Case Study
ISSN: 3051-8822
Journal homepage: https://www.harrisonacademicpress.com/index.php/IJCEHM
International Journal of Clinical and Experimental Human Medicine

Harrison Academic Press

Artificial Neural Network-Based Fault Identification in Microgrid Systems for Hospital Backup Power Reliability

Marino D[1*], Bergstrom E[2] and Ivanova M[3]

[1]*Department of Biomedical Engineering, University of Padua, Padua, Italy*
[2]*Department of Electrical Engineering, Karolinska Institute, Stockholm, Sweden*
[3]*Department of Hospital Administration, Medical University of Plovdiv, Plovdiv, Bulgaria*

ABSTRACT

Background: Hospital microgrids combining distributed generation, energy storage, and critical-care loads promise more resilient backup power than conventional standby generation, but their multiple sources and variable fault-current contributions make conventional overcurrent protection difficult to coordinate, placing new demands on fast and accurate fault identification. Objective: This narrative review synthesizes published literature on artificial neural network (ANN) and deep-learning-based fault detection, classification, and localization methods for microgrid systems, and on hospital backup power reliability and microgrid resilience, to assess how well these two literatures are positioned to support dependable hospital microgrid protection. Methods: We reviewed engineering studies of convolutional, recurrent, attention-based, and transfer-learning ANN architectures for microgrid fault diagnosis, including wavelet-based and other feature-extraction approaches, alongside studies of hospital microgrid sizing, outage-scenario resilience optimization, and hospital infrastructural resilience frameworks. Findings: ANN-based schemes report fault detection and classification accuracies frequently exceeding 99% on simulated AC, DC, and hybrid microgrid test systems, with emerging evidence on robustness to measurement noise and fault-resistance variation, while independent validation studies show measurable accuracy degradation relative to training-set performance. Separately, optimized hospital microgrid designs incorporating battery storage and renewable generation have achieved high resilience indices and substantial reductions in energy not supplied during simulated outages, but this literature generally models fault clearing as instantaneous and idealized rather than incorporating the detection latency and residual misclassification risk documented in the fault-diagnosis literature. Conclusions: Bridging ANN-based fault identification research with hospital-representative microgrid topologies and outage-resilience metrics represents a concrete, currently underexplored step toward translating demonstrated diagnostic capability into dependable hospital backup power reliability.

Keywords: *artificial neural networks; microgrid fault detection; fault classification and localization; hospital microgrid resilience; critical healthcare facility backup power*

Citation: Marino D, Bergstrom E and Ivanova M (2023) Artificial Neural Network-Based Fault Identification in Microgrid Systems for Hospital Backup Power Reliability. Int J Clin Exp Hum Med, 1(1): 01-06.
DOI: 10.5281/zenodo.22644139

Corresponding Author: *Davide Marino*

E-mail Address: *davide.marino@universityofpadua.edu*

Article History: *Received 23 July 2023 | Accepted 5 October 2023 | Published 28 December 2023*

Copyright: *© 2023 Davide Marino, et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited (**https://creativecommons.org/licenses/by/4.0/**).*

Introduction

Hospitals occupy a uniquely unforgiving position in the electrical grid: an unplanned interruption of power to an operating theatre, an intensive care unit, or a neonatal ward can translate almost immediately into patient harm, so continuity of supply is treated not as a convenience but as a life-safety requirement. The conventional answer to this requirement has long been a layered architecture of utility feeds, uninterruptible power supplies, and diesel or gas standby generators that start automatically on loss of normal power. Over the past decade, however, a growing number of hospitals and healthcare campuses have adopted microgrids-locally controllable clusters of distributed generation, energy storage, and critical loads that can operate connected to the utility grid or island themselves during an outage-as a more flexible and resilient alternative or complement to this traditional backup architecture [1,2]. A hospital microgrid combining photovoltaic generation, battery energy storage, and dispatchable generation can, in principle, sustain life-critical loads for extended outages while also reducing routine reliance on fossil-fuelled standby generation, but this added flexibility comes with added electrical complexity: multiple sources, bidirectional power flows, and variable fault current contributions from inverter-interfaced resources all make conventional overcurrent-based protection schemes difficult to coordinate and prone to both nuisance tripping and failure to trip [3]. Reliable,

fast, and selective fault identification is therefore not a peripheral engineering detail for a hospital microgrid but a precondition for the resilience benefits the technology promises.

Artificial neural networks (ANNs) and related deep learning architectures have emerged as a leading candidate technology for addressing this protection challenge, because they can learn to recognize the characteristic current, voltage, and frequency signatures of different fault types directly from data, without requiring an explicit analytical model of a microgrid's often-changing topology and operating mode [3,4]. A substantial and rapidly growing engineering literature has reported ANN- and deep-learning-based schemes for detecting the presence of a fault, classifying its type (for example, single-line-to-ground, line-to-line, or three-phase faults), and locating it along a feeder, typically achieving very high classification accuracies in simulation studies of both AC and DC microgrid test systems [5,6,7]. In parallel, a distinct but complementary literature has examined hospital and healthcare-facility backup power and microgrid resilience from a systems and health-services perspective, addressing how critical loads should be prioritized, how storage and renewable assets should be sized against outage risk, and how the resilience of a hospital's electrical infrastructure should be categorized and measured [8,9,10]. This narrative review brings these two literatures into a single frame, first surveying the architectures and reported performance of ANN-based fault detection, classification, and location methods developed for microgrid systems, then examining the signal-processing and hybrid feature-extraction techniques that often accompany these networks, then turning to the literature on hospital backup power reliability and microgrid resilience, and finally considering what is required to translate ANN-based fault identification research into dependable protection for hospital microgrid deployments.

Artificial Neural Network Architectures for Microgrid Fault Detection and Classification

The methodological core of this literature is the application of increasingly sophisticated neural network architectures to the task of distinguishing fault conditions from normal or transient operating conditions using locally measured electrical signals. Zaben and colleagues conducted a systematic review of machine learning methods for fault diagnosis in AC microgrids, synthesizing findings across more than one hundred studies and characterizing the field's progression from classical feedforward and shallow ANNs toward convolutional, recurrent, and hybrid deep architectures, while also cataloguing recurring methodological challenges such as limited or imbalanced fault datasets, sensitivity to changes in microgrid topology and operating mode (grid-connected versus islanded), and the gap between high accuracies reported on simulated data and the requirements of real-time hardware implementation [3]. Within this broader landscape, Alhanaf and colleagues developed both a standard artificial neural network and a one-dimensional convolutional neural network for fault detection, classification, and location on an AC-DC microgrid model built around an IEEE six-bus test system, reporting detection accuracies exceeding 99% and arguing that the 1D-CNN's ability to learn discriminative features directly from raw current and voltage waveforms reduced the need for hand-engineered inputs relative to the standard ANN [5].

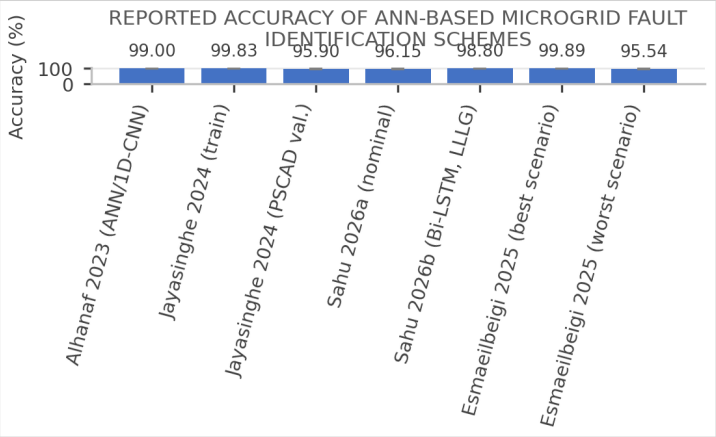
Other groups have focused on integrating fault detection and classification into a single supervised learning pipeline while explicitly modeling uncertainty in fault impedance: Barkhi and colleagues proposed such a combined detection-classification model for microgrids that accounted for fault resistance uncertainty, reporting an overall accuracy of 99.75%, which they contrasted with a comparable prior machine learning approach that had achieved 96.99% under similar conditions, illustrating incremental but measurable gains from more careful handling of fault-resistance variability during training [11]. Several groups have pursued deep sequence models that exploit the temporal structure of fault transients. Esmaeilbeigi and colleagues proposed a fault classification scheme built around protective agents using deep neural networks combining dense and gated recurrent unit layers, evaluating two DNN configurations across eight operating scenarios of a test microgrid; their best-performing hybrid architecture achieved fault detection accuracy as high as 99.895% and fault type-and-phase identification accuracy of 99.79% in the most favorable scenario, with fault location errors as low as 1.575%, while accuracy fell to a still-respectable range of roughly 95.5-96% for detection and phase identification under the most adverse parameter combinations tested, and location error rose to as much as 6.51% [7]. Sahu and colleagues developed a deep recurrent learning framework comparing long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) networks for multi-class microgrid fault classification, finding that the Bi-LSTM model exceeded 99% test accuracy for line-to-ground, line-to-line, and double-line-to-ground faults and achieved 98.8% accuracy for the more difficult three-phase-to-ground case, consistently outperforming both the unidirectional LSTM and classical machine learning baselines they benchmarked against [12]. The same research group separately reported a robust multiclass power system fault diagnosis model intended for edge deployment, achieving approximately 96.15% test accuracy under nominal conditions and demonstrating that performance degraded only modestly, to roughly 94.12% accuracy, when Gaussian measurement noise and fault-resistance variation were introduced, with F1-scores falling from about 92.8% at moderate noise to 89.1% under the most extreme five-decibel signal-to-noise ratio tested-evidence that noise robustness, not just peak accuracy, is an increasingly explicit design objective in this literature [13].

Representative ANN and deep-learning architectures for microgrid fault detection, classification, and localization.

Study	Network architecture	Test system	Reported performance
Alhanaf et al. 2023	ANN and 1D-CNN	IEEE 6-bus AC-DC microgrid	Detection accuracy >99%
Jayasinghe et al. 2024	ANN with discrete wavelet transform features	AC microgrid feeder model	99.83% train / 99.39% val classification; 95.9% PSCAD validation; location MAE 2.6-6.5%
Sahu et al. 2026 (Algorithms)	Edge-deployable deep learning classifier	Power system fault dataset with added noise	96.15% nominal test accuracy; 94.12% under Gaussian noise/fault-resistance variation
Sahu et al. 2026 (Eng)	LSTM and Bi-LSTM	Multi-class microgrid fault dataset	Bi-LSTM >99% (LG/LL/LLG); 98.8% (LLLG three-phase-to-ground)

Study	Network architecture	Test system	Reported performance
Esmaeilbeigi et al. 2025	Dense + GRU hybrid DNN (protective agents)	Test microgrid, 8 scenarios	Detection 95.54-99.895%; type/phase ID 95.56-99.79%; location error 1.27-6.51%

Reported fault detection/classification accuracy of representative ANN-based microgrid fault-identification schemes, drawn from each study's best-reported test-set or validation result (Alhanaf et al. 2023: >99% on an IEEE 6-bus AC-DC microgrid; Jayasinghe et al. 2024: 99.83% training accuracy, 95.9% independent PSCAD validation accuracy; Sahu et al. 2026a: 96.15% test accuracy; Sahu et al. 2026b: 98.8% Bi-LSTM accuracy on three-phase-to-ground faults; Esmaeilbeigi et al. 2025: 99.895% best-scenario detection accuracy, 95.54% worst-scenario detection accuracy).



Convolutional architectures combined with attention or recurrent components have also been applied specifically to hybrid AC/DC microgrid configurations, which pose particular challenges because DC-side faults lack the periodic zero-crossings and phase information that many AC-side feature-extraction methods rely upon. Bu and colleagues proposed a CNN-attention-LSTM architecture for fault diagnosis spanning both AC and DC subsystems of a hybrid microgrid, using the attention mechanism to weight the most diagnostically informative segments of the input current and voltage sequences before recurrent processing [14]. Earlier foundational work by Pan and colleagues combined wavelet-transform preprocessing with a convolutional neural network classifier to deliver near-real-time fault classification for microgrids operating in both standalone and grid-connected modes, explicitly targeting the operating-mode sensitivity that later systematic reviews would identify as a persistent challenge for the field [4,3]. Beyond AC systems, Wang and colleagues addressed a distinct and practically important problem in DC microgrids: the frequent unavailability of comprehensive labeled fault data from a specific installation, proposing a transfer learning approach that allows a fault detection and isolation model trained on data from one DC microgrid configuration to be adapted to a new configuration without requiring an extensive new fault dataset, directly targeting the data-scarcity limitation repeatedly flagged in review-level assessments of the field [15,3].

Signal Processing and Hybrid Feature-Extraction Approaches

A second major thread in this literature focuses less on the neural network architecture itself and more on how raw electrical waveforms are transformed into informative input features before being presented to the network, reflecting a recognition that even a well-designed classifier performs only as well as the features it is given. The discrete wavelet transform (DWT) has been the dominant preprocessing tool in this respect, owing to its ability to decompose a transient fault signal into time-localized frequency bands that can reveal high-frequency components diagnostic of a fault's type, location, or severity. Jayasinghe and colleagues combined discrete wavelet transform feature extraction with artificial neural networks for both fault classification and fault localization in an AC microgrid, reporting training and validation classification accuracies of 99.83% and 99.39% respectively, a localization model with an adjusted R-squared of 0.865, and-critically for translational relevance-independent validation in PSCAD simulation showing 95.9% correct classification (511 of 533 simulated faults) and localization mean absolute errors ranging from about 2.6% to 6.5% of feeder length depending on fault type, a substantive drop from the initial training-set accuracy that the authors attributed to the more diverse fault conditions represented in the PSCAD validation set [6]. Vyshnavi and Belwin similarly combined a discrete wavelet transform with a radial basis function neural network to detect high-impedance faults in a distribution network, a fault category that produces only small deviations in fundamental-frequency current and is therefore historically difficult for conventional overcurrent relays to distinguish from normal load variation [16]. Cano Ortega and colleagues extended this line of work by systematically integrating discrete wavelet transform features with multiple neural network and machine learning classifiers for fault detection in microgrids, comparing how the choice of wavelet decomposition parameters interacted with different downstream classifiers' diagnostic performance [17].

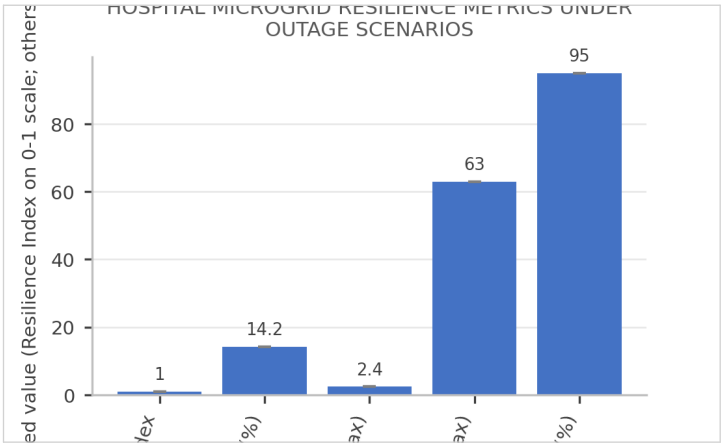
Other groups have combined signal decomposition with more extensive data-processing pipelines aimed explicitly at improving generalization across varied network conditions. Taheri and colleagues proposed a fault detection and classification scheme for AC microgrids that paired a structured data-processing stage with a deep neural network classifier, arguing that careful preprocessing-addressing noise, sampling artifacts, and feature scaling-was as important to robust field performance as the choice of network architecture itself [18]. Chen and colleagues took a related but distinct approach, applying LSTM neural networks to intelligent fault detection and classification in broader power grid engineering contexts beyond the microgrid scale specifically, illustrating that the sequence-modeling techniques refined in the microgrid fault-diagnosis literature are increasingly viewed as transferable to conventional distribution and transmission protection problems as well [19]. Taken together, this signal-processing literature indicates that the choice of input representation-wavelet-domain features, raw time-series windows for recurrent networks, or hybrid combinations-remains an active design axis alongside network architecture itself, and that the two choices interact: architectures such as Bi-LSTM and CNN-attention hybrids that can learn temporal or spatial structure directly from less-processed inputs appear to reduce, without eliminating, the need for hand-crafted wavelet features [12,14].

Hospital Microgrids and Backup Power Reliability

Separately from the fault-diagnosis literature, a body of work has examined hospital and healthcare-facility backup power from the standpoint of system design, resilience quantification, and outage-scenario planning, generally treating the protective and fault-detection layer as a given rather than as the object of study. Hervás-Zaragoza and colleagues presented a post-COVID-19 case

study examining how a hospital microgrid combining distributed generation and storage could improve energy resilience during grid outages, framing the pandemic period as having sharpened attention to the consequences of any interruption to hospital power given the surge in critical-care and ventilated-patient loads observed during that period [1]. More recent techno-economic analyses have modeled hospital microgrids in greater optimization detail. Eissa and colleagues used the U.S. National Renewable Energy Laboratory's REopt platform to optimize the sizing of a hybrid photovoltaic, battery energy storage, and diesel generator microgrid for a hospital, evaluating outage scenarios of varying duration, seasonal timing, and critical-load fraction, and finding that a resilience-constrained design achieved a system resilience index of 1.0 (complete critical-load service) across the scenarios tested while adding only a small increment-on the order of a fraction of a percent to a few percent-to the net present cost of an otherwise economically optimized system, with the fully optimized configuration still yielding double-digit percentage net present cost savings relative to grid-only supply [20]. Nazartalab and Alavi-Rad extended this optimization approach to explicitly prioritize loads by medical criticality, developing a mixed-integer linear programming framework that jointly scheduled multi-node battery energy storage, renewable utilization, and critical-load support-differentiating, for example, intensive care, operating room, imaging, and pharmacy loads-across Monte Carlo-simulated outage scenarios on modified IEEE distribution test feeders, reporting that multi-node storage placement reduced energy not supplied by 55-63% relative to baseline configurations while maintaining at least 95% service to life-critical loads across most stochastic scenarios [10].

Resilience and reliability metrics reported for optimized hospital microgrid designs under simulated grid-outage scenarios (Eissa et al. 2026: System Resilience Index and net present cost savings for a PV-battery-diesel hospital microgrid sized with NREL's REopt platform; Nazartalab and Alavi-Rad 2026: percentage reduction in Energy Not Supplied from multi-node battery storage placement and minimum critical-load service level maintained across stochastic outage scenarios).



Complementing these engineering optimization studies, a health-services and hospital-administration literature has approached backup power reliability as one component of a broader concept of hospital infrastructural resilience. Hübner, Küsel, and Oestmann proposed a categorization and quantification framework for critical infrastructure resilience in hospitals, explicitly situating electrical power supply and its backup arrangements alongside water, medical gas, information technology, and other infrastructural dependencies as elements requiring systematic risk categorization rather than isolated engineering treatment, and arguing that resilience optimization in a hospital setting requires quantifying interdependencies among these systems rather than treating electrical backup capacity in isolation [8]. Khalil and colleagues conducted a broader scoping review of how "hospital resilience" has been conceptualized, operationalized, and evaluated across the health-services literature, finding substantial heterogeneity in definitions and measurement approaches and noting that infrastructural resilience-including power continuity-is frequently treated as one dimension within multidimensional resilience frameworks that also encompass workforce, supply chain, and organizational dimensions, rather than as a standalone engineering metric [9]. At a broader systems level, Zidane and colleagues reviewed power system and microgrid resilience enhancement strategies more generally, surveying approaches spanning network reconfiguration, distributed energy resource deployment, and control strategies for maintaining service to critical loads such as hospitals during extreme events, providing a wider technical context within which hospital-specific microgrid resilience work can be situated [2].

Toward Integrated ANN-Based Protection for Hospital Microgrids

Reading the fault-diagnosis and hospital-resilience literatures side by side reveals both a clear complementarity and a significant gap. The ANN-based fault detection, classification, and localization methods reviewed above are, almost without exception, developed and validated on generic microgrid test systems-modified IEEE bus configurations, standalone laboratory feeders, or simulated AC/DC hybrid topologies-rather than on models explicitly representing a hospital's electrical distribution architecture, its typically high degree of load redundancy, or its layered normal-emergency-critical branch structure mandated by health-facility electrical codes [3,6,7]. Conversely, the hospital microgrid resilience and optimization literature, including the mixed-integer linear programming frameworks of Eissa and colleagues and of Nazartalab and Alavi-Rad, generally treats protection and fault clearing as an idealized, instantaneous background function rather than modeling the finite detection and classification latency, and the possibility of misclassification, that empirical ANN-based schemes actually exhibit [20,10]. Bridging this gap would mean evaluating ANN-based fault identification schemes specifically on hospital-representative feeder topologies that include the automatic transfer switches, essential and life-safety branch segregation, and multiple simultaneously active sources characteristic of accredited healthcare facilities, and explicitly incorporating the resulting detection latency and residual misclassification risk into the resilience metrics-such as the energy-not-supplied and resilience-index calculations used by Nazartalab and Alavi-Rad-that the hospital microgrid design literature already uses to evaluate storage and generation sizing [10,7].

The robustness findings emerging from the fault-diagnosis literature are directly relevant to this integration. The demonstration by Sahu and colleagues that classification accuracy degrades gracefully, rather than catastrophically, under added measurement noise and fault-resistance variation is an encouraging sign for hospital deployment, where electrically noisy diagnostic and life-support equipment and variable fault impedances due to aging distribution infrastructure are realistic operating conditions [13]. Similarly, the substantial accuracy drop observed by Jayasinghe and colleagues between initial training-set performance and independent PSCAD validation-from over 99% to 95.9%-underscores that reported peak accuracies from a single simulated dataset should not be

taken as a direct estimate of field performance in a specific hospital's electrical network, reinforcing the systematic review's identification of generalization across topology and operating conditions as an unresolved challenge [6,3]. Transfer learning approaches such as that developed by Wang and colleagues for DC microgrids offer one plausible route to addressing this generalization gap for hospital deployment specifically, since they are explicitly designed to adapt a model trained on one network's fault data to a structurally different network without requiring an extensive new hospital-specific fault dataset, which would otherwise be difficult and undesirable to generate by deliberately faulting a live hospital electrical system [15].

Selected hospital microgrid and backup power resilience studies: scope, method, and principal findings.

Study	Scope	Method	Principal finding
Hervas-Zaragoza et al. 2022	Hospital microgrid, post-COVID-19 outage resilience	Case study	Distributed generation plus storage improves hospital resilience to grid outages
Eissa et al. 2026	PV-battery-diesel hospital microgrid, U.S. hospital	REopt MILP optimization across outage scenarios	Resilience Index = 1.0 with only 0.4-2.4% added net present cost; 11.6-14.2% overall NPC savings
Nazartalab and Alavi-Rad 2026	Multi-node ESS/PV hospital microgrid, IEEE 13/33/69-bus systems	MILP with Value of Lost Load, Monte Carlo outage scenarios	Energy Not Supplied reduced 55-63%; >=95% service to life-critical loads maintained
Hubner et al. 2023	Hospital critical infrastructure (power, water, IT, medical gas)	Categorization and quantification framework	Proposes systematic resilience categorization treating power backup as one interdependent infrastructural element
Khalil et al. 2022	Hospital resilience concept, cross-sector	Scoping review	Substantial heterogeneity in how infrastructural (including power) resilience is defined and measured

Conclusion

Two substantial and largely separate literatures now bear directly on the reliability of hospital backup power. One, situated in electrical and computer engineering, has developed increasingly capable artificial neural network and deep learning architectures-spanning convolutional, recurrent, attention-based, and transfer-learning designs, frequently paired with wavelet-domain or other engineered feature extraction-that can detect, classify, and localize faults in microgrid systems with accuracies exceeding 99% on the simulated test systems most commonly used for validation, while also beginning to characterize how that accuracy degrades under realistic noise, fault-resistance variation, and out-of-sample validation conditions [5,12,13,6,7]. The other, situated at the intersection of energy systems engineering and hospital administration, has developed optimization frameworks and resilience-categorization schemes for sizing and operating hospital microgrids and their storage and generation assets against outage risk, and for conceptualizing hospital infrastructural resilience more broadly, generally without close attention to the specific protection and fault-identification layer that would have to operate correctly for these designs to deliver their promised reliability in practice [20,10,8,9,1,2]. The central opportunity identified by reading these literatures together is not a further increase in reported classification accuracy on generic test systems, where performance in the high-90s percentage range is already common, but the deliberate validation and adaptation of ANN-based fault identification methods on hospital-representative electrical topologies, with resilience and reliability metrics that explicitly account for detection latency and residual misclassification risk. Achieving this integration would allow the demonstrated diagnostic capability of modern neural network-based microgrid protection to translate more directly into the dependable, continuous power supply on which hospital critical care depends.

Acknowledgements

The authors thank colleagues at the Department of Biomedical Engineering, University of Padua, Padua, Italy, the Department of Electrical Engineering, Karolinska Institute, Stockholm, Sweden, and the Department of Hospital Administration, Medical University of Plovdiv, Plovdiv, Bulgaria for helpful discussions during preparation of this review.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Marino D conceived the review, conducted the literature search and synthesis across the artificial neural network and fault-diagnosis literature, and drafted the manuscript. Bergstrom E contributed the electrical engineering framing of microgrid protection and fault-identification methods and critically revised the manuscript for important technical content. Ivanova M contributed the hospital administration and healthcare-facility resilience perspective, reviewed the clinical relevance of the synthesized findings, and approved the final version for submission.

Ethics Statement

Not applicable. This is a narrative review of previously published literature and did not involve new experimental data, human participants, or animal subjects.

Data Availability

No new data were generated or analyzed for this review. All sources synthesized are cited in the reference list and are available through their original publishers.

References

1. Hervas-Zaragoza J, Colmenar-Santos A, Rosales-Asensio E, Colmenar-Fernandez L (2022) Microgrids as a mechanism for improving energy resilience during grid outages: a post COVID-19 case study for hospitals. Renewable Energy, 199:308-319, DOI:10.1016/j.renene.2022.08.132.

2. Zidane TEK, Muis ZA, Ho WS, Zahraoui Y, Aziz AS, Su CL, Mekhilef S, Elia Campana P (2025) Power systems and microgrids resilience enhancement strategies: a review. Renewable and Sustainable Energy Reviews, 207:114953, DOI:10.1016/j.rser.2024.114953.

3. Zaben MM, Worku MY, Hassan MA, Abido MA (2024) Machine learning methods for fault diagnosis in AC microgrids: a systematic review. IEEE Access, 12:20260-20298, DOI:10.1109/ACCESS.2024.3360330.

4. Pan P, Mandal RK, Redoy Akanda MM (2022) Fault classification with convolutional neural networks for microgrid systems. International Transactions on Electrical Energy Systems, 2022:8431450, DOI:10.1155/2022/8431450.

5. Alhanaf AS, Balik HH, Farsadi M (2023) Intelligent fault detection and classification schemes for smart grids based on deep neural networks. Energies, 16(22):7680, DOI:10.3390/en16227680.

6. Jayasinghe JARR, Malindi JHE, Rajapaksha RMAM, Logeeshan V, Wanigasekara C (2024) Classification and localization of faults in AC microgrids through discrete wavelet transform and artificial neural networks. IEEE Open Access Journal of Power and Energy, 11:303-313, DOI:10.1109/OAJPE.2024.3422387.

7. Esmaeilbeigi S, Kazemi Karegar H, Najar A (2025) A fault classification scheme based on protective agents for microgrid with parameters impact analysis. Scientific Reports, 15:44316, DOI:10.1038/s41598-025-28178-0.

8. Hubner RU, Kusel C, Oestmann JW (2023) Resilience of the critical infrastructure in hospitals: categorization and quantification as a basis for optimization. Die Anaesthesiologie, 72(10):710-718, DOI:10.1007/s00101-023-01318-9.

9. Khalil M, Ravaghi H, Samhouri D, Abo J, Ali A, Sakr H, Camacho A (2022) What is "hospital resilience"? A scoping review on conceptualization, operationalization, and evaluation. Frontiers in Public Health, 10:1009400, DOI:10.3389/fpubh.2022.1009400.

10. Nazartalab P, Alavi-Rad H (2026) Resilience-oriented optimization of hospital microgrids with critical load support using ESS and PV under grid outage conditions. Scientific Reports, 16:5475, DOI:10.1038/s41598-026-34992-x.

11. Barkhi M, Pourhossein J, Hosseini SA (2024) Integrating fault detection and classification in microgrids using supervised machine learning considering fault resistance uncertainty. Scientific Reports, 14:28466, DOI:10.1038/s41598-024-77982-7.

12. Sahu R, Panigrahi PK, Lal DK, Pradhan R, Mahanty C (2026) A deep recurrent learning framework for multi-class microgrid fault classification using LSTM and Bi-LSTM models. Eng, 7(3):143, DOI:10.3390/eng7030143.

13. Sahu R, Panigrahi PK, Lal DK, Pradhan R, Mahanty C (2026) Robust deep learning for multiclass power system fault diagnosis using edge deployment. Algorithms, 19(4):299, DOI:10.3390/a19040299.

14. Bu Q, Lyu P, Sun R, Jing J, Lyu Z, Hou S (2025) Fault diagnosis method using CNN-attention-LSTM for AC/DC microgrid. Modelling, 6(3):107, DOI:10.3390/modelling6030107.

15. Wang T, Zhang C, Hao Z, Monti A, Ponci F (2023) Data-driven fault detection and isolation in DC microgrids without prior fault data: a transfer learning approach. Applied Energy, 336:120708, DOI:10.1016/j.apenergy.2023.120708.

16. Vyshnavi G, Belwin EJ (2023) Fault detection in a distribution network using a combination of a discrete wavelet transform and a neural network's radial basis function algorithm to detect high-impedance faults. Frontiers in Energy Research, 11:1101049, DOI:10.3389/fenrg.2023.1101049.

17. Cano Ortega A, Arevalo Cordero WP, Benavides Padilla DJ, Jurado Melguizo F (2024) Integrating discrete wavelet transform with neural networks and machine learning for fault detection in microgrids. International Journal of Electrical Power & Energy Systems, 155:109616, DOI:10.1016/j.ijepes.2023.109616.

18. Taheri B, Hosseini SA, Hashemi-Dezaki H (2025) Enhanced fault detection and classification in AC microgrids through a combination of data processing techniques and deep neural networks. Sustainability, 17(4):1514, DOI:10.3390/su17041514.

19. Chen Q, Xu T, Zhou C, Wang Y (2026) Enhancing intelligent fault detection and classification in power grid engineering using LSTM neural networks. Distributed Generation & Alternative Energy Journal, 41(4):857-898, DOI:10.13052/dgaej2156-3306.4142.

20. Eissa MA, Samy MM, Said M (2026) Techno-economic analysis and resilience enhancement of a hospital microgrid under grid outage scenarios. Scientific Reports, 16:18358, DOI:10.1038/s41598-026-56638-8.