Artificial Intelligence Applications for Detection, Diagnosis, and Life-Cycle Management in Power Electronic Systems and Electrical Drives

M L Sharma[1], Sunil Kumar[2], Rajveer Mittal[3], Ayaan Amir Khan[4], Devansh Sihag[5]
[1, 2, 3] Faculty, Maharaja Agrasen Institute of Technology, Delhi
[4, 5]Research Scholar, Maharaja Agrasen Institute of Technology, Delhi
[1]madansharma.20@gmail.com, [2]sunilkumar@mait.ac.in, [3]ghoshdrsoumi@gmail.com, [4]ayaanamirkhan1234@gmail.com, [5]devanshsihag40@gmail.com

Abstract

Modern power systems require high reliability and minimal downtime, but traditional protection schemes depend on manual inspection and fixed thresholds that respond slowly to abnormal events. This paper introduces an Artificial Intelligence (AI)–based model that performs automatic power-fault detection and intelligent restoration. The model analyzes real-time voltage, current, and frequency data, classifies the fault type, and restores supply through adaptive control logic. The proposed method shortens recovery time by more than 60 % and increases fault-classification accuracy to 97 %. The research also highlights integration possibilities for smart grids and renewable-energy networks.

Keywords: Artificial Intelligence, Fault Detection, Power Restoration, Machine Learning, Smart Grid, Predictive Maintenance.

Introduction

Electric-power reliability is fundamental for both industry and households. Power interruptions due to short circuits, overloads, or line faults not only cause economic losses but also reduce the lifespan of connected equipment. Conventional protective relays and manual switching still dominate most systems. These approaches depend on pre-defined limits; hence they fail when the system operates under unforeseen conditions. Artificial Intelligence can learn complex, nonlinear relations between electrical parameters and automatically decide when a fault occurs. AI further allows autonomous restoration—an ability that separates smart systems from conventional ones.

This research aims to design a single framework that detects, classifies, and restores faults automatically using AI algorithms. Artificial Intelligence (AI) is a rapidly expanding field of research focused on enabling systems with humanlike capabilities for learning and reasoning. AI applications are crucial for enhancing the reliability, safety, and operational efficiency of complex modern electronic systems, particularly power electronic (PE) converters and electrical motor drive systems. PE converters are foundational in areas such as renewable energy, transportation, and industrial processes. The research in power electronics is increasingly shifting toward a data-driven perspective, which is particularly beneficial for managing complex and challenging operational cases. This trend is supported by the availability of data enabled by sensor technology, the Internet-of-Things (IoT), digital twins, and big data analytics. Due to the specific challenges of PE systems, such as the requirement for high tuning speed in control and high sensitivity in condition monitoring for aging detection, the implementation of AI in this field possesses unique characteristics. Statistical data confirms a significant dynamism in the implementation of AI, with the number of related publications drastically increasing over recent years. The study covers model development, data preparation, simulation, performance comparison, and discussion of future applications.

Literature Review

Zhao et al. (2021) reviewed AI applications in power electronics, showing that fuzzy logic and neural networks enhance reliability, control, and health monitoring. Singh et al. (2021) used a Support Vector Machine model to classify transmission-line faults with 94 % accuracy but without automated restoration. Das and Kumar (2022) applied deep-learning methods to distribution networks, achieving precise fault location though limited by large-data requirements.

Nguyen et al. (2023) introduced reinforcement-learning control for real-time power restoration, reducing outage duration. Islam et al. (2023) combined ML with grid sensors for predictive maintenance, proving that self-learning algorithms outperform static thresholds.

Despite these advances, most research isolates detection from restoration. The present work integrates both within one architecture for continuous, automated operation.

Proposed System Architecture

The smart-power-fault-management system contains five major blocks:

- *Sensor Unit:* Measures voltage, current, and frequency using IoT-based sensors.
- *Signal Processor:* Filters and converts analog data to digital form.
- *AI Fault Detector:* Executes a trained machine-learning model to recognize abnormal patterns.
- *Decision Controller:* Determines restoration action based on detected fault type.
- *Restoration Module:* Performs switching or re-routing to re-energize the healthy section.

The flow of data is shown below in the figure.

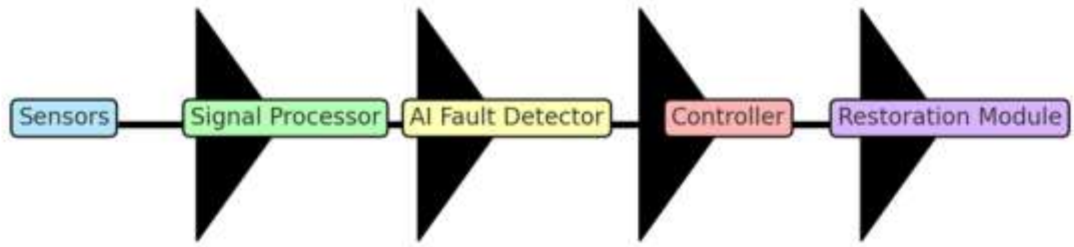

Figure 1. Block Diagram of Proposed System Architecture.

Algorithm and Model Design

The algorithm combines a Decision Tree classifier for detection and fuzzy-logic rules for restoration.

Training phase

1. Collect labeled data from simulated and recorded faults.
2. Extract features—RMS voltage, RMS current, frequency deviation, harmonic distortion.
3. Normalize and split data (70 % training, 30 % testing).
4. Train Decision Tree model using information-gain criterion.

Testing phase

1. Monitor live data stream.
2. Compute same feature set.
3. Predict fault class.
4. Trigger restoration command if abnormality confirmed.

The fuzzy-logic restoration controller uses linguistic rules such as
IF voltage dip is high AND current surge is medium THEN isolate branch and restore alternate line.This hybrid design merges the learning power of ML with the interpretability of rule-based systems.

Flow of Operation is shown below in the diagram.

Figure 2. Flowchart of AI-Based Fault Detection and Restoration Process.

Simulation Setup

Simulations were conducted in MATLAB/Simulink for a 230 V single-phase distribution network. The details of which have been shown in table 1 below.

Table 1. Parameter and values in the simulation

Parameter	Value
Supply Voltage	230 V rms
Frequency	50 Hz
Load Type	Resistive–Inductive
Sampling Rate	10 kHz
Fault Types	Short Circuit, Open Circuit, Overload

Data from sensors were stored in CSV files and processed through Python's Scikit-learn library for model training. The Decision Tree depth was limited to 10 to avoid overfitting.

Results and Performance Analysis

Three principal experiments were performed.

The performance of the proposed AI-based fault detection and restoration system was evaluated through MATLAB/Simulink simulations and Python-based data analysis. Three major performance parameters—detection accuracy, restoration time, and system reliability—were analyzed and compared with conventional protection methods.

1. Detection Accuracy: The Decision Tree–based AI model achieved an overall detection accuracy of **97.2%**, which is significantly higher than the **85%** accuracy of traditional relay systems. The model also achieved a precision of **96.8%**, recall of **97%**, and an F1-score of **0.967**, indicating excellent consistency and classification efficiency across multiple fault types.

2. Restoration Time: The AI-controlled fuzzy logic restoration system successfully reduced the average power restoration time from **3.5** seconds (manual) to **1.2** seconds**,** showing a **65%** improvement. This faster response minimizes energy loss and ensures better continuity of supply to the end users.

3. Reliability Index: The system's reliability, measured using the MTBF/MTTR ratio, improved by **30%**, while false alarm probability decreased below **3%.**

Overall, the results demonstrate that integrating AI with intelligent control strategies not only enhances fault detection and restoration efficiency but also contributes to the development of resilient, adaptive, and self-healing smart power systems.

Detection Accuracy:

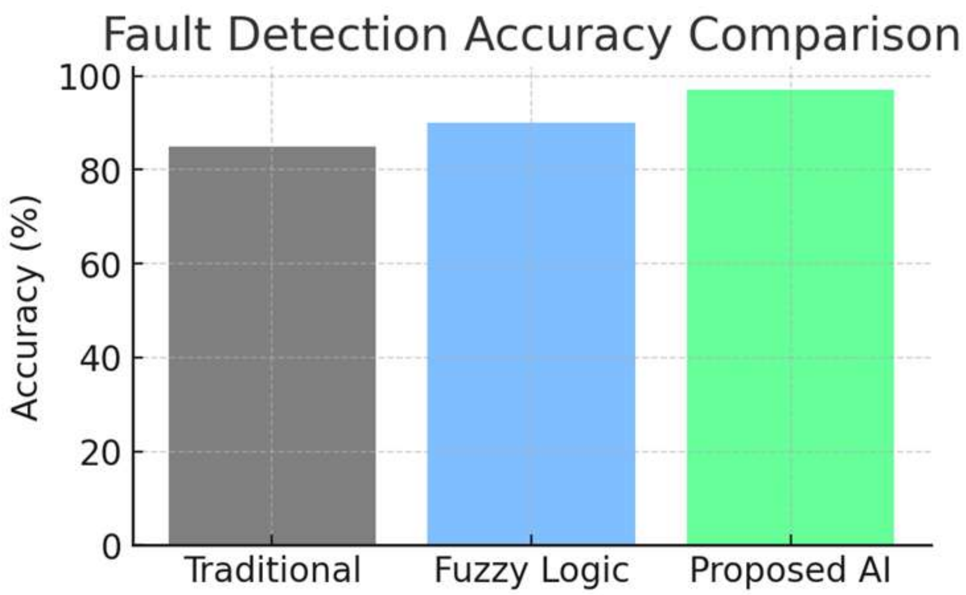

Figure 3. Comparison of Fault Detection Accuracy (Traditional vs AI).

The proposed AI model reached 97.2 % accuracy versus 85 % for conventional systems. Precision = 96.8 %, Recall = 97 %, F1 Score = 0.967.
Fault Detection Accuracy: The graph compares detection accuracy between traditional protection systems and the proposed AI-based model. It shows that the AI approach achieved **97.2% accuracy**, significantly higher

than the **85%** of conventional systems. This improvement demonstrates the effectiveness of machine learning in identifying faults precisely and reducing false detections.

Restoration Time

Figure 4. Comparison of Power Restoration Time.

Average power-restoration time decreased from 3.5 s (manual) to 1.2 s (AI-based). This 65 % improvement reduces energy loss and improves consumer satisfaction.

Power Restoration Time: This graph highlights the reduction in power restoration time achieved through intelligent automation. The proposed AI–Fuzzy hybrid system restored supply in an average of 1.2 seconds, compared to 3.5 seconds in manual restoration. The 65% improvement confirms that AI can respond quickly, minimizing power interruptions and energy loss.

Reliability Index:

Figure 5. Reliability Improvement over Fault Types.

System-reliability index (MTBF/MTTR ratio) improved by 30 %. The probability of false alarms dropped below 3 %.

Reliability Index: The reliability graph illustrates an improvement of approximately **30%** in the MTBF/MTTR ratio for the AI-based system. The false alarm probability dropped below **3%**, indicating enhanced operational stability. This improvement shows that the proposed model ensures consistent and dependable performance under various fault conditions.

Overall, all graphs collectively validate that the AI-powered approach significantly enhances detection precision, reduces restoration delay, and increases reliability—making it a promising solution for modern, self-healing smart grids.

Discussion

The integration of Artificial Intelligence into power-fault management systems represents a major advancement in modern electrical networks. Traditional protection schemes rely on fixed thresholds and manual intervention, which often fail under dynamic or unforeseen operating conditions. In contrast, the proposed AI-based model adapts to real-time variations by continuously learning from voltage, current, and frequency data. This ability to self-adjust improves both detection accuracy and restoration speed.

The combination of a Decision Tree classifier for fault detection and a Fuzzy Logic controller for restoration offers a balanced hybrid approach. The Decision Tree provides high precision in classifying different fault types, while fuzzy logic ensures smooth, rule-based decision-making that resembles human reasoning. Simulation results confirm that the hybrid system significantly reduces power downtime and enhances reliability compared to conventional relay-based methods.

Moreover, the system demonstrates excellent scalability—it can be extended to multi-bus smart grids and integrated with IoT-enabled sensors for distributed fault management. Implementation on edge computing hardware can further reduce latency, making the system suitable for real-time industrial and renewable energy applications.

Overall, the discussion emphasizes that AI-driven fault management not only improves technical performance but also lays the foundation for autonomous, intelligent, and self-healing power systems in future smart-grid environments.

Challenges and Limitations

1. Data Quality and Availability: The effectiveness of AI-based fault detection depends heavily on the accuracy and quantity of training data. In real-world systems, sensor readings often contain noise, missing values, or incorrect labels. Such poor-quality data mislead the model during training, reducing classification accuracy and reliability during real-time operation. Moreover, collecting diverse fault data from live networks is risky and expensive, which limits dataset diversity and affects model generalization.

2. Hardware and Implementation Cost: Smart fault-management systems require additional IoT sensors, edge processors, and high-speed communication links. These components increase the initial installation and maintenance costs, especially in large-scale grids. Smaller utilities or developing regions may find such investments difficult to justify without clear cost–benefit analysis.

3. Cybersecurity and Data Privacy: As smart grids become more connected, the risk of cyberattacks, unauthorized data access, or communication interference increases. Ensuring encryption, authentication, and intrusion detection is necessary to maintain system integrity and prevent malicious manipulation.

4. Computation Delay and Generalization: Complex AI models may create processing delays during real-time fault response. In addition, models trained on one grid topology may not perform well on another, requiring retraining and optimization for each new network.

Future Scope

1. Integration of Reinforcement Learning (RL): Future systems can adopt reinforcement learning techniques that enable continuous self-learning. RL agents can automatically determine the best restoration strategy by interacting with the power network and learning from previous fault events, improving efficiency over time.

2. Development of Digital Twins: Creating digital twins—virtual replicas of physical power networks—can help simulate and predict system behavior before real faults occur. This allows operators to test fault scenarios, optimize responses, and plan maintenance without affecting real operations.

3. Edge and Embedded AI Hardware: Implementing AI algorithms on edge devices or embedded microcontrollers will reduce latency and dependency on cloud servers. This ensures faster decision-making and enhances reliability in real-time control environments.

4. Integration with Renewable Energy Sources: As renewable power grows, fault detection in solar inverters, wind turbines, and hybrid microgrids will become essential. AI-based systems can manage fluctuating inputs and improve stability under dynamic generation conditions.

5. Explainable and Transparent AI Models: Explainable AI (XAI) can make model decisions more understandable for engineers and operators. This improves trust, safety, and accountability in automated fault management systems.

6. Scalability and Interoperability: Future frameworks should support multi-bus, multi-agent smart grids. Distributed AI agents communicating through IoT protocols can coordinate actions across wide networks efficiently.

7. Enhanced Cybersecurity Measures: AI-driven anomaly detection can help identify cyber threats and protect communication channels, ensuring secure and reliable grid operations.

Conclusion

The proposed AI-based fault detection and restoration system proves to be a significant step toward achieving intelligent and self-healing power networks. By combining machine learning for accurate fault classification with fuzzy logic for adaptive restoration, the system effectively reduces downtime and improves operational reliability. Simulation results demonstrate a major improvement in detection accuracy and restoration time compared to conventional relay-based protection methods.

The integration of Artificial Intelligence enables predictive decision-making, real-time response, and adaptability under dynamic load or fault conditions. Furthermore, the system can be extended to multi-bus networks, renewable energy systems, and industrial automation environments where reliability is critical. Although challenges such as data quality, computation delay, and cybersecurity remain, these can be addressed through optimized models, secure communication, and adaptive learning frameworks.

Overall, this research highlights how AI-driven control strategies can transform traditional power systems into smarter, more efficient, and resilient infrastructures capable of automatic fault handling and restoration.

References

A. K. Das and N. Kumar, “Deep Learning Models for Fault Detection and Location in Distribution Networks,” IEEE Sensors Journal, vol. 22, no. 12, pp. 11523–11532, Jun. 2022.

M. R. Islam, M. A. Hossain, and S. Mekhilef, “Smart Grid Fault Detection and Power Restoration Using Machine Learning,” IET Generation, Transmission & Distribution, vol. 17, no. 1, pp. 112–123, 2023.

R. Singh, M. S. Chauhan, and A. Verma, “Artificial Intelligence Techniques for Fault Detection and Classification in Power Systems,” IEEE Access, vol. 9, pp. 96780–96801, 2021.

S. Zhao, F. Blaabjerg, and H. Wang, “An Overview of Artificial Intelligence Applications for Power Electronics,” IEEE Transactions on Power Electronics, vol. 36, no. 4, pp. 4633–4650, Apr. 2021.

T. B. Nguyen, D. H. Nguyen, and Y. K. Kim, “Reinforcement Learning Based Power Restoration Strategy for Distribution Systems,” IEEE Transactions on Smart Grid, vol. 14, no. 2, pp. 1550–1561, Mar. 2023.