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Machine Learning for Optimized Microgrid Management: Advances, Applications, Operational Efficiency, System Resilience, Cybersecurity, and Future Technologies

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Abstract

The increasing penetration of distributed energy resources and renewable generation has intensified the complexity of microgrid management, necessitating intelligent and adaptive control mechanisms. Machine learning (ML) has emerged as a transformative approach for optimizing microgrid operations by enabling data-driven decision-making, predictive control, and real-time optimization. This study provides a comprehensive technical review of recent advances and applications of machine learning in optimized microgrid management, with a specific focus on operational efficiency, system resilience, and cybersecurity. The review examines state-of-the-art ML techniques, including supervised and unsupervised learning, deep learning, reinforcement learning, and hybrid optimization models, applied to load forecasting, energy dispatch, fault detection, demand response, and energy storage management. Furthermore, the role of ML in enhancing microgrid resilience against disturbances, extreme weather events, and component failures is critically analyzed, alongside emerging cybersecurity challenges such as data integrity, intrusion detection, and adversarial attacks on intelligent control systems. The study also explores future technological directions, including the integration of artificial intelligence of things (AIoT), digital twins, edge computing, blockchain-enabled energy transactions, and quantum machine learning for next-generation microgrids. By synthesizing current research trends and identifying key challenges and research gaps, this work offers valuable insights for researchers, system operators, and policymakers aiming to design secure, resilient, and intelligent microgrid infrastructures.

Keywords: Microgrid, applications, operational efficiency, cybersecurity, future technologies

Introduction

The rapid global transition toward low-carbon and decentralized energy systems has positioned microgrids as a critical enabler of resilient, efficient, and sustainable power infrastructure. By integrating distributed energy resources (DERs) such as photovoltaic systems, wind turbines, energy storage units, electric vehicles, and controllable loads, microgrids offer enhanced reliability, flexibility, and autonomy compared to conventional centralized grids. However, the increasing penetration of intermittent renewable sources, coupled with stochastic demand patterns, dynamic pricing mechanisms, and multi-objective operational constraints, has significantly increased the complexity of microgrid management. Traditional rule-based, optimization-driven, and model-dependent control approaches often struggle to cope with high-dimensional decision spaces, system uncertainties, and real-time operational requirements.

In this context, machine learning (ML) and artificial intelligence (AI) have emerged as transformative technologies for optimized microgrid management. Recent advances demonstrate that data-driven and learning-based techniques can effectively capture nonlinear system dynamics, adapt to evolving operating conditions, and support autonomous decision-making across forecasting, control, optimization, and coordination layers. Comprehensive reviews highlight that ML-enabled microgrid energy management systems consistently outperform classical methods in terms of economic efficiency, operational robustness, and scalability, particularly in environments characterized by renewable intermittency and market uncertainty (Negi et al., 2026).

A major area of progress lies in the application of deep learning for load, price, and renewable generation forecasting. Hybrid deep learning architectures and data-driven models integrating external factors have significantly improved short-term load forecasting accuracy, enabling proactive scheduling and improved dispatch decisions in grid-connected and networked microgrids (Zohaib et al., 2026; Martinez-Zapata et al., 2026; Patel et al., 2026). Big-data-oriented forecasting frameworks further enhance situational awareness by leveraging high-resolution operational data and heterogeneous information sources, thereby supporting real-time energy management under uncertainty (Le et al., 2026). These forecasting capabilities form a foundational layer for intelligent microgrid control and optimization.

Beyond forecasting, reinforcement learning (RL) and deep reinforcement learning (DRL) have gained prominence as powerful tools for real-time energy management and control. Unlike conventional optimization techniques that rely on accurate system models, RL-based approaches learn optimal policies directly through interaction with the environment. This model-free property has enabled their successful deployment in complex microgrid scenarios, including nonconvex energy management problems, voltage and frequency regulation, and multi-objective dispatch under flexible energy markets (Boghrabadi et al., 2026; Wu et al., 2026). Survey studies further indicate that RL-driven control strategies are particularly effective in DC and hybrid microgrids, where system dynamics are highly nonlinear and difficult to model explicitly (Shi et al., 2026; Maurya et al., 2026).

Recent research has also shifted toward multi-agent reinforcement learning (MARL) frameworks to address the coordination challenges of networked and multi-microgrid systems. Lean and network-aware MARL architectures enable decentralized decision-making while maintaining global operational objectives, reducing communication overhead and improving scalability (Esan et al., 2026a; Esan et al., 2026b). These approaches are increasingly applied in aggregated virtual power plants, where multiple microgrids interact with energy markets and pricing mechanisms, necessitating coordinated control under uncertainty (Khalil et al., 2026). Furthermore, advanced agent-based RL frameworks have demonstrated improved voltage stability, power quality, and dynamic performance in hybrid microgrids and energy storage–based systems (Ponnuru et al., 2026; Bharaneedharan et al., 2026).

Another important research direction involves the integration of ML with optimization, model predictive control, and domain knowledge. Hybrid frameworks combining RL with model predictive control or physics-aware constraints have shown promise in enhancing frequency stabilization, cyber-resilience, and operational safety in specialized microgrid applications, including marine and building-integrated microgrids (Prusty et al., 2026; Liu et al., 2026). AI-powered battery management systems further contribute to cost optimization and asset longevity by learning optimal charging and discharging strategies under degradation and operational constraints (Hoummadi et al., 2026).

Sustainability considerations have also become central to ML-driven microgrid research. Recent studies incorporate carbon emission flows, low-carbon economic dispatch, and emission-aware coordination into learning-based energy management frameworks, aligning microgrid operation with climate mitigation objectives (Qiu et al., 2026; Esan & Shareef, 2026). Machine learning–based carbon footprint and pricing prediction further support informed decision-making at both operational and planning levels (Li et al., 2026). Despite these advancements, challenges remain related to data dependency, training stability, explainability, cyber-security, and real-world deployment, highlighting the need for systematic analysis and future-oriented research directions.

Literature Review

Machine learning (ML) has emerged as a transformative approach for optimized microgrid management, enabling intelligent decision-making across energy forecasting, control, and optimization layers. Recent studies highlight the growing adoption of deep learning and reinforcement learning techniques to address nonconvex energy management problems, enhance power flow optimization, and improve system resilience under dynamic operating conditions (Boghrabadi et al., 2026; Wu et al., 2026). Comprehensive reviews emphasize that ML-driven microgrid energy management systems significantly outperform traditional rule-based and model-dependent methods, particularly in handling uncertainty, renewable intermittency, and flexible energy markets (Negi et al., 2026). Reinforcement learning-based control strategies have been extensively explored for DC and hybrid microgrids, demonstrating improved voltage stability, power quality, and multi-objective optimization without requiring precise system models (Ajewole et al., 2026; Shi et al., 2026; Maurya et al., 2026). Additionally, ML-enabled short-term solar and wind power forecasting has proven critical for proactive scheduling and reliable microgrid operation (Patel et al., 2026). Emerging applications further integrate deep meta-reinforcement learning and stochastic optimization for large-scale, multi-area microgrids and hybrid battery–hydrogen storage systems, supporting cost minimization, loss reduction, and operational flexibility (Singh, 2026; Liu et al., 2026). Despite these advancements, challenges related to scalability, data dependency, and real-time implementation remain, guiding future research toward robust, explainable, and adaptive ML frameworks for next-generation microgrids (Negi et al., 2026). Machine learning–driven energy management has advanced significantly through the integration of deep reinforcement learning, multi-agent systems, and data-driven forecasting models for networked and grid-connected microgrids. Recent work proposes lean multi-agent deep reinforcement learning frameworks to manage uncertainty and decentralized coordination in networked microgrids with multiple stakeholders, demonstrating improved scalability and reduced computational burden compared to centralized approaches (Esan et al., 2026). Hybrid deep learning architectures have also been employed for short-term load forecasting combined with AI-driven energy management systems, enabling accurate demand prediction and optimized power dispatch in multi-microgrid environments (Zohaib et al., 2026; Martinez-Zapata et al., 2026). Big-data-oriented forecasting methods further enhance renewable integration by leveraging hybrid machine learning and deep learning pipelines for real-time microgrid energy management (Le et al., 2026). Reinforcement learning–based intelligent control has been extended to energy storage–based power systems and hybrid microgrids, where agent-based and dual-agent RL frameworks improve voltage stability, economic dispatch, and low-carbon operation under uncertain renewable generation (Bharaneedharan et al., 2026; Qiu et al., 2026; Ponnuru et al., 2026). Moreover, physics-aware reinforcement learning–guided model predictive control has emerged as a promising solution for enhancing cyber-resilience and adaptive control in building-integrated microgrids (Liu et al., 2026). These developments collectively indicate a shift toward scalable, data-efficient, and autonomous ML frameworks capable of supporting complex, interconnected microgrid ecosystems. Recent research extends machine learning–based microgrid optimization toward AI-enhanced, carbon-aware, and sector-specific applications, emphasizing intelligent coordination, cost efficiency, and operational resilience. Reinforcement learning–driven energy management strategies have been proposed for smart microgrid organisms, demonstrating improved power optimization and autonomous decision-making under dynamic demand and renewable variability (Muthukumar et al., 2026). Hybrid optimization techniques combined with model predictive control have been applied to frequency stabilization in marine microgrids, highlighting the role of machine learning in adaptive real-time control for specialized microgrid environments (Prusty et al., 2026). Artificial intelligence–powered battery management systems integrating IoT and learning-based optimization have shown significant potential for cost reduction, lifespan enhancement, and reliability improvement in microgrid storage infrastructures (Hoummadi et al., 2026). Multi-objective AI–ML frameworks further support optimized energy distribution and dispatch in grid-connected microgrids, balancing economic, technical, and environmental performance indices (Gautam et al., 2026; Masood et al., 2026). In parallel, multi-agent deep reinforcement learning has been leveraged for coordinated energy management and price prediction in aggregated virtual power plants, enabling scalable interaction among multiple microgrids under market uncertainty (Khalil et al., 2026). Recent IEEE and Elsevier studies also incorporate tariff-aware and safety-constrained reinforcement learning for EV charging networks and carbon-aware multi-microgrid coordination, addressing grid stability and emission minimization simultaneously (Hossen et al., 2026; Esan & Shareef, 2026). Furthermore, intelligent optimization of coupled energy systems and machine learning–based carbon emission prediction underscores the growing integration of sustainability objectives within next-generation microgrid management frameworks (Liu et al., 2026; Li et al., 2026).

Methodology

This study adopts a structured, multi-stage methodological framework to systematically analyze and synthesize recent advancements in machine learning–based optimized microgrid management. The methodology integrates literature screening, thematic classification, comparative analysis, and conceptual framework development, following established practices in high-impact review and methodology-driven energy systems research (Negi et al., 2026).

1. Literature Selection and Screening Strategy

The primary dataset consists of peer-reviewed journal articles published in 2026, sourced from high-quality publishers including Elsevier, Springer, IEEE, Wiley, MDPI, Taylor & Francis, and ASME. The selected studies focus on machine learning, deep learning, reinforcement learning, and hybrid AI–optimization techniques applied to microgrid energy management, forecasting, control, coordination, and sustainability objectives. Emphasis is placed on works addressing real-time decision-making, uncertainty handling, decentralized architectures, and multi-objective optimization, as highlighted in recent comprehensive surveys and application-driven studies (Negi et al., 2026; Shi et al., 2026; Maurya et al., 2026).

2. Thematic Categorization of Methodological Approaches

To enable structured analysis, the selected studies are categorized into five primary methodological themes based on their core technical contributions:

(i) Data-Driven Forecasting Models:

Studies employing machine learning and deep learning for short-term load, renewable generation, price, and carbon emission forecasting are grouped under this category. Hybrid deep learning architectures and big-data analytics frameworks are examined for their ability to improve forecasting accuracy and support proactive microgrid scheduling (Le et al., 2026; Zohaib et al., 2026; Martinez-Zapata et al., 2026; Patel et al., 2026; Li et al., 2026).

(ii) Reinforcement Learning–Based Energy Management:

This category includes single-agent and deep reinforcement learning approaches for optimal energy management, voltage and frequency regulation, and economic dispatch under uncertainty. Model-free learning strategies addressing nonconvex optimization and flexible energy markets are analyzed to assess their adaptability and operational efficiency (Boghrabadi et al., 2026; Wu et al., 2026; Ajewole et al., 2026; Singh, 2026).

(iii) Multi-Agent and Decentralized Learning Frameworks:

Multi-agent reinforcement learning methodologies designed for networked, multi-microgrid, and virtual power plant environments are examined. Lean, network-aware, and coordinated agent architectures are evaluated for scalability, reduced communication overhead, and robustness against stochastic disturbances (Esan et al., 2026a; Esan et al., 2026b; Khalil et al., 2026; Liu et al., 2026).

(iv) Hybrid AI–Optimization and Control Integration:

This theme covers methodologies combining machine learning with model predictive control, physics-aware constraints, and hybrid optimization algorithms. Such frameworks aim to enhance stability, cyber-resilience, and safety in specialized microgrid applications, including marine, building-integrated, and industrial microgrids (Prusty et al., 2026; Liu et al., 2026; Gautam et al., 2026).

(v) Sustainability-Oriented and Asset-Centric Optimization:

AI-powered methodologies focusing on battery management, low-carbon dispatch, emission-aware coordination, and asset longevity are reviewed. These approaches integrate environmental and economic objectives into microgrid operation through learning-based optimization and intelligent control (Hoummadi et al., 2026; Qiu et al., 2026; Esan & Shareef, 2026; Bharaneedharan et al., 2026).

Discussion

The review of recent literature demonstrates that machine learning (ML) and artificial intelligence (AI) have profoundly transformed microgrid energy management, enabling intelligent, adaptive, and autonomous control strategies that were previously unattainable with traditional optimization and rule-based approaches. Across the surveyed studies, deep learning, reinforcement learning (RL), and hybrid AI–optimization frameworks have emerged as central tools for forecasting, control, coordination, and sustainable operation. Forecasting methods, particularly hybrid deep learning and big-data analytics models, have significantly enhanced short-term load, renewable generation, and price predictions, allowing microgrids to proactively schedule energy dispatch and mitigate uncertainty arising from stochastic demand and renewable intermittency (Le et al., 2026; Zohaib et al., 2026; Martinez-Zapata et al., 2026; Patel et al., 2026; Li et al., 2026). These methods outperform traditional statistical and model-based approaches in both accuracy and adaptability, thereby providing a robust foundation for downstream optimization and decision-making. Complementing forecasting, reinforcement learning and deep reinforcement learning approaches have demonstrated exceptional capability in real-time energy management, voltage and frequency regulation, and multi-objective optimization under dynamic market and environmental conditions. Studies focusing on single-agent and dual-agent RL frameworks have illustrated the ability of learning-based controllers to handle nonconvex optimization problems and multi-objective dispatch efficiently, while also reducing reliance on precise mathematical models of microgrid systems (Boghrabadi et al., 2026; Wu et al., 2026; Ajewole et al., 2026; Singh, 2026; Qiu et al., 2026). These findings underscore the increasing shift from deterministic optimization toward adaptive, data-driven control paradigms capable of learning from operational feedback.

Another prominent trend is the adoption of multi-agent reinforcement learning (MARL) architectures for networked and multi-microgrid environments. The lean, network-aware MARL frameworks facilitate decentralized decision-making while maintaining global objectives, improving scalability, reducing communication overhead, and enhancing resilience against uncertainties across distributed energy resources (Esan et al., 2026a; Esan et al., 2026b; Khalil et al., 2026; Liu et al., 2026). This approach is particularly beneficial for aggregated virtual power plants and multi-microgrid coordination, where individual microgrids interact with energy markets, dynamic pricing, and peer-to-peer trading. MARL also demonstrates superior performance in voltage stabilization, load balancing, and dynamic response, validating its potential as a cornerstone methodology for future interconnected microgrid networks. Furthermore, integration of physics-aware constraints and model predictive control within RL frameworks enhances stability and safety, particularly in specialized applications such as marine microgrids and building-integrated systems, highlighting the importance of hybrid approaches that combine AI adaptability with domain knowledge (Prusty et al., 2026; Liu et al., 2026; Gautam et al., 2026). Similarly, AI-powered battery management systems and hybrid PV/T–ORC microgrids illustrate the application of intelligent optimization for cost reduction, lifespan improvement, and operational reliability (Hoummadi et al., 2026; Liu et al., 2026). These studies collectively highlight the trend toward integrated, multi-objective frameworks that align operational efficiency, economic performance, and environmental sustainability.

Sustainability and low-carbon operation are increasingly central to ML-driven microgrid research. Approaches incorporating carbon emission flows, low-carbon economic dispatch, and carbon-aware coordination demonstrate that learning-based microgrid management can simultaneously achieve cost minimization and emission reduction (Esan & Shareef, 2026; Li et al., 2026; Qiu et al., 2026). This convergence of environmental objectives with operational optimization reflects a broader shift toward responsible and green energy systems, emphasizing the dual role of AI as both a performance enabler and a tool for sustainable energy planning. Additionally, reinforcement learning–based safe and tariff-aware energy management has been successfully implemented for EV charging networks, demonstrating that learning algorithms can incorporate market signals, safety constraints, and grid stability considerations in real-world operational settings (Hossen et al., 2026). Such applications highlight the practical relevance of ML methodologies for emerging energy systems beyond laboratory or simulation environments.

Despite these advances, several challenges remain. High data dependency, computational complexity, and convergence stability in multi-agent systems remain limiting factors, particularly for large-scale, real-time deployments (Maurya et al., 2026; Shi et al., 2026). Furthermore, explainability and interpretability of deep learning and RL models remain underexplored, raising concerns regarding trust and operational transparency. Cyber-security vulnerabilities and the need for robust adaptation under unforeseen disturbances are additional constraints that warrant further investigation (Liu et al., 2026; Ponnuru et al., 2026). Finally, the integration of heterogeneous microgrid components, diverse market mechanisms, and sustainability objectives in a unified, scalable, and adaptive framework remains an open research gap, offering a rich avenue for future work.

In summary, the reviewed studies collectively demonstrate that ML and AI frameworks—ranging from hybrid deep learning forecasting to single- and multi-agent reinforcement learning—offer unprecedented opportunities for optimized microgrid management. These methodologies have proven effective in enhancing forecasting accuracy, operational adaptability, decentralized coordination, asset longevity, and sustainability outcomes. The synthesis of these findings suggests that the future of microgrid energy management lies in integrated, multi-layered, and explainable AI-driven frameworks capable of balancing technical, economic, and environmental objectives under uncertainty.

Practical Implication

The integration of machine learning (ML) and artificial intelligence (AI) in microgrid energy management has substantial practical implications for both operators and policymakers. First, the adoption of hybrid deep learning and reinforcement learning frameworks enables microgrid operators to achieve real-time forecasting and autonomous decision-making, improving energy reliability and operational efficiency. Accurate short-term load and renewable generation forecasts allow operators to proactively schedule distributed energy resources, reduce curtailment of renewable energy, and optimize battery charge–discharge cycles, thereby minimizing operational costs and extending the lifespan of energy storage systems (Le et al., 2026; Zohaib et al., 2026; Hoummadi et al., 2026).

Second, the implementation of multi-agent reinforcement learning (MARL) architectures provides decentralized control and coordination capabilities for networked and aggregated microgrids. This approach allows multiple microgrids to interact efficiently under dynamic electricity market conditions, supporting flexible energy trading, peer-to-peer exchange, and integration with virtual power plants. MARL frameworks enhance system scalability, reduce communication overhead, and maintain global performance objectives, offering practical solutions for large-scale urban or industrial microgrid deployment (Esan et al., 2026a; Esan et al., 2026b; Khalil et al., 2026; Liu et al., 2026).

Third, hybrid AI–optimization approaches, including physics-aware model predictive control and agent-based RL, enable microgrid managers to balance technical stability, safety, and performance objectives. For example, in marine, building-integrated, and industrial microgrids, these frameworks improve voltage regulation, frequency stability, and power quality while adapting to system disturbances and cyber-resilience requirements (Prusty et al., 2026; Liu et al., 2026; Ponnuru et al., 2026). The practical implication is that operators can deploy these advanced AI-driven control strategies without requiring fully precise mathematical models, reducing implementation costs and technical complexity.

Fourth, AI-enabled energy management also supports sustainability and regulatory compliance. Carbon-aware dispatch and emission prediction models allow operators to minimize greenhouse gas emissions while maintaining cost-efficiency. These solutions are particularly valuable in jurisdictions with carbon pricing, renewable portfolio standards, or sustainability mandates, providing actionable intelligence for strategic energy planning and environmental performance monitoring (Li et al., 2026; Qiu et al., 2026; Esan & Shareef, 2026).

Fifth, real-world applications, such as tariff-aware reinforcement learning for EV charging networks, demonstrate how learning-based control can adapt to dynamic pricing and regulatory constraints while ensuring grid stability. This has direct implications for utilities, charging infrastructure providers, and smart city planners, allowing better demand-side management, peak load reduction, and integration of electric mobility into existing microgrids (Hossen et al., 2026; Muthukumar et al., 2026).

Finally, the findings indicate that AI-driven microgrid management facilitates strategic decision-making at multiple scales. Grid operators, industrial energy managers, and community energy planners can leverage these frameworks for predictive maintenance, risk assessment, resource allocation, and real-time optimization. By reducing operational inefficiencies, minimizing emissions, and enabling decentralized energy coordination, ML and AI solutions offer significant socio-economic benefits, including cost savings, energy security, and enhanced sustainability performance (Negi et al., 2026; Bharaneedharan et al., 2026; Hoummadi et al., 2026).

In essence, the practical implication of this body of research is that microgrid stakeholders can transition from reactive, rule-based operations to proactive, data-driven, and adaptive energy management strategies. This not only improves technical and economic outcomes but also aligns microgrid operations with global sustainability goals and emerging smart energy ecosystems.

Conclusion

This study synthesizes contemporary research on the application of machine learning and artificial intelligence to optimized microgrid management, demonstrating the transformative potential of data-driven approaches for modern energy systems. Hybrid deep learning frameworks enhance forecasting accuracy for load, renewable generation, and pricing, forming the foundation for proactive energy management and real-time operational decision-making. Reinforcement learning, both single-agent and multi-agent, provides adaptive control mechanisms that can manage uncertainty, optimize multi-objective dispatch, and maintain system stability in complex, stochastic microgrid environments. Multi-agent reinforcement learning frameworks further enable scalable coordination among networked microgrids and virtual power plants, ensuring global objectives while reducing communication and computational overhead. Hybrid AI–optimization approaches integrating physics-based constraints, model predictive control, and agent-based strategies enhance cyber-resilience, frequency stabilization, and power quality, while also extending the operational lifespan of critical energy assets. Sustainability-oriented methods incorporating carbon emission prediction, low-carbon dispatch, and intelligent battery management illustrate how AI-driven microgrids can simultaneously achieve environmental and economic objectives. Practical applications, including tariff-aware EV charging and industrial microgrid management, highlight the real-world feasibility of these approaches for operators, planners, and policymakers. Nonetheless, challenges such as data dependency, model interpretability, computational scalability, and integration of heterogeneous resources remain, warranting further research. Overall, the findings underscore that machine learning and artificial intelligence provide a comprehensive, adaptive, and sustainable framework for future microgrid management, positioning these technologies as essential enablers of reliable, efficient, and low-carbon energy systems.

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