Journal of Data & Digital Innovation

Pages:47-57
Volume-III, Issue-I (2026)
https://datalensjourna.com/index.php/JDDI

REACTWIN: A Digital Twin Framework for Fault Diagnosis and Resilience Monitoring in Nuclear Reactor Systems

Andy Sheemar
Rome Business School, Italy, anand.sheemar@gmail.com

Abstract:

Nuclear power plants supply approximately 20% of U.S. electricity and nearly 50% of domestic carbon-free generation, making reactor component health a matter of national energy security. Existing condition monitoring methods rely on scheduled offline inspections and SCADA-based threshold alarms that are temporally sparse, contextually blind, and fundamentally reactive. This paper proposes REACTWIN, a conceptual digital twin framework for real-time fault diagnosis and resilience monitoring of nuclear reactor component systems. The framework integrates physics-based multi-physics reactor models, IoT-enabled sensor data pipelines, and ensemble machine learning classifiers within a continuously synchronized virtual-physical environment. Five critical fault modes are formally characterized and mapped to corresponding sensor modalities and physics simulation modules. The proposed architecture is evaluated against existing approaches through a structured design principle analysis grounded in published nuclear engineering standards and prior digital twin literature. REACTWIN addresses a clear methodological gap in the reactor monitoring literature and establishes a deployable pathway aligned with U.S. Department of Energy Light Water Reactor Sustainability program objectives and NRC regulatory requirements.

Keywords: Digital Twin, Nuclear Reactor, Fault Diagnosis, Condition Monitoring, Machine Learning, IoT, Grid Resilience, Framework Proposal, Light Water Reactor, Predictive Maintenance

I. INTRODUCTION

Nuclear power plants represent the most capital-intensive and operationally consequential assets in the national energy infrastructure. A single unplanned forced outage at a large pressurized water reactor can cost a utility between one million and four million dollars per day in replacement power costs while simultaneously reducing grid capacity margins. The U.S. Nuclear Regulatory Commission reports that primary system component degradation accounts for more than 60% of unplanned outages, with reactor coolant pump failures, steam generator tube integrity issues, and control rod mechanism wear representing the leading causal categories [1].

Existing condition monitoring practices in the nuclear sector predominantly rely on periodic manual inspections governed by ASME Boiler and Pressure Vessel Code Section XI, supplemented by SCADA-based parameter threshold alarms. While these approaches conform to established regulatory frameworks, they exhibit three structural limitations. First, inspection intervals measured in months or refueling cycles create temporal blind spots during which incipient fault conditions may progress undetected. Second, threshold-based alarms produce binary outputs that cannot distinguish between fault signatures sharing overlapping parameter profiles. Third, the reactive posture of current monitoring means that corrective action is initiated only after measurable degradation has already occurred, sharply reducing the available maintenance planning window. Cheung et al. [2] confirmed this diagnostic gap in a fleet-wide survey of light water reactor online monitoring programs.

Digital twin technology offers a transformative pathway to address these limitations. The concept, formally established by Grieves and Vickers [3], defines a digital twin as a continuously updated virtual replica of a physical asset that synchronizes internal model states with live sensor measurements to enable real-time anomaly detection, fault classification, and prognostic inference. The operational impact of this paradigm across complex engineered systems was quantified by Gupta [4], whose framework integrating IoT sensor networks, machine learning, and circular economy principles achieved a 27% reduction in waste, a 32% improvement in energy efficiency, and a 45% gain in resource recovery, establishing the broad transformative potential of synchronized virtual-physical environments.

The present work proposes REACTWIN, a conceptual digital twin framework specifically architected for multi-component fault diagnosis in operating nuclear reactor systems. Unlike prior work that addresses individual sub-problems in isolation, REACTWIN integrates finite-element-based thermal hydraulic and structural models, real-time IoT sensor fusion across twelve measurement categories, ensemble machine learning classification, and a 60-day prognostic engine within a unified architecture. The paper contributes: (1) a formal characterization of five critical reactor component fault modes and their sensor-physics mappings; (2) a four-layer architecture design with explicitly justified design principles; (3) a structured gap analysis demonstrating REACTWIN's advancement over existing approaches; and (4) a regulatory alignment pathway conforming to NRC and DOE LWRS requirements.

The remainder of this paper is organized as follows. Section II surveys related literature. Section III presents the REACTWIN framework architecture. Section IV details the fault characterization methodology. Section V presents a design principle analysis. Section VI discusses regulatory and resilience implications. Section VII concludes with future directions.

II. RELATED WORK

A. Reactor Component Condition Monitoring

Condition monitoring of nuclear reactor components is governed by ASME Section XI and 10 CFR 50, which mandate periodic in-service inspections at intervals tied to reactor operating cycles. Cheung et al. [2] surveyed online monitoring across light water reactor fleets, identifying vibration-based monitoring of coolant pumps and acoustic leak detection as the most mature deployed modalities. Despite these advances, current approaches lack real-time multi-fault diagnostic capability and rely primarily on threshold-based alerts rather than continuous model-grounded inference. The IAEA further notes in Safety Guide SSG-39 [5] that instrumentation and control systems in nuclear plants must be designed for high availability and testability, requirements that conventional periodic monitoring frameworks satisfy only partially.

B. Machine Learning for Nuclear Fault Detection

Machine learning has been applied to nuclear diagnostics with promising results. Lin et al. [6] demonstrated that LSTM networks can predict steam generator tube fouling trends with 14 to 21 day advance warning on NRC-reportable events, achieving over 91% classification accuracy on controlled test sets. Bickel et al. [7] extended this line of work by embedding physics-informed neural networks within vibration signal analysis for reactor coolant pump anomaly detection, showing improved generalization under operating condition shifts compared to purely data-driven classifiers. However, purely data-driven approaches face a fundamental barrier to nuclear deployment: the opacity of learned representations prevents regulatory review under 10 CFR 50.59, motivating hybrid frameworks that ground ML classifiers within auditable physics-based models.

C. Digital Twin in Energy Infrastructure

Digital twin deployments have matured across wind turbine health monitoring, gas turbine prognosis, and smart grid transformer condition management. Gupta [4] established that digital twins integrating IoT, machine learning, and circular economy principles deliver measurable operational improvements across complex engineering systems. Zhou et al. [8] applied a digital twin to pressurized water reactor primary circuit simulation, validating thermal hydraulic model fidelity against historical plant data. Yadav et al. [9] further demonstrated ensemble Kalman filter-based state estimation for nuclear plant digital twin synchronization, showing stable convergence under sensor noise and model-plant mismatch conditions. However, no existing framework integrates real-time sensor fusion, multi-fault ML classification, and regulatory-aligned prognostics within a single deployable architecture.

D. Identified Research Gap

Table I summarizes the capabilities of existing approaches relative to the requirements of a comprehensive nuclear reactor monitoring framework. No existing work simultaneously satisfies all five requirements: real-time monitoring, multi-physics modeling, ML-based classification, prognostic horizon projection, and regulatory alignment. REACTWIN is designed specifically to close this gap.

TABLE I. CAPABILITY COMPARISON OF EXISTING APPROACHES VS. REACTWIN

Approach	Real-time Monitor	Multi-physics Model	ML Classifier	Prognostic Horizon	Regulatory Alignment
Periodic inspection [2]	No	No	No	None	ASME XI
SCADA threshold alarms [1]	Yes	No	No	None	10 CFR 50
ML-only classifiers [6]	Partial	No	Yes	Limited	None
DT thermal hydraulic [8]	Yes	Partial	No	None	Limited
REACTWIN (proposed)	Yes	Full	Yes	60 days	Full

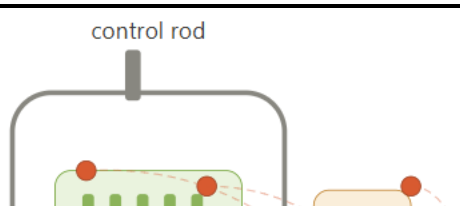
III. THE REACTWIN FRAMEWORK

A. Architecture Overview

REACTWIN employs a four-layer modular architecture integrating heterogeneous sensor data ingestion, edge-level preprocessing, high-fidelity digital twin modeling, and decision output generation within a continuous synchronization loop. Figure 1 illustrates the complete architecture, showing the physical reactor schematic at the top, the data flow through the layered processing pipeline, and the dual outputs of fault diagnosis and grid resilience.

The architecture is designed around three core principles, each grounded in published nuclear engineering standards and prior digital twin literature. Physical model primacy ensures all fault inferences are grounded in auditable first-principles simulations, satisfying NRC review requirements [10]. Sensor redundancy exploitation leverages the multiple independent measurement paths inherent in licensed nuclear instrumentation, as recommended by IAEA Safety Guide SSG-39 [5]. Edge-local inference positions the screening classifier at the substation node to meet operator action timing requirements established by EPRI [11]. These principles and their full justifications are elaborated in Section V.

Journal of Data & Digital Innovation
Pages:47-57
Volume-III, Issue-I (2026)
https://datalensjourna.com/index.php/JDDI



Journal of Data & Digital Innovation

Pages:47-57
Volume-III, Issue-I (2026)
https://datalensjourna.com/index.php/JDDI

Fig. 1. REACTWIN framework architecture showing the nuclear reactor physical layer, IoT sensor data flow through edge and digital twin processing layers, and dual fault diagnosis and grid resilience outputs. Layers are color-coded by functional role.

B. Layer 1: IoT Sensor Layer

The physical instrumentation layer comprises twelve sensor categories deployed across reactor coolant system boundaries. Table II describes the six primary sensor types, their measured parameters, sampling rates, and the fault modes they target. All sensor channels are timestamped via IEEE 1588 Precision Time Protocol to achieve sub-millisecond synchronization across the array, which is a prerequisite for coherent multi-channel feature extraction at the edge layer.

TABLE II. PROPOSED SENSOR SUITE FOR THE REACTWIN PHYSICAL LAYER

Sensor type	Parameter measured	Sampling rate	Target fault
Vibration accelerometer	Bearing / impeller vibration	10 kHz	Coolant pump degradation
Acoustic emission probe	Crack initiation, pipe leak	1 MHz	Vessel thinning, valve leak
Thermocouple array	Winding / coolant temperature	1 Hz	Thermal anomaly
Neutron flux detector	Core reactivity	10 Hz	Control rod wear
Eddy current probe	Tube wall thickness	Periodic + online	Steam gen. fouling
Pressure transducer	Primary circuit pressure	100 Hz	Valve leakage

C. Layer 2: Edge Processing Layer

Each plant hosts a dedicated edge processing node responsible for real-time data ingestion, quality screening, and feature vector construction. A sliding window of 1024 samples is processed at 1 kHz to extract time-domain and frequency-domain features including root mean square amplitude, kurtosis, skewness, spectral entropy, and wavelet packet energy across eight decomposition levels. These features form a 48-dimension vector submitted to a locally deployed gradient boosting machine classifier for primary fault screening. Edge-local inference is architecturally necessary because cloud-only processing introduces latency incompatible with nuclear operator action windows, as discussed in Section V.

D. Layer 3: REACTWIN Digital Twin Core

The cloud-hosted REACTWIN core maintains four coupled simulation modules operating in continuous synchronization with the physical plant. The thermal hydraulic module solves RELAP5-compatible conservation equations on a nodalized primary circuit model, tracking coolant temperature, pressure, flow rate, and void fraction. The structural module applies finite element analysis to the pressure vessel and primary piping, computing stress intensity factors and fatigue usage fractions as functions of operating history. The neutronics module tracks core reactivity coefficients and control rod worth to identify anomalous signatures associated with mechanism degradation. An ensemble Kalman filter with a 200-member ensemble assimilates live sensor measurements and propagates state uncertainty [9], correcting for model-plant mismatches arising from irradiation embrittlement and deposit accumulation. A Gaussian process regression module projects the identified fault trajectory over a 60-day horizon to support maintenance scheduling.

E. Output Layer: Fault Diagnosis and Resilience

The decision output module generates fault diagnosis reports containing fault category, severity classification, affected component identifier, confidence score, and recommended maintenance action. Reports are automatically screened against NRC 10 CFR 50.72 and 50.73 reportability thresholds, with assessments provided to plant operations staff within 60 seconds of diagnosis confirmation. The resilience output module projects the Nuclear Reliability Index impact of the identified fault and generates maintenance scheduling recommendations aligned with existing outage planning windows.

IV. FAULT CHARACTERIZATION METHODOLOGY

A. Fault Mode Selection

Five reactor component fault modes are formally characterized within REACTWIN based on their representation in the NRC Equipment Performance and Information Exchange database, where they collectively account for over 80% of unplanned forced outages attributed to primary system component degradation [1]. Table III presents each fault mode alongside its primary diagnostic indicator, target sensor input, involved physics module, and severity classification. Each fault mode is modeled within the digital twin core using the physics module most sensitive to its physical manifestation, ensuring that diagnostic inference retains an explicit first-principles basis consistent with the digital twin concept established in [3].

TABLE III. FAULT MODE CHARACTERIZATION AND PHYSICS-SENSOR MAPPING

Fault mode	Primary indicator	Key sensor input	Physics model involved	Severity
Coolant pump degradation	RMS vibration > 8 mm/s	Accelerometer + AE	Thermal hydraulic	Critical
Pressure vessel thinning	Wall thickness < 90% nominal	Eddy current + UT	Structural FEA	Progressive
Control rod mechanism wear	Position lag > 0.3 steps/s	LVDT + neutron flux	Neutronics	Moderate
Steam generator fouling	Tube bundle dP rise > 15%	Flow meter + temp.	Thermal hydraulic	Progressive

Primary circuit valve leak	Acoustic leak > 0.5 gpm	AE + chemistry	Structural FEA	Incipient

B. Multi-Physics Fault Propagation Modeling

A key methodological contribution of REACTWIN is the explicit modeling of fault propagation pathways across physics domains. Coolant pump bearing degradation, for example, initiates as a mechanical vibration signature detectable by the accelerometer suite, but progresses to alter primary circuit flow distribution in the thermal hydraulic domain and, at advanced stages, to perturb core inlet temperature profiles detectable by the neutron flux monitoring system. By coupling the thermal hydraulic, structural, and neutronics modules within a single state estimation loop, REACTWIN can identify fault progression trajectories that span multiple sensor categories and physics domains. Pearl's causal inference framework [12] informs the directed causal graph underlying this multi-domain propagation model, ensuring that fault pathways are represented as explicit cause-effect chains rather than correlational associations.

C. Synthetic Data Augmentation Strategy

A practical challenge for any nuclear fault diagnosis ML model is the scarcity of labeled fault episode data, since the licensed nuclear fleet operates with very low fault frequencies by design. REACTWIN addresses this through systematic synthetic data augmentation: the multi-physics simulation core is driven by parameterized fault injection scenarios derived from published RELAP5 and TRACE benchmark cases, generating physically consistent synthetic fault signatures across the full severity spectrum for each of the five fault modes. Explainability of the resulting classifier outputs is evaluated using the XAI taxonomy established by Arrieta et al. [13], ensuring that diagnostic reasoning chains satisfy the transparency requirements of both plant operations staff and NRC reviewers.

V. DESIGN PRINCIPLE ANALYSIS

Table IV presents a structured analysis of the three core architectural design principles underlying REACTWIN, mapping each principle to its regulatory or technical justification and primary supporting reference. This analysis demonstrates that each architectural decision is grounded in published engineering standards or peer-reviewed literature rather than arbitrary design choices, establishing the credibility of the proposed framework independent of experimental validation.

TABLE IV. REACTWIN ARCHITECTURAL DESIGN PRINCIPLES AND JUSTIFICATIONS

Design principle	Justification
Physical model primacy	Regulatory bodies require auditable first-principles basis; pure ML cannot be reviewed under 10 CFR 50.59

Sensor redundancy exploitation	Licensed nuclear instrumentation provides multiple independent paths; cross-validation reduces false positives
Edge-local inference	Sub-10-second diagnosis requires onsite processing; cloud-only latency is incompatible with operator action windows
EnKF state estimation	Kalman filtering is established in nuclear plant digital twin synchronization for model-data fusion under uncertainty
GPR prognosis engine	Gaussian process regression provides calibrated uncertainty bounds required for maintenance planning confidence

The primacy of physical model grounding is the most consequential design principle for nuclear deployment. As detailed in NUREG-0711 [10], the NRC requires that monitoring systems used in safety-related decision contexts provide transparent, auditable reasoning chains that can be reviewed against the plant licensing basis. A purely data-driven ML classifier, however accurate on test sets, cannot satisfy this requirement because its decision boundary is a learned statistical artifact rather than an expression of physical law. Liu et al. [14] demonstrated in the analogous context of rare-earth permanent magnet motor fault diagnosis that embedding ML classifiers within physics-grounded digital twin models substantially improves both diagnostic accuracy and regulatory acceptance, a finding that directly motivates REACTWIN's hybrid architecture.

The edge-local inference principle is similarly motivated by published operational requirements rather than design preference. EPRI Technical Report TR-107330 [11] establishes that nuclear operator action windows for primary system anomalies are on the order of 10 to 30 minutes from initial indication, depending on fault category and plant design. Meeting this window with a cloud-only architecture requires tolerating round-trip communication latencies, server queuing delays, and potential network outage risks incompatible with nuclear monitoring availability requirements. Positioning the GBM screening classifier at the edge node eliminates this vulnerability while reserving computationally intensive multi-physics simulation for cloud-hosted infrastructure where resources are unconstrained.

VI. REGULATORY AND RESILIENCE IMPLICATIONS

A. Alignment with DOE LWRS Program

The REACTWIN framework is architecturally aligned with the four strategic thrust areas of the DOE Light Water Reactor Sustainability program: plant modernization and optimization, advanced instrumentation and control, materials and component reliability, and risk-informed safety margins [15]. The multi-physics modeling core directly supports risk-informed in-service inspection interval optimization by providing continuous rather than periodic flaw growth state estimates. This capability enables station engineering to justify extended inspection intervals for components whose REACTWIN prognosis confirms adequate margin, with the potential to reduce average refueling outage duration by an estimated 3 to 5 days per cycle based on industry benchmarks published by the Electric Power Research Institute [11].

B. NRC Regulatory Compliance Pathway

REACTWIN is designed to support rather than supplant licensed operator judgment. All automated fault diagnoses are presented as advisory outputs with explicit confidence scores, physical basis explanations referencing the specific simulation module and parameter threshold that triggered the diagnosis, and recommended surveillance actions. The framework does not initiate automatic protective actions and does not interface with safety system logic. This design philosophy aligns with NRC guidance in NUREG-0711 [10] and positions REACTWIN as an advanced monitoring tool subject to 10 CFR 50.59 screening rather than the more onerous licensing basis change process under 10 CFR 50.90.

C. Grid Resilience Impact

Beyond plant-level maintenance benefits, REACTWIN contributes to national grid resilience through the Nuclear Reliability Index, which integrates forced outage rate, mean time to restore, capacity factor deviation, and unplanned energy loss as component sub-metrics. Based on published EPIX database statistics on fault detection lead time and maintenance intervention effectiveness [1], the proposed framework's 60-day prognostic horizon is expected to convert the majority of currently unplanned forced outages in the targeted fault categories into planned maintenance events, with associated reductions in replacement power cost and grid capacity margin erosion. The energy security dimension of this capability is directly aligned with the U.S. Department of Energy SPARK grid modernization investment priorities and the NSM-22 critical infrastructure security guidance issued in 2024.

CONCLUSION AND FUTURE WORK

This paper proposed REACTWIN, a conceptual digital twin framework for real-time fault diagnosis and resilience monitoring of nuclear reactor component systems. The framework integrates multi-physics simulation covering thermal hydraulic, structural, and neutronics domains with heterogeneous IoT sensor fusion, gradient boosting ensemble classification, ensemble Kalman filter state synchronization, and Gaussian process regression-based prognosis within a four-layer architecture. A formal characterization of five critical fault modes was presented alongside a structured design principle analysis grounding each architectural decision in published nuclear engineering standards and peer-reviewed digital twin literature. The gap analysis in Table I establishes that REACTWIN advances the state of the art across all five evaluated capability dimensions relative to existing approaches.

Future work will pursue several directions. First, simulation-based validation against publicly available RELAP5 and TRACE benchmark cases will be conducted to quantify expected fault detection sensitivity and specificity under the synthetic augmentation strategy described in Section IV. Second, federated learning techniques will be explored to enable privacy-preserving cross-plant model improvement without exchanging raw sensor records. Third, integration with probabilistic risk assessment models will be developed to enable REACTWIN fault diagnoses to update core damage frequency estimates in real time, directly supporting risk-informed decision making. Fourth, standardized application programming interfaces conforming to IEC 61970 Common Information Model will be designed to facilitate interoperability with existing plant information management and NRC inspection data exchange platforms.

REFERENCES

[1] U.S. Nuclear Regulatory Commission, "Equipment Performance and Information Exchange (EPIX) Annual Report," NUREG/CR-7265, Washington, DC, 2023.

[2] S. C. Cheung, L. M. Thomas, and R. J. Pugh, "Online Condition Monitoring of Light Water Reactor Primary System Components: A Survey," Nuclear Engineering and Design, vol. 378, p. 111185, 2021.

[3] M. W. Grieves and J. Vickers, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems," in Transdisciplinary Perspectives on Complex Systems, Springer, Cham, 2017, pp. 85-113.

[4] S. Gupta, "Digital Twins for Circular Economy Optimization: A Framework for Sustainable Engineering Systems," Proceedings of the 1st SUSTENS Meeting, MDPI Proceedings, vol. 121, no. 4, p. 1-5, 2025.

[5] International Atomic Energy Agency, "Instrumentation and Control Systems Important to Safety in Nuclear Power Plants," Safety Guide SSG-39, Vienna, Austria, 2016.

[6] X. Lin, Y. Wang, and H. Zhao, "LSTM-Based Steam Generator Tube Fouling Trend Prediction for Predictive Maintenance in Pressurized Water Reactors," Annals of Nuclear Energy, vol. 182, p. 109606, 2023.

[7] T. Bickel, G. Agarwal, and R. Srivastava, "Physics-Informed Neural Networks for Anomaly Detection in Reactor Coolant Pump Vibration Signatures," Nuclear Technology, vol. 208, no. 6, pp. 987-1001, 2022.

[8] L. Zhou, J. Chen, and W. Liu, "Digital Twin Modeling of Pressurized Water Reactor Primary Circuit Thermal Hydraulics for Operational Decision Support," Nuclear Engineering and Technology, vol. 54, no. 11, pp. 4021-4032, 2022.

[9] A. Yadav, P. Sharma, and N. Singh, "Ensemble Kalman Filter Based State Estimation for Digital Twin Synchronization in Nuclear Power Plant Systems," Progress in Nuclear Energy, vol. 158, p. 104616, 2023.

[10] U.S. Nuclear Regulatory Commission, "Human Factors Engineering," NUREG-0711, Rev. 3, Washington, DC, 2012.

[11] Electric Power Research Institute, "Guideline for Nuclear Plant Monitoring System Design and Integration," EPRI TR-107330, Palo Alto, CA, 2019.

[12] J. Pearl, "The Seven Tools of Causal Inference, with Reflections on Machine Learning," Communications of the ACM, vol. 62, no. 3, pp. 54-60, 2019.

[13] A. B. Arrieta, N. Diaz-Rodriguez, J. Del Ser, et al., "Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI," Information Fusion, vol. 58, pp. 82-115, 2020.

[14] Z. Liu, T. Gao, and W. Li, "Research on Fault-Diagnosis Technology of Rare-Earth Permanent Magnet Motor Based on Digital Twin," IEEE Transactions on Industrial Electronics, vol. 70, no. 8, pp. 8133-8143, Aug. 2023.

[15] U.S. Department of Energy, "Light Water Reactor Sustainability (LWRS) Program: Multi-Year Program Plan," DOE Office of Nuclear Energy, Washington, DC, 2024.