularly in complex and high-stakes environments such as nuclear power plant (NPP) control systems. These systems generate large volumes of diverse and often non-linear sensor data, which deep learning algorithms are uniquely suited to analyze. Among the most commonly applied architectures, Convolutional Neural Networks (CNNs) have proven highly effective in interpreting spatial correlations in multi-dimensional sensor data. When sensor outputs such as temperature fields or vibration patterns are formatted as image-like matrices, CNNs can extract meaningful features automatically, enabling high-precision fault classification with minimal manual intervention (Zhou, *et al.,* 2022).

Recurrent Neural Networks (RNNs), and their advanced variant Long Short-Term Memory networks (LSTMs), are especially well-suited for handling time-series data typical of NPP control systems. These models retain temporal context by storing past information, allowing them to detect fault patterns that evolve over time. For example, subtle changes in pressure or flow rate trends preceding a fault can be captured and flagged using LSTM-based models, which have demonstrated superior performance over traditional statistical models in early fault prediction tasks (Wang & Zhao, 2021). Autoencoders, another deep learning architecture, are particularly valuable for unsupervised anomaly detection. These networks are trained to reconstruct input data, learning the normal operational behavior of the system. During inference, reconstruction errors serve as a proxy for anomaly scores—higher errors typically indicate deviations from normal behavior,



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suggesting the presence of a fault. This approach is especially powerful in nuclear systems where labeled fault data is limited or unavailable (Kim, *et al.,* 2020). Transfer learning, although less explored in nuclear applications, offers a promising direction for improving model generalizability across plant configurations or even across domains. By leveraging knowledge learned from one dataset such as sensor patterns from a simulated environment models can be fine-tuned on smaller, real-world datasets, reducing the time and data required to achieve high performance. This is particularly useful in nuclear settings where collecting fault data is both expensive and risky (Huang, *et al.*, 2023). Overall, deep learning offers robust tools for extracting complex patterns from data-rich control environments. With their ability to model non-linear relationships, capture temporal dependencies, and detect previously unseen anomalies, these techniques are poised to significantly enhance the safety and reliability of nuclear power plant operation

**Hybrid and Ensemble Models**

Hybrid and ensemble approaches are gaining increasing attention in the field of fault detection and diagnostics (FDD) for nuclear power plant control systems, as they combine the strengths of various methodologies to improve accuracy, robustness, and interpretability. One of the most promising developments in this space is the integration of artificial intelligence (AI) with physics-based modeling, often implemented through digital twin frameworks. A digital twin is a virtual replica of a physical system that mirrors its real-time operations. When coupled with AI models especially machine learning algorithms—these twins can simulate a wide range of fault scenarios and predict future system behavior with greater fidelity. This synergy allows for early detection of anomalies while preserving the transparency and trust associated with traditional engineering models (Tao, *et al.,* 2018).

Ensemble learning techniques further bolster FDD capabilities by aggregating the outputs of multiple models to arrive at a more reliable decision. Popular ensemble strategies include voting classifiers, where predictions from various algorithms (e.g., decision trees, support vector machines, and neural networks) are combined using majority or weighted voting schemes. Other methods, such as bagging (bootstrap aggregating) and boosting, construct diverse models from different subsets of data or focus learning efforts on previously misclassified instances. These techniques reduce overfitting and enhance generalization—an essential quality when operating in dynamic and high-risk environments like nuclear facilities (Dietterich, 2000). Another valuable hybridization strategy is the fusion of rule-based expert systems with machine learning techniques. Rule-based systems offer clear logical reasoning paths and are often derived from decades of domain expertise in nuclear operations. However, they can be limited by rigidity and an inability to adapt to new or unforeseen conditions. By integrating these with adaptive machine learning models, it's possible to build systems that are both explainable and responsive, providing high-performance fault diagnostics that maintain operator trust and regulatory compliance (Shahbaz, *et al.,* 2021). These hybrid and ensemble strategies offer a robust path forward in the development of next-generation diagnostic tools that combine empirical knowledge with data-driven insights. Their ability to address complexity, uncertainty, and evolving operational conditions makes them particularly suited to the safety-critical demands of nuclear power plant control systems.

**Review of Applications in Nuclear Control Systems**

Artificial intelligence (AI)-driven fault detection and diagnostics (FDD) have increasingly been applied to various components of nuclear power plant (NPP) control systems. These applications span a wide range of critical subsystems—from reactor coolant pumps and steam generators to control rod drive mechanisms and sensor arrays. Across the literature, researchers have employed both supervised and unsupervised learning techniques, deep learning models, and hybrid approaches to improve fault identification accuracy and speed, especially under high-risk or time-sensitive conditions (Kim, *et al.,* 2020; Wang, *et al.*, 2021).

Several case studies stand out in showcasing the practical integration of AI into nuclear control systems. For instance, researchers have utilized convolutional neural networks (CNNs) to monitor sensor data streams from reactor coolant pumps, successfully identifying anomalies indicative of mechanical wear or cavitation long before failure occurs (Liu, *et al.,* 2021). In another study, recurrent neural networks (RNNs) and long short-term memory (LSTM) models were applied to detect and diagnose pressure anomalies in pressurizer systems, achieving superior temporal accuracy over traditional statistical methods (Chen, *et al.,* 2022). Other implementations



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focused on sensor health monitoring, where autoencoders were trained on normal operation data and used to flag deviations that signaled sensor drift or failure (Park, *et al.,* 2020).

One recurring theme across these applications is the nature of the data used. While simulated datasets—such as those from RELAP5 or MATLAB-based NPP models—are widely used for training and validation due to safety constraints, there is an increasing push toward incorporating real plant data from test reactors and historical operation logs (Gao, *et al.,* 2020). Although real data offer more robust performance evaluation, challenges such as data confidentiality, noise, and missing labels persist, limiting broad access and generalization. The implementation platforms for AI-FDD tools also vary, ranging from offline analysis for post-event diagnosis to real-time monitoring systems embedded in supervisory control and data acquisition (SCADA) or distributed control systems (DCS). Real-time deployment presents additional challenges, such as low-latency processing, high reliability, and fail-safe integration, which are essential in nuclear environments where human oversight and regulatory compliance remain non-negotiable (Zhou, *et al.,* 2023). As the field progresses, the convergence of real-time AI analytics with physical modeling, robust datasets, and explainable decision-making frameworks will be key to driving trust and adoption of these tools in operational settings.

**Challenges and Limitations**

Despite the promising advancements of AI-driven fault detection and diagnostics (FDD) systems in nuclear power plants (NPPs), several technical and operational challenges remain that limit their widespread adoption. Data availability and quality are among the most significant barriers. Many nuclear facilities are constrained by strict safety protocols, confidentiality agreements, and limited access to high-quality fault data due to the infrequency of actual fault events. Consequently, researchers often rely on simulated datasets or synthetic anomalies, which may not fully represent real-world plant behavior (Hu, *et al.,* 2022; Zhang & Zhao, 2019). This lack of diverse, annotated real-time operational data hinders the training and validation of robust AI models and limits their performance in unexpected conditions.

Model interpretability and explainability, especially in deep learning-based systems, pose another critical limitation. In high-stakes environments such as nuclear power plants, operators and regulators must understand how and why a system arrives at a particular diagnosis or prediction. However, many AI models function as “black boxes,” making their internal decision-making processes opaque and difficult to trust without additional interpretability tools (Wang, *et al.*, 2021).

Another challenge lies in generalization across plant configurations. AI models trained on one plant or reactor type may not easily transfer to others due to differences in architecture, operating conditions, instrumentation, and control logic. This lack of transferability necessitates retraining or fine-tuning of models, increasing computational costs and time before deployment (Gao, *et al.,* 2020). The development of more adaptable or transfer learning-based frameworks could help mitigate this issue.

Finally, cybersecurity implications must be considered when integrating AI into critical infrastructure. AI systems particularly those connected to supervisory control and data acquisition (SCADA) or distributed control systems (DCS) may introduce new attack surfaces or vulnerabilities. If compromised, these systems could be manipulated to provide false readings or suppress fault alerts, potentially leading to catastrophic consequences. As such, ensuring the cybersecurity resilience of AI-based diagnostic systems is imperative (Zhou, *et al.,* 2023). In sum, while AI offers transformative potential for fault detection in nuclear control systems, these challenges underscore the importance of cautious, transparent, and secure integration strategies. Future research must focus on developing explainable models, improving training datasets, and implementing robust cybersecurity protocols to ensure that AI systems are both effective and trustworthy in safety-critical environments.

**Emerging Trends and Future Directions**

The application of artificial intelligence in nuclear power plant control systems is rapidly evolving, driven by the need for smarter, more autonomous, and trustworthy fault detection and diagnostics (FDD) solutions. Several emerging trends are shaping the future landscape of AI-based FDD in nuclear environments.

One of the most promising developments is the use of digital twins—virtual replicas of physical assets and systems that are continuously updated with real-time data. Digital twins allow for dynamic simulation, real-time monitoring, and predictive



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analysis of plant behavior under both normal and faulted conditions. When combined with AI models, they enable more accurate and context-aware fault diagnosis, offering insights that are difficult to obtain from traditional control systems alone (He & Bai, 2022). The growing emphasis on Explainable AI (XAI) is another key direction. In nuclear environments, where safety and accountability are paramount, the ability to interpret and validate AI decisions is critical. XAI techniques are being developed to make machine learning models more transparent, helping operators and regulators understand the rationale behind fault classifications or anomaly alerts. This not only enhances trust in AI systems but also supports their integration into regulatory frameworks and operator workflows (Samek, *et al.*, 2019).

Integration with predictive maintenance systems is also gaining momentum. By coupling FDD models with maintenance scheduling tools, nuclear facilities can move toward condition-based maintenance strategies. AI can help predict not just when a fault might occur, but also estimate its severity, potential impact, and optimal maintenance timeline, ultimately improving asset utilization and reducing unplanned outages (Lee, *et al.*, 2020).

Another frontier is the adoption of federated learning and edge AI. These technologies allow machine learning models to be trained and deployed across multiple decentralized systems without the need for centralized data aggregation. In nuclear plants where data security and latency are critical, edge computing ensures timely fault detection while federated learning maintains data privacy across geographically dispersed units (Li, *et al.*, 2022).

Moreover, the rise of open-source tools and benchmark datasets is helping to democratize AI research in this domain. Efforts are underway to develop standardized platforms, datasets, and simulation environments that can accelerate algorithm development, validation, and comparison. Open access to such resources is crucial for fostering collaboration across academia, industry, and regulatory bodies. Lastly, the ultimate vision for many researchers is the realization of autonomous fault-tolerant control systems. These would go beyond detection and diagnostics to include self-healing mechanisms, adaptive control, and reconfiguration capabilities that ensure system stability in the presence of faults without the need for manual intervention.

In conclusion, the convergence of real-time analytics, transparency, edge computing, and intelligent automation signals a paradigm shift in how nuclear power plants may operate in the coming decades. These advancements promise to enhance safety, efficiency, and resilience in one of the most critical sectors of modern energy infrastructure.

## CONCLUSION

Artificial Intelligence (AI) has increasingly become a transformative force in the fault detection and diagnostics (FDD) landscape of nuclear power plant control systems. With its ability to process vast amounts of complex sensor and system data, AI offers faster, more accurate, and adaptive solutions compared to traditional rule-based or model-based approaches. Techniques such as deep learning, unsupervised anomaly detection, and hybrid models are already showing promise in identifying faults at early stages, minimizing downtime, and supporting timely corrective action.

Despite these advances, several critical gaps remain. Data availability and quality continue to limit the scalability and generalizability of AI models, especially across different plant configurations. Moreover, concerns around model interpretability, cybersecurity, and integration with existing safety protocols hinder widespread adoption. Regulatory standards have yet to fully evolve to accommodate these fast-moving technologies, and real-time, explainable AI implementations are still in early stages.

Nevertheless, the road ahead is promising. The integration of digital twins, federated learning, and edge AI systems, coupled with advances in explainable AI and open benchmarking datasets, offers a strong foundation for the next generation of nuclear diagnostics. As research continues to bridge these gaps, AI will play an increasingly central role in advancing the safety, efficiency, and resilience of nuclear energy systems. Ultimately, the evolution toward smarter, AI-powered FDD systems is not just a technological shift—it is a necessary advancement to meet the growing global demand for safe, low-carbon energy. Continued interdisciplinary collaboration between AI researchers, nuclear engineers, policymakers, and regulators will be essential to fully realize this



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potential and ensure a secure and intelligent future for nuclear power.

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