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AI-Driven Microgrids: A Review of Enabling Technologies and Future Prospects

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Abstract: Microgrids represent a transformative paradigm in modern energy systems, enabling localized, efficient, and resilient energy management. With the growing urgency to decarbonize power systems and accommodate the increasing penetration of renewable energy sources, microgrids have emerged as a practical solution for integrating distributed energy resources (DERs), such as solar photovoltaics, wind turbines, and energy storage systems. Their ability to operate in grid-connected and islanded modes enhances energy reliability and autonomy, particularly in remote or disaster-prone areas. However, microgrids face significant operational challenges, including the intermittency of renewables, load uncertainty, and communication latency. To address these issues, artificial intelligence (AI) technologies have become increasingly central to microgrid optimization. This review critically examines the role of AI, including Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), in enhancing key functions such as load forecasting, energy scheduling, fault detection, and cybersecurity. AI facilitates real-time decision-making and adaptive control through intelligent data-driven approaches, thereby improving microgrid efficiency and resilience. The paper also discusses microgrids' structural and functional design and highlights the need for interdisciplinary collaboration between power system engineers, data scientists, and control experts. It concludes by emphasizing the importance of translating AI models into practical applications to accelerate the deployment of innovative, low carbon microgrid infrastructures.

Keywords: Microgrids, Renewable Energy, Artificial Intelligence, Machine Learning, Deep Learning

I. Introduction

Microgrids have emerged as a significant innovation in the evolution of energy systems, driven by the increasing demand for sustainable and resilient energy solutions. The design of microgrids has evolved considerably, offering diverse options that cater to various local contexts and energy needs. This evolution is characterized by integrating renewable energy sources, which play a crucial role in enhancing the sustainability of microgrid systems. The literature highlights the necessity for strategic support to guide stakeholders in selecting appropriate design options tailored to their specific use cases, as the extensive design possibilities can complicate decision-making processes (Gerlach et al., 2024). Furthermore, integrating microgrids into local power systems has been recognized as vital to achieving energy independence and reliability, particularly in regions with limited access to centralized power infrastructure (Yadav et al., 2025). The socioeconomic implications of microgrid deployment are profound, as they can stimulate local economies and promote energy equity by providing access to clean energy solutions (Zhang et al., 2025). Additionally, the increasing adoption of digital and telecommunication technologies has the potential to enhance the effectiveness of microgrids. However, it also raises concerns about cybersecurity vulnerabilities that could threaten the reliability of these systems (Ahmed et al., 2025).

Microgrids are pivotal in transforming energy structure, particularly in addressing energy poverty in underserved communities. Microgrids can significantly enhance socio-economic outcomes by facilitating the adoption of renewable energy technologies, including improved livelihoods and increased access to essential services such as education and healthcare (Tamasiga et al., 2024).

The systematic review conducted by (Akter et al., 2024) emphasizes that renewable energy microgrids not only alleviate energy poverty but also contribute to broader sustainability goals, aligning with the United Nations Sustainable Development Goals (SDGs). The effectiveness of microgrids in promoting renewable energy adoption is underscored by their ability to provide reliable and affordable energy solutions, which are crucial for economic growth and development in marginalized areas (Gerlach et al., 2024). Moreover, integrating microgrids into local energy systems fosters resilience against external shocks, enhancing community stability and sustainability (Zhang et al., 2025).

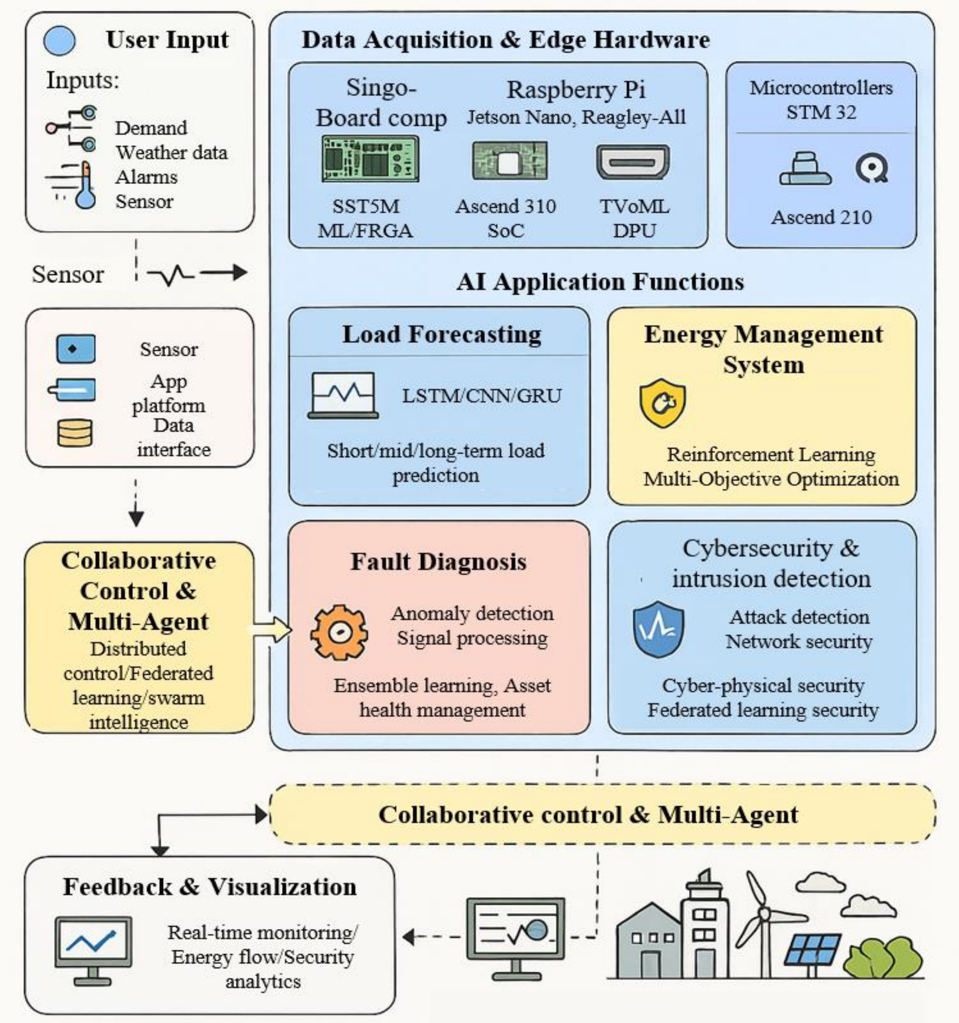

Figure 1: Technical Roadmap of AI-Driven Microgrid Applications

Integrating AI into microgrid operations presents significant opportunities for optimizing energy management systems. AI technologies can enhance the efficiency and reliability of microgrids by improving load forecasting and energy management strategies (Duan, 2023). For instance, (Wazirali et al., 2023) discuss applying machine learning techniques in predicting renewable energy generation and load demand, which is essential for effective system management and operation. AI can lead to more accurate forecasts, thereby reducing operational risks and improving the stability of microgrid systems (Ma et al., 2025). Furthermore, the potential of AI extends to optimizing the control of distributed energy resources, enabling microgrids to respond dynamically to changing energy demands and supply conditions (Hadi et al., 2025). As the energy landscape continues to evolve, the role of AI in microgrid technology will be crucial in facilitating the transition towards more sustainable and resilient energy systems (Ern & Tavalaei, 2025). Moreover, the increasing complexity of energy systems necessitates advanced AI solutions to manage the interactions between various components effectively, ensuring that microgrids can adapt to operational challenges and external threats, such as cyber-attacks (Ahmed et al., 2025).

This review aims to comprehensively analyze the enabling technologies and future prospects of AI-driven microgrids. The objectives include examining the current state of microgrid technologies, exploring the integration of AI in optimizing microgrid operations, and identifying the interdisciplinary approaches necessary for advancing these technologies. The review structure is organized into several key sections, each addressing different aspects of microgrid development and AI applications. The significance of this interdisciplinary approach is emphasized, as it fosters collaboration between various fields, including engineering, economics, and environmental science, to address the complex challenges associated with microgrid implementation and operation (S. Pan et al., 2025). By synthesizing insights from recent literature, this review aims to contribute to the ongoing discourse on the future of microgrids and the transformative potential of AI in the energy sector (Zahraoui et al., 2025). The comprehensive technical roadmap of AI application and edge technology in microgrids is shown in Figure 1.

This review systematically examined 61 peer-reviewed articles published between 2013 and 2025, covering various topics related to AI applications in microgrids. The literature was identified through keyword-based searches in leading academic databases, including IEEE Xplore, Scopus, ScienceDirect, and Web of Science. The search terms included combinations of "microgrid," "artificial intelligence," "machine learning," "deep learning," "load forecasting," "fault diagnosis," and "renewable energy." Articles were selected based on relevance, citation influence, and methodological clarity. This approach ensures a representative cross-section of state-of-the-art research while reflecting recent advancements in intelligent microgrid systems.

Structure and Operational Characteristics of Microgrids

Structure of microgrid: storage system, main control system, communication system

A well-functioning microgrid relies on the coordinated integration of its core subsystems: the storage infrastructure, the main control system, and the communication network, which is shown in Figure 2. The source-load-storage configuration forms the physical and functional backbone of a microgrid. By combining renewable energy sources, such as solar photovoltaic panels and wind turbines with energy storage systems like batteries, microgrids can buffer the volatility of renewables and respond to time-varying demand. This architecture enables short-term energy autonomy and supports long-term sustainability objectives. (Ma et al., 2025) reported a 64.1% renewable penetration through a hybrid renewable energy system (HRES), highlighting the efficacy of such designs. However, it is important to recognize that high reliance on storage technologies may introduce new challenges related to lifecycle cost, degradation rates, and disposal of battery materials areas often underexplored in techno-economic feasibility studies.

The main control system serves as the "brain" of the microgrid, maintaining equilibrium between supply and demand and optimizing operational decisions. Advanced control algorithms often powered by artificial intelligence and multi-objective optimization enable predictive and adaptive responses to dynamic conditions. For example, (Liu et al., 2025) demonstrated that such systems can simultaneously reduce operational costs and environmental impacts. Nonetheless, the increasing algorithmic complexity raises concerns about transparency and decision interpretability, particularly in safety-critical applications. While intelligent protection systems, such as those proposed by (Satpathy et al., 2025) enhance fault detection and system resilience, their dependence on high-quality training data and continuous calibration remains vulnerable, especially in low-data or rapidly evolving environments.

The communication system underpins the interoperability of all microgrid components by enabling real-time monitoring, data exchange, and coordinated control. Its importance is magnified in distributed and autonomous settings, where timely information flow is crucial for system stability and faulty isolation. (Zhang et al., 2025) emphasize that robust, secure, and low-latency communication infrastructures are foundational for cyber-physical microgrid resilience. However, as communication layers become complex, they also become potential entry points for cyberattacks, data corruption, and system synchronization errors. Moreover, communication delays, especially in wireless and cloud-based architectures, can impair system responsiveness and limit the effectiveness of time-sensitive control strategies. The work by (S. Pan et al., 2025) on power quality disturbance detection underscores the importance of diagnostic accuracy. Yet, real-world deployments may face signal noise, data loss, and sensor malfunctions, all of which warrant robust fault-tolerant designs.

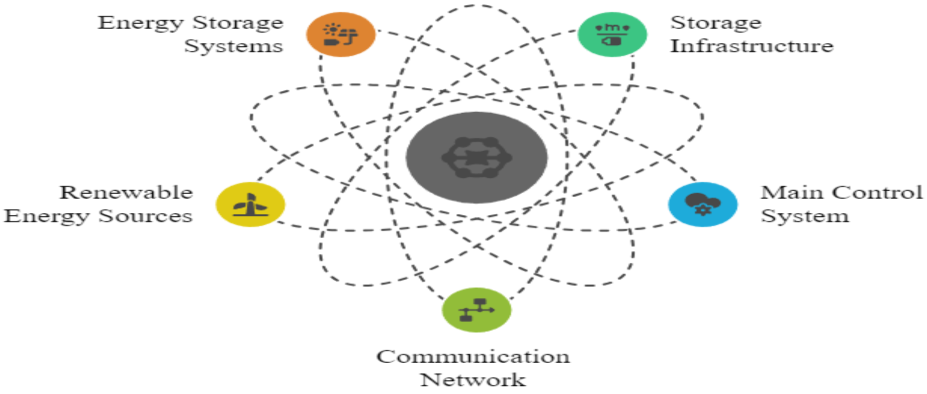

Figure 2: Components of a Microgrid

While integrating storage, control, and communication systems forms the foundation of microgrid architecture, their implementation must be critically evaluated beyond idealized simulation environments. Future research should focus on enhancing individual subsystems and ensuring their scalability, interoperability, and resilience under real-world constraints. Cross-disciplinary efforts involving energy engineering, data science, and cybersecurity are essential to bridge the gap between theoretical potential and practical deployment.

Operating modes: grid connected, off grid, hybrid

Microgrids are characterized by their flexible operational configurations, which can be broadly categorized into grid-connected, off-grid, and hybrid modes, which is shown in Figure 3. Each mode presents unique advantages and challenges, and local energy demand profiles, resource availability, infrastructure conditions, and resilience requirements often determine the configuration choice.

In the grid-connected mode, microgrids are synchronized with the main utility grid, allowing bi-directional power flow. This operational mode enables microgrids to draw electricity from the central grid during peak demand periods and inject excess energy generated often from renewables back into the grid. Such an arrangement not only improves energy reliability and economic efficiency but also enhances the overall stability of the larger power system by acting as a distributed support unit. As highlighted by (Yadav et al., 2025), grid-connected microgrids play a crucial role in facilitating the integration of distributed generation into existing grid infrastructure, thereby supporting decarbonization and decentralization objectives. However, this mode depends on the stability of the central grid and may expose the microgrid to upstream disturbances, underscoring the need for robust synchronization and protection mechanisms.

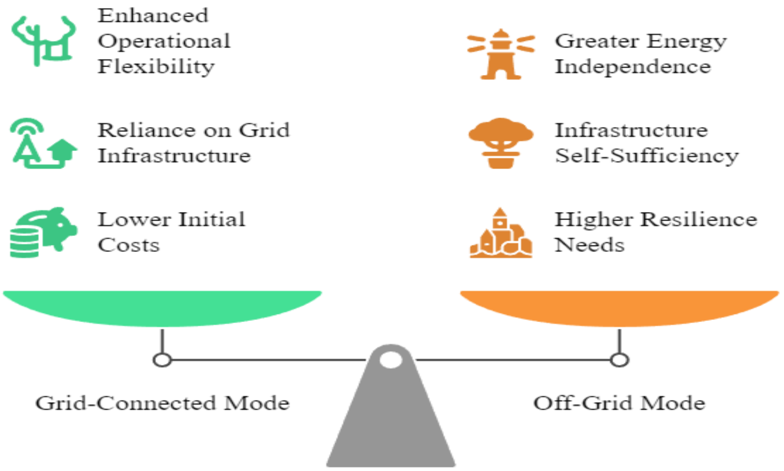

Figure 3: Comparing Microgrid Operational Modes

Transitioning from reliance on the central grid, off-grid (islanded) microgrids operate autonomously. They are especially valuable in remote, rural, or disaster-affected regions with limited or non-existent grid access. Off-grid microgrids enhance energy independence and service continuity by leveraging localized energy resources and storage systems. However, the absence of grid backup presents notable challenges, particularly in maintaining supply stability amidst the intermittency of renewable sources. This demands highly adaptive and predictive energy management strategies to balance generation, storage, and load. As (J. Zhao et al., 2025) discuss, compatibility centre (CC) microgrids designed with flexible and schedulable loads demonstrate potential in mitigating the variability of photovoltaic (PV) generation, offering a promising approach to off-grid reliability. Nevertheless, technical barriers like load forecasting uncertainty and limited storage capacity constrain off-grid scalability and economic viability.

Hybrid microgrids, which integrate grid-connected and off-grid operations features, offer an optimal balance between reliability and autonomy. These systems can seamlessly switch between operational modes based on real-time grid conditions, local generation output, and demand requirements. This adaptability makes hybrid configurations suitable for urban-rural fringe areas, industrial parks, and emergency-critical infrastructures. Despite their advantages, hybrid microgrids introduce significant integration complexities. Coordinating multiple energy sources, managing mode transitions, and ensuring operational continuity without performance degradation demand advanced control algorithms and real-time communication infrastructures. (Liu et al., 2025) underscore the importance of developing multi-objective scheduling models and intelligent controllers to manage such complexities, making hybrid microgrids a frontier topic in microgrid research and development.

In summary, while each operating mode offers distinct benefits tailored to specific application contexts, their effectiveness is closely tied to technological maturity, control sophistication, and system interoperability. Understanding and optimizing these operational paradigms are critical for successfully deploying resilient, flexible, intelligent microgrid systems.

Key challenges: volatility, uncertainty, scheduling optimization, communication latency

Despite the growing potential of microgrids in supporting sustainable and resilient energy systems, several persistent challenges continue to impede their optimal performance and large-scale deployment. Among these, the volatility of renewable energy sources remains one of the most pressing technical concerns, which is shown in Figure 4. Due to the intermittent and non-dispatchable nature of solar and wind energy, fluctuations in power generation can lead to significant supply-demand imbalances. This unpredictability necessitates implementing advanced scheduling and control strategies to ensure system stability. (Giri et al., 2024) emphasize the importance of intelligent protection schemes that dynamically respond to fluctuating input, safeguarding the system under variable operating conditions. However, the real-time coordination of distributed energy resources remains a complex problem, particularly in decentralized architectures.

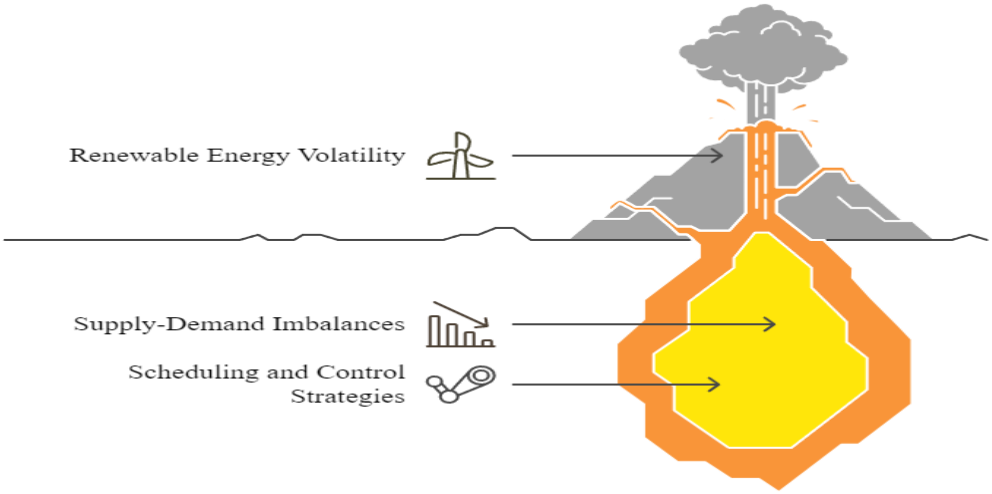

Figure 4: Challenges faced by Microgrids

Closely related to volatility is the challenge of load forecasting uncertainty. Accurate and timely predictions of electricity demand are critical for proactive energy dispatch, storage utilization, and resource allocation. Inaccurate forecasting not only results in inefficiencies but may also compromise the reliability of microgrid operations. (Y. Zhao et al., 2025a) propose an adaptive load forecasting model that balances prediction accuracy with computational efficiency, underscoring the importance of tailoring forecasting techniques to microgrid-specific temporal and spatial profiles. Beyond technical uncertainties, broader political and regulatory uncertainties further complicate the deployment and scaling of microgrids. As noted by (Hess, 2024), energy governance structures and policy inertia can hinder investment and innovation, making it imperative to align technological development with institutional reform in the context of sustainability transitions.

Another crucial dimension impacting microgrid performance is communication latency. As modern microgrids increasingly rely on distributed intelligence and real-time data exchange, delays in communication networks can lead to inefficiencies in control actions, especially during fault events or rapid demand shifts. Effective communication is, therefore, essential for timely system responses and coordinated operations. (Akter et al., 2024) advocate the integration of advanced communication protocols and heuristic optimization mechanisms to reduce latency and improve network responsiveness. However, the increasing reliance on digital infrastructure also raises concerns about system cyber-resilience, further reinforcing the need for robust, low-latency, and secure communication frameworks.

These challenges, ranging from technical volatility and prediction uncertainty to system coordination and communication latency, underscore the multi-dimensional complexity of microgrid management. Addressing them requires a concerted effort across disciplines, combining advancements in artificial intelligence, power electronics, control theory, and communication engineering. As microgrids move from experimental pilots to widespread adoption, future research must prioritize scalable, interoperable, and adaptive solutions to ensure that microgrids fulfil their promise as intelligent building blocks of next-generation energy systems.

Microgrid applications

Microgrids are localized energy systems capable of operating independently or in conjunction with the larger grid, providing a variety of applications that enhance energy reliability, resilience, and sustainability. They are increasingly recognized as essential infrastructure for residential, commercial, and industrial sectors, facilitating energy management strategies such as peak shaving, black start capabilities, and frequency control. Microgrids are positioned at the forefront of the transition towards cleaner and more resilient energy systems by offering solutions to modern energy challenges.

One of the main applications of microgrids is peak shaving, which is a strategy to reduce electricity demand during periods of high electricity consumption, as shown in Table 1. By employing energy storage systems and on-site generation, microgrids can help manage overall demand and eliminate short-term demand spikes, lowering utility costs and minimizing reliance on expensive peakier plants (Yang et al., 2025).

Table 1 Peak Shaving / Load Levelling

Objective	**Enabling Assets**	**Representative Control Methods**	**Typical Challenges**	**Delivered Value**
Lower the instantaneous demand peak and flatten the daily load curve	Battery Energy Storage System Distributed PV / Wind Flexible loads (HVAC, EV charging)	State of Energy constrained Model Predictive Control for BESS dispatch; stochastic scheduling that co-optimizes peak-shaving and tariff arbitrage	Forecast uncertainty may cause over-discharge / over-charge; valley filling can unintentionally raise the base load	Cuts demand charges & transformer sizing; Defers network reinforcements; Increases local RES utilization
Underlying Mechanisms				
Day-ahead & intra-day	integrates 15 min–1 h load forecasts, enforcing BESS SoE and cycle-life constraints			

optimization	
Price-difference coupling	when Time-of-Use spread exceeds a threshold (≈ 0.18 USD kWh^{-1}), the optimizer favors “charge-low / discharge-high”; otherwise, it limits action to critical spike periods
Co-ordinated flexible load	shiftable and interruptible loads provide an extra 5–15 % peak reduction
Edge/Fog execution	minimizes latency and preserves privacy by pushing inference to local controllers

Microgrids can provide basic black start functionality, enabling them to independently restore power after a complete grid failure, as shown in Table 2. This function is critical for ensuring vital services, such as hospitals and emergency response centers, can maintain operations during and after outages. Microgrids can disconnect from the main grid during disturbances and utilize their generation resources to bring systems back online (Zhang et al., 2025).

Table 2 Peak Shaving / Load Levelling

Black-out Recovery Phase	**Key Technology Elements**	**Performance Targets**
Islanding detection → DC link energization → Synchronous re-connection	Rate-of-change-of-frequency / residual-voltage (ROCOF/RV) logic for instant islanding <50 ms; BESS or diesel genset acting as a grid-forming voltage source; Virtual-Synchronous-Generator (VSG) control for synthetic inertia; Synch-check relay (ANSI 25) with fast Phase-Locked-Loop	Restore bus voltage to ±5 % and frequency to 49.5–50.5 Hz (50 Hz grids) within 5 min; close main-tie breaker with phase error < 10° in <200 ms
Stepwise Restoration Logic		
BESS	energizes the dead bus at 1.05 pu to absorb inrush current.	
Segmented load-pickup	critical loads first, then non-critical feeders in stages to avoid large surges.	
Smooth resynchronization	a sliding-mode PLL tracks the upstream grid; once $\Delta f < 0.1$ Hz and $\Delta\theta < 10°$, the breaker closes, after which the converter shifts from voltage-source to current-source to prevent back-feed.	

Frequency control is another crucial application of microgrids, enabling them to stabilize the grid by providing ancillary services, as shown in Table 3. Microgrids can help regulate frequency by managing the output of distributed generation resources and energy storage systems to match the grid's instantaneous demand (Tahmeed et al., 2025). This ability is critical in preventing frequency deviations that can lead to outages or equipment damage.

Table 3 Frequency Regulation

Control Layer	**Response Time**	**Actuators**	**Typical Strategy**
Primary	100 ms – 10 s	VSG inverter droop	P–f droop with 1–5 % slope, dynamically tuned by SoE
Secondary	10 s – 5 min	EMS + multiple inverters	Distributed consensus-based AGC (restores Δf to 0)
Tertiary / Economic	≥ 5 min	DSO / aggregator	Multi-objective optimization with carbon cost & market prices
Key Insights			
Low-inertia islands (< 2 s equivalent inertia) rely on synthetic inertia embedded in VSG/VSM firmware.			
Fixed droop lowers steady-state accuracy; an upper-layer distributed event-triggered droop can suppress communication traffic while keeping Δf within ±0.1 Hz.			

Overview of AI Technology and its Adaptability to Microgrids

Briefly describe the main AI methods

AI encompasses diverse computational methodologies that have demonstrated growing utility in optimizing microgrid operations.

Among these, Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and evolutionary algorithms have emerged as the most impactful techniques, each offering distinct advantages tailored to the complex, data-driven nature of modern energy systems, which is shown in Figure 5.

At the foundational level, Machine Learning (ML) enables systems to learn patterns from historical data and refine their predictive or control performance over time without being explicitly programmed. Within microgrids, ML models are widely applied to tasks such as load forecasting and energy management, where the ability to anticipate demand and adjust resource allocation is critical. For example, (Wazirali et al., 2023) demonstrated the effectiveness of ML-based models in accurately predicting energy consumption patterns across varying temporal horizons. To further enhance forecasting accuracy, hybrid approaches such as the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines the adaptive learning of Artificial Neural Networks (ANNs) with the linguistic handling of Fuzzy Logic have shown improved performance in short-term load forecasting (Ghenai et al., 2022).

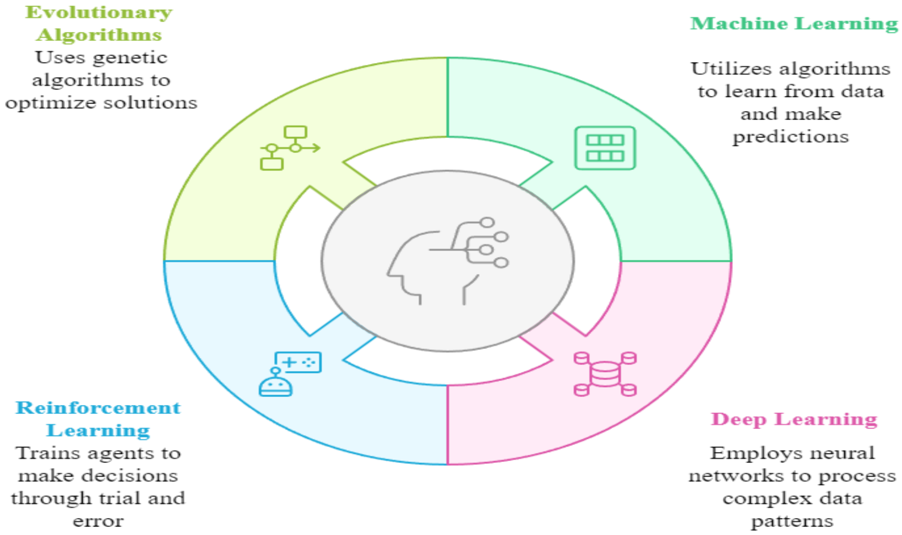

Figure 5: AI Techniques in Microgrid Optimization

Building upon ML principles, Deep Learning (DL) leverages multilayer neural networks to model highly nonlinear and hierarchical data relationships. DL methods have shown remarkable performance in handling complex sensory inputs and unstructured data, which are increasingly common in microgrid applications. For instance, DL has been effectively employed in fault detection for photovoltaic systems, enabling high-accuracy classification of operational anomalies (Ramadan et al., 2024). More advanced architectures, such as the Swin-Residual Network (SwResNET), have been introduced for identifying power quality disturbances (PQDs) in noisy environments, achieving superior classification results (Küçüker et al., 2025). Additionally, signal processing-enhanced DL models, such as those incorporating variational mode decomposition (VMD) and improved wavelet thresholding, further contribute to robust PQD detection under adverse conditions (S. Li et al., 2025).

While ML and DL focus on learning from data, Reinforcement Learning (RL) introduces a decision-making paradigm based on dynamic interaction with the environment. RL agents learn optimal control policies by receiving feedback through rewards or penalties, making it highly suitable for real-time energy management in dynamic and uncertain microgrid environments. (Zhang et al., 2025) underscore RL's value in tasks such as distributed energy resource control and adaptive load scheduling, where responsiveness to fluctuating conditions is essential.

Complementing these data-driven approaches, evolutionary algorithms inspired by the principles of natural selection offer powerful tools for solving multi-objective optimization problems. These algorithms have been employed in microgrids to determine optimal configurations of energy resources and storage systems while balancing competing criteria such as cost, reliability, and environmental impact. (Zahraoui et al., 2025) demonstrated the effectiveness of genetic algorithms in optimizing active and reactive power flows, particularly in smart grid environments with high renewable integration.

In summary, each AI methodology contributes uniquely to microgrid intelligence: ML and DL excel in prediction and pattern recognition, RL in real-time control and adaptation, and evolutionary algorithms in optimization and planning. Together, these techniques form a comprehensive toolkit for enhancing AI-driven microgrids' efficiency, resilience, and autonomy. Future developments will likely focus on hybridizing these methods and embedding them within robust, interpretable, and scalable frameworks for real-world deployment.

Adaptability and advantages of various AI methods in microgrids

The adaptability of AI methods to microgrid operations is demonstrated by their wide-ranging applications in areas such as energy load management, fault diagnosis, and predictive maintenance. Among them, Machine Learning (ML) techniques have proven particularly effective in short-term load forecasting (STLF), enabling microgrid operators to anticipate demand fluctuations and optimize generation and storage schedules accordingly. As (Giri et al., 2024) note, such forecasting capabilities are instrumental in reducing reliance on standby generation sources, improving resource allocation, and enhancing overall energy efficiency.

Building upon ML, Deep Learning (DL) techniques offer enhanced real-time fault detection and classification capabilities. DL models can swiftly and accurately identify abnormal conditions by analysing complex, high-dimensional sensor data, significantly minimizing unplanned outages and maintenance costs. For example, (Hadi et al., 2025) demonstrated the application of DL in intelligent fault diagnosis systems, while (Hamza et al., 2025) emphasized its role in predictive maintenance, wherein potential failures are detected proactively. Furthermore, advanced hybrid architectures such as the Stockwell transform-grouped convolution Squeeze-and-Excitation Residual Network (ST-GSResNet) have shown high accuracy in power quality disturbance (PQD) classification, particularly in noisy and variable operating environments (S. Pan et al., 2025).

Complementing the above, one of the most significant advantages of AI technologies lies in their real-time data processing and adaptive control capabilities. Microgrids, especially those heavily reliant on renewable energy sources, require constant generation, storage, and distribution strategies adjustment in response to volatile supply conditions. AI algorithms can process incoming data streams and optimize energy distribution in near real-time. This functionality not only improves system responsiveness but also facilitates the seamless integration of distributed energy resources (DERs) into the microgrid architecture (Ma et al., 2025).

In conclusion, integrating AI methods into microgrid systems brings substantial operational benefits. These include improved forecast accuracy, enhanced diagnostic precision, predictive maintenance, and adaptive energy control. Collectively, these advantages contribute to developing more intelligent, efficient, and resilient microgrids, positioning AI as a key enabler in the transition toward next-generation decentralized energy infrastructures.

The interpretability, real-time performance, and stability issues of the model

While AI models have demonstrated substantial potential in enhancing microgrid intelligence, several core limitations hinder their practical deployment. Among them, issues surrounding model interpretability, real-time responsiveness, and operational stability are particularly critical, especially in safety-sensitive and high-reliability environments.

First, interpretability remains a central concern for stakeholders aiming to trust and validate AI-driven decisions. In applications such as fault diagnosis and energy dispatch, understanding how and why a model arrives at specific outputs is essential for operational transparency and regulatory compliance. However, many advanced models especially those based on deep learning operate as complex "black boxes" with limited explainability. As (Hamza et al., 2025) observe, this lack of transparency can undermine stakeholder confidence, hinder fault traceability, and complicate system debugging, limiting AI's broader acceptance in mission-critical microgrid applications.

Closely linked to interpretability is the issue of real-time performance. Microgrid systems require rapid and accurate responses to dynamically changing conditions, such as load fluctuations, renewable energy variability, and fault events. AI models must process large volumes of sensor data in real time and generate actionable insights with minimal delay. (Zhang et al., 2025) highlight that latency in decision-making caused by excessive computational demands or inadequate algorithm optimization can result in suboptimal control actions or, worse, system instability and failure. Hence, balancing model complexity with execution speed is a key technical challenge.

Beyond interpretability and speed, stability in dynamic environments poses another major challenge. Microgrids are inherently non-stationary systems, subject to variable generation inputs and consumption patterns (Tavalaei et al., 2017). Ensuring that AI models maintain consistent performance under these fluctuating conditions is vital for maintaining system resilience. (Hamza et al., 2025) point out that models trained under static or narrow operating conditions may degrade when deployed in real-world scenarios, emphasizing the need for robust training methodologies, domain adaptation, and continuous learning frameworks.

In summary, while AI technologies offer transformative capabilities for microgrid optimization, their successful implementation depends on resolving key limitations in interpretability, real-time responsiveness, and stability. Future research must prioritize the development of explainable AI (XAI), lightweight model architectures, and adaptive control mechanisms to ensure that intelligent systems perform well in theory and deliver consistent and transparent outcomes in real-world energy applications.

AI Applications in Key Microgrid Problems

Load forecasting

Accurate load forecasting is a critical component in the operation of microgrids, particularly for short-term predictions that directly influence energy scheduling, storage control, and grid stability. However, the inherent nonlinearity and stochastic nature of load patterns, especially when influenced by environmental and behavioural factors, render traditional statistical methods insufficient, as shown in Figure 6. These conventional techniques often fail to capture the complex interactions between meteorological variables and energy consumption trends, leading to suboptimal performance under volatile operating conditions (Yeo et al., 2024).

Recent studies have increasingly adopted AI-based forecasting models that offer improved adaptability and accuracy to overcome these limitations. For example, (Jahani et al., 2023) proposed a fixed SPM-LSTM framework that effectively models the nonlinear correlation between meteorological parameters and load data. The model achieved a high coefficient of determination ($R^2 = 0.951$), significantly outperforming conventional approaches such as standard LSTM and CNN-GA models. This highlights the value of integrating structured preprocessing modules with deep learning architectures to enhance prediction robustness. The Hybrid CEEMDAN SSA BiGRU Attention Model proposed by (Lin, Yeo, et al., 2024) has an accuracy of 90.2% for long-term load forecasting, overcoming the characteristics of uncertainty and volatility.

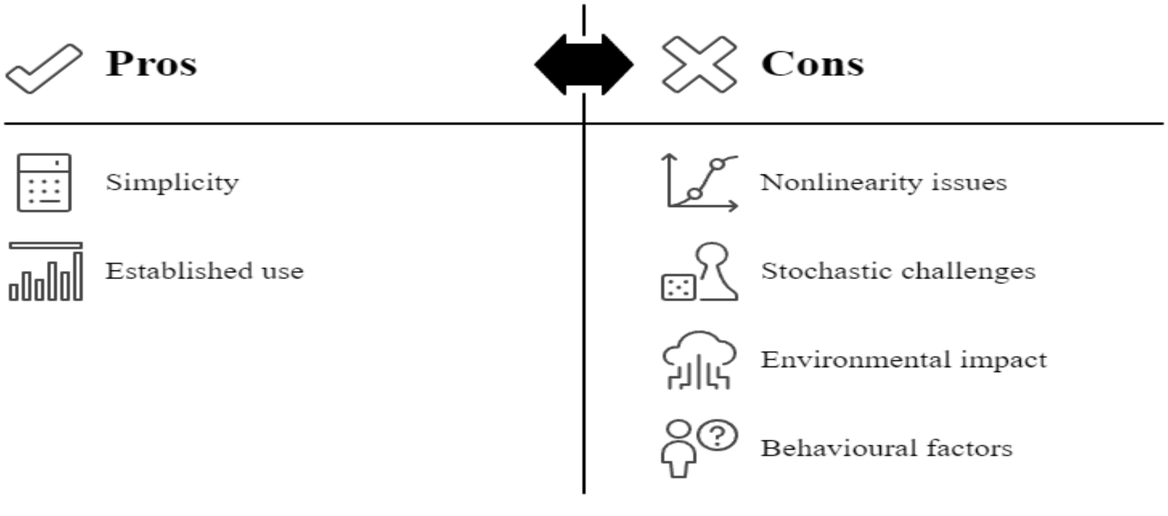

Figure 6: Traditional Forecasting Methods

Building on this foundation, systematic reviews by (Wazirali et al., 2023) have underscored the comparative advantages of machine learning (ML) and deep learning (DL) techniques across different temporal horizons. Their evaluation categorized AI methodologies based on their performance, scalability, and interpretability, offering guidance for model selection in diverse microgrid contexts. Notably, while ML models are typically faster and more interpretable, DL models tend to excel in capturing high-dimensional dependencies, especially when trained on large-scale sensor datasets.

In addressing the practical deployment of these models, (J. Zhao et al., 2025) introduced an adaptive load forecasting model that seeks to balance prediction accuracy with computational efficiency. Their approach involves a customized AI algorithm tailored to the operational characteristics of specific microgrid types, such as residential clusters, industrial zones, or isolated island systems. Validation on real-world datasets confirmed its effectiveness, reinforcing the importance of context-aware algorithm design in achieving reliable load forecasts.

Nonetheless, several challenges remain. One key difficulty is extracting meaningful data correlations, particularly when dealing with noisy, incomplete, or heterogeneous input sources. Moreover, external environmental uncertainties, such as sudden weather changes or atypical load behaviours, affect forecasting reliability. While AI provides a powerful framework to mitigate these issues, its success ultimately hinges on further refinement of model generalization, data preprocessing, and interpretability mechanisms.

Energy management system

Integrating AI into energy management systems (EMS) in microgrids has emerged as a transformative strategy for optimizing energy consumption, generation, and distribution, which is shown in Figure 7. By enabling data-driven decision-making, AI empowers EMS to respond dynamically to changing operating conditions, improving operational efficiency and energy reliability. Unlike conventional rule-based control systems, AI-driven EMS architecture can learn from historical data and adapt to the non-linear and uncertain nature of modern power systems.

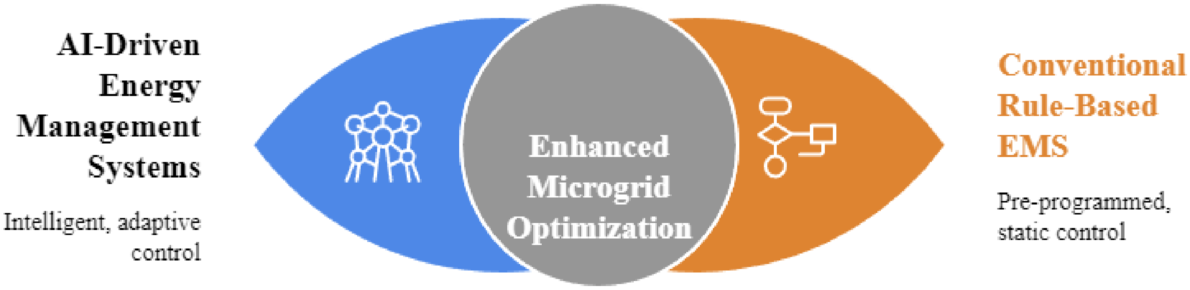

Figure 7: The Synergy of AI and EMS in Microgrids

One of the key advancements in this domain is the development of hybrid forecasting models that support long-term energy planning. (Ma et al., 2025) proposed a composite model integrating Long Short-Term Memory (LSTM) networks with eXtreme Gradient Boosting (XGBoost) to perform electricity demand forecasting. This combination leverages the temporal learning capability of LSTM and the high-precision gradient optimization of XGBoost, yielding improved prediction accuracy. Accurate long-term forecasting is crucial for EMS to manage resources efficiently, particularly in systems with high shares of renewable generation and variable demand profiles.

Building upon this predictive capacity, researchers have further explored AI's role in developing intelligent control strategies. (Hadi et al., 2025) highlighted the application of AI techniques for real-time energy scheduling, voltage regulation, and adaptive control in microgrids. Their findings stress that AI-enhanced EMS can effectively manage the operational complexity of integrating distributed energy resources (DERs), ensuring energy balance and quality even under fluctuating conditions. This adaptability is essential for modern EMS to maintain grid stability while accommodating renewable intermittency.

In addition to prediction and control, optimizing power flow, both active and reactive, is another critical function of EMS. (Zahraoui et al., 2025) introduced a genetic algorithm-based optimization approach that simultaneously considers active power dispatch and reactive power compensation. Their methodology addresses the multifaceted operational goals of EMS, such as minimizing line losses, enhancing voltage stability, and reducing operational costs. This underscores AI's automation and multi-objective system optimization capability, which is vital for ensuring performance in complex microgrid configurations.

Moreover, the evolution of EMS must be accompanied by enhanced protective and fault-handling capabilities to safeguard system integrity. (Satpathy et al., 2025) discussed integrating advanced protection devices into the AI-enabled EMS framework. These devices, equipped with real-time diagnostics and self-healing features, ensure rapid fault detection and system recovery, reinforcing the resilience and continuity of microgrid operations. Their synergy with AI-based energy management underscores a holistic approach to smart grid design where forecasting, optimization, control, and protection are seamlessly integrated.

In summary, AI applications in EMS significantly expand microgrids' functional scope and intelligence. AI enhances system adaptability, efficiency, and resilience, from forecasting and control to optimization and protection. As microgrids continue to evolve in scale and complexity, the role of AI in next-generation EMS will become increasingly indispensable for enabling secure, sustainable, and autonomous energy systems.

Figure 8: AI-Driven Microgrid Management Cycle

Fault diagnosis and asset management

AI application in fault diagnosis and asset management plays an increasingly vital role in improving the reliability, safety, and operational efficiency of microgrid systems. As microgrids become more complex with the integration of diverse energy sources and advanced control systems, the need for intelligent fault detection and proactive asset maintenance has grown correspondingly, which is shown in Figure 8.

A notable contribution in this domain is presented by (Giri et al., 2024), who proposed an intelligent protection technique based on Discrete Wavelet Transform (DWT) and an Ensemble Bagged Decision Tree (EBDT) classifier. Their method achieved 100% fault classification accuracy under varying operating scenarios, demonstrating the effectiveness of combining advanced signal processing with machine learning for high-precision fault identification. This approach underscores the capability of AI models to extract meaningful diagnostic features from transient signals, offering a significant improvement over conventional protection schemes.

Extending this line of research, (Ramadan et al., 2024) focused on the domain of photovoltaic (PV) systems, an increasingly common component of renewable-based microgrids. They introduced a deep learning model leveraging a Vision Transformer (ViT) to perform automatic fault detection using infrared thermography images. Achieving a diagnostic accuracy of 98.23%, their results emphasize the potential of AI not only in detection but also in the broader scope of asset condition monitoring, reducing unplanned outages and optimizing maintenance schedules.

Furthermore, integrating ensemble learning algorithms and feature extraction techniques has proven to be a powerful strategy for enhancing diagnostic performance. Reaffirming earlier findings, (Giri et al., 2024) demonstrated that the synergy between DWT-based signal decomposition and ensemble classifiers enables robust and scalable fault analysis, particularly in distributed microgrid environments. Complementing this, (S. Li et al., 2025) proposed intelligent diagnostic methods for detecting power quality disturbances (PQDs), which are critical indicators of underlying asset degradation and system instability. Their work exemplifies the importance of high-fidelity anomaly detection in maintaining long-term asset health and power quality.

These developments highlight AI's growing utility in tackling the dual challenges of fault resilience and asset longevity in microgrid operations. By enabling early fault identification, real-time condition monitoring, and predictive maintenance planning, AI-based approaches support the transition from reactive to proactive asset management. This reduces system downtime and contributes to more cost-effective and resilient energy infrastructures.

Power quality disturbance detection

Maintaining power quality is essential for microgrid systems' safe and stable operation, particularly as they increasingly integrate renewable energy sources and complex control mechanisms. Power quality disturbances (PQDs) such as voltage sags, swells, harmonics, and transients pose significant threats to system reliability and asset longevity, as shown in Figure 9. Recent advancements in AI have provided promising solutions for accurate, automated, and real-time detection of PQDs, addressing limitations in traditional rule-based and signal-thresholding methods.

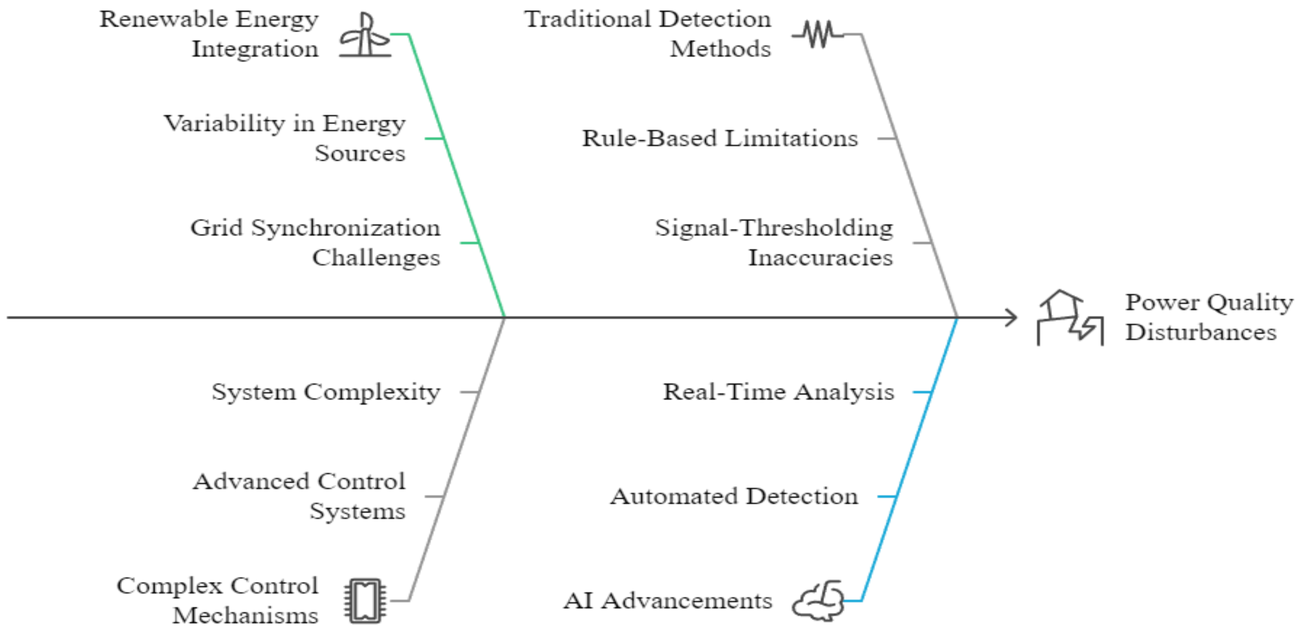

Figure 9: Enhancing Power Quality in Microgrids

A comprehensive review by (Jain et al., 2025) surveyed a range of machine learning (ML) and deep learning (DL) techniques applied to PQD classification. Their work emphasized the crucial role of digital signal processing (DSP) in feature extraction, noting that AI models built upon these enriched representations exhibit enhanced diagnostic precision. Notably, the Bagged Trees classifier reached a testing accuracy of 96.6%, illustrating the effectiveness of ensemble methods when paired with well-engineered signal features. This demonstrates the feasibility of AI-based classification frameworks in real-world PQD monitoring systems. (Lin, Tavalaei, et al., 2024) used the Hybrid CNN BiLSTM model to achieve accurate classification of single power quality, demonstrating the excellent performance of the combined deep learning model in signal recognition problems.

To further improve performance in real-time environments, (Rodríguez et al., 2025) introduced a computationally efficient detection methodology that utilizes Multiresolution Analysis (MRA) of the Discrete Wavelet Transform (DWT). Their approach enables fast and accurate detection of PQDs under dynamic grid conditions, highlighting the practical advantages of wavelet-based signal decomposition for capturing non-stationary disturbances. The model’s success underscores the importance of combining lightweight algorithms with effective time-frequency analysis techniques to meet real-time processing demands.

Building upon these foundations, researchers have also explored advanced deep-learning architectures to enhance detection granularity and robustness. (Küçüker et al., 2025) proposed a hybrid method using a Swin-Residual Network (SwResNet) to identify PQDs from scalogram images, achieving a classification accuracy of 98.22%. This image-based approach demonstrates the power of visual time-frequency representations in DL model training, especially when addressing complex or overlapping disturbances. Expanding on this direction, (S. Pan et al., 2025) introduced a more sophisticated architecture, the Stockwell Transform-Grouped Convolution Squeeze-and-Excitation Residual Network (ST-GSResNet). By combining signal decomposition, grouped convolution, and attention mechanisms, this model enhances both feature discrimination and classification performance, reflecting the continuous evolution of AI-based methods for PQD diagnosis.

Together, these studies highlight the multi-dimensional advantages of AI in PQD detection from improving diagnostic accuracy and computational efficiency to enabling real-time adaptability. The integration of AI techniques strengthens the monitoring infrastructure of microgrids. It supports proactive asset management and fault mitigation strategies, contributing to next-generation distributed energy systems' overall resilience and efficiency.

Cybersecurity and intrusion detection

As microgrids evolve into highly interconnected and intelligent energy systems, their reliance on digital communication networks and automated control infrastructures has grown substantially. While this digitalization enhances operational flexibility and efficiency, it also significantly increases the attack surface, exposing microgrids to cybersecurity threats. In this context, AI has emerged as a critical enabler for strengthening cybersecurity and intrusion detection mechanisms, offering capabilities beyond static rule-based approaches, which is shown in Figure 10.

A key contribution in this area is presented by (Zhang et al., 2025), who surveyed the application of machine learning (ML) and deep learning (DL) techniques for energy data analysis in support of cyber defence strategies. Their study categorized various attack types, such as Man-In-The-Middle (MITM) and Distributed Denial of Service (DDoS). It demonstrated how AI-driven models can accurately identify abnormal communication patterns and network anomalies. These models, trained on historical and real-time data, offer dynamic threat detection that adapts to evolving attack vectors, significantly improving traditional intrusion detection systems (IDS).

Building on this foundation, (Ahmed et al., 2025) examined the structural vulnerabilities inherent in microgrid architectures, particularly in distributed settings where security perimeters are blurred. They emphasized the need for multi-layered intrusion detection systems (IDS) that integrate AI algorithms for real-time monitoring, threat classification, and automated response. Their findings highlight the growing importance of intelligent cybersecurity frameworks that learn from previously unseen attacks, thus improving resilience against known and zero-day threats.

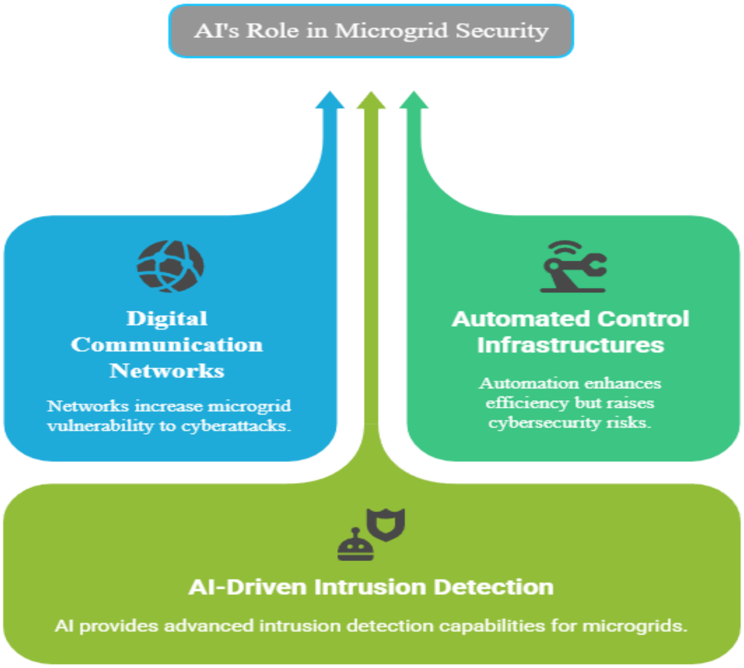

Figure 10: AI's Role in Microgrid Security

Further reinforcing these concerns, (Ahmed et al., 2025) pointed out that modern microgrid systems' increasing complexity and heterogeneity often involving heterogeneous IoT devices, cloud interfaces, and decentralized controllers pose new cyber-physical risks. To address these challenges, advanced AI-based security mechanisms are essential to ensure system integrity, data confidentiality, and operational continuity. These include anomaly detection algorithms, federated learning models, and reinforcement learning-based adaptive firewalls, which offer a proactive defence landscape.

In light of these developments, the continued evolution of AI technologies opens new frontiers for microgrid cybersecurity. By leveraging AI’s capabilities in pattern recognition, behavioural modelling, and adaptive learning, stakeholders can design resilient, self-healing security frameworks that dynamically respond to threats in real time. Such systems safeguard critical energy assets and ensure the trustworthiness and reliability of energy supply networks, which are foundational for smart grid transformation.

Single-board computers (SBCs)

The development and deployment of single-board computers (SBCs) tailored for artificial intelligence (AI) applications have seen significant advancements, reflecting their growing importance in various domains. Early uses of SBCs primarily focused on educational and embedded control applications, but recent innovations have expanded their capabilities to support complex AI workloads (Coelho et al., 2023).

Recent literature highlights a broad spectrum of SBCs equipped with integrated AI hardware, emphasizing their suitability for diverse AI projects. For instance, over the past decade, manufacturers have incorporated AI processing capabilities directly into SBCs, enabling more efficient edge computing solutions (Nain et al., 2022). These integrated AI hardware components facilitate real-time data processing and reduce reliance on cloud-based resources, which is crucial for latency-sensitive applications.

The selection criteria for AI-capable SBCs include processing power, AI acceleration features, connectivity options, and compatibility with AI frameworks. A comprehensive guide underscores the importance of powerful processors, such as quad-core A53 architectures, paired with dedicated AI accelerators and DSPs, to optimize AI performance (Cittadini et al., 2025). The BeagleY-AI SBC exemplifies this approach, combining a 64-bit quad-core processor with specialized AI accelerators, making it suitable for demanding AI tasks.

Furthermore, innovative SBCs like the Tachyon, which integrates 5G connectivity and AI acceleration, demonstrate the trend toward embedding advanced communication and processing capabilities into compact devices (Goswami & Mondal, 2024). Such features are vital for applications requiring real-time data transmission and processing at the edge.

Emerging trends also focus on applying Large Language Models (LLMs) and AI sensors within SBC ecosystems. These developments aim to enhance the ability of SBCs to handle sophisticated AI models and sensor data, broadening their utility in complex AI environments (Himeur et al., 2024). The evolution from basic educational tools to sophisticated AI platforms underscores the rapid progress in this field.

In summary, the landscape of SBCs with AI capabilities is characterized by increased processing power, integrated AI hardware, and enhanced connectivity features. These advancements are driving the adoption of SBCs in edge AI applications, where they serve as compact, efficient, and versatile platforms for deploying AI solutions across various sectors.

Microcontrollers

Integrating artificial intelligence (AI) with microcontrollers has garnered significant attention across various application domains, emphasizing the potential of microcontrollers as embedded AI processors. The application of microcontrollers in intelligent circuit breaker systems, specifically an intelligent MCB with multiple ports, highlights the microcontroller's role in real-time output recording and control functionalities. This underscores the microcontroller's ability to support AI-driven electrical safety systems decision-making.

Advancements in AI technology and its developmental trajectory are discussed by (Y. Pan, 2016), who introduces the concept of AI 2.0, characterized by new scientific breakthroughs and evolving goals. Although the paper primarily reviews AI's historical development, it sets the context for the increasing importance of embedded AI solutions, such as microcontrollers, in enabling smarter systems.

In healthcare, assistive robotics that leverage cloud-based AI services combined with local processing on microcontrollers. Their work illustrates how microcontrollers are local processing units within AI-enabled assistive robots, facilitating healthcare delivery through sensory computing and object processing. Similarly, (Jia et al., 2024) focus on implantable medical devices, developing AI/ML algorithms optimized for low-power microcontrollers to detect life-threatening arrhythmias in real time, exemplifying the role of microcontrollers in critical medical applications.

The manufacturing sector also benefits from AI integration with microcontrollers. (B. Li et al., 2017) review applications of AI in intelligent manufacturing, emphasizing the development of system architectures that incorporate AI technologies into manufacturing processes. (Lee et al., 2018) further elaborate on industrial AI, discussing the ecosystem and strategic frameworks necessary for deploying AI in Industry 4.0 environments, where microcontrollers can act as embedded AI processors within industrial systems.

Environmental and agricultural automation are also addressed through AI-enabled microcontrollers. (Shamshiri et al., n.d.) describe greenhouse automation systems utilizing wireless sensors integrated with AI algorithms on dual-core 32-bit microcontrollers, enhancing energy efficiency and yield predictability. (Khraisat et al., 2021) extend this concept to smart building management, where microcontrollers programmed with AI facilitate safer, more secure, and energy-efficient university buildings.

Recent developments in AI microcontrollers focus on optimizing performance and efficiency for specific applications. (Clay et al., 2022) benchmark the MAX78000 AI microcontroller, highlighting techniques such as model quantization to reduce memory footprint and improve computational efficiency, albeit with some trade-offs in accuracy. (Jia et al., 2024) demonstrate deploying AI/ML algorithms on low-power microcontrollers within implantable devices, addressing real-world medical challenges with embedded AI solutions.

Finally, (Kulkarni & Teodorescu, 2024) propose lightweight, computationally efficient machine-learning techniques suitable for online battery health monitoring, illustrating how microcontrollers can perform complex AI tasks in resource-constrained environments. Collectively, these studies underscore the expanding role of microcontrollers as vital components in AI-enabled systems across diverse fields, driven by advancements in hardware capabilities and AI algorithms tailored for embedded applications.

System on chip

AI within System Chip (SoC) architectures has garnered significant research interest, particularly in applications requiring high efficiency and low power consumption. Recent studies highlight the diverse approaches and technological advancements in this domain.

One notable area of application is in embedded sensing and edge computing systems. (M. Yuan et al., 2021) developed a self-powered edge sensing system utilizing a 3D-printed acoustic triboelectric nanogenerator (A-TENG) combined with an AI speech recognition chip, demonstrating the potential for low-cost, structurally controllable, and energy-efficient AI-enabled sensing solutions. Similarly, (Xu et al., 2023) introduced an ultra-low-power TinyML system designed for real-time visual processing at the edge, emphasizing the importance of resource-constrained AI workloads and the construction of efficient CNN models suitable for embedded platforms.

In industrial applications, (Ribeiro et al., 2024) explored deploying DPU-based edge devices for real-time machine vision supervision to enhance industrial safety, reduce downtime, and optimize resource utilization through AI-powered image analysis. These implementations underscore the critical role of AI-optimized SoC architectures in enabling intelligent edge devices capable of performing complex tasks with minimal power and latency.

Advancements in AI chip technology and their development stages have also been systematically analyzed. (Suo et al., 2024) provided a comprehensive review of AI chip technology routes, constructing a knowledge system across various development stages: preliminary, development, advanced, and future, highlighting the technical challenges and innovative solutions in AI chip design and optimization. This work underscores the importance of systematic evaluation and index optimization in the evolution of AI-enabled SoCs.

Furthermore, the application of AI in sensor systems and data processing has been explored in various contexts. (Y. Li et al., 2020) reviewed how AI enhances inertial sensing, including sensor calibration, error modelling, and multi-sensor data fusion, illustrating the potential for AI to improve the accuracy and robustness of sensing systems integrated within SoC platforms. Additionally, (H. Li, 2025) demonstrated a low-cost, high-precision pulmonary tuberculosis diagnosis system based on Huawei's Ascend 310 chip, showcasing the practical deployment of AI on edge chips for medical diagnostics.

Research also indicates the significance of FPGA-based implementations for AI algorithms. (Huang, 2013) presented an FPGA-based artificial immune system (AIS) algorithm for intelligent motion control in mobile robots, leveraging SoPC methodology to combine AI advantages with FPGA technology for embedded control applications. This approach exemplifies how programmable SoC components can facilitate real-time AI processing in robotics.

In the realm of aerospace and surveillance, (Song et al., 2010) described preliminary efforts to implement aeronautical surveillance transceivers using AIS transceivers based on ADS-B concepts, with potential altitude information extraction via GPS modules, illustrating the application of embedded AI systems in navigation and tracking.

These studies demonstrate the versatility and importance of integrating AI within SoC architectures across various fields, including sensing, industrial automation, medical diagnostics, and aerospace. The convergence of AI algorithms with programmable hardware platforms such as FPGA and specialized AI chips facilitates the development of efficient, low-power, and high-performance embedded systems, paving the way for future innovations in intelligent edge computing and autonomous systems.

Comparative analysis

Table 4 systematically compares four AI control architectures, centralized cloud inference, edge/local inference, federated learning, and swarm/distributed collaboration, across key metrics such as latency, bandwidth demand, privacy protection, and resilience.

Centralized cloud inference benefits from uniform model management and virtually unbounded compute, but the 100-–300 ms round-trip delay and complete data egress expose the system to (i) inadequate response times for sub-cycle protection and (ii) elevated privacy–security risks, corroborating the concerns raised by (Ahmed et al., 2025) and (Satpathy et al., 2025). In contrast, edge or on-premise inference satisfies stringent protection-relay deadlines (< 20 ms) and maintains data residency; however, every node must host dedicated hardware and a harmonized firmware stack, echoing implementation experiences reported by (Giri et al., 2024) and (Lin, Tavalaei, et al., 2024).

Federated learning frameworks sit between these extremes. By retaining raw data locally while exchanging only model gradients, FL preserves privacy and achieves near-edge latency yet still requires periodic synchronization bandwidth and a coordinating server. Experimental deployments in privacy-sensitive community microgrids show that FL scales almost linearly to hundreds of nodes, provided that communication scheduling and model-heterogeneity issues are carefully managed (Y. Zhao et al., 2025a) and (Zhang et al., 2025).

Finally, swarm and other fully distributed optimization paradigms deliver the highest scalability and fault tolerance: agents share only coarse fitness values or heuristics, so partial link failures do not paralyze global decision-making. (Zahraoui et al., 2025) and (Liu et al., 2025) demonstrate that such schemes can coordinate thousands of DER-storage units with sub-30 ms neighbour-to-neighbour latency, albeit at the cost of more complex online parameter tuning and less deterministic convergence.

Table 4 Comparison of centralized and distributed AI control architectures

Criterion	Centralized cloud inference	Edge / local inference	Federated Learning	Swarm / distributed collaboration
Round-trip Latency	100–300 ms	< 20 ms (on-board SoC)	Local < 20 ms + weight sync 50–100 ms	< 30 ms (neighbour messaging)
Bandwidth Demand	High – raw data streaming	Low	Medium – intermittent weight exchange	Low – heuristic / fitness exchange only
Privacy & Data Residency	Raw data leaves site → high risk	Data stays on site → high privacy	Raw data never leaves node; GDPR-compliant	Shares only local metrics – good privacy
Scalability	Bottlenecked by cloud; single point of failure	Improves with node count, needs protocol harmonisation	Linear scale to 100+ nodes	Very high; thousands of nodes feasible
Resilience	Cloud outage degrades service	Operates offline; high resilience	Nodes keep local models if link lost	Collective behaviour survives partial link loss
Maintenance / Updates	Single push, simple	Node-by-node upgrade	Two-level (global–local) model updates	Online self-adaptation; higher maintenance complexity
Hardware Cost	Cloud server + comms	Each node needs SoC or mini-GPU	Edge node + aggregation server	Many low-cost MCUs / SoCs
Typical Scenarios	Large commercial parks needing central oversight	Islanded grids, real-time protection	Privacy-sensitive community micro-grids	Suburban DER-storage clusters
Key References	(Ahmed et al., 2025);	(Giri et al., 2024); (Lin,	(Y. Zhao et al., 2025a); (Zhang et	(Zahraoui et al., 2025);

	(Satpathy et al., 2025)	Tavalaei, et al., 2024)	al., 2025)	(Liu et al., 2025)

Case study

In this chapter, we present an in-depth case study analysis of microgrid applications from security, predictability, and energy management perspectives. Specifically, we systematically examine representative cases that illustrate how advanced AI techniques are being deployed to enhance microgrid security, improve the predictability of load and renewable generation through data-driven forecasting models, and optimize energy management strategies for efficient resource allocation and cost reduction. By critically analyzing these cases, we aim to bridge the gap between theoretical advancements and practical implementation, thereby providing a comprehensive understanding of the opportunities and challenges associated with integrating AI in key microgrid domains.

Classification of power quality disturbances in microgrids using a multi-level global convolutional neural network and SDTransformer approach

With the increasing integration of renewable energy sources and advanced power electronic devices, microgrids face more frequent and complex power quality disturbances (PQDs), such as harmonics, voltage sags, and flickers (Jiang et al., 2025). Accurate and robust identification of these disturbances is crucial for microgrids' safe and reliable operation. However, traditional machine learning methods often fail to achieve high accuracy and generalization, especially under noisy conditions.

This case focuses on developing and evaluating a novel deep learning model, MGCNN-SDTransformer, designed to classify power quality disturbances in microgrids. The model integrates a Multi-level Global Convolutional Neural Network (MGCNN) with a Simplified Double-layer Transformer (SDTransformer) to fully exploit spatial and temporal features from raw one-dimensional PQD time-series data. The MGCNN uses multiple convolution layers combined with a one-dimensional global attention mechanism to extract and emphasize critical features and dynamics, while the SDTransformer leverages multi-head self-attention and multilayer perceptrons to enhance feature representation and classification accuracy, as shown in Figure 11.

Synthetic PQD datasets were generated according to IEEE 1159–2019 standards, covering 29 types of disturbances (single, double, and triple), with added white noise at various SNRs (noise-free, 50 dB, 30 dB, 20 dB). Each disturbance type included 1,200 samples, split into training, validation, and test sets. The raw 1D time-series signals were input directly into the MGCNN-SDTransformer model without complex preprocessing. The MGCNN module performed multi-scale feature extraction and attention weighting, followed by the SDTransformer for further temporal feature learning and robust classification. Model training was conducted on a workstation with an Intel i5-12600Kf CPU and an NVIDIA RTX 3060Ti GPU, utilizing Python 3.10.9 and VSCode 1.87.2.

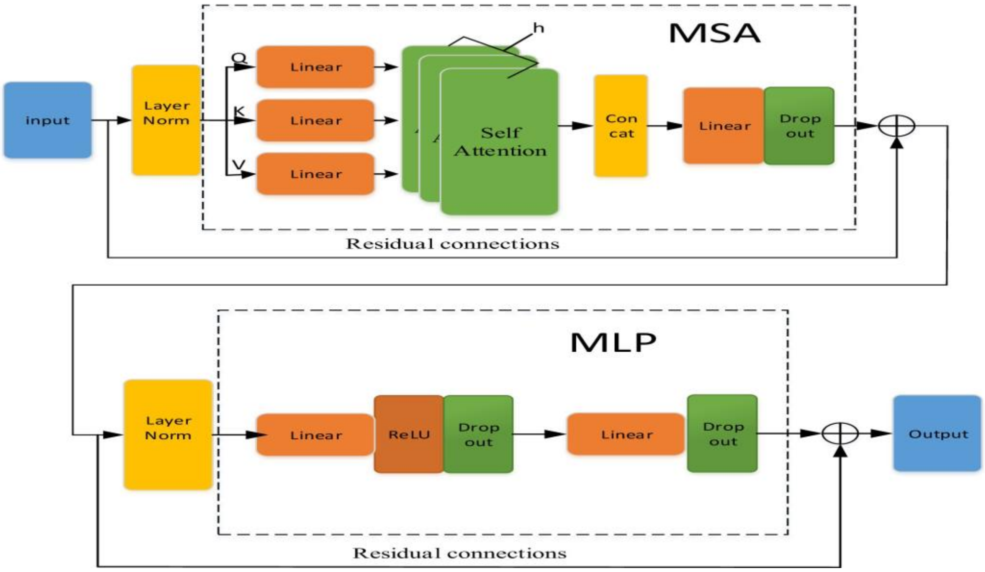

Figure 11: SDTransformer base model (Jiang et al., 2025)

The experimental results demonstrate that the proposed MGCNN-SDTransformer model performs well in classifying power quality disturbances in microgrids. Specifically, the model attains a recognition accuracy of 99.64% under noise-free conditions and maintains a high accuracy of 98.85% even in severely noisy environments (20 dB SNR), highlighting its robustness against signal interference. Comparative analysis further reveals that the MGCNN-SDTransformer significantly outperforms traditional deep learning models, such as CNN, LSTM, and vanilla Transformer architectures, as well as other state-of-the-art techniques, particularly in scenarios involving composite disturbances and high noise levels. In addition, the model demonstrates remarkable efficiency, sustaining high classification accuracy with a relatively shallow network configuration and direct processing of raw input data, thereby minimizing the computational resources required for data preprocessing. Validation on a real-world power quality disturbance dataset confirms the model's strong generalization capability, as evidenced by an average recognition accuracy of 99.7% across multiple disturbance types.

An adaptive load forecasting model in microgrids: A cloud-edge orchestrated approach tailored for accuracy, real-time response, and privacy needs

The MiRIS microgrid, located at the John Cockerill Group's international headquarters in Seraing, Belgium, provides an ideal testbed for evaluating advanced load forecasting methods (Y. Zhao et al., 2025b). Characterized by photovoltaic generation, energy storage devices, and non-dispatchable loads, the MiRIS microgrid represents typical microgrid challenges such as low load baseline, rapid load fluctuation, and the necessity for high-frequency data acquisition. These features demand forecasting models that are accurate, efficient, and adaptable to resource-constrained environments.

The authors developed an adaptive load forecasting framework leveraging cloud and edge computing resources to address these challenges. The system employs a modular AI-driven model that flexibly supports three forecasting task types: accuracy-oriented (cloud-based ensemble stacking), real-time response (efficient edge-deployed LightGBM), and privacy-preserving (entirely local, subsampled, low-complexity LightGBM). Key modules such as feature selection, model training, and hyperparameter optimization are strategically decoupled and assigned to either cloud or edge according to prediction accuracy, latency, and data privacy requirements. The hardware configuration features a standard PC for cloud-side computing and a Raspberry Pi 4 as the edge device, enabling the exploration of practical deployment scenarios. The hardware and software configuration of load forecasting model in different microgrids is shown in Figure 12.

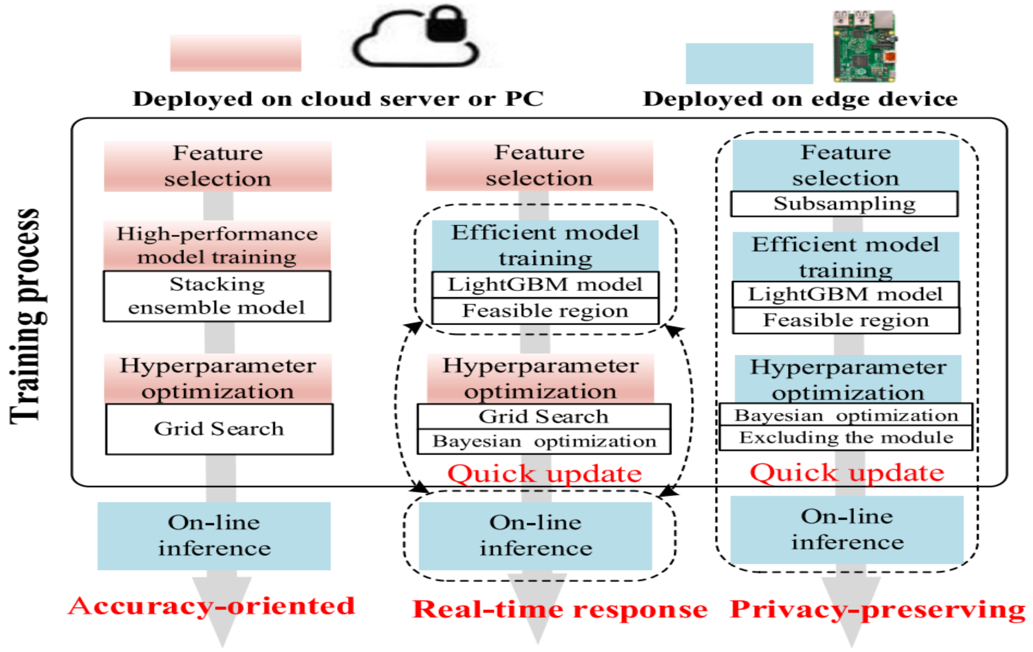

Figure 12: Hardware and software configuration for different microgrid scenario (Y. Zhao et al., 2025b)

The implementation used historical load data, weather observations, and calendar features from the MiRIS microgrid (with a resolution of 17,280 samples per hour at 5-second intervals) as inputs. Stepwise sampling and LightGBM-embedded feature importance analysis revealed that the most recent load values and weather parameters (notably temperature and irradiance) are the strongest predictors. For the highest accuracy, stacking ensemble learning (combining LightGBM, SVR, LSTM, and KNN) was applied on the cloud; for edge or privacy-oriented scenarios, a streamlined LightGBM model, optimized via Bayesian hyperparameter search and data subsampling, enabled efficient and secure local inference.

Empirical results demonstrate that the stacking ensemble model achieved the best accuracy for 15-minute-ahead forecasts (MAPE 9.56%), surpassing all single-model approaches but requiring substantial computational resources suitable only for cloud environments. In contrast, the LightGBM model delivered nearly comparable accuracy (MAPE 9.94%) with a fraction of the training time on the Raspberry Pi, validating its suitability for real-time, resource-limited tasks. For privacy-preserving scenarios, subsampling input data to just 1/12 of the original size retained high predictive performance ($R^2 = 0.818$) while drastically reducing training time. LightGBM's low sensitivity to hyperparameter tuning facilitated further simplification for embedded deployment. Feasible region analysis further illustrated that model settings could be dynamically tailored to the computational limits of the edge device without significant loss of accuracy.

Optimization schedule strategy of active distribution network based on microgrid group and shared energy storage

This case study demonstrates the effectiveness of a master-slave game-based scheduling strategy for an active distribution network (ADN) comprising multiple microgrids (MGs) and a shared energy storage system (SES) (Qiao et al., 2025). The test system is a modified IEEE 33-bus distribution network integrating three microgrids, one shared energy storage, two photovoltaic (PV) units, and one wind turbine (WT), forming a typical structure for evaluating collaborative optimization schemes in modern ADN.

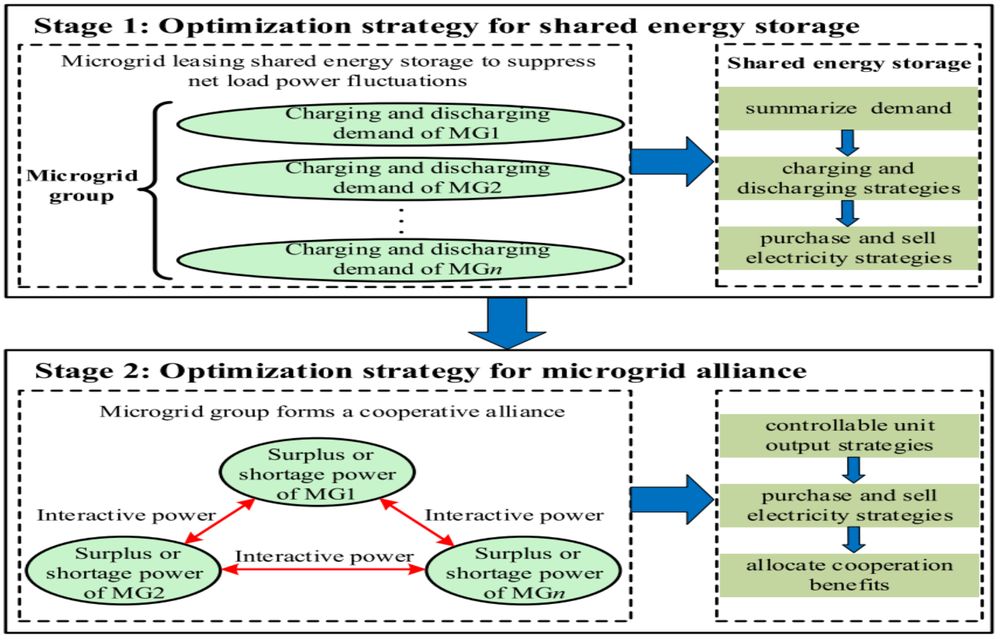

Figure 13: The two-stage optimization schedule strategy for microgrid group leasing SES (Qiao et al., 2025)

The proposed scheduling approach introduces a two-stage optimization strategy: first, each microgrid determines its energy storage leasing demand and charging/discharging profiles using a multi-objective optimization model that considers energy storage cost, netload fluctuation (mean square error), and surplus/shortage power. Second, the shared energy storage operator (SESO) coordinates charging and discharging among microgrids, while the distribution system operator (DSO) leads the scheduling by setting time-of-use electricity prices. The equilibrium among DSO, SESO, and the microgrid coalition (MGCO) is achieved through a distributed, multi-stage iterative algorithm, leveraging Quantum Particle Swarm Optimization (QPSO) and CPLEX solver, which avoids excessive nested iterations and enhances computational efficiency. The two-stage optimization schedule strategy for microgrid group leasing SES is shown in Figure 13.

Simulation results highlight that this collaborative approach yields substantial improvements in both economic and technical indices. The total SES capacity leased by the three MGs is 10,727 kWh, but the actual net capacity required is only 5,725 kWh, a savings of 46.6%, illustrating the efficiency of shared storage utilization. Similarly, power capacity demand is reduced by over 40%. The optimal operation significantly reduces net load fluctuations and surplus/shortage power across all microgrids. The game-theoretic model achieves equilibrium within 15 iterations, with stable operating costs for DSO (31,948 ¥), SESO (549 ¥), and MGCO (10,959 ¥). Compared to non-cooperative or single-slave scheduling baselines, the multi-entity game strategy delivers clear economic benefits: for example, after cooperative surplus allocation, the total MGCO cost is reduced by 706 ¥, and cost distribution among MGs is optimized according to power interaction ratios, enhancing fairness and operational incentives.

Furthermore, the case study reveals that time-of-use pricing by the DSO reduces overall operating costs and effectively suppresses ADN net load fluctuations (reducing mean square error and peak-valley differences), improves voltage quality, and lowers network losses by 11.7%. The interaction between microgrids facilitates local consumption of renewable energy such as PV output from MG1 and WT output from MG3 are balanced through energy exchanges, enhancing stability and operational efficiency.

Challenges and Future Directions

Data issues: missing, inconsistent, privacy

Deploying AI in microgrid systems has shown great potential in improving operational efficiency, fault detection, and energy optimization. However, data-related challenges remain a significant barrier to fully realising AI's capabilities in this context. Data quality, completeness, and confidentiality directly influence the performance and trustworthiness of AI models, and addressing these challenges is critical for successfully integrating intelligent algorithms into real-world microgrid environments (Asuhaimi Mohd Zin et al., 2017).

One of the foremost challenges is the prevalence of missing or inconsistent data, which can compromise model accuracy, generalizability, and robustness. AI algorithms, particularly those used for fault detection and predictive diagnostics, often rely on high-resolution, continuous datasets. (Hamza et al., 2025) highlight that incomplete data streams limit current fault diagnosis techniques and lack robust preprocessing mechanisms, reducing detection accuracy in practical applications. This underscores the urgent need for resilient data extraction and preprocessing frameworks to tolerate or correct incomplete input while preserving critical system information.

Equally important are the concerns related to data privacy, especially in scenarios involving smart meters, consumer usage profiles, and distributed energy transactions (Tavalaei et al., 2018). As AI models increasingly depend on fine-grained energy consumption data to deliver accurate load forecasting and user-level optimization, protecting user identity and sensitive usage patterns becomes paramount. In response, (Y. Zhao et al., 2025a) proposed an adaptive load forecasting model that integrates privacy-preserving mechanisms without compromising prediction accuracy. Their approach demonstrates that customized AI solutions can be designed to fulfil operational performance and compliance with data protection regulations, such as GDPR or local energy governance policies.

In addition to missing and private data, data inconsistency often resulting from the intermittent nature of renewable energy sources or faulty sensor readings poses another layer of complexity. (Akter et al., 2024) emphasize that fluctuations in generation and storage metrics introduce gaps or anomalies in the data stream, degrading the reliability of downstream AI tasks. To address this, they advocate using heuristic optimization techniques to develop adaptive data cleaning and smoothing algorithms, which can dynamically reconcile inconsistencies while maintaining temporal fidelity.

Comprehensive data governance frameworks must underpin future AI-enhanced microgrid systems to move forward. These should encompass data validation protocols, advanced imputation methods for missing values, and secure, scalable data-sharing architectures. Such strategies are essential for ensuring the technical robustness of AI models and building stakeholder trust in intelligent decision-making systems. Furthermore, embedding privacy-by-design principles into AI algorithm development will be vital to ensure ethical deployment and long-term social acceptance.

Model generalization ability, interpretability, robustness

The effectiveness of AI applications in microgrid systems critically depends on three interrelated attributes: generalization ability, interpretability, and robustness. These attributes determine how well a model performs under varied and uncertain operating conditions and influence its transparency and trustworthiness in real-world deployment. Despite recent advances, existing AI models often exhibit limitations in adapting to heterogeneous data environments, which restricts their scalability and practical utility in dynamic microgrid contexts (Khavari et al., 2016).

One of the primary concerns lies in the limited generalization capacity of many state-of-the-art AI models. Trained on historical datasets that may not capture the full spectrum of future operational variability, these models often underperform when exposed to novel or extreme conditions. (Küçüker et al., 2025) emphasized this issue in the context of power quality disturbance (PQD) detection in distributed generators, noting that environmental noise and signal non-stationarity significantly impact model accuracy. Their findings highlight the need for algorithms to maintain performance across various scenarios, including noisy or unseen conditions.

Closely related to generalization is the challenge of model interpretability. Their decision-making processes become increasingly opaque as AI models grow in complexity, particularly with the adoption of deep learning architecture. This “black box” nature creates barriers for operational engineers, regulators, and stakeholders who require transparency in critical applications such as energy dispatch, fault diagnosis, and protection system coordination. (Ramadan et al., 2024) pointed out that enhancing interpretability is essential for fostering trust and facilitating real-world acceptance. The development of explainable AI (XAI) frameworks is thus a crucial direction for enabling meaningful human-AI interaction in energy systems.

In response to these dual challenges, (S. Pan et al., 2025) proposed a novel classification framework for PQDs that integrates advanced neural network architectures with attention mechanisms to enhance robustness and interpretability. Their model demonstrated improved accuracy under noisy conditions, offering a more transparent mapping between input signals and classification outcomes. This approach illustrates the value of multi-objective model design, where robustness and interpretability are co-optimized rather than treated as trade-offs.

Future research should prioritize the development of hybrid models that combine the strengths of data-driven AI with physics-informed and rule-based approaches. Such models can leverage domain knowledge to guide learning, improving generalizations across operational regimes and the explainability of outputs. Moreover, uncertainty quantification, transfer learning, and meta-learning offer promising pathways to enhance robustness in non-stationary environments.

Multi agent collaboration (federated learning, swarm intelligence optimization)

As microgrid systems grow in scale and complexity, traditional centralized control and optimization methods are increasingly challenged by scalability, latency, and vulnerability issues. In response, exploring multi-agent collaboration frameworks, particularly those based on federated learning and swarm intelligence optimization offers promising pathways for enhancing intelligent microgrid operations' resilience, adaptability, and decentralization.

One emerging paradigm is federated learning (FL), which enables multiple agents such as distributed energy resources (DERs), microgrid controllers, or substations to train machine learning models collaboratively without sharing raw data. This approach is particularly relevant in microgrids where data privacy and cybersecurity are critical. (Zhang et al., 2025) highlight the role of FL in mitigating risks associated with centralized data aggregation by allowing local training on edge devices while synchronizing model parameters globally. This decentralized model training enhances privacy-preserving analytics, reduces communication overhead, and improves system robustness against cyber-physical threats.

In parallel, swarm intelligence optimization (SIO) represents another decentralized strategy inspired by the collective behaviour of biological systems, such as flocks of birds or colonies of ants. These algorithms allow distributed agents to explore the solution space for complex optimization problems cooperatively. (Zahraoui et al., 2025) demonstrate the efficacy of SIO in coordinating energy dispatch among renewable generators and storage units, enabling microgrids to make autonomous, real-time decisions that reflect local constraints while aligning with global performance objectives. Their findings suggest that swarm-based approaches can effectively balance multiple conflicting criteria such as cost minimization, voltage stability, and emission reduction in dynamic environments.

Given the complementary advantages of FL and SIO, a key future direction lies in integrating these two paradigms to form hybrid multi-agent collaboration frameworks. Such frameworks could leverage FL's secure learning capabilities and SIO's distributed decision-making efficiency, allowing microgrids to dynamically adapt to fluctuations in load demand, renewable generation, and network topology. This integration would be valuable in peer-to-peer energy trading, island-mode coordination, and multi-microgrid clustering.

However, several challenges must be addressed to realize this vision. These include model heterogeneity among agents, communication constraints in resource-limited environments, and the need for adaptive coordination protocols that can scale with system size. Developing standardized protocols, energy-aware communication models, and incentive-compatible collaboration mechanisms will ensure stable and scalable deployment of multi-agent AI systems in real-world microgrid infrastructures.

Potential for integration with traditional methods/rules (Physics informed AI)

Integrating AI with traditional physics-based methods represents a compelling research direction for advancing modelling accuracy and system interpretability in microgrid operations. Physics-Informed AI (PI-AI) approaches seek to embed known physical laws such as conservation principles, system dynamics, and energy flow constraints into data-driven models, enabling the development of hybrid frameworks that offer high predictive power and physical consistency (B. Yuan et al., 2025).

An example of this synergy is demonstrated by (Ma et al., 2025), who combined machine learning models with conventional forecasting techniques to improve the accuracy of electricity load predictions in hybrid renewable energy systems. By leveraging historical data patterns and deterministic system characteristics, their method provided more reliable forecasts, supporting operational planning and real-time scheduling.

Building on this concept, (Ahmed et al., 2025) underscored the value of physics-informed modelling in enhancing the robustness and interpretability of AI predictions, particularly under environmental uncertainties and system disturbances. By incorporating physics-based constraints such as Ohm’s law, Kirchhoff’s rules, or thermal limits into learning algorithms, models are more generalizable across diverse operating scenarios and more aligned with engineering standards and safety requirements. This alignment is crucial in mission-critical microgrid applications where erroneous predictions can lead to cascading failures or inefficient energy dispatch.

Given the growing complexity of modern microgrid systems marked by the increasing penetration of intermittent renewables, flexible loads, and distributed storage, the need for trustworthy and generalizable models has never been more urgent. Physics-informed AI offers a pathway toward resolving key challenges associated with model overfitting, lack of extrapolation ability, and limited transparency in black-box neural networks. Fusing physics-based priors with learning architecture can constrain the solution space, improve training efficiency, and ensure output remains physically plausible.

Future research should focus on designing scalable hybrid frameworks that can flexibly integrate different forms of domain knowledge, from partial differential equations to empirical control rules, into various AI paradigms. Moreover, methodological advancements in physics-guided loss functions, differentiable equation embedding, and transfer learning across physical regimes will be key enablers for robust and interpretable microgrid modelling.

II. Conclusion

This review comprehensively examined the evolution of AI-driven microgrids, highlighting their structural composition, operational characteristics, and the integration of AI in addressing key technical and management challenges. From load forecasting and energy management to fault diagnosis and cybersecurity, AI techniques ranging from machine learning and deep learning to reinforcement learning and evolutionary algorithms have demonstrated significant potential in improving microgrid systems' reliability, efficiency, and resilience. The adoption of AI has enhanced forecasting accuracy, intelligent control strategies, and real-time fault detection, thus advancing the operational intelligence of modern microgrids.

Despite these advances, several critical issues remain, particularly regarding model interpretability, generalization, real-time performance, and data integrity. The “black box” nature of deep learning models and challenges in adapting to diverse operational conditions limit the full-scale deployment of AI in real-world microgrid environments. Moreover, inconsistent or privacy-sensitive data further complicates robust model training and validation. To bridge these gaps, future research should prioritize the development of interpretable, robust, and adaptive AI models tailored to the complex dynamics of microgrid ecosystems.

Interdisciplinary collaboration will be pivotal in overcoming the engineering, regulatory, and implementation barriers that hinder the practical deployment of AI in energy systems. Emerging directions such as physics-informed AI, federated learning, and swarm intelligence optimization offer promising avenues for enhancing model accuracy, security, and collaborative decision-making. Ultimately, realizing the full potential of AI-driven microgrids requires technological innovation and a systemic integration of engineering, data science, and policy to enable intelligent, sustainable, and secure energy infrastructure in the coming decades.

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