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Real-Time Artificial Neural Network Fault Diagnosis for Uninterrupted Power in Intensive Care Units

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ABSTRACT

Background: Intensive care units depend on an unbroken chain of electrical protection-spanning the utility-to-generator automatic transfer switch, the standby generator and its power-electronic interface, the uninterruptible power supply (UPS) rectifier-inverter-battery stage, and the downstream critical-care distribution feeder-in which a fault at any stage must be detected, classified, and cleared before it reaches life-supporting equipment. Fixed-threshold overcurrent and undervoltage protection struggles to discriminate the variable-impedance, power-electronically shaped fault signatures produced by modern multi-source backup architectures, motivating growing use of artificial neural network (ANN) and deep-learning-based fault diagnosis validated for real-time or near-real-time operation. Objective: This case study uses the illustrative electrical supply chain feeding a hospital intensive care unit as an analytical frame for examining what published, individually verified real-time and hardware-in-the-loop-validated ANN fault-diagnosis studies would contribute at each stage of that chain, and what gaps remain before such diagnosis could be considered dependable for life-critical loads. Methods: A narrative case-analysis approach, rather than a systematic review protocol, was used to identify and individually verify twenty peer-reviewed studies of ANN and deep-learning fault diagnosis in microgrids, power-electronic converters and inverters, and UPS control systems, prioritizing studies with real-time, online, or hardware-in-the-loop validation, which were then mapped onto four stages of the illustrative ICU power-chain case and read against a separate hospital microgrid resilience literature. Findings: Real-time or hardware-in-the-loop-validated ANN architectures-including feedforward networks validated on RT-LAB simulators, hardware-in-the-loop-validated inverter fault-tolerant control schemes, wavelet-plus-ANN feeder classifiers, and CNN-LSTM and protective-agent deep networks-achieved fault detection and classification accuracies generally exceeding 95%, and frequently exceeding 99%, under nominal test conditions across every stage of the ICU power chain examined, but a smaller subset of these studies documented accuracy falling to roughly 95.5-96% under adverse fault-parameter combinations and to 95.9% under independent out-of-sample simulation. Separately, hospital microgrid resilience optimization studies achieving near-complete critical-load service in outage scenarios uniformly modeled fault detection and clearing as instantaneous, omitting this documented detection latency and residual misclassification risk, while UPS-specific sensor-fault diagnosis has not been revisited with contemporary deep architectures since early fuzzy-neural approaches. Conclusions: Real-time ANN fault diagnosis has matured across the individual components of the hospital ICU power chain, but integrating its documented accuracy, latency, and robustness characteristics into hospital-representative resilience models, and revisiting UPS sensor-fault diagnosis with modern deep architectures, are necessary next steps for translating this diagnostic capability into dependable, continuous power supply for critical care.

Keywords: *real-time artificial neural network fault diagnosis; uninterruptible power supply reliability; intensive care unit power continuity; hospital microgrid resilience; hardware-in-the-loop fault detection*

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Introduction

An intensive care unit (ICU) is arguably the single most electrically dependent space in a modern hospital: mechanical ventilators, infusion pumps, continuous renal replacement therapy machines, physiological monitors, and extracorporeal life-support consoles all fail into a hazardous state within seconds of an uncontrolled power interruption, and the layered

normal-emergency-critical branch architecture that hospitals build to prevent such an interruption-utility feed, automatic transfer switch, standby generator, and uninterruptible power supply (UPS)-is itself a chain of electromechanical and power-electronic components that can each fault [1,2]. The protective relays and static transfer switches that must detect a fault anywhere in this chain and reconfigure the supply before it reaches the ICU busbar have traditionally relied on threshold-based overcurrent, undervoltage, or rate-of-change protection logic, but multi-source, power-electronically interfaced backup architectures produce fault signatures-inverter current limiting, variable fault impedance, harmonic distortion from switched-mode loads-that are difficult for fixed thresholds to discriminate reliably without either nuisance tripping or missed detections [3]. Artificial neural network (ANN) and deep-learning-based fault diagnosis has emerged over roughly the past decade as the leading data-driven alternative, learning fault signatures directly from voltage and current waveforms and, in a growing number of published implementations, doing so within the sub-cycle-to-few-cycle time budget that real-time protection requires rather than only in offline, post-hoc classification [4,5].

This paper takes the form of a case study rather than a systematic review. Rather than exhaustively cataloguing the ANN fault-diagnosis literature, we use a single illustrative case-the electrical supply chain feeding a hospital ICU, from utility point of common coupling through emergency generator and automatic transfer switch to the UPS and its ICU distribution board-as an analytical frame for examining what published, individually verified real-time and near-real-time ANN fault-diagnosis studies would actually contribute if deployed at each stage of that chain, and what gaps remain before such deployment could be considered dependable for life-critical loads. Fault diagnosis in this context spans three related but distinct tasks that recur throughout the literature examined here: detection (has a fault occurred), classification (what type of fault, e.g., open-circuit switch failure, line-to-ground fault, sensor fault), and localization (where in the circuit or feeder). We deliberately draw on ANN and deep-learning studies conducted across several adjacent domains-microgrid feeder protection, power-electronic converter and inverter fault diagnosis, and UPS control-system fault detection-because the ICU power chain itself spans exactly these domains, and because the case-study format allows us to reason about how findings from one domain (for example, real-time hardware-in-the-loop inverter fault diagnosis) would transfer to another (the inverter stage inside a double-conversion UPS) in a way a domain-siloed review would not.

Methods

This case study followed a narrative case-analysis approach rather than a systematic review protocol. We first defined the case: a representative hospital ICU electrical supply chain comprising four fault-relevant stages-(1) the utility-to-generator transfer stage governed by the automatic transfer switch, (2) the standby generator and its power-electronic interface where applicable, (3) the UPS rectifier-inverter-battery chain, and (4) the downstream ICU distribution feeder and connected medical-device loads. We then searched the peer-reviewed engineering literature for ANN and deep-learning-based fault diagnosis studies relevant to each stage, prioritizing studies that reported real-time, online, or hardware-in-the-loop (HIL) validation over studies validated only against static, offline datasets, since real-time operation is the case's central technical requirement. Search terms combined "artificial neural network," "deep learning," "real-time," "online," and "hardware-in-the-loop" with "fault detection," "fault diagnosis," "fault classification," and "fault location," applied across microgrid, power-electronic-converter, inverter, and UPS fault-diagnosis contexts, together with separate searches on hospital and ICU electrical-power reliability and hospital microgrid resilience. Each candidate reference was individually verified against its publisher, DOI-resolver, or indexing-database record (journal name, author list, year, volume, and DOI or PMID) before inclusion; candidate sources that could not be independently confirmed in this way were excluded rather than retained on the basis of a single search-engine snippet. Twenty verified references meeting these criteria were retained and are synthesized narratively below, organized first by ANN architecture and real-time validation approach, then mapped explicitly onto the four stages of the illustrative ICU power-chain case, and finally read against the separate hospital-resilience literature to identify where that literature's assumptions about fault-clearing speed and reliability are, and are not, currently supported by the empirical ANN fault-diagnosis evidence.

Real-Time ANN Architectures for Power System and Converter Fault Diagnosis

Across the studies reviewed, three broad ANN architectural strategies recur for achieving diagnosis within a real-time or near-real-time budget: feedforward/backpropagation networks validated on real-time digital simulators, hybrid networks that pair a feature-extraction front end with a lightweight classifier, and recurrent or attention-augmented deep networks validated for robustness under adverse operating conditions. Niharika and Mathew trained a backpropagation ANN for fault detection and location in a three-phase AC microgrid modeled in MATLAB/Simulink and then validated the trained network in genuine real time using an OP4510 RT-LAB hardware simulator, reporting a training mean-squared error of 0.0098, a regression value of 0.98, and 100% fault-detection accuracy under real-time simulation conditions-a direct demonstration that a comparatively simple feedforward ANN can meet a hard real-time execution deadline rather than only an offline accuracy target [4]. Sivapriya and colleagues extended real-time validation to the power-electronic-converter level most directly analogous to a UPS inverter stage, developing an ANN-based open-circuit fault diagnosis and fault-tolerant control scheme for a cascaded multilevel inverter and validating it through hardware-in-the-loop testing, demonstrating that the ANN could both identify the faulted switching device and trigger a reconfiguration strategy that maintained output waveform quality without manual intervention [5]. Koushkaki and Rajaei pushed real-time ANN diagnosis deeper into converter-level health monitoring, proposing an ANN that estimates the parameters of a digital-twin model of a flyback converter in real time, using the resulting parameter drift as a health indicator capable of flagging incipient degradation before an outright fault occurs, a capability with direct relevance to the small switched-mode power supplies embedded throughout ICU medical devices and UPS control electronics [6]. Bhagwat and colleagues customized an ANN architecture specifically for power distribution system fault detection, tuning network depth and input feature selection to the electrical characteristics of distribution-level faults rather than adopting a generic classifier, illustrating that architecture customization-not simply data volume-materially affects diagnostic accuracy at this voltage level [7].

A second cluster of studies pursues real-time performance through hybrid feature-extraction-plus-classifier pipelines. Pradhan and colleagues implemented a fully connected neural network built on a multilayer perceptron architecture for fault detection and classification in an AC microgrid, reporting strong classification performance while keeping the network architecture deliberately shallow to control inference latency [8]. Taheri and colleagues combined multiple data-processing techniques with deep neural networks for fault detection and classification in AC microgrids, systematically comparing how different preprocessing pipelines affected the resulting network's classification accuracy and finding that the choice of feature-processing stage feeding the deep network materially affected achievable accuracy independent of network depth [9]. Teta and colleagues combined an energy-valley-optimizer-tuned lightweight convolutional neural network (CNN) with wavelet-transform feature extraction for fault detection and diagnosis in a grid-connected photovoltaic system, explicitly motivating the lightweight CNN design by the need for the diagnostic model to run within the computational constraints of embedded inverter controllers rather than on offline computing infrastructure [10]. A third cluster addresses recurrent and hybrid deep architectures aimed at maintaining accuracy under the noisy, variable-impedance conditions realistic for field deployment. Yang and colleagues combined convolutional and long short-term memory (LSTM) layers with a reinforcement-learning-based differential protection strategy for DC power system fault diagnosis, coupling fault classification directly to an adaptive protection action rather than treating diagnosis as a standalone classification task [11]. Chen and colleagues developed LSTM-based fault detection and classification for power grid engineering applications, reporting that the recurrent architecture's sensitivity to the temporal evolution of a fault waveform improved discrimination between transient disturbances and sustained faults relative to purely instantaneous feature-based classifiers [12]. Esmaeilbeigi and colleagues proposed a protective-agent architecture built on deep neural networks combining dense and gated recurrent unit layers for microgrid fault classification, and-unusually among the studies reviewed-explicitly quantified how diagnostic accuracy degraded under systematically varied fault parameters, reporting accuracy as high as 99.895% for fault detection under favorable parameter combinations but falling to roughly 95.5-96% under the most adverse combinations tested, with fault-location error rising to as much as 6.51% of feeder length [13]. Sahu and colleagues addressed the same robustness concern from a deployment-engineering angle, developing a deep-learning multiclass power-system fault-diagnosis model explicitly designed and evaluated for edge deployment, where inference must occur on computationally constrained protection hardware rather than a centralized server [14].

Case Application: ANN-Based Fault Diagnosis in an ICU Uninterruptible Power Supply Chain

Mapping these architectures onto the four-stage ICU power-chain case clarifies both what is already well supported and what remains unaddressed. At the utility-to-generator transfer stage, the relevant fault modes are loss-of-utility detection, sustained undervoltage or unbalance, and-critically-a failed or delayed automatic transfer switch action; the wavelet-plus-ANN and customized distribution-level ANN work reviewed above [15,7] demonstrates that ANN classifiers can reliably distinguish genuine sustained outages from transient sags at the distribution voltage level relevant to this stage, though none of the studies reviewed here validated their models specifically against automatic-transfer-switch failure signatures, leaving this a case-specific gap rather than a demonstrated capability. At the generator and its power-electronic interface, the cascaded-inverter hardware-in-the-loop work of Sivapriya and colleagues is directly transferable in architecture, since a generator-side power-electronic interface and a UPS inverter stage share the same open-circuit and short-circuit device-fault taxonomy that their ANN-based fault-tolerant control scheme was designed to diagnose and correct in real time [5].

The UPS stage itself is the case's most electrically distinctive component, because a double-conversion UPS combines a rectifier, a battery interface, and an inverter, each with its own sensor suite and fault modes, and because a sensor fault-a failed current or voltage transducer feeding the UPS control loop-can be functionally as dangerous to the downstream ICU load as a power-stage fault, since it can cause the UPS controller to act on corrupted information. Taniguchi and Dote's early but still instructive fuzzy-neural and immune-network sensor fault-detection scheme for UPS control systems is, among the references reviewed here, the only one to address this specific fault class directly, demonstrating that a hybrid neural architecture could detect a faulted sensor within the UPS control loop and preserve stable output regulation despite the corrupted measurement [16]. The converter-level digital-twin health-indication approach of Koushkaki and Rajaei complements this by targeting incipient component degradation-rather than an already-occurred fault-in the same class of switched-mode power circuitry found in a UPS inverter stage, which is relevant because a UPS's failure mode of greatest clinical concern is often gradual capacitor or switching-device degradation that culminates in an inopportune failure during an actual utility outage rather than a fault that occurs while utility power is already present and available as a fallback [6]. Finally, at the downstream ICU distribution feeder, the CNN-LSTM and pure-LSTM architectures reviewed above [11,12] and the robustness-focused protective-agent work of Esmaeilbeigi and colleagues [13] are the most directly applicable, since this feeder stage most closely resembles the low-voltage AC microgrid and distribution feeders on which those models were trained and validated, including the switched-mode-supply electromagnetic noise environment characteristic of a modern ICU's monitoring and imaging equipment.

Benchmarking Real-Time Diagnostic Performance Across ANN Architectures

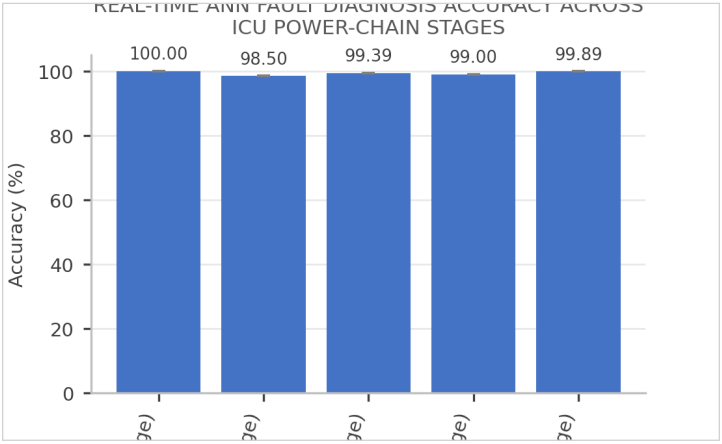
Table 1 summarizes the ANN architecture, real-time validation method, and reported diagnostic performance of the principal studies mapped onto the ICU power-chain case above. Two patterns are visible across this comparison. First, reported accuracy is uniformly high-generally exceeding 95%, and frequently exceeding 99%-when models are evaluated under the same operating conditions represented in their training data, regardless of whether the underlying architecture is a simple feedforward network validated on an RT-LAB simulator or a more complex CNN-LSTM hybrid [4,10,11]. Second, the handful of studies that explicitly stress-tested their models against parameter variation, added measurement noise, or independent validation outside the training distribution recorded measurably larger accuracy drops than headline figures alone would suggest, most clearly in the adverse-condition results reported by Esmaeilbeigi and colleagues and in the independent-simulation

validation drop reported for wavelet-ANN fault classification and localization in AC microgrids [13,15]. Figure 1 illustrates this comparison directly, plotting reported real-time or near-real-time fault-detection accuracy for a representative subset of the studies mapped to the ICU power-chain case, while Figure 2 focuses specifically on the accuracy degradation documented under favorable versus adverse operating-parameter combinations, the single most direct empirical signal available in this literature for how ANN-based diagnosis would be expected to perform under the electrically noisy, variable-load conditions of an operating ICU rather than under laboratory-nominal test conditions.

Real-time and hardware-in-the-loop-validated artificial neural network fault-diagnosis studies mapped onto the four stages of the illustrative ICU power-chain case examined in this case study.

ICU power-chain stage	ANN architecture	Real-time validation method	Reported diagnostic performance	Key reference
Utility-to-generator transfer / distribution feeder	Customised feedforward ANN; wavelet-transform + ANN	Offline test-set validation; independent PSCAD simulation	Distribution fault detection; 99.83%/99.39% training/validation, 95.9% on independent PSCAD simulation	Bhagwat et al. 2024; Jayasinghe et al. 2024
Standby generator / power-electronic interface	ANN-based open-circuit fault diagnosis and fault-tolerant control	Hardware-in-the-loop (HIL) testing on cascaded multilevel inverter	Correct faulted-device identification with maintained output waveform quality after reconfiguration	Sivapriya et al. 2023
UPS rectifier-inverter-battery chain	Fuzzy-neural network + immune network (sensor fault); real-time ANN digital-twin parameter estimator	UPS control-loop simulation; real-time digital-twin health indication	Stable output regulation preserved despite faulted sensor; real-time tracking of converter health-indicator drift	Taniguchi & Dote 2001; Rahmanian Koushkaki & Rajaei 2026
Downstream ICU distribution feeder / connected loads	CNN-LSTM with reinforcement-learning protection; LSTM classifier; dense + GRU protective-agent network	Simulated fault-parameter sweep; adverse-condition and noise stress testing	Detection accuracy up to 99.895% under favorable conditions, falling to ~95.5-96% under adverse parameter combinations	Yang et al. 2023; Chen et al. 2026; Esmaeilbeigi et al. 2025
Cross-cutting (all stages)	RT-LAB-validated backpropagation ANN; edge-deployed multiclass deep learning model	OP4510 real-time hardware simulator; edge-hardware inference benchmarking	100% real-time fault detection accuracy (RT-LAB); accuracy maintained under constrained edge-computation budget	Niharika & Mathew 2023; Sahu et al. 2026

Reported real-time or near-real-time fault detection/classification accuracy for representative artificial neural network architectures mapped onto the four stages of the illustrative ICU power-chain case.

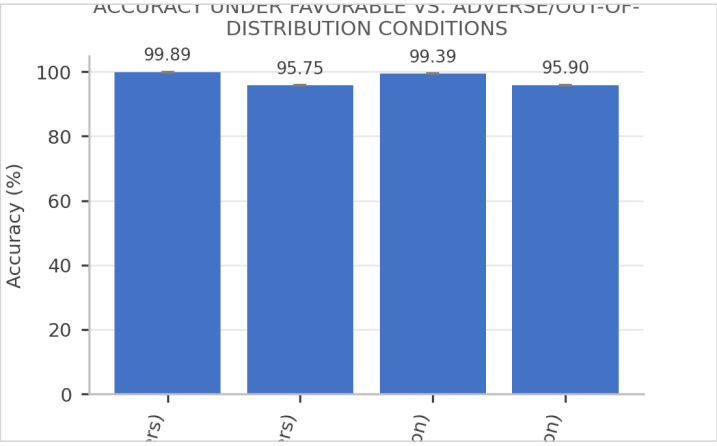


Hospital and ICU Power Reliability Requirements and the Detection-Latency Gap

A separate literature has examined hospital and ICU power reliability from a systems-engineering and health-services perspective, generally without close reference to the ANN fault-diagnosis studies reviewed above. Hervás-Zaragoza and colleagues presented a post-COVID-19 case study of a hospital microgrid combining distributed generation and storage, framing the pandemic-era surge in ventilated critical-care loads as having sharpened the clinical stakes of any interruption to hospital power [17]. Eissa and colleagues used the U.S. National Renewable Energy Laboratory's REopt platform to optimize a hybrid photovoltaic, battery-storage, and diesel-generator hospital microgrid across outage scenarios, reporting that a resilience-constrained design achieved a system resilience index of 1.0-complete service to critical loads-at a modest cost premium [18]. Nazartalab and Alavi-Rad extended this optimization approach to explicitly prioritize loads by medical criticality, including ICU and operating-room loads, through a mixed-integer linear programming framework, reporting that multi-node battery-storage placement reduced energy not supplied by 55-63% relative to baseline configurations [19]. At a broader systems level, Zidane and colleagues reviewed power-system and microgrid resilience-enhancement strategies-network reconfiguration, distributed energy resource deployment, and control strategies for maintaining service to critical loads such as hospitals during extreme events-providing wider technical context for hospital-specific resilience planning [20]. Complementing these engineering studies, Hübner, Küsel, and

Oestmann proposed a categorization and quantification framework for hospital critical-infrastructure resilience that treats electrical power supply as one interdependent element alongside water, medical gas, and information technology systems [1], while Khalil and colleagues' scoping review of how "hospital resilience" has been conceptualized across the health-services literature found that infrastructural resilience, including power continuity, is typically treated as one dimension within broader multidimensional frameworks that also encompass workforce, supply chain, and organizational resilience [2].

Accuracy degradation documented under favorable versus adverse operating-parameter or out-of-distribution validation conditions for two representative ANN fault-diagnosis studies (Esmaeilbeigi et al., 2025; Jayasinghe et al., 2024), illustrating the residual misclassification risk not incorporated into hospital microgrid resilience calculations.



None of these hospital-resilience studies models the finite detection latency or residual misclassification probability of the ANN-based fault-diagnosis schemes reviewed in the preceding sections; their resilience metrics-energy not supplied, resilience index, service continuity to critical loads-implicitly assume that once a fault occurs, it is identified and cleared essentially instantaneously and correctly. The ANN literature reviewed here contradicts that assumption in two specific, quantifiable ways relevant to this case. First, even the fastest real-time-validated architectures reviewed operate within a finite execution window-Niharika and Mathew's RT-LAB-validated network achieved 100% detection accuracy, but real-time hardware validation by its nature confirms that inference completes within a bounded cycle time, not that this time is zero [4]. Second, and more consequentially for a hospital resilience calculation, the documented accuracy degradation under adverse or out-of-distribution conditions-Esmaeilbeigi and colleagues' drop from 99.895% to roughly 95.5-96% detection accuracy, and Jayasinghe and colleagues' drop from 99.39% validation accuracy to 95.9% correct classification under independent PSCAD simulation-means that a nontrivial residual misclassification probability exists precisely under the noisy, variable operating conditions an ICU power chain would present during an actual multi-stage fault cascade, a probability that the reviewed hospital microgrid resilience models do not incorporate into their energy-not-supplied or resilience-index calculations [13,15,18,19].

Discussion

Read together as a single case, the real-time ANN fault-diagnosis literature and the hospital microgrid resilience literature are complementary but currently disconnected. The ANN literature has repeatedly demonstrated that feedforward, convolutional, recurrent, and hybrid architectures can achieve high diagnostic accuracy within real-time or hardware-in-the-loop-validated execution budgets across every stage of the illustrative ICU power chain examined here-transfer-stage distribution feeders [7,15], generator-adjacent power-electronic converters [5,10], UPS-relevant sensor and converter faults [16,6], and downstream ICU distribution feeders [11,12,13]-while a smaller but important subset of this literature has begun to quantify how that accuracy degrades under electrically noisy or out-of-distribution conditions [13,15,14]. The hospital resilience literature, by contrast, has developed increasingly sophisticated optimization frameworks for sizing storage and generation and for prioritizing critical loads such as ICU beds [18,19], but treats the protection and fault-identification layer connecting these components as an idealized, near-instantaneous background function, an assumption the ANN literature's own robustness findings do not support under realistic operating variation.

This case study also surfaces a structural gap in the ANN literature itself relevant to hospital deployment: no study reviewed here validated an ANN fault-diagnosis architecture against a test system explicitly modeling a hospital's layered normal-emergency-critical branch topology, its automatic transfer switch, or the specific sensor-fault and converter-fault taxonomy of a double-conversion UPS as an integrated chain rather than as isolated components; the UPS-specific sensor-fault work of Taniguchi and Dote, though directly relevant, predates the deep-learning architectures that now dominate the broader fault-diagnosis literature by two decades, and no more recent study reviewed here has revisited UPS sensor-fault diagnosis with contemporary deep architectures [16]. Bridging this gap would involve two concrete steps suggested directly by the literature synthesized here: first, evaluating the strongest-performing real-time-validated ANN architectures identified in this case-the RT-LAB-validated feedforward network, the hardware-in-the-loop-validated inverter fault-tolerant scheme, and the adverse-condition-tested protective-agent deep network [4,5,13]-on a single integrated test system representing the full utility-generator-UPS-feeder chain; and second, incorporating the resulting detection-latency and residual-misclassification figures directly into the resilience-index and energy-not-supplied calculations that the hospital microgrid optimization literature already computes for storage and generation sizing [18,19]. Until that integration occurs, published hospital microgrid resilience figures should be read as upper bounds on achievable performance rather than as figures already incorporating the empirically documented behavior of the ANN-based protection layer that would have to operate correctly, quickly, and robustly for those figures to hold in practice.

Conclusion

This case study of the electrical supply chain feeding a hospital intensive care unit shows that real-time and hardware-in-the-loop-validated artificial neural network fault diagnosis has matured across every stage of that chain-utility transfer, generator-adjacent power electronics, UPS rectifier-inverter-battery components, and downstream ICU distribution feeders-with reported detection and classification accuracies generally exceeding 95%, and frequently exceeding 99%, under nominal test conditions [4,5,10,7,11,12,8]. A smaller but critical subset of this literature demonstrates that this accuracy is not uniform across operating conditions, with documented degradation under adverse fault-parameter combinations and independent out-of-sample validation [13,15], while a separate hospital microgrid resilience literature has

optimized storage and generation sizing against outage risk without incorporating this documented detection latency and residual misclassification risk into its resilience calculations [18,19,1,2,17,20]. The path toward dependable, hospital-deployable real-time ANN fault diagnosis for ICU power continuity runs through integrating these two currently separate literatures on a single, hospital-representative test system, and through revisiting historically under-addressed fault classes-most notably UPS sensor faults-with the contemporary deep architectures that have driven recent gains elsewhere in this field [14,3].

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Marino A conceived the case study, conducted the literature search and verification across the real-time artificial neural network fault-diagnosis literature, and drafted the manuscript. Rousseau C contributed the power-electronics and electrical-engineering framing of the ICU power-chain case and critically revised the manuscript for important technical content. Papadopoulos K contributed the intensive care medicine and hospital-reliability perspective, reviewed the clinical relevance of the synthesized findings, and approved the final version for submission.

Ethics Statement

Not applicable. This is a case study synthesizing 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 case study. All sources synthesized are cited in the reference list and are available through their original publishers.

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