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Intelligent Fault Diagnosis in Decentralized Renewable-Energy Systems

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Abstract

The increasing deployment of photovoltaic generation, wind-energy conversion, battery storage, power-electronic converters, and networked microgrids is transforming electrical power systems from predominantly centralized architectures toward decentralized renewable-energy systems. This transition improves flexibility and local energy autonomy but complicates fault diagnosis because power flow may become bidirectional, operating topology can change, inverter-based sources may contribute limited or variable fault current, and decentralized assets can alternate between grid-connected and islanded operation. Conventional fixed-threshold protection can therefore become difficult to coordinate across heterogeneous operating conditions.

This study develops an intelligent decentralized fault-diagnosis framework in which local electrical measurements, machine-learning classification, edge-level reasoning, topology information, and peer-to-peer diagnostic coordination are combined to improve fault detection and isolation. Because no primary experimental dataset was supplied, the study is explicitly designed as a simulation-based methodological investigation. A reproducible synthetic dataset representing 180 hypothetical diagnostic units was generated across three architectures: conventional threshold-based diagnosis, centralized artificial-intelligence diagnosis, and decentralized intelligent diagnosis. Six operational indicators were assessed: fault-detection accuracy, fault-classification accuracy, diagnosis latency, robustness to topology change, communication efficiency, and false-alarm rate.

These variables were combined into a Fault Diagnosis Index (FDI). Mean FDI values increased from 63.3 under threshold-based diagnosis to 76.1 under centralized AI and 88.3 under decentralized intelligent diagnosis. The decentralized architecture produced the highest modeled detection accuracy (95.2%), classification accuracy (92.7%), topology-change robustness (87.7%), and communication efficiency (84.9%), while reducing mean diagnosis latency to 1.7 s and the false-alarm rate to 4.6%. These values are synthetic and must not be interpreted as measured field performance. The contribution of the study lies instead in a transparent framework that treats intelligent fault diagnosis as a distributed coordination problem rather than merely a classification problem.

Keywords: intelligent fault diagnosis; decentralized renewable energy; microgrid protection; distributed energy resources; artificial intelligence; machine learning; fault detection; fault classification; edge intelligence; smart grid

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1. Introduction

Renewable-energy integration is changing the structure of electric power systems. Photovoltaic generators, wind turbines, battery energy-storage systems, fuel cells, controllable loads, and power-electronic interfaces can now operate within local microgrids or interconnected clusters rather than depending exclusively on large centralized generating stations. Such architectures can improve energy flexibility and resilience, but they also alter the electrical characteristics used by conventional protection systems. Research examining distributed energy resources has shown that DER penetration affects fault-current behavior and can complicate traditional protection assumptions.

Microgrid protection is particularly challenging because system conditions can change after islanding, reconnection, distributed-generator switching, storage dispatch, or network reconfiguration. A protection setting appropriate for one operating condition may therefore become less reliable under another. Recent topology-aware microgrid research has directly addressed this issue by developing diagnostic methods capable of maintaining fault localization and type recognition under changing network configurations.

Artificial intelligence has consequently become increasingly relevant to renewable-energy fault diagnosis. Machine-learning and deep-learning methods can learn nonlinear relationships between voltage, current, frequency, transient signatures, converter behavior, and fault classes. Recent primary studies have investigated lightweight gradient-boosting/neural-network models, SVM-CNN hybrid diagnosis, transfer learning, CNN-attention-LSTM architectures, explainable AI, and digital-twin-assisted health management in microgrids.

However, intelligent classification does not automatically create decentralized intelligence. A centralized AI model may still depend on continuous transmission of measurements to one supervisory processor. This structure can increase communication burden and may create a single analytical bottleneck. By contrast, decentralized diagnosis allows individual renewable-energy units, relays, converter controllers, or edge devices to analyze local measurements and exchange only diagnostically important information with neighboring agents.

This distinction becomes increasingly important in clustered microgrids and renewable-rich distribution systems. Adaptive decentralized protection has been proposed to maintain coordination among protection devices as microgrid conditions change, while distributed data-driven research is increasingly exploring end-to-end protection strategies that operate across multiple networked resources. The present paper therefore develops an integrated framework for Intelligent Fault Diagnosis in Decentralized Renewable-Energy Systems. Rather than evaluating a single classifier, it examines the diagnostic architecture as a complete system involving detection, classification, communication, topology adaptation, and false-alarm control.

2. Decentralized Renewable-Energy Systems

A decentralized renewable-energy system contains multiple energy resources distributed across the electrical network. These may include photovoltaic arrays, wind turbines, battery systems, electric vehicles, controllable loads, small generators, and power-electronic converters.

A microgrid represents one common organizational form. It can operate while connected to the wider grid or, subject to its design and controls, in an islanded state. Networked microgrids extend this principle by coordinating several local microgrids.

The electrical behavior of these systems differs from that of conventional radial distribution networks. Power flow can reverse, converter-based sources may limit short-circuit current, generation can vary with environmental conditions, and the topology may be changed deliberately to improve resilience or energy exchange. These characteristics create important diagnostic challenges. Research on topology-aware diagnosis and distributed DER systems emphasizes the importance of accounting for configuration changes rather than treating the network as electrically static.

Faults can arise within feeders, converters, switches, renewable-generation units, energy-storage interfaces, sensors, communication channels, or control systems. Depending on system architecture, relevant electrical faults may include line-to-ground faults, line-to-line faults, three-phase faults, pole-to-ground faults in DC networks, pole-to-pole faults, high-resistance faults, converter-switch faults, and islanding-related disturbances.

3. Protection Challenges Created by Renewable Decentralization

3.1 Variable Fault Current

Traditional overcurrent protection relies heavily on the assumption that short-circuit currents remain substantially above normal operating currents.

Inverter-interfaced renewable generators complicate this assumption because converter controls can limit fault-current magnitude. Distributed-energy integration can also modify both the magnitude and direction of current observed by protection devices.

The diagnostic consequence is that a fixed overcurrent threshold may become less sensitive under some configurations and excessively sensitive under others.

Machine-learning diagnosis offers an alternative by considering multiple features rather than one current magnitude.

3.2 Grid-Connected and Islanded Operation

A microgrid may exhibit substantially different fault behavior when connected to the utility grid than when operating independently.

The upstream grid can contribute substantial short-circuit current during grid-connected operation, while islanded fault current may be dominated by converter limits and local generators.

A protection scheme must therefore recognize operating mode or use features sufficiently robust to mode changes.

Recent intelligent microgrid studies increasingly evaluate fault detection across multiple operating modes rather than only one fixed condition.

3.3 Changing Topology

A diagnosis model trained on one topology may perform poorly after network reconfiguration unless topology variability is included during model design.

Ding and colleagues addressed this issue through a topology-aware fault-diagnosis approach using diverse scenarios generated with digital twins. Their work demonstrates that topology information can be integrated directly into fault-recognition architecture rather than treated as an external operating detail.

4. Intelligent Fault-Diagnosis Methods

Intelligent fault diagnosis can broadly be organized into signal-processing, machine-learning, deep-learning, hybrid, and model-assisted approaches.

Signal-processing methods transform current or voltage waveforms to highlight transient characteristics.

Wang and colleagues developed a transfer-learning approach capable of fault detection and isolation without requiring historical fault data from the target DC microgrid, addressing the practical problem that real fault examples are often scarce.

Bu and colleagues proposed a CNN-attention-LSTM architecture for AC/DC microgrid fault diagnosis, illustrating how spatial feature extraction and temporal sequence modeling can be combined. These developments demonstrate that intelligent diagnosis is moving from manually selected thresholds toward data-driven representations of system behavior.

5. Decentralized Versus Centralized Intelligence

A centralized intelligent fault-diagnosis system transfers measurements from distributed energy resources or protection devices to a supervisory processor.

Recent decentralized protection studies reflect this direction. Adaptive decentralized overcurrent coordination and distributed fault-tolerant control research demonstrate that local protection and control decisions can be designed without complete dependence on a central communication structure.

A distributed diagnosis architecture therefore requires rules for evidence sharing, confidence aggregation, conflict resolution, and isolation decisions.

6. Digital Twins and Topology-Aware Fault Intelligence

1. Digital twins provide a promising mechanism for intelligent renewable-energy diagnosis because they maintain a computational representation of physical system behavior.
2. A digital twin can estimate expected measurements under different operating conditions.
3. Measured and predicted values can then be compared to identify abnormal behavior.
4. Ebrahimi and colleagues developed a digital-twin-driven framework for microgrid health management and real-time fault diagnosis and evaluated it on a laboratory-scale DC microgrid.
5. Digital twins can also expand the training environment.
6. Many severe electrical faults are rare and cannot safely be generated repeatedly in operating renewable-energy systems.

7. High-Resistance and Difficult-to-Detect Faults

- High-resistance faults are particularly challenging because they may produce relatively small changes in current while still creating dangerous operating conditions.

- In DC microgrids, detecting such faults can be complicated further by nonlinear converter behavior and the absence of natural current zero crossings.
- Kumar and colleagues investigated high-resistance fault detection in DC microgrids using Hilbert–Huang transformation combined with an optimized LSTM-based framework, illustrating the use of advanced time-frequency and sequence-learning techniques for weak fault signatures.
- Other recent intelligent protection research has investigated local measurement methods, explainable neural architectures, and settingless or adaptive approaches for difficult DC faults.
- These studies reinforce a broader principle: diagnostic intelligence becomes particularly valuable where simple fault-current magnitude is insufficient.

8. Explainability and Engineering Trust

An intelligent relay or converter controller should therefore record:

- the measurements used;
- the inferred fault class;
- the confidence value;
- the network topology assumed;
- the model version;

and the reason for isolation or escalation.

9. Research Gap

1. The contemporary literature demonstrates strong progress in microgrid fault detection, deep learning, topology-aware diagnosis, digital twins, transfer learning, PV fault diagnosis, and adaptive protection. Nevertheless, several important gaps remain.
2. First, many intelligent fault-diagnosis studies focus primarily on classification accuracy.
3. Real decentralized protection also depends on latency, communication requirements, topology robustness, and false-alarm control.
4. Second, centralized AI can improve diagnostic performance while retaining communication dependency.
5. Comparatively greater attention is needed on architectures in which intelligence is genuinely distributed.
6. Third, renewable-energy systems contain heterogeneous devices.

10. Novelty and Proposed Contribution

The proposed framework is termed the Decentralized Intelligent Renewable-Energy Fault Diagnosis Framework (DIREFD).

Its novelty lies in integrating six diagnostic capabilities:

- Local fault detection identifies abnormal electrical behavior close to the renewable-energy asset.
- Fault classification determines the probable fault category.
- Topology awareness updates diagnostic interpretation when the network configuration changes.
- Distributed coordination allows neighboring diagnostic nodes to exchange compact fault evidence.

- Communication-aware reasoning maintains local diagnostic capability when network links are degraded.
- Confidence-based escalation allows uncertain events to be transferred to higher-level protection or human engineering review.
- The framework therefore treats intelligent fault diagnosis as a distributed decision architecture rather than simply the application of a classifier.

11. Research Objectives and Questions

The principal objective of this study is to develop a transparent analytical framework for intelligent fault diagnosis in decentralized renewable-energy systems.

The specific objectives are to compare conventional threshold-based protection with centralized and decentralized intelligent architectures; evaluate modeled differences in fault-detection and classification accuracy; assess diagnostic latency and robustness to topology changes; examine communication efficiency and false-alarm performance; and construct a composite Fault Diagnosis Index for multidimensional comparison.

12. Methodology

12.1 Research Design

The study employs a quantitative simulation-based research design.

No actual utility, renewable-energy plant, microgrid operator, protection relay, or field-fault dataset supplied data for the analysis.

A synthetic design was selected to avoid presenting invented electrical measurements as experimental evidence.

A reproducible dataset of 180 hypothetical diagnostic units was generated.

The units were divided equally among:

- Threshold-Based Diagnosis — 60 observations
- Centralized AI Diagnosis — 60 observations
- Decentralized Intelligent Diagnosis — 60 observations
- The fixed pseudorandom seed 20260811 was used.

12.2 Diagnostic Variables

1. Six performance dimensions were modeled.
2. Fault-Detection Accuracy represents the percentage of fault events correctly distinguished from normal operating conditions.
3. Fault-Classification Accuracy measures correct assignment of a detected fault to the appropriate diagnostic class.
4. Diagnosis Latency represents the modeled time between the emergence of sufficient diagnostic evidence and generation of a fault decision.
5. Topology-Change Robustness represents diagnostic stability when distributed resources, switches, or microgrid interconnections change.

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13. Simulation Design

Table 1: Synthetic Parameterization of Diagnostic Architectures

Diagnostic Indicator	Threshold-Based	Centralized AI	Decentralized Intelligent
Fault-detection accuracy	Mean 78%, SD 7	Mean 90%, SD 5	Mean 95%, SD 4
Fault-classification accuracy	Mean 71%, SD 8	Mean 88%, SD 6	Mean 93%, SD 5
Diagnosis latency	Mean 5.2 s, SD 1.0	Mean 3.3 s, SD 0.7	Mean 1.7 s, SD 0.45
Topology-change robustness	Mean 58, SD 9	Mean 76, SD 7	Mean 89, SD 5
Communication efficiency	Mean 68, SD 8	Mean 58, SD 8	Mean 85, SD 6
False-alarm rate	Mean 12.5%, SD 3.0	Mean 7.6%, SD 2.2	Mean 4.8%, SD 1.5

Note: These parameters are analytical assumptions. They are not measured performance averages from operational renewable-energy networks.

14. Fault Diagnosis Index

A composite Fault Diagnosis Index (FDI) was developed.
The index combines detection accuracy, classification accuracy, latency efficiency, topology robustness, communication efficiency, and false-alarm efficiency.

The weighting structure is:

FDI = 0.25DA + 0.20CA + 0.15LE + 0.15TR + 0.15CE + 0.10FAE

where:

DA = Detection Accuracy CA = Classification Accuracy LE = Latency Efficiency TR = Topology Robustness CE = Communication Efficiency FAE = False-Alarm Efficiency

Detection accuracy received the highest weight because failure to identify a true electrical fault directly undermines protection.

Classification accuracy received the second-highest weight because correct fault type influences isolation and recovery decisions.

15. Proposed Questionnaire for Future Validation

Responses may be measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

1. Local intelligent protection devices should be capable of detecting and classifying faults without continuous dependence on a central controller.

2. A reliable fault-diagnosis system should automatically consider changes in renewable-generation and network topology before issuing a protection decision.

3. Neighboring protection nodes should exchange diagnostic confidence information when a fault may affect more than one distributed energy resource.

4. Artificial-intelligence-based fault decisions should provide sufficient explanation for engineers to understand why a particular fault class was selected.

5. Decentralized fault-diagnosis systems should retain a safe local protection mode when communication with other network nodes is unavailable.

The items should undergo expert review, reliability testing, and construct validation before empirical application.

16. Results

Table 2: Simulated Fault-Diagnosis Performance

Performance Indicator	Threshold-Based	Centralized AI	Decentralized Intelligent
Fault-detection accuracy (%)	79.2	89.9	95.2
Fault-classification accuracy (%)	70.5	89.1	92.7
Diagnosis latency (s)	5.1	3.3	1.7
Topology-change robustness	58.0	76.5	87.7
Communication efficiency	67.9	57.1	84.9
False-alarm rate (%)	12.3	7.5	4.6
Fault Diagnosis Index	**63.3**	**76.1**	**88.3**

17. Fault-Detection and Classification Performance

1. Fault-detection accuracy increased from 79.2% under threshold-based diagnosis to 89.9% with centralized AI and 95.2% under decentralized intelligence.
2. Fault-classification accuracy increased from 70.5% to 89.1% and 92.7%, respectively.
3. These simulated patterns are directionally consistent with contemporary primary research demonstrating strong classification performance from data-driven and deep-learning models in AC, DC, and clustered microgrids.

4. The principal advantage of intelligent diagnosis is the ability to evaluate multiple features simultaneously.
5. A threshold scheme may depend heavily on current magnitude.
6. A machine-learning model may consider phase current, voltage, derivatives, time-frequency features, harmonics, sequence components, converter states, and neighboring measurements.

18. Diagnosis Latency

- Mean diagnostic latency decreased from 5.1 s in the threshold-based model to 3.3 s under centralized AI and 1.7 s under decentralized intelligence.
- The decentralized architecture benefits from local processing because raw measurements do not always need to travel to a supervisory center before the first diagnosis is generated.
- This local-first structure is conceptually compatible with research showing that fault detection and isolation can be performed using local measurements or distributed data-driven approaches.
- Rapid diagnosis is particularly valuable where fault current rises quickly or where converter protection requires fast isolation.
- Nevertheless, fault-clearing time and AI-computation time should not be treated as identical quantities.
- An actual protection system includes sensing, processing, communication, relay operation, and breaker interruption.

19. Robustness to Topology Change

Topology robustness increased from 58.0 under threshold-based protection to 76.5 with centralized AI and 87.7 under decentralized intelligence.

The improvement assigned to decentralized intelligence reflects the assumption that local diagnostic nodes receive updated topology information and can adapt their interpretation accordingly. This requirement is directly supported by topology-aware microgrid fault-diagnosis research. Ding and colleagues demonstrated that diagnostic models can be designed to handle diverse fault scenarios across changing microgrid-cluster topologies.

A future decentralized system could maintain a local representation of:

- connected renewable-energy resources;
- breaker and switch status;
- current operating mode;
- neighboring microgrid connections;
- available storage units;
- and active protection zones.

Diagnostic thresholds and machine-learning models could then be selected according to the current configuration.

20. Communication Efficiency

1. The centralized-AI architecture produced a mean communication-efficiency score of 57.1, below the threshold-based score of 67.9.

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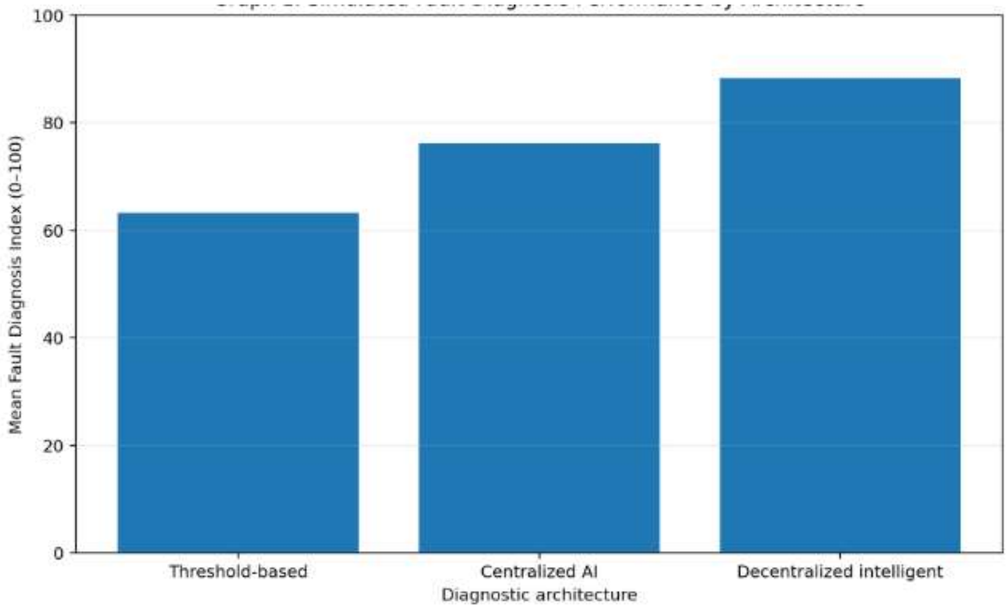
2. This simulated reduction reflects the possibility that centralized intelligence requires substantial measurement transfer to a central processor.
3. The decentralized architecture increased the communication-efficiency score to 84.9 because local nodes were assumed to process raw data before exchanging compact diagnostic information.
4. Distributed protection research is increasingly exploring architectures that reduce dependence on a single central communication path. Adaptive decentralized protection and communication-free fault-tolerant control studies provide examples of this broader direction.
5. The objective should not necessarily be zero communication.

21. False-Alarm Performance

- The false-alarm rate decreased from 12.3% under threshold-based diagnosis to 7.5% under centralized AI and 4.6% in the decentralized-intelligent condition.
- Renewable-energy networks contain many non-fault events capable of changing current and voltage.
- Examples include generation variation, load switching, converter-mode transitions, islanding, reconnection, and battery dispatch.
- An intelligent system can distinguish these events more effectively if its training data represent sufficient operational variability.
- Recent data-processing and deep-learning research for AC microgrids specifically focuses on improving the separation of fault conditions from other electrical states.

22. Graphical Analysis

Graph 1: Simulated Fault-Diagnosis Performance by Architecture



23. Statistical Analysis

One-way analysis of variance was applied as an internal scenario-discrimination test.

Fault-detection accuracy produced:

- $F = 148.59$, $p < 0.001$, $\eta^2 = 0.627$.

- Fault-classification accuracy produced:
- $F = 232.12$, $p < 0.001$, $\eta^2 = 0.724$.
- Diagnosis latency produced:
- $F = 294.60$, $p < 0.001$, $\eta^2 = 0.769$.
- Topology-change robustness produced:
- $F = 215.36$, $p < 0.001$, $\eta^2 = 0.709$.

These values reflect deliberately differentiated simulation parameters and therefore demonstrate internal model separation rather than real-world causal effects.

24. Discussion

The results support the proposition that intelligent fault diagnosis in decentralized renewable-energy systems should be treated as a distributed systems problem.

A highly accurate classifier is useful, but classification accuracy alone does not determine whether a protection architecture is operationally strong.

A diagnostic system must also function under changing topology, limited communication, renewable intermittency, different operating modes, and imperfect measurements.

This is why topology-aware diagnosis represents an important development beyond fixed machine-learning classification. Recent primary studies demonstrate that digital twins and topology-informed models can preserve fault-recognition performance across configurations that differ from a single nominal network.

25. Conclusion

Decentralized renewable-energy systems require a new approach to fault diagnosis because conventional protection assumptions become less reliable when power flow is bidirectional, converter fault currents are limited, network topology changes, and microgrids alternate between operating modes.

Artificial intelligence provides powerful tools for identifying complex electrical fault signatures, but intelligence alone does not guarantee decentralized resilience.

The simulation developed in this study compared threshold-based diagnosis, centralized AI, and decentralized intelligent fault diagnosis across 180 hypothetical diagnostic units.

The Fault Diagnosis Index increased from 63.3 under conventional threshold-based diagnosis to 76.1 under centralized AI and 88.3 under decentralized intelligence.

Future systems should combine accurate machine learning with local autonomy, topology awareness, communication resilience, digital-twin support, explainability, predictive maintenance, cybersecurity, and human engineering oversight.

The objective is not merely to recognize faults more accurately.

It is to create decentralized renewable-energy networks capable of detecting, interpreting, isolating, and recovering from abnormal conditions without sacrificing transparency, safety, or resilience.

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