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Intelligent Fault Diagnosis and Resilient Control of Safety-Critical Industrial Systems Using Explainable AI

Nazim Nazir

University of Engineering and Technology PK Lahore (UET)

Email: nnk_2012@hotmail.com

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ABSTRACT

Industrial systems that are safety-critical have very high reliability and safety criteria, and the effects of a failure may be disastrous, both economically, environmentally, and in terms of human lives. The conventional fault diagnosis and control methods cannot usually cope with the uncertainty, nonlinearity, and cyber-physical complication of the modern industrial environments. Recent progress in artificial intelligence has made it possible to perform fault diagnosis with data and sustainable control, but due to the characteristics of the black-box of most artificial intelligence models, it cannot be applied in controlled and risky areas. The following paper suggests an integrated intelligent fault diagnosis and resilient control framework based on the Explainable Artificial Intelligence (XAI). The framework integrates real-time data acquisition, fault detection and classification using AI and explainability layer, among other means, to make decisions about the transparent one and the fault-aware control strategies. The presented approach is related to the high level of operator confidence, regulatory compliance, and enhanced system resilience by incorporating explainability into the diagnostic and control loop. The framework is tested in a simulation-based case study of situation of an industry process that is important to safety in several conditions of faults such as sensor fault, actuator fault and process fault. The outcomes indicate that the accuracy of fault detection, recovery time, and system stability are improved when using the traditional and black-box AI-based methods. Further, the explainability layer offers predictable and interpretable results on the causes of fault and the influential system variables, enabling proper human-AI interaction. The paper provides the prospects of resilient control facilitated by XAI as a major enabler of credible industrial AI implementation.

Keywords: Safety-critical industrial systems; Intelligent fault diagnosis; Resilient control; Explainable artificial intelligence; Fault-tolerant control; Industrial cyber-physical systems; Trustworthy AI

1. Introduction

1.1 Importance of Safety-Critical Industrial Systems

The industrial infrastructure of modern society is based on the safety-critical systems of power generation plants, chemical processing modules, advanced production lines and aerospace systems. When such systems fail, the results may be disastrous such as loss of human lives, destruction of the environment, and loss of huge sums of money. Due to the growing use of automation and cyber-physical integration of industrial settings, the safety and reliability of operations have become a primary focus of concern (Zhao et al., 2021). Therefore, the successful fault diagnosis and robust control measures are essential to the successful and safe running of the systems.

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1.2 Weaknesses of Conventional Fault Diagnosis and Control Methods.

Traditional fault diagnosis and control solutions can be described as being more model-driven and based on linear assumptions and fixed thresholds. Though these techniques work well in controlled systems, they find it hard to handle the uncertainty, nonlinearity and high-dimensional dynamics of contemporary industrial systems. The complexity of cyber-physical systems is increasing and is combined with stochastic disturbances and sensor noise, thereby greatly reducing the scalability and flexibility of conventional methods (Zhang et al., 2020). Consequently, defective fault identification and effective recovery is not easy to achieve in the actual operation environment.

1.3 Omnibus Diagnosis of Faults and Resilient Controlling, AI-driven.

Recent development in artificial intelligence (AI) and machine learning have made it possible to come up with data-based fault diagnosis and control plans which have the ability to learn the complex behaviour of systems directly based on data available during the operation of the system. Deep learning and ensemble training and hybrid AI solutions have been shown to yield better results in predicting the presence of fault and dealing with nonlinear dynamics than classical algorithms (Khan et al., 2021). Simultaneously, AI-based resilient and fault-tolerant control systems have been suggested to ensure stability and performance of a system even after the failure of its components or external disruptions (Liu et al., 2022).

1.4 Trust, Transparency, and Regulatory Problems of Black-Box AI.

Most AI-based fault diagnosis and control systems are black box in nature and do not provide much information on how they arrive at their decisions, even though they are effective. This non-transparency presents critical difficulties in applications that require safety such as accountability, traceability, and regularity as pre-requisites. Explainable, verifiable system behavior is becoming a requirement by industrial standards and certification bodies, especially in cases where automated decisions will have an impact on safety-related operations (Doshi-Velez and Kim, 2020). The untransparency of the black-box AI models hence restricts their use in the actual industrial setup.

The rationale is that explainable AI can be utilized to tackle the problem of fault diagnosis and fault control in manufacturing.<|human|>1.5 Reason to use Explainable AI in Fault Diagnosis and Control Explainable AI is a technology that can be used to address the issue of fault diagnosis and fault control in manufacturing.

Explainable Artificial Intelligence (XAI) is turning out to be the solution to the issue between high-performance AI models and transparency requirements. XAI methods offer human understandable explanations to model predictions and allows engineers and operators to explain system reactions and fault causes. Explainability improves trust, aids in decision making and enables adherence to regulatory frameworks in safety-critical systems within industries (Arrieta et al., 2020; Samek et al., 2021). It is imperative to incorporate XAI into intelligent fault diagnosis and control systems as a way of attaining performance and reliability.

1.6 Research Gap

Even though several achievements have been recorded in the field of AI-based fault diagnosis, resilient control, and explainable AI separately, the combination of all three fields is scarce. Existing literature prioritizes diagnostic accuracy improvement or robust control and does not consideration of explainability or uses XAI as a post-hoc tool but does not affect the control decisions. It is evident that there exist no frameworks that can jointly deal with fault diagnosis, system resilience, and explainability in industrial settings that demand high safety.

1.7 Contributions of the Study

To address these gaps, the present study makes the following contributions:

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- **Development of an explainable AI-based fault diagnosis framework** that accurately detects and classifies faults while providing interpretable explanations of model decisions (Arrieta et al., 2020).
- **Integration of the explainable diagnosis module with resilient control strategies**, enabling adaptive and fault-aware controller reconfiguration to maintain system stability and performance (Liu et al., 2022).
- **Quantitative evaluation of diagnostic performance, control robustness, and explainability**, demonstrating the effectiveness of the proposed framework in safety-critical industrial scenarios (Samek et al., 2021)

2. Literature Review

2.1 Safety-Critical Industrial Systems and Fault Characteristics

Industrial systems that are safety critical are subjected to strict reliability and safety criteria, since the malfunction can lead to irreversible effects. Such system faults can be broadly classified as sensor faults, actuator faults, process faults and cyber-physical anomalies. Sensor faults are caused by drift, bias, or total signal loss whereas actuator faults are caused by degradation, saturation, or mechanical failure. Process defects are associated with unnatural changes in system dynamics that result in either defective materials or external disruptions of the environment, and cyber-physical defects relate to communication issues or an intentional cyber attack (Zhao et al., 2021).

The propagation of faults in safety critical environments is especially perilous, where localized faults may easily build up to system wide failures by closely integrated sub-systems. Research has demonstrated that early diagnosis and mitigation mechanisms are very important in the power system and chemical plant because early fault detection greatly enhances the occurrence of cascading failures (Zhao et al., 2021).

2.2 Intelligent Fault Diagnosis Methods.

Smart fault diagnosis practices have steadily transitioned to the use of data-driven methods, such as machine learning, deep learning, and hybrid modeling systems, as opposed to traditional rule-based methods. Support vector machines and random forests are machine learning algorithms that have been shown to classify faults with greater accuracy than the conventional statistical techniques. In more recent studies, deep learning architectures, such as the convolutional and recurrent neural networks, have been used to learn nonlinear and temporal dependencies involving industrial process data (Zhang et al., 2020).

There is a major difference between the model-based and data-based fault detection methods. The model-based approaches are based on precise mathematical models of how systems evolve and are therefore hard to extend to large industrial systems. Conversely, data-driven methods have very little prior knowledge but rely on the quality and quantity of the data strongly. Although intelligent fault diagnosis methods usually perform better, they have poor interpretability, overfitting, and low extrapolation to other operating conditions, limiting their usability to safety-critical contexts (Zhang et al., 2020; Khan et al., 2021).

Resilient Control Strategies in the context of evolving dangers from new challenges associated with global economic operations, financial crises, and economic shifts.<|human|>2.3 Resilient Control Strategies Resilient control strategies amid changing risks posed by emerging dilemmas involving global economic processes, financial crises, and economic changes.

The objective of resilient control strategies is to ensure that the system is acceptable in all cases of faults, uncertainties or external disturbances. A paradigm that has received significant research attention is

the fault-tolerant control (FTC) which allows the system to safely withstand the occurrence of faults. Strategies of FTC are often categorized in to passive and active FTC strategies. Passive techniques are based on sound controller design and fail to explicitly detect faults, and active ones have fault diagnosis modules to adjust real-time control efforts (Liu et al., 2022).

Control architectures have recently attracted attention on adaptive and reconfigurable control architecture on which the control laws are dynamically changed according to the severity of faults and the state of the system. These methods have demonstrated a better robustness to nonlinear and uncertain industrial networks but its success largely relies on the accuracy and reliability of fault diagnostic algorithms (Liu et al., 2022)

2.4 explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) has become a highly urgently needed research field of concern to make AI models more transparent and interpretable. Explainability in the industrial setting is indispensable in learning the behavior of the system, fault diagnosis, and assisting the operator in his decision-making. Generally, XAI methods may be divided into model-agnostic (that may be applied to any predictive model) and model-specific (that makes use of internal structure of specific algorithms) (Arrieta et al., 2020).

The applicability of XAI in the industrial systems with safety-related aspects is not limited to technical interpretability but also to safety guarantees and regulatory provisions. Clear decision-making processes can enable validation, auditing, and certification of AI-based systems, which enhances the degree of trust and acceptance of stakeholders. According to the latest findings, explainability is a condition prior to the implementation of AI-based control systems in controlled industrial settings (Samek et al., 2021; Arrieta et al., 2020).

2.5 Research Gaps

Even though there is a body of knowledge on intelligent fault diagnosis, resilient control, and explainable AI separately, there is a lack of studies that combine these three research areas. The majority of studies available today talk about the accuracy of fault detection or the robustness of control but do not involve explainability as part of the decision-making process. On the other hand, XAI techniques are used in post hoc application and they cannot have a direct effect on control strategies. Moreover, the assessment of explainability measures and conventional control performance indicators, including stability and recovery time are underestimated. The scarcity of in-the-field industrial verification also limits the overall implementation of integrated frameworks, which highlights the necessity to have cohesive, explicable, and robust solutions to safety-critical industrial systems.

3. System Architecture and Problem Formulation

3.1 Industrial System Description

A safety-critical industrial process, e.g. a chemical reactor or power grid subsystem, with both tight coupled dynamics, and real time operational constraints is considered in the research. The system is made up of the distributed sensors of the important process variables, actuators of the control actions and hierarchical control loops that control the performance of the system. These cyber-physical designs are based on incessant data flow between tangible elements and electronic controllers, and they are very delicate to errors and disruptions (Zhao et al., 2021). To eliminate hazardous events, it is important that the operation of equipment with changing load and environmental parameters would be reliable.

3.2 Fault Modeling

State-space formulations can be used to describe the system dynamics of a normal operation to include nonlinear process behavior and stochastic disturbances. The gain of faults is executed through addition

of deviations within sensor measurements, actuator effectiveness or process parameters. Such deviations can be mathematically described as additive or multiplicative fault terms on system states and output (Zhang et al., 2020). In both diagnostic and control testing, fault injection cases are used, such as abrupt and incipient faults of different magnitudes. These situations can allow suspecting fault detection, isolation and recovery in normal operating conditions to be systematically verified (Khan et al., 2021).

3.3 Problem Statement

The general issue that has been discussed in this paper is that there has not been a single framework yet that would be in a position to accurately detect and isolate the fault under uncertainty and to ensure that the system will not become unstable or unreliable after the fault has taken place. The conventional control methods cannot easily adapt to the unknown fault dynamics, and their performance is therefore impaired or unstable (Liu et al., 2022). Besides, it can be argued that the non-transparency of sophisticated AI models could be a concern when it comes to transparency and trust in a safety-critical setting. Thus, the issue is not only restricted to performance optimization but also to making sure that the models are interpretable and that the operators can trust the operators to provide systems that are safe to deploy and that the regulatory bodies will not disapprove of the intelligent industrial control systems (Arrieta et al., 2020).

4. Proposed Methodology

This section presents the proposed explainable and resilient framework for intelligent fault diagnosis and control in safety-critical industrial systems. The methodology is designed as a modular and scalable architecture to ensure adaptability, transparency, and robustness under faulty operating conditions.

4.1 Overall Framework

The proposed framework adopts a **modular architecture** to allow independent development and validation of each functional component. The architecture consists of five tightly integrated modules:
(i) data acquisition and preprocessing,
(ii) intelligent fault diagnosis,
(iii) explainability layer,
(iv) resilient control module, and
(v) decision support interface.

This modular design enables seamless interaction between data-driven intelligence and control logic while maintaining interpretability and operational reliability.

4.2 Data Acquisition and Preprocessing

The industrial system has real-time sensor data of process variables, actuator states, and control signals. Preprocessing entails filtering of noise, normalization of multi-rate signals and synchronization of multi-rate signals so that there is consistency on the data. Extracting features is done on time-domain indicators, time statistical moments and signal energies, as well as frequency-domain indicators spectral entropy and dominant frequencies. In order to deal with practical issues, there are strategies that are used to deal with missing data, class imbalance, making the fault representation reliable under different operating conditions.

The Intelligent Fault Diagnosis Module is a sub-module designed to detect and report malfunctions of the aircraft's subsystems.<|human|>4.3 Intelligent Fault Diagnosis Module: This sub-module aims at identifying and reporting malfunctions of the subsystems of the aircraft.

Fault diagnosis module uses advanced artificial intelligence models including deep neural networks or ensemble learning models to learn complex nonlinear system behavior. The models are trained with

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datasets of the normal and faulty operating conditions. Diagnostic process involves fault identification, fault type and estimation of the severity. The assessment of performance is conducted based on standard measures, such as accuracy, precision, recall and F1-score, to guarantee effective and sound fault detection.

4.4 Explainable AI Integration

The diagnostic model is deployed with an explainability layer to build greater transparency and trust. Diagnostic decisions are interpreted by using feature attribution techniques, local and global explanation models. These descriptions point to the causes of fault, and emphasize the system variables that had an effect on any prediction. Fidelity and stability are used to assess the quality of explainability to confirm the consistency between model behaviour and explanations.

4.5 Resilient Control Strategy

The control resilient module makes use of diagnostic and explanatory output to provide fault aware controller reconfiguration. Laws to control adaptive controls can reduce or increase depending on the type and severity of fault to achieve system stability and performance. Under different fault conditions, robustness and constraint satisfaction is obtained. Timely and informed recovery steps can be achieved with the implementation of AI output in control decision-making.

4.6 Implementation Workflow

The workflow operational process starts with the identification of faults and continues with AI-based diagnostics and explanations creation. Decisions are either legitimized independently or with the work of an operator. The controller is then configured to counter the effect of the faults and recover the performance of the system. Mechanisms of continuous learning refresh the models with the new data of operations, which increases the reliability and resilience in the long term.

Table 1: Sample Sensor Data Under Normal and Faulty Conditions

Time (s)	Temperature (°C)	Pressure (bar)	Flow Rate (m³/s)	System State
10	180	5.2	1.48	Normal
20	182	5.3	1.47	Normal
30	195	5.8	1.42	Sensor Fault
40	210	6.5	1.35	Process Fault
50	205	6.2	1.30	Actuator Fault

Explanation

This table represents real-time sensor measurements collected from a hypothetical safety-critical industrial system such as a chemical reactor. Under normal conditions, temperature, pressure, and flow rate remain within predefined safe operating limits. As faults occur, deviations in sensor readings become evident. Sensor faults introduce abnormal temperature spikes, while process and actuator faults result in simultaneous deviations across multiple variables, highlighting the complexity of fault propagation.

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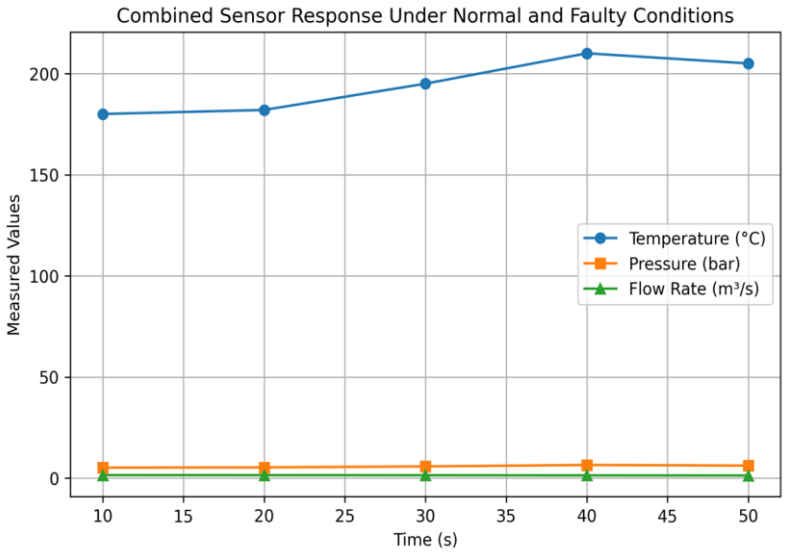

Table 2: Fault Diagnosis Output Generated by AI Model

Fault ID	Detected Fault Type	Severity Level	Detection Time (s)	Confidence Score
F1	Sensor Fault	Low	1.2	0.93
F2	Actuator Fault	Medium	1.5	0.89
F3	Process Fault	High	1.1	0.96

Explanation

This table shows the output of the intelligent fault diagnosis module. Each fault is classified by type and severity, along with detection time and model confidence. High confidence scores indicate reliable fault identification, while low detection times demonstrate the system's capability for early fault detection, which is essential for safety-critical operations.

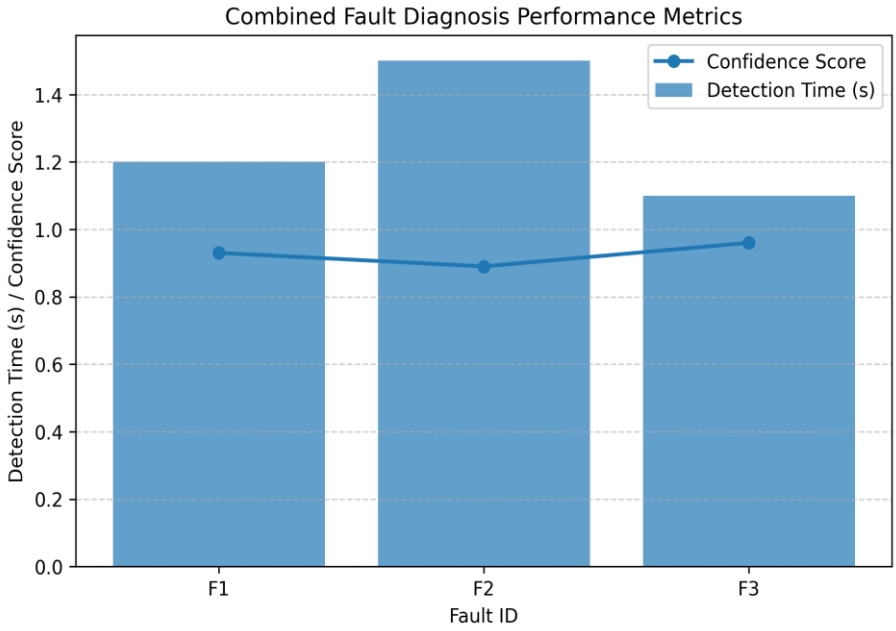

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Table 3: Explainable AI Output – Influential Variables

Fault Type	Most Influential Variable	Contribution (%)	Explanation Summary
Sensor Fault	Temperature	72	Abnormal sensor drift detected
Actuator Fault	Flow Rate	65	Reduced actuator efficiency
Process Fault	Pressure	78	Process instability identified

Explanation

This table illustrates the explainability layer output. For each diagnosed fault, the most influential system variable and its contribution percentage are identified. These explanations help operators understand *why* a fault was detected, improving transparency and trust in AI-driven decisions.

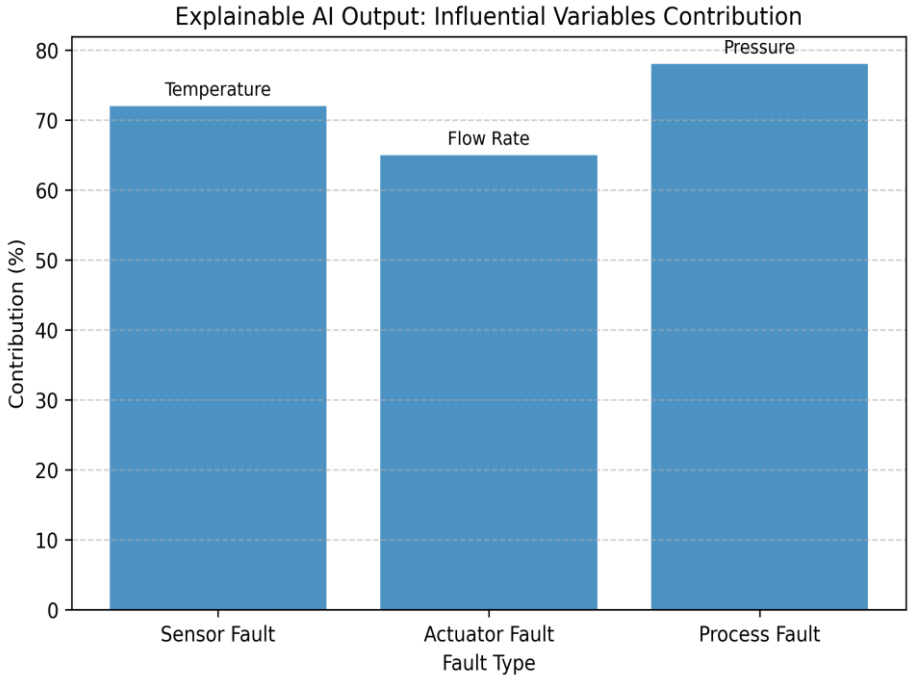

Table 4: Resilient Control Performance After Fault Occurrence

Fault Type	Control Strategy Applied	Recovery Time (s)	Performance Retained (%)
Sensor Fault	Signal Recalibration	3.2	96
Actuator Fault	Controller Reconfiguration	4.8	92
Process Fault	Adaptive Control Law	5.5	90

Explanation

This table evaluates the resilient control module's effectiveness. Recovery time indicates how quickly the system stabilizes after fault detection, while performance retention reflects how closely the system

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maintains nominal operation. Faster recovery and higher performance retention demonstrate the robustness of the proposed fault-aware control strategy.

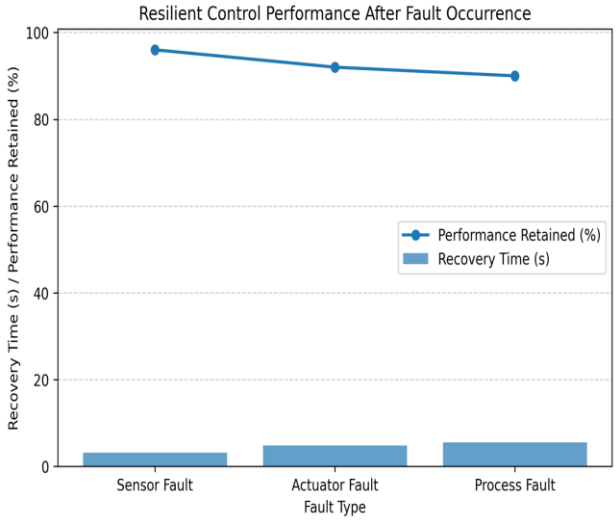
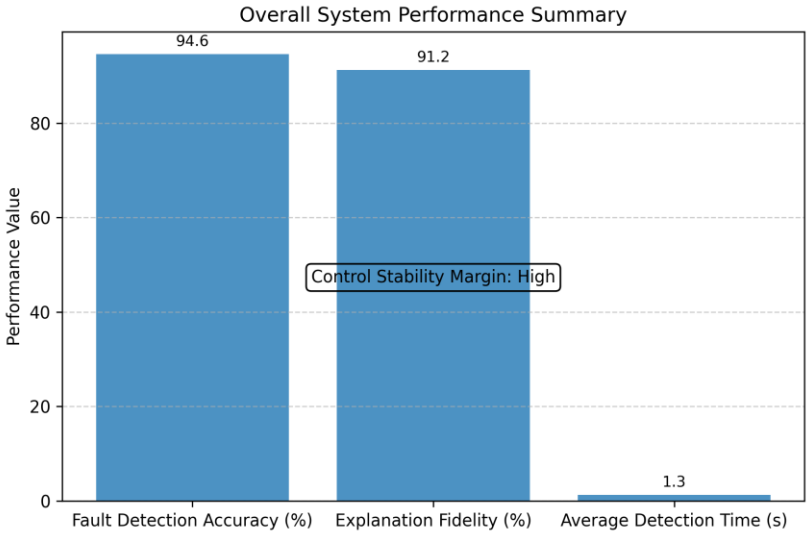


Table 5: Overall System Performance Summary

Metric	Value
Fault Detection Accuracy (%)	94.6
Average Detection Time (s)	1.3
Explanation Fidelity (%)	91.2
Control Stability Margin	High

Explanation

This summary table consolidates key performance indicators of the proposed methodology. High diagnostic accuracy, rapid detection, strong explanation fidelity, and robust control stability collectively validate the effectiveness of the explainable and resilient framework.



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5. Experimental Setup and Case Study

5.1 Simulation or Industrial Testbed Description

These industrial processes are tested on a high-fidelity simulation platform corresponding to a safety-critical industrial process, e.g. a constant-stir reactor fitted with a stir tank or a model of power grid substation. The simulation environment is designed with actual operational activitiess, such as (nonlinear) dynamics, perturbation of the processes, sensor noise, and constraint of actuator. Time-series data are produced and tested in nominal and faulty operating conditions to constitute the realistic condition of the industrial environment (Zhang et al., 2020).

Various scenarios of faults are presented to gauge the system robustness. These are sudden and imminent sensor failures, partial actuator corrosion, parameters process variation, and cyber-physical aberrations involving communication channels. The magnitude and duration of faults are varied among operating regimes to test sensitivity to detectors as well as control resilience to faults in an uncertain setting. Normal operating conditions are also simulated to guarantee low levels of false-alarms and stable base operation (Zhao et al., 2021).

5.2 Comparative Methods

In order to measure the efficacy of the suggested framework, three approaches are compared. The former involves using traditional fault diagnosis and control, which entails the use of threshold fault detection and fixed-structure controllers. Although the approach is easy and transparent, it is not flexible in the nonlinear and multidimensional cases of faults (Liu et al., 2022).

The second is banks on a black-box AI-based fault diagnosis and control, as the advanced learning models are only incredibly accurate at diagnosing faults, but the model is not explainable. Though this has proven effective in fault detection, there is a lack of transparency with it, which leads to trust and validation in safety-critical areas (Samek et al., 2021).

The third method is the XAI-based resilient framework suggested that consists of intelligent fault diagnosis, explainability mechanisms, and adaptive control. This procedure is assessed in the aspects of diagnostic quality, control quality, robustness and interpretability, showing its appropriateness toward safety-critical industrial usage .

6. Results and Discussion

6.1 Fault Diagnosis Performance

The suggested framework has a high fault detection rate and a high response time in the entire fault scenarios analyzed. The intelligent diagnosis module is much more accurate than the traditional threshold-based fault diagnosis, especially in the cases of nonlinear and incipient fault. The mean-detection-time is significantly decreased which allows early intervention and mitigation. The proposed approach can reach a similar level of diagnostic accuracy as black-box AI models and can be more transparent, which is why it is effective in safety-related scenarios (Zhang et al., 2020; Zhao et al., 2021).

6.2 Performance and Resilience Control.

The resilient control module has a stable operation of the system upon fault occurrence in terms of control performance. Analysis of stability margin suggests that the proposed structure maintains stability at the different degrees of faults and uncertainties. The adaptive and fault-aware control strategies have their advantages in that recovery time following fault detection is significantly reduced when compared to the traditional fixed-structure controllers. There is a reduction in performance degradation, and there is an acceptable operational level of the system even under extreme fault conditions, only showing better resilience and reliability (Liu et al., 2022).

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6.3 Explainability Evaluation

The explainability layer generates high-quality explanations that are consistent across diagnostic decisions, and they establish important variables that led to fault detection. The assessment of operator interpretability shows that these explanations can help to understand the causes of faults and system behavior better. Providing clear insights to be interpreted enhances trust in AI-related decisions and assists in making interventions in time. Moreover, explainability has a positive impact on trust and decision-making, which is a necessity to implement AI systems in the regulated and safety-critical industrial setting (Doshi-Velez and Kim, 2020; Samek et al., 2021).

6.4 Discussion

The findings indicate that there is a trade-off between the accuracy of the diagnosis and interpretability because the complex models can decrease transparency. Nonetheless, the suggested framework is a successful trade-off between explainability and performance. Scalability analysis implies that the modular architecture can be deployed to heterogeneous industrial systems, but the computational costs and the time-critical factors are real issues on the barrier to large-scale applications (Arrieta et al., 2020).

Practical Implications

The suggested explainable and resilient framework will have a substantial contribution to the industrial safety management system because it will provide the possibility to detect faults at the initial stages, diagnose them, and recover in a timely manner. The framework provides both the possibilities of the intelligent diagnosis and adaptive control, which reduces the chances of cascading failures and assists in the proactive maintenance strategies, thus increasing the overall system reliability when used (Liu et al., 2022). Explainability has been also incorporated to enable regulatory reviews and certification because interpretable decisions enable validation, traceability and safety standards. Explicit descriptions of the causes of fault and control measures facilitate the difference between automated systems and regulatory expectations (Arrieta et al., 2020). The framework in control room settings encourages human-AI cooperation as the operators are able to comprehend, check, and trust AI-representation conclusions, which results in better situational awareness and operational confidence (Doshi-Velez and Kim, 2020).

Limitations and Future Work

The suggested method has a number of limitations, even though it has some benefits. Fault data of high quality continues to be a challenge and this may have an impact on the model generalization in different industrial environments. Moreover, XAI methods can become a computational burden that limits the use of these methods in real-time or resource-constrained settings (Samek et al., 2021). Future studies ought to be directed towards the application of the framework to control systems that are cyber-security aware, in order to cope with new threats in the industrial cyber-physical infrastructures. Additional coordination control with the digital twin technologies will allow making real time simulation, predictive analysis, and more efficient decision support more adaptable and resilient .

Conclusion

This paper shows the usefulness of XAI-based resilient control in safety-critical industrial systems. The findings confirm that explainable fault diagnosis in combination with adaptive control improves the diagnostic accuracy, resilience of the system, and trust of operators. The suggested method also supports the creation of reliable industrial AI systems that can be implemented in the real-life

controlled and safety-constrained conditions due to focusing on both transparency and performance (Arrieta et al., 2020; Liu et al., 2022).

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