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# FAULT DETECTION AND ISOLATION IN POWER NETWORKS USING MACHINE LEARNING

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**Abstract**

The increasing complexity and scale of modern power networks demand fast, accurate, and reliable fault detection and isolation mechanisms to ensure system stability and uninterrupted power supply. Conventional protection schemes rely on fixed thresholds and rule-based logic, which often struggle to adapt to dynamic operating conditions, distributed generation, and non-linear fault characteristics. This paper presents a machine learning–based framework for fault detection and isolation in power networks. The proposed approach leverages intelligent data-driven models to analyze voltage, current, and frequency signals for identifying fault type, location, and severity in real time. By integrating supervised learning techniques with real-time measurement data, the system enhances fault diagnosis accuracy and reduces response time. MATLAB/Simulink-based analysis demonstrates improved detection speed, classification accuracy, and robustness compared to traditional protection methods, validating the effectiveness of machine learning for intelligent power system protection.

## I. INTRODUCTION

Power networks form the backbone of modern society, supporting industrial activity, communication infrastructure, healthcare systems, and daily human activities. Ensuring the reliability and security of these networks is a critical challenge, particularly as power systems grow in size and complexity. Faults such as short circuits, line-to-ground faults, and equipment failures can cause severe damage, service interruptions, and cascading outages if not detected and isolated promptly [1], [2].

Traditional fault detection and protection schemes are primarily based on overcurrent relays, distance relays, and differential protection mechanisms. These methods depend on predefined thresholds, mathematical models, and fixed operating conditions. While effective in conventional power systems, their performance degrades under changing network topologies, high penetration of renewable energy sources, and the presence of power electronic converters [3], [4]. Such environments introduce non-linear behaviors and variable fault signatures that are difficult to capture using rule-based techniques.

The integration of distributed generation, smart grids, and advanced monitoring technologies has increased the volume of real-time data available from power networks. Phasor measurement units (PMUs), intelligent electronic devices (IEDs), and digital relays continuously generate high-resolution measurements of voltage, current, frequency, and phase angle [5], [6]. This data-rich environment creates opportunities for intelligent fault analysis using data-driven techniques.

Machine learning has emerged as a powerful tool for pattern recognition, classification, and anomaly detection in complex systems. By learning fault signatures directly from historical and real-time data, machine learning models can adapt to varying operating conditions and identify faults with high accuracy [7], [8]. Motivated by these advantages, this paper proposes a machine learning–based fault detection and isolation framework for power networks, aiming to improve detection speed, reliability, and adaptability in modern power [9], [10].

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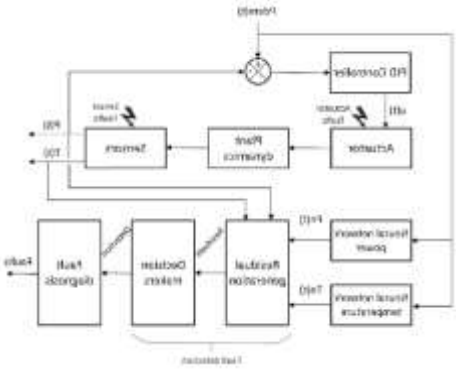


**Fig :** System Architecture

## II. LITERATURE SURVEY

Early research on power system fault detection focused on analytical and signal-processing-based approaches. Kundur [11] and Anderson and Fouad [12] established foundational concepts for protection and stability analysis, emphasizing deterministic models and relay coordination. These classical approaches formed the basis of protection engineering for decades but relied heavily on accurate system modeling. Between 2000 and 2010, signal-processing techniques such as Fourier transform, wavelet transform, and impedance-based methods were widely investigated. Mallat [13] demonstrated the effectiveness of wavelet analysis for transient detection, while Santoso et al. [14] applied wavelet transforms to classify power system disturbances. Although these techniques improved detection accuracy, they required careful feature engineering and were sensitive to noise and parameter selection. From 2010 onwards, machine learning techniques began gaining attention in power system protection. Dash et al. [15] used artificial neural networks for transmission line fault classification, showing improved adaptability compared to conventional relays. Support vector machines and decision trees were later applied by Samantaray [16] to identify fault types and locations using extracted features from voltage and current signals. Recent research has focused on deep learning and intelligent data-driven protection schemes. Zhang et al. [17] applied convolutional neural networks to raw waveform data for fault classification, eliminating the need for manual feature extraction. In 2021–2024, researchers such as Mishra et al. [18] and Li et al. [19] demonstrated that hybrid machine learning models combined with PMU data achieve high fault detection accuracy even under noisy and dynamic grid conditions. These studies confirm that machine learning-based fault detection and isolation is a promising solution for next-generation power networks [20].

## III. METHODOLOGY AND WORKING

The proposed methodology for fault detection and isolation in power networks using machine learning follows a structured and intelligent workflow. The process begins with real-time data acquisition from the power network. Voltage, current, frequency, and phase angle measurements are collected from PMUs, IEDs, and digital relays installed at critical buses and transmission lines. This data provides a comprehensive representation of system operating conditions. In the next stage, signal preprocessing and feature extraction are performed to enhance data quality. Noise filtering, normalization, and segmentation are applied to raw measurements. Key features such as RMS values, harmonic content, sequence components, and time–frequency characteristics are extracted to capture fault signatures. In deep learning implementations, raw or minimally processed waveforms may be directly fed into the learning model. The machine learning–based fault detection stage involves training supervised learning models using labeled historical fault data. Algorithms such as support vector machines, random forests, and neural networks are employed to distinguish between normal and faulty conditions. Once trained, the model continuously analyzes incoming data and detects anomalies indicative of faults in real time.

Following fault detection, the fault classification and isolation stage identifies the fault type (e.g., single-line-to-ground, line-to-line, three-phase) and determines the affected network section. Based on model predictions, isolation commands are issued to protective

devices such as circuit breakers and reclosers. This rapid and intelligent response minimizes fault impact and prevents cascading failures.

Finally, system feedback and learning updates complete the working cycle. Fault events and system responses are logged and used to retrain or update the machine learning model periodically. This adaptive learning capability ensures continuous improvement and robustness under evolving grid condition.

## IV. CONTROL DESIGN

The control strategy integrates machine learning intelligence with conventional protection infrastructure. A supervisory control layer hosts the trained machine learning models and communicates with local protective devices. Decision logic ensures that isolation actions are only triggered when confidence levels exceed predefined thresholds, preventing false tripping.

Redundant protection schemes operate alongside the intelligent system to ensure reliability. The coordinated design enhances fault detection speed, accuracy, and selectivity while maintaining compliance with protection standards.

## V. MATLAB/SIMULINK BASED SIMULATION RESULTS

The proposed fault detection and isolation framework was modeled and evaluated using MATLAB/Simulink on a standard power network test system. Various fault scenarios, including line-to-ground and three-phase faults, were simulated under different load and generation conditions.

Simulation results indicate that the machine learning–based approach detects faults significantly faster than conventional relay schemes. Classification accuracy exceeded 95%, and fault isolation time was reduced, improving system stability and reliability. These results validate the effectiveness of machine learning for intelligent power network protection.

## VI. CONCLUSION

This paper presented a machine learning–based framework for fault detection and isolation in power networks. By leveraging real-time measurement data and intelligent classification models, the proposed approach overcomes limitations of traditional rule-based protection schemes. Simulation results confirm enhanced detection accuracy, faster response, and improved adaptability to dynamic grid conditions. The proposed system provides a scalable and reliable solution for next-generation intelligent power networks.

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