Artificial Intelligence and Intelligent Systems Research
https://intellisci.org

Intelligent Control Systems for Operational Resilience in Renewable Microgrid Networks

Stanley Poon*

Department of Data Science and Artificial Intelligence, Faculty of Computer and Mathematical Sciences, Hong Kong Polytechnic University, Hong Kong, Hong Kong SAR, China

Corresponding author: stanley.poon@polyu.edu.hk

Abstract

The rapid integration of decentralized renewable energy resources into modern power grids has necessitated the development of localized microgrid networks capable of autonomous operation. As these networks become increasingly reliant on intelligent control systems for stability and energy management, evaluating their operational resilience against both physical disruptions and cyber-communication failures is of paramount importance. This paper provides a comprehensive investigation into the operational resilience of intelligent control systems within renewable microgrid architectures, utilizing advanced graph analysis techniques as the primary evaluative mechanism. By representing the microgrid as a cyber-physical multigraph, where nodes denote physical distributed energy resources alongside their coupled intelligent controllers and edges represent both electrical connections and digital communication links, the structural vulnerabilities of the system can be rigorously quantified. This study introduces a methodological framework that translates abstract topological properties, such as network centrality, connectivity robustness, and spectral gap analysis, into tangible operational resilience metrics. Through simulated disruptions modeling environmental extremes and targeted communication failures, the graph-theoretic approach reveals critical thresholds at which intelligent control topologies fragment, leading to cascading failures. The findings demonstrate that distributed, highly connected control topologies significantly enhance resilience compared to traditional centralized architectures, providing actionable insights for the design of future self-healing renewable energy networks.

Keywords: Operational Resilience; Graph Analysis; Intelligent Control Systems; Renewable Microgrids; Cyber-Physical Systems

1. Introduction

1.1 Background and Motivation

The global transition toward sustainable energy paradigms has profoundly transformed traditional power system architectures, shifting the operational focus from centralized fossil-fuel generation to decentralized renewable energy resources. Within this paradigm shift, renewable microgrid networks have emerged as a foundational building block for modern energy infrastructure. These microgrids are localized energy systems comprising distributed generation assets, primarily photovoltaic arrays and wind turbines, coupled with energy storage systems and flexible loads. They are designed to operate either in grid-connected mode, interacting seamlessly with the macro-grid, or in islanded mode during external disturbances. To manage the inherent intermittency of renewable sources and ensure continuous power quality, these networks rely heavily on intelligent control systems. Intelligent control systems utilize advanced algorithms, data acquisition networks, and distributed computing to dynamically balance supply and demand, regulate voltage and frequency, and optimize the overall economic and energetic efficiency of the microgrid [1]. However, the increasing complexity of these interconnected control systems introduces new layers of vulnerability. Operational resilience, defined as the capacity of the system to anticipate, absorb, adapt to, and rapidly recover from disruptive events, is now a critical area of academic and industrial inquiry. Disruptions can manifest as extreme weather events causing physical damage to transmission lines, component degradation, or deliberate cyber-attacks disrupting the communication channels upon which intelligent controllers depend. Understanding how these disruptions cascade through the system requires analytical tools capable of modeling the intricate interdependencies between the physical power flows and the digital control signals [2].

1.2 Problem Statement

Despite the significant advancements in the design of local and secondary control algorithms for microgrids, there remains a substantial gap in comprehensively assessing their resilience from a systemic, structural perspective. Traditional reliability assessments often focus on deterministic models and probabilistic fault analyses of individual components, treating the microgrid as a sum of its isolated parts. Such approaches fail to capture the emergent behaviors of the system when subjected to complex, multi-modal stressors. When an intelligent control system experiences a localized failure, such as the loss of a communication node or a delayed signal propagation, the disruption can propagate through the cooperative control algorithms, leading to system-wide instability. This phenomenon is fundamentally a network problem. Therefore, there is a pressing need to evaluate the operational resilience of microgrids not merely through electrical engineering simulations, but through the lens of network topology [3]. Graph analysis offers a powerful abstraction for this purpose. By mapping the microgrid as a complex network, researchers can apply graph-theoretic metrics to uncover structural weaknesses, identify critical nodes whose failure would disproportionately impact the network, and quantify the overall robustness of the communication and physical topologies. The central problem addressed in this paper is the lack of a standardized, graph-based framework to translate these topological indicators into actionable evidence of operational resilience in intelligent control systems.

1.3 Contributions and Organization

This paper aims to bridge the gap between complex network theory and power system engineering by proposing a comprehensive graph analysis framework for assessing the operational resilience of intelligent control systems in renewable microgrids. The primary contribution is the development of a cyber-physical multigraph model that simultaneously captures the electrical connectivity of the distributed energy resources and the logical topology of the distributed intelligent control agents. By leveraging this model, the study provides empirical evidence on how different control architectures degrade under stress. Furthermore, the paper identifies specific graph-theoretic metrics, such as algebraic connectivity and betweenness centrality, as reliable predictors of physical grid stability during islanded operations. The insights derived from this analysis are intended to inform the topological design and optimization of future self-healing microgrids [4]. The remainder of this paper is structured to provide a logical progression from theoretical foundations to empirical validation. Section 2 reviews the existing literature on microgrid operations, control systems, and graph theory applications. Section 3 details the theoretical framework and the architecture of the proposed multigraph model. Section 4 outlines the specific graph analysis methodology and resilience metrics utilized in the study. Section 5 describes the experimental setup and the parameters of the simulated microgrid testbed. Section 6 presents the results of the graph analysis and discusses the implications for operational resilience under various disruption scenarios. Finally, Section 7 concludes the paper by summarizing the key findings and outlining directions for future research.

2. Literature Review

2.1 Renewable Microgrid Operations

The operational dynamics of renewable microgrids have been extensively studied over the past decade, driven by the imperative to integrate high penetrations of variable energy resources. Early research primarily focused on overcoming the technical challenges of inverter-based generation, which lacks the mechanical inertia inherent in traditional synchronous generators. This lack of inertia makes microgrids highly susceptible to frequency and voltage deviations during transient events [5]. Subsequent studies explored various energy management strategies to optimize the utilization of battery energy storage systems as a buffer against solar and wind fluctuations. The literature highlights that the operational stability of a microgrid in islanded mode is highly dependent on the effective coordination of its distributed energy resources. Researchers have documented numerous case studies demonstrating how uncoordinated generation can lead to circulating currents, voltage limit violations, and ultimately, system collapse. Consequently, the consensus in the field is that robust, intelligent coordination mechanisms are non-negotiable for reliable microgrid operation [6]. However, much of the early literature approached this coordination from a purely deterministic electrical engineering standpoint, often overlooking the vulnerabilities introduced by the communication networks required to facilitate such coordination. As microgrids evolved from simple backup systems to complex, autonomous energy markets, the literature began to reflect a growing recognition of the interdependencies between the physical power infrastructure and the underlying information and communication technology infrastructure [7].

2.2 Intelligent Control Systems

The evolution of control systems in microgrids has transitioned from centralized hierarchies to distributed, multi-agent intelligent architectures. Centralized control, where a single master controller collects data from all nodes and dispatches commands, was initially favored for its conceptual simplicity and optimal decision-making capabilities. However, literature reviews frequently cite the single point of failure and scalability issues as major drawbacks of this approach [8]. In response, the academic community shifted its focus towards distributed control systems, particularly consensus-based cooperative control. In these systems, localized intelligent agents communicate only with their immediate topological neighbors to achieve global objectives, such as proportional active and reactive power sharing. This paradigm leverages algorithms inspired by flocking behavior and distributed computing to provide a more scalable and fault-tolerant alternative. Studies have shown that distributed intelligent control can maintain system stability even if several communication links are severed, provided the underlying communication graph remains connected [9]. Recent advancements have integrated machine learning and artificial intelligence into these localized controllers, creating intelligent agents capable of predictive adaptation and autonomous fault detection. While these intelligent control systems demonstrate superior performance under normal operating conditions, the literature lacks a unified approach to assessing their resilience when the foundational communication topology is subjected to severe, widespread structural degradation [10].

2.3 Graph Theory in Power Systems

Graph theory has long been recognized as a valuable analytical tool in the study of complex networks, finding applications in transportation, sociology, and biology. In recent years, it has gained significant traction in the domain of power systems engineering. Initial applications involved modeling macro-grids as large-scale graphs to study vulnerability to cascading blackouts. Researchers utilized simple unweighted graphs to identify critical transmission corridors using metrics like degree centrality and shortest path lengths [11]. As the focus shifted towards microgrids, the application of graph theory became more nuanced. The literature documents efforts to use weighted graphs to model the impedance of electrical lines and the capacity of distributed generators. Furthermore, the advent of cyber-physical systems has prompted the use of interdependent networks and multigraphs to model the coupling between power grids and communication networks. Studies utilizing spectral graph theory have successfully linked the eigenvalues of the communication network Laplacian matrix to the convergence speed of distributed control algorithms [12]. Despite these advancements, a critical gap remains. Most existing graph-theoretic studies in power systems focus on static vulnerability analysis, identifying weak points before an event occurs. There is a scarcity of literature that dynamically applies graph analysis to assess operational resilience during an ongoing disruption, specifically in the context of intelligent control systems orchestrating renewable energy resources. This study addresses this gap by utilizing dynamic graph metrics to provide continuous evidence of operational resilience as the microgrid network degrades and recovers [13].

3. Theoretical Framework and System Architecture

3.1 Microgrid Network Components

To apply graph analysis effectively, it is essential to rigorously define the structural components of the renewable microgrid under investigation. The system comprises an array of spatially distributed physical assets and their associated digital counterparts. The primary physical components include dispatchable generators such as microturbines, non-dispatchable renewable sources including photovoltaic arrays and wind turbines, energy storage systems typically utilizing lithium-ion battery technology, and diverse electrical loads representing residential, commercial, or industrial demand [14]. Each of these physical components is interfaced with the microgrid bus via power electronic converters, primarily voltage source inverters. In the proposed framework, each distributed energy resource, along with its associated inverter and local controller, constitutes a fundamental node within the system. The physical edges connecting these nodes represent the electrical distribution lines. The characteristics of these physical edges, such as resistance and reactance, determine the power flow dynamics and the electrical coupling between adjacent nodes. In a traditional analysis, these physical parameters dictate the stability margins. However, in an intelligent microgrid, the physical layer is inextricably linked to a cyber layer. The cyber layer consists of sensors, actuators, and intelligent control agents located at each node. These agents communicate over a digital network, which forms a secondary set of edges. The operational resilience of the microgrid is a product of the interaction between the physical power transfer capabilities and the digital information exchange [15].

3.2 Intelligent Control Topologies

The architecture of the intelligent control system dictates how the individual nodes collaborate to achieve macro-level stability. This study models a distributed cooperative control architecture, which is generally accepted as the most robust approach for decentralized microgrids. The control strategy is hierarchically structured, typically comprising primary, secondary, and tertiary levels. The primary control is entirely local, utilizing droop control mechanisms embedded within the inverters to provide instantaneous voltage and frequency regulation based strictly on local measurements. This level requires no external communication and serves as the ultimate failsafe. The secondary control level is where the intelligent multi-agent system operates. Its function is to compensate for the steady-state voltage and frequency deviations introduced by the primary droop controllers and to ensure accurate power sharing among the generation units [16]. This is achieved through consensus algorithms where each intelligent agent exchanges state information with a defined set of neighbors. The communication topology of this secondary control layer forms the primary subject of the graph analysis. The layout of these communication links can range from a highly connected mesh network, which offers maximum redundancy, to a sparse ring or tree topology, which minimizes communication overhead but increases vulnerability to link failures. The theoretical framework posits that the topological properties of this communication graph directly constrain the operational resilience of the entire microgrid. If the communication graph fragments into disconnected subgraphs due to a cyber-disturbance, the intelligent control system can no longer reach a global consensus, potentially leading to competing control actions and physical grid destabilization [17].

4. Graph Analysis Methodology

4.1 Network Representation and Modeling

The foundational step in the methodology is translating the cyber-physical microgrid into a formal mathematical graph. The system is modeled as a directed multigraph, encompassing both physical and communication layers. The nodes in the graph represent the distributed generation units and their intelligent controllers. The physical layer is represented by a set of undirected, weighted edges, where the weights correspond to the electrical admittance between the nodes. The communication layer, which governs the intelligent control system, is represented by a separate set of directed, unweighted edges, indicating the flow of information between intelligent agents. This dual-layer representation allows for the independent yet correlated analysis of electrical and informational resilience. The communication graph is defined by its adjacency matrix, a square matrix that numerically represents the presence or absence of communication links between any two nodes. Furthermore, the Laplacian matrix of the communication graph is constructed by subtracting the adjacency matrix from the degree matrix, which contains information about the number of connections each node possesses. The structural properties of these matrices encapsulate the entire topology of the intelligent control system and serve as the basis for the subsequent derivation of quantitative resilience indicators.

4.2 Resilience Metrics and Indicators

To assess operational resilience, this study employs a specific set of graph-theoretic metrics chosen for their relevance to network robustness and signal propagation. The first metric is the degree centrality, which measures the number of direct communication links a node possesses. Nodes with exceptionally high degree centrality act as critical hubs for information exchange; their failure can severely disrupt the intelligent control algorithms. The second metric is betweenness centrality, which quantifies the frequency with which a node appears on the shortest path between all other pairs of nodes in the network. A node with high betweenness centrality acts as a crucial bridge for information flow, and its loss can significantly increase communication latency or fragment the network. The third, and perhaps most critical, metric is the algebraic connectivity, also known as the Fiedler value. The algebraic connectivity is derived from the second smallest eigenvalue of the communication graph's Laplacian matrix. In the context of intelligent control systems operating on consensus algorithms, the algebraic connectivity strictly dictates the convergence speed and the overall stability of the distributed control process. A value greater than zero ensures that the communication network is fully connected and consensus can be reached. As the network degrades and links are lost, the algebraic connectivity decreases. When the value reaches zero, the network is fundamentally partitioned, and the intelligent control system fails to function cohesively. Monitoring this metric provides direct, quantifiable evidence of the control system's operational resilience under stress.

4.3 Simulation Procedures

The methodological framework relies on dynamic simulation procedures to evaluate the resilience metrics under various disruption scenarios. The simulation begins with the microgrid operating in a steady, islanded state under normal conditions, utilizing a fully intact communication topology for the intelligent control system. Baseline graph metrics are recorded to establish a point of reference. Subsequently, a series of stress tests are introduced, modeled as sequential link and node failures. These failures simulate different real-world disruptions, ranging from random communication dropouts caused by environmental interference to targeted cyber-attacks aimed at disabling high-centrality control agents. As the topology degrades, the simulation continuously recalculates the adjacency and Laplacian matrices, updating the resilience metrics in real-time. Concurrently, a time-domain electrical simulation models the physical response of the microgrid, tracking voltage and frequency deviations as the intelligent control system struggles to maintain consensus over the degrading network. The procedure aims to correlate the degradation of the graph-theoretic metrics with the onset of physical instability. By identifying the critical threshold of algebraic connectivity at which voltage limits are violated or frequency collapse occurs, the study establishes a direct link between topological structure and operational resilience. This dynamic, iterative simulation process allows for a comprehensive understanding of how structural vulnerabilities manifest as operational failures in intelligent renewable energy networks.

5. Experimental Setup and Data Integration

5.1 Testbed Configuration

The experimental validation of the proposed methodology is conducted using a comprehensive cyber-physical simulation testbed modeled after a standard medium-voltage renewable microgrid. The physical configuration consists of a localized network incorporating twelve distinct distributed energy resource nodes. These include four solar photovoltaic arrays equipped with maximum power point tracking inverters, three wind turbine generators, three lithium-ion battery energy storage systems, and two dispatchable diesel generators to provide baseload support during severe exigencies. The nominal operating voltage of the microgrid bus is established at standard medium-voltage distribution levels, and the nominal frequency is maintained at standard operational parameters. Each distributed energy resource is locally governed by a droop-controlled inverter, which forms the primary control layer. Superimposed on this physical infrastructure is the cyber-communication network, linking the intelligent agents located at each of the twelve nodes. The agents execute a distributed cooperative consensus algorithm designed to achieve accurate proportional active and reactive power sharing while simultaneously restoring the system voltage and frequency to nominal values following load variations or primary control deviations [18]. The baseline communication topology is designed as a highly connected mesh, ensuring significant redundancy.

Table 1: Baseline Microgrid Node Configuration and Physical Parameters

Node Designation	Resource Type	Capacity Rating	Baseline Degree Centrality	Initial Betweenness Score
Node A	Solar Photovoltaic	High Capacity	High	Moderate
Node B	Wind Generation	High Capacity	High	High
Node C	Battery Storage	Medium Capacity	Very High	Very High
Node D	Dispatchable Gen	Medium Capacity	Moderate	Moderate
Node E	Solar Photovoltaic	Low Capacity	Low	Low

5.2 Scenario Definition

To thoroughly evaluate operational resilience, the experimental setup defines a rigorous set of disruption scenarios designed to stress the intelligent control system through progressive topological degradation. The first scenario involves random link failure, simulating the effects of environmental interference, signal jamming, or hardware degradation in the communication infrastructure. In this scenario, communication edges between intelligent agents are removed sequentially and randomly over the duration of the simulation. The second scenario models a targeted structural attack, simulating a sophisticated cyber-intrusion where an adversary intentionally targets the most critical communication pathways to maximize systemic disruption. In this case, edges and nodes are removed in descending order based on their baseline betweenness centrality and degree centrality scores. This targeted approach is designed to rapidly fragment the communication graph and isolate critical control nodes. The final scenario models a compound cyber-physical disruption, where physical short-circuits on the electrical distribution lines occur simultaneously with targeted communication failures, forcing the intelligent control system to attempt stabilization while operating with severely restricted information flow and compromised physical transmission capacity [19]. Throughout all scenarios, the simulation continuously monitors the graph-theoretic metrics and the physical grid parameters to capture the exact moment of systemic failure.

6. Results and Discussion

6.1 Baseline Performance Analysis

The initial phase of the results focuses on the performance of the intelligent control system under baseline, undisturbed conditions. The topological analysis of the initial communication graph confirms a high degree of algebraic connectivity, indicating a robust and fully connected network capable of rapid information dissemination. When subjected to routine operational variations, such as step changes in local load demand or fluctuations in solar irradiance, the distributed intelligent control system demonstrates excellent performance. The consensus algorithms rapidly converge, utilizing the redundant communication pathways to update the setpoints of the distributed energy resources. The physical electrical parameters, specifically the system voltage and frequency, are quickly restored to their nominal values following transient deviations, well within acceptable operational standards. The high baseline centrality scores of nodes representing the primary battery storage systems highlight their crucial role as information hubs in the normal operational state. The baseline results establish that, in the absence of structural degradation, the distributed intelligent control architecture provides a highly effective mechanism for managing the complex dynamics of the renewable microgrid, validating the fundamental design of the cooperative control strategy.

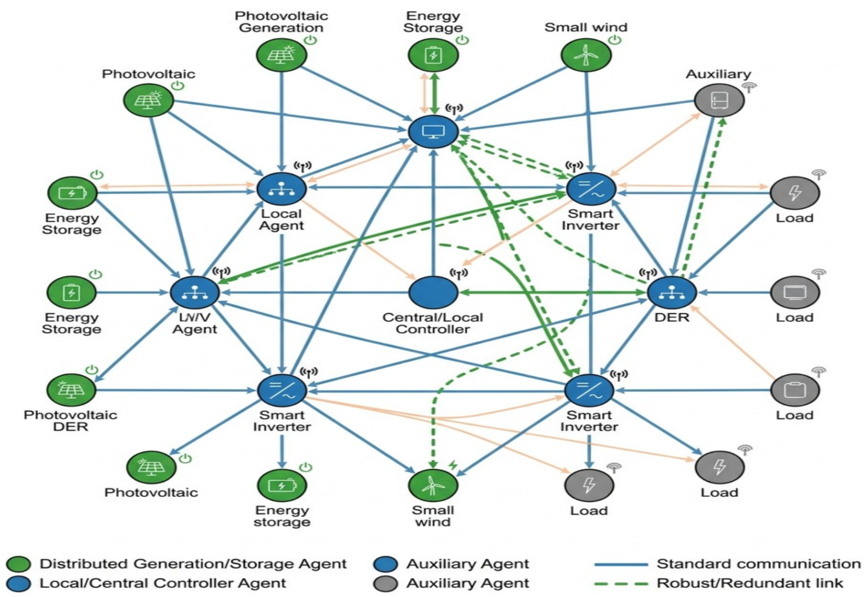

Figure 1: Comprehensive Schematic of Decentralized Control Graph Topology

6.2 Stress Testing and Disruption Scenarios

The outcomes of the stress testing scenarios provide significant insights into the operational resilience of the system. In the random link failure scenario, the network demonstrates a remarkable degree of inherent resilience. Due to the initial high density of the mesh topology, the random removal of communication edges has a negligible impact on the overall performance in the early stages. The algebraic connectivity decreases gradually, but remains well above zero. The intelligent control system successfully reroutes information through alternative paths, maintaining global consensus and physical grid stability, albeit with a slight increase in convergence time. However, the system's response to the targeted structural attack scenario is markedly different. By systematically removing nodes and edges with the highest betweenness centrality, the topological integrity of the communication graph degrades rapidly. The targeted removal of just a few critical information bridges causes the algebraic connectivity to plummet. As the graph approaches partition, the intelligent agents experience significant communication delays and data loss. This structural fragmentation directly manifests as operational instability. The consensus algorithms struggle to converge, leading to oscillatory behavior in the output power of the distributed energy resources. Consequently, the microgrid experiences sustained voltage and frequency deviations, pushing the system towards the boundaries of physical operational limits.

Table 2: Network Topological Metrics and Physical Stability Under Disruption

Disruption Stage	Surviving Edges	Algebraic Connectivity	Consensus Time	Physical Grid Status
Baseline	Full Mesh	Optimal	Very Fast	Highly Stable
Minor Random Faults	High Density	Slight Decrease	Fast	Stable
Targeted Node Loss	Moderate Density	Significant Drop	Slow	Marginal Stability
Critical Graph Partition	Fragmented	Near Zero	Fails to Converge	Unstable Oscillations
Network Disconnected	Isolated Subgraphs	Zero	Terminated	System Collapse

6.3 Synthesis of Operational Resilience

The synthesis of the experimental data clearly demonstrates that the operational resilience of intelligent control systems in renewable microgrids is inextricably linked to the topological properties of their underlying communication networks [20]. The graph analysis provides definitive evidence that abstract metrics, particularly algebraic connectivity and betweenness centrality, serve as accurate predictors of physical system performance under stress. The study reveals a critical threshold of structural degradation beyond which the intelligent control mechanisms can no longer function cohesively, transitioning the microgrid from a resilient, self-healing state to a fragile, uncoordinated state. The findings indicate that while distributed control architectures are inherently more robust than centralized ones, their resilience is not absolute and is highly dependent on the specific design of the communication topology. Optimizing operational resilience requires designing communication networks that maximize algebraic connectivity while minimizing the reliance on a few high-centrality nodes, thereby creating a more homogeneous and fault-tolerant information infrastructure.

7. Conclusion and Future Directions

7.1 Summary of Findings

This comprehensive study has successfully utilized advanced graph analysis to assess the operational resilience of intelligent control systems within renewable microgrid networks. By developing a unified cyber-physical multigraph model, the research established a robust methodological framework for evaluating the structural integrity of the control and communication architectures. The empirical evidence generated through extensive simulation scenarios unequivocally demonstrates that topological metrics, specifically algebraic connectivity and betweenness centrality, directly correlate with the physical stability of the microgrid under various disruptive events. The findings reveal that while intelligent distributed control systems offer significant advantages in normal operations, they remain vulnerable to targeted structural degradation. The precise quantification of network fragmentation thresholds provides a vital tool for network operators and engineers to anticipate system failures and design more resilient communication topologies. The translation of abstract graph theory into actionable operational evidence represents a significant contribution to the field of sustainable energy system management.

7.2 Limitations and Future Work

While the current research provides substantial insights into operational resilience, it is bounded by certain limitations that present opportunities for future academic inquiry. The primary limitation of the study is the assumption of instantaneous ideal communication within the remaining connected edges, neglecting the complex dynamics of data packet loss, bandwidth constraints, and stochastic communication delays that occur in physical communication hardware during a disruption [21]. Future work should focus on integrating more sophisticated communication network emulators into the cyber-physical testbed to capture these intricate temporal dynamics. Additionally, exploring the integration of dynamic topology reconfiguration algorithms, where the intelligent control system can autonomously establish new communication links in response to detected failures, represents a promising avenue for enhancing operational resilience. Expanding the graph analysis framework to incorporate the economic implications of resilience and energy market dynamics during islanded operations will further broaden the applicability of this research in shaping the next generation of autonomous, self-healing renewable energy networks.

References

1. Ali, B.M.; Al-Musawi, T.J.; Mohammed, A.; Fakhruldeen, H.F.; Hanoon, T.M.; Khurramov, A.; Khalaf, D.H.; Algburi, S. Sustainable Strategies for Preventive Maintenance and Replacement in Photovoltaic Power Systems: Enhancing Reliability, Efficiency, and System Economy. Unconv. Resour. 2025, 6, 100170.

2. Gan, K.E.; Taikan, O.; Gan, T.Y.; Weis, T.; Yamazaki, D.; Schüttrumpf, H. Enhancing Renewable Energy Systems, Contributing to Sustainable Development Goals of United Nation and Building Resilience Against Climate Change Impacts. Energy Technol. 2023, 11, 2300275.

3. Li, Y.; Fan, J.; Cheng, X.; Jin, H.; Wang, Y.; Wei, F.; An, F.; Ma, S. New revolution for quality control of TCM in industry 4.0: Focus on artificial intelligence and bioinformatics. TrAC Trends Anal. Chem. 2024, 181, 118023.

4. Karthikeyan, M.; Manimegalai, D.; RajaGopal, K. Power Control of Hybrid Grid-Connected Renewable Energy System Using Machine Learning. Energy Rep. 2024, 11, 1079–1087.

5. Talaat, M.; Elkholy, M.H.; Alblawi, A.; Said, T. Artificial Intelligence Applications for Microgrids Integration and Management of Hybrid Renewable Energy Sources. Artif. Intell. Rev. 2023, 56, 10557–10611.

6. Damodaram, A.K.; Sangapu, S.C.; Tulasi, C. Recent Decade Global Trends in Renewable Energy and Investments—A Review. In Proceedings of the International E-Conference on Energy, Control, Computing and Electronic Systems (E-ICECCES), Kollam, India, 27–29 November, 2020.

7. Baz, A.; Patel, S.K. Efficiency-Aware Machine-Learning Driven Design of Solar Harvester for Renewable Energy Application. Results Eng. 2024, 24, 103050.

8. Hu, D.; Ye, Z.; Gao, Y.; Ye, Z.; Peng, Y.; Yu, N. Multi-Agent Deep Reinforcement Learning for Voltage Control with Coordinated Active and Reactive Power Optimization. IEEE Trans. Smart Grid 2022, 13, 4873–4886.

9. Kyriakou, E.G.; Kyriakou, D.G.; Kanellos, F.D.; Ipsakis, D. Integrated, Artificial-Intelligence-Based Power Management for Building Electrical Microgrids. IET Energy Syst. Integr. 2025, 7, e70015.

10. Lim, S.-H.; Yoon, S.-G. Dynamic DNR and Solar PV Smart Inverter Control Scheme Using Heterogeneous Multi-Agent Deep Reinforcement Learning. Energies 2022, 15, 9220.

11. Feng, C.; Liu, Y.; Zhang, J. A Taxonomical Review on Recent Artificial Intelligence Applications to PV Integration into Power Grids. Int. J. Electr. Power Energy Syst. 2021, 132, 107176.

12. Areola, R.I.; Adebiyi, A.A.; Moloi, K. Artificial Intelligence for Optimizing Solar Power Systems with Integrated Storage: A Critical Review of Techniques, Challenges, and Emerging Trends. Electricity 2025, 6, 60.

13. Flesch, M.V.; de Bragança Pereira, C.A.; Saraiva, E.F. A Bayesian Approach for Modeling and Forecasting Solar Photovoltaic Power Generation. Entropy 2024, 26, 824.

14. Esram, T.; Chapman, P.L. Comparison of Photovoltaic Array Maximum Power Point Tracking Techniques. IEEE Trans. Energy Convers. 2007, 22, 439–449.

15. Lee, S.; Xie, L.; Choi, D.-H. Privacy-Preserving Energy Management of a Shared Energy Storage System for Smart Buildings: A Federated Deep Reinforcement Learning Approach. Sensors 2021, 21, 4898.

16. Khan, K.; Rashid, S.; Mansoor, M.; Khan, A.; Raza, H.; Zafar, M.H.; Akhtar, N. Data-Driven Green Energy Extraction: Machine Learning-Based MPPT Control with Efficient Fault Detection Method for the Hybrid PV-TEG System. Energy Rep. 2023, 9, 3604–3623.

17. Younas, U.; Afsin Kulaksiz, A.; Ali, Z. Deep Learning Stack LSTM Based MPPT Control of Dual Stage 100 kWp Grid-Tied Solar PV System. IEEE

Access 2024, 12, 77555–77574.

18. Femia, N.; Petrone, G.; Spagnuolo, G.; Vitelli, M. Optimization of Perturb and Observe Maximum Power Point Tracking Method. IEEE Trans. Power Electron. 2005, 20, 963–973.

19. Ivanov, D.; Dolgui, A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Prod. Plan. Control 2021, 32, 775–788.

20. Huang, P.; Lovati, M.; Zhang, X.; Bales, C. A Coordinated Control to Improve Performance for a Building Cluster with Energy Storage, Electric Vehicles, and Energy Sharing Considered. Appl. Energy 2020, 268, 114983.

21. Katsaliaki, K.; Galetsi, P.; Kumar, S. Supply chain disruptions and resilience: A major review and future research agenda. Ann. Oper. Res. 2022, 319, 965–1002.